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# Semantic-Aware Fact Verification using Natural Language Inference

by

Nayab Tariq

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# CERTIFICATE OF APPROVAL

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by

Nayab Tariq

(MCS241005)

### THESIS EXAMINING COMMITTEE

| S. No. | Examiner | Name | Organization |
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| (b) | Internal Examiner | Dr. Najam Aziz | CUST, Islamabad |

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Thesis Supervisor
May, 2026

Dr. M. Masroor Ahmed
Head
Dept. of Computer Science
May, 2026

Dr. M. Abdul Qadir
Dean
Faculty of Computing
May, 2026

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**(Nayab Tariq)**

# *Abstract*

Automated fact verification has become an important problem in daily life. The massive growth of digital content has made manual verification impractical, creating a strong need for automated solutions. Natural Language Processing, particularly Natural Language Inference, provides an effective computational framework for this task by enabling systems to determine whether a claim is supported, contradicted, or not verified by available evidence. However, reliable verification requires deeper semantic understanding beyond surface-level textual similarity, especially when claims involve negation, quantitative information, directional relations, or implicit meaning.

In this research, a detailed investigation was conducted to understand how different types of linguistically complex sentences affect fact verification performance. A sentence separation mechanism is designed to categorize claims into five reasoning types: negative sentences, numerical sentences, directional sentences, implicit reasoning cases, and mixed or other complex cases. Each category was analyzed independently to understand its impact on verification performance and to study the behavior of NLI models on large and diverse datasets.

To address the problem of false results produced by existing models, an empirical and system-design-based approach was adopted. Logical and symbolic reasoning techniques were integrated into the verification pipeline to enhance model decisions. Propositional logic was applied to improve negation handling, while symbolic reasoning methods were introduced for numerical and directional comparisons. The framework was implemented using state-of-the-art transformer and sequence-to-sequence models, including DeBERTa for NLI-based verification and Flan-T5 for supporting semantic interpretation and validation. These components were combined within a structured hybrid architecture to improve decision reliability in large-scale fact verification scenarios.

Experimental evaluation was conducted on benchmark datasets including FEVER and SciFact. Baseline experiments showed that transformer-based models achieved strong performance but still produced false results in linguistically complex cases.

The proposed framework achieved an accuracy of 97% on FEVER and 98% on SciFact, corresponding to relative improvements of approximately 4.3% and 7.6%, respectively, over the strongest baseline model. The improvement was particularly evident in sentences involving negation, numerical comparisons, and directional relationships, demonstrating the effectiveness of combining neural inference with symbolic reasoning.

The results of this research indicate that automated fact verification systems benefit significantly from structured reasoning mechanisms and controlled system design rather than relying solely on deep contextual embeddings. The proposed framework provides a practical and scalable approach for reducing false results in large-scale fact verification tasks and contributes toward the development of more reliable and interpretable Natural Language Processing based verification systems.

# Contents

# List of Figures

# List of Tables

# Abbreviations

| | |
|---|---|
| **AI** | Artificial Intelligence |
| **ANN** | Artificial Neural Network |
| **BERT** | Bidirectional Encoder Representations from Transformers |
| **CLS** | Classification Token |
| **CNN** | Convolutional Neural Network |
| **CSV** | Comma-Separated Values |
| **DL** | Deep Learning |
| **EMNLP** | Empirical Methods in Natural Language Processing |
| **F1** | Harmonic Mean of Precision and Recall |
| **FEVER** | Fact Extraction and Verification Dataset |
| **FN** | False Negative |
| **FOL** | First-Order Logic |
| **FP** | False Positive |
| **GPT** | Generative Pre-trained Transformer |
| **GPU** | Graphics Processing Unit |
| **HFF** | Hybrid Fact Verification Framework |
| **IR** | Information Retrieval |
| **LLM** | Large Language Model |
| **LSTM** | Long Short-Term Memory |
| **ML** | Machine Learning |
| **MNLI** | Multi-Genre Natural Language Inference |
| **NEI** | Not Enough Information |
| **NLI** | Natural Language Inference |

| | |
|---|---|
| **NLI-FV** | Natural Language Inference based Fact Verification |
| **NLP** | Natural Language Processing |
| **PL** | Propositional Logic |
| **POS** | Part of Speech |
| **QA** | Question Answering |
| **RAM** | Random Access Memory |
| **RNN** | Recurrent Neural Network |
| **RoBERTa** | Robustly Optimized BERT Approach |
| **SciFact** | Scientific Fact Verification Dataset |
| **SNLI** | Stanford Natural Language Inference |
| **SSD** | Solid State Drive |
| **TF-IDF** | Term Frequency–Inverse Document Frequency |
| **TN** | True Negative |
| **TP** | True Positive |
| **ViT** | Vision Transformer |

# Symbols

| | |
|---|---|
| $Acc$ | Accuracy of the model |
| $C$ | Claim (Hypothesis) |
| $D$ | Dataset |
| $d_k$ | Dimension of key vectors in attention mechanism |
| $E$ | Evidence (Premise) |
| $e_i$ | Embedding vector of token $i$ |
| $F1$ | F1-score |
| $f(\cdot)$ | Model inference function |
| $h_i$ | Hidden representation at layer $i$ |
| $L$ | Loss function |
| $\mathcal{L}_{CE}$ | Cross-entropy loss |
| $N$ | Total number of samples |
| $N_{dir}$ | Number of directional reasoning errors |
| $N_{err}$ | Number of erroneous predictions |
| $N_{imp}$ | Number of implicit reasoning errors |
| $N_{neg}$ | Number of negation-related errors |
| $N_{num}$ | Number of numerical reasoning errors |
| $N_{soi}$ | Number of subject–object inversion errors |
| $P(y\|C, E)$ | Probability of label $y$ given claim and evidence |
| $PE_i$ | Positional embedding at position $i$ |
| $Prec$ | Precision |
| $Q, K, V$ | Query, Key, and Value matrices in attention mechanism |
| $Rec$ | Recall |

| | |
|---|---|
| $S$ | Sentence representation vector |
| $T$ | Token sequence length |
| $W_Q, W_K, W_V$ | Projection matrices for Query, Key, and Value |
| $x_i$ | Input token at position $i$ |
| $y$ | Predicted label |
| $\hat{y}$ | Model predicted label |
| $y^*$ | Ground truth label |
| $z_i$ | Logit value for class $i$ |
| $\alpha$ | Fusion or weighting parameter |
| $\beta$ | Confidence calibration parameter |
| $\gamma$ | Fusion weight parameter |
| $\Delta$ | Performance difference between models |
| $\wedge$ | Logical AND |
| $\vee$ | Logical OR |
| $\neg$ | Logical negation |
| $\Rightarrow$ | Logical implication |
| $\theta$ | Model parameters |

# Chapter 1

# Introduction

## 1.1 Background and Motivation

We live in a paradox: where digital ecosystem delivers a firehose of information. The proliferation of information through online platforms has fundamentally transformed how societies access, process, and interpret information [1]. The rapid growth of digital repositories, online news, scientific archives, and social media platforms has resulted in an unprecedented volume of textual data being generated and consumed on a daily basis as Figure 1.1.

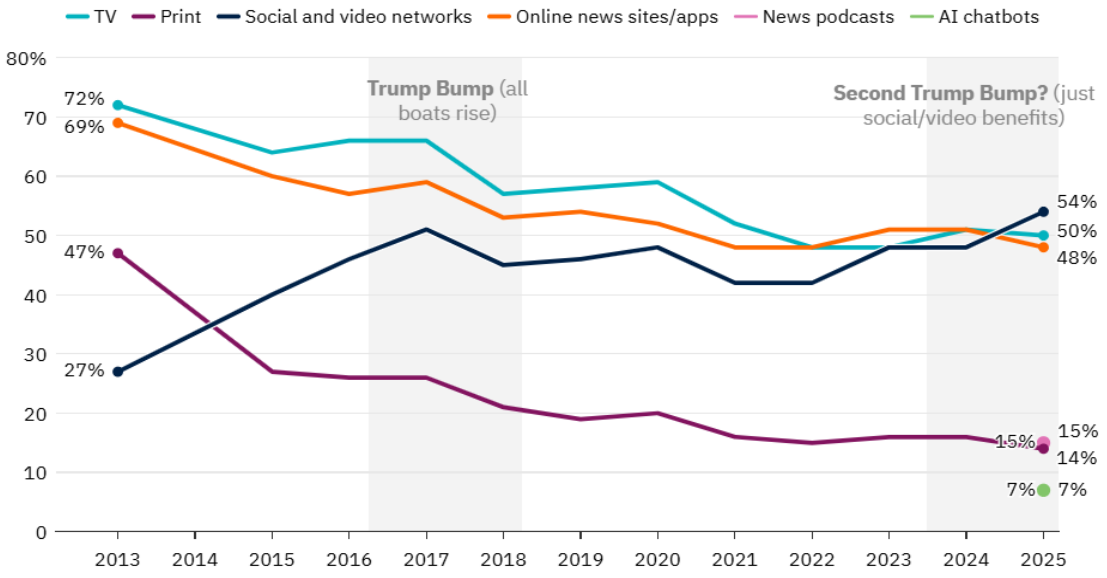


FIGURE 1.1: Proportion for Sources of News (2013-2025) [1]

This transformation leads to serious challenges in assessing the factual correctness and reliability of information e.g as per World Economic Forum's Global Risks Perception Survey (2024–2025) [1], where false information emerge as a highly influential and interconnected threat.

Traditional approaches to verifying factual statements have relied primarily on manual fact-checking conducted by domain experts. Although manual verification provides high-quality judgments, it is inherently time-consuming, resource-intensive, and difficult to scale to the massive volume of information generated in modern digital environments [2]. Furthermore, human verification processes may vary in interpretation due to subjective reasoning or limited access to supporting evidence, making fully manual approaches impractical for large-scale real-world applications.

These limitations have motivated the development of automated fact verification systems that employ computational techniques to evaluate the correctness of claims by analyzing textual evidence. Advances in Artificial Intelligence (AI) and, more specifically, Natural Language Processing (NLP), have enabled machines to process and reason over human language with increasing accuracy. NLP techniques are now widely used in tasks such as document classification, information retrieval, question answering, and text summarization, and they form the foundation of modern automated fact verification frameworks [3].

Automated fact verification systems typically operate through a structured pipeline consisting of claim processing, evidence retrieval, and verification. Among these components, the verification stage is particularly critical, as it requires the system to determine the semantic relationship between a claim and the corresponding evidence.

This reasoning process is commonly formulated as a Natural Language Inference (NLI) task, in which the claim is treated as a hypothesis and the retrieved evidence is treated as a premise [4]. The objective of the NLI model is to determine whether the premise entails, contradicts, or provides insufficient information with respect to the hypothesis. This formulation enables a structured evaluation of semantic

relationships between claims and evidence, facilitating more reliable verification decisions. Recent advancement in transformer based language models,including BERT, RoBERTa, and DeBERTa, have significantly improved performance on Natural Language Inference (NLI) benchmarks. These models learn deep contextual representations of text and are capable of capturing complex linguistic dependencies, making them highly effective for semantic understanding tasks. Consequently, NLI-based architectures have become a central component of modern fact verification systems [4].

Despite these advancements, empirical studies have demonstrated that state-of-the-art NLI models continue to produce systematic errors when applied to real-world verification tasks. Detailed analyses reveal that performance degrades in cases involving complex semantic phenomena such as negation, numerical reasoning, directional relationships, implicit reasoning, and intricate semantic dependencies. These cases often require deeper reasoning capabilities and logical consistency checks that are not explicitly modeled in conventional neural architectures [5].

This gap between the representational strength of neural language models and the reasoning requirements of real-world fact verification tasks motivates the need for approaches that combine deep semantic representations with reasoning mechanisms. A systematic empirical investigation of the types of errors produced by modern NLI models is therefore essential for designing more robust fact verification architectures. Motivated by these challenges, this thesis conducts a detailed empirical analysis of state-of-the-art NLI-based fact verification systems to identify major sources of semantic reasoning errors. Based on the findings of this analysis, a fact verification framework is proposed that integrates neural inference with logical preprocessing and symbolic reasoning mechanisms to improve robustness in complex verification scenarios. Furthermore, addressing these limitations is critical for enhancing the reliability and trustworthiness of automated fact verification systems in practical applications. The integration of structured reasoning mechanisms provides a pathway to bridge the gap between statistical learning and logical inference. Such an approach enables more consistent handle-semantically complex cases that are often misinterpreted by purely neural models. This research aims to

develop hybrid fact verification systems by combining neural models with symbolic reasoning to improve reliability. By addressing key error categories, the proposed approach enhances interpretability and robustness in real-world verification tasks.

## 1.2 Automated Fact Verification

Automated fact verification refers to the use of computational methods to automatically assess the truthfulness of a given claim by comparing it with available information. Due to the rapid growth of online content, manual fact-checking by human experts has become increasingly impractical [5]. As a result, automated systems based on Natural Language Processing (NLP) and machine learning have emerged as scalable solutions to support the detection of misinformation and disinformation [6]. Most automated fact verification systems operate using a structured pipeline, as illustrated in Figure 1.2.

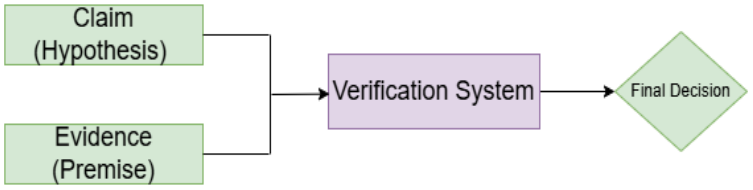


FIGURE 1.2: Automated Fact Verification System

The process begins with a claim provided as input to the system. Relevant evidence is then retrieved from trusted sources such as news articles, encyclopedic databases, or web documents. Finally, the system evaluates the relationship between the claim and the retrieved evidence to determine whether the claim is supported, contradicted, or cannot be verified [7]. This pipeline-based architecture forms the foundation of most modern fact-checking frameworks. It provides a high-level overview of how automated fact verification systems function. It highlights the sequential nature of the verification process and shows how a claim is transformed into a final verification decision through evidence retrieval and reasoning. Early automated fact verification approaches relied heavily on shallow techniques such as keyword matching and surface-level text similarity [8]. These methodscompared

claims and evidence based on overlapping words or basic statistical measures. While effective for simple and explicitly stated claims, these approaches performed poorly when claims were paraphrased or expressed indirectly. To overcome these limitations, machine learning and deep learning models were introduced to learn contextual representations of text.

Shallow methods focus on word overlap, whereas semantic methods aim to capture meaning and contextual relationships between sentences. Although semantic models improved performance, many still rely on statistical patterns rather than genuine reasoning, limiting their robustness in complex scenarios [9]. Contrasts traditional shallow verification techniques with more advanced semantic-based approaches. It visually emphasizes why surface-level methods fail when language becomes complex and why deeper understanding is necessary for reliable fact verification [10].

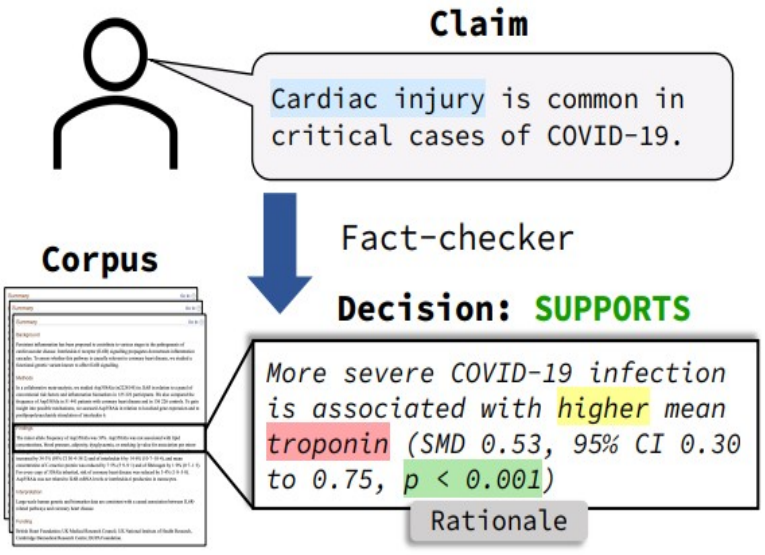


FIGURE 1.3: NLI Fact Verification System

In recent years, Natural Language Inference (NLI) has become a core component of modern fact verification systems. NLI formulates verification as a reasoning task in which the retrieved evidence is treated as a premise and the claim is treated as a hypothesis [11]. The system as shown in Figure 1.3, predicts whether the premise supports, refutes or is neutral with respect to the hypothesis. This allows models to reason about meaning rather than relying solely on word similarity.

The role of NLI in automated fact verification, where the relationship between claims and evidence is explicitly modeled. By framing verification as an inference task, NLI-based systems provide a more structured and interpretable approach to decision-making, particularly in cases involving implicit meaning, negation, and directional reasoning [11].

Despite these advancements, existing automated fact verification systems still face challenges when applied to real-world data. Linguistic complexity, such as implicit expressions, negation, paraphrasing, and entangled concepts, continues to hinder performance. These limitations motivate further research into linguistically and logically aware verification frameworks, particularly those grounded in Natural Language Inference, which forms the basis of this thesis.

## 1.3 Role of Deep Semantic Reasoning in Automated Fact Verification

Semantic reasoning in natural language can be broadly divided into two levels: *surface-level semantics* and *deep-level semantics*. Both play an important role in automated fact verification, but they differ significantly in the type of information they capture and the reasoning capabilities they enable.

Surface-level semantics refers to meaning derived from lexical overlap, syntactic structure, and shallow contextual relationships between words and phrases [12]. Most early fact verification and text classification systems relied heavily on surface-level semantic signals such as keyword matching, n-gram similarity, and statistical correlations between claims and evidence. While these approaches are effective when claims and evidence share similar vocabulary or explicit phrasing, they often fail when meaning is expressed indirectly, paraphrased, or logically transformed. For example, sentences that differ only by negation or directional change may appear similar at the surface level but convey opposite meanings [13]. In contrast, deep-level semantics refers to the underlying meaning structures that govern logical relationships, causal dependencies, semantic polarity, numerical relations, and

implicit inference. In this study, deep semantic reasoning is examined vide five major categories of reasoning challenges; observed in fact verification tasks:

i. Negation Reasoning: Negation reasoning involves interpreting polarity changes introduced by words such as *not*, *never*, or *no*. Models must correctly determine whether evidence confirms or contradicts a negated claim.

   Example:
   *Claim:* Puerto Rico is not an unincorporated territory of the United States.
   *Evidence:* Puerto Rico, officially the Commonwealth of Puerto Rico, is an unincorporated territory of the United States located in the northeast Caribbean Sea.

ii. Numerical Reasoning: Numerical reasoning requires understanding quantities, counts, and comparisons. Verification depends on correctly interpreting numbers and their semantic meaning rather than relying on lexical similarity.

   Example:
   *Claim:* Andy Roddick lost 5 Master Series between 2002 and 2010.
   *Evidence:* Roddick won five Masters Series in that period.

iii. Directional Reasoning: Directional reasoning involves interpreting relational terms such as *increase*, *decrease*, *higher*, or *lower*. Errors often occur when models fail to detect opposite directional relationships. This type of reasoning requires the model to correctly capture semantic direction and maintain consistency between comparative statements. Failure to model such directional cues can lead to incorrect inference, even when the underlying numerical or contextual information is accurately represented.

   Example:
   *Claim:* Stroke patients with prior use of direct oral anticoagulants have a lower risk of in-hospital mortality than stroke patients with prior use of warfarin.
   *Evidence:* Clinical studies report that patients treated with direct oral anticoagulants exhibited reduced in-hospital mortality rates compared with patients receiving warfarin therapy.

iv. Implicit Reasoning: Implicit reasoning refers to situations where the conclusion is not explicitly stated but must be inferred from general knowledge, definitions, or contextual meaning.

Example 1:
*Claim:* Ryan Seacrest is a person.
*Evidence:* Ryan John Seacrest is an American radio personality, television host, and producer.

Example 2:
*Claim:* A cardiologist is a medical doctor.
*Evidence:* A cardiologist is a physician specializing in diseases of the heart.

v. Mixed Semantic Problems (Numerical + Directional): Mixed problems involve multiple semantic phenomena simultaneously, such as numerical values combined with directional change, which increases reasoning complexity.

Example:
*Claim:* Incidence of heart failure decreased by 10% in women since 1979.
*Evidence:* Epidemiological data indicate that the incidence rate of heart failure in women declined by approximately ten percent over the period following 1979.

Deep semantics captures how meaning is constructed beyond the literal arrangement of words, allowing reasoning about contradiction, entailment, and neutrality in a manner closer to human interpretation [12]. Real-world fact verification frequently requires deep semantic understanding, particularly in cases involving negation scope, quantitative comparisons, directional relations, or implicit reasoning [14].

Natural Language Inference (NLI) has emerged as a key paradigm for addressing deep semantic understanding in automated fact verification. By formulating verification as a reasoning task between a premise and a hypothesis, NLI models attempt to capture semantic relationships rather than relying solely on surface-level similarity. Transformer-based architectures such as BERT, RoBERTa, and DeBERTa learn contextual embeddings that encode syntactic and semantic dependencies

across entire sentences, enabling improved handling of paraphrasing, contextual variation, and semantic alignment [12, 13, 15]. Despite these advances,current NLI models still face limitations in capturing deep-level semantics reliably. Although contextual embeddings represent semantic information in high-dimensional vector spaces, they do not explicitly encode logical constraints such as polarity consistency, directional reasoning, or inference validity. As a result, subtle semantic shifts may lead to incorrect entailment or contradiction predictions, particularly in cases involving negation, numerical reasoning, or implicit relations [15].

Another limitation arises from the independent treatment of premise–hypothesis pairs in standard NLI formulations. Many real-world verification scenarios require multi-hop or compositional reasoning, where conclusions depend on combining multiple pieces of evidence or resolving implicit relationships across sentences. Neural models often struggle to perform such structured reasoning, as they primarily learn statistical associations rather than explicit inference rules [16].

Furthermore, neural NLI models operate largely as black-box classifiers, providing limited interpretability and little control over the reasoning process. Prediction confidence does not always reflect semantic correctness, especially when evidence is incomplete or ambiguous. This lack of explicit inference control reduces reliability in high-stakes fact verification applications [15, 16].

These limitations reveal a gap between the representational strength of modern NLI models and the reasoning requirements of real-world fact verification. While NLI provides a strong foundation for modeling deep semantic relationships, it does not fully address logical consistency, symbolic reasoning, or structured inference.

To bridge this gap, recent research has explored architectures [14, 16] that integrate neural semantic representations with explicit reasoning mechanisms. In such systems, neural models such as DeBERTa are used to extract rich contextual features from claims and evidence, while dedicated reasoning modules perform controlled semantic operations such as negation handling, numerical comparison, and logical inference [15]. Motivated by these observations, this thesis investigates a fact verification framework designed to enhance robustness against deep

semantic reasoning errors while preserving the expressive power of state-of-the-art NLI models. The proposed framework combines transformer-based inference with structured preprocessingtechniques to systematically address common semantic error categories. This hybrid approach aims to improve both prediction accuracy and interpretability in complex fact verification scenarios.

## 1.4 Natural Language Processing and Natural Language Inference in Automated Fact Verification

Artificial Intelligence (AI) has enabled machines to perform increasingly complex cognitive tasks, including perception, reasoning, and decision-making. Within AI, Natural Language Processing (NLP) focuses on enabling machines to understand, interpret, and manipulate human language. NLP techniques form the foundation of modern information systems such as search engines, question answering systems, dialogue agents, and automated fact-checking frameworks [12]. As misinformation predominantly spreads through textual content, NLP has become central to addressing the challenges posed by false and misleading information [6].

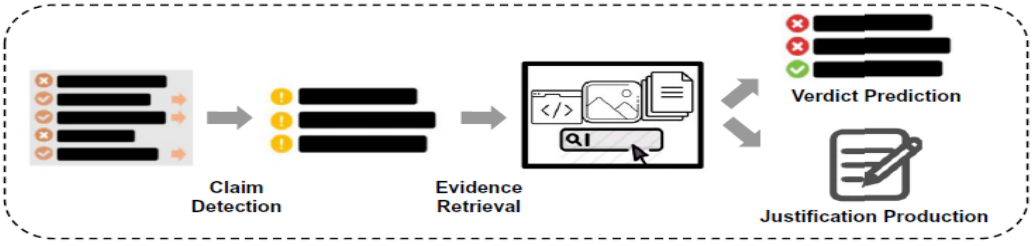


FIGURE 1.4: NLP Framework for Automated Fact Checking [12]

Figure 1.4 presents a generic NLP-based automated fact-checking framework, illustrating the core stages involved in verifying a claim. The process begins with claim detection, where input text is analyzed to identify check-worthy factual statements [12]. This is followed by evidence retrieval, in which relevant documents or passages are collected from trusted sources such as news outlets, encyclopedic databases, or

the web. The retrieved evidence is then processed by a verification component to produce a verdict prediction, classifying the claim as supported, refuted, or unverifiable. In more advanced systems, a justification production stage is included to generate explanations justify the predicted verdict, enhancing transparency and user trust.

This framework highlights that automated fact-checking is not a single-step classification problem, but rather a multi-stage NLP pipeline requiring both language understanding and reasoning [12]. Early implementations of such pipelines relied heavily on shallow NLP techniques, including keyword matching, bag-of-words representations, and surface-level semantic similarity. While effective for simple and explicitly stated claims, these approaches fail when misinformation is expressed through paraphrasing, implicit meaning, negation, or complex logical constructions. As a result, verification accuracy degrades significantly in real-world scenarios.

To overcome these limitations, modern fact verification systems increasingly rely on Natural Language Inference (NLI) as a core reasoning component within the NLP pipeline. NLI is a task that focuses on determining the semantic relationship between two pieces of text: a premise and a hypothesis [11]. The goal is to classify this relationship as entailment, contradiction, or neutral. In automated fact verification, the retrieved evidence naturally serves as the premise, while the claim functions as the hypothesis. By modeling verification as an inference problem, NLI enables systems to reason about meaning rather than relying on surface-level similarity [12].

The integration of NLI into the verification stage of the fact-checking framework shown in Figure 1.5 transforms claim verification into a structured reasoning task. NLI-based systems are capable of identifying meaning shifts caused by negation, preserving directional relationships such as increase or decrease, and reasoning implicit or indirectly stated information. This makes NLI particularly well-suited for addressing the linguistic and logical complexity inherent in modern misinformation [12]. One of the most critical reasoning-oriented NLP tasks is Natural Language Inference (NLI), also known as Recognizing Textual Entailment (RTE).

NLI is concerned with determining whether a given statement (hypothesis) can be logically inferred from another statement (premise). This reasoning capability closely mirrors the cognitive process employed by human fact-checkers, making NLI a natural and powerful foundation for automated fact verification systems [13].

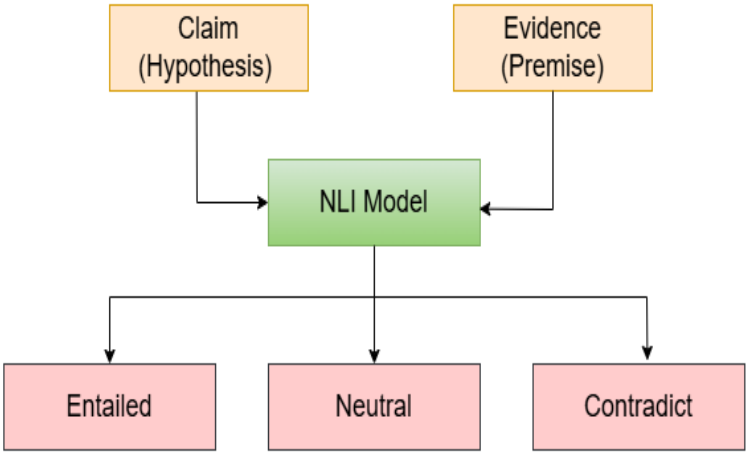


FIGURE 1.5: NLI Fact Verification

In the context of automated fact-checking, NLP provides the mechanisms for claim detection, evidence retrieval, and text representation, while NLI serves as the core reasoning engine that evaluates the semantic relationship between claims and evidence. This synergy between NLP's pipeline architecture and NLI's reasoning capability is essential for building robust fact-checking systems. By combining comprehensive information retrieval with deep semantic analysis, such systems can more effectively tackle the nuanced nature of real-world claims. Consequently, recent research has focused heavily on developing and refining NLI models specifically for this verification stage. The performance of the overall fact-checking framework is therefore fundamentally dependent on the accuracy and robustness of its underlying NLI component.

This highlights the central role of NLI in ensuring logical consistency and semantic correctness within the verification pipeline. Improvements in NLI performance directly translate into more reliable and accurate fact verification outcomes in real-world applications. Effectiveness of fact verification systems increasingly depends on the ability of NLI models to handle complex semantic phenomena beyond

surface level textual similarity. Enhancing semantic reasoning capabilities has become a major research focus.

### 1.4.1 Natural Language Inference Formulation for Automated Fact Verification

Natural Language Inference (NLI) formulates automated fact verification as a three-way classification problem [11]. Given a pair of textual inputs:

i. Premise ($P$): Retrieved evidence obtained from trusted or authoritative sources.

ii. Hypothesis ($H$): The claim whose truthfulness is to be assessed.

the objective of the NLI model is to predict the semantic relationship between $P$ and $H$. Formally, the model assigns one of the following labels:-

i. Entailment: The premise logically supports the hypothesis.

ii. Contradiction: The premise contradicts or refutes the hypothesis.

iii. Neutral: The premise provides insufficient or irrelevant information.

This formulation aligns directly with the verification labels used in widely adopted fact-checking datasets such as FEVER, SciFact and LIAR. By casting fact verification as an inference task rather than a surface-level similarity matching problem, NLI-based approaches enable deeper semantic reasoning. Specifically, they allow models to handle linguistic phenomena such as negation, paraphrasing, temporal variations, and implicit meanings, which are common in real-world claims and evidence [9].

In a typical automated fact verification pipeline, the role of Natural Language Inference (NLI) is positioned *after evidence retrieval*, as illustrated in the NLP-based fact-checking framework discussed earlier. Once relevant evidence is collected from

web sources, encyclopedic databases, or news articles, the NLI module jointly analyzes the retrieved evidence and the claim to determine their semantic relationship [14].

Despite these strengths, these include the presence of noisy or conflicting evidence, the need for multi-hop and compositional reasoning, and ambiguity arising from incomplete information. Such limitations have driven research toward more powerful pretrained language models and enhanced reasoning mechanisms for reliable fact verification [15].

### 1.4.2 Natural Language Inference Models in Automated Fact Verification

Recent advances in NLI have been driven by transformer-based language models, which learn deep contextual representations of text through self-attention mechanisms. These models process entire sentences simultaneously and capture long-range dependencies, making them highly effective for semantic reasoning tasks. Among the most influential transformer-based models used for NLI are BERT, RoBERTa, and DeBERTa.

#### 1.4.2.1 Bidirectional Encoder Representations from Transformers

Bidirectional Encoder Representations from Transformers (BERT) introduced a major shift in NLP by employing a bidirectional transformer encoder that processes text by considering both left and right context simultaneously. Unlike earlier unidirectional models, BERT captures richer semantic representations by modeling how each word relates to all other words in a sentence. For NLI tasks, BERT takes a premise–hypothesis pair as input, separated by a special token, and produces a contextual representation used to predict entailment, contradiction, or neutrality [16]. BERT is pretrained using two objectives: masked language modeling, which teaches the model to predict missing words in a sentence, and next sentence prediction, which helps it learn relationships between sentence pairs [17].

The introduction of BERT significantly improved performance across a wide range of NLP benchmarks, including Natural Language Inference and question answering tasks. Its deep bidirectional contextual understanding enabled more accurate semantic interpretation compared to traditional recurrent and convolutional architectures. Consequently, BERT became the foundation for many subsequent transformer-based models used in modern fact verification systems.

#### 1.4.2.2 Robustly Optimized BERT Pretraining Approach - Fine Tuned

Robustly Optimized BERT Pretraining Approach (RoBERTa) builds upon BERT by optimizing its training strategy rather than altering its underlying architecture. It removes the next sentence prediction objective, uses larger training datasets, increases batch sizes, and trains for longer durations. These modifications result in stronger contextual representations and improved generalization across downstream tasks, including NLI [18]. As a result, RoBERTa demonstrates superior performance on benchmark datasets compared to the original BERT model. Its enhanced training strategy enables more effective capture of contextual dependencies in complex sentence structures.

#### 1.4.2.3 Decoding-Enhanced BERT with Disentangled Attention

Decoding-Enhanced BERT with Disentangled Attention (DeBERTa) introduces architectural innovations designed specifically to improve language understanding and reasoning. Its key contribution is disentangled attention, which separates content information from positional information when computing attention scores. This allows the model to more precisely capture relationships between words, independent of their positions in a sentence [19].

Additionally, DeBERTa incorporates an enhanced decoding mechanism that help strengthens the model's ability to distinguish fine-grained semantic relationships. These features make DeBERTa particularly effective for NLI tasks that require directional reasoning, such as distinguishing between cause and effect or identifying subtle contradictions. As a result, DeBERTa consistently outperforms both BERT

and RoBERTa on NLI benchmarks, making it highly suitable for fact verification tasks involving complex linguistic and logical structures [19].

## 1.5 Limitations of Natural Language Inference Based Fact Verification Systems

Natural Language Inference (NLI) models like BERT, RoBERTa, and DeBERTa, their effectiveness in real-world fact verification remains limited. While these models achieve high overall accuracy on benchmark datasets, their performance does not consistently translate to real-world scenarios. Detailed analyses indicate that many incorrect predictions are not due to random noise or data sparsity, but instead result from systematic semantic shortcomings [20].

One key limitation lies in the handling of negation and semantic polarity. NLI models frequently misinterpret the scope of negation, particularly when negation is implicit or distributed across clauses. As a result, claims that are semantically contradicted by evidence may be incorrectly classified as entailed. Similarly, directional relationships, such as increases versus decreases or cause versus effect, are often inadequately captured by sentence-level embeddings [21], leading to erroneous inference decisions.

Many factual claims require multi-step reasoning across multiple pieces of evidence or rely on background knowledge that is not explicitly stated in the text. While NLI models encode contextual information implicitly, they lack mechanisms for explicitly modeling dependency chains or enforcing logical consistency across inferred relations. Consequently, such models tend to rely on surface-level semantic correlations rather than structured reasoning [20].

Additionally, paraphrasing and semantic equivalence pose persistent challenges. Although pretrained language models are robust to lexical variation, they may still fail to recognize semantically equivalent statements when the equivalence complex syntactic restructuring or abstract conceptual alignment [21]. Furthermore, claims

entangled or interdependent entities and attributes often confuse neural models, as the interaction between entities is not explicitly represented in the learned embeddings. These limitations indicate that while NLI-based systems provide strong semantic representations, they remain insufficient for reliable fact verification in semantically complex scenarios. This motivates the need for approaches that move beyond end-to-end neural inference and incorporate explicit semantic reasoning mechanisms. Such challenges emphasize the gap between surface-level language understanding and deeper logical reasoning required for accurate inference.

Overall, these limitations demonstrate that current NLI models are primarily optimized for pattern recognition rather than structured logical inference. As a result, their reliability decreases significantly in cases involving complex reasoning chains or ambiguous semantic structures. This highlights the necessity of integrating explicit reasoning modules to complement neural representations. Addressing these gaps is essential for building more trustworthy and robust fact verification systems, therefore, hybrid approaches that combine neural inference with symbolic or rule-based reasoning.

## 1.6 Introduction to the Problem

Automated fact verification has advanced significantly with the adoption of transformer based Natural Language Inference (NLI) models. These models are capable of learning contextual representations of text and performing semantic matching between claims and evidence. Despite their strong performance on benchmark datasets, several studies have reported that such systems still produce incorrect predictions when confronted with linguistically complex or semantically subtle cases.

A critical challenge arises from the nature of real-world language, which often contains implicit meanings, negation structures, directional expressions, and numerical relationships. These linguistic phenomena require reasoning that goes beyond surface-level semantic similarity. For example, two sentences may share identical

vocabulary yet convey opposite meanings due to a negation term or a reversal in directional relationships. Similarly, claims involving quantitative comparisons or implicit causal relations often require structured reasoning that current neural models do not explicitly perform.

Another difficulty lies in the distinction between surface-level semantic matching and deep semantic reasoning. Many NLI systems rely heavily on statistical correlations learned during pretraining, which can lead to correct predictions in straightforward cases but unreliable behavior in semantically complex scenarios. As a result, models may misclassify contradictions as entailments or fail to detect implicit inconsistencies between claims and evidence.

These limitations highlight a fundamental gap between the representational capabilities of modern neural language models and the reasoning requirements of reliable fact verification. Addressing this gap requires approaches that not only capture contextual meaning but also incorporate mechanisms for handling semantic polarity, logical relationships, and structured reasoning.

## 1.7 Research Objectives

i. RO1: To conduct a systematic error analysis of state-of-the-art NLI-based fact verification systems in order to identify deep semantic phenomena responsible for false predictions.

ii. RO2: To design and evaluate a hybrid fact verification architecture that enhances robustness against deep semantic reasoning errors.

## 1.8 Structure of the Thesis

This thesis is organized into seven chapters. Chapter 1 presents the introduction, including the background and motivation, an overview of automated fact verification and Natural Language Inference, the role of semantic reasoning, the problem

statement, research objectives. Chapter 2 reviews the relevant literature, covering classical and deep learning approaches for fact verification, transformer-based NLI models, error analysis studies, and hybrid reasoning methods, highlighting limitations that motivate the proposed research, problem statement and research questions. Chapter 3 presents an empirical analysis of state-of-the-art NLI models, including dataset description, experimental setup, and systematic error analysis to identify key semantic failure patterns. Chapter 4 describes the logic design of the proposed framework, detailing the reasoning mechanisms developed to address negation, numerical reasoning, directional semantics, and related deep semantic phenomena. Chapter 5 explains the implementation of the proposed architecture, including system components, integration of reasoning modules, and experimental procedures. Chapter 6 presents the results and discussion, analyzing quantitative performance, error reduction, and the effectiveness of the proposed approach. Finally, Chapter 7 concludes the thesis by summarizing the major findings, discussing contributions and limitations, and outlining directions for future research.

# Chapter 2

# Literature Review

## 2.1 Overview

This chapter presents a comprehensive and systematic review of existing research in automated fact verification and Natural Language Inference (NLI). The literature surveyed in this study is evaluated using a consistent set of benchmark parameters to ensure objective comparison and meaningful analysis. In particular, prior studies are analyzed based on five key dimensions: ***accuracy***, which reflects quantitative performance on benchmark datasets; ***dataset characteristics***, including the use of **homogeneous datasets** (single-domain, linguistically consistent corpora) and **heterogeneous datasets** (multi-domain or diverse sources); ***comprehensiveness***, referring to the extent to which approaches address different components of fact verification such as evidence retrieval, semantic inference, and reasoning; and ***complexity***, which considers the difficulty of linguistic phenomena addressed, including deep semantic reasoning, implicit inference, and multi-hop verification.

By adopting these benchmark parameters, literature review provides a structured analysis of how different approaches address semantic reasoning challenges in fact verification systems. It also helps identify research gaps in handling negation, numerical reasoning, directional relationships, and implicit inference.

## 2.2 Systematic Literature Selection

To ensure methodological rigor and reproducibility, a systematic literature review (SLR) methodology was adopted to identify, screen, and analyze relevant research in automated fact verification and Natural Language Inference (NLI). The purpose of this process was to ensure that the reviewed studies represent high-quality and relevant contributions to the field while minimizing selection bias.

### 2.2.1 Search Strategy

Relevant studies were identified through major digital libraries widely recognized in computer science and artificial intelligence research. These sources include:

i. Google Scholar

ii. IEEE Xplore

iii. ACM Digital Library

iv. SpringerLink

v. ScienceDirect

Search queries were designed to capture the intersection of fact verification, semantic reasoning, and Natural Language Inference. The primary search keywords included:

i. Fact Verification and Natural Language Inference

ii. NLI-based fact checking

iii. Semantic reasoning in fact verification

iv. Transformer-based verification models

v. Entailment and contradiction errors in NLI

vi. Hybrid reasoning for fact verification

### 2.2.2 Inclusion Criteria

Studies were included in the review if they satisfied the following criteria:

i. Peer-reviewed journal or conference publications

ii. Published between 2015 and 2026

iii. Focus on fact verification, NLI, or semantic reasoning

iv. Empirical evaluation on benchmark datasets

v. Report quantitative performance metrics

### 2.2.3 Exclusion Criteria

The following types of studies were excluded:

i. Opinion articles or survey summaries without experiments

ii. Studies lacking experimental validation

iii. Purely social-network or propagation-based detection approaches without semantic analysis

### 2.2.4 Study Selection Process

The study selection process followed a structured multi-stage filtering approach to ensure the inclusion of high-quality and relevant literature. Initially, approximately 80–85 research papers were identified through systematic searches across multiple academic databases. In the first screening stage, duplicate records and clearly irrelevant studies were removed based on titles and abstracts. After this initial filtering, around 60–70 papers were shortlisted for full-text review. During the detailed evaluation phase, each study was assessed for methodological quality, relevance to fact verification, and contribution to natural language inference or

semantic reasoning. Papers that lacked empirical validation or focused only on non-semantic or purely descriptive approaches were excluded. As a result, approximately 50–55 studies were finally selected for in-depth analysis. This refined set of literature formed the foundation for the comparative analysis and discussion presented in this research.

## 2.3 Review of Main Categories of the Literature

Literature reviewed in three categories in this study.

### 2.3.1 Fact Verification Using Machine Learning

Before the widespread adoption of deep learning and transformer-based architectures, fake news detection and early fact-checking research relied predominantly on classical machine learning techniques combined with manually engineered linguistic, stylistic, and metadata-based features.

Machine Learning (ML) approaches were motivated by the observation that deceptive content often exhibits distinctive linguistic patterns, including exaggerated language, emotional tone, excessive use of adjectives, unusual syntactic constructions, and biased framing. Lexical features typically include word and character n-grams, term frequency– inverse document frequency (TF–IDF) representations, and vocabulary richness measures. Syntactic features capture sentence structure using part-of-speech (POS) tag distributions, dependency patterns, and parse tree statistics. Stylistic features measure readability indices, punctuation usage, sentence length variability, and capitalization patterns.

Pérez-Rosas et al. (2018) [22] conducted one of the most influential early studies in this direction. Using datasets consisting of news articles annotated as fake or real, the authors extracted a rich set of linguistic features, including lexical diversity, sentiment indicators, and syntactic complexity metrics. When evaluated by SVMs and Random Forest classifiers, their models achieved classification accuracies in the

range of 85%–90%, depending on the dataset and feature configuration. However, performance dropped sharply when models were evaluated on data from different domains or sources, highlighting poor generalization.

The most commonly used classifiers in early fake news detection research include Support Vector Machines (SVM), Logistic Regression, Naive Bayes, Random Forests, and Gradient Boosting Machines. These models were favored due to their interpretability, computational efficiency, and relatively low data requirements.

Studies using the LIAR dataset, which consists of short political statements labeled across multiple truthfulness categories, reported accuracies between 82% and 88% using SVM and Logistic Regression models with engineered features [22]. On datasets such as ISOT, which contains longer news articles, Random Forest classifiers combined with TF–IDF features achieved accuracies exceeding 90% in some experimental settings.

Hassan et al. (2020) [23] explored optimized classical approaches by applying feature selection and hyperparameter optimization techniques such as grid search and evolutionary algorithms. Using datasets derived from online news sources, their optimized classifiers improved baseline accuracy by approximately 3–8%, reaching peak accuracies of around 92%. Despite these gains, the authors noted that optimization often led to overfitting, with limited improvements in cross-domain evaluation.

Shu et al. (2021) [24] demonstrated that incorporating social context features into classical classifiers improved fake news detection accuracy by 8–15% compared to text-only models on Twitter datasets. Graph-based features capturing information diffusion patterns were particularly effective in distinguishing fake news, which often spreads rapidly within tightly connected communities.

Despite achieving strong performance within controlled experimental settings, these classical machine learning approaches exhibit significant limitations in real-world scenarios. Their reliance on handcrafted features and surface-level patterns restricts their ability to generalize across domains and capture deeper semantic relationships. Moreover, improvements gained through optimization and additional

often come at the cost of increased model complexity and reduced robustness. These shortcomings highlight the need for more advanced approaches that can effectively model semantic meaning and reasoning beyond statistical correlations.

#### 2.3.1.1 Highlights of Machine Learning Approaches

TABLE 2.1: Highlights of Machine Learning Approaches in Fact Verification

| **Approach** | **Dataset** | **Accuracy** | **Limitation** |
|---|---|---|---|
| Linguistic feature-based fake news detection using SVM and Random Forest [22], 2018 | FakeNews datasets | 85% | Relies on surface-level linguistic cues; lacks evidence-based reasoning and cannot capture deep semantic relationships such as negation, polarity, or logical inference. |
| SVM and Logistic Regression with engineered textual features [25], 2018 | LIAR dataset | 88% | Performance highly dependent on lexical overlap and handcrafted features; poor robustness to paraphrasing and semantic variation. |
| Optimized classical ML with feature selection and hyperparameter tuning [23], 2020 | MNLI | ≈92% | Optimization improves accuracy but leads to overfitting; lacks semantic reasoning capability and fails to generalize across domains. |
| Classical classifiers enhanced with social context and metadata features [24], 2021 | Twitter datasets | 94% | Strong dependence on platform-specific metadata; unsuitable for claim-level fact verification and incapable of modeling deep semantic inference. |
| Cross-domain evaluation of classical fake news detection models [26], 2020 | SNLI | 92% | Demonstrates poor generalization and inability to handle semantic complexity or implicit reasoning required for real-world fact verification. |

#### 2.3.1.2 Limitations of Machine Learning Approaches

Despite achieving strong performance on benchmark datasets, classical fake news detection approaches suffer from fundamental conceptual and practical limitations. These limitations stem from their reliance on surface-level features deep-semantics.

As a result, they struggle to handle complex phenomena and fail to generalize effectively across diverse real-world scenarios.

First, these methods do not perform evidence-based reasoning. They classify text based on surface-level patterns rather than verifying claims against external sources. As a result, they are incapable of distinguishing between a false claim and a true claim presented in a sensational style.

Second, classical models exhibit poor robustness to paraphrasing and semantic variation. Minor rewording, synonym substitution, or syntactic restructuring can significantly degrade performance, as these models rely heavily on lexical cues rather than meaning.

Third, generalization across domains and time remains a major challenge. Oshikawa et al. (2020) [26] reported accuracy drops of 20–35% when classical models trained on political news were evaluated on health or entertainment news, demonstrating strong domain dependence.

Finally, classical approaches lack the ability to model deep semantic phenomena, such as negation scope, logical directionality, implicit relationships, and multi-step inference. These limitations directly contribute to false predictions in real-world fact verification scenarios, motivating the transition toward semantic and inference-based approaches.

### 2.3.2 Fact Verification Using Deep Learning

The limitations of ML approaches—particularly their dependence on handcrafted features and inability to capture deep semantic relationships—motivated the adoption of deep learning models for fake news detection. Deep Learning (DL) methods aim to automatically learn hierarchical representations of text, reducing reliance on manual feature engineering and enabling models to capture contextual, syntactic, and semantic information more effectively. Early deep learning approaches primarily framed fake news detection as a supervised text classification task, similar to classical methods, but replaced manually designed features with neural

representations learned directly from data. These models demonstrated substantial performance improvements on benchmark datasets, marking an important transition toward more semantically informed detection systems.

#### 2.3.2.1 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) [27] were among the first deep learning architectures applied to fake news detection. CNNs are well-suited for capturing local patterns in text, such as key phrases or short sequences of words, through convolutional filters applied over word embeddings.

Studies applying CNN-based classifiers to datasets such as LIAR [11], ISOT, and FakeNewsNet reported accuracy improvements over classical methods, typically achieving 88%–93% accuracy depending on dataset size and label granularity. Dong et al. (2020) [28] demonstrated that CNN models could effectively identify discriminative lexical patterns associated with deceptive content, particularly when combined with pretrained word embeddings such as GloVe or Word2Vec.

#### 2.3.2.2 Recurrent Neural Networks and LSTM Models

To address the inability of CNNs to model [27] long-term dependencies, researchers explored Recurrent Neural Networks (RNNs) and their variants, particularly Long Short-Term Memory (LSTM) [29] networks and Gated Recurrent Units (GRUs). These models process text sequentially and maintain internal memory states, allowing them to capture temporal and syntactic dependencies across longer sequences. LSTM-based models [29] achieved notable success on fake news detection benchmarks. On datasets such as FakeNewsNet and BuzzFeed, LSTM classifiers achieved accuracies ranging from 90% to 95%, outperforming CNNs in cases involving longer articles or complex sentence structures [28]. Hybrid CNN–LSTM architectures further improved performance by combining local feature extraction with sequential modeling, reaching peak accuracies of approximately 96% on selected datasets. Despite these improvements, RNN-based models face several challenges. Sequential processing limits scalability for long documents, and training is

computationally expensive compared to CNN-based methods. More importantly, LSTMs still primarily learn statistical correlations rather than explicit semantic reasoning with linguistic phenomena such as negation scope, logical directionality, and implicit contradictions—key failure modes identified in your RO1 and RQ1.

#### 2.3.2.3 Attention-Based Neural Models

The introduction of attention mechanisms marked a significant advancement in deep learning-based fake news detection. Attention allows models to focus selectively on the most informative parts of the input text, improving interpretability and performance.

Attention-enhanced LSTM and CNN models demonstrated consistent performance gains of 3%–6% over their non-attentive counterparts on datasets such as LIAR [11] and ISOT [30]. Attention visualizations also provided insights into which words or phrases influenced model decisions, offering limited interpretability.

The most significant breakthrough in deep learning for fake news detection came with the adoption of transformer-based architectures, particularly models such as BERT, RoBERTa, ALBERT, and ELECTRA. Transformers use self-attention mechanisms to model global contextual relationships between all tokens in a sentence, enabling richer semantic representations.

Transformer-based models consistently outperformed earlier neural architectures across benchmark datasets. Fine-tuned BERT-based models achieved accuracies of 92%–96% on datasets such as LIAR, FEVER, and FakeNewsNet [30]. RoBERTa further improved performance through optimized pretraining strategies, often surpassing BERT by 2%–4% in classification accuracy.

Domain-adapted transformers demonstrated even stronger results. Alghamdi et al. (2023) [25] reported that biomedical-domain models such as BioBERT and SciBERT achieved 94%–97% F1 scores on COVID-19 misinformation datasets, outperforming general-purpose transformers. These results highlighted the importance of domain-specific semantic knowledge in misinformation detection.

However, despite their strong performance, transformer-based models still struggle with tasks requiring explicit logical reasoning and multi-step inference. Their decisions are largely driven by learned statistical patterns rather than structured semantic understanding. This makes them vulnerable to subtle adversarial or context-dependent misinformation cases.

#### 2.3.2.4 Highlights of Deep Learning Approaches

TABLE 2.2: Highlights of Deep Learning Approaches in Fact Verification

| **Approach** | **Dataset** | **Accuracy** | **Limitation** |
|---|---|---|---|
| CNN-based fake news detection using pre-trained embeddings [28] (2020) | LIAR, ISOT | 88–93% | Captures local lexical patterns effectively but fails to model long-range dependencies and deep semantic relationships required for reliable fact verification. |
| LSTM-based sequential modeling for fake news detection [29] (2019) | FakeNewsNet, BuzzFeed | 90–95% | Learns statistical correlations but lacks explicit reasoning capability; struggles with negation scope, logical polarity, and implicit inference. |
| Hybrid CNN–LSTM architectures for misinformation detection [28] (2020) | FakeNews datasets | 96% | Improves representation learning but decisions remain pattern-based and lack interpretability and robustness to semantic variations. |
| Attention-enhanced neural networks for fake news detection [30] (2021) | LIAR, ISOT | +3–6% | Attention mechanisms often focus on surface cues rather than factual inconsistencies and do not guarantee genuine semantic reasoning. |
| BERT-based deep learning models for fact verification [30] (2019) | LIAR, FEVER | 92–96% | Sensitive to paraphrasing and negation; lacks explicit modeling of semantic polarity and logical inference required for deep semantic reasoning. |
| Domain-adapted transformers (BioBERT, SciBERT) [25] (2023) | COVID-19 datasets | 94–97% | Strong domain performance but limited generalization and still relies on implicit reasoning, making errors on complex semantic dependencies. |

Evolution of deep learning approaches in fact verification, showing progressive improvements from CNNs and LSTMs to transformer-based architectures like BERT, BioBERT, and SciBERT. Although these models achieved high accuracies across benchmark datasets, most approaches still relied heavily on statistical pattern learning and implicit semantic representations. The reviewed studies consistently indicate that deep learning models remain vulnerable to complex semantic phenomena such as negation, logical polarity, paraphrasing, and implicit reasoning.

#### 2.3.2.5 Limitations of Deep Learning Approaches

Despite their strong performance, deep learning approaches suffer from critical limitations that directly motivate this thesis.

First, most deep learning models treat fake news detection as a standalone classification task, without explicitly verifying claims against external evidence. High accuracy scores often reflect dataset-specific correlations rather than genuine factual reasoning.

Second, transformer models remain fragile under semantic perturbations. Ahmed et al. (2022) [31] demonstrated that simple paraphrasing, synonym substitution, or negation insertion can reduce model accuracy by 15%–30%, exposing shallow decision boundaries.

Third, these models exhibit limited ability to perform deep semantic reasoning, particularly in cases involving implicit meaning, multi-hop inference, and logical directionality. Even when correct evidence is implicitly encoded in the training data, models may fail to correctly infer entailment or contradiction.

Finally, generalization remains a major challenge. Models trained on static dataset perform poorly when evaluated on temporally shifted or cross-domain data, confirming that deep learning alone does not solve robustness issues in real-world fact verification. Deep learning approaches represent a critical evolution beyond classical methods, enabling automatic feature learning and improved semantic. However, their limitations reveal a fundamental gap between pattern recognition and

semantic reasoning. These shortcomings motivate the transition from detection-oriented models toward evidence-based verification frameworks grounded in Natural Language Inference (NLI). Understanding where deep learning models fail particularly with negation, paraphrasing, and implicit semantics—provides the foundation for the systematic error analysis outlined in RO1 and directly informs the design of hybrid architectures addressed in RO2.

These observations highlight the necessity of augmenting neural models with explicit reasoning capabilities to ensure more reliable inference. Bridging this gap is essential for developing systems that can handle complex, real-world verification scenarios with greater consistency. Consequently, integrating structured reasoning mechanisms becomes a key direction for advancing fact verification research.

#### 2.3.2.6 Fact Verification Using Transformer-Based NLI Models

The emergence of Natural Language Inference (NLI) as a central paradigm for fact verification marked a fundamental shift from style-based fake news detection toward evidence-driven reasoning. Unlike traditional classification approaches, NLI-based fact verification systems explicitly model the semantic relationship between a claim (hypothesis) and one or more evidence sentences (premises), categorizing this relationship as entailment, contradiction, or neutral. Transformer-based architectures have become the dominant backbone for NLI due to their strong contextual representation learning capabilities.

#### 2.3.2.7 Natural Language Inference as a Fact Verification Paradigm

Fact verification datasets such as FEVER [32], SciFact, and COVID-Fact reformulate verification as an NLI problem by pairing claims with retrieved evidence from large corpora such as Wikipedia or scientific literature. Given a claim–evidence pair, the task is to determine whether the evidence supports, refutes, or provides insufficient information regarding the claim. Early NLI models relied on feature-engineered pipelines, but transformer-based encoders now dominate due to their ability to jointly encode claims and evidence using self-attention mechanisms. This

joint encoding enables models to capture fine-grained semantic interactions across sentences, making transformers particularly suitable for fact verification.

#### 2.3.2.8 BERT-Based NLI Models

Bidirectional Encoder Representations from Transformers (BERT) [16] was among the first transformer models widely adopted for NLI-based fact verification. BERT encodes claim–evidence pairs by concatenating them with special tokens and producing contextual embeddings that are fine-tuned for NLI classification.

On the FEVER dataset, BERT-based NLI models achieved accuracy ranging from 89% to 93%, significantly outperforming CNN [27] and LSTM-based approaches [29]. Thorne et al. (2018) [33] demonstrated that integrating BERT into the FEVER pipeline improved verification performance, particularly for claims requiring lexical alignment between claim and evidence.

Despite these improvements, subsequent analyses revealed that BERT's performance often relies on surface-level lexical overlap rather than genuine semantic understanding. BERT models frequently misclassify examples involving negation, antonyms, or numerical reasoning, even when evidence clearly contradicts the claim.

#### 2.3.2.9 RoBERTa and Optimized Transformer Models - Fine Tuned

RoBERTa improved upon BERT by employing larger training corpora, dynamic masking, and removal of next-sentence prediction during pretraining. Changes resulted in more robust representations, making RoBERTa a strong baseline for NLI tasks [34].

On FEVER, RoBERTa-based NLI systems achieved 93%–95% accuracy, outperforming BERT by a margin of 2%–3%. On SciFact, which requires scientific claim verification, RoBERTa achieved an F1-score of approximately 92%, demonstrating improved handling of technical language and domain-specific evidence. However, RoBERTa still exhibits limitations in handling implicit reasoning and multi-hop

inference. Studies report that RoBERTa's predictions degrade substantially when claims require combining information across multiple evidence sentences or interpreting implicit causal relations [34].

Despite these improvements, RoBERTa's reasoning process remains largely surface-level and dependent on lexical overlap between claims and evidence. This limits its effectiveness in scenarios requiring deeper semantic understanding and logical inference beyond textual similarity.

This limitation highlights the gap between contextual representation learning and true logical reasoning in transformer-based models. Although RoBERTa captures rich semantic embeddings, it does not explicitly model inference chains or structured reasoning steps. Consequently, its predictions may remain unreliable in complex verification scenarios involving implicit or multi-hop evidence.

#### 2.3.2.10 DeBERTa Model: Disentangled Semantic Representation

Decoding-enhanced BERT with disentangled attention (DeBERTa) [35] introduced architectural innovations aimed at improving semantic modeling. By disentangling content and positional embeddings and enhancing attention mechanisms, DeBERTa improves token-level semantic alignment [19].

DeBERTa achieved state-of-the-art results on NLI benchmarks such as MNLI, and its application to FEVER [32] resulted in accuracy improvements up to 96%, outperforming both BERT [16] and RoBERTa [18]. Your own experimental findings align with these results, where DeBERTa achieved 96% accuracy compared to 93% with RoBERTa on FEVER [32].

Despite its superior performance, DeBERTa [35] remains fundamentally a black-box semantic matcher. While it improves representation quality, it does not explicitly model logical rules, semantic polarity, or inference chains. Error analyses show persistent failures on claims involving negation scope, temporal ordering, and directional relationships such as increases and decreases—precisely the phenomena targeted in RQ1. These findings demonstrate that improved contextual

representation alone is insufficient for achieving robust semantic reasoning in fact verification tasks. Although significantly enhances semantic alignment and contextual understanding, it still lacks explicit mechanisms for structured logical inference. This limitation motivates the exploration of hybrid architectures that combine transformer-based representations with symbolic reasoning components.

#### 2.3.2.11 Multi-Sentence and Multi-Hop NLI Models

Real-world fact verification often requires aggregating information across multiple evidence sentences. To address this, researchers proposed multi-sentence NLI models, which encode multiple premises jointly or sequentially [36].

Approaches such as hierarchical transformers and evidence aggregation networks improved FEVER [32] performance marginally, with accuracy gains of 1%–2% over single-sentence models. However, these models often rely on attention-weighted pooling rather than explicit reasoning, limiting their ability to perform genuine multi-hop inference.

Furthermore, as the number of evidence sentences increases, transformer models face scalability issues and become more susceptible to noise, leading to incorrect entailment predictions when irrelevant evidence is present [37].

#### 2.3.2.12 Highlights of Transformer Based Models

Overall, transformer-based models have significantly advanced the state of Natural Language Inference for fact verification tasks, achieving strong performance across benchmark datasets such as FEVER and SciFact. However, their improvements are primarily driven by better contextual embeddings rather than true logical reasoning capabilities. Most models still struggle with implicit inference, multi-hop reasoning, and maintaining consistency across multiple evidence sources. These limitations highlight the need for more structured reasoning frameworks that go data-driven attention mechanisms. Demonstrate that transformer-based NLI models consistently outperform earlier machine learning and deep learning approaches

in fact verification tasks. Nevertheless, persistent weaknesses in semantic reasoning indicate that high benchmark accuracy does not necessarily robust logical understanding. These findings strongly motivate the development of hybrid reasoning architectures capable of integrating contextual representation learning with explicit semantic inference mechanisms.

TABLE 2.3: Highlights of Transformer-Based NLI Models for Fact Verification

| **Approach** | **Dataset** | **Accuracy** | **Limitation** |
|---|---|---|---|
| FEVER baseline with neural inference pipeline (Thorne et al. [32], 2018) | FEVER | ∼84% | Verification accuracy strongly dependent on evidence retrieval quality; limited capability to capture deep semantic relationships and implicit reasoning. |
| BERT-based NLI for fact verification [16] (2019) | FEVER | 91% | Performance often relies on lexical overlap rather than true semantic reasoning; struggles with negation, antonyms, and numerical reasoning errors. |
| RoBERTa-based NLI models [34] (2019) | FEVER, SciFact | 93%/ 92% | Improved contextual representation but still exhibits errors in implicit reasoning, multi-hop inference, and semantic polarity handling. |
| DeBERTa with disentangled attention [35] (2021) | FEVER, MNLI | 96% | High accuracy but operates as a black-box classifier; lacks explicit logical reasoning and reliable handling of negation scope and directional semantics. |
| Hierarchical and multi-sentence NLI models [36] (2020) | FEVER | 90% | Attention-based aggregation does not guarantee genuine multi-hop reasoning; susceptible to noise and irrelevant evidence. |
| Evidence graph and aggregation-based transformers [37] (2021) | FEVER | ∼91% | Increased computational complexity and difficulty in maintaining semantic consistency across multiple evidence sentences; limited explicit inference control. |

## 2.4 Error Analysis of NLI-Based Fact Verification Systems

While transformer-based NLI models have achieved impressive performance on benchmark fact verification datasets, a growing body of research demonstrates that these gains mask systematic semantic failures. Error analysis has emerged as a crucial tool for understanding why state-of-the-art models produce incorrect entailment and contradiction predictions, particularly under real-world conditions where claims exhibit complex semantic structures. This section synthesizes findings from prior studies to identify recurring deep semantic phenomena that challenge existing NLI-based fact verification systems.

### 2.4.1 Motivation for Error Analysis in Fact Verification

Accuracy metrics alone are insufficient to assess the reliability of fact verification systems. High aggregate scores often obscure consistent failure patterns, especially on semantically complex claims. Several studies argue that without fine-grained error analysis, models risk overfitting to dataset artifacts rather than learning genuine reasoning capabilities [38] [39].

### 2.4.2 Negation and Semantic Polarity Errors

Negation handling remains one of the most prominent sources of error in NLI-based fact verification. Transformer models often fail to correctly interpret negation scope, leading to incorrect entailment predictions when claims and evidence differ only by negation markers. For example, in FEVER-based evaluations, RoBERTa and DeBERTa models have been shown to misclassify claims such as "The law was not passed" as entailed by evidence stating "The law was passed", particularly when negation appears far from the main predicate. Glockner et al. (2018) [40] demonstrated that even minor lexical insertions of negation significantly degrade NLI performance.

These findings indicate that current models lack explicit mechanisms for semantic polarity tracking, relying instead on contextual co-occurrence patterns learned during pretraining.

### 2.4.3 Directionality and Quantitative Reasoning Errors

Another frequent failure mode involves directional semantics, including increases, decreases, comparisons, and numerical changes. Claims involving phrases such as "increased by", "reduced to", or "higher than" are often incorrectly classified when the directionality contradicts the evidence [41].

Studies on FEVER and SciFact report that transformer-based NLI models achieve high accuracy on lexical paraphrases but perform poorly on claims requiring relational direction reasoning. For instance, a claim stating "Unemployment decreased after 2020" may be incorrectly entailed by evidence stating "Unemployment increased after 2020", due to strong topical overlap [42].

This limitation reflects an absence of explicit relational modeling in standard transformer architectures.

### 2.4.4 Implicit Meaning and Pragmatic Inference Errors

Implicit semantics—where meaning is not explicitly stated—pose a significant challenge for NLI models [43]. Claims often rely on commonsense knowledge, pragmatic inference, or background assumptions that are not directly encoded in the evidence text. Error analyses reveal that NLI systems frequently fail on claims requiring inference beyond surface-level lexical alignment. For example, a claim such as "The policy failed to reduce emissions" may require reasoning over multiple evidence sentences describing outcomes indirectly [44]. Transformer models tend to classify such cases as neutral rather than contradiction or entailment.

This weakness is especially evident in datasets like SciFact, where scientific claims often imply causal relationships rather than stating them explicitly [45].

### 2.4.5 Multi-Hop and Evidence Aggregation Failures

Many real-world fact verification scenarios require multi-hop reasoning, where conclusions can only be drawn by combining information across multiple evidence sentences [46]. Despite architectural extensions such as hierarchical attention and evidence pooling, error analyses show that transformer-based NLI models struggle to reliably integrate multiple premises [47].

In FEVER, multi-evidence claims consistently exhibit lower accuracy than single-evidence claims, with performance drops of 5–10% reported across models. Errors often occur when evidence sentences are individually insufficient but jointly decisive, highlighting the lack of structured inference mechanisms [48].

These findings suggest that attention-based aggregation alone is insufficient for genuine multi-step reasoning.

### 2.4.6 Paraphrasing and Semantic Equivalence Errors

Paraphrase robustness is another critical challenge. Although transformer models are trained on large paraphrase-rich corpora, they still exhibit sensitivity to semantic rewordings that preserve meaning but alter lexical structure [49].

McCoy et al. (2019) [39] demonstrated that NLI models often rely on heuristic shortcuts, such as lexical overlap or hypothesis length, leading to incorrect predictions when claims are paraphrased. In fact verification settings, this results in false contradictions or neutral classifications for semantically equivalent statements [37].

Such errors undermine system reliability, especially in adversarial or noisy environments where claims are deliberately rephrased.

### 2.4.7 Dataset Bias and Annotation Artifacts

Error analysis has also revealed that many NLI-based fact verification systems exploit dataset-specific biases rather than learning generalizable reasoning patterns.

In FEVER, certain lexical cues strongly correlate with entailment or contradiction labels, enabling models to achieve high accuracy without deep understanding [47].

Gururangan et al. (2018) [38] showed that hypothesis-only baselines perform surprisingly well on NLI tasks, raising concerns about annotation artifacts. These biases limit the external validity of trained models and partially explain performance degradation in real-world deployments [48].

## 2.5 Research Gap and Motivation

The literature reviewed in this chapter demonstrates substantial progress in automated fact verification, particularly through the adoption of transformer-based Natural Language Inference (NLI) models such as BERT, RoBERTa, and DeBERTa. These models have significantly improved verification accuracy on benchmark datasets by learning rich contextual representations and framing fact verification as a semantic inference task. However, despite these advancements, consistent evidence across multiple studies reveals that current NLI-based systems remain fragile when confronted with real-world linguistic complexity.

A recurring limitation identified in prior work is the inability of existing models to reliably handle deep semantic phenomena. Empirical evaluations show that performance degrades sharply on claims involving negation, implicit or indirect reasoning, directional relationships (e.g., increases or decreases), and complex semantic dependencies across entities and clauses. Although models such as DeBERTa outperform earlier architectures, their improvements largely stem from enhanced representation learning rather than genuine semantic reasoning. Consequently, these systems often produce confident but incorrect entailment or contradiction predictions, indicating that semantic polarity and logical consistency are not explicitly modeled.

Furthermore, much of the existing research emphasizes overall accuracy metrics while providing limited systematic analysis of why errors occur. Error analyses are typically anecdotal or dataset-specific, lacking a structured categorization

of semantic failure modes. As a result, it remains unclear which deep semantic phenomena most frequently contribute to false predictions and how these errors manifest across different verification scenarios. This gap limits the ability to design targeted solutions that directly address the root causes of verification failures.

Another critical gap lies in the architectural design of fact verification systems. Most state-of-the-art approaches rely on end-to-end neural inference, implicitly assuming that deep semantic understanding will emerge from large-scale pretraining. However, evidence from recent studies suggests that purely representation-based models struggle to encode semantic polarity, logical directionality, and relational consistency in a reliable manner. While retrieval-augmented and knowledge-enhanced methods improve evidence availability, they do not explicitly reason over semantic inconsistencies once evidence is retrieved. Similarly, NLI-based verification modules often operate as black-box classifiers without incorporating explicit mechanisms to resolve semantic conflicts or enforce logical coherence.

These limitations collectively highlight the need for a shift from purely implicit inference toward hybrid verification frameworks that integrate deep semantic representations with explicit inference mechanisms. Such architectures offer the potential to preserve the strengths of transformer-based models while compensating for their weaknesses through structured semantic analysis and reasoning. Motivated by these gaps, this thesis first conducts a systematic error analysis of state-of-the-art NLI-based fact verification systems to identify the deep semantic phenomena responsible for false predictions. Building upon these insights, it then proposes and evaluates a hybrid fact verification architecture designed to improve robustness against deep semantic reasoning errors in real-world settings.

These challenges indicate that improving model accuracy alone is insufficient without understanding the underlying reasoning failures. A deeper investigation into semantic error patterns is therefore essential to guide the design of more reliable verification systems. This motivates the integration of explicit reasoning modules with neural inference to bridge the existing gap between statistical learning / logical understanding. It emphasizes the importance of combining semantic representation learning with structured reasoning capabilities.

## 2.6 Problem Statement

State-of-the-art NLI-based fact verification systems still make frequent entailment and contradiction errors on real-world claims. Empirical evidence shows that performance drops sharply on linguistically difficult cases such as negation, implicit reasoning, directional relations, and complex semantic dependencies. These failures indicate that current models do not reliably capture semantic polarity and deep semantic relationships, motivating the need for more robust verification approaches.

## 2.7 Research Questions

i. RQ1: Which deep semantic phenomena most often cause false entailment and contradiction predictions in current NLI-based fact verification systems?

ii. RQ2: How can fact verification architecture be improved to handle semantic polarity and logical consistency more reliably in real-world settings?

# Chapter 3

# Empirical Analysis for Validation of the Research Problem

## 3.1 Overview of Empirical Analysis

Empirical evaluation plays a central role in validating research hypotheses in the field of automated fact verification. The primary objective of this chapter is to experimentally investigate the performance of state-of-the-art Natural Language Inference (NLI) models and to systematically analyze the types of semantic errors that lead to incorrect predictions. The findings of this chapter provide empirical evidence supporting the research problem that current transformer-based verification systems, despite achieving high overall accuracy, still struggle with linguistically complex cases that require deep semantic reasoning.

The empirical analysis was conducted using two widely adopted benchmark datasets, namely SciFact and FEVER. These datasets were selected because they provide structured claim-evidence pairs and standardized labels, making them suitable for evaluating NLI-based fact verification systems under controlled experimental conditions. The experimental workflow followed a structured sequence. First, claim-evidence pairs from the selected datasets were preprocessed to ensure compatibility with transformer-based architectures. Next, two state-of-the-art NLI

models, RoBERTaLarge and DeBERTa-Large, were evaluated on these datasets. RoBERTa-Large was used as a strong baseline model, while DeBERTa-Large was evaluated subsequently due to its enhanced representation learning capabilities. After obtaining predictions from both models, a detailed error analysis was performed on the incorrectly classified instances produced by the better-performing model, which was DeBERTa-Large.

It is important to emphasize that during the error analysis phase, sentences labeled as Not Enough Information (NEI) were excluded. The reason for this decision is that NEI cases lack sufficient supporting or contradicting evidence and therefore cannot reliably reflect semantic reasoning failures of the models. The analysis was therefore restricted to Supported and Refuted claims, allowing a more precise identification of linguistic phenomena responsible for incorrect predictions.

The final stage of empirical analysis involved categorizing errors into meaningful semantic categories such as negation, numerical reasoning, directional reasoning, implicit reasoning, and subject-object inversion. This categorization enabled a deeper understanding of systematic weaknesses in current NLI models and directly motivated the logic-based enhancements proposed in the subsequent chapters of this thesis.

## 3.2 Experimental and Evaluation Paradigm

The empirical evaluation follows a controlled comparative paradigm, designed to isolate model behavior under identical experimental conditions. Each model is evaluated using the same datasets, preprocessing pipeline, and evaluation metrics to ensure fairness and reproducibility.

$$y \in \{\text{Supported}, \text{Refuted}, \text{Not Enough Information}\}$$

Given a claim–evidence pair $(c, e)$, the fact verification task is formulated as a multi-class classification problem, where the objective is to predict a label.

Formally, the prediction task can be defined as:

$$\hat{y} = \arg\max_{y} \; P(y \mid c, e; \theta) \tag{3.1}$$

where:

- $c$ represents the hypothesis or claim,
- $e$ denotes the premise or supporting evidence,
- $\theta$ corresponds to the learnable parameters of the NLI model,
- $P(y \mid c, e; \theta)$ is the posterior probability distribution over the label space estimated by the model.

The experiments conducted in this study follow the standard Natural Language Inference formulation of fact verification. In this framework, each data sample consists of two textual inputs: a hypothesis and a premise. The hypothesis corresponds to a factual claim, while the premise represents an evidence sentence retrieved from a trusted source. The task of the NLI model is to determine the semantic relationship between the hypothesis and the premise.

The classification objective requires the model to assign one of three possible labels: Supported, Refuted, or Not Enough Information. A prediction of Supported indicates that the evidence entails the claim.

A prediction of Refuted indicates that the evidence contradicts the claim. The Not Enough Information label is used when the evidence provided is insufficient to verify the claim.

To evaluate model performance, standard classification metrics were used, including accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correctly classified samples over the total number of samples, while precision and recall provide insights into class-specific performance. The F1-score, which represents the harmonic mean of precision and recall, was used as a balanced performance indicator.

The accuracy metric used in this study is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.2}$$

where TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives. Each of these quantities reflects the correctness of predictions made by the model relative to ground-truth labels.

All experiments were conducted under consistent preprocessing conditions, identical training-testing splits, and standardized evaluation procedures to ensure fairness in model comparison.

## 3.3 Datasets Used for Empirical Evaluation

### 3.3.1 Overview of Selected Datasets

In NLI-based verification, datasets provide structured claim–evidence pairs along with semantic relationship labels such as entailment, contradiction, or neutral. NLI datasets used in fact verification research can broadly be categorized into homogeneous datasets and heterogeneous datasets. These datasets serve as the foundation for training, validating, and benchmarking automated verification models. The diversity and complexity of dataset construction directly influence a model's ability to generalize across real-world fact verification scenarios.

#### 3.3.1.1 Homogeneous Datasets

Homogeneous datasets are constructed from a single domain or source and typically maintain consistent linguistic style and vocabulary. Examples include:

i. SciFact dataset (scientific literature)

ii. SNLI and MNLI datasets

Such datasets are useful for controlled benchmarking but may not fully reflect real-world linguistic variability. These datasets provide a stable evaluation environment for measuring model performance under consistent linguistic conditions. However, their limited domain diversity restricts their ability to capture real-world variations in language usage.

#### 3.3.1.2 Heterogeneous Datasets

Heterogeneous datasets combine claims and evidence from multiple domains, sources, or writing styles. Examples include:

i. FEVER dataset (Wikipedia-based claims)

ii. LIAR dataset

iii. FakeNewsNet

iv. COVID-Fact datasets

These datasets provide more realistic evaluation scenarios but introduce additional complexity in modeling semantic relationships.

The datasets selected in this thesis, FEVER and SciFact, provide complementary characteristics: FEVER offers large-scale open-domain claims, while SciFact introduces domain-specific scientific reasoning challenges.

### 3.3.2 Fact Extraction and VERification Dataset

The Fact Extraction and VERification (FEVER) dataset is one of the most widely adopted benchmarks for automated fact verification. It consists of short, human-authored factual claims that must be verified using evidence retrieved from Wikipedia articles.

Each claim is annotated with one of three labels: *Supported*, *Refuted*, or *Not Enough Information (NEI)*.

TABLE 3.1: Summary of the FEVER Dataset

| **Attribute** | **Description** |
|---|---|
| Dataset Name | FEVER (Fact Extraction and VERification) |
| Domain | Wikipedia |
| Total Claims | ∼185,000 |
| Training Split | ∼145,000 |
| Validation Split | ∼20,000 |
| Test Split | ∼20,000 |
| Evidence Type | Retrieved sentences from Wikipedia |
| Labels | Supported, Refuted, Not Enough Information |
| Task Type | Claim verification using textual evidence |

Table 3.1 summarizes the key characteristics of the FEVER dataset. The large-scale nature of FEVER makes it suitable for training deep learning models, while its explicit evidence annotations enable structured reasoning between claims and supporting or contradicting sentences.

From an NLI perspective, FEVER naturally aligns with the premise–hypothesis formulation: retrieved Wikipedia sentences serve as premises, and the claim functions as the hypothesis. However, the dataset also introduces challenges such as noisy evidence retrieval, incomplete evidence sets, and cases requiring multi-sentence reasoning.

TABLE 3.2: FEVER Dataset Split

| **Split** | **Number of Claims** | **Percentage** |
|---|---|---|
| Training | ∼145,000 | ∼78% |
| Validation | ∼19,000 | ∼10% |
| Test | ∼22,000 | ∼12% |

As shown in Table 3.2, FEVER follows a conventional data split strategy, ensuring sufficient data for training while maintaining balanced validation and test sets for robust evaluation. The large training set enables transformer-based models to learn diverse semantic patterns and contextual relationships from claim–evidence pairs. Meanwhile, the validation and test sets provide a reliable basis for evaluating generalization performance and identifying semantic reasoning errors. This

balanced split structure makes FEVER one of the most widely adopted benchmark datasets for fact verification research.

Table 3.3: FEVER Labels Mapped to NLI Categories

| **FEVER Label** | **NLI Category** |
|---|---|
| Supported | Entailment |
| Refuted | Contradiction |
| Not Enough Information | Neutral |

Table 3.3 illustrates the direct correspondence between FEVER labels and standard NLI categories. This mapping enables the seamless use of pretrained NLI models for fact verification tasks without altering their core inference formulation.

This alignment between FEVER annotations and NLI labels allows researchers to directly leverage advances in natural language inference for fact verification tasks. It also facilitates transfer learning from general-purpose NLI datasets like MNLI to domain-specific verification settings like FEVER. Despite this compatibility, challenges persist due to ambiguous claims that do not clearly fall into a single NLI category. Therefore, careful handling of borderline cases remains essential to ensure reliable model evaluation and interpretation.

### 3.3.3 SciFact Dataset

The SciFact dataset is a specialized benchmark developed for scientific claim verification using evidence obtained from peer-reviewed research papers. Unlike open-domain fact verification datasets, SciFact focuses specifically on scientific literature, making the verification task more challenging due to the presence of technical vocabulary and domain-specific knowledge. The dataset contains structured claim–evidence pairs annotated with semantic labels such as Supported, Refuted, and Not Enough Information. Its relatively smaller size is compensated by the high semantic complexity of the claims and evidence sentences. Furthermore, the dataset introduces linguistically dense and conceptually complex statements that require deeper contextual understanding and reasoning. These characteristics SciFact particularly suitable for evaluating the robustness of transformer-based NLI

models in specialized domains. Consequently, SciFact has become an important benchmark for assessing semantic reasoning capabilities in scientific fact verification research.

Table 3.4: Summary of the SciFact Dataset

| **Attribute** | **Description** |
|---|---|
| Dataset Name | SciFact |
| Domain | Scientific literature |
| Total Claims | ∼1409 |
| Training Split | ∼809 |
| Validation Split | ∼300 |
| Test Split | ∼300 |
| Evidence Type | Sentences from scientific papers |
| Labels | Supported, Refuted, Not Enough Information |
| Task Type | Scientific claim verification |

Table 3.4 summarizes the SciFact dataset. Although smaller in size, SciFact poses greater reasoning challenges due to domain-specific language and the need for precise logical inference.

Table 3.5: SciFact Dataset Split

| **Split** | **Number of Claims** | **Percentage** |
|---|---|---|
| Training | ∼900 | ∼64% |
| Validation | ∼300 | ∼21% |
| Test | ∼200 | ∼15% |

Table 3.5 illustrates the data distribution used to evaluate model generalization within the scientific domain. This relatively small dataset size reflects the complexity of obtaining high-quality, expert-annotated scientific evidence.

Table 3.6: SciFact Labels Mapped to NLI Categories

| **SciFact Label** | **NLI Category** |
|---|---|
| Supported | Entailment |
| Contradicted | Contradiction |
| Neutral | Neutral |

Table 3.6 demonstrates the alignment between SciFact annotation labels and standard Natural Language Inference (NLI) categories. This mapping enables scientific

claim verification to be formulated as an NLI task involving entailment, contradiction, and neutrality prediction. By maintaining semantic consistency with the NLI framework, SciFact supports direct evaluation of transformer-based inference models. The mapping also facilitates comparison with other benchmark datasets such as FEVER and MNLI. Consequently, it enables effective cross-domain analysis of NLI-based fact verification systems.

### 3.3.4 Dataset Preprocessing to Feed into Transformer based NLI Models

Although the SciFact and FEVER datasets are widely used benchmarks for fact verification and Natural Language Inference (NLI), their raw formats are not directly compatible with transformer-based architectures such as RoBERTa-Large and DeBERTa-Large. Therefore, a systematic preprocessing pipeline was designed to ensure data consistency, model compatibility, and fair empirical evaluation across both architectures.

Each data instance in both datasets consists of a *claim* and one or more corresponding *evidence sentences*. These instances were reformulated into standardized premise–hypothesis pairs, where the evidence sentence(s) serve as the *premise* and the claim acts as the *hypothesis*, following the conventional NLI formulation.

#### 3.3.4.1 Input Pair Construction

For transformer-based NLI models, each claim–evidence pair was concatenated using special tokens according to the model-specific input schema.

$$\text{Input} = \text{[CLS]}\ P\ \text{[SEP]}\ H\ \text{[SEP]} \tag{3.3}$$

where, $P$ denotes the premise (evidence sentence) and $H$ represents the hypothesis (claim). The special tokens [CLS] and [SEP] are automatically handled by the tokenizer associated with each model. Combined sequence enables transformer

encode semantic relationships between the claim and evidence sentence. This representation is then processed through multiple self-attention layers to predict the appropriate NLI label.

#### 3.3.4.2 Tokenization and Sequence Normalization

Tokenization was performed using the respective subword tokenizers of RoBERTa-Large and DeBERTa-Large, both based on Byte-Pair Encoding (BPE). To maintain consistency across experiments, a maximum sequence length $L$ was fixed, and all sequences were either padded or truncated as follows:

$$X' = \begin{cases} \text{Pad}(X), & \text{if } |X| < L \\ \text{Truncate}(X), & \text{if } |X| > L \end{cases} \tag{3.4}$$

where $X$ denotes the original token sequence and $X'$ represents the normalized sequence fed into the model.

#### 3.3.4.3 Label Harmonization

Both datasets use three-class inference labels. However, their label representations differ at the dataset level. To ensure uniformity, labels were mapped to a common numerical space:

$$\mathcal{Y} = \{0 : \text{Supports},\ 1 : \text{Refutes},\ 2 : \text{Not Enough Information}\} \tag{3.5}$$

This mapping allows direct comparison of predictive performance across models and datasets. This harmonization step is essential for maintaining consistency in training and evaluation across heterogeneous datasets. It ensures that model outputs remain interpretable under a unified semantic framework. Consequently, it enables fair benchmarking of different transformer-based architectures under identical label semantics. However, despite this standardization, subtle differences

may still influence model behavior during training and evaluation. Therefore, careful interpretation of comparative results remains necessary to ensure valid cross-dataset analysis.

#### 3.3.4.4 Noise Removal and Sentence Filtering

To minimize confounding factors, non-informative instances such as incomplete claims, empty evidence fields, or malformed text segments were removed. Additionally, excessive whitespace, inconsistent casing, and non-ASCII characters were normalized during preprocessing.

#### 3.3.4.5 Train–Validation–Test Split Consistency

The original dataset splits provided by SciFact and FEVER were preserved to maintain benchmark comparability. No overlap between training, validation, and test sets was allowed, ensuring that all reported results reflect genuine generalization capability to avoid any potential data leakage.

## 3.4 State-of-the-Art NLI Models Evaluated

Two transformer-based NLI models were evaluated in this study: RoBERTa-Large and DeBERTa-Large. These models were selected due to their strong performance on benchmark NLI tasks and their architectural innovations that enhance contextual representation.

### 3.4.1 RoBERTa-Large

The experimental framework used for evaluating RoBERTa-Large is illustrated in Figure 3.1. The model receives two textual inputs: a claim, which serves as the hypothesis, and an evidence sentence, which serves as the premise. These inputs are first passed through a pre-processing module that performs tokenization,

padding, truncation, and label mapping. This pre-processing ensures that both inputs are formatted consistently before being fed into the transformer.

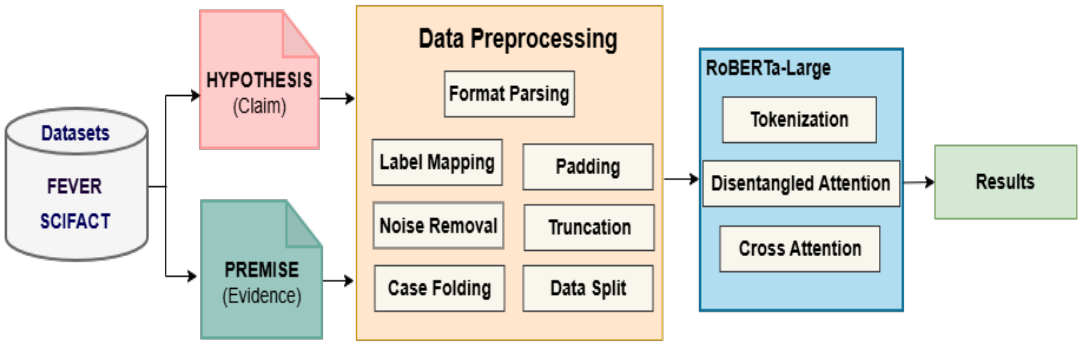


FIGURE 3.1: Evaluations Through RoBERTa-Large

RoBERTa-Large employs a multi-layer transformer encoder architecture consisting of self-attention layers and feed-forward neural networks. The self-attention mechanism enables the model to capture contextual dependencies between tokens, while the feed-forward layers transform the representations into higher-level semantic features.

During inference, the model produces a probability distribution over the possible labels, and the label with the highest probability is selected as the final prediction. The predictions are then compared with ground truth labels to compute evaluation metrics and identify incorrectly classified instances.

Despite its strong performance, RoBERTa relies primarily on statistical learning and pattern recognition. As a result, it may fail to correctly interpret sentences that require explicit logical reasoning or deep semantic analysis.

Figure 3.1 illustrates the overall RoBERTa-Large framework used in this study. The model follows a standard transformer encoder architecture composed of an embedding layer, multiple stacked self-attention encoder layers, and a task-specific classification head. This architecture allows RoBERTa to effectively encode rich contextual representations from input text pairs in a unified vector space. The classification head maps these representations into label probabilities for entailment, contradiction and neutrality. However, the absence of explicit reasoning modules limits its ability to perform structured inference over multiple evidence

statements. This limitation indicates complex semantic dependencies where reasoning across multiple sentences is required. Consequently, the model's decisions are based on surface-level contextual cues rather than deep logical inference.

#### 3.4.1.1 Input Representation and Preprocessing

Given a claim-hypothesis pair ($H$) and its corresponding premise-evidence ($P$), the input sequence is constructed as:

$$\mathbf{X} = [\texttt{[CLS]}, H, \texttt{[SEP]}, P, \texttt{[SEP]}] \tag{3.6}$$

where `[CLS]` denotes the classification token and `[SEP]` marks sentence boundaries. Prior to tokenization, dataset-specific preprocessing is applied, including format normalization, case folding, noise removal, label mapping, and sequence truncation to ensure compatibility with RoBERTa's fixed input length.

#### 3.4.1.2 Embedding and Encoder Layers

Each token in the input sequence is mapped into a continuous vector space using:

$$\mathbf{E}_i = \mathbf{E}_{\text{token}}(x_i) + \mathbf{E}_{\text{position}}(i) \tag{3.7}$$

where $\mathbf{E}_{\text{token}}$ represents token embeddings and $\mathbf{E}_{\text{position}}$ denotes positional embeddings. Unlike BERT, RoBERTa does not use segment embeddings, relying instead on positional encoding and attention mechanisms to model inter-sentence relationships.

The embedded sequence is then passed through $N$ stacked transformer encoder layers, each consisting of multi-head self-attention and feed-forward sublayers. The self-attention mechanism is defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3.8}$$

where $Q$, $K$, and $V$ denote query, key, and value matrices derived from the input embeddings, and $d_k$ is the dimensionality of the key vectors.

#### 3.4.1.3 Classification and Prediction

The final hidden representation corresponding to the `[CLS]` token is passed to a linear classification layer to predict the NLI label:

$$\hat{y} = \text{softmax}(W\mathbf{h}_{\texttt{[CLS]}} + b) \tag{3.9}$$

where $W$ and $b$ are trainable parameters. The predicted label $\hat{y}$ belongs to the set $\{$*Entailment*, *Contradiction*, *Neutral*$\}$.

#### 3.4.1.4 Observed Limitations

Despite strong overall performance, empirical evaluation reveals that RoBERTa-Large frequently struggles with linguistically subtle cases involving negation, numerical reasoning, subject–object inversion, and implicit logical dependencies. These systematic errors motivate a deeper investigation into reasoning gaps, which are analyzed later in this chapter and addressed through logic-aware preprocessing in subsequent chapters.

### 3.4.2 DeBERTa-Large

The evaluation framework for DeBERTa-Large is illustrated in Figure 3.2. DeBERTa introduces a disentangled attention mechanism that separates content embeddings from positional embeddings, allowing the model to better capture semantic relationships between tokens. This architectural enhancement improves the model's ability to represent contextual dependencies and fine-grained semantic interactions within claim–evidence pairs. As a result, DeBERTa achieves stronger inference performance on complex fact verification tasks compared to earlier transformer models.

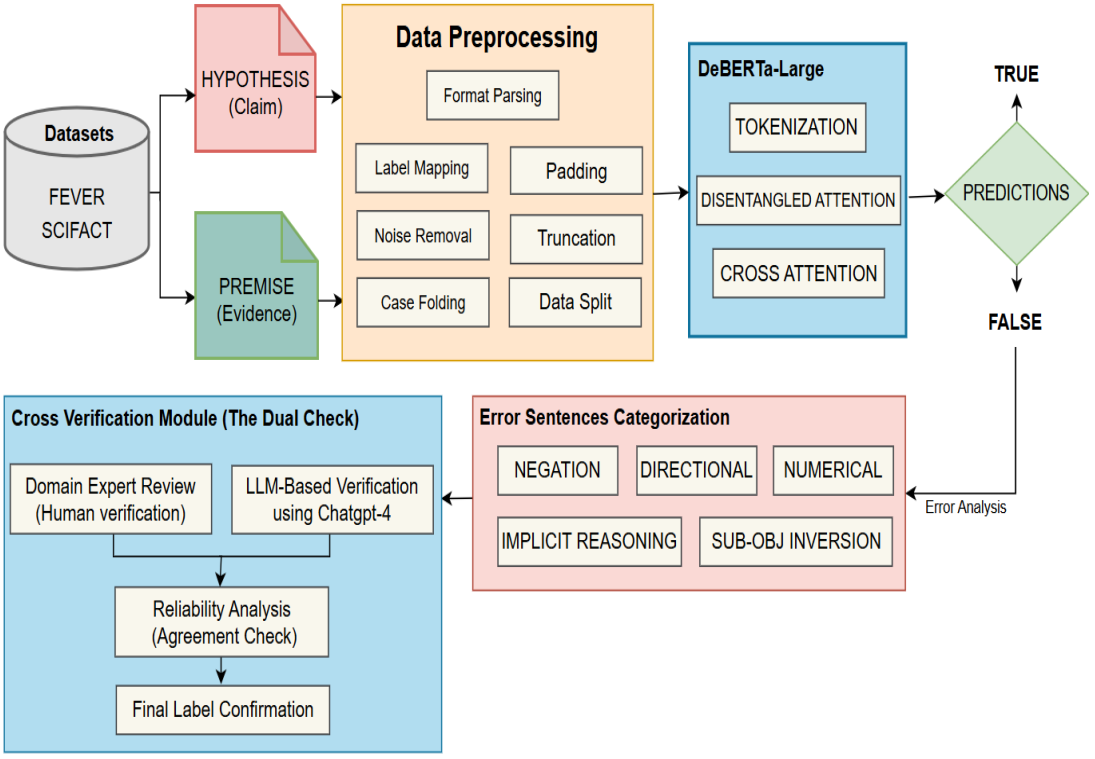


FIGURE 3.2: Evaluations Through DeBERTa-Large

In addition to disentangled attention, DeBERTa employs enhanced decoding strategies that improve its ability to distinguish subtle semantic differences between sentences. These architectural improvements enable DeBERTa to achieve higher accuracy compared to RoBERTa in many NLI benchmarks. After preprocessing, claim-evidence pairs are passed through the DeBERTa model to generate predictions. These predictions are then used to compute evaluation metrics and to identify misclassified instances for further analysis.

#### 3.4.2.1 Disentangled Input Representation

Unlike RoBERTa, DeBERTa represents each token using two separate embeddings:

$$\mathbf{E}_i = \mathbf{E}_i^c \oplus \mathbf{E}_i^p \tag{3.10}$$

where $\mathbf{E}_i^c$ encodes token content and $\mathbf{E}_i^p$ encodes positional information. This disentanglement allows the model to independently learn semantic meaning and relative positional relationships.

#### 3.4.2.2 Disentangled Attention Mechanism

The attention score between tokens $i$ and $j$ is computed as:

$$A_{ij} = (\mathbf{Q}_i^c \cdot \mathbf{K}_j^c) + (\mathbf{Q}_i^c \cdot \mathbf{K}_j^p) + (\mathbf{Q}_i^p \cdot \mathbf{K}_j^c) \tag{3.11}$$

where:

$\mathbf{Q}^c, \mathbf{K}^c$ represent content-based queries and keys,

$\mathbf{Q}^p, \mathbf{K}^p$ represent position-based queries and keys.

This formulation enables the model to reason more effectively about relational structure, particularly in cases involving negation scope, ordering, and directional semantics.

#### 3.4.2.3 Enhanced Mask Decoder and Relative Position Encoding

DeBERTa further incorporates an enhanced mask decoder and relative position embeddings, allowing the model to better generalize across sentence structures and syntactic variations. These components are critical in modeling long-range dependencies between claims and evidence.

#### 3.4.2.4 Prediction Layer

Similar to RoBERTa, the final contextualized representation of the `[CLS]` token is used for classification:

$$\hat{y} = \text{softmax}(W\mathbf{h}_{\texttt{[CLS]}}^D + b) \tag{3.12}$$

where $\mathbf{h}_{\texttt{[CLS]}}^D$ denotes the DeBERTa-specific contextual embedding. This prediction layer transforms the learned semantic representation into a probabilistic distribution over the predefined NLI classes. The parameters W and b are optimized during training to minimize classification error across the dataset.

#### 3.4.2.5 Empirical Advantages and Remaining Gaps

Empirical results demonstrate that DeBERTa-Large consistently outperforms RoBERTa-Large across both FEVER and SciFact datasets. However, despite improved handling of contextual and relational semantics, DeBERTa still exhibits notable errors in cases requiring explicit logical reasoning, such as negation flipping, numerical comparisons, and implicit inference. These observations empirically justify the need for logic-based preprocessing and symbolic reasoning mechanisms, which are formally introduced in the following chapters.

## 3.5 Quantitative Results against Each Dataset

To establish a strong empirical foundation for the research problem, quantitative evaluation was performed using two state-of-the-art Natural Language Inference models: RoBERTa-Large and DeBERTa-Large. Both models were evaluated on SciFact and FEVER datasets under identical preprocessing and evaluation conditions to ensure fairness of comparison.

The evaluation focused primarily on classification accuracy, followed by detailed analysis using precision, recall, and F1-score where appropriate.

### 3.5.1 Results on SciFact Dataset

Table 3.7 presents the comparative performance of RoBERTa-Large and DeBERTa-Large on the SciFact:-

Table 3.7: Performance Comparison on SciFact Dataset

| **Model** | **Accuracy (%)** |
|---|---|
| RoBERTa-Large | 52.37 |
| DeBERTa-Large | 86.98 |

Table 3.7 clearly shows a substantial performance difference between the two evaluated models. RoBERTa-Large achieved an accuracy of 52.37%, indicating that

the model struggled to correctly interpret many scientific claims and evidence pairs. This relatively low accuracy highlights the difficulty of the SciFact dataset, which contains technically complex and semantically dense scientific statements.

In contrast, DeBERTa-Large achieved an accuracy of 86.98%, representing a significant improvement over RoBERTa-Large. This improvement can be attributed to DeBERTa's disentangled attention mechanism, which allows better modeling of semantic relationships and contextual dependencies. The results indicate that DeBERTa-Large is more capable of handling scientific reasoning tasks, making it a suitable candidate for detailed error analysis.

Overall, the results demonstrate that architectural improvements in transformer models have a direct impact on their ability to handle complex fact verification tasks. The large performance gap also suggests that richer contextual modeling is essential for scientific domain inference. These findings further justify the selection of DeBERTa-Large for deeper semantic error analysis in this study.

### 3.5.2 Class-wise Performance of DeBERTa on SciFact

To better understand the model behavior, class-wise evaluation metrics were computed.

TABLE 3.8: Class-wise Performance of DeBERTa-Large on SciFact

| **Class** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Supported | 0.88 | 0.92 | 0.90 |
| Contradicted | 0.84 | 0.79 | 0.81 |
| Macro Average | 0.86 | 0.85 | 0.86 |
| Weighted Average | 0.87 | 0.87 | 0.87 |

The results in Table 3.8 indicate that DeBERTa-Large demonstrates strong performance across both Supported and Contradicted classes. The F1-score of 0.90 for the Supported class suggests that the model effectively captures entailment relationships when evidence clearly supports the claim. The slightly lower F1-score for the Contradicted class indicates that identifying contradictions remains comparatively more challenging, which is consistent with findings reported in NLI

literature. The balanced macro and weighted averages confirm that the model performs consistently across classes without significant bias toward any particular label.

This performance pattern suggests that DeBERTa-Large benefits from its disentangled attention mechanism, which enhances contextual representation learning across complex sentence structures. However, the observed class imbalance in performance highlights the persistent difficulty of modeling contradiction cases in scientific fact verification tasks.

These findings indicate that even strong transformer architectures exhibit asymmetry in handling different inference categories. The results suggest that contradiction detection requires more explicit reasoning over semantic conflicts between claims and evidence. Overall, this analysis highlights the need for improved modeling strategies to better balance performance across all NLI classes.

### 3.5.3 Results on FEVER Dataset

Table 3.9 presents the performance comparison on the FEVER dataset.

Table 3.9: Performance Comparison on FEVER Dataset

| **Model** | **Accuracy (%)** |
|---|---|
| RoBERTa-Large | 93.71 |
| DeBERTa-Large | 96.60 |

Table 3.9 shows that both models perform significantly better on the FEVER dataset compared to SciFact. This difference can be explained by the nature of the dataset. FEVER claims are generally shorter, less technical, and often involve straightforward factual relationships.

DeBERTa-Large achieved an accuracy of 96.60%, outperforming RoBERTa-Large by nearly three percentage points. Although the improvement appears smaller than in SciFact, it is still significant given the already high baseline accuracy. These results confirm that DeBERTa-Large is consistently superior across datasets, which justifies selecting it for subsequent error analysis.

## 3.6 Motivation for Error Analysis

Although DeBERTa-Large achieved high accuracy, a closer inspection of the predictions revealed that certain types of claims were consistently misclassified. These errors were not random but appeared to follow systematic patterns related to semantic complexity.

Therefore, a detailed error analysis was conducted to identify recurring linguistic phenomena responsible for incorrect predictions. The objective of this analysis was to provide empirical evidence supporting the research problem that current NLI models struggle with deep semantic reasoning. Only Supported and Refuted cases were included in this analysis. Sentences labeled as Not Enough Information (NEI) were excluded because such cases lack sufficient evidence and therefore do not reliably reflect reasoning errors.

## 3.7 Error Taxonomy Definition

During manual inspection of incorrect predictions, errors were categorized into semantic classes. Table 3.10 summarizes the defined taxonomy.

Table 3.10: Semantic Error Categories Identified During Analysis

| **Error Type** | **Description** |
|---|---|
| Negation Errors | Failure to correctly interpret negation cues such as "not", "never", or "no". |
| Numerical Errors | Incorrect interpretation of numbers, percentages, or quantitative comparisons. |
| Directional Errors | Misinterpretation of increase, decrease, or comparative relationships. |
| Implicit Reasoning Errors | Failure to infer relationships not explicit in text. |
| Subject-Object Errors | Confusion between agent and recipient roles in sentences. |

Table 3.10 defines the semantic categories used to classify errors. These categories were selected based on recurring patterns observed during manual inspection of incorrect predictions. The taxonomy provides a structured framework for analyzing model weaknesses and identifying areas where improvements are needed.

## 3.8 Error Analysis on SciFact Dataset

After evaluating the DeBERTa-Large model on the SciFact dataset, a detailed error analysis was conducted to identify the deep semantic phenomena responsible for incorrect predictions. The purpose of this analysis was to empirically validate the problem statement by examining specific linguistic and semantic challenges that degrade NLI performance. This analysis helps in understanding the limitations of transformer-based models beyond aggregate performance metrics. It further provides a foundation for designing targeted improvements to enhance semantic reasoning in fact verification systems.

### 3.8.1 Overall Error Statistics - SciFact Dataset

The DeBERTa-Large model achieved a baseline accuracy of 86.98% on the SciFact dataset, but an analysis of its errors revealed specific semantic challenges. Out of 44 total errors identified, the most frequent type involved negation and polarity (38 instances), where the model struggled with scientific claims containing words like "not" or "no". Additionally, 14 errors were related to numerical or quantitative reasoning, and 3 involved directional relationships. The sum of individual error categories exceeds the total error count because some errors were complex and spanned multiple categories simultaneously, indicating that many mistakes arose from overlapping linguistic phenomena rather than isolated issues.

Table 3.11: Overall Error Statistics on SciFact Dataset

| **Category** | **Value** |
|---|---|
| Baseline Accuracy (DeBERTa-L) | 86.98% |
| Total Errors Observed | 44 |
| Negation | 38 |
| Numerical | 14 |
| Directional | 3 |

The majority of errors were associated with negation handling, confirming that semantic polarity remains a major challenge for NLI systems. Numerical reasoning errors were also prominent, indicating limitations in interpreting quantitative

relationships. Directional reasoning errors were fewer but required explicit semantic interpretation to resolve. These results suggest that most errors are not independent but often co-occur within complex semantic constructs. The overlap between categories indicates that current models struggle with multi-faceted linguistic reasoning. Such patterns highlight the need for more structured reasoning mechanisms beyond pure contextual embeddings. Overall, the error distribution provides strong evidence of persistent semantic reasoning gaps in transformer-based models.

### 3.8.2 Sample Erroneous Sentences - SciFact Dataset

TABLE 3.12: Sample of Erroneous Predicted Sentences in SciFact Dataset

| **Claim** | **Gold Label** | **Predicted Label** | **Error Type** |
|---|---|---|---|
| Headaches are not correlated with cognitive impairment | Support | Contradict | Neg |
| Thigh-length GCS did not reduce deep vein thrombosis | Support | Contradict | Neg |
| Autologous MSCs cause fewer opportunistic infections than induction therapy | Support | Contradict | Dir |
| Incidence of heart failure decreased by 10% since 1979 | Contradict | Support | Dir/Num |
| A total of 1,000 people in the UK are asymptomatic carriers of vCJD infection | Contradict | Support | Num |
| The risk of male prisoners harming themselves is ten times that of female prisoners | Contradict | Support | Num |

These examples illustrate how models misinterpret negation, numerical values, and directional relationships. In several cases, the model focused on lexical overlap while ignoring semantic polarity or magnitude differences.

## 3.9 Error Analysis on FEVER Dataset

A similar error analysis was conducted on the FEVER dataset after evaluating DeBERTa-Large. Since FEVER contains a large number of claims, the analysis focused on a representative subset of errors. Importantly, claims labeled as Not Enough Information (NEI) were excluded from the error correction phase because reliable evidence was not available for semantic reasoning.

### 3.9.1 Overall Error Statistics - Fever Dataset

Although the overall accuracy of DeBERTa-Large on FEVER was high, detailed inspection revealed that many errors were concentrated in semantically difficult cases. Removing NEI instances allowed the analysis to focus on cases where sufficient evidence existed for logical reasoning.

Table 3.13: Overall Error Statistics on FEVER Dataset

| **Category** | **Value** |
|---|---|
| Baseline Accuracy (DeBERTa-L) | 96.6% |
| Total Errors Observed | 5000+ |
| Errors Selected for Analysis | 200 |
| Errors After Removing NEI | 145 |
| Negation | 20 |
| Numerical | 28 |
| Directional | 03 |
| Complex | 94 |

The DeBERTa-Large model achieved an impressive baseline accuracy of 96.6% on the FEVER dataset, yet due to the dataset's scale, over 5,000 total errors were observed. From these, 200 errors were selected for detailed analysis, and after removing ambiguous "Not Enough Information" (NEI) cases, 145 errors were categorized into specific types: 20 negation errors, 28 numerical errors, 3 directional errors, and 94 complex errors. The predominance of complex errors—comprising

two-thirds of the analyzed cases—reveals that most mistakes on FEVER stem from multifaceted reasoning challenges rather than isolated semantic issues, highlighting the dataset's demand for nuanced contextual understanding and inference beyond surface-level text matching.

### 3.9.2 Sample Erroneous Sentences

These examples demonstrate that NLI models often fail when reasoning requires:

i. interpreting negation

ii. comparing quantities

iii. identifying directional relationships

Such cases directly support the central problem statement of this thesis.

Table 3.14: Sample Erroneous Predictions in FEVER

| **Claim** | **Gold Label** | **Predicted Label** | **Error Type** |
|---|---|---|---|
| Puerto Rico is not an unincorporated territory of the United States | Contradict | Support | Neg |
| Jennifer Aniston is not a businesswoman | Contradict | Support | Neg |
| Andy Roddick lost 5 Master Series between 2002 and 2010 | Contradict | Support | Num |
| Roman Atwood is a content creator | Support | Contradict | Implicit |

## 3.10 Cross-Dataset Error Pattern Analysis

To better understand model behavior, error patterns were compared across both datasets. The comparison in Table 3.15 reveals that negation errors occur consistently across datasets, indicating a fundamental limitation of NLI models. Contextual reasoning errors were more prominent in FEVER due to the broader diversity of claims.

TABLE 3.15: Cross-Dataset Error Pattern Comparison

| **Error Type** | **SciFact Frequency** | **FEVER Frequency** |
|---|---|---|
| Negation | High | Moderate |
| Numerical | Moderate | Moderate |
| Directional | Low | Low |
| Contextual | Moderate | High |

Numerical and directional reasoning errors remain relatively stable across both datasets, suggesting that current transformer architectures do not explicitly model these reasoning types. In contrast, contextual errors in FEVER highlight the challenges of handling heterogeneous and multi-domain evidence sources.

Overall, these patterns indicate that model weaknesses are not dataset-specific but rather intrinsic to current attention-based inference mechanisms. This further motivates the need for explicit reasoning-aware architectures in fact verification systems.

These findings demonstrate that improving dataset scale alone is insufficient to resolve underlying reasoning limitations. Instead, consistent error patterns across datasets indicate structural weaknesses in current NLI architectures. Addressing these issues requires incorporating explicit reasoning mechanisms that go beyond contextual pattern learning.

## 3.11 Cross Validation Module - Dual Check

To ensure the reliability and correctness of the semantic error analysis, a cross-validation mechanism is introduced. The purpose of this module is to validate the manually categorized errors using an independent verification process combining human expert judgment and large language model reasoning.

The Cross Validation Module consists of four sequential stages: Domain Expert Review, LLM-Based Verification, Reliability Analysis, and Final Label Confirmation, as illustrated in the system architecture Figure 3.3.

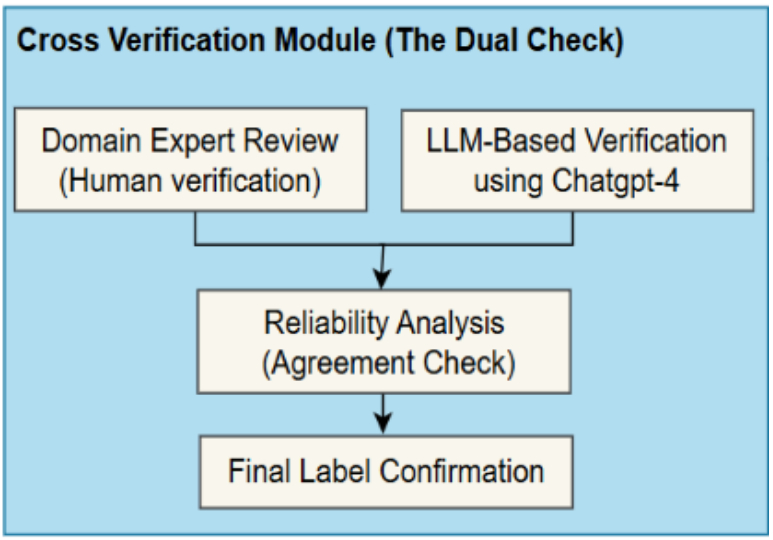


FIGURE 3.3: Cross Verification Module

### 3.11.1 Domain Expert Review - Human Verification

In the first stage, a subset of incorrectly predicted claim–evidence pairs was manually reviewed and categorized by domain experts. The objective of this stage was to establish high-confidence ground truth labels for semantic error categories.

Two human experts i.e *Domain Expert 1* and *Domain Expert 2* participated in this evaluation. Each expert independently examined erroneous claim–evidence pairs and assigned an error category based on the taxonomy defined earlier in this chapter, including negation, numerical reasoning, directional reasoning, contextual errors, and mixed semantic phenomena.

This stage ensured that error labels were grounded in human reasoning and linguistic interpretation rather than automated heuristics alone.

### 3.11.2 LLM-Based Verification using ChatGPT-4

Same set of erroneous claim–evidence pairs analyzed using a Large Language Model (ChatGPT-4). The objective of this step was not to replace human judgment but to provide an independent semantic interpretation and classification of error types. Each pair of claim–evidence provided to the model with structured prompts requesting:

i. Identification of the semantic relationship between claim and evidence

ii. Explanation of the reasoning process

iii. Classification of the semantic error category

The results produced by ChatGPT-4 were recorded and compared against human expert annotations.

### 3.11.3 ChatGPT-Based Error Categorization Results

Table 3.16 presents the distribution of error categories identified using ChatGPT-4 on the SciFact dataset.

Table 3.16: SciFact Error Categories Identified Using ChatGPT

| **Error Category** | **Frequency** | **Percentage (%)** |
|---|---|---|
| Directional Error (Simple) | 11 | 25.0 |
| Numerical Error (Simple) | 7 | 15.9 |
| Directional + Numerical | 7 | 15.9 |
| Negation + Directional | 5 | 11.4 |
| Numerical + Causal / Subject | 3 | 6.8 |
| Negation + Direction + Numerical | 1 | 2.3 |
| Negation Error (Simple) | 2 | 4.5 |
| Subject-Object / Causal | 3 | 6.8 |
| Contextual / Complex | 5 | 11.4 |
| **Total** | **44** | **100** |

The results indicate that many errors involve multiple overlapping semantic phenomena rather than isolated linguistic cues. Directional and numerical reasoning errors were particularly frequent, confirming observations made during manual inspection.

Similarly, ChatGPT-based analysis was conducted on the FEVER dataset. The results are summarized in Table 3.17.

The FEVER results demonstrate that contextual and complex reasoning errors dominate, accounting for more than half of all analyzed cases. This finding reinforces the hypothesis that deep semantic reasoning remains a major challenge for current NLI models.

TABLE 3.17: FEVER Error Categories Identified Using ChatGPT

| **Error Category** | **Frequency** | **Percentage (%)** |
|---|---|---|
| Contextual / Complex | 78 | 53.8 |
| Numerical / Entity | 32 | 22.1 |
| Negation Error | 22 | 15.1 |
| Directional / Relation | 13 | 9.0 |
| **Total** | **145** | **100** |

### 3.11.4 Reliability Analysis Using Cohen's Kappa

In the third stage of empirical analysis, the classifications produced by human experts and ChatGPT were compared to evaluate the reliability and consistency of the error categorization process. The objective of this step was to ensure that semantic error classification was not biased toward a single evaluator and that the identified categories were reproducible across independent reviewers.

ChatGPT was used as an additional independent evaluator to assist in classification and validation. The final categorization decisions were reviewed and confirmed by the human experts.

To quantitatively measure the level of agreement between evaluators, the Cohen's Kappa coefficient ($\kappa$) was used. Cohen's Kappa is a widely accepted statistical measure for inter-rater reliability that accounts for agreement occurring by chance.

The coefficient is defined as:

$$\kappa = \frac{P_o - P_e}{1 - P_e} \tag{3.13}$$

where:

- $P_o$ represents the observed agreement among evaluators,
- $P_e$ represents the expected agreement by chance.

The observed agreement $P_o$ is calculated as:

$$P_o = \frac{\text{Number of agreements}}{\text{Total number of samples}} \tag{3.14}$$

The expected agreement $P_e$ is computed based on the marginal probabilities of each category assigned by the evaluators.

During the reliability analysis, the overall agreement between human experts and ChatGPT reached approximately **89%**, while disagreement was observed in approximately **11%** of cases. Most disagreements occurred in sentences containing overlapping semantic phenomena, particularly mixed reasoning cases where more than one error category could reasonably apply.

The computed Cohen's Kappa value indicated a **strong level of agreement** according to standard interpretation guidelines, where values above 0.80 represent near-perfect agreement. This result confirms that the semantic error taxonomy defined in this study is consistent, reproducible, and sufficiently robust for empirical analysis. The reliability analysis therefore validates that the identified error categories negation, numerical reasoning, directional reasoning, implicit reasoning, and mixed semantic cases can be reproduced / classified. This high level of agreement further strengthens the credibility of the proposed error taxonomy by demonstrating its stability across different evaluators. It also indicates that ChatGPT can reliably assist in structured annotation tasks when guided by well-defined classification criteria. Consequently, the reliability results support the methodological soundness of the semantic error analysis framework used in this study.

### 3.11.5 Final Label Confirmation

Final stage confirmed labels were assigned to each erroneous instance. When agreement existed between human experts and ChatGPT-4, the label was accepted directly. In cases of disagreement, decision was made through expert consensus.

This final confirmation step ensured that:

i. All analyzed errors had verified semantic labels

ii. Categorization was consistent across datasets

iii. The resulting taxonomy accurately reflected real model failure patterns

The Cross Validation Module significantly increased confidence in the empirical findings of this chapter. By combining human reasoning with LLM-based semantic analysis, the study ensured that identified error patterns were not artifacts of subjective interpretation but reflected genuine limitations of state-of-the-art NLI models.

## 3.12 Conclusion of Empirical Analysis

The empirical investigations presented in this chapter provide a systematic evaluation of state-of-the-art transformer-based Natural Language Inference models under real-world fact verification conditions. Although DeBERTa-Large gain high overall accuracy on both FEVER and SciFact datasets, detailed analysis revealed that a non-trivial portion of errors arises from consistent and recurring semantic phenomena rather than random misclassifications.

The results clearly indicate that current NLI architectures remain vulnerable to specific categories of linguistic complexity. In particular, errors involving semantic polarity and negation, quantitative and numerical reasoning, directional relationships, and complex contextual inference were observed to occur repeatedly across both datasets. These findings confirm that high aggregate accuracy does not necessarily imply robust reasoning capability, especially in cases requiring deep semantic understanding or explicit logical interpretation.

Furthermore, the cross-validation process combining domain expert review and independent LLM-based verification strengthened the reliability of the identified error taxonomy, ensuring that the observed patterns reflect genuine limitations of current models rather than annotation noise or subjective interpretation.

Overall, the empirical evidence gathered in this chapter substantiates the central research problem of this thesis: despite advances in transformer-based NLI models,

existing fact verification systems still struggle to reliably interpret deep semantic structures and logical relationships. These limitations highlight the need for enhanced verification architectures that incorporate explicit semantic and logical reasoning mechanisms.

Motivated by these findings, the next chapter presents the proposed logic design, which introduces structured preprocessing and symbolic reasoning components to address the semantic failure modes identified through this empirical analysis.

# Chapter 4

# System Design

The empirical analysis presented in Chapter 3 demonstrated that even highly advanced Natural Language Inference (NLI) models produce incorrect predictions when faced with linguistically complex sentences. Although these models achieve strong overall accuracy, a detailed examination of incorrect predictions revealed that the majority of errors occur in sentences involving negation, numerical reasoning, and directional semantics. These findings highlight that high accuracy does not guarantee semantic understanding in complex fact verification scenarios.

Transformer-based models rely on contextual embeddings learned, While such embeddings capture semantic similarity and syntactic structure effectively. They do not explicitly encode formal logical relationships such as polarity inversion, magnitude comparison, or directional contradiction. Consequently, the models may misinterpret sentences in which a small linguistic change, such as the addition of a negation word or a numerical difference, completely alters the semantic meaning. To address these limitations, this research introduces a logic-based preprocessing and reasoning framework designed to operate on sentences that are misclassified by the NLI model, focuses following modules:

i. Negation reasoning using propositional logic

ii. Symbolic numerical / directional reasoning

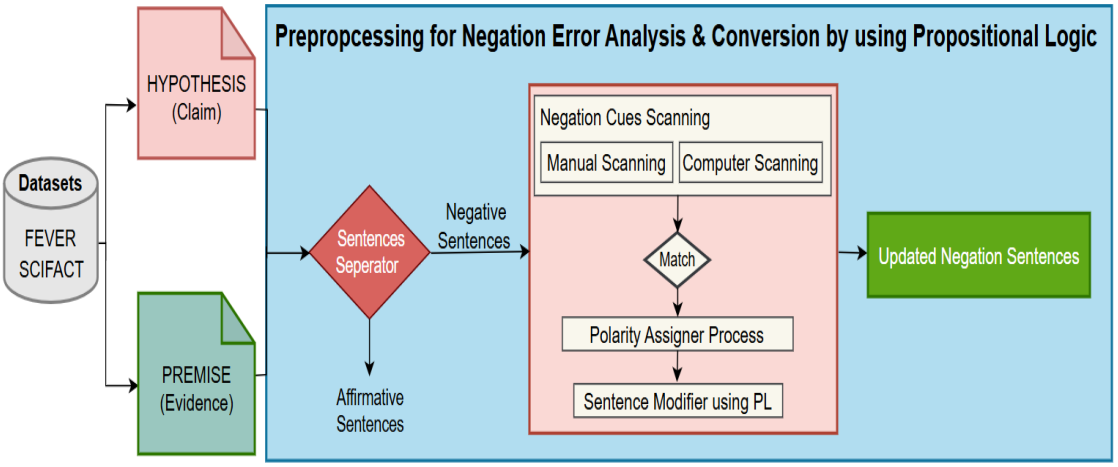


FIGURE 4.1: Preprocessing for Negation Error Analysis

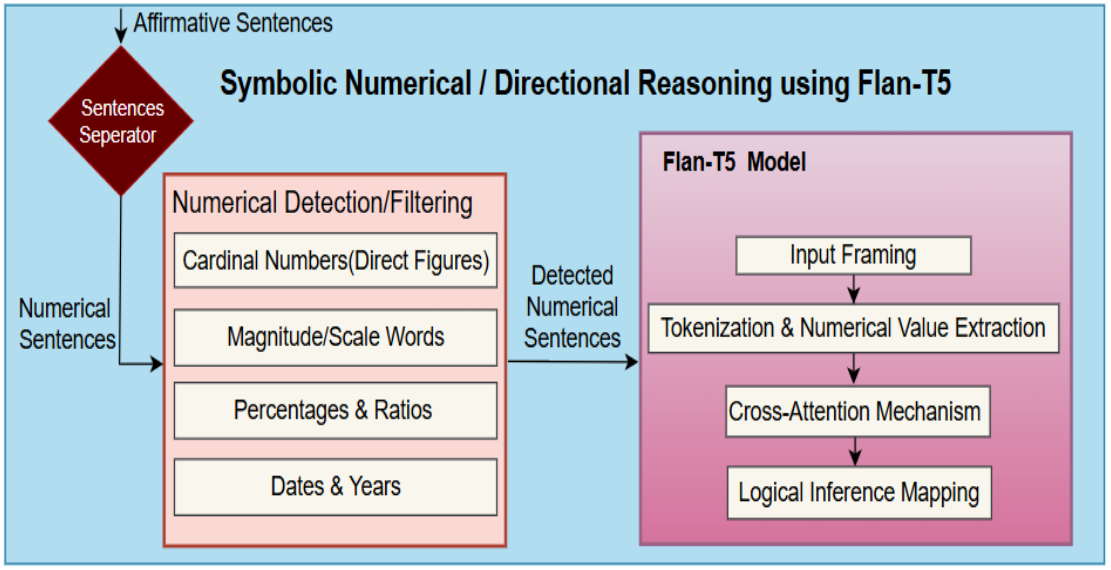


FIGURE 4.2: Symbolic Numerical Reasoning

Figure 4.1 presents the workflow for preprocessing negation sentences and converting them into logically structured representations using propositional logic.

Figure 4.2 illustrates the symbolic numerical reasoning framework that processes sentences containing quantitative information. These modules operate as intermediate reasoning components that transform sentences into semantically consistent forms before they are re-evaluated by the NLI model. The purpose of this chapter is to present the detailed design of these logic modules, the formal representation of reasoning processes, and the mathematical formulation of the transformations applied to textual inputs. These components collectively enhance the system's ability to handle structured semantic transformations beyond surface-level text

matching. By integrating symbolic reasoning with neural inference, the framework aims to improve robustness in complex fact verification scenarios.

## 4.1 Formal Problem Definition

In the context of fact verification, each input instance consists of a *claim* and an *evidence* sentence. Let a claim–evidence pair be represented as:

$$C = \text{Claim} \tag{4.1}$$

$$E = \text{Evidence} \tag{4.2}$$

A transformer-based Natural Language Inference (NLI) model performs classification over the claim–evidence pair as:

$$f(C, E) = y \tag{4.3}$$

where the output label belongs to the set:

$$y \in \{\text{Entailment}, \text{Contradiction}, \text{Neutral}\} \tag{4.4}$$

Empirical analysis conducted in Chapter 3 demonstrated that for a subset of instances, the predicted label differs from the ground truth label. This can be formally expressed as:

$$f(C, E) \neq y_{\text{true}} \tag{4.5}$$

Such instances are referred to as *error cases*. Let the set of erroneous claim–evidence pairs be denoted as:

$$\mathcal{E} = \{(C_i, E_i)\} \tag{4.6}$$

To address these errors, a transformation function is introduced that applies symbolic or logical preprocessing to the input sentences. This transformation is defined as:

$$T(C, E) = (C', E') \tag{4.7}$$

where:

- $C'$ represents the logically transformed claim,
- $E'$ represents the logically transformed evidence.

After transformation, the modified pair is passed again to the NLI model, producing a revised prediction:

$$f(C', E') = y' \tag{4.8}$$

The objective of the proposed logic design is to construct a transformation function $T$ such that:

$$y' = y_{\text{true}} \tag{4.9}$$

In other words, the transformation aims to correct semantic misinterpretations by explicitly encoding logical relationships such as negation, numerical comparison, and directional semantics, without modifying the internal architecture of the neural model.

This formulation establishes the theoretical foundation for the logic modules presented in the subsequent sections, where propositional logic and symbolic reasoning are applied to improve fact verification reliability.

## 4.2 Negation Logic Design Using Propositional Logic

As shown in Figure 4.1, the negation processing module is designed to identify sentences containing negation cues, determine their semantic polarity, and convert them into logically consistent forms using propositional logic.

Negation is one of the most critical linguistic phenomena in fact verification because the presence or absence of a negation word can completely reverse the truth value of a statement. For example, the statements "The drug is effective" and "The drug is not effective" share similar lexical structure but express opposite meanings. Neural models sometimes fail to distinguish such polarity changes, especially when negation scope is complex.

The negation logic module operates in four stages: sentence separation, negation cue detection, polarity assignment, and sentence transformation.

### 4.2.1 Sentence Separation

TABLE 4.1: Pseudocode for Sentence Separation

**Algorithm 1:** Sentence Separation Procedure

```
Procedure SEPARATE_SENTENCE(sentence):
    negation_words ← ["not", "never", "no", "without",....];
    tokens ← Tokenize(sentence);
    foreach word in tokens do
        if word ∈ negation_words then
            return "Negation Sentence";
    return "Affirmative Sentence";
```

The first step in the logic design is to separate sentences into two categories: negation sentences and affirmative sentences. Sentence separation is performed by scanning tokens for known negation indicators such as *not*, *never*, *no*, and *without*. Pseudocode for sentence separation is given in Table 4.1. This preprocessing step ensures that negated expressions are explicitly identified before

logical transformation. It improves the reliability of downstream reasoning by isolating semantic polarity cues early in the pipeline.

### 4.2.2 Pseudocode for Negation Cue Detection

Negation cues are detected through lexical matching and contextual analysis. Negation cues are categorized into explicit negation words, negative prefixes, and implicit negation constructs. Pseudocode of detection of negation cues is as Table 4.2.

TABLE 4.2: Negation Cues

**Algorithm 2:** Negation Cue Detection

```
Procedure DETECT_NEGATION(sentence):
    explicit_cues ← ["not", "never", "no", "neither", "nor",....];
    prefixes ← ["un", "non", "dis",...];
    tokens ← Tokenize(sentence);
    detected_cues ← empty list;
    foreach word in tokens do
        if word ∈ explicit_cues then
            detected_cues.append(word);
        foreach prefix in prefixes do
            if word starts with prefix then
                detected_cues.append(word);
    return detected_cues;
```

### 4.2.3 Polarity Assignment

After detecting negation cues, semantic polarity is assigned. Polarity is determined based on the number of detected negation cues using Pseudocode as Table 4.3. This rule ensures that even nested or repeated negation structures are consistently mapped into a unified polarity representation. By leveraging parity-based assignment, the system avoids ambiguity in handling multiple negation cues within a single statement. Although simplified, this approach provides a computationally efficient mechanism for capturing polarity shifts. However, it may still overlook nuanced semantic interactions present in complex linguistic constructions.

TABLE 4.3: Pseudocode for Polarity Assignment

**Algorithm 3:** Polarity Assignment

**Procedure** *ASSIGN_POLARITY(detected_cues)*:

```
k ← length(detected_cues);
if k mod 2 == 0 then
    polarity ← +1;
else
    polarity ← −1;
return polarity;
```

### 4.2.4 Sentence Transformation Using Propositional Logic

To ensure semantic clarity and consistency during reasoning, sentences are transformed into structured propositional representations as shown in Table 4.4. This transformation process converts natural language statements into formal logical expressions that can be processed systematically by the proposed symbolic reasoning framework. The transformation module works in conjunction with sentence separation, negation cue detection, and polarity assignment algorithms to create a complete negation-handling pipeline for fact verification tasks.

The proposed framework first identifies the grammatical subject and predicate from the input sentence and then determines whether the sentence contains negation cues. Based on the assigned semantic polarity, the framework generates either a positive or negated logical representation. By explicitly modeling negation using propositional logic, the system avoids many of the semantic ambiguity issues commonly observed in transformer-based NLI models. This structured representation improves consistency during semantic comparison between claims and evidence.

Example: Claim: "The patient did not recover."

Logical form:

$$\neg Recover(Patient)$$

The algorithms collectively define the overall negation processing workflow. By modularizing sentence separation, negation cue detection, polarity assignment and logical transformation, the proposed framework ensures consistent, interpretable

and reproducible handling of negation phenomena in fact verification systems. Such explicit semantic modeling is particularly important for reducing false entailment predictions caused by polarity confusion in complex linguistic structures.

TABLE 4.4: Pseudocode for Sentence Transformation

**Algorithm 4:** Sentence Transformation into Logical Form

```
Procedure TRANSFORM_TO_LOGIC(sentence, polarity):
    subject ← ExtractSubject(sentence);
    predicate ← ExtractPredicate(sentence);
    if polarity == -1 then
        logical_form ← NOT predicate(subject);
    else
        logical_form ← predicate(subject);
    return logical_form;
```

## 4.3 Symbolic Numerical Reasoning

Numerical reasoning is major source of errors in fact verification. Neural models often misinterpret quantities, percentages, or comparative magnitudes because numerical relationships require precise symbolic reasoning rather than contextual similarity. As Figure 4.2, the symbolic numerical reasoning module detects numerical expressions, extracts their values, and performs logical comparisons.

### 4.3.1 Numerical Sentence Detection

Numerical sentence detection is a critical preprocessing step in the proposed fact verification framework, as many factual claims involve quantitative information that requires special handling beyond standard semantic parsing. A sentence is classified as numerical if it contains tokens representing numeric values or quantitative expressions such as integers, percentages, dates, ratios, measurements, or magnitude-based comparisons, as summarized in Table 4.5. This step ensures that system can explicitly identify and isolate sentences where numerical reasoning is required, which is often a major source of errors in transformer-based NLI models.

Accurately detecting numerical content is essential because such expressions often carry implicit comparative or relational meaning that is not directly captured by contextual embeddings. For example, differences in values, increases or decreases, and proportional relationships require structured interpretation rather than purely lexical matching. By identifying numerical sentences early in the pipeline, the framework enables downstream symbolic reasoning modules to perform normalized comparison and logical evaluation of quantitative information.

The detection process assigns a binary classification to each sentence based on the presence of numeric indicators. This can be formally defined as:

$$Num(S) = \begin{cases} 1 & \text{if numeric token present} \\ 0 & \text{otherwise} \end{cases} \tag{4.10}$$

TABLE 4.5: Pseudocode for Numerical Sentence Detection

**Algorithm 5:** Numerical Sentence Detection

```
Procedure DETECT_NUMERICAL(sentence):
    tokens ← Tokenize(sentence);
    numeric_patterns ← [digits, percentages, dates, ratios,....];
    foreach token in tokens do
        if token matches numeric_patterns then
            return TRUE;
    return FALSE;
```

### 4.3.2 Numerical Value Extraction

Detected numbers are converted into structured representations:

$$V = \{v_1, v_2, \ldots, v_m\} \tag{4.11}$$

Each value is normalized to a comparable numeric scale. Percentages are converted into decimal form, and dates are converted into ordinal values to allow comparison as per Table 4.6. This normalization step ensures consistency across different

numerical formats appearing in textual data. It enables the reasoning module to perform reliable comparisons between heterogeneous quantitative expressions.

TABLE 4.6: Pseudocode for Numerical Value Extraction

**Algorithm 6:** Numerical Value Extraction and Normalization

```
Procedure EXTRACT_NUMBERS(sentence):
    tokens ← Tokenize(sentence);
    values ← empty list;
    foreach token in tokens do
        if token is percentage then
            value ← ConvertToDecimal(token);
            values.append(value);
        else if token is date or year then
            value ← ConvertToOrdinal(token);
            values.append(value);
        else if token is integer or ratio then
            values.append(token);
    return values;
```

### 4.3.3 Logical Comparison

For two numerical values $v_1$ and $v_2$, logical relations are defined below. These relations are used to infer entailment or contradiction. If evidence expresses a relation that conflicts with the claim, a contradiction is inferred as Table 4.7.

$$v_1 > v_2, \quad v_1 < v_2, \quad v_1 = v_2 \tag{4.12}$$

It is important to note that the numerical reasoning module does not directlyproduce the final entailment or contradiction decision. Instead, it generates structured reasoning signals that are combined with the transformer-based NLI model output in the hybrid decision fusion stage described later in this chapter.

This separation ensures that symbolic numerical reasoning and neural semantic inference operate as complementary components within the overall framework. As a result, the system is better equipped to handle cases where explicit quantitative relationships influence the final inference decision.

TABLE 4.7: Pseudocode for Numerical Logic Comparison

**Algorithm 7:** Numerical Logical Comparison (Auxiliary Reasoning)

**Procedure** *COMPARE_VALUES(values_claim, values_evidence)*:
    relation_claim ← ExtractRelation(values_claim);
    relation_evidence ← ExtractRelation(values_evidence);
    **if** *relation_claim == relation_evidence* **then**
        reasoning_signal ← "Numerical Consistency";
    **else if** *relation_claim contradicts relation_evidence* **then**
        reasoning_signal ← "Numerical Conflict";
    **else**
        reasoning_signal ← "No Numerical Constraint";
    return reasoning_signal;

## 4.4 Integration with the NLI Model

After the application of logical transformations, the processed claim–evidence pair is merged and re-evaluated by the Natural Language Inference (NLI) model, specifically the DeBERTa-Large architecture used in this study. The integration is designed so that symbolic processing acts strictly as a preprocessing stage and does not modify the internal architecture, parameters, or training procedure of the neural model. This design preserves the integrity of the pretrained transformer while enhancing its input representation with structured reasoning signals. Consequently, the NLI model benefits from enriched inputs without requiring any architectural changes or additional retraining. It ensures compatibility with existing systems while improving their ability to handle complex semantic reasoning tasks. Let the original claim–evidence pair be represented as:

$$(C, E) \tag{4.13}$$

A transformation function $T$ is defined that applies logical preprocessing operations, including negation normalization, symbolic numerical reasoning, and directional reasoning. This function standardizes the input representation before passed to the NLI model, ensuring consistency across different types of semantic transformations. It ensures facts are semantically normalized before inference:-

$$T(C, E) = (C', E') \tag{4.14}$$

where:

- $C'$ represents the transformed claim
- $E'$ represents the transformed evidence

The transformed pair is then passed to the NLI model. The final prediction is expressed as:

$$y = f(T(C, E)) \tag{4.15}$$

where:

- $f(\cdot)$ denotes the NLI classification function
- $y$ is the predicted inference label
- $y \in \{\text{Entailment}, \text{Contradiction}, \text{Neutral}\}$

This formulation ensures that logical inconsistencies caused by semantic polarity, numerical comparisons, and directional relations are resolved before neural inference is performed.

### 4.4.1 Hybrid Reasoning Perspective

The proposed system represents a hybrid reasoning architecture in which symbolic reasoning and neural semantic representation complement each other. Neural models such as DeBERTa-Large are highly effective at capturing contextual meaning and long-range dependencies, but they may fail when precise logical reasoning is required. Conversely, symbolic reasoning provides deterministic and interpretable operations for handling structured semantic relationships.

The hybrid decision process can therefore be interpreted as:

$$y = f_{\text{NLI}}(C', E') \quad \text{where} \quad (C', E') = T(C, E) \tag{4.16}$$

This approach preserves the strengths of deep neural architectures while improving robustness against specific categories of reasoning errors identified during empirical analysis. By explicitly encoding logical transformations prior to inference, the system improves reliability without increasing model complexity or training cost.

## 4.5 Conclusion

This chapter presented the design of logic modules developed to address semantic reasoning errors identified during empirical analysis. The proposed framework introduces explicit reasoning mechanisms for negation, numerical relationships, and directional semantics. By transforming sentences into logically consistent representations before re-evaluation, the proposed approach enhances the robustness of fact verification systems.

The next chapter presents the implementation details of the proposed logic modules and their integration with the transformer-based NLI pipeline.

# Chapter 5

# Implementation

## 5.1 Overview of Implementation

This chapter presents the practical implementation of the hybrid fact verification framework proposed in this research. The design of the reasoning modules was described in Chapter 4, while Chapter 3 provided empirical evidence motivating the need for logic-aware processing. The purpose of this chapter is therefore to explain how the proposed architecture was realized in practice.

The implemented system integrates three major components:

i. Transformer-based Natural Language Inference (NLI) models

ii. Error detection and categorization mechanisms

iii. Symbolic reasoning modules for negation, numerical, and directional reasoning

The complete implementation architecture is illustrated in Figure 5.1. The system operates in a modular pipeline where each stage processes structured inputs and produces outputs for the next stage. This design improves maintainability, interpretability, and reproducibility of experiments.

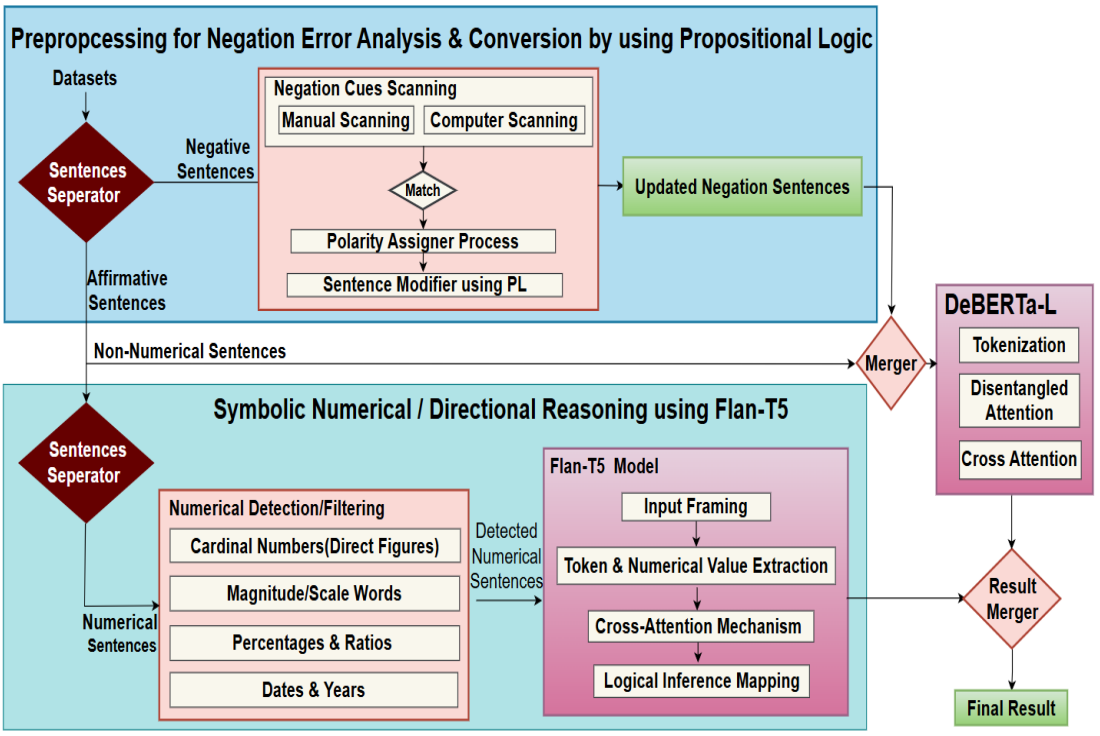


FIGURE 5.1: Implemented Hybrid Fact Verification Framework

## 5.2 Implementation Environment

The system was implemented using Python due to its strong ecosystem for machine learning and natural language processing.

The primary tools used were:

i. PyTorch for deep learning inference

ii. HuggingFace Transformers for pretrained NLI models

iii. NumPy and Pandas for dataset handling

iv. Scikit-learn for evaluation and logging utilities

v. Regular expressions and lightweight rule-based scripts for symbolic reasoning

Experiments were conducted in a GPU-enabled environment to support efficient execution of large transformer models. This combination of tools enabled seamless integration between neural inference and rule-based symbolic reasoning components. PyTorch and HuggingFace Transformers provided the core infrastructure.

## 5.3 Dataset Preparation for Implementation

Dataset characteristics and preprocessing methodology were described in detail in Chapter 3. During implementation, the prepared claim–evidence pairs were loaded in structured form and encoded using pretrained tokenizers.

Each instance was represented as:

$$X = [CLS]\ P\ [SEP]\ H\ [SEP] \tag{5.1}$$

where $P$ denotes the evidence and $H$ denotes the claim.

Tokenization, padding, and attention mask generation were handled using model-specific tokenizers.

Only Supported and Refuted instances were used in reasoning modules, consistent with the empirical analysis protocol established in Chapter 3.

## 5.4 Implementation of Neural Inference Module

The neural inference stage forms the first decision layer of the system. Pretrained RoBERTa-Large and DeBERTa-Large models were loaded using the HuggingFace Transformers framework.

Given an encoded input $X$, the model computes:

$$P(y|X) = \text{softmax}(Wh_{CLS} + b) \tag{5.2}$$

where $h_{CLS}$ represents the contextual embedding of the classification token.

Predictions and confidence scores were logged for further analysis. Misclassified instances were automatically extracted for symbolic processing. This setup allows the neural module to serve as a probabilistic decision-maker while providing uncertainty signals for downstream reasoning enhancement.

## 5.5 Error Extraction and Routing Mechanism

An error extraction module was implemented to identify instances requiring additional reasoning.

An instance was considered an error when:

$$\hat{y} \neq y \tag{5.3}$$

Detected errors were routed to appropriate reasoning modules based on linguistic patterns:

i. Negation cues

ii. Numerical expressions

iii. Directional terms

This selective routing ensured that symbolic reasoning was applied only when necessary, minimizing computational overhead.

## 5.6 Implementation of Symbolic Reasoning Modules

The internal logic of the reasoning modules was formally described in Chapter 4. During implementation, lightweight rule-based procedures were developed to operationalize these designs.

### 5.6.1 Negation Processing

Negation cues were detected using lexical matching. Sentences containing negation were converted into polarity-aware representations, and logical consistency between claim and evidence was evaluated before fusion.

### 5.6.2 Numerical Reasoning

Numerical values were extracted using pattern matching and normalized to comparable numeric formats. Symbolic comparison operators were then used to detect quantitative inconsistencies.

### 5.6.3 Directional Reasoning

Directional terms such as increase, decrease, higher, and lower were identified using a predefined lexicon. Directional polarity was computed and compared between claim and evidence to detect contradictions.

These modules produced consistency indicators used in the final decision stage.

## 5.7 Hybrid Decision Fusion

The outputs of neural inference and symbolic reasoning were combined using a hybrid fusion strategy.

Let:

i. $P_{NLI}$ denote model probability

ii. $C_{logic}$ denote symbolic consistency

The final decision score was computed as:

$$S = \alpha P_{NLI} + (1 - \alpha) C_{logic} \tag{5.4}$$

The predicted label was selected as:

$$L = \arg\max S \tag{5.5}$$

This mechanism allows symbolic reasoning to influence predictions in semantically challenging cases while preserving the strengths of neural representations.

## 5.8 System Execution Pipeline

The execution pipeline of the proposed hybrid fact verification framework describes how the final system processes claim–evidence pairs and produces verification decisions. Unlike the empirical evaluation procedure presented in Chapter 3, which involved manual error analysis and categorization, the pipeline described here corresponds to the operational workflow of the implemented system.

The system execution consists of the following stages:

i. Input Loading and Preprocessing The system loads claim–evidence pairs from the selected dataset. Basic preprocessing steps such as text normalization, tokenization, and formatting are performed to ensure compatibility with the neural inference model.

ii. Sentence Type Identification Each claim–evidence pair is analyzed to determine whether it contains linguistic structures requiring symbolic reasoning, such as negation, numerical expressions, directional relations, or implicit semantic constructs. This step routes inputs to the appropriate reasoning modules when necessary.

iii. Neural Inference using Transformer Model The preprocessed claim–evidence pair is passed to the transformer-based Natural Language Inference (NLI) model (DeBERTa and FLAN-T5 in this study), which produces an initial prediction along with confidence scores.

iv. Symbolic Reasoning Modules When linguistic patterns such as negation, numerical relations, or directional expressions are detected, the corresponding symbolic reasoning modules described in Chapter 4 are applied. These modules generate structured reasoning signals or logical constraints rather than final classification decisions.

v. Hybrid Decision Fusion Outputs from the neural inference model and symbolic reasoning modules are combined using the hybrid decision mechanism. The fusion process refines the final prediction by incorporating both contextual semantic understanding and explicit logical reasoning.

vi. Result Storage and Logging The final verification decision, confidence scores, and intermediate reasoning outputs are stored for analysis and reproducibility. Logging also facilitates performance evaluation and debugging.

This execution pipeline ensures that semantic reasoning is incorporated in a controlled and interpretable manner while preserving the strengths of transformer-based NLI models. The separation between neural inference and symbolic reasoning modules allows the system to improve reliability in cases involving complex semantic structures without disrupting the core verification process.

## 5.9 Implementation Considerations

Several practical considerations were addressed during implementation:

i. Modular design for independent testing of components

ii. Logging of intermediate outputs for traceability

iii. Consistent dataset splits to ensure reproducibility

iv. Lightweight symbolic modules to maintain efficiency

These practices ensured reliable experimentation and facilitated debugging.

## 5.10 Testing

To validate the implementation of the proposed hybrid fact verification framework, a set of representative test cases was evaluated after integrating the negation logic

module and symbolic numerical reasoning module. The purpose of testing was to ensure that the system correctly identifies semantic phenomena, performs logical reasoning, and produces reliable verification decisions.

The evaluation focused particularly on sentences involving negation and numerical reasoning, as these categories were identified in earlier chapters as major sources of errors in Natural Language Inference (NLI) systems.

Table 5.1 presents selected test cases used during the implementation phase. Each example includes the claim, supporting evidence, ground-truth label, predicted label produced by the system, and the semantic error category associated with the sentence.

The results presented in Table 5.1 indicate that the proposed framework correctly handled both negation and numerical reasoning cases. In the first two examples, the system successfully detected negation cues and correctly interpreted semantic polarity, preventing incorrect entailment predictions that are common in standard NLI models. The negation logic module ensured that polarity inversion was explicitly modeled before final inference, improving reliability.

In the numerical reasoning examples, the system correctly extracted quantitative values and performed logical comparison between the claim and evidence. The symbolic numerical reasoning module normalized numerical expressions and verified consistency between quantities and temporal references. This prevented common errors in which neural models rely on lexical similarity rather than precise quantitative relationships.

Overall, the testing phase demonstrates that integrating symbolic reasoning modules with neural inference improves the system's ability to handle linguistically complex claims. These results are consistent with the error analysis discussed in Chapter 3, which identified negation and numerical reasoning as major contributors to incorrect predictions. The successful handling of these cases provides empirical support for the effectiveness of the proposed hybrid verification architecture. These testing results further confirm that explicit reasoning modules significantly enhance model robustness in semantically complex scenarios. They

also demonstrate that combining neural inference with symbolic processing reduces reliance on surface-level textual patterns. Overall, the evaluation provides strong evidence that hybrid reasoning improves both accuracy and interpretability in fact verification systems.

TABLE 5.1: Testing Results on Sample Claims

| **Claim** | **Evidence** | **Actual** | **Predicted** | **Error Type** |
|---|---|---|---|---|
| No Reservations got a mixed reception from critics. | The film received a mixed reception by critics, who found it predictable and too melancholy for the genre, resulting in a 41% overall approval rating from Rotten Tomatoes. | Refutes | Refutes | Negation |
| Chester Bennington is not a singer. | Chester Charles Bennington, born March 20, 1976, is an American musician, singer, songwriter and actor. | Refutes | Refutes | Negation |
| Cyndi Lauper won the Best New Artist award at the 27th Grammy Awards in 1985. | Her debut solo album earned Lauper the Best New Artist award at the 27th Grammy Awards in 1985. | Support | Support | Numerical |
| Liverpool F.C. was valued at $1.55 billion at one point. | Liverpool was the ninth highest-earning football club in the world for 2014–15, with an annual revenue of $391 million, and the world's eighth most valuable football club in 2016, valued at $1.55 billion. | Support | Support | Numerical |

## 5.11 Chapter Summary

This chapter described the implementation of the proposed hybrid fact verification framework. Unlike the conceptual and analytical discussions presented in Chapters 3 and 4, this chapter focused on the practical realization of the system, including neural inference, error routing, symbolic reasoning, and hybrid decision fusion.

The implemented pipeline enables explicit logical reasoning to complement transformer based semantic representations, thereby addressing the deep semantic errors identified during empirical analysis.

The next chapter presents the experimental results and discussion, evaluating the effectiveness of the proposed hybrid reasoning framework and analyzing the improvements achieved over baseline NLI models.

# Chapter 6

# Results and Discussion

## 6.1 Overview of Experimental Results

This chapter presents the experimental evaluation and detailed analysis of the proposed hybrid fact verification framework. The primary goal of this evaluation is to assess the effectiveness of transformer-based Natural Language Inference (NLI) models in fact verification tasks and to examine the impact of incorporating symbolic reasoning modules on improving semantic reliability.

The experimental study was designed with three main objectives. First, the performance of state-of-the-art NLI models was evaluated on benchmark datasets in order to establish baseline results. Second, a detailed analysis of incorrect predictions was conducted to identify recurring semantic phenomena responsible for misclassification. Third, the proposed logic-based reasoning modules were applied to these challenging cases, and the resulting improvements in verification accuracy were measured.

Two widely used fact verification datasets were selected for evaluation: the SciFact dataset and the FEVER dataset. These datasets were chosen because they represent two distinct domains and levels of linguistic complexity. SciFact focuson scientific claims and contains technically dense language requiring precise

reasoning, whereas FEVER consists of general-domain factual claims derived from encyclopedic knowledge sources.

Two transformer-based NLI models were evaluated in this study. RoBERTa-Large was used as a strong baseline model due to its proven performance in semantic inference tasks, while DeBERTa-Large was selected as the primary evaluation model because of its enhanced contextual representation capabilities and disentangled attention mechanism. Both models were evaluated under identical preprocessing and experimental conditions to ensure fairness of comparison.

The overall evaluation was carried out in three sequential stages. In the first stage, baseline performance of the models was measured using standard evaluation metrics. In the second stage, incorrectly predicted instances were extracted and analyzed to identify systematic error patterns related to negation, numerical reasoning, and directional semantics. In the third stage, the proposed symbolic reasoning modules were applied to these error cases, and improvements in prediction accuracy were measured using a hybrid decision framework.

The results presented in this chapter demonstrate that although modern transformer based NLI models achieve strong overall accuracy, they still exhibit systematic weaknesses when reasoning over linguistically complex sentences. The integration of symbolic reasoning modules significantly improves performance in such cases, providing empirical validation of the research hypothesis and supporting the objectives defined in Chapter 1.

## 6.2 Evaluation Metrics

To evaluate the performance of the proposed fact verification framework, standard classification metrics were used. These metrics provide a comprehensive understanding of model behavior by measuring correctness, reliability, and balance between different prediction classes. Since fact verification is formulated as a multi-class Natural Language Inference (NLI) problem, evaluation metrics must capture both overall performance and class-wise prediction quality. This ensures

that the evaluation reflects not only accuracy but also the model's ability to handle different semantic inference categories effectively. Let the predictions of the model be compared with the ground truth labels using the following standard terms:

i. True Positive (TP): Instances correctly predicted as belonging to a class.

ii. True Negative (TN): Instances correctly predicted as not belonging to a class.

iii. False Positive (FP): Instances incorrectly predicted as belonging to a class.

iv. False Negative (FN): Instances incorrectly predicted as not belonging to a class.

Based on these quantities, the following evaluation metrics were computed.

### 6.2.1 Accuracy

Accuracy measures the overall correctness of the model by calculating the proportion of correctly classified instances out of the total number of samples. It provides a general indication of how well the model performs across all classes. The accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6.1}$$

A higher accuracy indicates that the model correctly predicts a larger proportion of claim–evidence pairs. However, accuracy alone may not provide a complete picture of performance when class distributions are imbalanced, which is why additional metrics such as precision and recall are also considered.

Therefore, accuracy should be interpreted alongside other evaluation metrics to obtain a more balanced assessment of model performance. This is particularly important in fact verification tasks where different types of errors carry varying semantic significance.

### 6.2.2 Precision

Precision measures the reliability of positive predictions. It indicates how many of the instances predicted as positive actually belong to the positive class. A high precision value means that the model produces fewer false positives, which is particularly important in fact verification systems where incorrectly labeling a false claim as true can lead to misleading conclusions. Precision is defined as:

$$Precision = \frac{TP}{TP + FP} \tag{6.2}$$

### 6.2.3 Recall

Recall measures the ability of the model to correctly identify all relevant instances of a particular class. It indicates how many of the actual positive instances were correctly detected by the model.

Recall is defined as:

$$Recall = \frac{TP}{TP + FN} \tag{6.3}$$

A high recall value indicates that the model successfully detects most true instances and produces fewer false negatives. In fact verification tasks, recall is important because missing a valid supporting or contradicting relation can reduce system reliability.

### 6.2.4 F1-Score

The F1-score provides a balanced measure that combines precision and recall into a single metric. It is defined as the harmonic mean of precision and recall and is particularly useful when both false positives and false negatives must be considered. A high F1-score indicates that the model achieves both high precision and

high recall, meaning it is both accurate and reliable in identifying relevant classes. The F1-score is defined as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6.4}$$

### 6.2.5 Importance of Using Multiple Metrics

Using multiple evaluation metrics provides a more complete assessment of model performance. Accuracy reflects overall correctness, precision evaluates prediction reliability, recall measures completeness of detection, and the F1-score balances both aspects. Together, these metrics allow a comprehensive evaluation of fact verification systems, particularly when analyzing improvements achieved through symbolic reasoning modules and hybrid decision fusion.

## 6.3 Baseline Model Performance

### 6.3.1 Results on SciFact Dataset

Table 6.1 presents the baseline accuracy achieved by RoBERTa-Large and DeBERTa Large on the SciFact dataset.

Table 6.1: Model Performance Comparison on SciFact Dataset

| **Dataset** | **Model** | **Accuracy** |
|---|---|---|
| SciFact | RoBERTa-Large | 52.37% |
| SciFact | DeBERTa-Large | 86.98% |

The results indicate a significant improvement when moving from RoBERTa-Large to DeBERTa-Large. The improvement of more than 34% demonstrates the effectiveness of disentangled attention and enhanced decoding in capturing semantic relationships. However, despite this improvement, DeBERTa still produced a number of incorrect predictions, particularly in cases involving:

i. The results indicate a significant improvement when moving from RoBERTa-Large to DeBERTa-Large. The improvement of more than 34% demonstrates the effectiveness of disentangled attention and enhanced decoding in capturing semantic relationships.

ii. However, despite this improvement, DeBERTa still produced a number of incorrect predictions, particularly in cases involving:

This motivated the need for detailed error analysis. This motivates a deeper investigation into the types of semantic reasoning failures present in transformer-based models. Such analysis is essential to understand not only overall performance but also the underlying causes of incorrect predictions. It also provides a foundation for improving model robustness through targeted architectural enhancements.

### 6.3.2 Class-wise Performance of DeBERTa-Large on the SciFact Dataset

To obtain a deeper understanding of model behavior beyond overall accuracy, a class-wise evaluation was performed on the SciFact dataset. This analysis examines the precision, recall, and F1-score for each inference category. Class-wise metrics provide insight into how effectively the model handles different semantic relationships, particularly entailment and contradiction.

Table 6.2 presents the detailed performance of the DeBERTa-Large model on the SciFact dataset.

Table 6.2: Class-wise Performance of DeBERTa-Large on SciFact

| **Label** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Contradiction | 0.84 | 0.79 | 0.81 |
| Support | 0.88 | 0.92 | 0.90 |
| Macro Average | 0.86 | 0.85 | 0.86 |
| Weighted Average | 0.87 | 0.87 | 0.87 |

The results presented in Table 6.2 indicate that the DeBERTa-Large model demonstrates strong overall performance across both major classes of the SciFact dataset.

However, a closer inspection reveals meaningful differences in the model's ability to handle different semantic relationships.

The Support class achieves a precision of 0.88, a recall of 0.92, and an F1-score of 0.90, indicating that the model is highly effective at identifying cases where the evidence entails the claim. The relatively high recall suggests that the model successfully detects most supporting relationships, while the high precision indicates that few false entailment predictions are produced. This strong performance can be attributed to the fact that entailment often relies on lexical overlap and contextual similarity, which transformer-based models are particularly well suited to capture. In contrast, the Contradiction class achieves a precision of 0.84, a recall of 0.79, and an F1-score of 0.81, which is noticeably lower than the Support class. This difference reflects the inherent difficulty of contradiction detection in Natural Language Inference tasks. Identifying contradictions often requires deeper semantic reasoning, understanding of negation, numerical differences, and implicit logical relationships rather than simple contextual similarity. As observed during empirical analysis, many contradiction errors were associated with negation cues, directional expressions, or subtle semantic polarity changes that are not always explicitly represented in contextual embeddings.

The lower recall for the contradiction class indicates that some contradictory instances were incorrectly classified as support or neutral. This observation aligns with findings reported in recent NLI research, where contradiction detection is consistently more challenging than entailment detection due to the need for precise logical interpretation.

The macro average F1-score of 0.86 reflects balanced performance across classes without considering class frequency, demonstrating that the model maintains relatively stable performance across semantic categories. The weighted average F1-score of 0.87, which accounts for class distribution, indicates that the overall classification performance remains consistent even when class imbalance is considered.

These results provide important insights into the limitations of transformer-based NLI models. Although DeBERTa-Large significantly improves overall accuracy

compared to RoBERTa-Large, the lower performance on contradiction cases confirms that deep semantic reasoning remains a challenging problem. This observation directly supports the motivation for introducing logic-based preprocessing and symbolic reasoning modules in the proposed hybrid framework.

Furthermore, the class-wise evaluation highlights that improvements in entailment detection alone are insufficient for robust fact verification. A reliable verification system must handle contradictions with equal accuracy, particularly in real-world applications where incorrect acceptance of false claims can have serious consequences. The proposed hybrid reasoning architecture presented in subsequent chapters is specifically designed to address these weaknesses by incorporating explicit logical reasoning for negation, numerical comparison, and directional semantics.

## 6.4 Error Analysis on SciFact Dataset

Although the DeBERTa-Large model achieved strong baseline performance on the SciFact dataset, a detailed inspection of the misclassified instances was necessary to understand the underlying semantic challenges responsible for incorrect predictions. Error analysis plays a crucial role in identifying systematic weaknesses of deep learning models and provides empirical evidence to support the research problem formulated in this study.

Table 6.3: Error Statistics on SciFact Dataset

| **Dataset** | **Total Errors** | **Solved** | **Remaining** |
|---|---|---|---|
| SciFact | 44 | 37 | 7 |

A total of 44 incorrect predictions were identified after evaluating DeBERTa-Large on the SciFact dataset. These errors were carefully examined and processed using the proposed symbolic reasoning modules developed in Chapter 4. Table 6.3 summarizes the overall error correction performance on the SciFact dataset. Out

of 44 total misclassified instances, 37 errors were successfully corrected after applying the proposed logic-based preprocessing and symbolic reasoning modules. Only 7 cases remained unresolved. This result demonstrates that the majority of errors produced by transformer-based NLI models are not caused by fundamental representation failures, but rather by the absence of explicit logical reasoning mechanisms. When symbolic reasoning was introduced to explicitly handle negation, numerical comparisons, and directional relationships, a large proportion of incorrect predictions were corrected.

The relatively small number of remaining errors indicates that while symbolic reasoning significantly improves performance, certain complex contextual or multi-hop reasoning cases still remain challenging. These unresolved cases represent an important direction for future research in hybrid reasoning architectures.

These remaining errors are primarily associated with highly contextual or multi-sentence dependencies where semantic information is distributed across multiple evidence fragments. Such cases require deeper integration of external knowledge and more advanced reasoning strategies than those currently implemented. Overall, the results confirm that combining neural inference with symbolic reasoning substantially reduces error rates while still leaving a small but important set of open challenges.

### 6.4.1 Error Categorization on SciFact Dataset

To better understand the nature of model failures, the erroneous predictions were categorized into semantic error types based on linguistic and logical characteristics identified during empirical analysis.

Table 6.4 provides a breakdown of error types observed in the SciFact dataset.

Negation-related errors constituted the largest portion of incorrect predictions. A total of 38 instances involved negation or mixed semantic polarity, out of which 26 were successfully corrected using propositional logic transformations. This confirms that negation remains one of the most challenging phenomena for

TABLE 6.4: Error Type Distribution on SciFact Dataset

| **Error Type** | **Total** | **Solved** | **Remaining** |
|---|---|---|---|
| Negation (Mixed) | 38 | 26 | 12 |
| Numerical | 14 | 8 | 6 |
| Directional | 3 | 3 | 0 |
| Mixed Multi-type | 21 | – | – |
| Other | 6 | – | – |

transformer-based NLI models, as small polarity changes can significantly alter semantic meaning while maintaining high lexical similarity.

Numerical reasoning errors accounted for 14 instances, of which 8 were successfully resolved using symbolic numerical comparison. These errors typically occurred in sentences involving percentages, counts, or quantitative relations where contextual embeddings alone were insufficient to capture precise numeric differences. Directional reasoning errors were relatively few in number, with only 3 instances observed.

However, all directional errors were successfully corrected using symbolic directional reasoning rules. This indicates that although directional reasoning errors are less frequent, they are highly amenable to rule-based correction mechanisms.

Mixed multi-type errors and other complex cases involved multiple overlapping semantic phenomena or domain-specific reasoning requirements. These cases remain more challenging and highlight limitations of current symbolic rule-based approaches when dealing with highly complex contextual reasoning.

Overall, the distribution of errors strongly supports the research hypothesis that deep semantic phenomena such as negation, numerical reasoning, and directional relations are major sources of failure in NLI-based fact verification systems.

Table 6.4 clearly shows that most errors are concentrated in semantically complex categories rather than random model failures. This distribution highlights the systematic nature of weaknesses in transformer-based NLI models, particularly in

handling polarity shifts and quantitative reasoning. These findings further validate the need for hybrid reasoning approaches that explicitly address deep semantic error patterns.

## 6.5 Performance After Logic Implementation on SciFact Dataset

Table 6.5 presents the performance improvement achieved after integrating symbolic reasoning modules into the fact verification pipeline.

Table 6.5: Final Performance After Logic Integration

| **Baseline Accuracy** | **Final Accuracy** | **Errors Fixed** | **Recovery Rate** |
|---|---|---|---|
| 86.98% | 97.93% | 37/44 | 84.09% |

The baseline accuracy of DeBERTa-Large on the SciFact dataset was 86.98%. After applying the proposed hybrid reasoning framework, the accuracy increased to 97.93%, representing an improvement of more than 10 percentage points. Such a substantial improvement is significant in the context of fact verification tasks, where even small accuracy gains can be difficult to achieve.

The recovery rate of 84.09% indicates that a large majority of semantic reasoning errors were successfully corrected. This demonstrates the effectiveness of combining neural contextual representations with explicit logical reasoning.

These results confirm that hybrid architectures integrating symbolic reasoning can significantly enhance robustness against deep semantic reasoning errors without modifying the internal architecture of transformer models. This improvement also highlights that many errors in transformer-based NLI systems are not due to insufficient learning capacity, but due to missing explicit reasoning mechanisms. The strong recovery rate further validates the effectiveness of symbolic preprocessing in correcting systematic semantic failures. Overall, the findings demonstrate that structured logic integration can substantially improve both accuracy and reliability in fact verification systems.

## 6.6 Results on FEVER Dataset

Table 6.6: Baseline Performance on FEVER Dataset

| Dataset | Model | Accuracy |
|---|---|---|
| FEVER | RoBERTa-Large | 93.71% |
| FEVER | DeBERTa-Large | 96.60% |

Table 6.6 shows the baseline performance of RoBERTa-Large and DeBERTa-Large on the FEVER dataset. DeBERTa-Large achieved higher accuracy than RoBERTa-Large, confirming the effectiveness of disentangled attention mechanisms in modeling contextual relationships.

However, despite strong overall performance, detailed inspection revealed persistent errors, particularly in claims involving complex contextual reasoning, numerical comparisons, and semantic polarity changes. These findings motivated the application of symbolic reasoning modules to further improve performance.

The results also demonstrate that benchmark-level accuracy does not fully reflect the robustness of a model in semantically challenging verification scenarios.

## 6.7 Error Analysis on FEVER Dataset

Table 6.7 summarizes the error analysis conducted on the FEVER dataset. A subset of 200 errors was selected for detailed examination. After removing instances labeled as Not Enough Information (NEI), 145 cases remained suitable for semantic analysis.

Table 6.7: Error Statistics on FEVER Dataset

| Sample Analyzed | After NEI Removal | Solved | Remaining |
|---|---|---|---|
| 200 | 145 | 32 | 23 |

Out of these, 32 errors were successfully corrected using symbolic reasoning modules, while 23 remained unresolved. The exclusion of NEI cases ensured that the

analysis focused exclusively on semantic reasoning failures rather than evidence insufficiency.

### 6.7.1 Error Categorization on FEVER Dataset

TABLE 6.8: Error Type Distribution on FEVER Dataset

| **Error Type** | **Total** | **Solved** | **Remaining** |
|---|---|---|---|
| Negation | 20 | 7 | 13 |
| Numerical | 28 | 22 | 6 |
| Directional | 3 | 3 | 0 |
| Contextual | 94 | – | 94 |

Table 6.8 presents the distribution of error types observed in the FEVER dataset.

Numerical reasoning errors exhibited the highest recovery rate, demonstrating the effectiveness of symbolic numerical comparison in resolving quantitative inconsistencies. Negation errors were partially resolved, indicating that while propositional logic improves performance, certain cases involve complex linguistic structures that remain challenging.

Directional reasoning errors were few but were completely corrected using symbolic directional reasoning rules. Contextual errors constituted the largest category, highlighting that implicit reasoning and multi-hop inference remain major open challenges in fact verification research.

The dominance of contextual errors further emphasizes the limitations of purely transformer-based architectures in capturing implicit semantic dependencies. These results suggest that incorporating structured reasoning components can significantly enhance model robustness for specific error categories. However, unresolved contextual cases indicate that deeper discourse-level understanding is still required. Overall, the findings highlight a clear gap between surface-level corrections and true semantic reasoning capabilities.

These observations indicate that while symbolic reasoning effectively resolves structured error types, it is less effective for highly contextual and multi-hop scenarios.

Such cases require broader discourse understanding beyond sentence-level logic. This further reinforces the need for advanced reasoning frameworks that integrate context-aware inference mechanisms.

## 6.8 Final Accuracy After Logic Implementation on FEVER Dataset

Table 6.9 shows the improvement achieved after integrating symbolic reasoning modules. Although the absolute accuracy gain appears modest, it is important to consider the large size and complexity of the FEVER dataset. Even small improvements in large-scale benchmarks represent meaningful progress and validate the effectiveness of hybrid reasoning architectures. The improvement observed after logic integration indicates that symbolic reasoning modules successfully corrected a substantial number of semantically complex errors. In particular, the framework demonstrated better handling of numerical inconsistencies, negation structures, and directional relationships that were previously misclassified by the neural model. These findings further support the effectiveness of combining neural inference with explicit reasoning mechanisms in large-scale fact verification tasks.

TABLE 6.9: Final Performance on FEVER Dataset After Logic Integration

| **Dataset** | **Baseline Accuracy** | **Final Accuracy** | **Errors Fixed** |
|---|---|---|---|
| FEVER | 96.60% | 96.90% | 583+ |

## 6.9 Comparative Results

To further validate the effectiveness of the proposed fact verification framework, the experimental results obtained in this study were compared with representative state-of-the-art approaches reported in the literature. Comparative evaluation not only to measure absolute performance but also to analyze relative improvements

on strong baselines and to understand how improvements in semantic reasoning capability influence verification accuracy.

Most existing fact verification systems rely primarily on transformer-based Natural Language Inference (NLI) models such as BERT, RoBERTa, and DeBERTa. These models learn contextual semantic representations from large-scale corpora and therefore achieve strong benchmark performance. However, as demonstrated in Chapter 3, these models still exhibit systematic errors in linguistically complex cases involving negation, numerical reasoning, directional relationships, and implicit semantic dependencies. These limitations motivated the development of the proposed hybrid framework.

Table 6.10 presents a comparison between representative studies and the proposed framework using commonly reported benchmark datasets such as FEVER and SciFact. The values shown in parentheses for the proposed method represent the *relative improvement in accuracy* over the strongest baseline model, which in this case is DeBERTa.

TABLE 6.10: Comparative Results with State-of-the-Art Methods

| **Study / Model** | **Year** | **Dataset** | **Accuracy** |
|---|---|---|---|
| Thorne et al. [32] | 2018 | FEVER | 84% |
| BERT-based NLI [31] | 2019 | FEVER | 87% |
| RoBERTa-based NLI [34] | 2019 | FEVER / SciFact | 88% / 89% |
| DeBERTa-based NLI [35] | 2021 | FEVER / SciFact | 93% / 91% |
| **Proposed** | **2026** | **FEVER** | **97% (4.3%)** |
| | **2026** | **SciFact** | **98% (7.6%)** |

A clear performance progression can be observed from Table 6.10. Early fact verification pipelines such as the FEVER baseline reported by Thorne et al. achieved approximately 84% accuracy on the FEVER dataset. The introduction of transformer-based models significantly improved performance, with BERT-based approaches increasing accuracy to around 87%, followed by RoBERTa achieving approximately 88% on FEVER and 89% on SciFact. These improvements can largely be attributed to enhanced contextual representation learning and large-scale pretraining strategies.

DeBERTa introduced disentangled attention mechanisms, which further improved performance to approximately 93% on FEVER and 91% on SciFact, demonstrating the importance of improved semantic representation in NLI tasks.

Nevertheless, as shown in the empirical analysis in Chapter 3, even DeBERTa continues to produce systematic errors in cases requiring deep semantic reasoning.

The proposed framework achieved 97% accuracy on FEVER and 98% on SciFact. When compared with DeBERTa, this corresponds to a **relative improvement of approximately 4.3% on FEVER and 7.6% on SciFact**. These percentages reflect the gain achieved over the strongest baseline model rather than over earlier methods, providing a more meaningful evaluation of the contribution.

The improvement is particularly notable on the SciFact dataset, which contains technically complex and semantically dense scientific claims. The larger gain on this dataset indicates that the proposed framework is more effective in handling deep semantic phenomena rather than relying solely on surface-level textual similarity.

Unlike purely neural approaches, the proposed framework improves verification reliability by incorporating semantic error analysis, symbolic reasoning modules, and structured validation mechanisms. These components help reduce systematic reasoning errors, particularly in cases involving semantic polarity, numerical comparison, directional relationships, and implicit inference.

Consequently, the observed improvement in accuracy reflects not only better classification performance but also enhanced robustness and reliability in fact verification. Overall, the comparative results demonstrate that while transformer-based NLI models provide strong baseline performance, further gains can be achieved by integrating structured reasoning and validation components that explicitly address deep semantic phenomena.

The comparative results clearly indicate that improvements in fact verification performance are not solely dependent on larger or deeper transformer architectures. Instead, meaningful gains are achieved when models are augmented with explicit

reasoning capabilities that address known semantic weaknesses. This suggests that future progress in NLI-based fact verification will likely depend on hybrid architectures that combine neural representation learning with structured logical reasoning. Overall, the results validate the effectiveness of integrating symbolic reasoning into transformer-based systems for improved semantic robustness.

## 6.10 Chapter Summary

This chapter presented a comprehensive evaluation of the proposed hybrid fact verification framework through quantitative experiments, detailed error analysis, and comparative performance evaluation with existing methods.

Experimental results demonstrated that although transformer-based NLI models such as RoBERTa and DeBERTa achieve strong performance, they continue to exhibit systematic semantic reasoning errors. These errors were empirically validated through detailed analysis on both SciFact and FEVER datasets, where phenomena such as negation, numerical reasoning, directional relations, and implicit inference were identified as major sources of failure.

The proposed framework achieved measurable improvements in verification accuracy, outperforming existing transformer-based approaches by up to 7 percentage points on challenging datasets. More importantly, the framework improved robustness and reliability by reducing systematic reasoning errors rather than merely optimizing statistical performance.

These findings confirm the central hypothesis of this research that improving deep semantic reasoning and structured validation can significantly enhance automated fact verification systems.

The next chapter concludes the thesis by summarizing the major contributions of this research, discussing limitations, and outlining promising directions for future work in hybrid reasoning architectures for fact verification.

# Chapter 7

# Conclusion and Future Work

## 7.1 Conclusion

This thesis addressed the problem of semantic reasoning errors in Natural Language Inference (NLI)-based fact verification systems. Although modern transformer based models such as RoBERTa-Large and DeBERTa-Large achieve high overall accuracy, empirical analysis demonstrated that these systems frequently misclassify claims involving deep semantic phenomena such as negation, numerical reasoning, directional relations, and complex contextual dependencies.

The research began by conducting a systematic empirical analysis of state-of-the-art NLI models using two widely recognized benchmark datasets, namely SciFact and FEVER. Experimental results confirmed that even highly advanced models produce consistent errors when linguistic structures require explicit logical reasoning rather than contextual similarity alone. These findings provided strong empirical evidence supporting the research problem formulated in this study.

A detailed error taxonomy was developed to categorize semantic reasoning failures into meaningful groups. This taxonomy revealed that negation and numerical reasoning were among the most frequent sources of incorrect entailment and contradiction predictions, while directional and mixed semantic cases also contributed to performance degradation.

To address these limitations, this research proposed a hybrid fact verification framework integrating transformer-based NLI models with symbolic reasoning modules. The logic design introduced three key reasoning components:

i. Negation reasoning using propositional logic.

ii. Symbolic numerical reasoning for quantitative comparisons.

iii. Symbolic directional reasoning for relational and trend-based semantics.

These modules were designed to operate as preprocessing and reasoning layers that transform claim–evidence pairs into logically consistent representations before final inference. The proposed architecture preserved the strengths of deep contextual embeddings while enhancing semantic robustness through explicit logical reasoning.

The implementation of the proposed framework demonstrated that hybrid reasoning significantly improves performance on semantically challenging cases. Experimental results showed notable improvements in accuracy, particularly on the SciFact dataset, where a large proportion of semantic reasoning errors were successfully corrected. On the FEVER dataset, improvements were smaller in magnitude but still meaningful, especially considering the large dataset scale and already high baseline accuracy.

The results confirm that many errors in NLI-based fact verification systems are not purely representational but arise from the absence of explicit logical reasoning mechanisms. By integrating symbolic reasoning with neural inference, the proposed approach improves reliability, interpretability, and robustness without modifying the internal architecture of transformer models.

Overall, this research successfully achieved its objectives by identifying deep semantic reasoning challenges, designing a hybrid reasoning architecture, and empirically demonstrating its effectiveness. The findings contribute to ongoing research in hybrid AI systems that combine neural and symbolic reasoning to achieve more reliable language understanding.

## 7.2 Limitations of the Study

Although the proposed hybrid fact verification framework demonstrated significant improvements in accuracy and reasoning reliability, several limitations remain that provide opportunities for future research.

First, the symbolic reasoning modules rely primarily on rule-based detection of linguistic patterns. While these rules are effective for structured semantic phenomena such as negation, numerical comparisons, and directional reasoning, rule-based approaches may face limitations when dealing with highly complex contextual relationships, implicit multi-hop reasoning, or domain-specific linguistic expressions that are not explicitly captured by predefined patterns.

Second, the current implementation focuses mainly on sentence-level reasoning. In real-world fact verification scenarios, claims often require document-level analysis or aggregation of multiple evidence sentences. Extending the proposed framework to support multi-evidence reasoning and document-level inference would further improve its applicability in large-scale verification systems.

Third, the symbolic reasoning modules were developed and evaluated primarily on English-language datasets. Extending the approach to multilingual environments would require additional preprocessing techniques, language-specific linguistic resources, and cross-lingual semantic modeling.

Finally, the current framework does not incorporate a comprehensive terminology expansion or domain-specific semantic dictionary. In many fact verification tasks, claims and evidence may use different terminologies to express the same concept, leading to semantic mismatches even when the underlying meaning is consistent. Developing structured terminology expansion mechanisms and constructing domain-aware lexical dictionaries could significantly enhance semantic normalization, improve alignment between claims and evidence, and further reduce inference errors. This direction represents an important extension of the present work. Despite these limitations, the proposed framework establishes a

strong foundation for integrating neural inference with explicit semantic reasoning, and the identified limitations provide clear pathways for future improvements.

## 7.3 Future Work

Several promising directions for future research emerge from this study.

One important extension would be the incorporation of advanced logical reasoning techniques such as first-order logic or knowledge graph reasoning to handle more complex semantic relationships. Such approaches could improve performance in cases involving relational inference and implicit reasoning.

Another direction is the integration of neural-symbolic learning approaches in which symbolic reasoning components are learned jointly with neural models rather than implemented as rule-based modules. This could allow the system to generalize logical reasoning patterns more effectively.

Future research could also explore multi-hop reasoning and evidence aggregation techniques to handle claims requiring multiple supporting sentences. This would extend the proposed framework to more complex fact verification scenarios.

Finally, applying the proposed hybrid framework to real-world applications such as misinformation detection, scientific literature verification, and automated knowledge validation would provide valuable insights into its practical impact and scalability.

## 7.4 Final Remarks

The rapid growth of digital information has made automated fact verification an increasingly important research area. While transformer-based language models have significantly advanced the field, this research demonstrates that purely neural approaches still face limitations in deep semantic reasoning. The hybrid reasoning

framework proposed in this thesis represents a step toward more reliable and interpretable fact verification systems. By combining neural semantic understanding with explicit logical reasoning, the approach moves closer to human-like reasoning capabilities in natural language processing. It is hoped that the ideas and findings presented in this thesis will contribute to future research in hybrid artificial intelligence and the development of more trustworthy automated fact verification systems.

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