CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Classification of Mini-UAVs Using EMD and LSTM Based Classification Framework

by

Osama Bahar

A thesis submitted in partial fulfillment for the degree of Master of Science

in the

Faculty of Engineering
Department of Electrical Engineering

2023

This work is dedicated to my parents and brother

CERTIFICATE OF APPROVAL

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(MEE183002)

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Author's Declaration

I, **Osama Bahar** hereby state that my MS thesis titled "**Classification of Mini-UAVs Using EMD and LSTM Based Classification Framework**" is my own work and has not been submitted previously by me for taking any degree from Capital University of Science and Technology, Islamabad or anywhere else in the country/abroad.

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(Osama Bahar)

Registration No: MEE183002

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In those regions with high security requirements, accurate detection and classification of mini UAVs is really important. This is especially true considering the difficulties in identifying existing mini UAVs because of their small size, moderate flying speed, and flying low altitude.

Radar technology is commonly employed in surveillance systems due to its quick remote sensing capabilities despite the weather. Among the several signal processing approaches for radar signals, the micro-Doppler signature (mDS) is the one that is most commonly used for mini UAV classification. This is so that the distinctive micro motion features caused by the mini UAV rotor blades can be captured by the mDS retrieved from radar echo signals.

In this thesis, EMD based method for classification of mini UAVs is proposed. Initially, EMD is used to decompose the multicomponent radar echo signal into a set of oscillating waveforms. The feature vectors are formed based upon the data obtained from IMFs. Training data is generated for different types of UAVs to train the Long Short Term Memory (LSTM) classifier and finally testing is done to observe the performance of the proposed classification technique. The proposed technique outperforms other state-of-the-art techniques in the literature as depicted by Confusion matrix plots.

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m-DS	m-DS Micro Doppler Signatures
mDS	mDS micro-Doppler signatures

Symbols

f_v	Vibration frequency
f_D	Doppler frequency
D_v	Vibration Amplitude
$z(t)$	Complex-valued signal
ht	Outputs
xt	Inputs
C_t	Cell state
C_{t-1}	Old cell state
$e_{min}(t)$	Min envelop
$e_{max}(t)$	Max envelop
l	No of IMFs
$r(t)$	residual

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$e_{min}(t)$	Min envelop
$e_{max}(t)$	Max envelop
l	No of IMFs
$r(t)$	residual

Chapter 1

Introduction

We are currently experiencing a surge in the use of drones for commercial, professional, and entertainment purposes, in addition to defense. This rise is due to the vast commercial offer, which is constantly expanding, the relatively low cost of drones, their effectiveness in surveillance tasks and package delivery, and the inherent allure of this cutting-edge technology's ease of use. Drones offer a new form of entertainment to everyone, with incredible multimedia results. Perhaps one day, seeing drones on the road will be as common as seeing mail trucks or any other toy at home [1]. There have been tremendous developments in the UAV business and technology during the past decade. UAVs have dramatically improved in both flying performance and equipment cost. The development of this UAV has broadened its potential uses. However, if UAVs are utilized for surveillance, reconnaissance, or even assault, they might compromise security. Existing mini-sized unmanned aerial vehicles (UAVs) might be difficult to detect because of their tiny size, relatively low flying altitude, and modest flying speed. Miniature unmanned aerial vehicles (UAVs) require precise automated identification and categorization whenever security is a concern. So, radar is widely utilized in monitoring infrastructure [2].

However, this rapid evolution implies the emergence of a new threat to global security from a variety of perspectives. On the one hand, individuals' right to privacy may be easily violated, and their security may be jeopardised due to the proximity of these aircrafts in flight. Furthermore, when flying through protected airspace or near airports, drones pose a potential risk of plane collision. Finally, the same mentioned usability and ease of access to these systems may provide an advantage for terrorists, allowing them to carry out their attacks in a more effective and less exposed manner [2].

1.1 Basic Idea of Radar Systems

Radar is a long-distance electromagnetic sensor that detects, locates, tracks, and recognizes objects. It works by directing electromagnetic energy toward targets and then observing the echoes that are returned from them. Aircraft, ships, spacecraft, automobiles, astronomical bodies, and even birds, insects, and rain could be targets. Radar can sometimes determine the size and shape of such objects in addition to determining their presence, location, and velocity. Radar differs from optical and infrared sensing devices in its ability to detect distant objects and precisely determine their range, or distance, even in adverse weather conditions.

When it comes to detecting objects, radar is an active sensing technology since it relies on its own light source (a transmitter) to do so. It is most commonly used at frequencies between 400 MHz and 40 GHz, which is considered to be the microwave area of the electromagnetic spectrum (GHz). In contrast, it has been put to use for long-distance purposes at optical and infrared frequencies, as well as at lower frequencies (reaching as low as a few megahertz, which is considered to be part of the high-frequency or shortwave band. Depending on the frequency, the radar system's circuit components and other gear can range in size from the palm of your hand to several football fields.

Radar technology grew significantly in the 1930s and 1940s as a result of the need to satisfy military demands. Many technical improvements may be traced back to this system, which is still in widespread use by the military. Radar has a wide variety of important civilian applications, including but not limited to the management of air traffic, the observation of weather patterns, the remote sensing of the surrounding environment, the navigation of aircraft and ships, the measurement of speeds for the interests of industry and law enforcement, planetary observation, space monitoring, and other similar activities.

1.2 RADAR History

1.2.1 Early Experiments

Maxwell performed the calculations necessary to derive the general equations that describe the EM field. He came to the realisation that light and radio waves would both be types of EM waves that operate in accordance with the same fundamental principles, despite the fact that their frequencies are very different from one another. Based on his research, Maxwell concluded that a dielectric medium may reflect and refract radio signals in the same way as it does light waves.

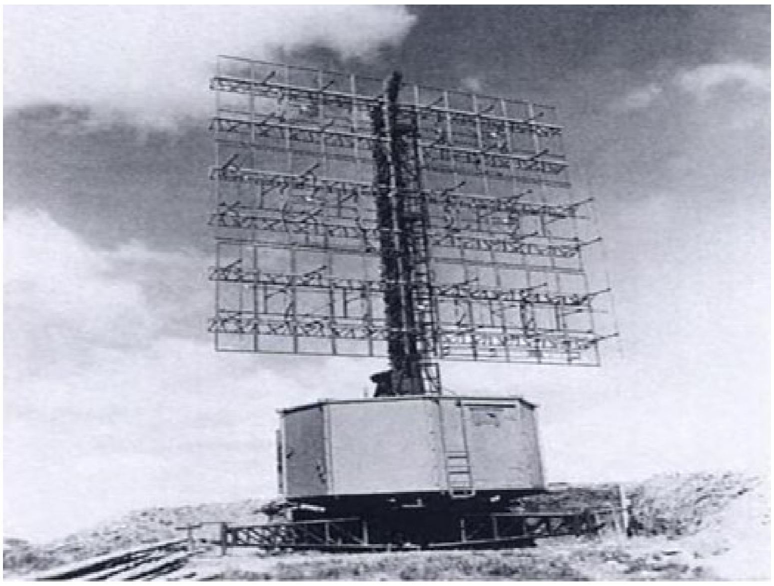

FIGURE 1.1: German Freya RADAR

The work of Hertz was recognized at the time as having the potential to be useful as a basis for identifying objects of practical relevance. This was a recognition that took place at the time. 1904, a German engineer by the name of Christian Hülsmeyer got a patent in multiple nations for "an obstacle detector and ship navigation device” that was based on the ideas that Hertz had shown. Hülsmeyer constructed and exhibited his device to the German navy, but the navy paid little attention to it. Before the early 1930s, when long-range military bombers were developed that were capable of delivering considerable payloads, there was simply no need for radar on any level, whether it be the economic front, the sociological front, or the military front. As a consequence of this, the powerful nations of the world started looking for a way to detect the approach of hostile aircraft.

1.2.2 Before WW II

The vast majority of nations that later developed radar had already investigated and experimented with a variety of alternative approaches to aero plane detection. One of the things that they did was listen for sound audible that aeroplane engines emit and detect the electrical noise that is created by their firing. Sensosr that was investigated by the researchers was an IR sensor. In spite of this, none of them ended up being successful in the end.

1.2.3 First Radar

The first radars developed by the United States Army were the SCR-268 (at 205 MHz) for controlling antiaircraft gunfire and the SCR-270 (at 100 MHz) for detecting aircraft. Both of these radars, as well as the navy’s CXAM shipboard surveillance radar, were available at the start of World War II (at a frequency of 200 MHz). On December 7, 1941, One of the six SCR-270s that were stationed in Hawaii at the time was able to detect the arrival of Japanese aeroplanes toward Pearl Harbor, which is located near Honolulu; The importance of the radar information, however, was not understood until the bombs began to drop. Before World War II, all the effective radar systems that were developed were in the very high frequency (VHF) band, which encompasses the frequency range that is lower than about 200 MHz. The few of German radars that operated at 375 and 560 MHz respectively. The utilization of these frequencies led to a variety of problems and difficulties as a direct consequence of the wide beamwidths that are associated with VHF frequencies. The utilization of this technology results in narrow beamwidths, which makes it feasible to get rid of unwanted echoes coming from ground or even other types of clutter. Second, the portion of the EM spectrum (VHF) does not offer the huge bandwidths that are required for the short pulses that allow for enhanced range determination precision. Third, noise from the environment can interfere with VHF transmissions, which can make receivers less sensitive to signals.

1.2.4 Advances During World War II

The concept of the magnetron was graciously divulged to the United States by the British in 1940, and it provided the foundation for work performed by the newly founded MIT. The cavity magnetron oscillator was conceived by British scientists at the University of Birmingham in late 1939. It allowed for higher frequencies (those in the microwave area) to be utilized for radar, with all of the benefits that this entailed. The cavity magnetron oscillator was During World War II, the magnetron was the key component that made microwave radar a practicable option. The MIT Laboratory is responsible for the development of some of the most renowned microwave radars, including the SCR-584, which is a gunfire-control system that is extensively utilized. It made use of conical scan tracking, in which a single offset (squinted) radar beam is continually rotated about the central axis of the radar antenna, and its four-degree beam width gave enough angular accuracy to position antiaircraft weapons on target without the need for searchlights or optics, as previous radars with wider beam widths did. This was in contrast to prior radars that had greater beam widths (such as the SCR-268). The SCR-584 made use of the frequency zone that is commonly known to as the S-band, which is between 2.7 and 2.9 GHz, and it had a parabolic reflector antenna that had a diameter of around 6.6 feet. The S-band is a common term for the frequency range that it utilizes (2 meters). At the beginning of 1944, it participated in combat for the first time at the beachhead of Anzio, which was in Italy. Due to the fact that the Germans had already found a means to jam its predecessor, the SCR-268, by the time that it was introduced, its introduction came at the ideal time. The Germans were caught off guard and taken by surprise when the creation of the SCR-584 microwave radar was completed.

1.2.5 Postwar Progress

The end of the war caused a substantial slowdown in the advancement of radar technology. The second half of the 1940s, namely the decade's second half, was mostly focused on postwar developments. The "moving-target indication (MTI)" radar and the "monopulse tracking radar" are two examples of the technology that was utilized here (Doppler frequency and target velocity). Both of these radar techniques required many more years of study and development before they were able to attain their full potential. In the 1950s, a variety of brand-new radar systems were developed along with major advancements in existing ones. One of them was the AN/FPS-16, which had an extremely precise monopulse tracking radar with an angular accuracy of around 0.1 mmilliradians (roughly 0.006^o). These apparatuses, which were outfitted with enormous antennas that rotated mechanically and had horizontal diameters of more than 37 meters (120 feet), made it possible for us to detect aeroplanes at extremely great distances. Another significant advance that was made was the invention of the klystron amplifier. This device was able to provide extremely long-range radars with a reliable source of high power.

The synthetic aperture radar was first shown at the beginning of the 1950s; nevertheless, it was not until approximately 30 years later that it attained a high degree of development after it was first introduced. This was only made feasible after the development of digital processing, in addition to other advancements. At the tail end of the 1950s, the Bom arc surface-to-air missile was upgraded to incorporate an airborne pulse-Doppler radar as well.

1.2.6 Pulse Doppler Radars

Doppler frequency shift and its value for radar were recognized before to World War II it took years of work to reach the technology necessary for broad deployment.

Eventually, the Doppler frequency shift was used in radar. The Doppler Effect was first significantly used to radar in the 1950s, and since that time, it has become an essential component in the operation of a great many different types of radar systems. This first important application of the Doppler Effect occurred in the 1950s. As was covered in the part that came before this one, the Doppler frequency shift of the reflected signal is caused when there is relative motion between the radar and the target.

The utilization of Doppler frequency is vital in the operation of continuous wave, MTI, and pulse Doppler radars. This is due to the fact that these types of radars are required to detect moving objects in spite of the presence of a significant number of clutter echoes. The Doppler frequency shift is the principle upon which radar weapons used by the police are based. SAR and ISAR imaging radars make use of doppler frequency in order to create high-resolution pictures of the terrain and the targets they are aimed at. In Doppler-navigation radar, the Doppler frequency shift has also been utilized to detect the velocity of the aircraft that is carrying the radar system.

In addition, the extraction of the Doppler shift in weather radars enables the identification of severe storms and dangerous wind shear, which is not possible using any other approach. The reason for this is because other techniques are unable to accurately capture the Doppler shift.

1.2.7 Phased-Array Radars

The United States military began using its first big phased-array radars in the 1960s. These radars had the capability of being electronically guided. At the time, the United States Navy was working on developing a Grumman E-2 AEW aircraft that would be equipped with an airborne MTI radar for the purpose of aircraft detection. The decade of the 1960s saw the development of the very first radars that were intended to intercept ballistic missiles as well as satellites. These radars came into being during this decade.

Table 1.1: Frequency Bands

Band Designation	**Normal Frequency Range**	**Specific Radiolocation(radar) Bands Based on ITU Assignments for Region 2**
HF	3-30 MHz	
VHF	30-300 MHz	138-144 MHz, 216-225 MHz
UHF	300-1000 MHz	420-450 MHz, 890-942 MHz
L	1000-2000 MHz	1215-1400 MHz
S	2000-4000 MHz	2300-2500 MHz, 2700-3700 MHz
C	4000-8000 MHz	5250-5925 MHz
X	8000-12000 MHz	5250-5925 MHz
K_u	12-18 GHz	13.4-14 GHz, 15.7-17.7 GHz
K	18-27 GHz	24.25-24.5 GHz
K_a	27-40 GHz	33.4-36 GHz
Mm	40-3000 GHz	

1.2.8 Advancement in Digital Technology

Further developments in signal and data processing were made possible as a result of improvements made in digital technology throughout the first decade of the 21st century. These developments led to the creation of phased-array radars that are (nearly) entirely digital. Below is the table that is explaining the evolution of technologies in Radars from the year 1920 to 2000.

Table 1.2: Radar Technology Evolution

Year	**Evolution of Radar Technology**
1920	Aircraft (bomber) detection and early warning
1930	Bi-static CW(continuous wave) radar
1940	Mono-static pulse radar
1950	Pulsed Doppler radar and signal processing concept
1960	Phased array radar
1970	Digital MTI(moving target indicator) and imaging radar
1980	SAR(synthetic aperture radar) and OTH(over-the-horizon) radar
1990	Multifunction radar (Patriot Missile Defense Radar)
2000	Evolution in 2000: • pace borne radar(SIR-E/SRTM) • SRTM(Shuttle Radar Topography Mission) • PESA(passive electronically scanned array): single source per radar • AESA(active electronically scanned array): one source per an element

1.2.9 Radar in the Digital Age

The digital technology that was used to handle signals and data became significantly more accessible in the 1970s, which made it possible for contemporary radar to be developed. The capability of airborne pulse-Doppler radar to identify aeroplanes in the midst of intense ground clutter has also seen significant improvements as a result of significant developments achieved in this area. The AWACS radar of the United States Air Force and the military airborne intercept radar both utilize the pulse-Doppler concept in their operations. In the 1970s, radar made its debut as a tool for the distant sensing of the environment aboard spacecraft for the first time. This fact should also be mentioned.

1.3 RADAR Hardware

Most radar models share the same basic hardware. There are differences; some models are only for stationary use, whereas others can be used in both stationary and moving modes. Some models are single-piece constructions, while others are made up of two or more parts (boxes) and/or have multiple antennas. Many units only detect approaching targets, whereas others detect both approaching and receding targets. Some radars in moving mode can detect traffic in the same lane (direction) as the patrol car (front and/or rear). A typical traffic radar system is depicted in the diagram below. In multi-piece radars, the antenna is usually separate from the rest of the electronics.

1.3.1 Basic Components of Radar

1.3.1.1 Transmitter

A radio-frequency electromagnetic wave is reflected off a target by a radar system, which then utilizes this reflected signal to determine information about the target. In every radar system, the signal that is sent out and received will display many of the characteristics that are outlined in the following paragraphs.

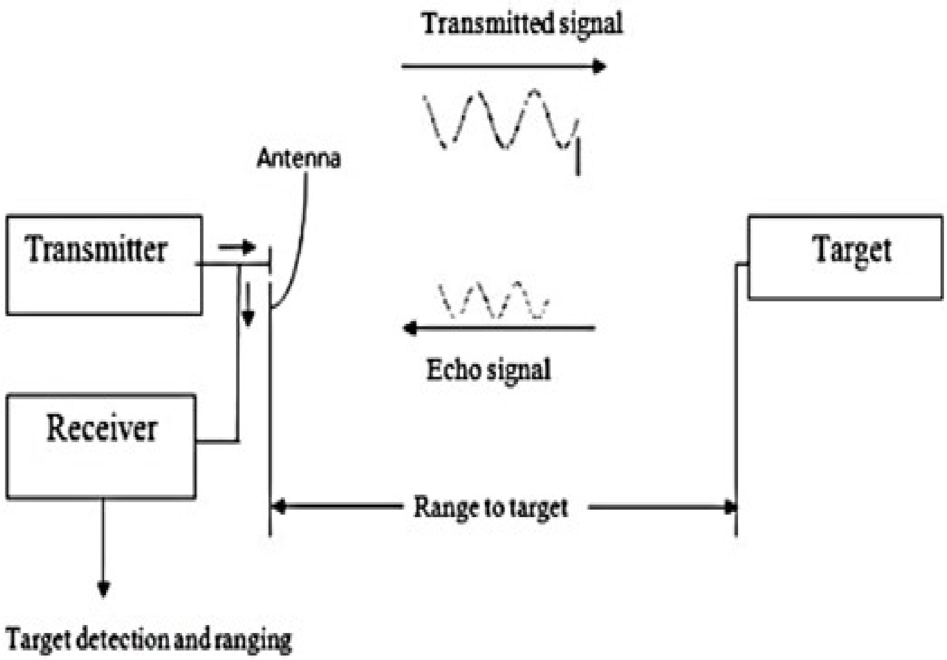

FIGURE 1.2: Radar Components

1.3.1.2 Pulse modulator

A power amplifier is responsible for producing a megawatt-level signal when it sends out its output. The pulse modulator on the block acts as a switch, allowing the power amplifier to be turned on and off as needed. Waveform generator: The power amplifier receives a signal with a low power output that was created by the waveform generator.

1.3.1.3 Duplexer

A duplexer is an electronic device that allows a single antenna to simultaneously broadcast and receive data. When transmitter operates, the duplexer opens a circuit that shorts out the input of the receiver. This allows high power to travel to the antenna instead of the reception. Whenever the duplexer is being used for receiving, the echo signal is sent to the receiver rather than the broadcaster. In addition to these components, the duplexer could additionally have solid-state ferrite circulators and receiver protectors.

1.3.1.4 Receiver

When there is a need for a low noise RF amplifier, the super heterodyne receiver is nearly invariably the device of choice. LNA comes into play just after the antenna in the signal chain. Mixer and local oscillator: This component take the RF signal and raises its frequency so that it may be amplified by the IF amplifier.

1.3.1.5 Amplifier

- It boosts the intensity of the IF pulse.
- A matching filter structure, the IF amplifier improves the signal-to-noise ratio in the most important bands.
- Matched filter helps pick up on faint echo signals while dampening out noise.

1.4 Emerging Radar Technologies

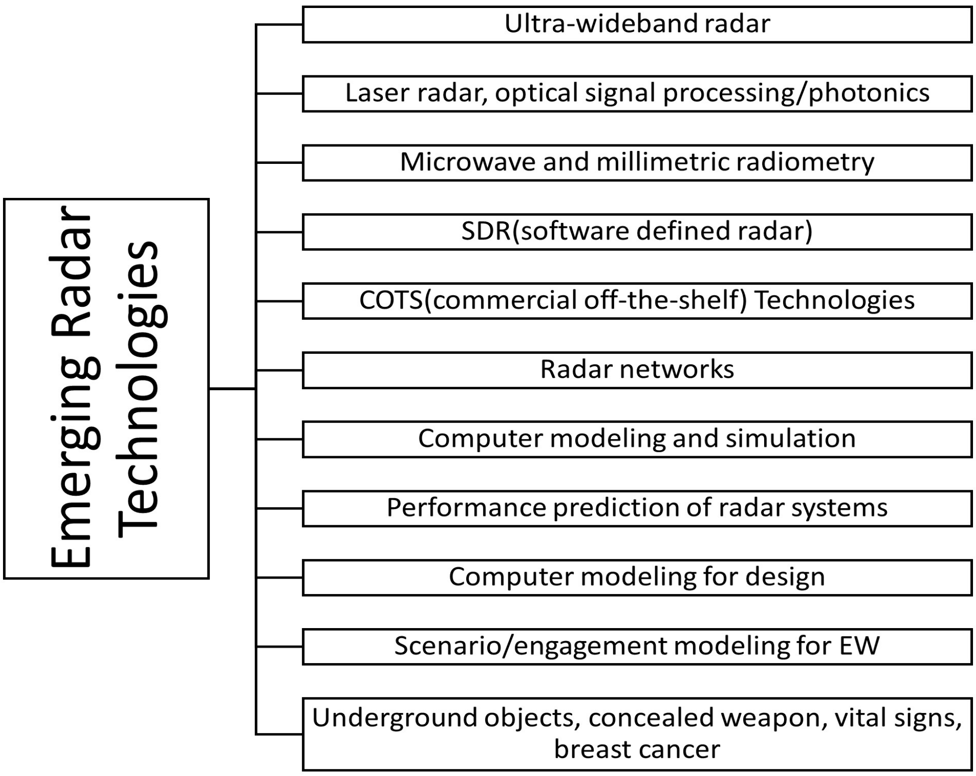

FIGURE 1.3: Emerging Radar Technologies

1.5 Classification of RADAR

The four types of radar are as follows:

- PRF Pulse
- Frequency
- Waveform
- Application

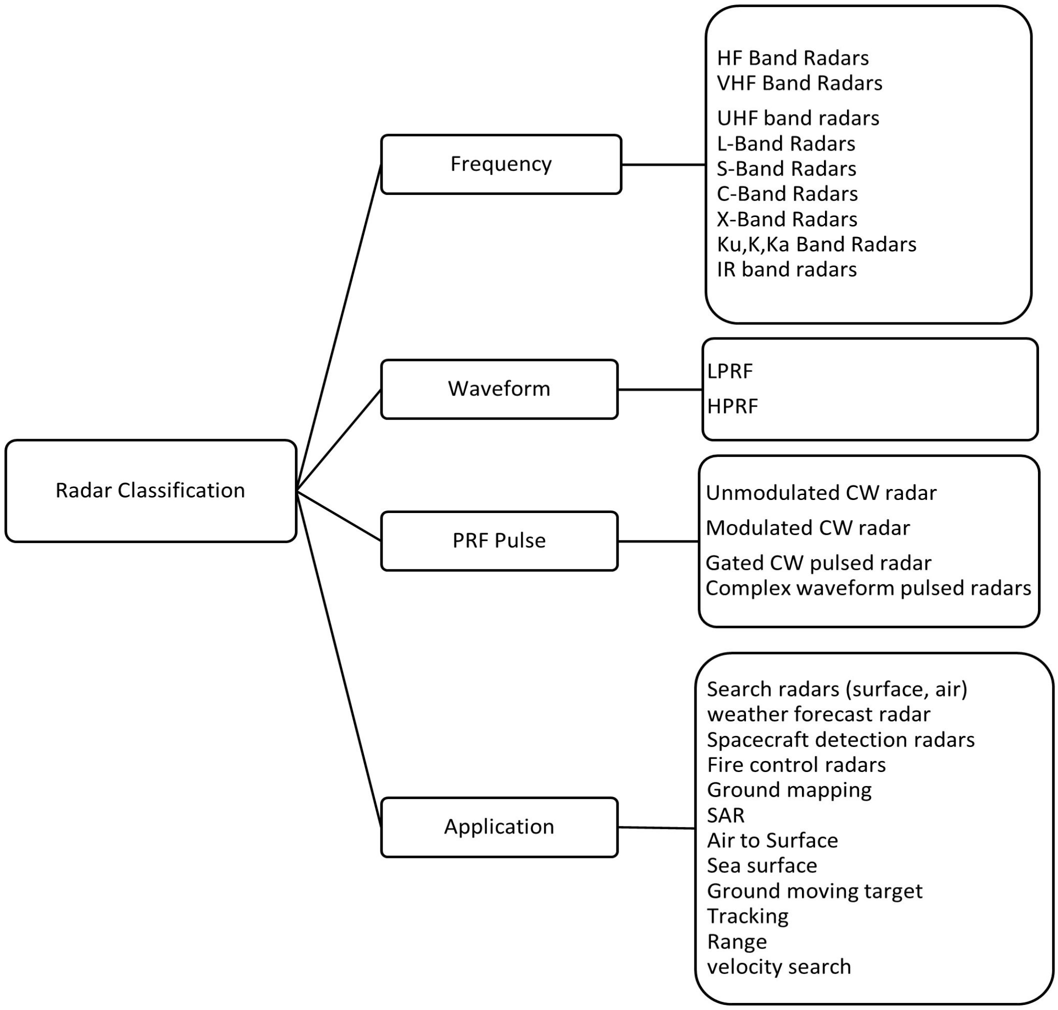

Figure 1.4: Radar Classification

Depending upon the types of antenna used, transmitted pulse, and function, radars are classified into different categories

- 2D RADAR
- 3D RADAR
- Weather Radar
- Synthetic Aperture Radar
- Early Warning Radar
- Acquisition Radar
- Terminal guidance Radar

Antenna types based on the classification

- Monostatic radar
- Bistatic Radar

1.6 Unmanned Aerial Vehicle (UAV)

The market for and development of unmanned aerial vehicles (UAVs) has grown rapidly during the past decade. UAVs' flying performance has been drastically enhanced while the price of the equipment has dropped significantly. Because of their small size, moderate flight speed, and low Altitude, current mini-sized UAVs are notoriously difficult to detect. In these high-risk environments, it is crucial to be able to automatically recognize and categorize mini-UAVs.

1.6.1 Mini-Size Unmanned Aerial Vehicles

Mini UAVs are becoming used in industries including package delivery, filmmaking, and farming. Miniature unmanned aerial vehicles (UAVs) have many potential applications; nevertheless, they also present a security concern due to their potential for surveillance, reconnaissance, and even assault. Among the most active areas of study over the last 10 years has been the automated detection and classification of mini-UAVs to a certain degree of accuracy.

Data collected by UAVs is rarely shared with smaller units to aid in their operations. Miniaturized, longer-lasting devices designed to back up smaller forces are being studied as a solution to this problem.

The vehicle consists of a drive system, cargo, avionics, power, and data connection systems. For flight, larger UAVs rely on fuel-powered engines. Smaller UAVs often run-on fuel or electricity.

1.6.2 RCS

As a result, the radar cross section of the target plays a significant role in how easily a target can be detected at a given distance. Table 1.3 displays a table of RCS values for various objects. It is important to note that can also be expressed in dBsm (dB relative to a square meter, or 10 $log\ \sigma$).

TABLE 1.3: RCS Values of Various Objects

Target	$\sigma(m^2)$
Insect	10^{-4}
Bird	0.01
Missile	0.5
Person	1
Jet fighter	5 to 100
Airliner	100 to 1000
Ship	3000 to 1000000
B-2 Stealth Bomber	10^{-6} to 10^{-4}

1.6.3 Classes of UAVs

Currently present unmanned aerial vehicle (UAV) systems fall into the categories of micro-UAV, mini-UAV, tactical UAV, medium altitude UAV, and high-altitude UAV. Mini UAV tend to fly at low altitudes, less weigh and have limited capabilities when used independently. The limited range of micro-UAV is a direct result of their small size, which is often less than half a foot.

TABLE 1.4: UAV Classification Based on Altitude and Range

Types of UAV	**Altitude**	**Range**
Handheld	Less than 600 m	Less than 2 km
Close	Less than 1500 m	Less than 10 km
NATO	Less than 3000 m	Less than 50 km
Tactical	Less than 5500 m	Less than 160 km
Medium Altitude Long Range	Less than 9100 m	Less than 200 km
High Altitude Long Range	Greater than 9100 m	NA
Hypersonic	Less than 15200 m	Greater than 200 km

It is necessary for there to be line-of-sight (LOS) between both the UAV and the base station while using mini-UAVs. Because of their limited space, these UAV are not able to transport equipment for satellite communications aboard to provide over-the-horizon (OTH) communication. Because of their limited space needs and their compact designs, mini unmanned aerial vehicles (UAVs) are straightforward to maintain and service. These systems are designed to provide smaller troops, including those in Special Operations, as well as company and squad groups, the capacity to operate their own unmanned aerial vehicles (UAVs).

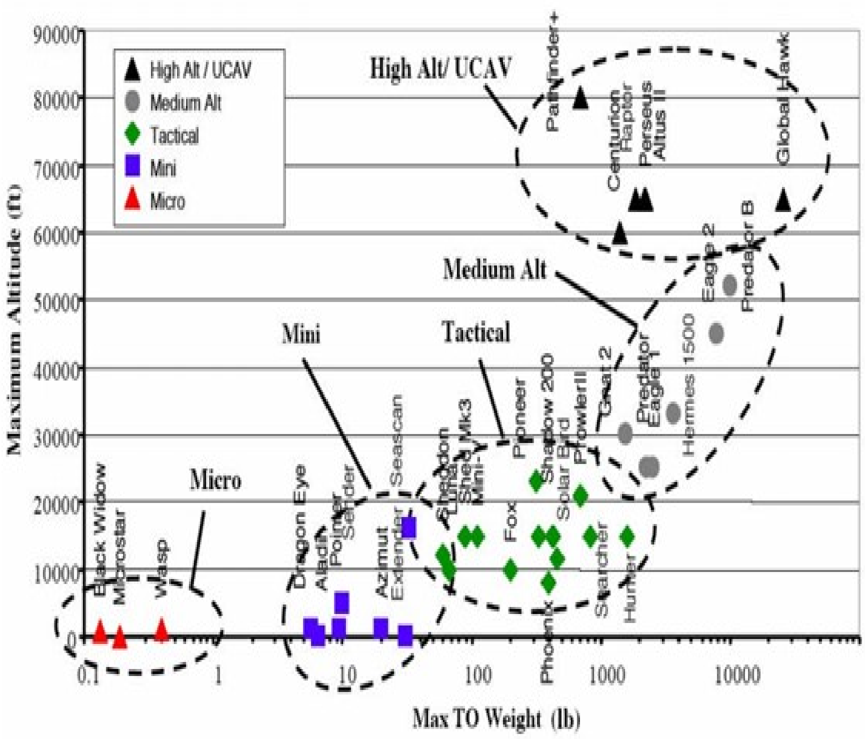

FIGURE 1.5: Altitude and Weight Classification of UAVs

These unmanned aerial vehicles (UAVs) may have their flight range increased by using cameras that are more compact, weigh less, and have a lower line count of resolution. This makes it possible to employ batteries and motors that are bigger, heavier, and more powerful. The trade-off for larger motors' ability to achieve greater altitudes and quicker speeds is that they use more power and space. These compact systems will have more range and endurance because to developments in technology, which will also result in the subsystems themselves being more competent and more compact.

1.6.3.1 Rotary-Wing UAVs

Drones with many rotors are the easiest to operate and the most affordable option. They also allow more control over location and framing, which makes them suitable for surveillance applications. Because they include more than one motor, they are referred to as multi-rotors, and the most popular varieties are tricopters (with three rotors), quadcopters (with four rotors), hexacopters (with six rotors), and octocopters (with eight rotors). The vast majority of multi-rotor drones that are now in use are quadcopters [3].

FIGURE 1.6: Tricopter, Quadcopter, Hexacopter and Octocopter

1.6.3.2 Fixed-Wing UAVs

A fixed-Wing UAV is characterized by the absence of vertical lift rotors in favor of a single rigid wing that is fashioned to resemble and perform in a manner like that of an airplane.

As a direct consequence of this, the sole use of energy that is required for this kind of drone is for it to go ahead it is not able to hover. Because of this, they have a low impact on the environment and their energy consumption is low [3].

FIGURE 1.7: Fixed wing UAVs

1.6.3.3 Small UAV

Only recreational usage is permitted for this UAV, since it is not equipped to carry out the commercial tasks that are possible with other kinds of drones. The smaller unmanned aerial vehicles (UAV) are not stable enough to obtain precise images since they are too light.

1.6.3.4 Micro UAV

These Micro UAVs are rather small, but thanks to their miniature cameras, they are able to deliver significant information. The micro-unmanned aerial vehicle (UAV) like the "Black Hornet" is used rather regularly by the British armed forces. Its range of almost one mile and can fly for up to twenty-five minutes on a single charge of their batteries.

1.6.3.5 Tactile UAV

These unmanned aerial vehicles (UAVs) are big without being heavy. They have an overall length of 1.3 meters, a weight of almost 2 kilograms, and are equipped with infrared cameras and GPS technology. They see widespread use in the field of surveillance work.

1.6.3.6 Reconnaissance UAVs

These UAVs have a length of around five meters, weigh more than one thousand kg, and have the ability to hover at 35,000 feet for 52 hours. Both HALE and MALE are able to be launched from the ground and are referred to by their respective designations (MALE).

1.6.3.7 Large Combat UAV

The primary purpose of these unmanned aerial vehicles, which have a length of about 11 meters and can fire air-to-surface missiles or laser-guided bombs at targets, is to gather intelligence.

They have a range of more than one thousand miles and can function at full capacity for up to fourteen hours straight.

1.6.3.8 Large Non-Combat UAVs

Despite their size, these unmanned aerial vehicles are not intended for use in combat and should not be used as such.

They are more advanced than the Black Hornet, and they are used for larger-scale reconnaissance operations than the Black Hornet can handle. The Global Hawk, manufactured by Northrop Grumman, is primarily used over combat zones, but not meant for combat. Rather, it is used for surveillance, such as scanning cell phone calls.

1.6.3.9 Drones of Target and Decoy

This kind of UAV is employed to keep an eye on targets as well as attack them. The mission will often serve as the primary factor in determining the look of the decoy drone.

TABLE 1.5: UAV Classification Based on Weight

Types of UAV	**Weight**	
	Greater than	**Less than**
Nano		250 g
Micro	250 g	2 kg
Small	2 kg	25 kg
Medium	25 kg	150 kg
Large	150 kg	

1.6.3.10 GPS UAVs

This kind of UAVs use global positioning system (GPS) technology to establish connections with satellites to plot the remainder of their journey and gather data that may be utilized to make informed judgments [3].

1.7 UAV Monitoring

There are a few different methods one may use to maintain tabs on the whereabouts of UAVs and to plan for retaliatory strikes. It is an important sector that is quickly growing as a direct result of the fast growth in the number of UAVs. Industry and academics are both focusing on the implementation of current approaches as well as the development of new ones. UAV monitoring consists primarily of four operations:

1. Detection: detecting the UAV.
2. Classification: The UAV and its properties are verified and analyzed.
3. Localization: UAV's position Tracking.
4. Responding: Taking actions such as broadcasting a warning or neutralizing

There are many different techniques to UAV monitoring, but not all of them are capable of performing all of the aforementioned tasks in an effective manner. The following table provides a summary of the many methods that may be used for detection, classification, and localization.

Table 1.6: UAV Monitoring Techniques

Techniques	Pros	Cons
	Long Range	Very expensive
Radar	Constant tracking that can handle hundreds of targets at once	Range is determined by the size of the UAV
	Precise positioning	Licensing is required
	Weather conditions are unaffected by autonomous UAVs	Extra assistance is required for classification between birds and UAVs.
	Low Cost	Short range
RF Analyzers	Licensing is not required	Unable to detect autonomous UAVs
	Multiple UAVs can be detected, classified, and triangulated	In RF noisy environments, it is ineffective
	Low Cost	Directional and short range
Video Surveillance	With IR support, it can operate in dark	Dependent on the light conditions

	The UAV's visuals can be used for classification and forensic work.	Public privacy may be a concern
	Medium cost	Short range
Audio Surveillance	Licensing is not required	Ineffective in noisy environments
	Can classify and detect autonomous UAVs based on their acoustic signatures	High number of false positives

1.8 Thesis Organization

Chapter 1:

This chapter discusses the principles of radar systems in addition to providing some background on the development of radar. Classification of radar based on its many functions, applications, and their types. Additionally included are unmanned aerial vehicles (UAVs) and the many classifications that these UAVs fall into according to their weight, relative clinginess, altitude, and range (neon, micro, small, medium, and large). In the end of the chapter, we stopped using various UAV monitoring methods including radar, RF analyzers, video surveillance, and audio surveillance.

Chapter 2:

The idea of Doppler, as well as the micro–Doppler Effect, has been covered in depth throughout this chapter. A literature review on micro-Doppler signatures, micromotion, and the micro-Doppler effect in radars is also included. In addition to that, it offers mathematical formulae that can be applied in order to ascertain micro-Doppler signatures. At the very end of the meeting, we discussed a number of different research methodologies, in addition to motivation, gap analysis, and issue statements.

Chapter 3:

This chapter addresses several different approaches to the process of extracting features from micro-Doppler signatures. Some of these approaches include image processing, OMP decomposition, EMD analysis, and HOMF analysis. After that, a comparison of several feature extraction methods is performed, and as a consequence of that comparison, the EMD approach is selected for the feature extraction of the mDS.

Chapter 4:

This chapter will examine the categorization structure and break it down into its component parts. It uses neural networks such as CNN (Convolutional Neural Networks), RNN (Recurrent Neural Network), and LSTM (Long Short-term Memory), amongst others, to accomplish its goals. An investigation into the inner workings of CNN, RNN, and LSTM, as well as a comparison of these three neural networks, is presented here. In the end, the LSTM algorithm was chosen because it was deemed to be the most suitable choice for the classification of the Mini UAV.

Chapter 5:

This chapter discusses the simulation as well as the conclusions that it produced. To simulate the outcomes of Long Short-term Memory (LSTM) network training, it employs signal generation, EMD (Empirical Mode Decomposition), IMF (Intrinsic mode functions) feature extraction, dataset construction, and modelling of findings.

1.9 Chapter Summary

This chapter covers the fundamentals of radar systems as well as the history of radar. Radar classification based on application, functions, and type. It also includes UAVs and their various classes based on weight, RCS, altitude, and range (neon, micro, small, medium, and large). Finally, we decommissioned UAV monitoring techniques such as radar, RF analyzers, video surveillance, and audio surveillance.

Chapter 2

Literature Survey

A monostatic radar is one that sends out an electromagnetic signal in the direction of a target and afterwards receives the signal which is reflected back from the target. The transmitter and receiver are co-located. Radar can determine the distance to an object based on the signals received signal's time delay. The Doppler Effect results from a discrepancy between the transmitted and received signal frequencies that occurs when an object moves. [4] [5].

The radial velocity of a moving object is used in the calculation of the Doppler frequency shift. Radial velocity is the component of an object's velocity that points in the direction of the radar's direct line of sight. A moving object's radial velocity can be determined by radar by using the Doppler frequency shift of the received signal as the basis for the calculation.

In addition to the typical Doppler shifted frequency that is induced by the translational motion of the item, sidebands may be generated around the typical Doppler shifted frequency if the object or even any structural component of the object oscillates. This can cause sidebands to be generated around the typical Doppler shifted frequency. This type of incremental Doppler modulation is referred to as the MD Effect.

It is possible to detect an object's signature by using the radar's MD effect, which is apparent in the radar's received signal. The complex frequency modulation that is produced by the structural components and is represented in the combined time as well as Doppler frequency domain even as mDS is one of the distinguishing features of the object [6–8].

2.1 Doppler Effect

Christian Johann Doppler (1803–1853), an Austrian mathematician and physicist, discovered a phenomenon involving the colored light effect of stars in 1842. The motion of the light source changes its apparent color. When a light source moves toward an observer, the color of the light appears bluer, while when it moves away from an observer, the color of the light appears redder. It was initially found by Doppler, who gave his name to the effect that he named after himself. According to this effect, the velocity of a light source in relation to an observer has an impact on the frequency (or wavelength) that is seen to be emitted by the source. The waves in the vicinity of the source experience compression as a result of its velocity, whereas the waves in its wake experience stretching [4].

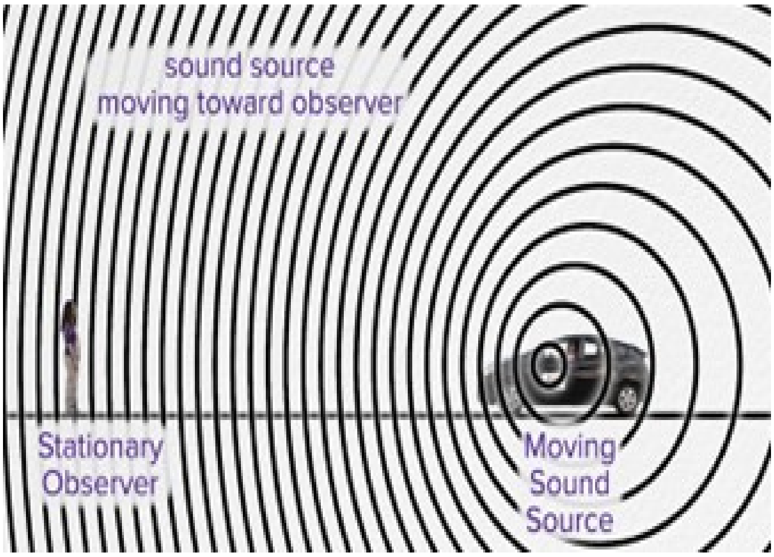

Figure 2.1: Doppler Effect

2.2 Doppler Frequency Shifts

The Doppler Effect is used by Doppler radars to calculate the radial velocity of a moving target. A quadrature detector can extract the Doppler frequency shift by producing an in-phase (I) component and a quadrature-phase (Q) component from the input signal.

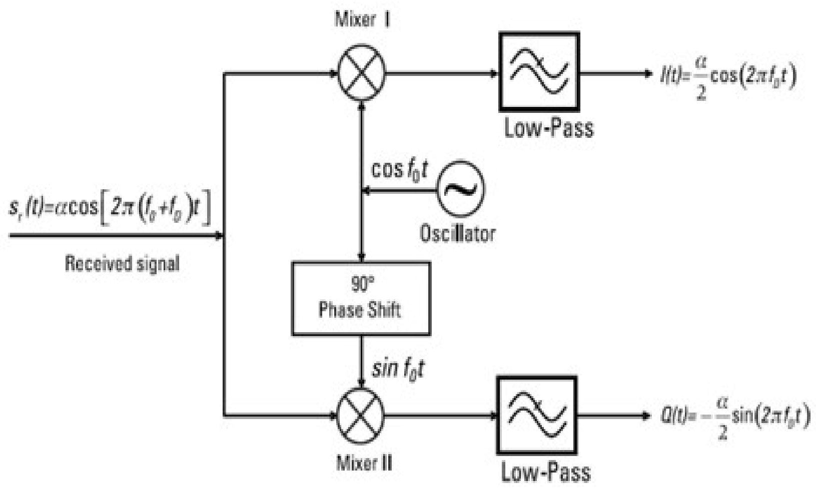

FIGURE 2.2: Doppler Shifts Extracted by a Quadrature Detector

In the quadrature detector, the received signal is divided and sent to two separate mixers that are referred to as synchronous detectors. Within synchronous detector I, the received signal is combined with a reference signal. In the other channel, the transmitted signal is combined with a signal that has been mixed by ninety degrees relative to the transmitted signal.

$$s_r(t) = a\cos[2\pi(f_o + f_D)t] = a\cos[2\pi f_o t + \varphi(t)] \tag{2.1}$$

$$s_t(t) = \cos(2\pi f_o t) \tag{2.2}$$

$$s_r(t)s_t(t) = \frac{a}{2}\cos[4\pi f_o t + \varphi(t)] + \frac{a}{2}\cos\varphi(t) \tag{2.3}$$

The I-channel output is obtained after lowpass filtering.

$$I(t) = \frac{a}{2}\cos\varphi(t) \tag{2.4}$$

By combining the received signal with the 90 phase-shifted transmitted signal

$$s_t^{90^o} = \sin(2\pi f_o t) \tag{2.5}$$

The synchronous detector II's output is

$$s_r(t)s_t^{90^o} = \frac{a}{2}\sin[4\pi f_o t + \varphi(t)] - \frac{a}{2}\sin\varphi(t) \tag{2.6}$$

The Q-channel output is obtained after low-pass filtering.

$$Q(t) = -\frac{a}{2}\sin\varphi(t) \tag{2.7}$$

A complex Doppler signal can be created by combining the I and Q outputs.

$$S_D(t) = I(t) + jQ(t) = \frac{a}{2}exp[-j\varphi(t)] = \frac{a}{2}exp[-j2\pi f_D(t)] \tag{2.8}$$

Using a frequency measurement tool, one can estimate the Doppler frequency shift f_D from the complex Doppler signal $s_D(t)$. The periodogram can be used to calculate the signal's spectral density to estimate the Doppler frequency shift of a single sinusoidal signal. The maximum likelihood estimation method can then be used to locate the periodogram's maximum [9] [10].

$$\hat{f}_D(t) = \max_{f_D(k)}\{|\sum_{K=1}^{N} a(k)exp(-j)2\pi f_D(k)|^2\} \tag{2.9}$$

The quadrature detector's I and Q outputs can also be used to determine whether the target is approaching or away from the radar. As shown in Figure, by comparing the relative phase of the I-channel and the 90°-shifted Q-channel, two flow channels (one approaching the radar and the other "away") can be generated.

Doppler radars may be categorized into one of three categories: frequency-modulated continuous-wave (FMCW) radar, pure continuous-wave (CW) radar (with no modulation), and coherent pulsed Doppler radar. Pure CW radars are only capable of measuring velocity, and nothing else. To attain high range resolution and monitor both range and Doppler information, FMCW and coherent pulsed radars are able to have a frequency bandwidth that is rather broad. While maintaining the phase of the signals they send out, coherent Doppler radars are able to monitor phase shifts in the signals they receive. The rate of phase change in a signal is directly proportional to the frequency shift that is generated by Doppler.

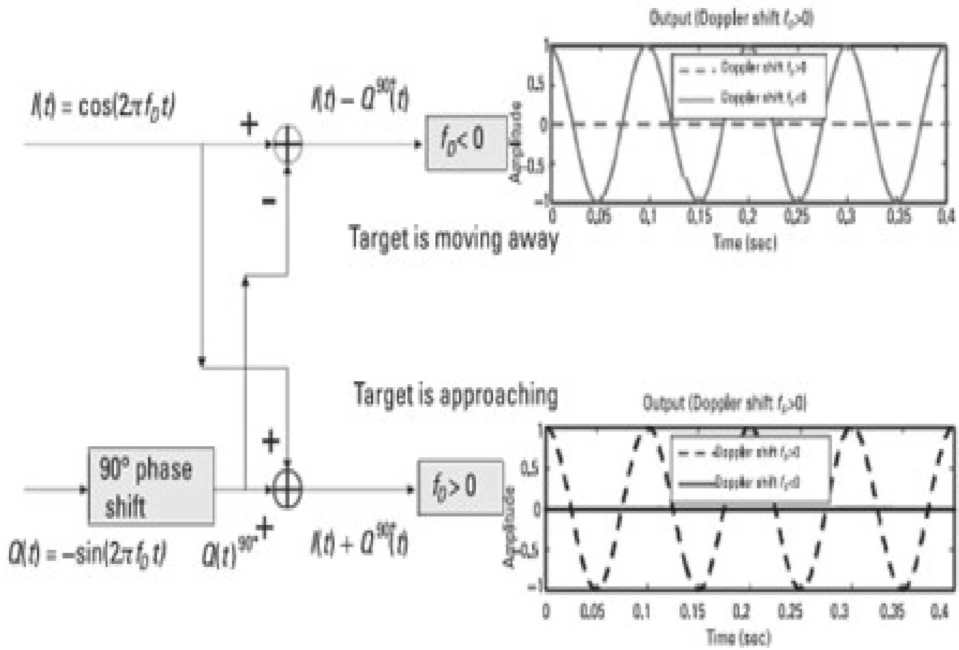

FIGURE 2.3: The Phase Difference between the I-Channel and the 90-Shifted Q-Channel

If the phase change is greater than $\pm\pi$, the estimated Doppler frequency becomes ambiguous, which is referred to as Doppler aliasing. The discrete discrete-time of a continuous-time signal causes this. To avoid aliasing in pulsed radars, a very high PRF should be chosen. To avoid ambiguous range, a very low PRF is required. However, the low PRF limits the amount of Doppler information that can be extracted. Multiple PRFs are frequently used to achieve appropriate range ambiguity and aliasing [11].

2.3 The Micro-Doppler Effect

The incoherent laser radar systems were the first to make advantage of the micro-Doppler effect [8]. These devices amplified light by stimulated emission of radiation. Laser detection and ranging (LADAR) systems work by first sending an electromagnetic wave at optical frequencies to an object, and then detecting the light wave that is reflected or backscattered from the item. This allows the system to identify the object's range, velocity, and other parameters by changing the laser beam's amplitude, frequency, phase, and even polarisation.

2.4 Micro Doppler

It is possible for the target or just any structure on the target to experience mechanical vibration as well as rotation in addition to bulk translation. It might induce frequency modulation on the returning signal, which results in sidebands around the target's Doppler frequency shift. The micro-Doppler effect is the name given to this phenomenon. Radar signals that are received from a target that has vibrating or spinning structures, such the propellers or rotors of a fixed-wing aircraft or a helicopter, or the compressor and blade assembly of a jet engine, have micro-Doppler characteristics that are connected to these structures.

We are able to identify the dynamic qualities of the target via the use of the micro-Doppler effect, which also gives a fresh method to the study of target signatures. The properties given by Micro-Doppler are extra target features that enhance those provided by the technologies that are already in use. The micro-Doppler effect may be used to identify certain makes and models of motor vehicles, in addition to determining the speed of their engines and the direction in which they are travelling. The vibrations that are created by the engine may be picked up by radar signals that are returned from the surface of the vehicle. The micro-Doppler modulations seen in the engine vibration signal may be used to differentiate between the gas turbine engine found in a tank and the diesel engine found in a bus.

2.5 Micro-Motions

In many instances, a target or a structure located on the target may demonstrate microscopic movements such as vibrations or rotations. Rotations and vibrations might have been caused by a revolving rotor on a helicopter, a rotating antenna on a ship, mechanical oscillations in a bridge or structure, an engine-induced vibrating surface, or one of a number of other potential reasons. Additional Doppler shifts are produced on top of the bulk translational motion's continuous Doppler frequency shift as a result of micro-motion dynamics, which induce frequency modulations on the back-scattered signal. When a target simply translates at a fixed velocity, the Doppler frequency shift that is caused by translation is a time-invariant function. This means that it does not change during the course of the translation.

If the target is also vibrating or rotating, the Doppler frequency shift generated by the vibration or rotation seems to be a time varying frequency function that enforces a periodic time-varying modulation upon that carrier frequency. If the target is not vibrating or rotating, the Doppler frequency shift is the same as described above. Micro-motions cause the target's signature to take on new characteristics that are distinguishable from the target's signature as it existed before micro-motions were introduced.

When there is pure periodic vibration or rotation, micro-motion dynamics will cause sideband Doppler frequency shifts that are centered on the core carrier frequency that has been Doppler-shifted. These frequencies are dictated by the modulation's carrier frequency. Because frequency modulation results in a phase shift in the signal, coherent processing is required to accurately monitor the phase shift and derive usable information from the modulation.

Coherent LADAR is more sensitive to phase changes and can compute object velocity based on the phase change rate. This is because it maintains the phase information of the scattered light wave in respect to a reference laser wave created in the local oscillator. So, because phase of a received signal from such an object is sensitive with range variation in such a coherent system, a change in range that is equivalent to half a wavelength will result in a change in phase that is equivalent to 360 degrees. For LADAR systems with a wavelength of $2 - \mu m$, a phase change of 360 degrees is caused by a range variation of $1 - \mu$ m. In the case of vibration, the maximum Doppler frequency variation may be calculated using the following formula: where f_v is the vibration frequency, and D_v is the amplitude of the vibration.

$$max\{f_D\} = \frac{2}{\lambda} D_v f_v \tag{2.10}$$

As a consequence of this, even at a very low vibration rate f_v, a very little vibration amplitude D_v may induce a significant phase change in such a high-frequency system, and as a result, Doppler frequency shifts can be clearly identified. An item or any structural component of an object may display micromotions in addition to bulk motion in many instances. Micromotions can occur in conjunction with bulk motion (including zero bulk motion).

The term "micromotion" encompasses a broader definition of the word "micro," such that any small motion (such as vibration, oscillation, rotation, swinging, flapping, or fluctuation) can be referred to as a "micromotion." This is because the term "micro" encompasses a wider definition of the word "micro." Micromotion may be caused by a number of different things, including a vibrating surface, the revolving rotor blades of a helicopter, a human walking with swinging arms and legs, the flapping wings of a bird, and many other things. Frequency modulations in radar transmitted signals are caused by micromotion, which acts on the carrier frequency.

When there is a pure periodic vibration or rotation, micromotion will cause side-band Doppler frequency changes near the center of the Doppler-shifted carrier frequency. The modulation consists of harmonic frequencies, which are established by the carrier frequency, the rate of vibration or rotation, and the angle that exists between the direction of vibration and the direction that the incident wave travels.

The frequency modulation provides us with the ability to ascertain the kinematic qualities of the item of our attention. The time-varying frequency modulation has the potential to serve as an object signature, which may then be utilized for further classification, recognition, and identification processes.

2.6 Micro-Doppler Effect in Radar

The micro-Doppler effect is affected by the frequency band of the signal. The micro-Doppler effect of a vibrating target may be visible to a radar system operating in the microwave frequency band if the product of the vibration rate and displacement of the vibration is large enough.

2.7 Micro-Doppler Frequency Shifts

The MD shift is a time varying frequency shift that may be derived from the quadrature detector of a complex output signal in conventional Doppler radar. This shift can be used to pinpoint the location of an object moving through space. Because it does not give information that is time-dependent in regards to frequency, the Fourier transform is unsuccessful when it comes to the analysis of time-varying frequency characteristics. Both the instantaneous frequency analysis and the combined time-frequency analysis are examples of typical analysis techniques that may be used to describe a signal in the time domain as well as the frequency domain simultaneously. Because the amplitude and phase functions are not unique, the terminology of the instantaneous frequency defined by the time derivative of the phase function in a time-varying signal has been argued for decades. A well-accepted instantaneous frequency definition employs a pair of Hilbert transforms to form the real and imaginary parts of an analytic signal [12]. Thus, the term ”instantaneous” refers to the present time instant, and its measurement requires only knowledge of the analyzed signal from the past, not from the future. The time-derivative operation yields only one frequency value at a given time instant. This means that it can only handle monocomponent signals and not multicomponent signals.

A monocomponent signal has energy in a contiguous portion of the joint time-frequency domain at all times and is narrowband at all times. A multicomponent signal, on the other hand, has energy in several isolated frequency bands at the same time. An obvious approach for dealing with multi-component signals is to decompose the multicomponent signal into multiple addable monocomponent signal components [13]. The signal's complete time-frequency distribution is obtained by computing the instantaneous frequencies for each component signal and then combining these individual instantaneous frequencies. For decades, the time-varying frequency spectrum has been analysed using joint time-frequency analysis. It is intended to localize the energy distribution of a given signal in the time and frequency domains in two dimensions. It works well with both mono-component and multicomponent signals.

2.8 Instantaneous Frequency Analysis

For nonstationary signal analysis, the instantaneous frequency is an important representation. The complex-valued signal $z(t)$ associated with a real-valued signal $s(t)$ is defined as

$$z(t) = s(t) + jH\{s(t)\} = a(t)exp[\varphi(t)] \tag{2.11}$$

Where $H\{.\}$ denotes the signal's Hilbert transform

$$H\{s(t)\} = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{s(\tau)}{t-\tau} d\tau \tag{2.12}$$

The analytic signal associated with $s(t)$ is denoted by $z(t)$, the amplitude function by a(t), and the phase function by $\varphi(t)$.

The analytic signal's Fourier transform, $Z(f)$, is single sided in the frequency domain, with zero values at negative frequencies and double values at positive frequencies. As a result, the signal's instantaneous frequency $z(t)$ is the time derivative of the analytic signal's uniquely defined phase function $\varphi(t)$.

$$f(t) = \frac{1}{2\pi}\frac{d}{dt}\varphi(t) \tag{2.13}$$

A discrete real-valued signal $s(n)$ sampled at time instants $t = n \bigtriangleup t$, $n = 1, 2, ..., N$ may be used in practice. The discrete analytic signal z(n) then becomes

$$z(n) = z(n) + jH\{s(n)\} \tag{2.14}$$

The instantaneous frequency of a discrete signal is similar to $f(t)$, but with discrete derivatives of the phase, which can be estimated using the central finite difference equation of the phase function [14].

$$f(n) = \frac{1}{2\pi}\frac{1}{2 \triangle t}[\varphi(n+1) - \varphi(n-1)]_{2\pi} \tag{2.15}$$

Where $\triangle$ t denotes the sampling interval, 2π denotes the reduction modulo 2, and n denotes the number of discrete-time samples.

Instantaneous frequency only provides one value at a time and is therefore only useful for describing signals made up of a single oscillating frequency component at a time, known as a mono-component signal. It is not suitable for signals with multiple oscillating frequency components at the same time (i.e., multi-component signal). To distinguish frequency contributions in a multicomponent signal, the multi-componen signal must be preprocessed into its mono-component elements. Huang proposed empirical mode decomposition (EMD) as a method for separating a multicomponent signal into mono-component constituents through a progressive sifting process, yielding the intrinsic mode functions. Later, Olhede and Walden proposed replacing the EMD with a wavelet packet-based decomposition in preprocessing the multicomponent signal [13] [15].

The EMD decomposes a signal adaptively into a finite number of zero-mean, narrowband IMFs. Then, using the normalized Hilbert transform, known as the Hilbert- Huang transform (HHT), the instantaneous frequency of each IMF is calculated [13]. The Hilbert spectrum is the complete time-varying frequency spectrum when combined. The EMD's original formulation can only be applied to signals with real values. Signals in radar applications, on the other hand, are always complex with I and Q components. In [16] [17], it is proposed that the EMD be extended to handle complex-valued signals.

2.9 Distinguishing Birds and Mini-UAVs

The practice of identifying helicopters has gained in popularity in recent years. Blades, the length of the blades, and the velocity at which the rotor rotates are all essential aspects that may be used to identify the kind of helicopter. Other distinguishing elements include the form and size of the helicopter. Estimation of these characteristics is possible via the use of the mDS of helicopters. Studies [18–21] have been conducted on the mDS of blades retrieved by monostatic, bistatic, and multistatic radars respectively.

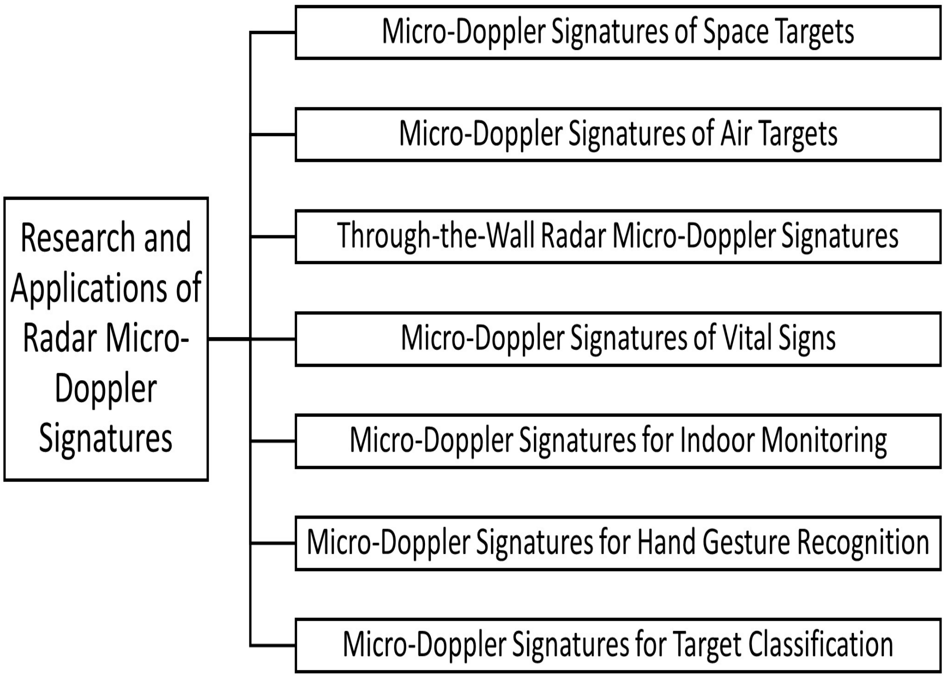

FIGURE 2.4: Research and Applications of Radar Micro-Doppler Signatures

They may either be used to estimate the rotational parameters of the blades for the purpose of identification or to reduce the influence that they have on the radar received signals for the purpose of imaging.

Studies of mDS for multicopters, mini-UAV are regularly undertaken, in addition to studies of the mDS of rotor blades. Mini UAVs, in contrast to more conventional air targets, are more diminutive in size and travel at slower speeds and lower altitudes. Since a result of this, UAVs are difficult to detect, as they are readily disguised by complicated terrain, difficult to differentiate from birds, therefore difficult to Classify.

Even though the RCS of birds is normally rather low (varying from 40 dBsm to 10 dBsm), contemporary surveillance radars are able to identify birds from a considerable distance. On radar displays, high concentrations of birds may generate a huge number of tracks that resemble those of miniature unmanned aerial vehicles (UAVs) or drones. As a consequence of this, flying birds may cause false alarms while detecting unmanned aerial vehicles (UAVs).

To distinguish arriving UAVs from flying birds, radars are necessary. It is essential to provide reliable techniques that can differentiate between birds and mini-UAVs. Doppler spread analysis of the wingbeats of flying birds has been used to classify flying birds for more than three decades [22]. The action of flying birds, in particular the raising and lowering of their wings, may produce unique micro-Doppler signals. As a consequence of this, micro-Doppler signatures may be used in the process of distinguishing birds and mini-UAVs [23].

Table 2.1: Existing Radar M-DS-based Mini UAV Classification Works

Year	**Author**	**Number of Target Class**	**Radar m-DS analysis**	**Classification**
2014	Molchanov [24]	Mini-UAV Model/ Type Classification	Spectrogram	NBC, Linear and Non-linear SVM
2015	Harmanny [25]	Mini-UAV Type Classification	Spectrogram	Maximum a Posteriori
2015	Fioranelli [26]	Mini-UAV payloads Classification	Spectrogram	NBC, DDA

2016	Torvik [27]	Quadcopter vs. Birds Classification	Radar polarimetry	Neast neighbour classifier
2017	Kim [28]	Quadcopter vs. Hexa-copter Classification	Spectrogram CVD	CNN
2017	Ren and Jiang [29]	Mini vs. Birds Classification	2-D Complex-log-FT	Subspace reliability analysis
2018	Beom and Fangyuan [2]	Mini-UAV Model Classification	EMD	Nonlinear SVM
2019	Ezuma [30]	UAV and Non-UAV Classification	Discrete Wavelet Transform (DWT)	Random Forest (RF)
2022	Ting and Shiyou [31]	UAVs and Birds Classification	LMD (Local Mean Decomposition)	SVM

Here are some limitations of each classification method mentioned in the papers: Artificial Neural Networks (ANN): ANN may suffer from overfitting when trained with a limited amount of data. Additionally, the structure of the network, including the number of layers and neurons, may need to be carefully chosen to achieve good performance.

K-Nearest Neighbors (KNN): KNN can be sensitive to the choice of the number of neighbors (k) and the distance metric used. Additionally, KNN may not perform well when the number of features is high, which can lead to the curse of dimensionality. Linear Discriminant Analysis (LDA): LDA assumes that the data is normally distributed and that the covariance matrix is the same for all classes. Therefore, LDA may not perform well when these assumptions are not met.

Convolutional Neural Networks (CNN): Convolutional Neural Networks requires a large amount of training data to achieve good performance, which can be a limitation in applications where the data is limited. Additionally, the choice of network architecture and hyperparameters can affect the performance of the classifier. Deep Learning: Deep learning methods require a large amount of training data and computational resources to achieve good performance. Additionally, the choice of network architecture and hyperparameters can affect the performance of the classifier. Nonlinear Support Vector Machines (Nonlinear SVM): The performance of Nonlinear SVM can be sensitive to the choice of kernel function and parameters. Additionally, Nonlinear SVM may not perform well in cases where the data is not linearly separable Support Vector Machines (SVM): SVM can be sensitive to the choice of kernel function and parameters, which can affect the performance of the classifier. Additionally, SVM (Support Vector Machine) may not perform well in cases where the data is not linearly separable.

Empirical Mode Decomposition (EMD) is a data-driven technique that decomposes a signal into a finite number of intrinsic mode functions (IMFs), which are components of the signal with a specific frequency and amplitude modulation.

EMD (Empirical Mode Decomposition) can be applied to micro-Doppler signals to extract intrinsic mode functions IMFs that represent the oscillation or rotation of small moving parts of a larger object, such as the blades of a UAV or the limbs of a walking person.

Once the intrinsic mode functions (IMFs) are obtained, various feature extraction techniques can be applied to estimate the micro-Doppler characteristics of the signal, such as the frequency content, speed, and direction of movement of the small parts on the Mini-UAVs.

EMD (Empirical Mode Decomposition) is better than other micro-Doppler feature extraction methods like spectrogram, radar polarimetry, and CVD (Cardiovascular Disease Prediction)for several reasons:

TABLE 2.2: Literature Review of Classification Method

Classification Method	Pros	Cons
Spectrogram and cepstrograms-based classification	Robust to changes in UAV orientations and flight patterns	Performance degrades in presence of strong clutter or noise
mDS-based classification with LSTM [32]	Accurate classification of UAVs	Performance depends on the quality and quantity of training data
CNN-based classification	High accuracy in classification of UAVs	Requires large amounts of labeled training data and performance may degrade in presence of strong clutter or noise
Nearest-neighbor classifier-based classification	Simple and easy to implement	Performance may affected by the curse of dimensionality and imbalanced class distribution

Maximum a posteriori-based classification	Effective in discriminating between different UAV models	Performance may affected by the curse of dimensionality and imbalanced class distribution and requires prior knowledge
Linear and nonlinear SVM-based classification	Effective in discriminating between different UAV models and it an handle high-dimensional feature space	Performance may affected by the curse of dimensionality and imbalanced class distribution sensitivity to choice of kernel
Naive Bayes classifier-based classification	Simple and easy to implement and can handle high-dimensional feature space	Performance may affected by the curse of dimensionality and imbalanced class distribution and assumes conditional independence

Random Forest-based classification	It can handle complex and nonlinear relationships between variables and can be used for both classification and regression tasks and provide feature importance ranking	It can overfit the data if the number of trees is not optimized,RF models can be difficult to interpret compared to simpler algorithms like logistic regression and may require hyperparameter tuning to achieve optimal performance, which can be time-consuming

- EMD is a non-parametric method that does not require any assumptions about the underlying signal model or distribution. This makes it more robust to noise and signal variations.
- It provides a high-resolution time-frequency representation of the signal, which is important for micro-Doppler analysis.
- EMD can handle non-stationary and nonlinear signals, which are common in micro-Doppler signatures of mini-UAVs.
- EMD is computationally efficient and can be implemented in real-time applications.

Based on these advantages, the authors argued that EMD is a suitable feature extraction method for micro-Doppler analysis of mini-UAVs and can improve classification performance compared to other methods.

There are several reasons why the LSTM neural network is able to achieve better performance compared to the other classifiers. One possible reason is that the LSTM network is able to effectively capture the temporal dynamics of the micro-Doppler signatures, which are important for discriminating between different UAV classes. The LSTM architecture is designed to model and remember sequential information, which is crucial for capturing the time-varying patterns in the micro-Doppler signatures. Another reason why LSTM may perform better is that it is

less susceptible to overfitting than other classifiers. Micro-Doppler signatures can be affected by various factors such as distance, angle, and velocity of the UAVs, as well as environmental conditions, such as wind and clutter. These factors can introduce noise and variability in the micro-Doppler signatures, making it challenging to classify the UAVs accurately. The LSTM architecture is able to learn robust features that are less affected by the noise and variability, leading to better classification performance.

2.10 Gap Analysis

The limitations of analysis methods based on the short-time Fourier transform (STFT), such as spectrograms, which are commonly used in the analysis of micro-Doppler signature data.

One limitation is that Fourier analysis requires signals to have a longer dwell period to collect the required spectrum information, and the temporal frequency resolution of approaches based on STFT may also be considered a restriction.

Analyzing the micro-Doppler signature using a time-frequency analysis technique not based on Fourier transform can overcome these limitations. Specifically, using Empirical-Mode Decomposition (EMD) for analyzing micro-Doppler signature data collected from mini-Unmanned Aerial Vehicles (UAVs).

The ability of LSTM to handle sequential data, its long-term memory, feature extraction capabilities, and regularization techniques make it a powerful classifier for analyzing micro-Doppler signatures of mini-UAVs, especially when dealing with smaller numeric datasets.

The combination of Empirical Mode Decomposition (EMD) for feature extraction and Long Short-Term Memory (LSTM) neural network for classification has shown promising results for classifying Mini-UAVs using micro-Doppler signatures.

This approach has demonstrated high accuracy and robustness, particularly when dealing with sequential, small datasets and multi-class classification problems.

2.11 Problem Statement

The classification of Mini-UAVs based on their micro-Doppler signatures is a challenging task due to the complexity and variability of these signatures. The current state-of-the-art methods for micro-Doppler feature extraction include Continuous Wavelet Transform (CWT), and Short-Time Fourier Transform (STFT), their limitations in terms of computational complexity and sensitivity to noise need to be addressed. While EMD has shown promising results in the classification of Mini-UAVs. Additionally, the use of Long Short-Term Memory (LSTM) neural networks for classification has also shown potential, but their performance needs to be further evaluated and compared with other classifiers such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). To develop an efficient and accurate classification method for Mini-UAVs based on their micro-Doppler signatures using a combination of Empirical-Mode Decomposition (EMD) feature extraction method and Long Short-term Memory (LSTM) classifier, while addressing the limitations of current state-of-the-art methods.

2.12 Research Methodology

First of all, the echo signals of the mini UAV are generated in MATLAB, and then the EMD technique is implemented on those signals in order to obtain IMFs. We are able to extract various features of mini UAVs with the help of IMFs, and after these features have been extracted, feature vectors are generated from them. Following all of that, a dataset consisting of feature vectors is created in order to train the LSTM classifier for the classification of the various classes of mini UAVs.

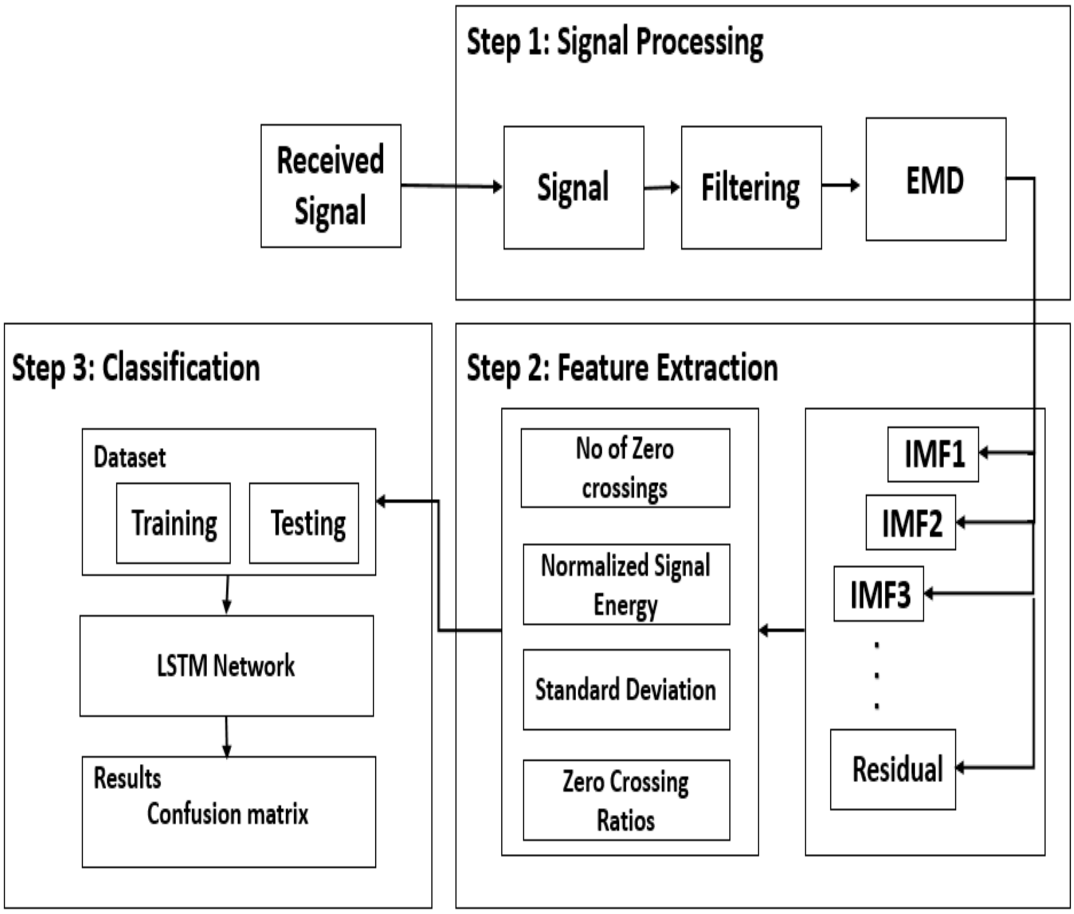

Figure 2.5: Research Methodology

2.13 Chapter Summary

The concept of Doppler, as well as the micro–Doppler Effect, has been discussed in this chapter. It also includes a literature review on micro-Doppler signatures, micromotion, and the micro–Doppler Effect in radars. It also includes mathematical equations for determining micro-Doppler signatures. Finally, we discussed motivation, gap analysis, problem statement, and research methodology.

Chapter 3

Micro-Doppler Feature Extraction

3.1 Introduction

A solid body that does not deform is represented by a rigid body, which means that even when the body is moving, the separation between any two different particles remains constant. A reference point, such as the center of gravity or center of mass, is placed within the body to determine the location. The angular position maintains the orientation.

A rigid body that moves will eventually change in both location and orientation. In fact, related to a reference co-ordinates, the body's translation and rotation are measured. A rigid body's constituent particles all move with the same translational speed. All a body's particles change positions when it rotates, with the exception of those that are on the rotational axis. Because of this, any two particles in the body may have different linear velocities.

Radar scattering from such an object that is rotating or translating variations throughout both phase and amplitude. The phase operation of scattered EM waves can be modulated by an object's motion, per theoretical analysis. If the item oscillates often, the modulation will produce sideband frequencies that are near to the frequency of something such as the incident wave. If the object vibrates frequently, the modulation will produce sideband frequencies.

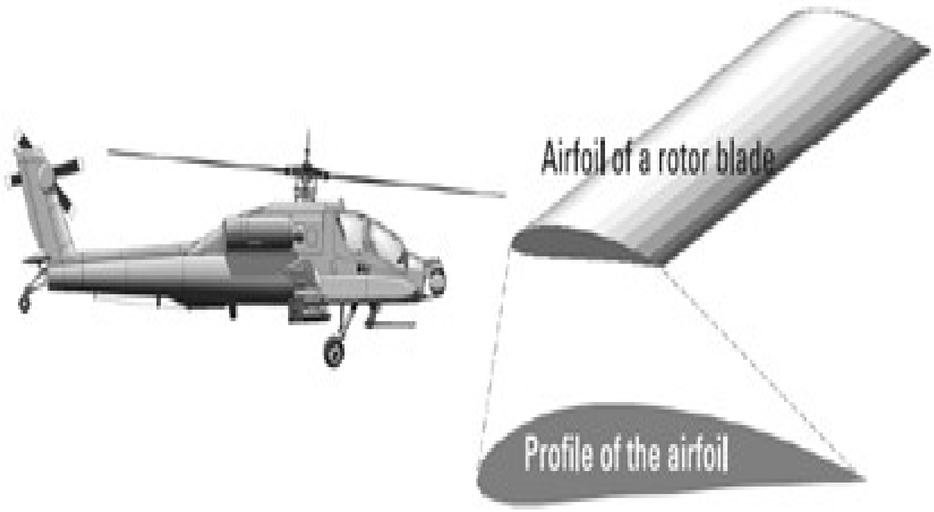

FIGURE 3.1: Helicopter Blade Airfoil

A high amount of radar reflectivity is often produced by the blade material, which can be a composite material. Specular reflections off the surfaces of blades are the most common kind of electromagnetic scattering that may be produced by an airfoil.

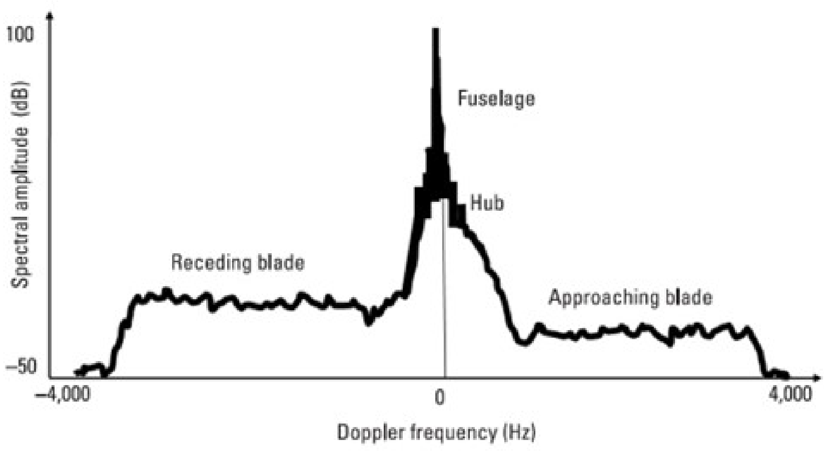

FIGURE 3.2: Spectral Signature of Radar Backscattering from a Helicopter

The radar returns produced by a helicopter each have their own unique spectral signature. The spectral signature of helicopters with rotating rotor blades is depicted in Figure.

The spectral signature has spectral components that come from the primary rotor's blades that are moving away from the observer as well as the blades that are moving toward the observer. The spectral amplitude is greatest in the fuselage of the aircraft.

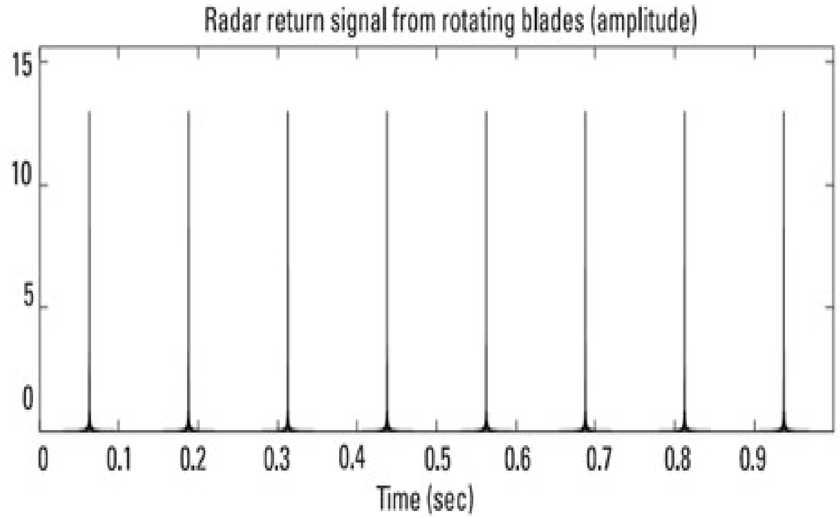

FIGURE 3.3: Time Domain Signatures of Blades

The amplitude of the blade that is approaching is greater than that of the blade that is retreating because the approaching blade has leading edges and the receding blade has trailing edges.

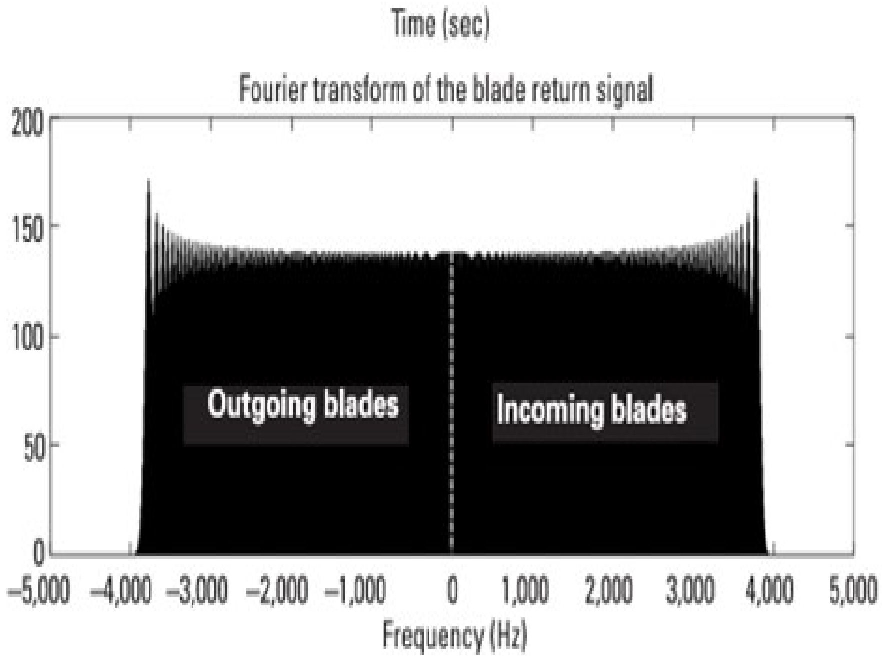

FIGURE 3.4: Frequency Spectrum of the Signatures of Blades

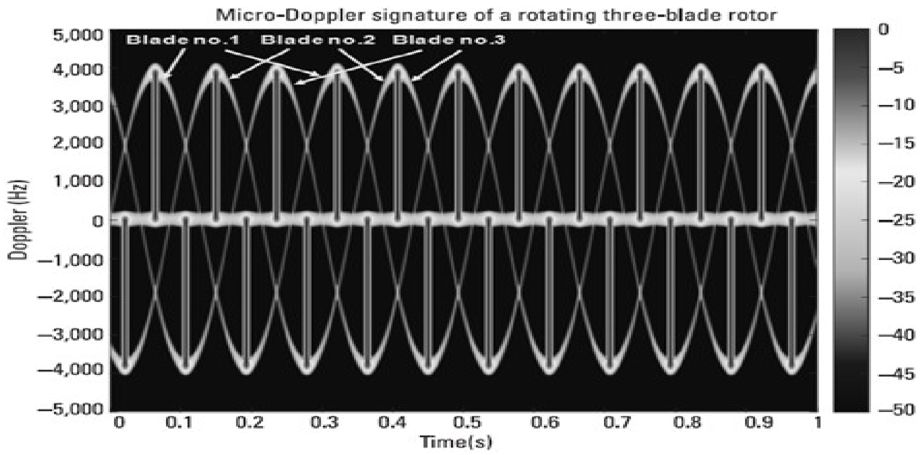

Figure 3.5: Blades mDS

3.2 Micro-Doppler Feature Extraction Methods

Several techniques for extracting micro-Doppler features are presented here

1. Image Processing
2. Orthogonal Matching Pursuit (OMP)
3. Empirical Mode Decomposition (EMD)
4. High-Order Moment Function (HOMF)

In the process of sinusoidal micro-Doppler signal analysis, OMP is helpful. The EMD approach is a typical nonlinear analytic method, and there is some published research on its applicability in extracting the micro doppler frequencies of spinning objects [33], [34].

3.2.1 Image processing Method

Micro-Doppler characteristics may be obtained via the application of image processing methods. In-depth research into these diverse approaches led to the identification of a method for image processing that is both simple to implement and produces very reliable result. The Hough transform is useful for finding patterns, but it requires an exponentially increasing amount of storage and computing time as the number of parameters increases [35]. Additional processing to speed up the algorithm's computation can be utilized to lower the computation cost during implementations [36].

3.2.2 OMP Method

OMP methods are superior to image processing for extracting MD features because they take use of phase and amplitude from the echo. The OMP approach incurs higher computing costs than do other image processing techniques. Additional processing may be employed to accelerate computations; for instance, the StOMP [37], a variation of OMP that is more suited to solving large scale challenges, may be easily adjusted to deconstruct the mDS.

3.2.3 HOMF Method

While the HOMF analysis approach outperforms OMP and image processing in terms of computational complexity and calculation speed, it is less effective at filtering out background noise in wideband radar [38]

3.2.4 EMD Method

It is more efficient to extract mDS of targets using the EMD decomposition method. Incredibly nuanced micro-Doppler effect is generated by procession. A major drawback of the Hough transform, as well as the OMP decomposition approach, is the excessive number of search parameters and the enormous calculation amount required. Using EMD decomposition, it is possible to separate complex micro-Doppler curves into their individual IMF components. The IMF subcomponents allow us to extract the target's process parameters, which is something that cannot be done with other approaches.

3.3 Comparison

Four distinct methods (Image Processing, High-Order Moment Function (HOMF), Orthogonal Matching Pursuit (OMF) and Empirical-Mode Decomposition) for analyzing and extracting features from micro doppler signature (mDS) data are demonstrated here. Micro-Doppler feature (mDS) extraction performances also vary depending on the chosen method, which has both advantages and disadvantages.

TABLE 3.1: Comparison of Feature Extraction Methods

Feature Extraction method	Pros	Cons
Image Processing	High robustness and easy Implementation	High Computational Time and Computer Storage required
OMP	High robustness than image processing method	High computational cost than image processing method
HOMF	easy Implementation, Fast calculation, and Low computational Complexity than image processing and OMP	Anti-noise performance is worse than image processing and OMP
EMD	Easy Implementation, fully data driven approach, mDS extraction of targets with procession, adapted to be used with nonlinear oscillations	Lack of Mathematical Framework and limited numerical simulations

3.4 Empirical-Mode Decomposition Method

EMD was first suggested in 1998 by NASA's Huang and his team. EMD "shifts" the signal to decompose it into a set of intrinsic mode functions (IMFs) [?]. IMF, per Huang's definition, is a signal with the following features:

- First, there are exactly as many max and min values as there are zero-crossings, or at most one fewer.
- Both the max and min value ranges have t -axis symmetry in their envelopes.

For the purpose of calculating the instantaneous frequency, the Hilbert transform is utilised to produce the phase function of the IMF, while the derivative of both the phase provides the necessary information. However, the signals do not share the same IMF characteristics. Therefore, the EMD decomposition method can be used to reposition the IMF's constituent parts. Maximum and lowest values of are used to determine the average upper and lower envelopes.

$$m = \frac{1}{2}(v_1(t) + v_2(t)) \tag{3.1}$$

The variable "h" represents the difference between "a(t)" and "m". Then, we'll treat "h" as a new "a(t)" and continuing processing the echo signal until h manages to find the IMF. This is the case when IMF1=h is chosen. Then let the residual r(t) become the new "a(t)". Repeat until r(t) becomes very small, at which point we will have IMF2. Keep decomposing the original signal into its multiple IMFs until we found residual r(t).

$$a(t) = \sum_{l=1}^{L} IMF_l + r(t) \tag{3.2}$$

When the signal $a(t)$ is decomposed using EMD and we have different IMFs the

first IMF component (IMF1) has the highest frequency $a(t)$ and second IMF has lower frequency as compared to IMF1 as the order increase in IMF, the frequency continuously decreases. The monotonic term of the signal, which is the lowest frequency component, is represented by the residual $r(t)$. Each frequency's IMF components can be analyzed separately because they each have a unique physical significance because to the EMD feature. Obtaining the mini-UAVs micro-Doppler feature using EMD requires the radar's PRF to be twice as large as the spectrum of the MD signal. In wideband radar, the extraction of MD features is more common when the radar's PRF would be less than twice the spectrum of the MD signal as well as the micro-motion point moves across the resolution cell. Despite the fact that the HT and OMP decomposition form the basis of the MD feature extraction EMD approach outlined in the previous approaches. For more intricate motions like precession, the algorithms calculated amount will be very significant [38].

3.5 Feature Extraction using EMD

Therefore, to complete effective feature extraction mini-UAVs, it is required to have a more suitable technique, and EMD is presented as a feasible solution to address the problem. The mDS can be easily and effectively obtained from EMD. For the purpose of analyzing mini-UAVs mDS, we propose EMD.

IMFs (Intrinsic Mode Functions) are the output of the Empirical Mode Decomposition (EMD) process. EMD is a signal decomposition method that separates a signal into a finite number of intrinsic mode functions (IMFs) and a residue, such that each IMF represents a component with a specific frequency range. The IMFs are extracted by iteratively finding the local maxima and minima of the signal, and then averaging the upper and lower envelopes until a function that satisfies the conditions of an IMF is obtained. Once the signal has been decomposed into

IMFs, various signal processing techniques can be applied to each IMF to extract features that can be used for classification, such as zero-crossing rate, energy, entropy, etc. These features are often used as inputs to machine learning algorithms, such as neural networks, to classify or detect signals of interest.

Table 3.2: Features (Statical and Geometrical)

Features	Feature Vectors
Number of zero crossing [39]	$f_{i,1} = [Z_1, ..., Z_K]^T \in \Re^K$
Normalized signal Energy [40]	$f_{i,2} = [E_1/E, ..., E_K/E]^T \in \Re^K$
Standard deviation [41]	$f_{i,3} = [Std(m_1), ..., Std(m_K)]^T \in \Re^K$
Entropy [42]	$f_{i,4} = [En(m_1), ..., En(m_K)]^T \in \Re^K$
Entropy of two connected IMF	$f_{i,5} = [En(M_1), ..., En(M_{K-1})]^T \in \Re^{K-1}$
Normalized mix-mean difference	$f_{i,6} = [D_1, ..., D_K]^T \in \Re^K$
Distance between two frequency peaks	$f_{i,7} = [P_1, ..., P_K]^T \in \Re^K$
Ratio of zero crossing number	$f_{i,8} = [Z_2/Z_1, ..., Z_K/Z_{K-1}]^T \in \Re^{K-1}$

Zero-crossings are defined as the points where a signal changes from being positive to negative or vice versa. In other words, they are the points where the signal crosses the zero-axis. Zero-crossings can be used to extract useful information from signals, such as the frequency content, as the number of zero-crossings per unit time is directly related to the frequency of the signal. In the context of EMD, the number of zero-crossings is used as a feature to characterize the micro-Doppler signatures of Mini-UAVs.

Zero crossing ratio is a metric used to characterize a signal's shape by calculating the number of times the signal crosses the zero-axis in a given time period. It is defined as the ratio of the number of times the signal crosses the zero-axis to the signal's total number of samples. It provides information about the number of times a signal changes polarity, which can be useful in certain applications such as speech recognition, audio analysis, and image processing. Zero crossing ratio is a simple and effective feature for signal classification and analysis.

Normalized signal energy is a feature extracted from the Intrinsic Mode Functions (IMFs) obtained through Empirical Mode Decomposition (EMD). It is calculated as the ratio of the energy of each IMF to the total energy of the signal. This normalization makes the feature independent of the signal's total energy and allows for comparison between signals of different energy levels.

The formula for calculating the normalized energy of an IMF is:

Normalized Energy = (Energy of IMF) / (Total Energy of all IMFs)

where the energy of an IMF is calculated as the sum of the squares of the IMF's samples. The total energy of all IMFs is the sum of the energies of each IMF.

By calculating the normalized energy of each IMF, we obtain a set of features that represent the energy distribution of the signal across different frequency bands. These features can be used for classification and other signal processing tasks.

Entropy is a measure of the amount of disorder or randomness in a signal. In the context of EMD, entropy is often used as a feature to characterize the complexity of the IMFs. The entropy of an IMF is calculated by dividing its energy into sub-bands and computing the Shannon entropy for each sub-band. The entropy value is then obtained by summing up the entropy values for all sub-bands. In

general, the higher the entropy value of an IMF, the more complex and random the signal is. The entropy feature is used in the classification of micro-Doppler signatures because it can capture the differences in the complexity of the IMFs between different types of Mini-UAVs.

Using EMD, signal can be broken down into its component IMFs. The IMFs are mined for four properties, all of which are built for label discrimination. After features are extracted and then they are used to train the LSTM classifier for classification of the target. To classify mini-UAVs, an efficient EMD-based technique extracts four characteristics from the IMFs. The spectrogram as well as the IMFs are related to one another in terms of the blade flash phenomenon, as shown by an empirical investigation conducted on radar mini-UAV mDS. Mini UAV classification performance is improved through feature extraction from a complex valued signal with the use of a real valued EMD.

3.6 Chapter Summary

In this chapter several techniques for extracting features from micro-Doppler signatures are covered. These include image processing, OMP decomposition, OMF, and EMD. The EMD approach is then selected for feature extraction of mDS after a comparison of possible techniques.

Chapter 4

Classification Framework

In recent years, there has been a remarkable amount of progress in the use of RNNs to a wide range of tasks, including voice recognition, language modelling, translation, picture captioning, and many more. The utilization of "LSTMs," a highly specific kind of recurrent neural network that performs significantly better than the regular version for a variety of tasks, is an essential component to the success of these endeavors. They are essential to accomplishing nearly all the fascinating achievements that are based on recurrent neural networks. In principle, RNNs should have no trouble coping with "long-term dependencies" of this kind. A human being might carefully set the parameters to solve issues of this kind using toys. Regrettably, RNNs are incapable of learning them via actual application. Hochreiter (1991) and Bengio et al. (1994) conducted in-depth research on the issue and uncovered some rather basic reasons why it would be tough to solve. LSTMs do not struggle with this issue at all.

4.1 Neural network

A neural network replicates the structure and operation of the human brain by consisting of many layers that are interconnected and working in concert with one another. To train a neural net, it analyses vast quantities of data and makes use of complicated algorithmic processes.

4.2 Convolutional Neural Networks (CNN)

When analyzing visual data, convolutional neural networks, often known as CNNs, are commonly employed. In terms of accuracy, CNN performs far better than any other picture categorization system. Convolution layers, pooling layers, and a fully connected layer make up the CNN Model's layer structure. The fully connected layer is the last component of the CNN Model. In the convolution layer, the input picture is convolved with a filter that has a certain form. This process results in the creation of a feature map from the original image. The pooling layer is beneficial to the process of input dimension reduction. The capacity of artificial intelligence to close the gap in capability between humans and machines has significantly increased during the last several years. Researchers contribute to the area to work on its many facets and accomplish remarkable outcomes. One of these fields is known as computer vision, although there are many more like it. The objective of this discipline is to give computers the ability to see the environment in the same manner that people do, and then to put that knowledge to use in several contexts, including picture and video recognition, image analysis and categorization, media reproduction, recommendation systems and natural language processing etc. Deep Learning is an area of computer vision that has seen significant development and improvement over the course of time, particularly because of one particular method known as a Convolutional Neural Network.

4.3 Recurrent Neural Network (RNN)

A network of neuron-like nodes that is organized in layers is referred to as a recurrent neural network (RNN). The use of feedback contributes to the greatly increased adaptability of RNNs in comparison to those of CNNs. RNNs are distinguished by a crucial characteristic known as the hidden state, which stores information about a sequence. In addition to that, it includes memory, which may be used to store the results of the calculations. RNN is distinguished from other neural networks in that, in contrast to other networks, the complexity of its parameters is substantially simplified by virtue of this property. RNN is based on the premise of "storing the output of a given layer and giving feedback to the input to predict the output." This is how RNN is able to function.

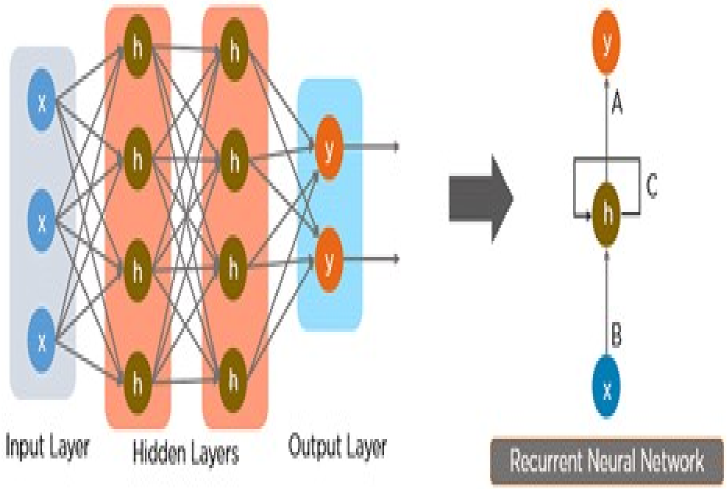

FIGURE 4.1: Simple Recurrent Neural Network

RNNs were created as a solution to various problems that feed-forward neural networks exhibited, including the following:

- Unable to process sequential data
- Considers just the current data
- No capacity to remember previous inputs

These issues may now be addressed thanks to the RNN. To process sequential information, an RNN takes in inputs from the present as well as the past. Since RNNs have their own internal memory, they may utilize it to recollect information they were given in the past. The Recurrent Neural Network will normalize the parameters for each hidden layer, including the activation functions, weights, and biases. Instead of making a bunch of secret layers, it'll just make one and iteratively go back over it as many times as needed.

4.3.1 RNN and Feed Forward

All data must flow from the input nodes through the hidden layers and out to the output nodes in a feed-forward neural network. There are no loops or cycles in the system. A feed-forward neural network uses the most recent data to make choices. It can't recall any prior information and can't predict anything in the future. It is normal practice to employ feed-forward neural networks for such tasks as regression and classification.

4.3.2 Types of RNN

Recurrent Neural Networks are classified into four types:

1. One to One
2. One to Many
3. Many to One
4. Many to Many

4.3.2.1 One to One

The Vanilla Neural Network is a type of neural network. It is applied to general machine learning problems with a single input and output.

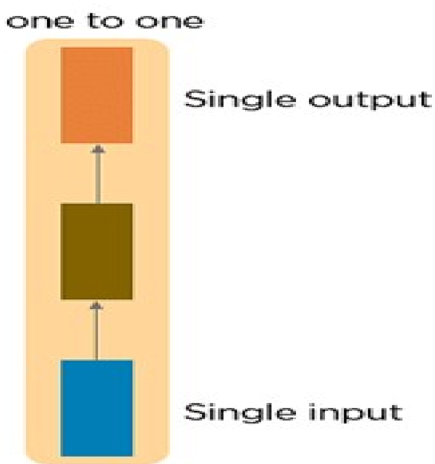

FIGURE 4.2: One to One RNN

4.3.2.2 One to Many

This neural network has a single input and several outputs. The image caption is an example of this.

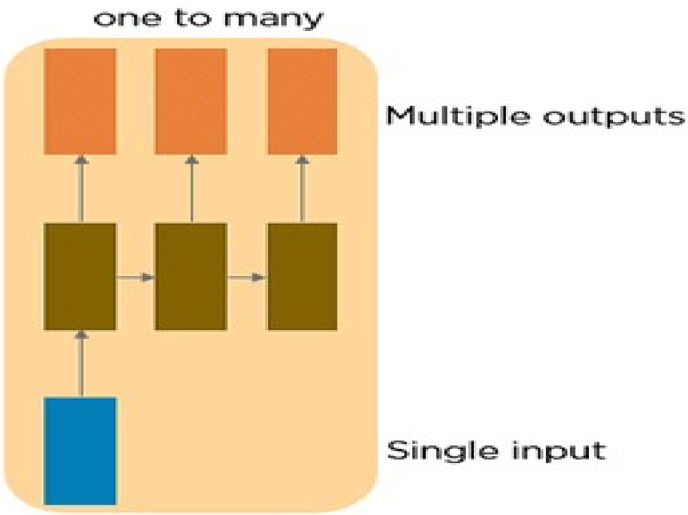

FIGURE 4.3: One to Many

4.3.2.3 Many to One

This RNN takes in a sequence of inputs and outputs a single value. Sentiment analysis is an excellent illustration of this sort of network, where each given statement may be labelled as having positive or negative sentiments.

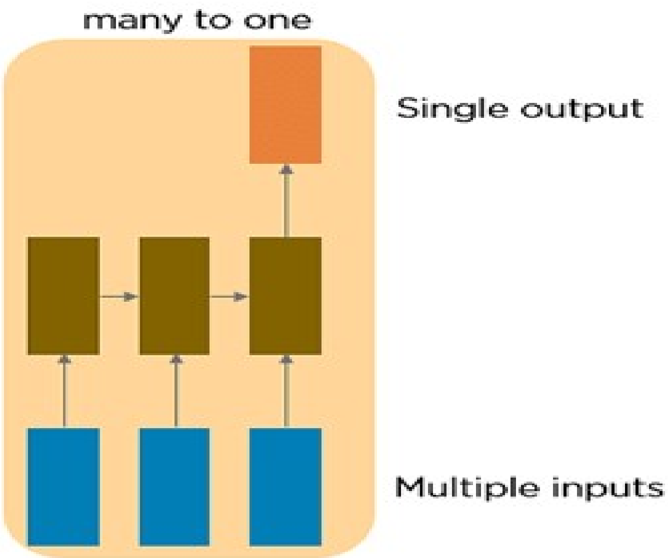

FIGURE 4.4: Many to One

4.3.2.4 Many to Many

This RNN is fed a sequence of inputs and outputs the same sequence. Robotic translation is one such example.

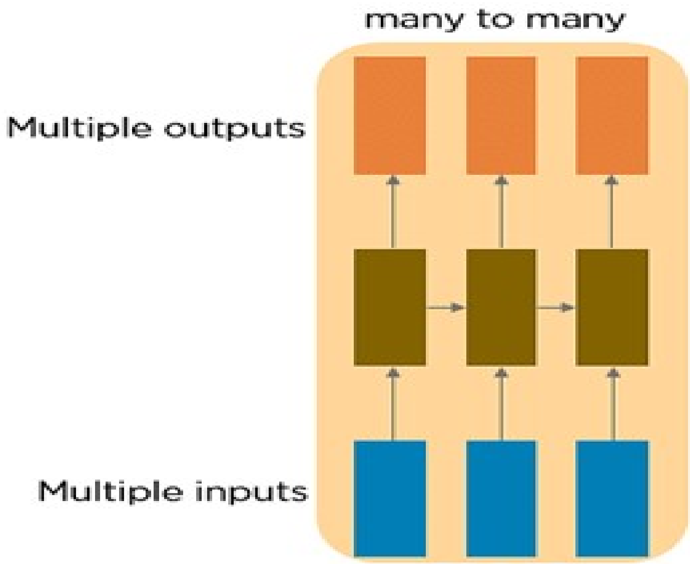

FIGURE 4.5: Many to Many

4.3.3 Issues of Standard RNNs

The conventional RNNs have the following problems

1. Vanishing Gradient Problem
2. Exploding Gradient Problem

4.3.3.1 Vanishing Gradient Problem

Time-dependent and sequential data issues, such as stock market prediction, classification, and text creation, may be modelled with recurrent neural networks. On the other hand, we shall learn that RNNs are challenging to train because of the gradient problem. RNNs suffer from the issue of vanishing gradients. Updates to the parameters cease to be meaningful when the gradient is too slight. This complicates the task of learning from extended sequences of data.

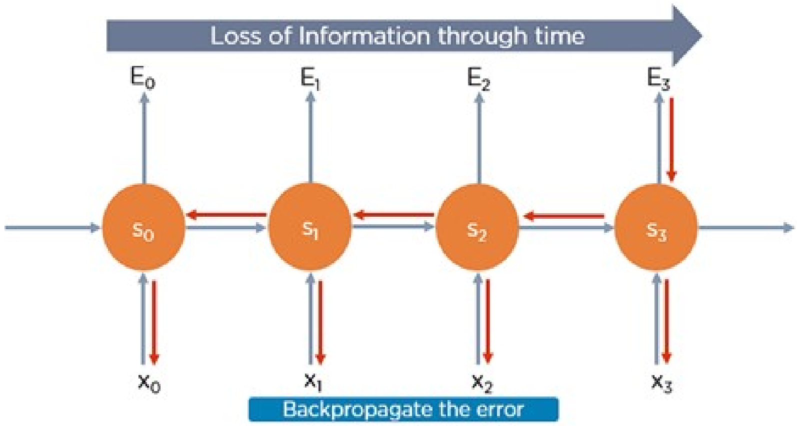

FIGURE 4.6: Gradient Vanishing Problem

4.3.3.2 Exploding Gradient Problem

When the gradient's slope climbs exponentially during training rather than gradually decreasing, we say that the gradient is "exploding." During the training phase of a neural network model, relatively significant changes to the weights are produced when incorrect gradients accumulate. Training takes too long, performance and accuracy degrade, and that's only the beginning of the problems with gradient problems.

4.3.3.3 Gradient Problem Solutions

The Long Short-Term Memory (LSTMs) Network is currently the approach that has gained the greatest popularity and is the most effective in solving gradient issues.

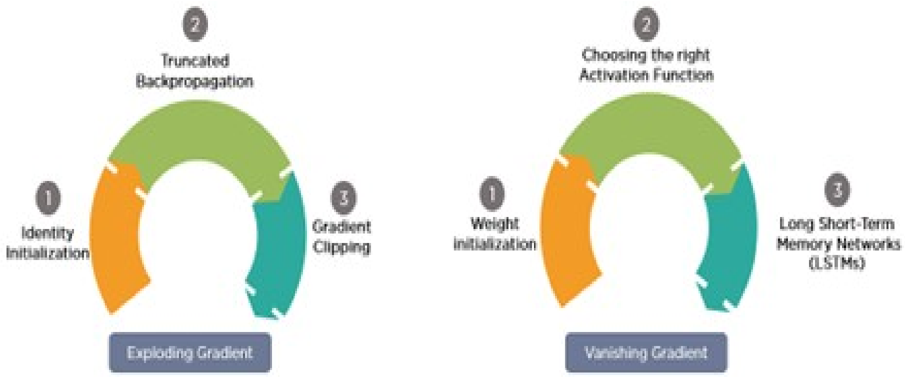

FIGURE 4.7: Gradient Problem Solutions

4.4 LSTM

Deep learning system equipped with Long Short-term Memory (LSTM), which is adaptable to a broad variety of data types including photos, videos, audios, and so on. Because it is made up of a cell, an input gate, a forget gate, and an output gate, an LSTM is able to store information for a considerable amount of time due to its construction. In this aspect, LSTM performs better than RNN. Processing, predicting, and categorizing time series data is the major use for this application.

4.4.1 Working

LSTMs place a significant emphasis on the cell state, which is denoted by the horizontal line that traverses the top of the figure. The status of the cell is analogous to that of a conveyor belt. The whole chain is followed, and there are just a few small linear interactions. It is incredibly simple for data to just travel through it without being altered in any way.

The cell state, which is precisely regulated by structures that are known as gates, can have information subtracted from it or added to it by the LSTM. Gates are a means of permitting information to move through a system on a conditional basis. They are constructed using a layer of sigmoid neural network, as well as an operation called pointwise multiplication. Numbers ranging from 0 to 1 are generated by the sigmoid layer, and these numbers indicate the proportion of each component that should be let to pass through. To safeguard and maintain control over the cell state, an LSTM typically has three of these gates.

LSTMs make a conscious effort to steer clear of long-term dependencies. They basically operate with long-term memory as their default mode of operation. They do not have to put in a lot of effort to understand it. The structure of recurrent neural networks is always in the form of a series of modules that are repeated from the network.

The normal RNN will have a relatively simple structure for this repeating module, single tanh layer. Although LSTMs have a chain-like topology, repeating module seems to have a completely distinct structure. There is not just one neural network layer, but rather four, and each of these layers interacts in a different way.

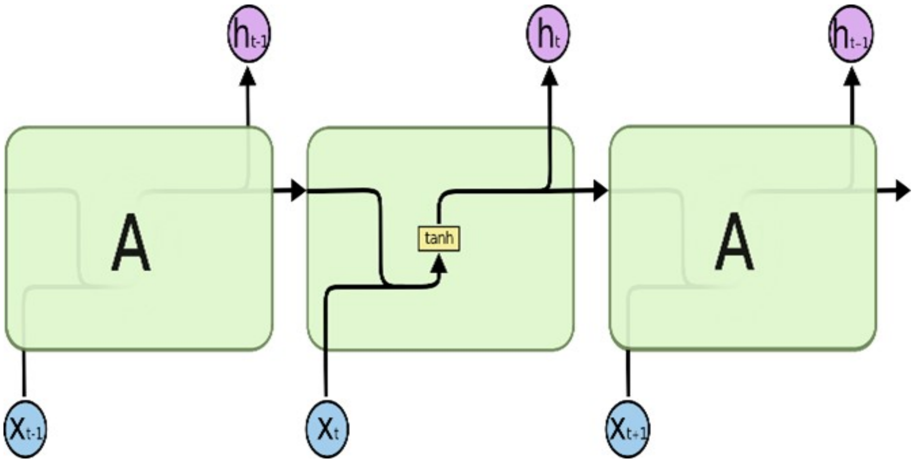

FIGURE 4.8: LSTM Network with tanh Layer

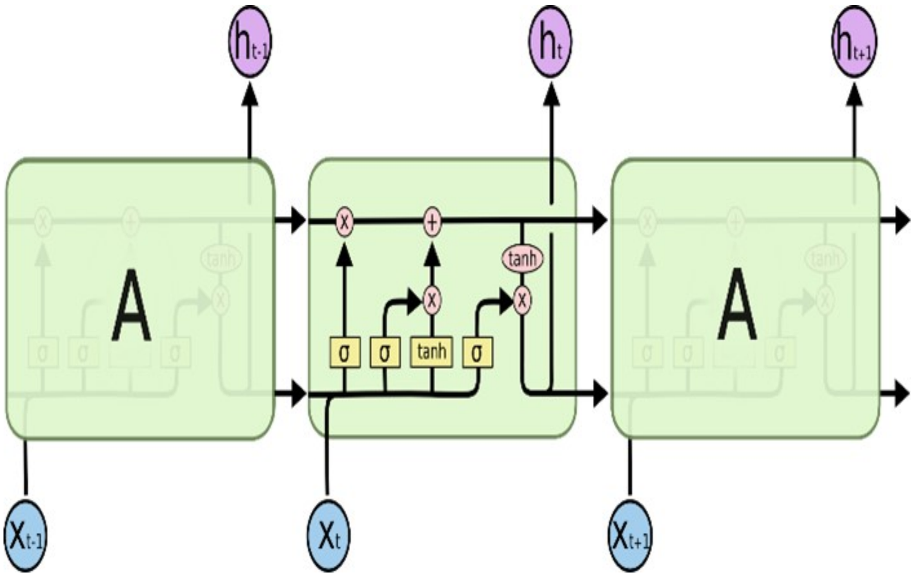

FIGURE 4.9: LSTM with Multiple Sigmoid and tanh Layers

4.5 Why LSTM

LSTM (Long Short-Term Memory) is a type of Recurrent Neural Network (RNN) that can effectively model time-series data. It has shown impressive performance in many sequence classification tasks and can handle variable-length input sequences.

Therefore, LSTM can be useful for testing and training of classifiers on smaller datasets, particularly when the input data has a time-dependent structure.

LSTM is a type of recurrent neural network (RNN) that is particularly effective in modeling sequential data, such as time series or speech. The micro-Doppler signature generated by a mini UAV can be seen as a time series of signals, which makes LSTM a suitable choice for classification.

LSTM can learn and model the temporal dependencies in the micro-Doppler signature, which can help improve the classification accuracy. Additionally, LSTM can handle variable-length input sequences and can be trained on smaller datasets without overfitting, which is particularly useful when working with limited data.

However, it is important to note that LSTM requires more computational resources and training time compared to other methods such as SVM and Naive Bayes. Also, LSTM models can be difficult to interpret, which may limit their applicability in some domains.

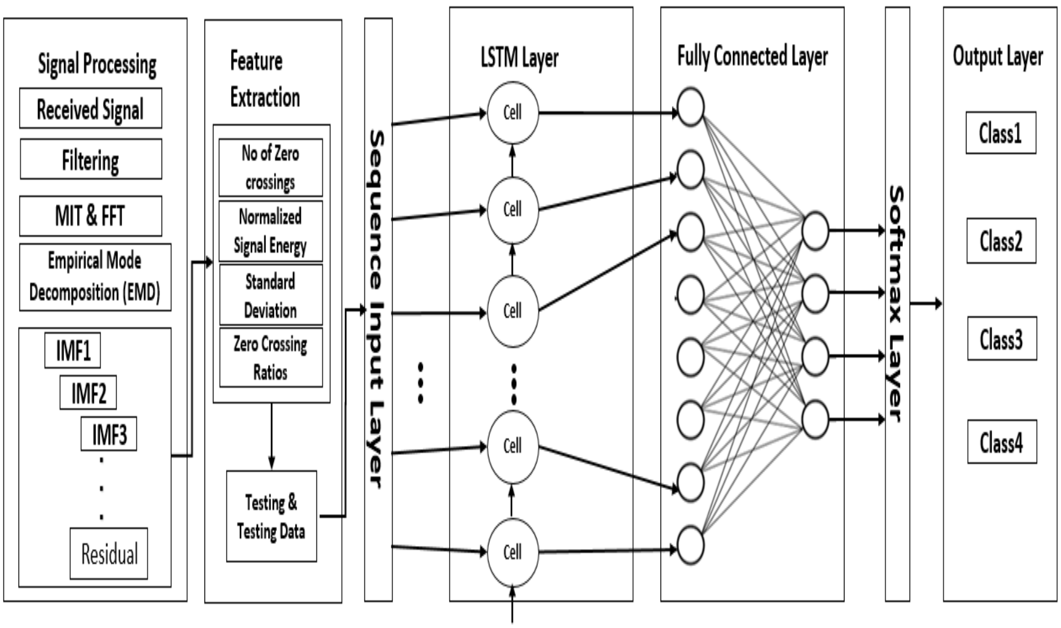

FIGURE 4.10: LSTM Working Structure

In summary, LSTM is a suitable choice for classification of mini UAVs based on their micro-Doppler signatures due to its ability to model sequential data and handle variable-length input sequences. One advantage of using LSTM for smaller datasets is that it can capture temporal dependencies in the data, even with limited training examples. For example, when classifying the flight patterns of mini UAVs, the micro-Doppler signatures generated by the UAVs can be seen as a sequence of signals over time. LSTM can effectively model these sequences and learn the underlying patterns that differentiate different classes of UAVs.

4.6 Chapter Summery

In this chapter, we will talk about the framework for classification. It makes use of neural networks like CNN, RNN, and LSTM among others. The workings of CNN, RNN, and LSTM are analysed, along with a comparison of the three. In the end, LSTM was selected as the classification system for the MINI-UAV.

Chapter 5

UAV Classification Results

5.1 Feature Extraction in MATLAB

Because of the Doppler Effect, the frequency of the radar return will change when there is a moving target in the field of view. Most targets, however, are not rigid bodies; as a result, in addition to the movement of the platform, there are typically extra rotations and vibrations in various portions of the target.

As a helicopter travels through the air, the blades on its rotors turn. These micro-scale motions create additional Doppler shifts, also known as MD effects, which help in the identification of target characteristics. Micro-Doppler signatures are what are used to calculate the speed of the blades of a helicopter. In this simulation, the helicopter is depicted as having five scatterers, one in the center of rotation and one at each of the four tips of the blades.

The center of rotation moves in the same direction as the body of the helicopter. Each blade tip is separated by an angle of 90 degrees from the tip of the blades that are next to it. The blades turn at a consistent pace of four revolutions per second throughout the whole cycle. It is presumed that the reflectivity at each of the four blade tips are the same, however the reflectivity at the rotating center is supposed to be stronger.

5.1.1 Echo Simulation

MATLAB provides a variety of signal processing functions and toolboxes that can be used to simulate radar systems and analyze the micro Doppler signals. The following are the steps to create a radar and target environment of UAVs in MATLAB:

- Define the Radar System: Define the radar system parameters such as the carrier frequency, pulse width, PRF (Pulse Repetition Frequency), and antenna parameters.
- Define the UAV and Blade Models: Define the geometric and electromagnetic properties of the UAV and blade models. The blade motion can be modeled using a simple harmonic oscillator, and the blade geometry can be modeled using the CAD model.
- Generate the Radar Signal: Generate the radar signal using the radar system parameters and the UAV model.
- Perform Doppler Processing: Perform Doppler processing on the received radar signal to extract the micro Doppler signature of the UAV's blades.
- Analyze the Micro Doppler Signature: Analyze the micro Doppler signature to estimate the UAV's speed and the number of blades.

MATLAB provides several built-in functions for Doppler processing, such as FFT (Fast Fourier Transform), STFT (Short Time Fourier Transform), and WVD (Wigner-Ville Distribution). Additionally, MATLAB's Signal Processing Toolbox provides functions for filtering, spectral analysis, and time-frequency analysis.

Note that the accuracy of the simulation depends on the accuracy of the UAV and blade models and the radar system parameters. It is important to validate the simulation results with real-world measurements to ensure their accuracy.

Let us assume that the signal is sent across empty space. With each pulse, the chopper continues along its path toward its destination. While this is happening, the blades continue to spin, and as they do so, the tips of the blades add both angular speed and displacement. The range-Doppler response is illustrated here by making use of the first 128 pulses of the signal that was received. There is a display of three returns in front of us.

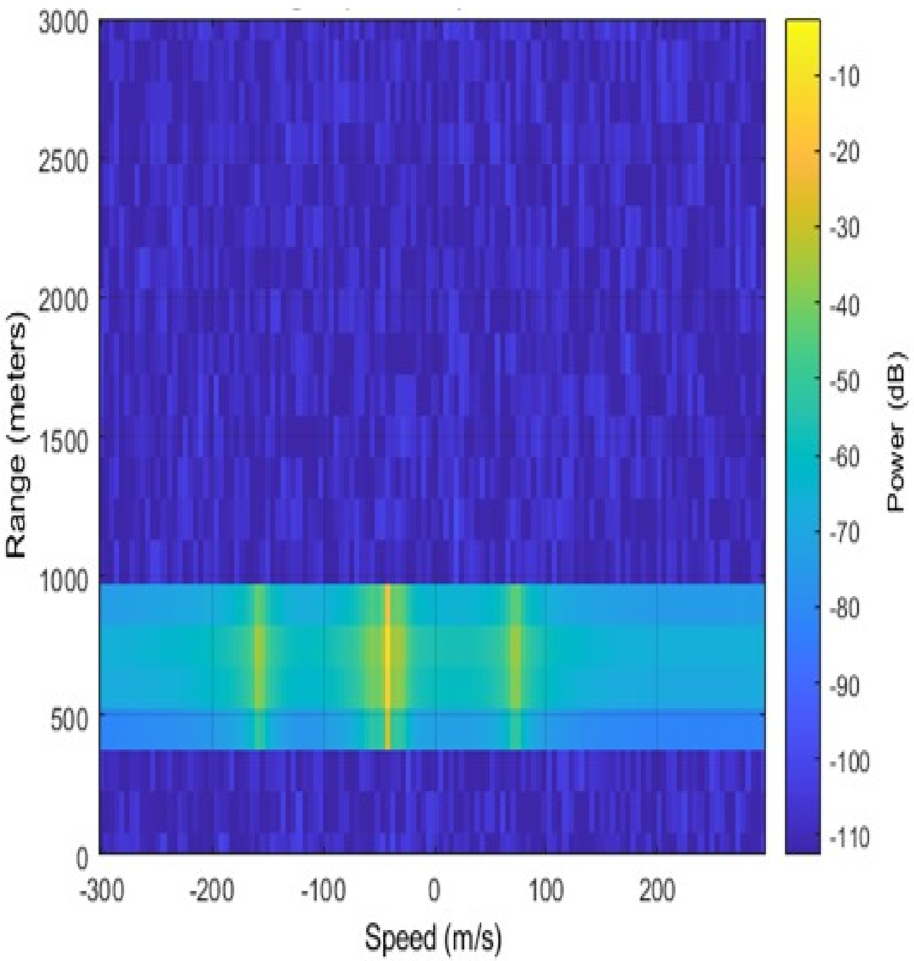

FIGURE 5.1: Range Speed Response Pattern

Although it may appear that the returns are coming from a variety of targets, in reality they are all coming from the same target. The center return originates from the center of the rotation and is noticeably more powerful than the other two returns. This intensity comes as a result of the fact that the reflection from the body of the helicopter is significantly stronger than the reflection from the tips of the blades.

The graph indicates that the center of rotation is traveling at a speed of -40 meters per second. This number corresponds to the real radial speed that the target should be moving at. The other two returns originate from the tips of the blades as they move at full speed toward or away from the target.

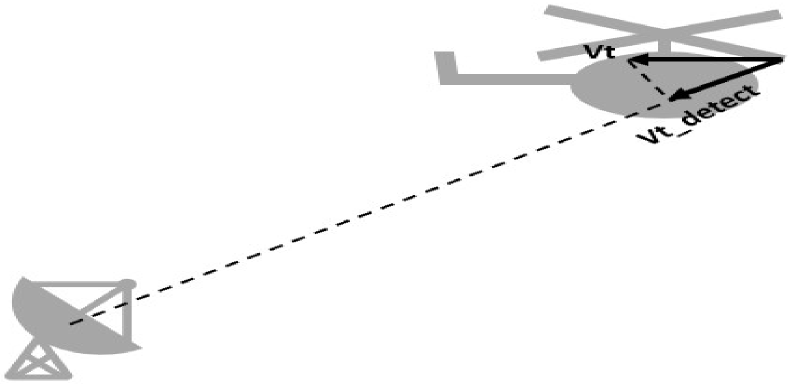

FIGURE 5.2: Orientation of tip velocity of rotating blades

5.1.2 Blade Return Micro-Doppler

The image depicts the MD modulation that is brought about by the blade tips in relation to a continuous Doppler shift. According to what can be seen in the picture, each blade tip produces a Doppler modulation that is sinusoidal in appearance. As may be seen in the image below, three more sinusoids arise at equal distances inside each cycle of the sinusoid. Based on its look, the helicopter appears to have four blades that are evenly spaced apart.

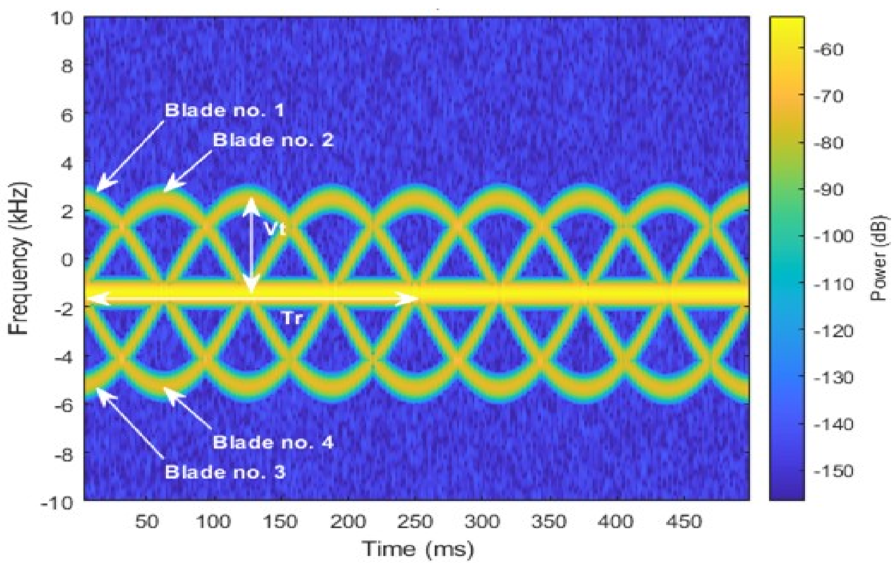

FIGURE 5.3: Micro-Doppler of four Blade Return

The maximum tip velocity along the radial direction is represented. The relative orientation must be considered to obtain the correct maximum tip velocity. Because the blades spin in a circle, the azimuth angle has no effect on detection. Only the elevation angle needs to be adjusted for the best tip velocity result.

The time-frequency representation of micro-Doppler effects in the detected target range bin. The matched filter is applied to the input signal resulting in the output signal. The range index corresponding to the peak value in the summed absolute values of the columns of matched filter using the 'max' and 'sum' functions.

This range index is stored. The 'pspectrum' function is used to generate a spectrogram of the signal in the range bin. The spectrogram is computed using the 'spectrogram' option, and the pulse repetition frequency (PRF). The resulting spectrogram displays the time-varying frequency content of the signal in the detected range bin, which can provide insight into the micro-Doppler effects caused by the motion of the target.

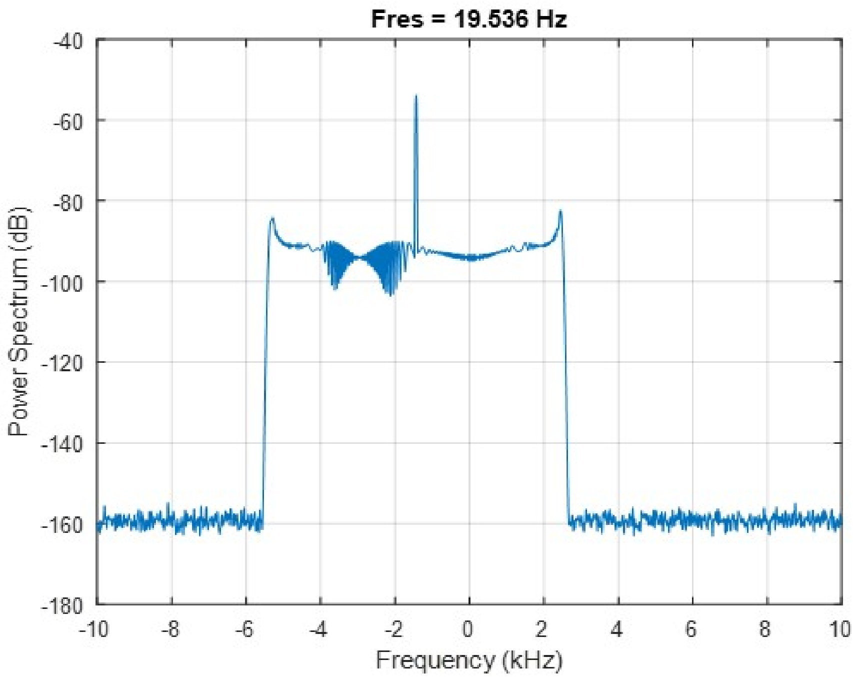

FIGURE 5.4: Spectral Signature of Blade return Signal

FFT is used to convert the time-domain signal obtained from the moving target indicator (MTI) processing into its frequency-domain representation. This is done to analyze the Doppler frequency shift introduced by the moving target, which can be used to identify the target's speed and direction. The FFT of the MTI signal is plotted to visualize the Doppler shift signature of the target.

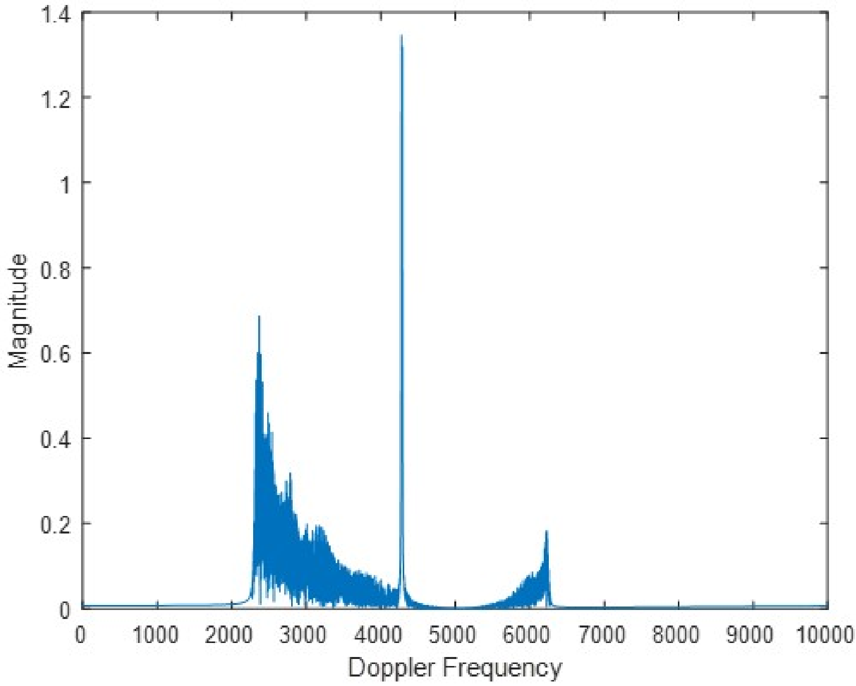

FIGURE 5.5: FFT of return Signal

5.2 Applying EMD for feature Extraction

Empirical Mode Decomposition (EMD) is a tool for adaptive signal analysis that decomposes a given signal into a number of "basis functions" that are derived directly from the signal. Intrinsic Mode Function (IMF) is the name given to the component decomposed by EMD. The first IMF can be obtained in a systematic manner, known as the sifting process:

- Determine the signal's local maxima and minima between them to create an upper envelope in signal $s(t)$.
- Determine the local minima of and interpolate between them to create a lower envelope by generating $e_{min}(t)$ and $e_{max}(t)$.
- Determine the local mean values $m(t) = (e_{min}(t) - e_{max}(t))/2$ of the upper and lower envelopes.

- Subtract the signal from the mean value $Sift1[s](t) = s(t) - m(t)$ to get IMF.
- Let Signal = IMF1, and repeat steps (1) - (4)

We store the residual as a new signal after obtaining the first IMF, and the next IMF can be obtained by applying the sifting process to the residual. Similarly, the remaining IMFS can be computed, and EMD concludes with a residual $r(t)$.

$$s(t) = \sum_{K=1}^{K} d_K[s](t) + r(t) \tag{5.1}$$

Where $d_k[s](t)$ represents the Kth IMF and l represents the number of IMFs

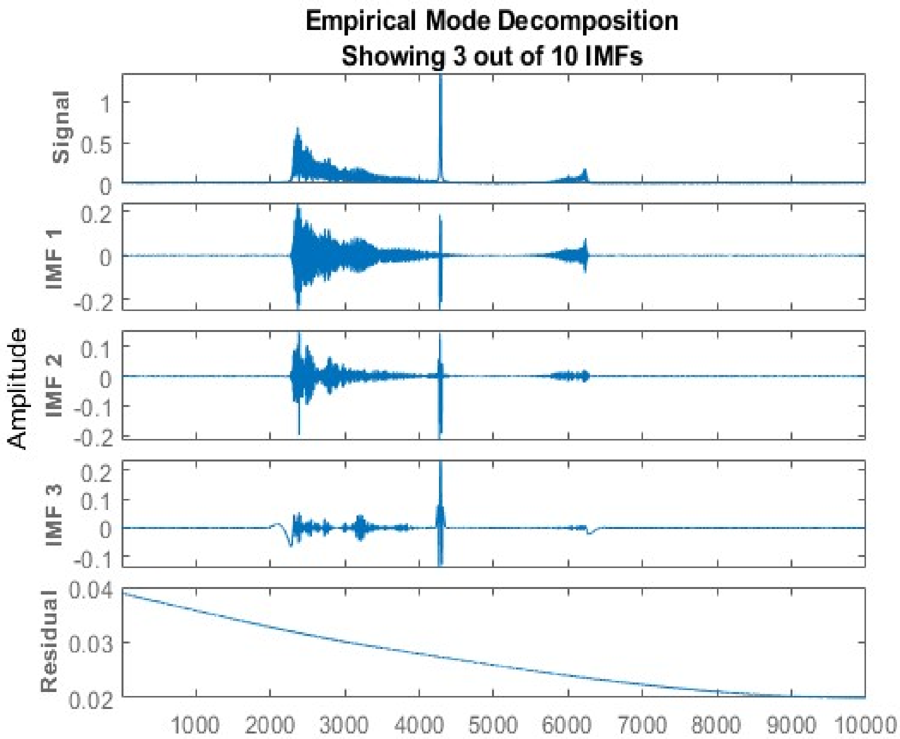

FIGURE 5.6: EMD Decomposed Results of our Signal

Micro Doppler features can be detected from the IMFs obtained from EMD because each IMF represents a frequency component of the original signal with a specific modulation. For example, if a signal contains a rotating blade or oscillating limb, the micro Doppler signature will be represented in one or more of the IMFs obtained from EMD.

The first IMF obtained from EMD represents the highest frequency component of the signal, while the last IMF represents the lowest frequency component. The IMF with the highest frequency can provide information about the fastest moving parts of the target, while the IMF with the lowest frequency can provide information about the slowest moving parts of the target. Therefore, micro Doppler features can be extracted from specific IMFs depending on the frequency range of interest.

In addition, the amplitude modulation of each IMF can also provide information about the micro Doppler signature. For example, the amplitude modulation of an IMF can provide information about the vibration or oscillation frequency of the target, while the phase modulation of an IMF can provide information about the direction of movement of the target.

5.3 Features Extraction from IMFs

The signal is broken down by the EMD into a certain IMFs and a residue. The amount of frequency content contained in the signals has an effect on the number of IMFs, denoted by l. IMFs are utilized in order to derive the aforementioned four characteristics. A feature vector is built in the same way as a row vector array is, using all the values that were retrieved from the features.

Firstly we computes some features from the empirical mode decomposition (EMD) of a signal. EMD is a signal processing technique that decomposes a signal into a set of intrinsic mode functions (IMFs), which are oscillatory functions with well-defined frequency components. Here are the features computed from IMFs:

- Zero-crossing rate: this is the number of times the signal crosses the horizontal axis (i.e., changes sign) per unit time. No. of zero crossings “Zl” is a vector that contains the zero-crossing rate of each IMF.
- Normalized signal energy: this is the total energy of the signal divided by the total energy of all the IMFs. ”El” is a vector that contains the normalized energy of each IMF.

- Ratio of zero-crossing rates: this is the ratio of the zero-crossing rate of one IMF to the zero-crossing rate of the previous IMF. "f4" is a vector that contains the ratio of zero-crossing rates for each pair of adjacent IMFs.
- Entropy: this is a measure of the disorder or randomness in the signal. "En(ml)" is a vector that contains the entropy of each IMF, and "En" is the total entropy of the signal (sum of entropies of all IMFs).

TABLE 5.1: Extracted Features

Features	Formula	Feature Vector
No. of zero crossings	$Z_l = \sum_{n=2}^{d}(sign[m_l(n)] - sign[m_l(n-1)])$	$f_1 = [Z_1, ..., Z_K]$
Entropy	$En(m_l) = -\Sigma P(m_l) log_2 P(m_l)$	$f_2 = [Em(m_1), ..., Em(m_k)]$
Normalized signal energy	$E_l = \sum_{n=1}^{d} \lvert m_l(n)\rvert^2$	$f_3 = [E_1/E, ..., E_K/E]$
Zero crossing ratio	$f_4 = [Z_2/Z_1, ..., Z_K/Z_{K-1}]$	$f_4 = [Z_2/Z_1, ..., Z_K/Z_{K-1}]$

5.4 Dataset Generation

Following that, the extracted four feature vectors of four different classes (class 1, class 2, class 3, and class 4) of UAVs are concatenated fi and stacked into a matrix form. To prepare for the future classification step, each row vector of FMag is first subjected to the min-max normalization method so that it may be brought within the appropriate range. As a result of the fact that the test data are not accessible in advance, the characteristics of the test data can only be standardized in reference to the minimum and maximum values of the training data. Finally, we created a dataset of four classes of drones. The dataset contains 1200 mini-UAV samples. For training and testing, the samples are divided into two parts. The first 800 samples are used for training, and the remaining 400 are used for testing the LSTM network.

TABLE 5.2: Classes of Mini-UAVs

Classes	Types	No. of rotors	No. of blades	UAVs
Class 1	UniRotor	1	2	Vapor
Class 2	Bicopter	2	4	Cobra fpv
Class 3	Tricopter	3	6	YI Erida
Class 4	Quadcopter	4	8	Phantom 4

5.5 LSTM Network

As was mentioned before, the EMD is capable of accurately capturing the unique patterns of m-DS that are a direct result of the micromotion of the mini-UAV blades. To extract and make use of such specific information for mini-UAV categorization, we take four characteristics from the collected IMFs. Following feature normalization and fusion, the resulting features are sent into an LSTM classifier to be trained. Long-term dependencies are not a problem for the LSTM network. The Long Short-Term Memory (LSTM) is made up of many isomorphic cells, each of which is capable of storing data for a significant amount of time provided that they regularly update their internal state. LSTM is the solution that has been suggested as the approach for classifying MINI-UAVs.

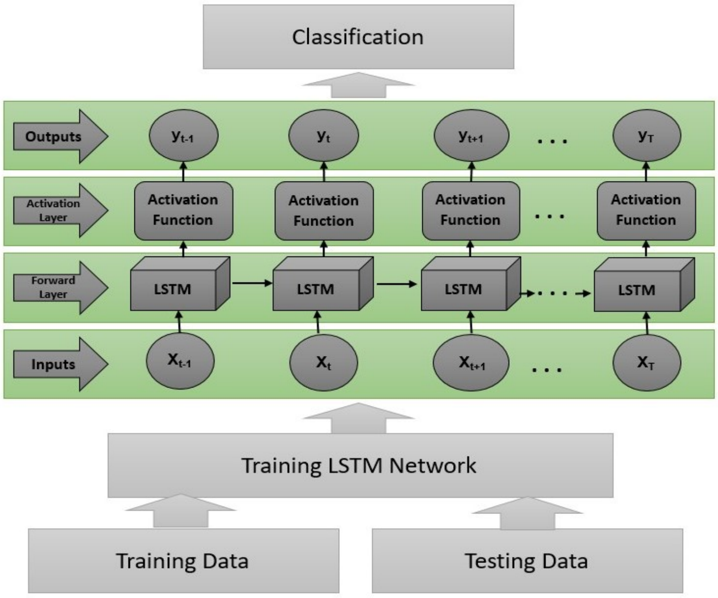

FIGURE 5.7: LSTM Network

5.5.1 LSTM Network Parameters

Our LSTM architecture requires a total of only 100 epochs for the network to be trained. After performing random runs from 10 to 150 with a gap of 10, we chose the setup that worked the best overall. The Adam optimizer is utilized to acquire the weights that have been taught most effectively. Each training iteration utilizes a mini batch with a size of 200 participants, which remains unchanged. The learning rate at the beginning of the training is 0.01. Since the program takes the learning rate schedule in pieces, it is automatically updated every 50 epochs by simply multiplying it by 0.1. It has been determined that the gradient threshold will be set to 1, and that the length of the sequence for one single iteration of a mini batch will be set to 200 samples. The table that follows contains a listing of the training parameters that were chosen for simulation, along with their respective values.Each training iteration utilizes a mini batch with a size of 200 participants, which remains unchanged. The learning rate at the beginning of the training is 0.01. Since the program takes the learning rate schedule in pieces, it is automatically updated every 50 epochs by simply multiplying it by 0.1.

TABLE 5.3: LSTM Layers Parameters

Layers	Parameters	Operations
Sequence Input Layers	1	Create a sequence input layer for multi-dimensional time series with 1 dimensions per time step
LSTM Layer	100	LSTM layer with 100 hidden units
	'last'	To output the last element only
Fully Connected Layer	4	A fully connected layer with an output size 4
softmax Layer		Creates a softmax layer that is useful for classification problems
Classification Layer		Create a classification output layer
ADAM		Adaptive Moment Estimation
Max Epoches	100	The maximum number of epochs that will be used for training

Mini Batch Size	200	The size of the mini-batch used for each training iteration
Initial Learn Rate	0.01	The initial learning rate that is used for training
Sequance Length	50	Pad or truncate sequences in a mini-batch to a specified length
Gradient Threshold	1	Positive threshold for the gradient
Plots	'training progress'	Plots to display during training
Shuffle	'never'	No shuffling is applied
Gradient Decay Factor	0.95	specifies the exponential decay rate for the gradient moving average in solver 'adam'
Squared Gradient Decay Factor	0.95	specifies the exponential decay rate for the squared gradient moving average in solver 'adam'

5.6 Training and Testing Results

To determine the number of misrecognitions, the recognition results are compared to the testing labels. The confusion matrix is used to evaluate a classification estimate phase-coded waveform identification accuracy for testing datasets.

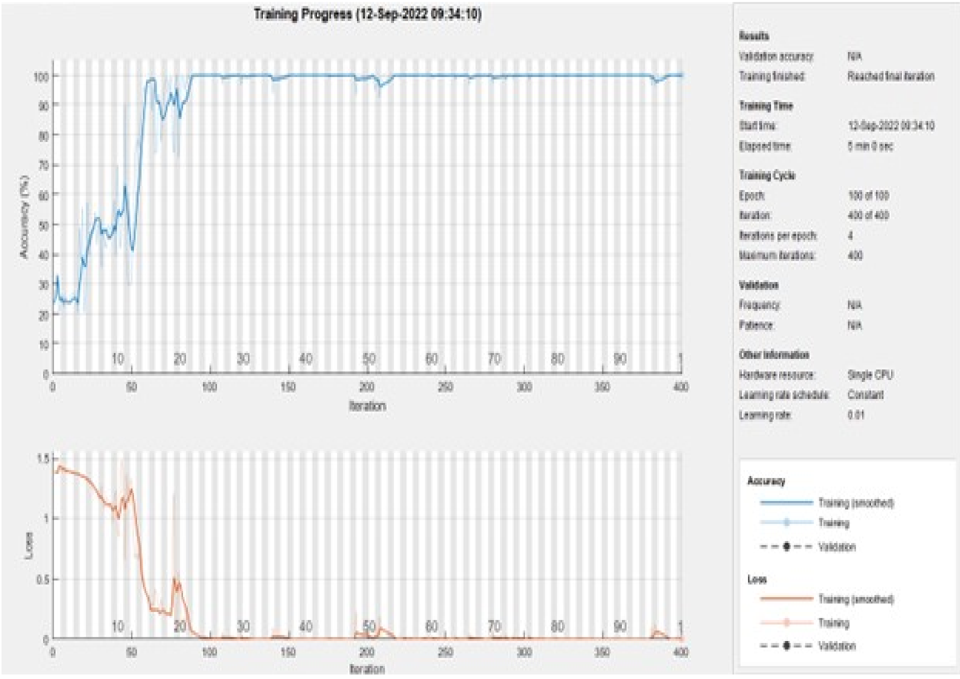

FIGURE 5.8: Training Process

Figure depicts the confusion matrix, which represents the training accuracy and Fig depicts the testing accuracy. The overall recognition accuracy for all four types of classes in the testing dataset is 100 percent.

Training

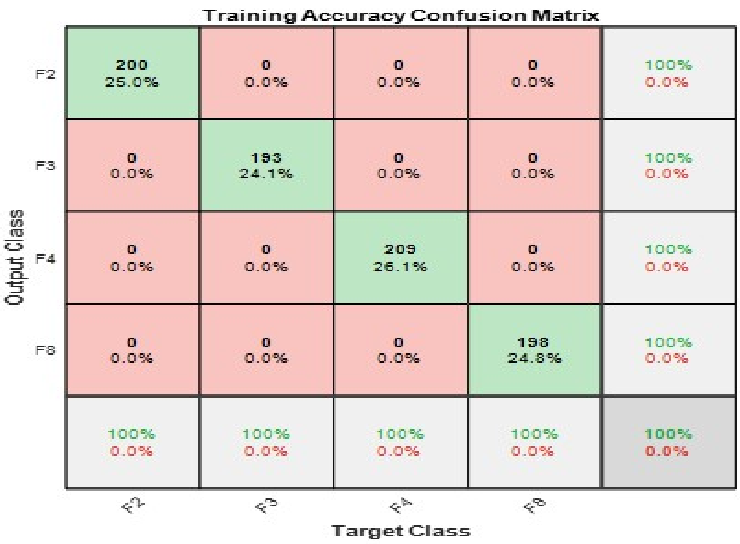

FIGURE 5.9: Training Confusion Matrix

All four classes have been correctly classified. All four classes are successfully classified. It demonstrates the effectiveness of this method in recognizing four different types of mini-UAVs.

Testing

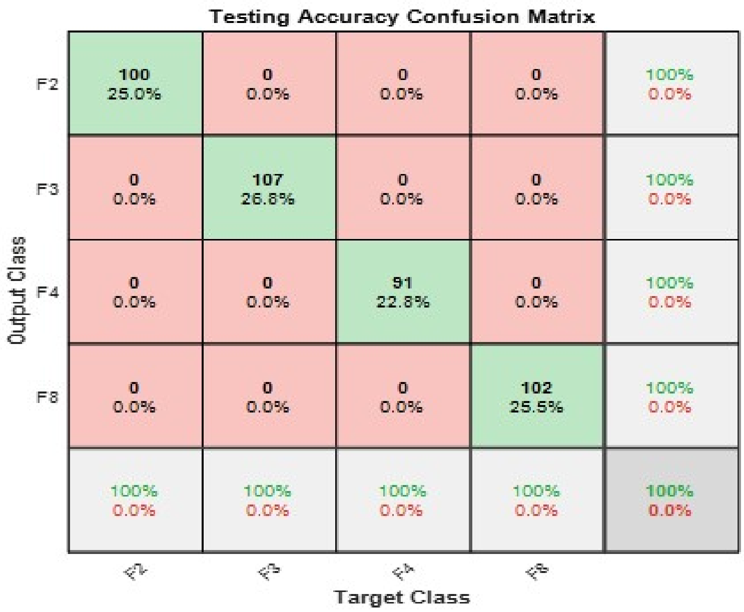

FIGURE 5.10: Testing Confusion Matrix

5.7 Chapter Summary

In this chapter, the simulation and its findings are covered. It makes use of signal creation, EMD, IMF feature extraction, dataset generation, and simulation of results after LSTM network training.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

The purpose of this thesis is to present an EMD-based approach for classifying micro-UAVs. The first step in the EMD process involves breaking down a multicomponent radar echo signal into a series of oscillating waveforms. The data from the IMFs are used in the construction of the feature vector. The LSTM classifier will be trained using data that was created for a variety of unmanned aerial vehicles (UAVs), and then testing will be carried out to evaluate how well the suggested method works. A radar echo signal is deconstructed into a group of IMFs using EMD. The IMFs are used to derive four characteristics, each of which is intended for label discrimination and is then extracted. Following the extraction of the features, they are utilized in the training of an LSTM classifier for the purpose of target categorization. The categorization of mini-UAVs is accomplished with the help of an effective EMD-based technique by first extracting four characteristics from a collection of IMFs. Empirical research of the links between the radar mini-UAV m-DS spectrogram and the IMF in terms of the blade-flash phenomena. Using an EMD with real values to extract features from a signal with complex values and then fusing those features together to improve the classification performance of a mini-UAV.

6.2 Future Work

In this research, we extracted four features of mini UAVs and divided them into four classes using those features. In further work, eight features will be recovered from mini UAVs. Additionally, the number of classes and dataset will be expanded to achieve a higher level of accuracy in classification.