CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Passive Missile Detection System for Aerial Platform

by

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I dedicate my work to my family including my loving parents and my husband whose words of encouragement have always been a force for me in completing my degree. I also dedicate my thesis to Pakistan Air Force which is nearest and closest to my heart.

CERTIFICATE OF APPROVAL

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Abstract

Passive missiles including short-range or within visual range air to air missiles (SRAAMs or WVRAAMs) and Man portable air defense systems (MANPADS) are an extraordinary danger for regular civilian and military airplane. This postulation intends to find approaches towards that could be utilized in a passive missile approach warning system. The initial segment of the study depends on spectrum analysis of the missile plume and determination of most suitable range for identifying Passive missiles. By looking at the benefits, drawbacks of working in different ranges and furthermore dissecting their innovative difficulties, this thesis closed to choose solar blind UV (SBUV) range for rocket recognition to be most appropriate.

After this basic quest, the two main objectives of the missile detection system are to detect the missile after de-cluttering from background and classifying it as a threatening or approaching missile from a sequence of images. The detection is based on convolution neural networks (CNN), moving object tracking algorithms and post processors. The greatest challenge in detection through CNN models is the availability of training data. This requirement of data synthesis has been catered for in this research through 3d simulations in decided spectrum.

Direction of motion of the detected threats and speed of motion has been estimated using moving object tracking techniques and extended Kalman filter (EKF), and same has been utilized to classify the missiles as approaching or non-approaching missiles. Same information has also been used to classify a moving target as a missile or another flying jet. Position and range estimation of the threats can also be done using EKF but unfortunately some of the desired parameters for this calculation were not available without actual sensor. Therefore, same has been left for future research work.

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Abbreviations

AoA	Angle of Attack
AlGaN	Aluminium Gallium Nitride
CNN	Convolutional Neural Networks
DIRCM	Directed Infrared Counter Measures
EKF	Extended Kalman Filter
EW	Electronic Warfare
ECM	Electronic Counter Measures
GAN	Generative adversarial networks
IIT	Image Intensifier Tubes
FMO	Fast Moving Object
MANPADS	Man Portable Air defense system
MAWS	Missile Approach Warning System
NIR	Near Infrared
R-CNN	Regional Convolution Neural Network
SAMs	Surface to Air Missiles
SRAAMs	Short-Range Air to Air Missiles
SBUV	Solar Blind Ultraviolet
TTI	Time to Impact
YOLO	You only look once

Chapter 1

Introduction

1.1 Background

Airplane flying in battle and other perilous regions constantly face the risk of being shot somewhere by Missiles.

Examination of airplane misfortunes because of enemy activity since the 1960s shows that basically 70% of all misfortunes were licensed to passive heat seeking missiles. This might be astonishing fact because radar guided Surface to Air Missile systems (SAMs) have larger engagement ranges, fast response, better maneuvering potential, greater warheads carrying capability and are much more precise. In any case, the primary driver why passive missile assaults were so powerful was that it is extremely hard to identify them. As shown in Figure 1.1, these missiles with their detectors, lock onto the heat signature of aircraft engine and quietly hit into their target.

In Recent Conflicts history, 80% of all achieved Missile kill were unobserved shots. One of the leading requirements to come out of the recent conflict in Iraq and Afghanistan is to know when you are being shot at. Capt. Paul over street, program manager for USN Electronic Warfare said that missile Kill were unobserved shots causing maximum damages and there was not much precaution available [1] (TMC News, Nov 13, 2008) [2].

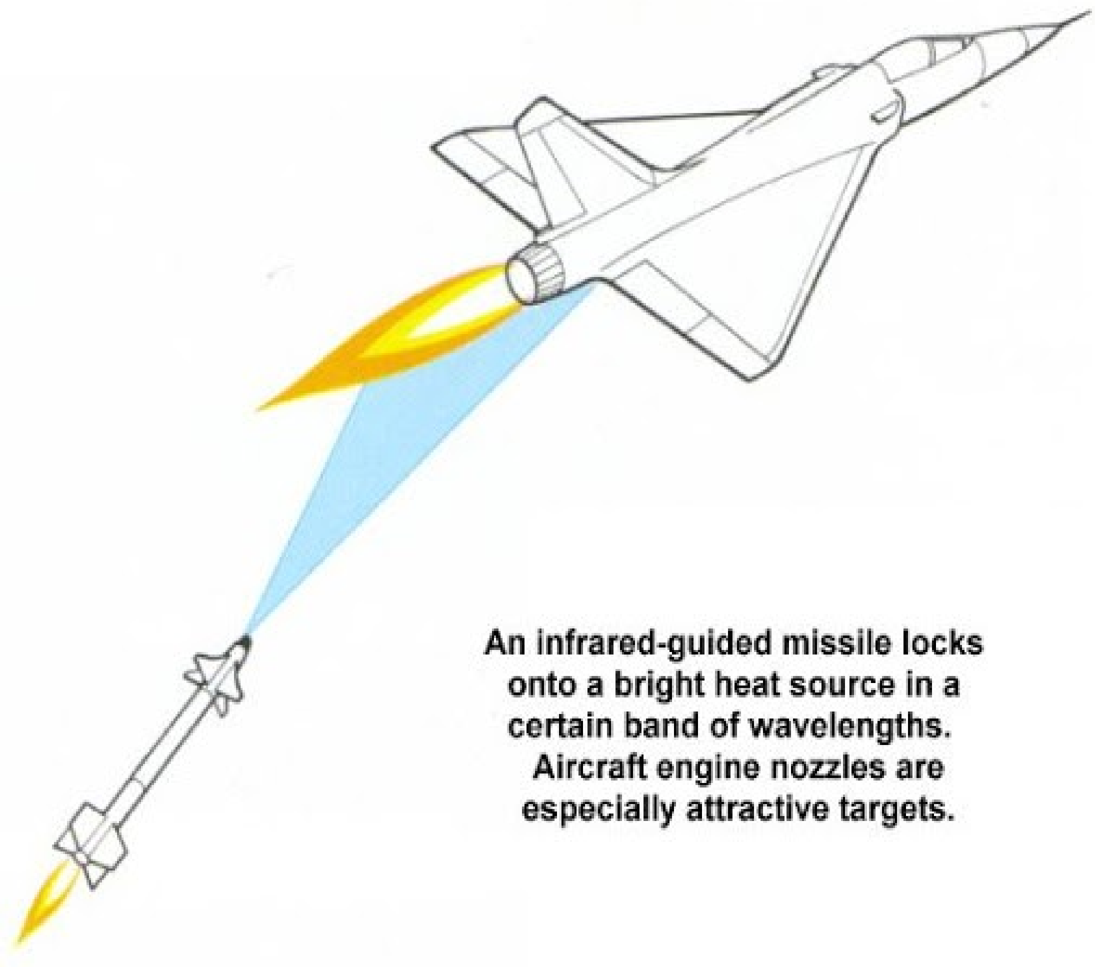

FIGURE 1.1: IR guided missile seeking aircraft tail [2]

1.2 Spectral Emissions of Missiles & MANPADS

A guided missile can be separated into three frameworks, control system, warhead and drive, all fixed in an air frame. Solid propellant rocket is utilized to give propulsion with a burn time of the order of seconds, which is sufficient for speed increase upto speeds 3.5 Mach which can be even higher for modern rockets and missiles as shown in Figure 1.2.

In any case, the primary driver why passive missile assaults were so powerful was that it is extremely hard to identify them.

The hot plume of a missile has characteristic spectral signatures. The emissions are in the Ultraviolet band (upto 400 nm), Visible band (450 – 750 nm), in Near Infrared (NIR) (750 – 1100 nm) and Mid Infrared (2 – 16 mm) spectrum. The

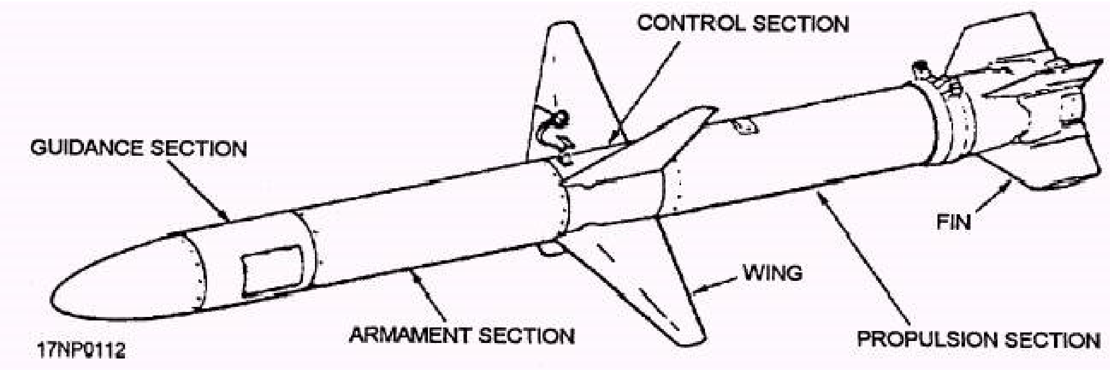

FIGURE 1.2: Constituents of a guided missile

FIGURE 1.3: Missiles plume

Infrared region falls between the microwave and visible portions of the electromagnetic spectrum. It is further divided into two regions. The Near IR & Short wave IR of the electromagnetic spectrum has wavelength range from 0.7 to 2.5 um. It has a frequency range from about 215 THz to 400 THz and lies close to the red end of the visible light spectrum. Then comes Mid wave IR (3 to 5 um) and Long wave IR (8 to 12 um) wavelengths as shown in Figure 1.4. Generally, Near Infra-Red (NIR) is used for detection of missile plumes because it is the highest energy content spectral radiation in IR band.

To the extent detection of a heat seeking missile is concerned, IR radiation from all

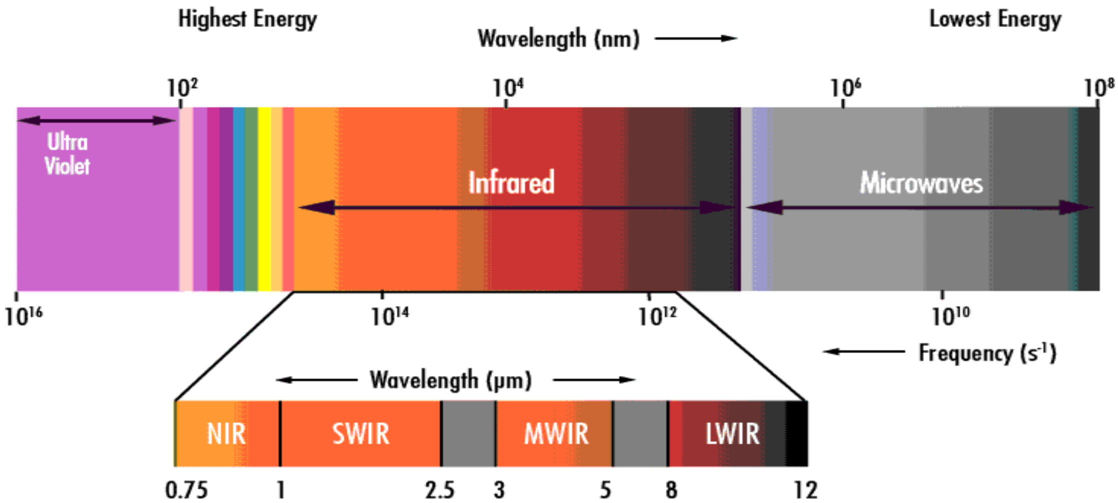

FIGURE 1.4: Infrared spectrum within electromagnetic spectrum of waves

sources except rocket are considered as background clutter which will bring down the recognition scopes of our missile detection system or even bog the emanations of the rocket. Luckily, the vast majority of the IR energy discharged by the outer layer of Earth lies into the window of 10 um, but the Sun's radiation tops in the visible band and reflected off the Earth's surface will generally overwhelm the locale above 3 um, henceforth leaving a window around 4 um accessible for recognition of rockets. The actual sky reflects and dissipates a specific measure of IR, however it's intensity is lower than that of the Earth's surface.

Figure 1.5 shows IR energy relative amounts discharged at various wavelengths for varying temperatures. The prominent wavelengths for CO, CO_2 and H_2O and their intensities can be observed in the plume of missile [3].

UV content is also available in missile plumes. The UV region is defined from 100 nm to 400 nm and for UV radiations atmosphere is transparent. Peak of Visible radiations are between 400 nm to 700 nm. The UV band is assumed to be composed of UVA (315 – 400 nm), UVB (280 – 315 nm) and UVC (100 – 280 nm including SBUV) as described in Figure 1.6.

SBUV region is generally defined from 240 to 280 nm. In this region solar radiation is blocked by the Earth's ozone layer so any radiation in this region is primarily man-made. Once under the ozone layer, the atmosphere is transparent to wavelengths as short as 200 nm where oxygen absorption limits the transmission. All of

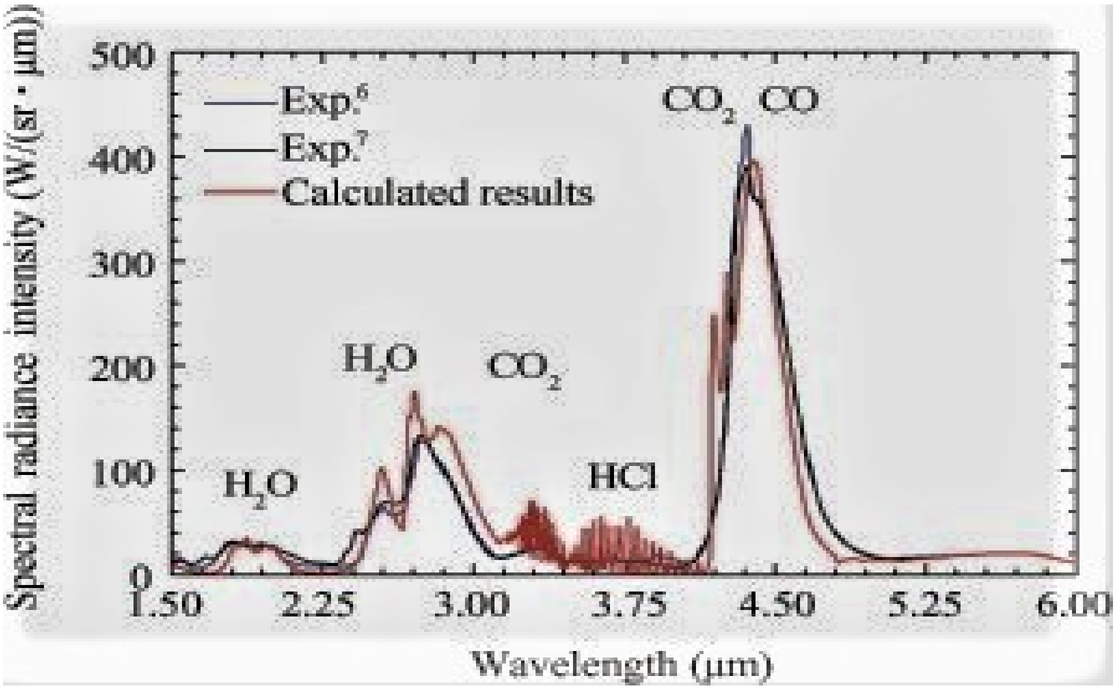

FIGURE 1.5: Spectral radiance intensity vs wavelength for missile plume showing "IR radiation characteristics of rocket exhaust plumes under varying motor operating conditions" [3]

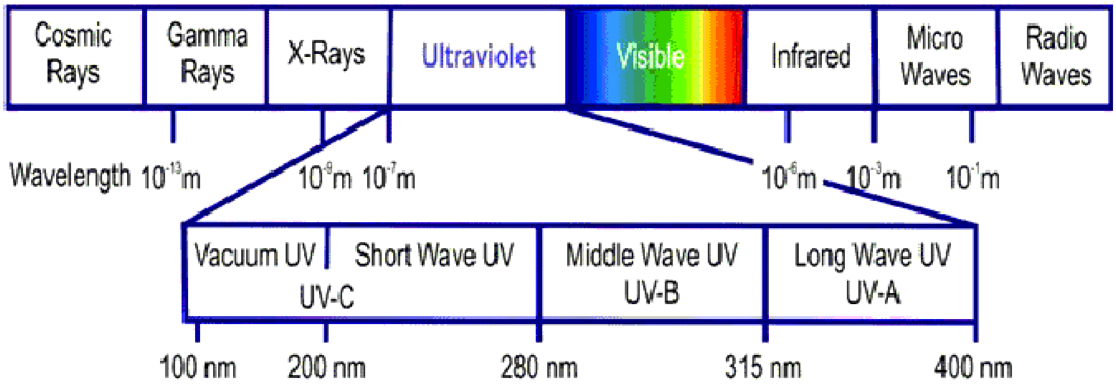

FIGURE 1.6: Constituents of UV spectral band UVC, UVB and UVA[4]

above described spectral components can be used for the detection of passive missiles however depending on the amount of background emissions in that particular wavelength spectrum, the false alarms will be different in each spectrum.

1.3 Gap Analysis

Guided surface-to-air missile (SAM) systems were developed during World War II and became influential in the 1950s. In response, Radar warning receivers as

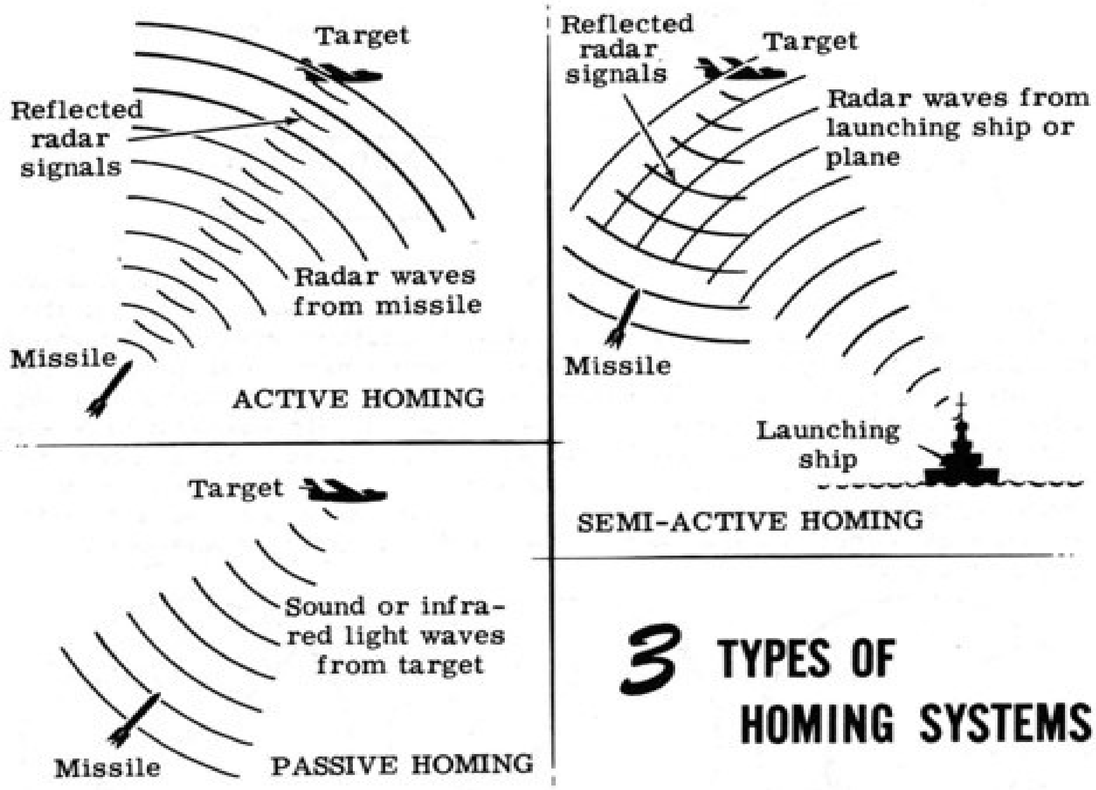

FIGURE 1.7: Types of homing systems [4]

a counter measure against active missiles have proved their effectiveness by the early 1970s which considerably improved the survival rate of aircraft against active radiating threats. Figure1.7 shows the three types of homing missile systems, Active or guided systems, passive or heat seeking systems and a third type is semi-homing which is a hybrid of both.

The primary air-to-air heat seeking missiles showed up in mid 1950s. The innovation permitted more compact missile designs and made it conceivable to foster Man Portable Air Defense Systems (MANPADS) likewise named as shoulder-mounted rockets, which became functional by the 1960s [4].

MANPADS are generally low-priced, very strong, simple to work and hard to distinguish weapon framework. Infrastructure regularly connected with radar-directed SAM arrangements is additionally not needed for MANPADS. This is the motivation behind why these kind of weapons has been used by numerous tactical powers all throughout the world. It is likewise a reasonable weapon for terrorist organizations in light of its accessibility on the underground market at

FIGURE 1.8: Swedish SAAB RBS 70 NG CREWPAD firing a BOLIDE “all-target” SAM[5]

a moderately modest cost. Figure1.8 shows a swedish crewpad terminating a BOLIDE all target MANPAD. Knowledge with respect to their accessibility in the possession of ”non-state” associations, is unclear which makes it hard to expect where and when to expect MANPADS assault [5].

At least 35 MANPADS hits on civilian aircraft have been recorded. Out of these, twenty-four were shot down and killed about 500 people in the process.Figure 1.9 shows the Engagement results for SA-14 Model v C-130K and Hovering CH-47 with no countermeasures. This Figure is referred from [6] that explains the work undertaken by the authors to demonstrate a second generation MANPAD, based on the Russian SA-14, and assess the vulnerabilities of aircraft both with and without flare countermeasures from these systems. The conclusions are the results of over $11,000$ simulated firings against targets of varying aspects, velocities and altitudes. It clearly shows the vulnerability of aircraft at an altitude as high as 4000 meters.

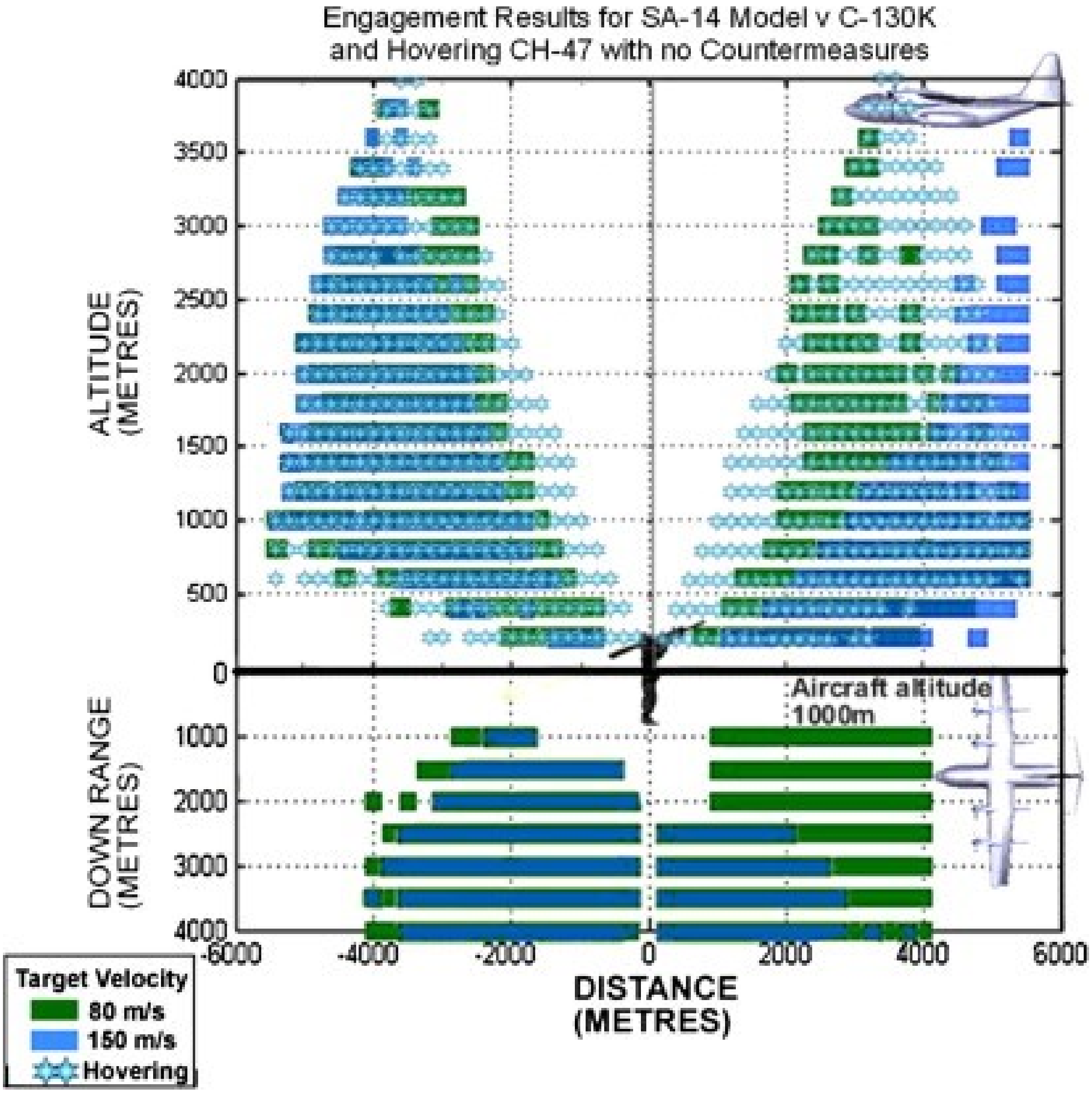

FIGURE 1.9: Engagement results for SA-14 Model v C-130K and hovering CH-47 with no countermeasures [6]

The 2^{nd} and 3^{rd}-generation MANPADS showed up in 1980s and because of cutting edge seeker head technology, further developed rocket engines and aerodynamic refinements, the effectiveness and viability of MANPADS was additionally improved. Their performance worked on as far as deadly reach, least dispatch point, moving potential and all aspect engagement angles. They additionally turned out to be more safe towards Electronic Counter Measures (ECM). Airplane flying fast or sufficiently high are generally protected, nonetheless, helicopters and fixed-wing airplane that are taking off or landing are amazingly helpless. Be that as it may, warriors fly additionally need security against passive missiles to get full functional abilities. During Dog fights,jets need assurance against extremely short reach Air to Air Missiles (AAM) not more than $5 - 10$ km. During ground assault/support missions and keeping in mind that working beneath 15 kft contenders need security against SAMS and MANPADS.

Therefore, some kind of Protection system is necessary in aircraft against passive heat seeking missiles including SAMS, Short range AAM and MANPADS. One part of the protection system is a Missile Approach Warning System (MAWS), which is used to warn the pilot about missiles heading toward the aircraft. If the warning can be generated fast enough, countermeasures can be deployed and can save the aircraft. MAWS is component of the avionics suite on only few military aircraft till date because the technology is still limited with only few countries. The AN/AAR-47 is one of the earliest Missile warning systems which was deployed around early 90s. This is the scenario of engagement of missiles with the aircraft around the world. If the warning is generated early then the aircraft can be safe otherwise aircraft face severe danger. MAWS is component of the avionics suite on only few military aircraft till date because the technology is still limited with only few countries.

1.4 Problem Formulation

To deal with the problem of passive missiles threats, study has to be done regarding various methods for identification of missiles and protecting aircraft from potential threats. To achieve this, the following problems must be solved step-wise in the course of this research:

1.4.1 Studying Most Effective Means of Passive Missiles Identification

The first step involves the study of the spectrum of missiles heat signatures, types of wavelengths available in heat signatures at various times of flight and advantages and disadvantages related with identification of each spectral content. Based on our comparative study, we have to select the spectrum in which we can operate and sense the passive missiles most effectively. We have to study optical sensor requirements and constraints which are necessary for missile identification in that selected spectral range.

1.4.2 Detecting Missiles

Given images from selected missile sensors, we need to detect the hotspots having radiometric properties which are similar to the radiometric properties of missiles. An experimental setup can be developed where an artificially created missile plume may be created in front of man-made clutter which is called Emulated Data or synthetic missile signatures may also be created utilizing GAN Models. Data Set Generation is done in this phase and data labeling will also be done with the aim of missile detection. Using this setup and labeled data, an initial deep learned model shall be trained to detect and identify the missile plume. The main objective of this phase shall be to train a machine learning model that is able to detect the missile plume and de-clutter it from the background. The main challenge in this project is to de-clutter the missile signature from the background clutter which is called missile identification and raise an early warning. This will help the pilot of the aircraft to deploy the available countermeasures to disrupt missile tracking.

1.4.3 Efficient Algorithms

Since the time from firing the missile to impact is only a few seconds, it is vital that the system can operate in real time so that an approaching missile is detected early enough to enable countermeasures. The real time constraint means that the time complexity of all algorithms are of great importance. Figure 1.10 depicts a MANPAD hitting a fighter jet near its take-off from the run way. MANPADS are short reach weapons regularly up to 5km with the core of kill encompass one to three kilometers. They consequently permit almost no edge for mistake to successfully counter them as time to impact (TTI) on the objective at one kilometer

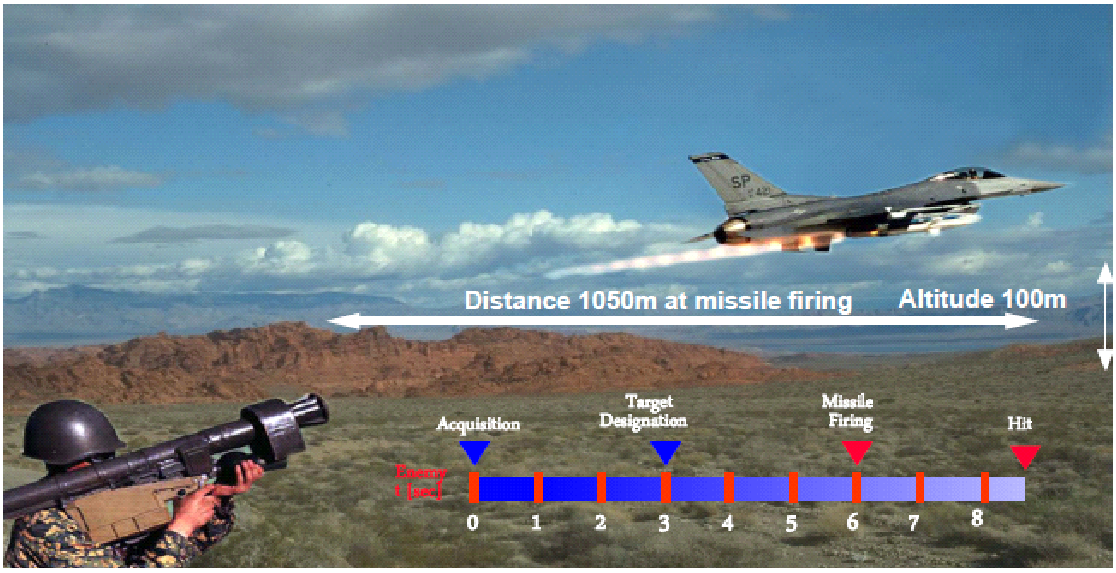

FIGURE 1.10: Typical IR MANPAD engagement scenario [7]

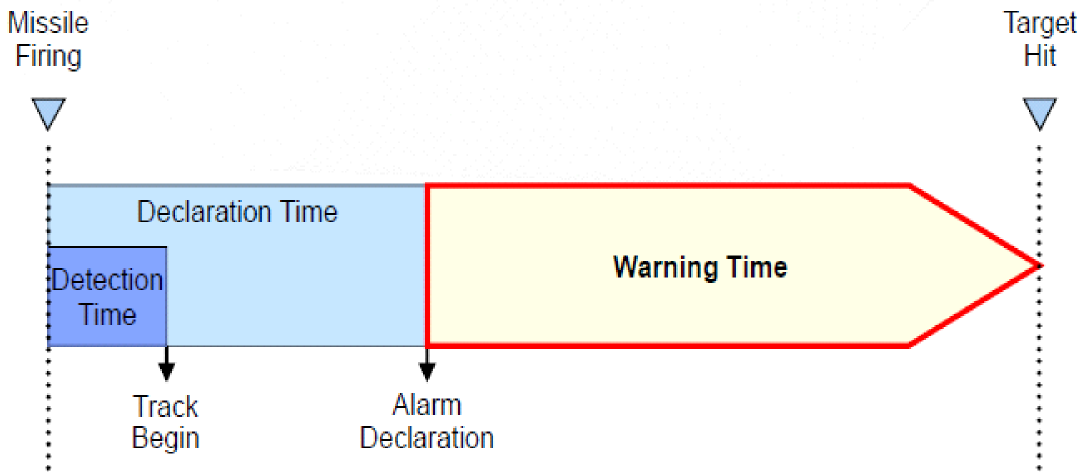

FIGURE 1.11: Missile warning time definition [7]

is around three seconds. The TTI for targets at five kilometers is likewise generally short, simply seven to somewhat more than eleven seconds separately.

Figure 1.11 shows the three time periods, detection time, declaration time and warning time of MAWS involved between missile fire till missile hit. Once a missile is fired towards the A/C, MAWS detects the threat and displays on the display within short span of time may be a few milli-seconds. This time period is called **Detection Time** . Once a target is detected, it is then tracked for its location, angle of attack (AoA) and approach velocity. This is the point where advanced processing is done by processor for removing the background clutter. Alarm is declared only when it is confirmed that the detected platform is not a clutter but an approaching threat and time consumed is called **Declaration Time**. Therefore, Warning is generated for the pilot to deploy his countermeasures like chaffs and flares known as **Warning Time**. The time between missile firing and Missile Hit is almost $5-7$ sec. Therefore, MAWS must be able to detect, track, and declare a missile in less than a second; to provide enough warning time for directional IR counter measure (DIRCM) or Electronic counter measure (ECM) deployment.

Chapter 2

Literature Review

2.1 Missile Detection Mechanisms

Passively guided infrared (IR) missiles can turn into a significant reason for airplane misfortune in fighting. Three distinct technologies have been utilized for discovery of missile signatures for example frameworks dependent on Pulse-Doppler radar; active detection and passive detection like Infrared sensors and Ultraviolet sensor. One more progressed variation of Ultraviolet detection is based on SBUV sensors [8]. Every innovation enjoys its benefits and hindrances which can be summed up as follows:

2.1.1 Active Detection: Pulse-Doppler Radar

Like Radar warning receiver which is intended to distinguish threatening radars and active guided missile threats for the airplane, a radar based detecting framework can be installed on airplane which detects the passive missiles and Manpads by noticing their cross sectional area through pulse Doppler strategy of recognition. Electromagnetic waves are transmitted and change in their frequency and wavelength is measured to perceive the threat speed, direction and sometimes size. This is called active detection.

2.1.1.1 Advantages of Active Sensing

1. Distance and speed of the approaching missiles can be measured. It can therefore define the time to impact (TTI) and upgrade the circumstance apportioning of countermeasures [9].
2. This detection does not require motor of missiles to be working so it provides a longer time frame for detection.
3. It is resistant to all types of weather conditions.

2.1.1.2 Disadvantages of Active Sensing

1. Aircraft's presence may be disclosed with the emissions by the Active MAWS and hence increase its susceptibility in delicate threat environments [10].
2. Negligible admonition time is given against small missiles with low radar cross section like MANPADS and thus brings about late decoy dispensing.
3. It cannot calculate the direction precisely enough to direct Directional IR Counter measure systems.
4. It is defenseless to false alarms brought about by other RF sources
5. If operating frequency is not selected vigilantly, it may interfere with ground air traffic control radars.
6. Due to limitations in space on aircraft and large size of active system, it is difficult to be integrated as compared to passive systems.

2.1.2 Passive Detection

Passive Missile Warning Systems detects the heat radiations discharged by the hot flame of the missile instead of emitting radiations itself and detecting the reflecting radiations from the threat. In case of passive detection, the challenge is separation of missile heat radiations from the background clutter. The heat radiations are toned down in the atmosphere through several kilometers from the missile to the detection sensors, where it has to compete against background clutter for proper detection. Two spectral regions are considered for passive detection Infra-Red band and the Ultra Violet (UV) band[11].

2.1.2.1 Infrared Sensing

All substances radiate IR energy, provided they are not at a temperature of absolute zero (0°K). The hotter objects emit more energy and the peak wavelength of emission decreases as T-1. IR energy has similar features as visible light for example it travels in a straight line at speed of light and it is reflected or absorbed upon hitting the surface of an object. In this regard, an IR based missile warning system is bound to have lots of detected objects which need to be scrutinized before indicating any warning for the pilot [12].

Advantages of Infrared Sensing

Following are the list of advantages of using this method of sensing for missile identification:

1. The IR radiations tends to pass through atmosphere better than that of UV radiations under good weather conditions [2].
2. Longer detection ranges are offered by IR sensors at higher altitude where there is no ground clutter.
3. At higher altitude , IR sensing can effectively detect the kinetic energy of the missiles after motor burnout , but it might not detect it at low altitude due to high IR background clutter [12].
4. IR detecting gives great AoA data to pointing a Directional IR Counter Measure (DIRCM) and better navigation can be given with respect to decoy dispensing direction and maneuvering for the pilot [13].

Disadvantages of Infrared Sensing

Following are the list of disadvantages of using IR method of sensing:

1. Due to low IR transmission through liquid water and ice, all-weather operation is not possible. Even a micrometer of water on the lens, or in the atmosphere between the threat and the sensor, is enough to effectively blind both MWIR and LWIR sensors.

2. It observes huge quantity of natural sun radiations and man-made IR clutter.

3. False alarm rate or probability of false warning is a big problem against surface-to-air missiles, because of high IR background clutter radiating from the surface of earth.

4. Vast computing power is required in IR sensing systems to deal with false alarm problem which directly increases the system cost and system response time [6].

5. IR detectors have extremely tight instantaneous fields of view to accomplish sensible signal to target ratio. Large focal plane arrays (FPA) of the sensors are needed to accomplish total 360° azimuth inclusion which is one more variable to hoist the expense.

6. For low noise response, IR system needs cooled IR detectors which complicates life cycle logistical support and again results in high cost of maintenance.

7. New low IR emission rocket motors have been developed and they have decreased detection ranges and less response time for pilot.

2.1.2.2 Ultraviolet Sensing

The study of UV detection technology was started in early 1950s. It is yet another dual-use photoelectric detection technology after the advent of technologies of infrared and laser detection. UV radiations are coming from the sun and is likewise firmly consumed by the environment. Notwithstanding, attributable to the dispersing of the UV radiation from the sun, which isn't unequivocally assimilated, and the and the long path length through the climate (the dissipating medium), the sky shows up at a somewhat uniform UV radiation. This implies that when the sky is seen in the UV there is regularly uniform force , whether or not the sky has mists present [14].

Aircraft, and other objects, can easily be discriminated against this ideal background. The wavelengths associated with UV are well defined, ranging from 100nm upto 400nm. However, the regions that are useful for detection of aircraft are much tighter [15].

Advantages of UV Sensing

Following are the list of advantages of using this method of sensing:

1. UV sensor works in UV spectral wavelength area and maximum of clutter in nature and on earth surface is in IR range. UV based MAWS frameworks subsequently have a much diminished False Alarm Rate when contrasted with IR based frameworks [16].
2. In high IR clutter background environments, UV sensors have very good probability of warning.
3. Since it is impervious to solar clutter, and hardly affected by liquid water droplets like rain or moisture , all-weather operation is possible [17].
4. UV sensors typically have wide instantaneous field of view therefore large FPAs are not necessary and cost is controlled.
5. It Provides very good Angle of Attack (AOA) information for accurate decoy dispensing decision making, maneuvering and for directing DIRCMs.
6. Response time against nearby missile launches is fast.
7. As compared with pulse Doppler & IR technologies , it is a simpler system.

8. cooling circuits are not needed and due to low false alarm rate , only moderate computing power is required.

Disadvantages of UV Sensing

Following are the list of disadvantages of using UV method of sensing:

1. To detect approaching missiles at Higher altitude , high effective burning temperatures are necessary which are linked with solid fuel rocket motors which becomes a constraint.

2. UV performance is better at lower altitudes like against surface-to-air missiles however its performance degrades at higher altitudes where changes in thickness of ozone layer interferes with UV propagation.

3. UV MAWS can derive Time to Impact in seconds from the rapid increase in amplitude of the approaching missile's signal but cannot provide actual range information.

2.1.2.3 Solar Blind UV Sensing

Sunlight radiation includes UVA, UVB and some small portions of UVC contents. It is known that the wavebands including the UVC and the Far UV is often referred to as 'solar blind' because these wavelengths are strongly absorbed by atmospheric elements in either bright sunny day or night.[18].

As last part of the 1970s, many nations have done the study of ultraviolet radiations. In the last part of the 1990s, foreign analysts have worked on "Solar blind UV imaging" detectors, and afterward these have been bit by bit brought to the market for some business employments. As of now, the main solar blind sensors available in market incorporate "Israel Ofil Company's SuperB", Luminar, DayCor , MicROM and South Africa UViRCO's CoroCAM series, etc, which are displayed in Figure 2.1.

(a) SuperB (b) Luminar (c) CoroCAM

FIGURE 2.1: Few renowned SBUV imaging cameras [19]

Advantages of SBUV Sensing

Following are the list of advantages of using this method of sensing:

1. Solar-blind detectors are intriguing for all applications where one needs to recognize ultraviolet light while not being disturbed by conceivably a lot more stronger visible light like corona identification in high power transmission lines. Corona release is consistently an indication of unwanted emissions on high-voltage electrical mechanical assembly, incorporating those used in electric rail route frameworks. Solar-blind detectors (UV) are successful instruments for corona investigation[9].

2. Since background sun radiations are not available in this spectrum, Target Missile is detected against an almost zero background so algorithms for target detection become much simple as shown in Figure 2.2.

3. False Alarm Rate is significantly low and the Probability of Detection is very high.

4. SBUV sensing system is much more reliable because it is insensitive to Visible, Infrared and near UV light background clutter available in background.

5. The UV sensors by and large proposition offer short recognition ranges of nearly 3 to 5 km in contrast with IR sensors which in some cases offer $10 - 15$ km location ranges. Notwithstanding, this can undoubtedly be

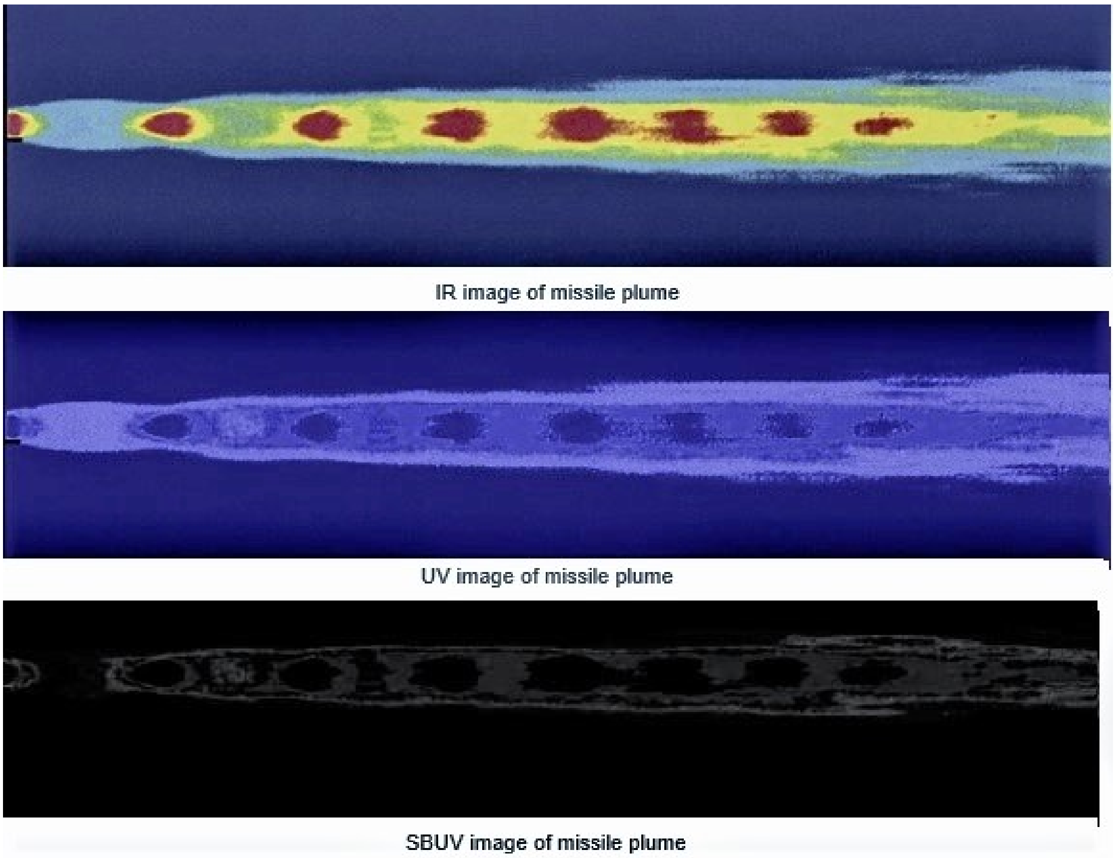

FIGURE 2.2: Comparison of missile plume in three different spectrum top(IR) / middle (UV) / bottom (SBUV)

disregarded on the grounds that missile approach warning system is conveyed to secure airplane against MANPADS whose hit range isn't more than 7 km and against SAM hits during low flying heights of air stream for instance during take-off or landing. For insurance against long reach missiles and BVRs, airplane is outfitted with radars for active guided missiles.

Challenges of SBUV Sensing

Following are the few challenges involved in using SBUV sensing technology:

1. **Cost-Intensive & Large Installation Space:** Existing missile warning systems running within the Solar blind ultraviolet (SBUV) a part of the spectrum are quite pricey and require massive installation space. [13] Currently , maximum sun blind imaging is finished with very excessive gain

FIGURE 2.3: Breakdown of image intensifier tube (IIT) [1]

that is performed via Image Intensifier Tubes (IIT) which contains either a photo-cathode and "micro-channel plate" aggregate or a UV-enhanced silicon image-diode along with a band pass filter. None of those alternatives is hopeful in light of the truth that the "photo-cathode" and "micro-channel" plate blend is a delicate vacuum tube requiring an incredibly high-voltage power supply requiring a good sized space. Similarly silicon photo-diode is not inherently solar based visually impaired and experiences extended size and intricacy while added with filters as shown in Figure 2.3.

2. **Complex Filter Structures:** Semiconductor detectors manufactured from substances like silicon (Si), silicon carbide (SiC) or gallium phosphide (GaP) do not accomplish the crucial details as as far as sensitivity and dark current to be considered for planning SBUV sensors [20]. Moreover, these materials aren't obviously solar blind, so complex filter structures are required for the use of them in SBUV sensors.

3. **Additional system Noise:** For detecting weak solar-blind UV signals , large scale magnification is required that also magnifies the noise signal.

Therefore, solar-blind ultraviolet images have poor contrast and low signal to noise ratio. Hence efficient noise reduction techniques will be required in SBUV missile detection systems [1].

4. **Specialized UV lens:** Transmittance of optical materials mostly decreases with reduction in working wavelength; therefore, at SBUV spectral range extremely specialized UV lens are needed to be incorporated in the system. Ordinary lens is made of glass material which does not allow UV light to pass through. UV lenses are made of specialized materials like Quartz and Calcium Fluoride and are very costly due to specialized machining and manufacturing requirements [21].

5. **Non availability of Commercially Available SBUV detectors:** In the domain of sensor technology, commercially available CCD or CMOS sensors are mostly Silicon (Si) based. Silicon can be easily excited by low-energy photons of longer wavelengths that are enormous in a typical environment, due to the low bandgap energy. Therefore, the sensor will become saturated in bright sunny day unable to perform as SBUV sensor.

Technology Advancements in SBUV Technology

To defeat the difficulties clarified above, broad examination has been completed on planning of effective optical filters, progressed SBUV sensor coatings and manufacture of wide band-gap semiconductors, films and 1-dimensional nano-structures as options in contrast to traditional Si based locators. A portion of these improvements are portrayed beneath:

1. **UV-enhanced coating technology:** Expensive low-pass phosphor coatings are done on normal Silicon based CCD and CMOS sensors to limit less-energy photons of longer wavelengths and allow only high energy photons of above 240 nm of wavelength to excite the sensors. These phosphor coatings are done in complex vacuum conditions. The vacuum coating also named as UV-enhanced technology is performed directly on the surface of

any Si based conventional sensors. As a response to this coating, sensor's response on SBUV spectrum may be improved. However, these methods require high costs and technical expertise.

2. **High-Aluminum-Composition AlGaN-Based Semiconductor Materials:** Technological advances in field of semiconductors and specifically "high Aluminum composition AlGaN-based semiconductor" materials facilitated the manufacturing of visible blind pin photo-diode Focal Plane Array cameras and intrinsically solar blind Focal Plane Array (FPA) cameras. Due to the relatively large band gap, AlGaN is intrinsically blind to visible and infrared light ("visible blind"). Variations in the composition also make it possible to design the semiconductor material "solar-blind". Furthermore, AlGaN detectors also have radiation resistance characteristics even at high optical powers. The solarization that often occurs with external filters can be avoided due to the integrated filter structure [21].

3. **AlGaN-based detectors:** AIGaN-based detectors were developed in a co-operation of several Fraunhofer Institutes of Germany with different applications in mind like Water treatment, exhaust gas analysis, UV curing of paints and adhesives, remote sensing, and detection of missiles. These are specialized detectors and perform better than Si detectors for SBUV spectrum.

A scanning line scan camera based on AlGaN line sensors was developed at Fraunhofer IOSB. The spectral sensitivity of the camera can be selected by changing the sensor used. Currently UVA, UVB and UVC detectors are available. The graph in Figure 2.4 gives spectral properties of these detectors. The developed line scan camera is shown in Figure 2.5 which shows the view from the laboratory window in three spectral ranges. This image compares the identification of a UV source in three different lights. First is in visible light then in UVA and then in Solar blind UVC region. The background is completely eliminated in third case and the UV source for example a missile can be clearly identified. After going through the detailed analysis of the three different spectrum for analysis of missile plume, it

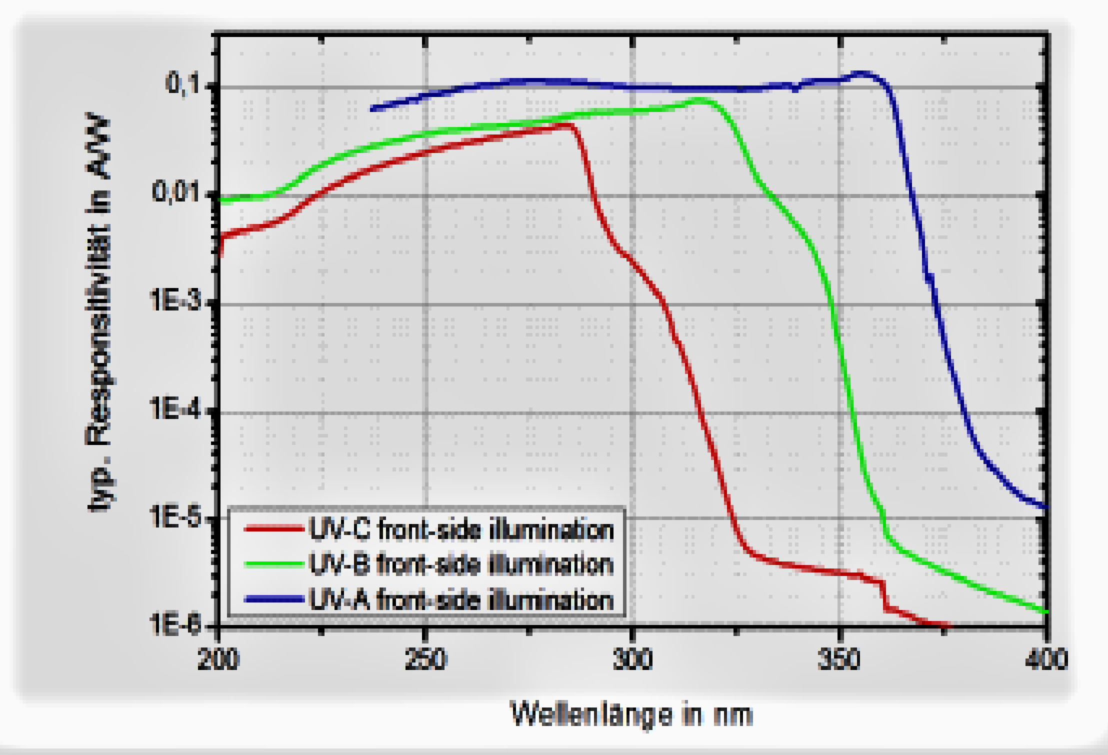

FIGURE 2.4: Spectral sensitivity of detectors [21]

TABLE 2.1: Comparison of various Passive missile detection mechanisms

Type	Advantages	Disadvantages
Active System	Long Detection range	Prone to detection
Passive System (IR)	Long detection range	High False alarm rate
Passive System (UV)	Low False Alarms	Atmospheric attenuation
Passive System (SBUV)	Extremely low False Alarms	High cost

can be deduced that every technology has pros and cones of its own few of which are discussed as shown in Table 2.1.

2.2 Previous Study & Work

After an IR-directed rocket is fired on and terminated, it is then independent. The rocket inactively follows the objective until it hits it or until it burns out in pursue. In this manner, it has a "fire-and-forget" ability [17]. The trajectory of the inactively directed IR rocket resembles a canine pursuit. The top of the rocket is constantly coordinated in the direction of the objective. Be that as it

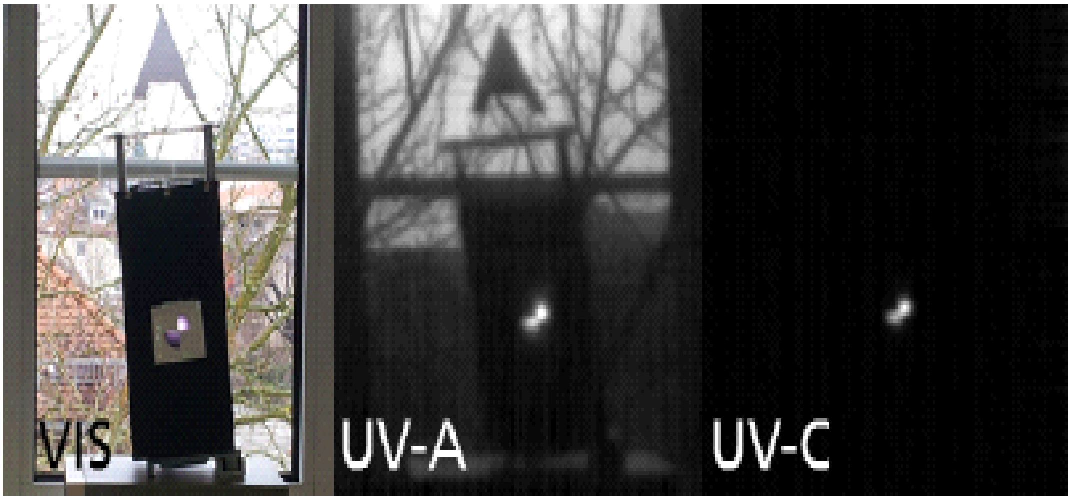

FIGURE 2.5: Test scenario with three spectral ranges UVA, UVC were recorded with a UV line scan camera, VIS as reference with a common CCD camera [1]

may, when the objective relocates to another position, the moving of the rocket direction doesn't occur quickly [7].

The danger of man portable latent infrared guided surface-to-air rockets has prompted the advancement of unguided rockets warning sensors which are utilized to trigger a caution when an airborne platform is locked in by a rocket. Unguided rockets cautioning sensors includes a wide field-of-view (FOV) UV or infrared indicators, detecting for rockets crest emanation [22].

2.2.1 Atmospheric Scattering of UV

Solar radiations are absorbed by stratospheric and tropospheric ozone and due to this the area visible from the earth atmosphere is hundred percent dark in the mid UV region. This darkness or black background with no UV emissions from sun, permits us to detect a missile plume UV emissions as a point source against a dark background, which appears with high contrast, especially in the "solar blind" band located approximately between 240 to 290 nm.

However, due to ozone absorption between the path in line of plume and the sensor and by atmospheric scattering, the detection range in UV is limited. Scattering occurs due to the molecular and aerosols particles and it gives rise to spreading of the plume image recorded by the UV sensor, and creates a radiance field in the surroundings of the point-like source [23]. With the help of UV and SBUV sensing, this scattering contribution is easily detected due to the low background and the high sensitivity of detectors [22].

2.2.2 UV Plume Signature Modeling

Detection Models need to guess about emissions of the missiles, propagation through the atmosphere and optical signals detection for the analysis of UV detection performances in certain conditions. The calculation of missile plume size is done in two steps. First of all, aero-thermo-chemical properties of the plume are obtained by solving flow-field equations and then, impression of the radiance or dependence in terms of angular distribution of the plume's intensity is acquired through the radiative transfer equation (RTE).

Majority of the solid propellant rockets use aluminum particles which are part of the fuel for achieving high intensity propulsion, and when this fuel burns the plume contains particles of aluminum in the micron sizes. Temperature increase is achieved with the after burning of intermediate products like H2 and CO with the help of external air and other elements like O and OH are also produced as by products. These particles are to be blamed for UV emissions through specific chemical reactions known as chemi-luminescence reactions [24].

2.2.3 Passive IR Airborne Threat Warning

Rocket and airplane danger cautioning is a troublesome issue for IR sensor frameworks in view of reconnaissance cross sectional area, of danger elements and generally bad ratio of signal to clutter that characterize air engagement scenarios. Deceiving moves and arrangement of counter measures should happen quickly after dispatch of a threatening rocket, here and there in practically no time. This outcomes in a prerequisite of almost nonstop reconnaissance over huge hunt volumes, which directs utilization of exceptionally productive sign handling calculations to deal with high constant information flow, and furthermore 2-D Infra Red gazing clusters rather than precisely filtered straight exhibits, that shows in-admissibly long return to times.

In order to perform continuous wide area coverage (e.g., 90° x 360°) and significant spatial resolution, unfortunately the current latest moving array technology is still not enough. In order to provide wide area coverage, pixel sizes in modern IR arrays for airborne threat warning systems will be of thousands of milli-radians, which is too coarse to resolve potential threats at desired detection ranges. At such distances an aircraft or incoming missile will make only a little fraction of a pixel's solid angle footprint. Even a high energy target might make a small impact to the pixel's overall IR signature under such conditions, therefore contributing in very less ration of target versus clutter [23]

Broad efforts have been coordinated towards improvement of single-frame, single-band location calculations for low difference point targets in high clutter backgrounds. The best in class in this space is that current single-frame,single-band calculations perform at or close to as far as possible as controlled by focus to mess proportions and by spatial properties (measurements) of messiness.

In this manner, while computational and structure factor contrasts might incline toward certain calculations over others for use in size, weight or potentially power restricted applications, for example, fighter airplane, it isn't reasonable that major discovery execution acquires will get from additional improvement of single-examine, single-band calculations. Significant upgrades in detached IR airborne danger cautioning will come about simply.

2.2.4 Time to Impact Calculation

The capability of determining the speed and the range of the approaching threat is one of the general properties of the active systems such as pulse-Doppler based missile warning systems . However, mostly used missile warning systems are passive systems and the ranging capability is not a general property for these systems. To add this property to the passive missile warning systems, some specific parameters have to be obtained about the objects whose distance is to be measured and some additional specific studies needs to be done. There are different algorithms which are proposed in open literature to find the distance of objects to the measurement systems or sensors. In these algorithms, distance finding studies are carried out using the area, intensity, and position change of the objects whose distance is to be estimated.

The temporal characteristics of the area, radiation and movement of the guided missiles are most broad highlights utilized by the passive missile warning systems. On the off chance that the acquired element attributes for a recognized article is like the element qualities of a guided missile warning systems which is drawing closer to the aircraft , the system gives an admonition. The remaining objects which do not have feature characteristics of a guided missile are set as false alarm sources [9].

2.2.5 Detection of Fast Moving Objects

The thought of a Fast Moving Object (FMO), for example an object that moves over a distance surpassing its size inside the exposure time, is presented in [26]. FMOs may, and regularly do, pivot with high precise speed. FMOs are exceptionally normal in sports recordings, yet are not uncommon somewhere else. In a solitary casing, such items are frequently scarcely apparent and show up as hazy streaks. The technique proposed in [26] comprises of three distinct algorithms, which structure a productive restriction pipeline that works effectively in an expansive scope of conditions. It is shown that it is feasible to recuperate the presence of the item and its pivot of turn, regardless of its obscured appearance. The proposed technique is assessed on a new explained data set. The outcomes show that current trackers are lacking for the issue of FMO confinement and another methodology is required. Two uses of limitation, transient super resolution and highlighting, are introduced in [27].

Fast moving objects are related with a de-blurring and matting issue, likewise called de-blatting. The proposed technique in [26] recognizes Fast moving objects as a shortened distance capacity to the direction by learning from synthetic data. For the sharp appearance assessment and precise direction assessment, a matting and fitting network that appraises the obscured appearance without foundation, trailed by an energy minimization based de-blurring is proposed.

It is depicted by this work that a shrewd mix of stereo vision and motion analysis can be used for a robust and fast detection of significant moving items . This methodology, known as 6 Dimensions Vision, gauges area and pixels movement at the same time which on a pixel level , empowers the discovery of moving items. Utilizing a Kalman channel joined to every followed pixel, the calculation proliferates the existing understanding for the upcoming picture [28].

Chapter 3

System Overview

3.1 Introduction

MAWS detection system consists of three subsystems each solving their own part of the problem without knowing very much about the other subsystems. The subsystems are connected such that the output from one subsystem can be the input of another subsystem as illustrated in Figure 3.1. Now each of these subsystems will be explained one by one.

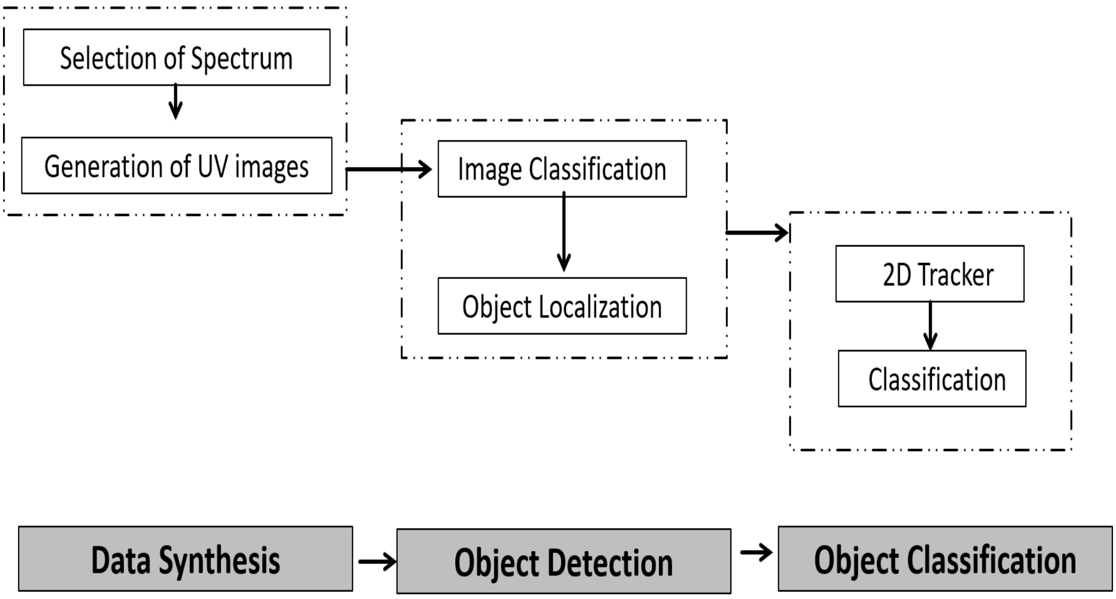

FIGURE 3.1: Development methodology

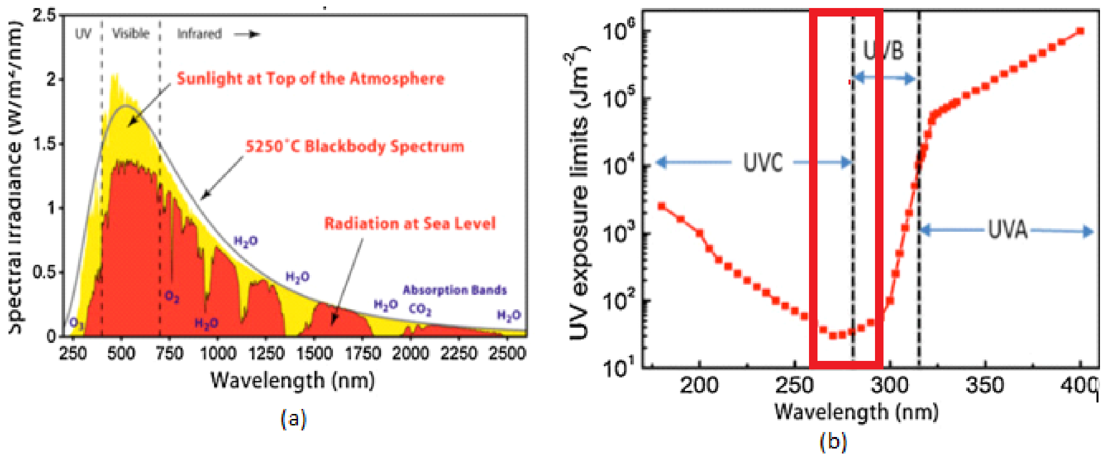

FIGURE 3.2: (a) Solar radiation spectrum of sun containing UV, visible, irradiation as clutter for missile plume but majority clutter is visible in IR band (b) UVA, UVB and UVC wavebands in sunlight along with exposure intensities showing maximum content of UVA

3.2 Selection of Spectrum

Three different technologies have been used for detection of missile signatures i.e. Pulse-Doppler radar based detection, Infrared sensors based sensing, and systems based on Ultraviolet sensor. Another advanced variant of Ultraviolet sensing is SBUV sensors. Every option of technology comes with advantages and disadvantages.

Sunlight radiation includes UVA, UVB and some small portions of UVC contents. The UVC region is often known as 'Solar blind'. It is observed that the wavebands including the UVC and the Far UV produce little background radiation as these wavelengths are greatly absorbed due to atmospheric particles in either day or night.

All radiations in solar spectrum act as clutter for missile plume but we can see majority clutter is in IR band. As shown in Figure 3.2(a) UVA, UVB and UVC wavebands in sunlight along with exposure intensities showing maximum content of UVA . SBUV region is generally defined from 250 to 280 nm indicated as red box on 3.2(b). In this region solar radiation is blocked by the Earth's ozone layer and due to this the area visible from the earth atmosphere is hundred percent dark

. This darkness or black background with no UV emissions from sun , permits us to detect a missile plume UV emissions as a point source. In this region, any radiation is most probably made by man like missile plumes , air jet exhaust or corona discharge. Therefore SBUV spectrum deems most appropriate for detection of missile plume with lowest possible false alarms.

3.3 Data Synthesis

There are multiple online data sets available on public platforms which are used to build a convolution neural network (CNN) image detector and classifier. Unfortunately my data set is unique and classified so it is not available on any public platform. In an ideal situation, a Solar Blind UV camera is required to record videos of missiles. Since such a camera is not available currently ,it was decided to move on with available missile videos on public forums. Initially some YouTube videos of missile plumes were downloaded as shown in Figure 3.3, but these are available in Visual RGB camera with all background clutter and no UV details of plume.

FIGURE 3.3: Missile plume videos on public forums

There is one other limitation in the publicly available missile videos. These videos are made in 3rd person perspective. No video could be found in which the camera was mounted on the aircraft being shot. Thus such videos do not provide desired parameters needed.

3.4 Object Detection

Once the required data has been gathered, the next step is Object Detection. In the present study, CNN deep learned model for detection and classification has been used. Numerous algorithms for deep learning are being utilized for object detection world wide like RCNN's: Fast RCNN, Faster RCNN, YOLO, Mask RCNN etc. YOLO (you only look once) v5 framework of CNN has been selected, which is an advanced, efficient and cutting edge technology for detection of objects in real time. This CNN model has peculiar characteristics of fast speed and efficient detection capabilities.

3.5 Object Classification

Moving Object detection with camera fixed on aerial platform (aircraft) requires post processing or in other words it is also called 2D tracking. After an object is detected through CNN model as a missile based on its parameters, then post processing with few other tracking algorithms has been performed to classify the detected missile as approaching or non-approaching missile.

Furthermore to differentiate between a missile and another flying aircraft is also part of this object classification step involved in complete development scheme.

Chapter 4

Data Synthesis : Simulations and Plume Modeling

This chapter presents a synthetic model to simulate Solar blind UV characteristics of missile plume, designed for training AI detection model. This methodology is adopted due to the non-availability of SBUV camera and difficulty in firing actual missiles for the training purposes.

4.1 Data Gathering

There are multiple online data-sets available on public platforms which are used to build a CNN image classifier. Unfortunately data-set needed in this study is unique and classified so it is not available on any public platform. In an ideal situation, a Solar Blind UV camera is required to record UV videos of missiles. Since such a camera is not available currently, it was decided to move on with available missile videos on public forums. Initially some YouTube videos of missile plumes were downloaded, but these are available in Visual RGB camera videos with all background clutter and no UV details of plume as shown in Figure 4.1. Missile plume is visible but a lot of masking and processing will be required to remove the background from these videos.

FIGURE 4.1: SAMS plume firing in visual spectrum

4.2 Rendering of Desired SBUV Scenarios

Therefore a specialized 3D rendering software was used to generate the desired scenario animations. Once few UV videos of missile are simulated, synthetic 2D images similar to the video can also be generated by utilizing GAN models. Since 4 or 6 MAWS sensors are mounted on aircraft in real time environment and perspective/field of view of each sensor is different. Therefore, camera position was also changed during simulations to see multiple perspectives.

FIGURE 4.2: Images rendered in blender software [16]

The size of the data set synthesized for this study is almost 1500 images / frames which is divided into training and validation data in a percentage of 60 and 40 percent respectively.

4.2.1 Case 1: Receding Missile

If a missile is fired by subject aircraft or if a missile is fired by a friendly jet flying in parallel or in formation flying, the missile will be going away from aircraft and hence image of missile plume will decrease in size in subsequent frames as seen by MAWS sensors as shown in Figure 4.3.

FIGURE 4.3: Decreasing plume size (frame 1 showing a large plume size (left) and frame 15 showing a small plume size (right))

4.2.2 Case 2: Approaching Missile

In this case a missile targets the aircraft from its tail side. The sensor is placed on the tail so it sees an enlarging ring of missile plume as it approaches towards the aircraft. Figure 4.4 shows the SBUV image of approaching missile where smaller plume is visible in initial frames however Larger plume ring is visible in later frames. Center area of plume is eluded by missile body which makes it look like a ring instead of circle.

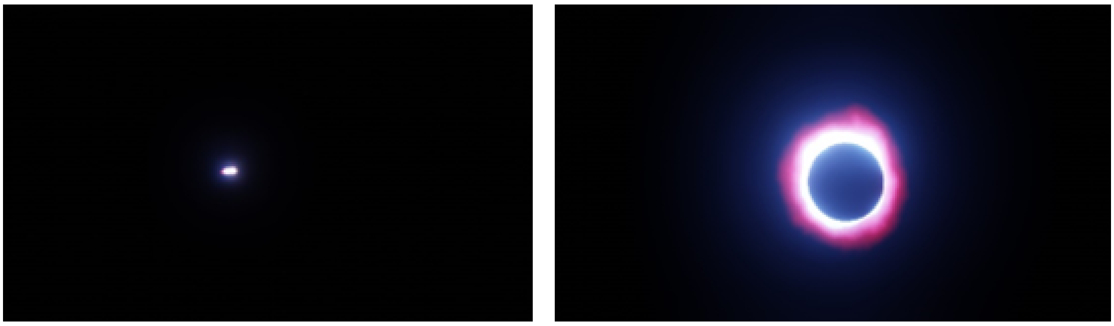

FIGURE 4.4: Increasing size of plume(frame 1 showing a small plume size (left) and frame 15 showing a Large plume (right) eluded by missile body from the center)

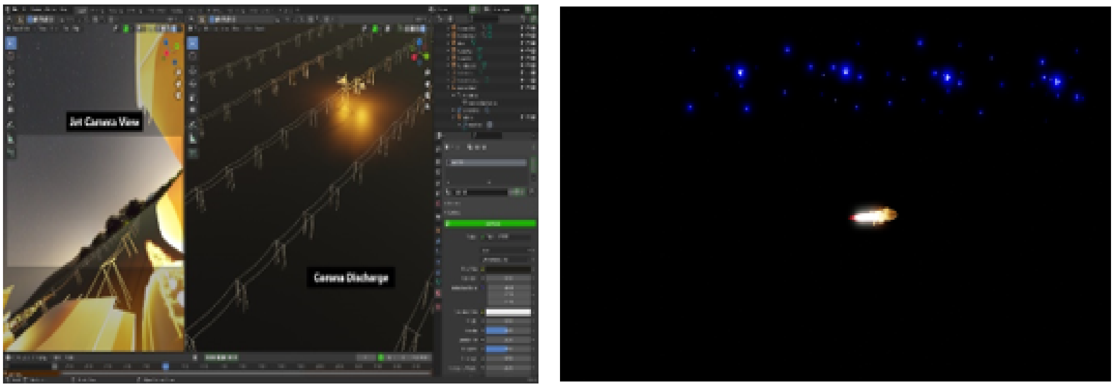

FIGURE 4.5: Aircraft flying over high power electric transmission lines(left window showing rendering environment display and right showing SBUV visual output)

4.2.3 Case 3: Aircraft Flying over High Power Electric Transmission Lines

Shown in Figure 4.5 is a jet flying on top of high power transmission lines. There is corona discharge on such high power lines whose spectral emission band is same as missile plume i.e 240 to 280 nm. It is invisible to naked eye and is visible with UV and SBUV sensors.

Therefore it is a major cause of background clutter for our application. This appears as a moving object due to the relative motion between aircraft and the wires. The only available option to get rid of this clutter will be to visualize its actual shape , pattern and train the CNN model on synthesized corona patterns / class. To achieve this object this simulation will be very helpful.

4.2.4 Case 4: Formation Flying

The scenario shown in Figure 4.6 is the formation flying and the missile chases both the aircraft initially. Camera was placed on one aircraft tail. Missile suddenly changes its trajectory and it follows the other aircraft instead of the subject jet. This scenario is rendered for training the system , to judge the case in which there is a missile detected by the system but it is not coming towards subject aircraft and therefore has not to be declared as a threat.

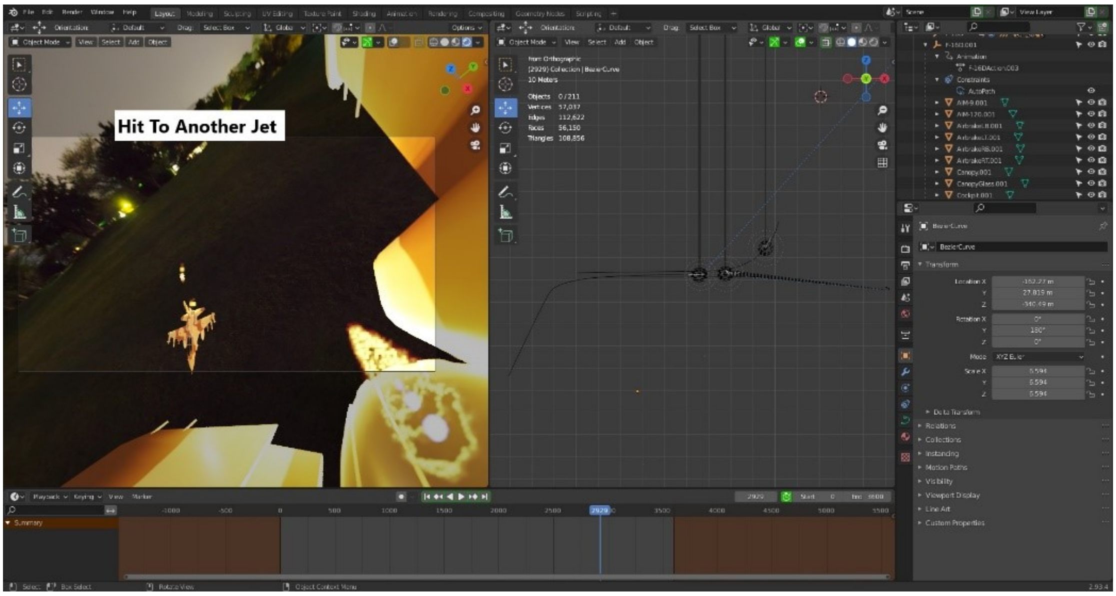

FIGURE 4.6: Missile chasing a parallel flying aircraft

This scenario is of great significance , because in this case , the detection CNN model can be easily fooled due to the increasing intensity, size and approaching coordinates of the plume however we can train the system only not to be fooled by this by synthesizing this scenario and extracting good quantity of training frames through this simulation.

4.2.5 Case 5: Missile Chasing Another Aircraft Flying in a Different Direction

In this particular scenario shown in Figure 4.7, MAWS sensor on subject aircraft is detecting a passive missile being fired towards another aircraft which is not flying parallel, instead flying in some other direction.

This scenario is created to train the system, to clearly understand which missile is an approaching threat and which is not. Furthermore, the tail plume of subject aircraft and tail plume of other jet also have to be excluded as clutter, so this synthesized scenario will also help the system for this clutter rejection.

All the above mentioned scenarios are key scenarios which will aid the detection system to be trained for majority of the possible types of encounters with passive

Figure 4.7: Missile chasing another aircraft flying in a different direction

missiles in real time environment. This simulation and modeling approach has been adopted due to the scarcity of resources like SBUV hardware, missile firing freedom efforts have been made while rendering these models to stay as close to reality as possible.

Chapter 5

Object Detection & Classification

5.1 Introduction

Detecting fast moving objects is an important and challenging problem. It has high applicability for tracking UAV (unmanned aerial vehicles), missiles called Object of Interest (ObI) in this study and other objects, especially when trying to predict the approach and possible collision.

As described in previous Chapter, In case of aerial platforms use of UV/Solar-blind (Ultra Violet) sensors are used to acquire UV signatures of the surrounding. Utilizing this spectrum first of all, objects visible in this spectrum are detected in first stage called object detection. In later stage, classes are made for the detected objects for de-cluttering and afterwards 2d tracking is done to eliminate all non-stationary clutter from the moving threats and discriminate the non-threatening cases from approaching missile threats. Same is shown in Figure 5.1.

5.2 Object Detection

The primary challenge is to de-clutter missile signature from background which contains some other objects in same solar blind UV domain and raise an early

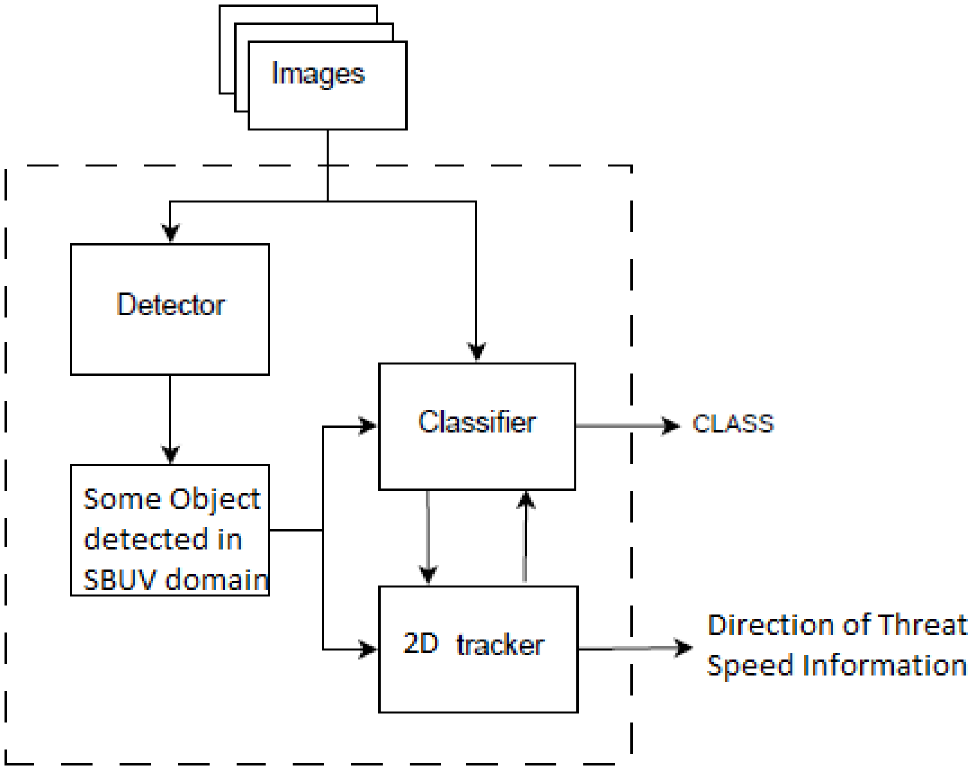

FIGURE 5.1: Object Detection and Classification

warning, increasing the possibility of defensive maneuver and/or deployment of the available countermeasures to disrupt the object's trajectory.

Once the required data has been gathered, the next step is Object Detection algorithm. In my research, detection model is based on deep learned algorithms. Conventionally many other approaches like Hidden Marcov Model have been used for this objective [2] but deep learned models offer some added advantages of efficiency and precision in detection which is difficult to achieve otherwise.

For object detection , numerous deep learning algorithms are available like RCNN's, Fast RCN, Faster RCNN, YOLO, Mask RCNN etc. YOLOv5 architecture is used in current study. Filters a.k.a. kernels are the building blocks of Convolutional Neural Networks (CNNs) [29]. Using the convolution operation, Kernels are utilized to derive the relevant features of the input image [19]. After object is detected as a missile based on its parameters , then post processing with few other tracking algorithms will be done which will be explained in next chapter [30].

5.2.1 Object Annotation

In the realm of deep learning , Object detection combines two tasks:

1. Image Classification
2. Object Localization

The image classification task requires to give object classes in an image thus classification can be for one or more objects. Object localization on the other hand, requires to find both the object class and bounding boxes i.e; location where class is detected for images. These two tasks as a whole are also called object annotation or data tagging or labeling as shown in Figure 5.2.

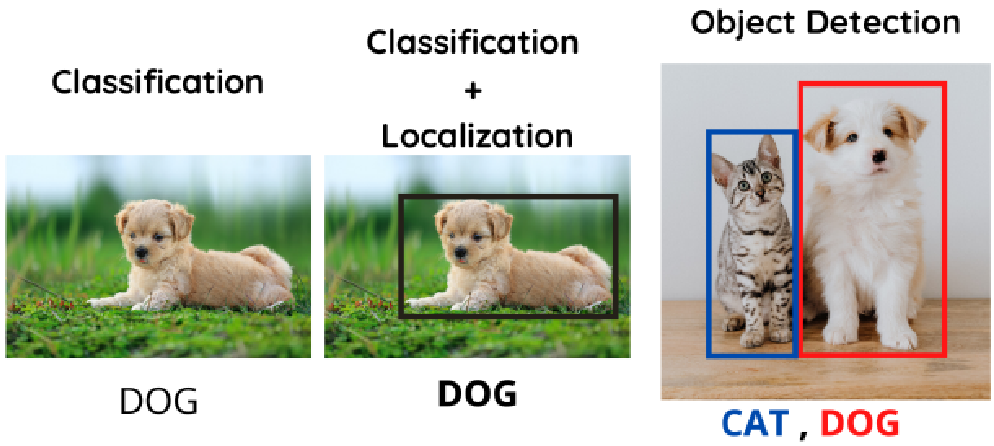

FIGURE 5.2: Image classification, classification plus localization and object detection [31]

5.2.1.1 Data Labeling

All the "supervised learning based models" require a ground truth i.e. a "Labeled Dataset" during their training phase. In the context of Deep Learning, Data labeling or Data Annotation is the procedure that involves detecting and tagging data samples. The process is manual and it is usually performed with the assistance of software[19]. For example, if it is desired to develop a system that can detect planes in an image, the deep learning-based model shall be trained over a data-set with video frames along with the details (coordinates) of a bounding box around the location of the plane in each frame as illustrated in the Figure 5.3. If there are multiple kinds of objects to be identified a class label also needs to be attached to each object. In the case of object detection, the dataset consists of the original image and 5 values are required representing the object class and the coordinates of the bounding box in which the object is located. These values are :([class xmin ymin xmax ymax] or [class xmin ymin width height]).

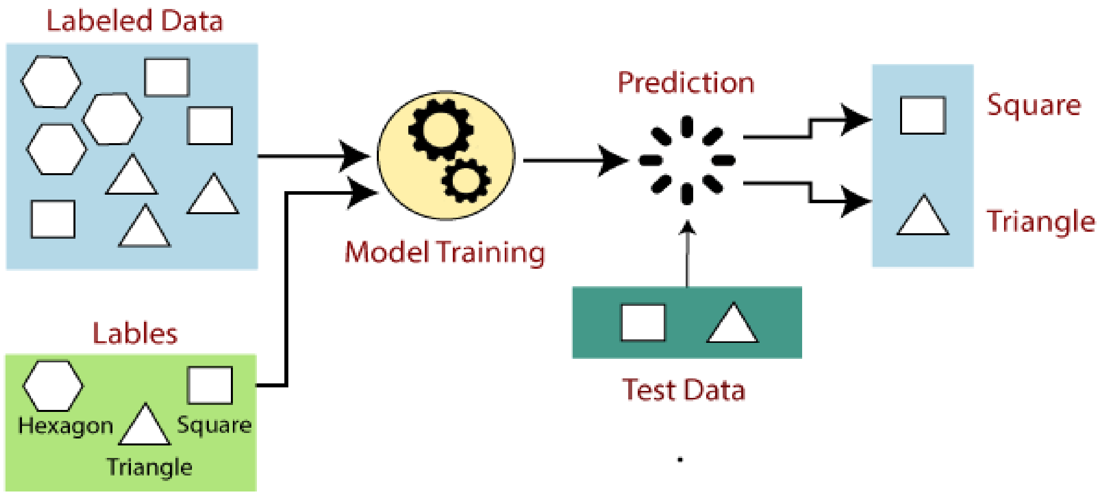

FIGURE 5.3: Labelled dataset or ground truth required by supervised learning models to detect similar unlabeled objects [31]

5.2.1.2 Labeling Tools Analyzed for MAWS

Data gathering is a complex task, requiring a reasonable number of annotators. Multiple procedures like getting porting of data tagged from multiple annotators are incorporated to maintain the quality of the tagging. The following is a list of tools evaluated for this project:

1. Computer Vision Ground Truth Labeler in MATLAB [31]
2. Intel's Computer Vision Annotation Tool (CVAT) - (open-source tool) [29][32]
3. LabelImg (open-source tool)
4. Microsoft's Visual Object Tracking Tool (VOTT)

5. MIT CSAIL's LabelMe (open-source tool)

6. Supervisely's Video/Image Labeling Tool

7. DarkLabel (for Windows only)

8. SuperAnnotate (paid)

5.2.1.3 Data Classes for MAWS

I have defined following three classes ;

1. Ring plume

2. Plume

3. Corona

These classes are defined because of differences in their features and shape.

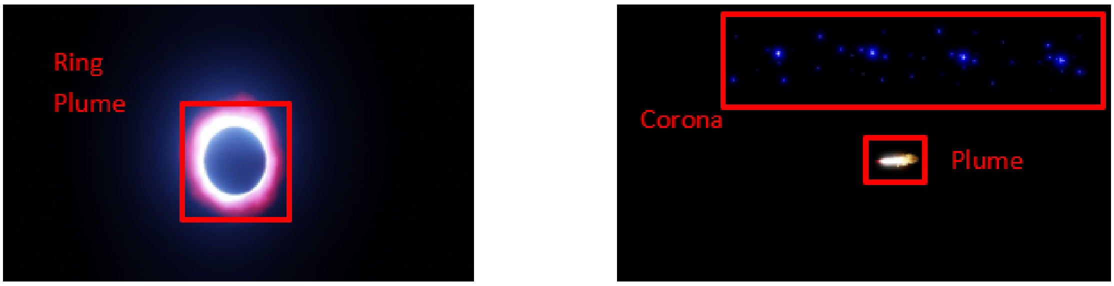

FIGURE 5.4: Three classes defined for data annotation

The tools selected for this project include Computer Vision Ground Truth Labeler in MATLAB , Labelme (open-source tool) which comes with Yolo v5 model format and DarkLabel as well.

Based on the defined classes, the data-set was labeled and then numerous training frames have been created through the data annotation process. These training frames include the information regarding class, (x , y) coordinates, width and height information regarding the detected object.

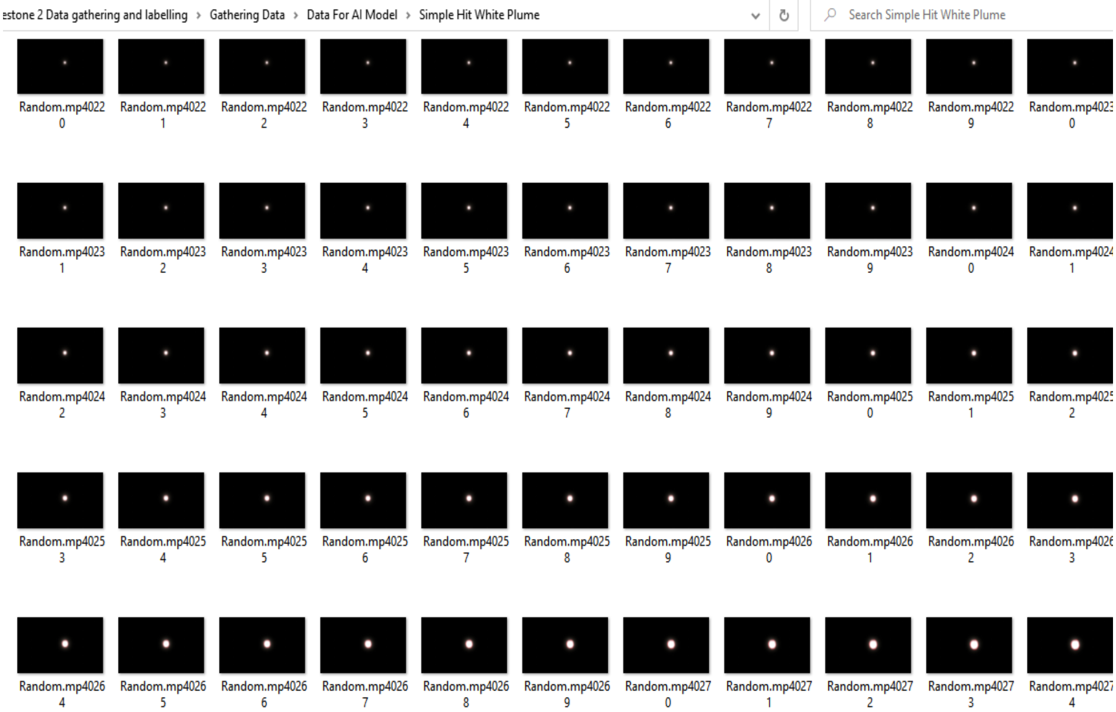

FIGURE 5.5: Multiple training frames annotated for training the model

5.2.2 Convolution Neural Network for Detection

A Convolution neural network (ConvNet/CNN) is a deep learning algorithm whose input is an image. Based on some learn able weights and biases values to various aspects/parameters in the image, it assigns importance and is able to differentiate one from the other.

CNN learns the filters routinely without bringing it up separately. These filters assist in extracting the right and relevant features from the input records. CNN additionally follows the idea of parameter sharing. A single filter is carried out across exceptional parts of an input to provide a characteristic map [29].Core building block of a Convolution network is the Conv layer that does most of the computational heavy lifting.

The convolutional Layer and the Pooling Layer, make up the i-th layer of a convolutional Neural Network. Depending on the complexities in the images, the number of such layers can be increased for capturing low-levels details even further, but at the cost of more computational power. In this study 9 layered convolutional

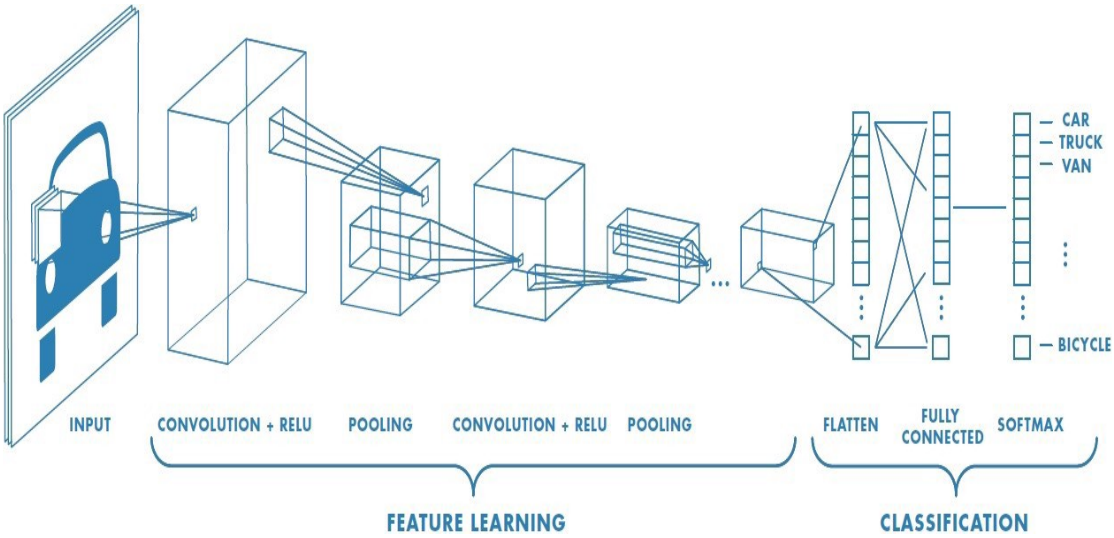

FIGURE 5.6: Convolution neural network architecture

network has been used amongst which 4 are the convolutional layers, 3 are the pooling layers and 2 layers are kept for flattening the information.

The element involved in carrying out the convolution operation in the first part of a convolutional Layer is called the Kernel/Filter, K, represented in the color yellow. In this study , K is selected as a 3x3x1 matrix.

Stride Length is kept as 1 (Non-Strided), therefore Kernel shifts 9 times for performing a matrix multiplication operation between K and the portion P of the image over which the kernel is hovering.

5.2.3 YOLOv5 Framework

In this study , YOLOv5 framework of convolutional neural networks has been utilized keeping in view the perspective of real time application development. YOLO is a synonym for 'You only look once'. It is an object detection algorithm which divides images into a grid system. Each cell in the grid is responsible for detecting objects within itself [33].

YOLO is one of the most famous object detection algorithms due to its speed and accuracy. Shortly after the release of YOLOv4 Glenn Jocher introduced YOLOv5 using the Pytorch framework. YOLOv5 is one of the best available models for

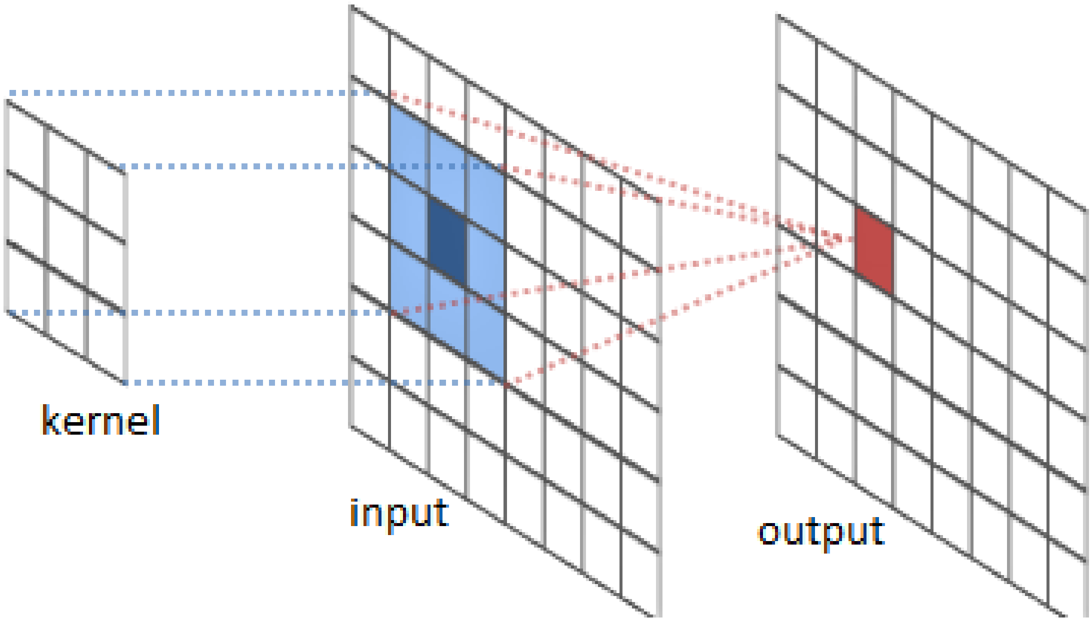

FIGURE 5.7: Kernel size and its function in convolution [33]

Object Detection at the moment [34]. It this study , time efficiency of the detection algorithm was a major concern which is the main reason for selection of this framework.

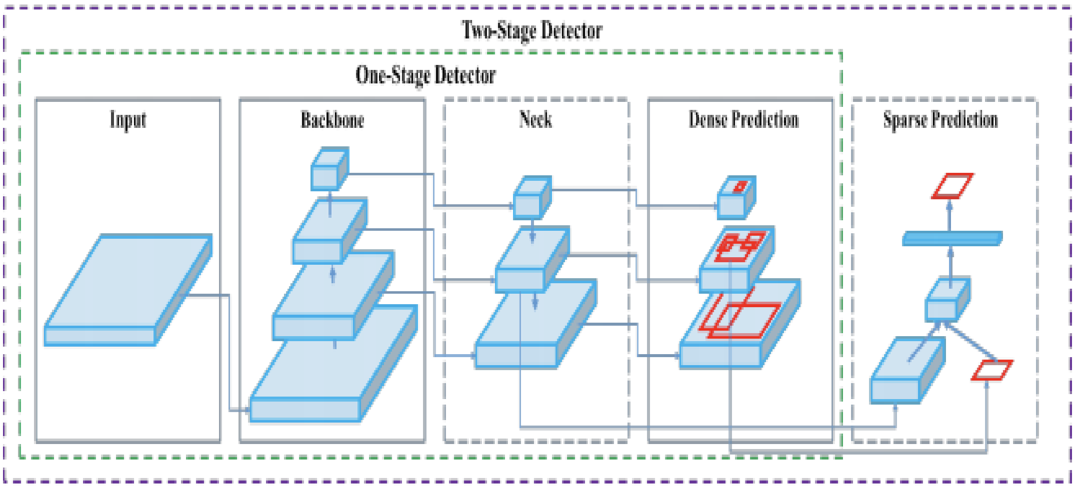

FIGURE 5.8: YOLOv5 architecture [33]

Object Detector generally have a backbone for pre-training and a head to predict classes and bounding boxes. The Backbones can be running on GPU or CPU platforms. The Head can be either one-stage (e.g., YOLO, SSD, RetinaNet) for prediction of dense properties or two-stage prediction(e.g., Faster R-CNN) for the less dense prediction object detector. Recent Object detectors have some layers (Neck) to collect feature maps, and it is between the backbone and the Head. In YOLOv4, CSP Darknet53 is used as a backbone and SPP block for increasing the receptive field, which separates the significant features, and there is no reduction of the network operation speed. PAN is used for parameter aggregation from different backbone levels. YOLOv3 (anchor-based) head is used for YOLOv4.

YOLOv4 introduced new methods of data augmentation like Mosaic and Self-Adversarial Training (SAT). Mosaic is meant to mix four training images. Self-Adversarial Training operates in two forward and backward stages. In the 1st stage, the network alters the only image instead of the weights. In the second stage, the network is trained to detect an object on the modified image. YOLOv5 almost resembles YOLOv4 with some of the following differences:

1. YOLOv4 is released in the Darknet framework, which is written in C however, YOLOv5 is based on the PyTorch framework.

2. YOLOv4 uses .cfg for configuration whereas YOLOv5 uses .yaml file for configuration.

5.3 Classification & Tracking

Once the object is detected with the help of CNN deep learned models , the next challenge is to classify it as an approaching missile or a random fire, or to differentiate between a missile plume and another aircraft. This type of classification cannot be achieved alone with CNN based object detection.

This comes under the paraphernalia of Moving Object detection which requires Post Processing or 2D Tracking. Moving object detection is defined as identification of the physical motion of an object within a certain space or area.[35]. Numerous procedures are used to examine if any moving object is detected by comparing Multiple consecutive frames from a video . The motion of moving objects may be tracked and can be analyzed later , by segmentation among moving objects and stationary area [36]. To accomplish this, a video is considered as a design based upon single frames, moving article location is to observe the closer view moving target(s), either in every video outline or just when the moving objective show the primary appearance in the video [37].

5.3.1 Moving Object Classification Techniques

Traditional moving object tracking and classification methods can be broadly divided into four major approaches:

1. Background subtraction
2. Frame differencing
3. Temporal Differencing
4. Optical Flow

All these methods have been extensively utilized for numerous types of utilities for example; video surveillance, recognition of terrorist activity, monitoring of roads condition, flight safety on airport, marine border monitoring etc. [38]. For this specific case of airborne application where the camera is mounted on a fast flying object and it has to detect other fast moving objects like missiles, all these approaches have been studied one by one and most appropriate approach has been seleted based on efficiency and reliability parameters citephansen2021novel.

5.3.1.1 Background Subtraction

It is popular and broadly utilized method for developing a foreground mask or a binary picture which contains the pixels indicating a place with moving articles in the scene with the help of static cameras. This methodology can't be utilized in this specific application because the camera will be mounted on flying aircraft instead of a static object.

5.3.1.2 Frame Differencing

Frame differencing method compares two successive frames to detect moving targets unlike image subtraction method where second and afterwards images are subtracted [10].

5.3.1.3 Temporal Differencing

Pixel-wise difference method with two or three consecutive frames is used in temporal differencing method and the moving object is identified [36].

5.3.1.4 Optical Flow or Optic Flow

A certain pattern of apparent motion of objects, surfaces, and edges is created in a visual imagery , due to the relative motion between an observer and a scene. This is known as optical flow and is used for object detection. It can also be defined as the distribution of apparent velocities of motion of brightness in an image [31], [39].

5.3.2 Tracking Algorithms

Object Trackers have been in active development in OpenCV for tracking of the detected objects. Few popular algorithms are explained below:

5.3.2.1 AdaBoost Algorithm

Tracking is considered as a binary classification problem in this algorithm and it is the easiest to implement algorithm with openCV. First of all, the linear combination of R, G, and B with integer coefficients is utilized to generate the candidate features [40].Features are later on selected for the design of weak classifiers according to the two-class variance ratio. Afterwards, a strong classifier is built on the weak classifiers. In this study , initially all the tracking is performed with this tracking algorithm. Later on, for specific cases like muti object tracking and very fast speed videos other algorithms like CSRT and KEF were utilized.

5.3.2.2 Kalman Filtering

A very famous signal processing algorithm utilized to predict the location of a moving object based on initial motion information. One of the early applications of this algorithm was in missile guidance and the on-board computer that guided the descent of the Apollo 11 lunar module to the moon had a Kalman filter [41]. Therefore it is studied in detail in this study for implementation.

5.3.2.3 CSRT Tracker

In situations where a fast object detector is needed, it makes sense to detect multiple objects in each frame and then run a tracking algorithm that identifies which rectangle in one frame corresponds to a rectangle in the next frame. For such requirements some other algos are utilized one example is CSRT algorithem [42].

In CSRT slgo , the discriminating Correlation Filter with Channel and Spatial Reliability (DCF-CSR)are used. Spatial reliability map for adjusting the filter support to the part of the selected region from the frame for tracking is utilized. This ensures enlarging and localization of the selected region and improved tracking of the non-rectangular regions or objects. It uses only 2 standard features (HoGs and Colornames). In this study , for multi target tracking this CSRT tracker has been utilized.

5.3.3 Implemented Tracking & Classification Technique

Frame differencing and temporal differencing methods as explained above are utilized in present work for post processing and two checks were implemented on the

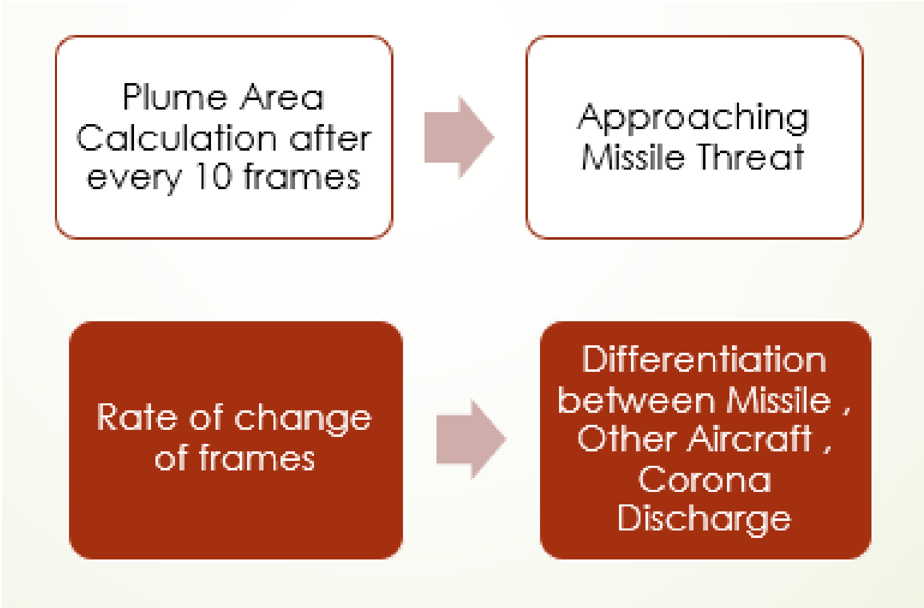

FIGURE 5.9: Object tracking and classification technique

consecutive frames. First of all , the frames are recorded in terms of area of the plume and after every 10 frames, the area of plume in each consecutive frame is compared with the area of plume in previous one. On basis of increase in area, the detected target is classified as approaching threat missile or receding missile.as shown in Figure 5.9.

Furthermore, the rate of change of area is also calculated. This gives an idea about the moving object speed. Since the speed of missile is much higher than any other flying aircraft in surroundings, therefore this check will help us to differentiate between the missile and other aircraft. This is done with implementation of Kalman Filter algorithm.

For real time tracking requirement of current problem statement , the constraints like low computational time, low memory requirement, minimal hardware are also kept in mind.

AdaBoost tracking algorithm for fast moving object detection has been studied and utilized in my work. AdaBoost algorithm, abbreviated for Adaptive Boosting, which is a technique used in machine learning as a grouping methodology. It is known as Adaptive Boosting because the weights are re-assigned to every event and wrongly classified instances are assigned with higher weights. AdaBoost is actually used to boost the performance and efficiency of any machine learning algorithm. It is suitable for weak learners or less data-set trained models as in my case the training data is limited. Decision trees with one level are the most suited and therefore most common algorithm used with AdaBoost and same is utilized in this study.

CSRT tracker based on mean shift techniques which is very good for high speed moving objects tracking has also been implemented [37]. All these techniques have been studied in detail to implement this code utilizing PyCharm and other open CV built in libraries.

Chapter 6

Results & Discussion

6.1 Introduction

The test results presented in this chapter deal with complete MAWS system which comprises of detecter , classifier and tracker. Initially performance of detector system is explained which is based on results of YOLOv5 model. Detector system will give objects detected in our desired spectrum with the pre-decided labels and classes. The outputs of this system are then given to the classifier portion and then to the tracker as explained in Section 5.3.3.

The performance of classifier is dependent on detector however the performance of 2D tracker is independent from the detector and its output is also different, thus the performance of tracker is explained separately.

6.2 Object Detection Model Performance

The performance of object detection model is measured through certain parameters. These parameters are widely used in computer vision and AI fields to examine the performance of algorithms before implementation of hardware. The details of these performance parameters are explained below:

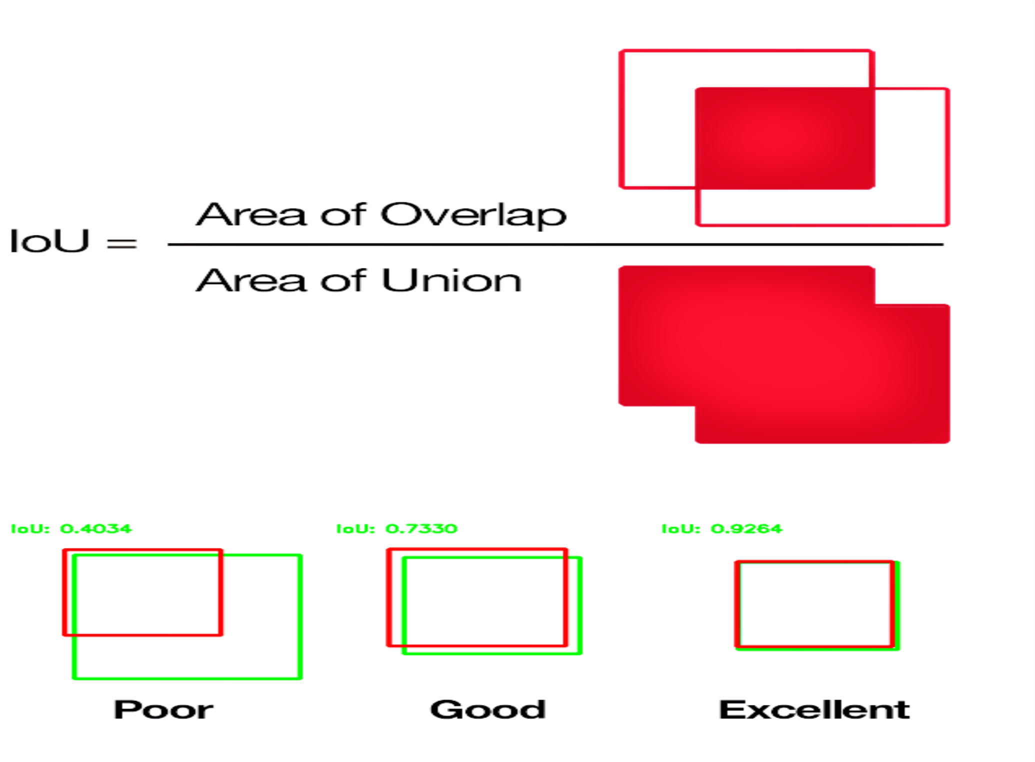

FIGURE 6.1: Intersection over union [20]

6.2.1 Performance Parameters Indicators

1. Intersection over union (IOU)
2. Precision and Recall Matrices
3. Mean Average Precision(mAP)
4. Performance Confidence Curve

Intersection over Union (IoU) estimates intersection over the union of two overlapping boxes; the bounding box for the ground truth and the bounding box for the predicted object. An IoU of 1 shows that the ground truth and predicted boxes overlap completely (100 percent) accurate detection. Generally IoU threshold value is set upto 0.5. It can also be set to $0.75, 0.9$ or 0.95 etc depending on the refinement of training data as shown in Figure 6.1. With the help of this data, percentage of loss of object, percentage of loss of class is plotted by increasing the number of Epoches (training cycles) gradually as shown in Figure 6.2.

On top is the training data graph and on bottom is the validation data graph. We can see and compare that both the training and validation data graphs can be related closely to one another. This depicts that the loss of detection of the class and loss of detection of the object reduces as the number of training cycles of the model are increased and finally when we do the training is done for 100 cycles the loss percentage is as low as 2 percent which is quite a good result for any CNN model.

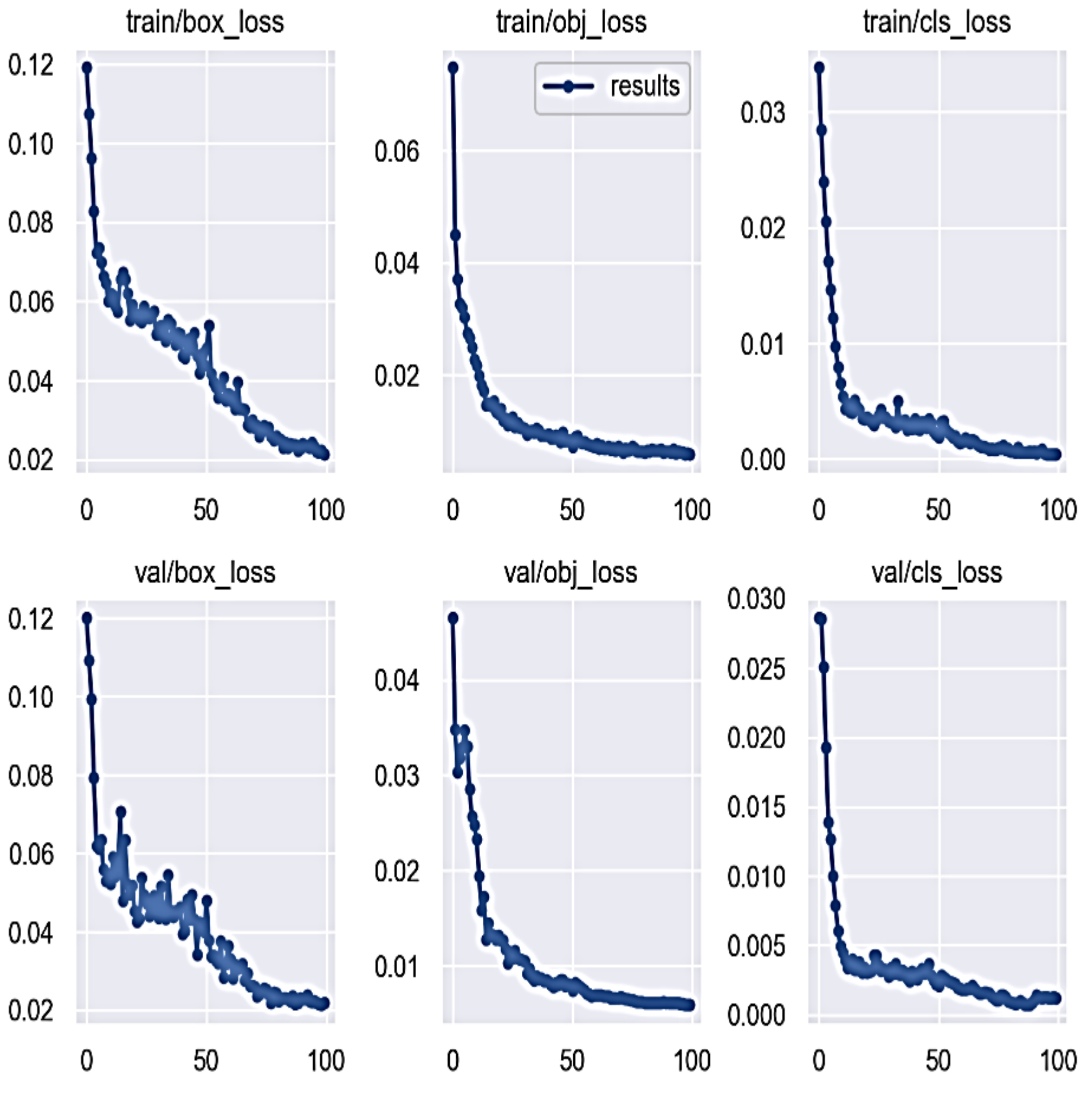

FIGURE 6.2: Class loss and object loss percentages graphs

After setting the value of IoU, True Positive (TP),False negative (FN) and False positive (FP) cases are identified and calculated through these formulas.

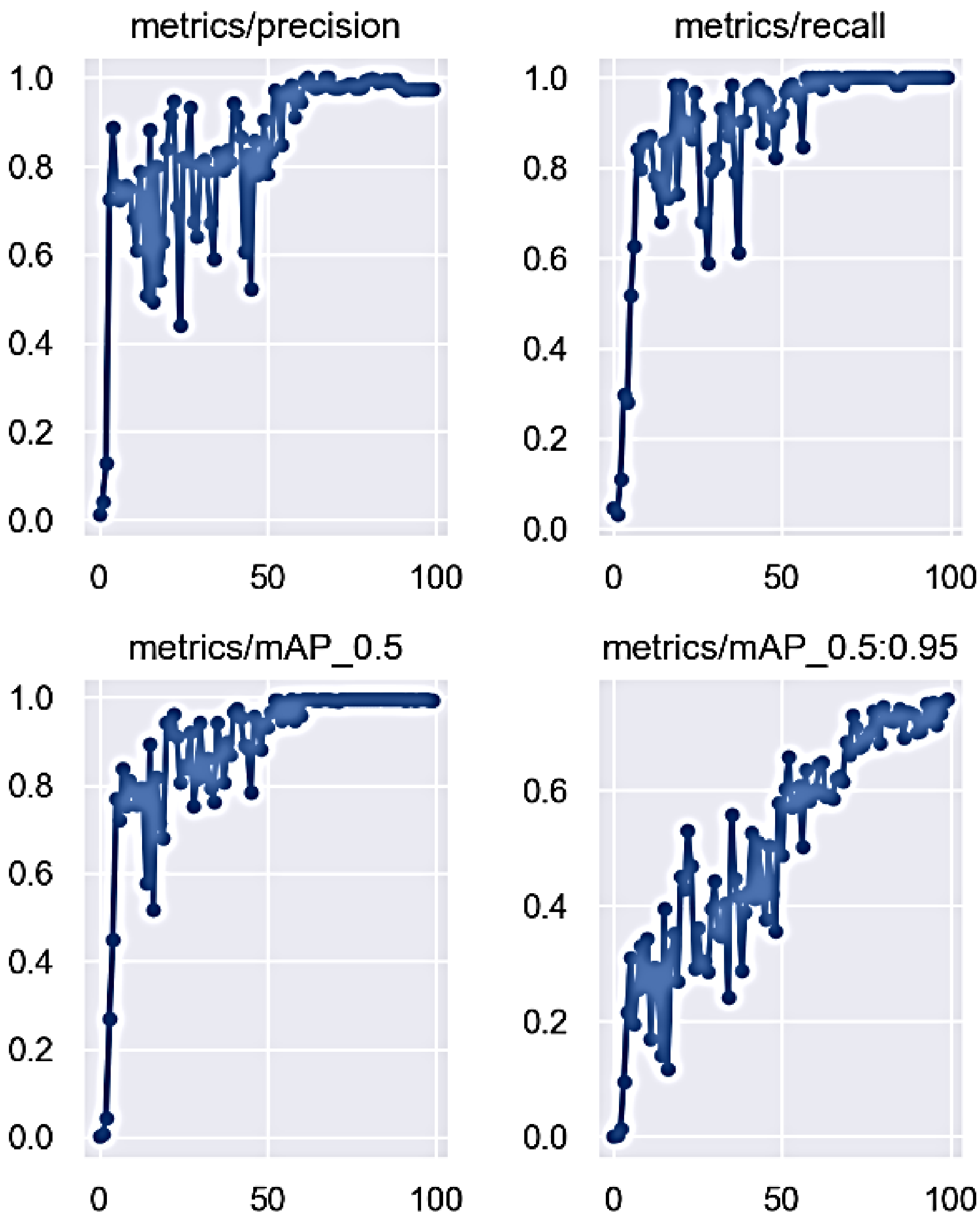

FIGURE 6.3: Precision and Recall matrices values and mean avg precision graphs

Mean Average Precision(mAP) as mentioned in above equation 6.3, using 11 point interpolation technique is also calculated.

6.3 show the plotted Precision and recall graphs on top and Mean Avg Precision graphs on bottom. As the number of epoches (training cycle) plotted on x-axis are increasing the percentage value of recall and precision is also increasing and it

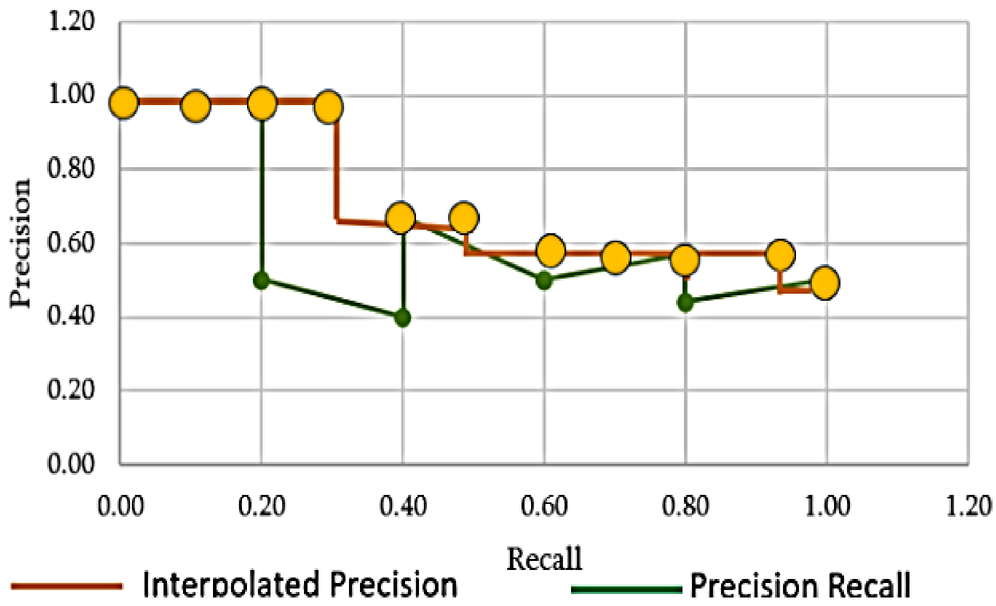

FIGURE 6.4: Precision Vs Recall curve

reaches as high as 85 to 90 percent. This is the characteristic of a good detection model.

Precision and Recall are two contradicting quantities. Higher value of one negatively effects the value of other. Figure 6.4 shows "Precision Vs Recall" (PR) graph of this study which is decreasing and trying to approach unity, as seen in above referred figure. Overall Performance curve of the detection system is also plotted in 6.5 which is showing increasing precision w.r.t. confidence level for all the three classes decided in last chapter

6.3 Tracking & Classification Results

Tracking and classification is done with the help of two separate algorithms.

6.3.1 2D Tracker Performance

With the help of recorded values of coordinates in detector system, the area of the plume is calculated for each frame. This calculated area is then compared after

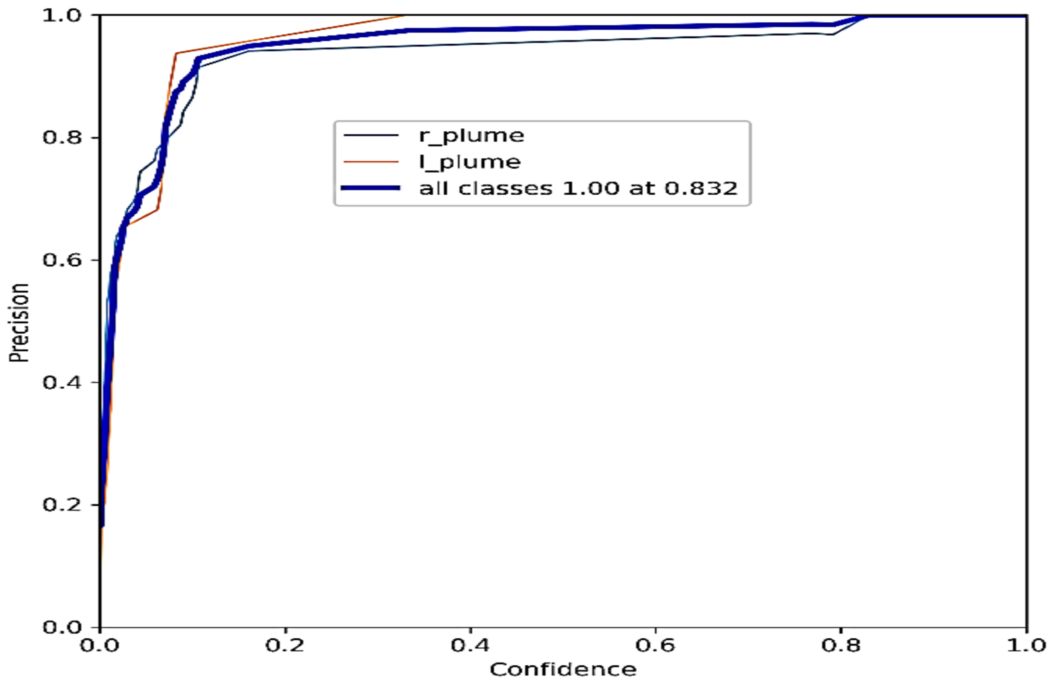

FIGURE 6.5: Performance curve

every ten frames in 2d tracking algorithm. Based on this calculation, the direction of the threat is determined as approaching or receding threat.

The area calculation and decision on direction of the threat is done through two different methods. One is the conventional technique of data storing in arrays and other is based on Kalman Filter estimation algorithm.

Both the approaches have been implemented and results are almost similar and accurate through both methods. As shown in Figures 6.6, 6.9 and 6.8, the developed algorithm is able to classify the directions of the threats with the help of its Area information.

6.3.2 Classifier Performance

Another calculation is done based on rate of change of area. This provides a good approximation for the approach velocity of the threat but does not provide the exact velocity value. This calculation has helped to classify the approaching threat as a missile or another aircraft since the approach speed is different for both.

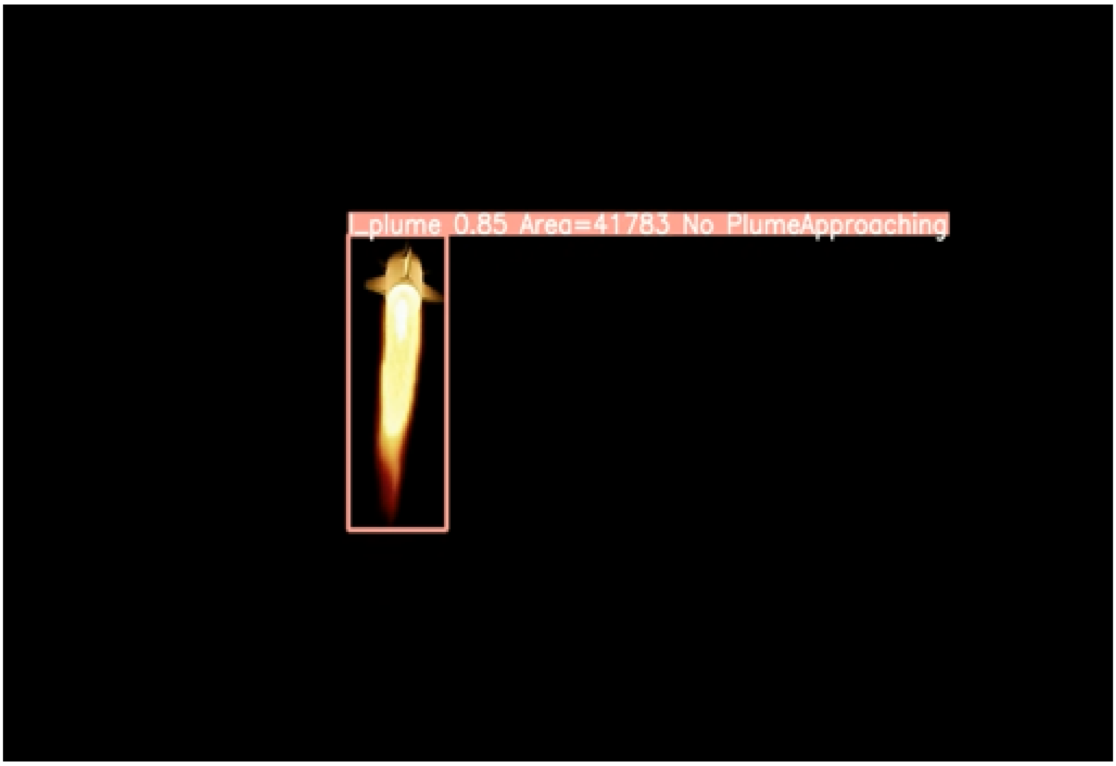

Figure 6.6: Area calculation for plume size

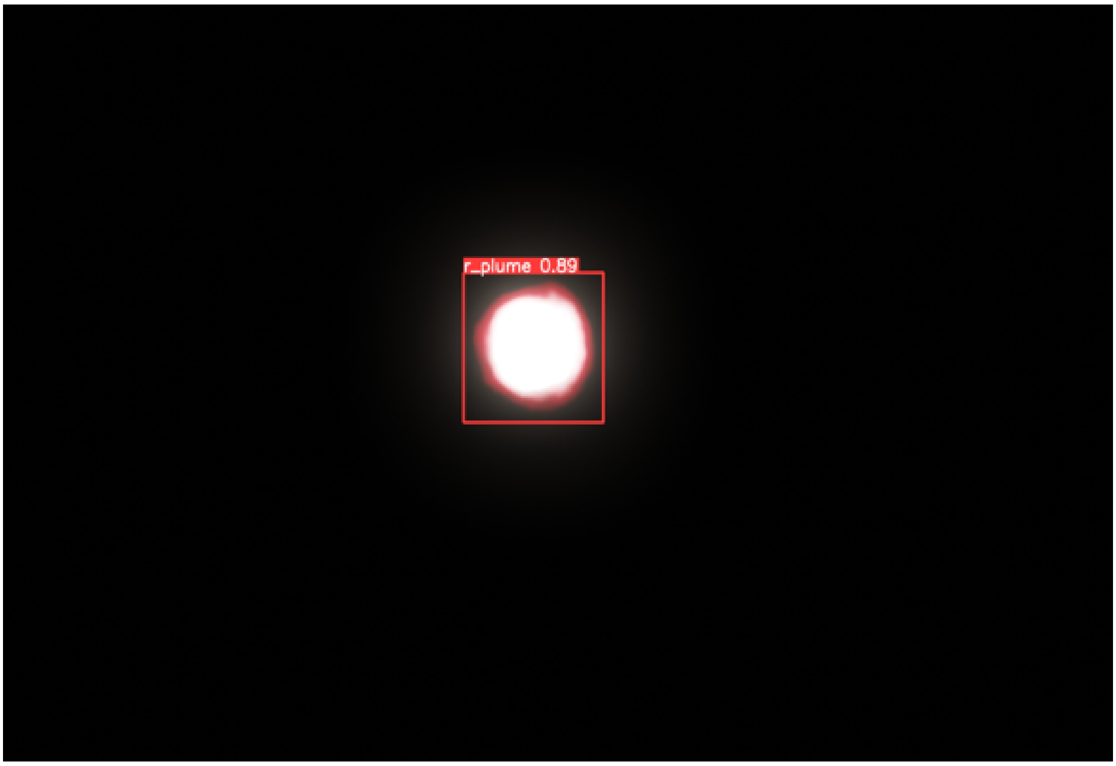

Figure 6.7: Circular plume area calculation for classifying it as approaching or receding missile

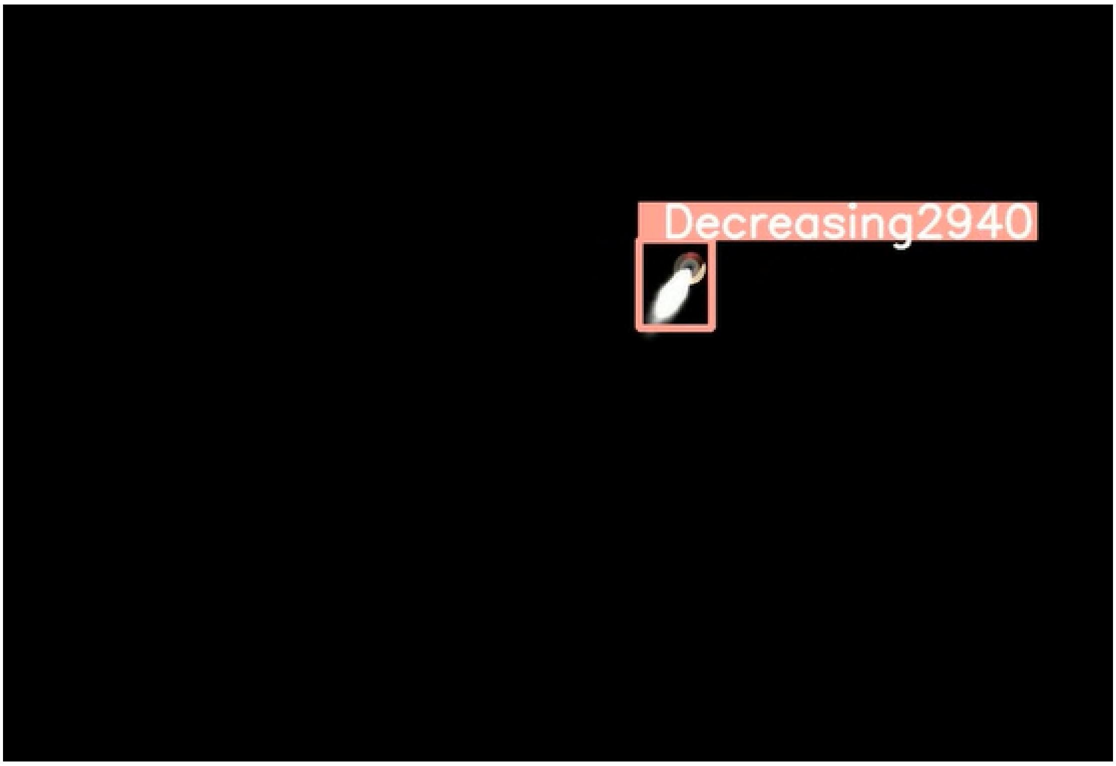

FIGURE 6.8: Decreasing plume area calculated with the tracking

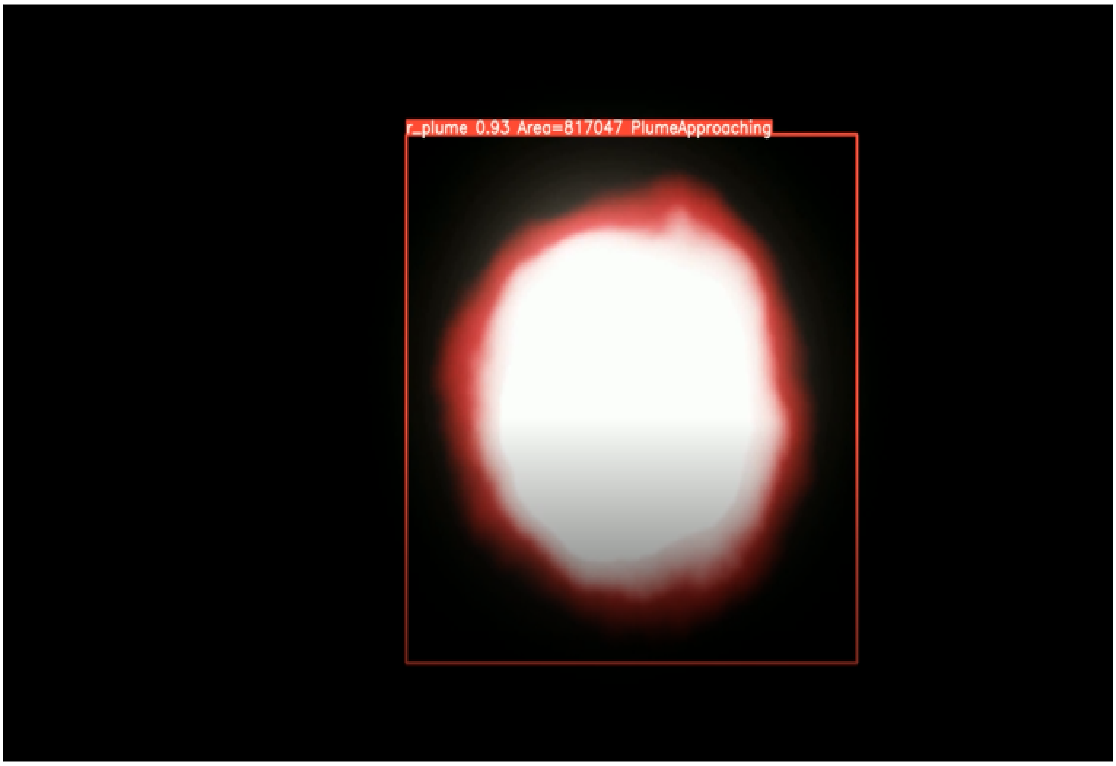

FIGURE 6.9: Approaching missile plume

Chapter 7

Conclusion and Future Work

7.1 Conclusion

Passive Missile warning systems are one of the most crucial Electronic Support (ES) systems of an Electronic Warfare (EW) suit on aerial platforms. These systems are used to warn the pilot and clue the Electronic counter measure(ECM) systems such as Directed counter measures (DIRCM) on the platform against the attacking guided missile.

Passive missile detection utilizing SBUV sensors has intrinsic advantages over old conventional means of detection. UV detection is better against surface-to-air missiles and MANPADS which are the primary threats faced by most aircraft.

The realms of deep learned supervised learning , Machine learning , conventional 2D tracking algorithms for moving object detection have been utilized in conjunction in this study to achieve desired results. The detection and classification based on these approaches has provided efficient and reliable results which was the main aim of this study. In future this study can be extended to deduce other essential parameters like approach velocity and time to impact of the threat and the developed system can prove to be a wholesome package for the EW suite of any modern aircraft.

7.2 Future Work

Tracking of Multiple targets at one time and prioritizing few threats over others in complex combat zone scenarios can be done in future by extending the developed algorithms.

Predicting the Missile's Position and exact Velocity in 3D using the Extended Kalman filter (EKF) can also be a valuable contribution. This will require many missile parameters which can be extracted with real time physics based modeling of the missiles , combustion models , particle scattering models and real time environment modeling of the terrain.

Time to Impact (TTI) calculation , Range calculation will also be possible once position and velocity is calculated.

Detection ranges of missile warning sensors may become less in front of advanced modern low IR and low UV emission motors of the missiles. This challenge can be met with research regarding alternate means of detection in future.

Advancements in SBUV sensor development technology can bring promising results in the field of development of more precise missile detection systems. Despite some promising results in the technology of SBUV sensor development, further research to enhance reliability and support reproducibility of these sensors is still needed.

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