AIR-TO-GROUND TARGET CLASSIFICATION AND HEADING ANGLE ESTIMATION USING RADAR RANGE PROFILES

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By

Murat Kökçü

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10 July 2024

We certify that we have read this dissertation and that in our opinion it is fully adequate, in scope and in quality, as a dissertation for the degree of Master of Science.

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LIST OF SYMBOLS

$\boldsymbol{\delta}$: Dirac Delta Function
$\boldsymbol{\mathcal{F}_{\alpha}^{-1}}$: Inverse Fourier Transform

ABBREVIATIONS

ATR	: Automatic Target Recognition
RCS	: Radar Cross Section
AESA	: Active Electronically Scanned Array
HRRP	: High Resolution Range Profile
ANN	: Artificial Neural Networks
CNN	: Convolutional Neural Network
IFT	: Inverse Fourier Transform
SNR	: Signal-to-Noise Ratio
LOS	: Line of Sight
TÜBİTAK	: Türkiye Bilimsel ve Teknolojik Araştırma Kurumu

RADAR MENZİL PROFİLLERİNİ KULLANARAK HAVADAN YERE HEDEF SINIFLANDIRMA VE YÖN AÇISI KESTİRİMİ

ÖZET

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Radar teknolojisinin gelişmesiyle birlikte, özellikle aktif elektronik tarama yapan sistemlerde yeryüzeyindeki hedeflerin otomatik olarak tanımlanması kritik bir öneme sahip hale gelmiştir. Bu tanımlama süreci, askeri ve sivil uygulamalarda operasyonel kararların alınmasında hayati bir rol oynamaktadır. Hedef tanıma aşamasında elde edilen bilgilerin doğruluğu ve kesinliği, gerçekleştirilen operasyonun seyrini doğrudan etkilemekte, bu da sistemin genel performansını ve etkinliğini belirlemektedir.

Bu çalışmada, X frekans bandında çalışan bir radar sisteminin yerde konuşlu farklı hedeflerden topladığı yüksek çözünürlüklü menzil profilleri incelenmiştir. Bu profiller, hedeflerin sınıflarını ve yatay yönelim açılarını belirlemede kullanılmıştır. Araştırma, modern radar sistemlerinin yalnızca hedefleri tespit etmekle kalmayıp, aynı zamanda bu hedeflerin türlerini ve konumlarını da yüksek doğrulukla belirleyebilme potansiyelini ortaya koymaktadır.

Çalışmanın metodolojisi, derin öğrenme temelli ardışıl sınıflandırıcı yapıları ile şablon eşleme tekniğinin kombine edilmesine dayanmaktadır. Bu yaklaşım, geleneksel radar sinyal işleme tekniklerinin ötesine geçerek, yapay zeka ve makine öğrenmesi alanlarındaki son gelişmeleri radar hedef tanıma problemine uygulamaktadır. Kullanılan derin öğrenme modelleri, radar sinyallerindeki karmaşık örüntüleri analiz ederek hedeflerin özelliklerini çıkarabilme yeteneğine sahiptir.

Araştırmanın sonuçları, önerilen sistemin performansının oldukça yüksek olduğunu göstermektedir. İşaret gürültü oranına bağlı olarak, ana hedef sınıfının %85'in üzerinde bir doğrulukla tanınabildiği tespit edilmiştir. Bu bulgu, önerilen yöntemin pratik uygulamalarda kullanılabilirliğini ve güvenilirliğini vurgulamaktadır. Ayrıca, çalışma hedeflerin yapılarındaki simetrinin, yatay yönelim başarımları üzerindeki etkisini de incelemiştir. Gözlemler, yatay yönelim başarımlarının genellikle simetrik yönelim açılarına bölüştüğünü ortaya koymuştur. Bu durum, hedef tanıma sistemlerinin tasarımında simetri faktörünün dikkate alınması gerektiğini göstermektedir.

Bu araştırma, radar tabanlı hedef tanıma sistemlerinin geliştirilmesinde önemli bir adım teşkil etmektedir. Elde edilen bulgular, gelecekteki radar sistemlerinin tasarımında ve optimizasyonunda kullanılabilecek değerli bilgiler sunmaktadır. Ayrıca, çalışmanın sonuçları, sivil hava trafiği kontrolü, doğal afet yönetimi ve çevresel izleme gibi alanlarda da potansiyel uygulamalara sahiptir. Gelecekteki araştırmalar, farklı çevresel koşullar altında sistemin performansını incelemeyi ve daha geniş bir hedef yelpazesini kapsayacak şekilde modeli genişletmeyi hedefleyebilir.

Anahtar sözcükler: Otomatik Hedef Tanıma, Radar Menzil Profili, Hedef, Yatay Yönelim Açısı, Derin Öğrenme

AIR-TO-GROUND TARGET CLASSIFICATION AND HEADING ANGLE ESTIMATION USING RADAR RANGE PROFILES

ABSTRACT

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The generation of radar technology has necessitated the recognition of targets on the ground through automatic functions and this has been vital in active electronic surveillance systems. This identification process is very critical in making the operational decisions as relate to the military and civilian purposes. It denotes that the nature of information collected in the target identification phase is a reproductive and definitive determinant of the course of the operation, which in turn defines the performance and efficiency of the system.

In this study, the dataset consists of range profiles acquired by an X frequency band radar system from various ground based objects. These profiles are used in the determination of the target classes and the horizontal orientation angles. Based on the results of this work, the effectiveness of new radar systems for target detection and determination of their type and position with high accuracy is shown.

The approach used in the conducted research is related to the use of deep learning based sequential classifier structures and template matching. It is not limited to the conventional radar signal processing methods, but incorporates the state-of-the-art artificial intelligence and machine learning methods to the problem of radar target recognition. The models of deep learning under consideration are ready to extract target features based on the peculiarities of the patterns and forms of radar signals.

The results of the study prove very high performance for a proposed system. Depending on the Signal-to-Noise Ratio, the main target class can be recognized at an accuracy of more than 85%. This result underlines the usability and reliability of the proposed method in practical applications. Indeed, the study investigates farther the impact of symmetry in target structure on horizontal orientation performance. These observations have revealed that the performance in horizontal orientation is essentially bifurcated between symmetric orientation angles. This may indicate that it will turn out to be very important to consider the symmetry factor when designing target recognition systems.

This research brings considerable opportunities for the development of radar-based systems of target recognition. These findings contribute useful information, which allows design and optimization of future radar systems. Such results could be used in many applications, including civil air traffic control, disaster management, monitoring of environmental systems, etc. Future studies could focus on checking system performance

under different environmental conditions or further develop the model for targets at a higher degree of complexity.

Keywords: Automatic Target Recognition, Radar Range Profile, Target, Horizontal Heading Angle, Deep Learning

CHAPTER 1

1. INTRODUCTION

Among the most investigated fields of radar technology, Automatic Target Recognition (ATR) using high-resolution range profiles (HRRP) is one of the most crucial. This means the identification and categorization of the target from the signals obtained from the radar on the target. Taking into account the trends of today's technologies, the role of radar systems is increasing steadily, and they are used in various spheres of civil and military use. Radar systems are the electronic devices that are employed for detecting and identifying objects by the means of the electromagnetic waves. Modern radars use radio waves to operate which means they periodically send out electromagnetic pulses [1]. These waves move through the unimpeded media of air or space right up to a surface or an interface. Depending on the nature of the electromagnetic waves some of these waves are reflected back by the object, some are absorbed by the object while the rest is transmitted back to the radar [2]. The structure of the echo signal includes information about the target, the distance in this case, from the radar. Radar is defined as the system that has been employed as a sensor for a target detection and tracking. But much more recently, high resolution radar systems have been advanced to a level where they can extract information concerning the type of target through the energy reflected by objects within the surroundings. This information obtained is known as the High Resolution Range Profile [3]. The high-resolution range profile represents a radar system's acquired data on a scale equal to the sensor resolution in the range dimension. This will be generated because the electromagnetic waves, along the radar's line of sight, scatter from the targets, and these scattered signals get collected at the radar receiver. Thus, the range profile provides a one-dimensional image of the target and is very useful for target recognition. It has a high resolution to provide detail in the range dimension, thus enabling it to detect and discriminate targets more precisely.

Essentially, radar systems exploit the properties of propagation and reflection of electromagnetic waves. In this way, they work across an extremely broad range. Radar systems have been used in both civil and military applications; they have turned into a necessity when it comes to long-range communications as well as target detection. However, for most cases, correct classification of the detected targets is very necessary. Correct identification of the types of targets that have been detected is paramount in deciding the next course of actions and the effective utilization of resources.

Today, high-precision classification algorithms are used to improve the target classification capabilities of radar systems [4]. These algorithms process and analyze radar signals to identify the exact types of targets. Target classification improves the performance and maximizes the operational efficiency of the radar system. Moreover, accurate target classification has the purpose of reducing false alarms and preventing the missing of a critical target.

High-precision classification algorithms allow for various methods to be utilized in order to make radar more effective. Those include artificial intelligence and machine learning methods. Based on the characteristics of the radar signals, which are complex, artificial intelligence and machine learning algorithms analyze them for the patterns necessary in the identification of the types of targets. This makes the radar systems more effective in their use for both civil and military purposes and contributes toward strategic decision-making. Due to this, high-precision classification algorithms will efficiently and accurately support radar systems for target detection and identification, thereby increasing the success of defense and security operations.

1.1. Literature Review

Target recognition by radar high-resolution range profile is of prime importance in many defense and civilian applications since it provides detailed information about the target structure. Classical machine learning methods do not provide very good results for the complex and high-dimensional nature of radar signals. During the past few years, deep learning methods have made tremendous improvements in HRRP target recognition by using their capabilities of automatic extraction and learning of hierarchical features from raw data. This study reviews the recent progress on radar HRRP target recognition techniques based on deep networks, with a focus on various neural network architectures and their performance.

The Target-attentional CNN focuses on improving the accuracy and robustness of HRRP-based ATR systems. Chen et al. (2022) developed this model with an intention to mitigate some limitations of traditional CNN, which usually fails in feature extraction in HRRP due to the complexity of radar return and noises. The Target-attentional CNN has an attention mechanism that focuses on the most informative parts of the HRRP, hence improving the discriminative ability of the model to targets. Chen et al. demonstrated that in their 2022 study, the Target-attentional CNN performed far above traditional CNN models in recognizing targets from HRRP data. Evidently, the attention mechanism had a role in the enhancement of feature extraction that led to high recognition accuracy and robustness under different conditions. Experimental results have shown that even with very limited training data, high performance of the model could be achieved, hence proving huge potential for practical applications in radar ATR systems [5].

CapsNets are no doubt more advanced variants of neural networks that capture the spatial correlations between different input features much more effectively than traditional CNNs in most cases. The authors applied the mechanism of convolutional dynamic routing between capsule layers for optimal performance, reduced size of parameters, and decreased computational expense. The length of those vectors within the capsules reflects the possibility of the goal class, growing interpretability and the robustness of this popularity process. The experiments carried out on real radar facts have proven that the proposed way outperforms the current ATR approaches with better accuracy and decreased sensitivity to the scale of the education dataset. This proves the potential of CapsNets applied to practical radar tasks, giving better performance beneath complicated obligations at the same time as doing recognition [6].

A detailed examination of deep learning applications in radar automatic target recognition (ATR) is given in a companion paper by Jiang et al. In order to improve ATR capabilities in a variety of domains, such as space, air, ground, and sea-surface targets, this review emphasizes the efficacy of deep learning techniques in feature extraction and recognition of radar targets [7].

A transformer-based model for HRRP sequence recognition is presented by Wang et al. The model improves the recognition of HRRP sequences by extracting deep global features through the use of temporal-spatial fusion and label smoothing. This approach shows better results in HRRP target detection, addressing the issues of long-range modeling and global information extraction [8].

An end-to-end integrated denoising and recognition network (IDR-Net) has been described by Liu et al. for the recognition of HRRP targets in low signal strength situations. This work presents a fresh collection of 10 features that are suited for HRRP recognition and show good real-time performance without amplitude sensitivity and low dimensionality. These characteristics are essential to a neural network-based classifier that detects radar targets and has remarkable flexibility in response to changing elevation angle and signal-to-noise ratios. The authors demonstrated the method's robustness through extensive experiments using simulated and real-world ground target data, achieving high recognition accuracy [9].

In order to identify novel target types with the least amount of training samples, Yan et al. suggest a few-shot radar target recognition technique that transfers meta-knowledge. With just a few samples, their method achieves high recognition rates by utilizing deep learning models' adaptability and generalization powers [10].

For the purpose of recognizing a small probability of intercept (LPI) radar signals, Quan et al. created a dual-channel CNN with feature fusion. Combining deep features from time-frequency images with Histogram of Oriented Gradients (HOG) features allows this model to attain great accuracy [11].

A two-stream deep fusion network that combines HRRP and synthetic aperture radar (SAR) data was presented by Du et al. [12]. This model improves overall identification rates by capturing multiple characteristics using lightweight CNNs and variational auto-encoders (VAEs).

Recurrent neural networks (RNNs) were investigated by Tang et al. for the purpose of classifying radar targets according to micro-Doppler characteristics. According to their research, RNN models—in particular, long short-term memory (LSTM) networks—can better classify L-band radar measured data by capturing the temporal relationships of micro-Doppler signatures [13].

RNNs have been used for HRRP target recognition because they operate well with sequential data, especially Long Short-Term Memory (LSTM) networks. A deep layered neural network with an attention mechanism that combines CNNs and bidirectional RNNs was proposed by Pan et al. Radar signal temporal relationships were successfully represented by this model, improving recognition robustness and accuracy [14].

CNNs' ability to capture spatial hierarchies in data has made them popular for radar HRRP target detection. CNNs have been shown to be more accurate than traditional approaches for HRRP target recognition and rejection, as proven by Wan et al. [15]. When compared to manually built features, their approach improved recognition performance by automatically learning features from radar data using a convolutional architecture.

A multi-channel CNN architecture was proposed by Song et al. to process different types of HRRP (amplitude, complex, and spectrum) technique demonstrates the advantage of deep features in capturing intrinsic target structures, outperforming both single-channel CNNs and typical handmade features in terms of recognition accuracy [16].

The ability of SAEs to learn features for HRRP target recognition has been investigated. In order to take advantage of Extreme Learning Machines (ELMs) quick learning rate and strong generalization capabilities, Zhao et al. paired SAEs with ELMs. This hybrid technique performed well in terms of accuracy and real-time processing, especially when there were limited training examples available [17].

Tang et al. developed a hierarchical learning framework based on ELM for multilayer perceptrons in order to address the drawbacks of shallow designs in natural signal processing. This framework's ability to do supervised classification and unsupervised feature extraction is advantageous for radar HRRP recognition [18].

The literature reviewed in this work indicates that great strides have been made in radar ATR using HRRP, primarily in the areas of feature extraction and target classification. In particular, deep learning methods, with special emphasis on CNNs and transformer models, demonstrate very high potential for improving the accuracy and robustness of recognition guided by HRRP. Hybrid feature extraction methods and fully investigating the potential of new deep learning architectures need to be focused on by future studies for the further improvement of radar ATR systems.

1.2. An Overview of Air-Ground Target Recognition

Modern defense systems are accompanied by fast and correct air and ground target recognition. The procedure of air and ground target recognition is quite complicated, with the processing and analysis flows of huge amounts of data received from technologies such as radar, infrared sensors, and electro-optical systems. In particular, radar-based approaches to target recognition describe the range profile analysis, motion characteristics, and geometric structures of targets. The process basically extracts, classifies, and tracks the distinct features of targets. This study will give an overview of different methods, technologies, and algorithms for air-ground target recognition.

1.2.1. Active electronically scanned array radar technology

Active Electronically Scanned Array (AESA) radar is one of the radical developments in the domain of radar technology and has already been massively deployed on modern air and naval platforms. These advanced radar devices have several advantages over conventional radar architectures.

AESA radars consist of a large number of small solid-state transceiver modules (TRMs). This structure is briefly illustrated in **Figure 1.1**. Each module emits individual radio waves, creating constructive interference in front of the antenna and thus directing the beam. This design enables fast and flexible operation through electronic scanning. Advanced AESA radars are capable of emitting waves over a wide frequency range. This makes them difficult to detect through background noise, allowing platforms to remain more stealthy. As a result, ships and aircraft equipped with AESA radars have a lower radar cross-section, even when emitting strong radar signals.

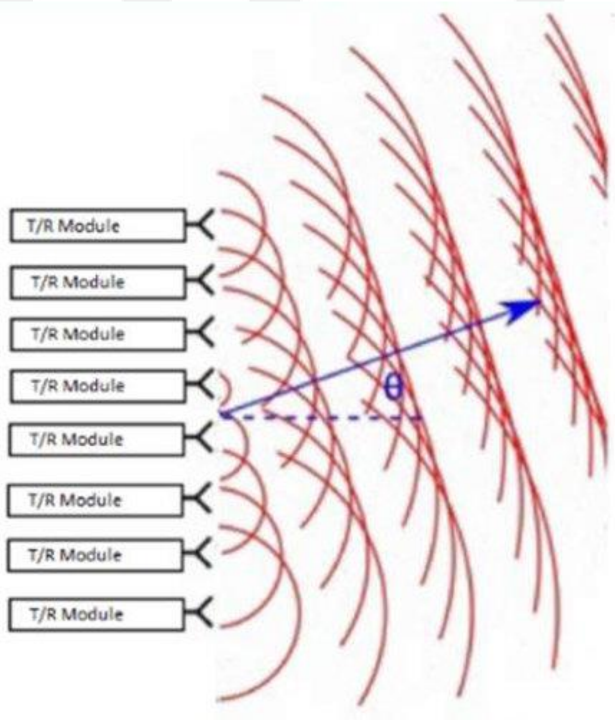

Figure 1.1: AESA radar architecture demonstrates multiple T/R modules transmitting electromagnetic radiation at a specified angle (θ), with red hemispherical lines indicating the direction of this radiation [19].

Other important AESA radar advantages are high reliability, fast beam steering, and reduced maintenance costs, coupled with small size. With the mentioned advantages, AESA radars have widely been adopted in modern air and naval defense systems. Academic research is focused on the further improvement of performance for these advanced radar architectures and the expansion of their various applications.

Active Electronically Scanned Array Radars (AESA) are highly resistant to jamming due to their ability to detect and adapt to jamming signals instantly. These radar systems can operate in harsh environments such as high temperatures and extreme weather conditions. Thanks to the advantages of solid-state technology, they have a longer lifetime and require less maintenance than PESA radars.

Overall, AESA radars have advanced radar capabilities that make a big impact in the military and aerospace fields. They offer better performance in the airborne and naval platforms for strategic advantages. AESA, with enhanced detection, tracking, and jamming resistance, plays some very key roles in modern defense and security systems. This is one of the major reasons why they have innumerable applications in the defense industry and in civil aviation.

1.2.2. Radar range profiles

Range profiles are the range-dependent representations of the reflection levels obtained parallel to the radar system LOS to the target. The principle behind these profiles is that reflections from scatterers on the target are detected by the transmitter-receiver radar system. Basically, each scatterer position projected on the target in the range profile is related to the times it takes for a reflected signal from that position to reach the radar system. Range profiles thus contain information about the relative position of the target with respect to the radar system and the physical characteristics of the target, which will be useful in the application of automatic target recognition and classification. Therefore, range profiles represent very important target information in radar technologies.

Using the example of an aircraft, the meaning of the range profile physically is analyzed as shown in **Figure 1.2**. The aim is to clarify how the range profile is formed and what information it carries by analyzing the spatial and temporal distribution of the backscattered waves reaching the radar receiver. When the radar waveform approaches the target, some of it is reflected back from different points on the target, called "scattering centers". These scattering centers may consist of various components such as the cockpit, engines, wings, tail, etc., and each has a different distance relative to the radar. This causes the return waves to reach the radar at different times. Of course, it will not be possible to resolve scattering centers at the same range using the range profile concept, since they appear in the same range box (or time position). In radar, the range profile is also referred to in the literature as the "radar signature" because the returning waveform is unique for a given target, since the returning waveform is unique in that different targets provide different range profiles.

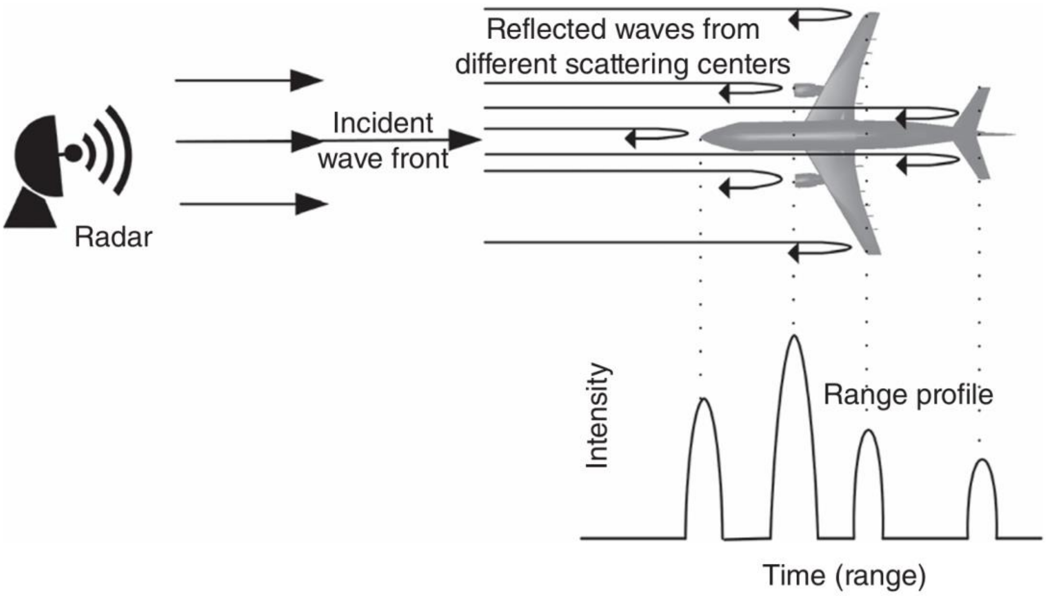

Figure 1.2: A target's range profile as acquired by a wideband radar system [20].

Radar range profile analysis plays an important role in radar system performance evaluation, target detection probability calculation and radar system design. Accurate modelling and understanding of the radar range profile is critical to improve the effectiveness of radar systems and optimize target detection capabilities.

1.2.3. Machine learning for object classification

The limited capacity of the human mind is insufficient to make sense of data as the variety and volume of data increases. Traditionally, human beings have analyzed data according to characteristics such as color, shape, smell, weight and length, and have been able to distinguish them by tracking changes. However, this method relies on the limits of human analysis as the complexity.

The variety of quantitative and qualitative characteristics of the data exceeds human analytical abilities and causes written rules and analyses to be incomplete. At this point, there is a need for systems that can automatically analyze changes in data without the need for human intervention. These systems can capture the essence of the data and detect changes by using machine learning technologies.

Machine learning is a technology that can penetrate deep into data and discover complex relationships without the need for human intervention. This technology opens new horizons in data analysis by exceeding human analytical limits. Machine learning can allow extracting meaningful information from large sets of data, making predictions, and detecting patterns in them.

In machine learning, classification is one of the most popular and hugely useful methods. It is a process that takes in data in certain specified categories, does an analysis, and then allots a correct label to each category every data falls into. This process consists of recognizing, categorizing, understanding and labelling the data.

After the completion of data preprocessing and cleaning phases, the most important step would be to choose a proper machine learning model that best fits the problem and characteristics of the dataset. This stage will turn out to be very critical for the success of the AI project, since correct model selection impacts the accuracy of results obtained and overall model performance.

1.2.3.1. Artificial neural networks

Artificial Neural Networks (ANN) are an artificial intelligence method inspired by biological nervous systems and used in solving many complex problems. The cores of the series have simple, interconnected processing units like artificial neurons. ANNs are used to learn from a specific output with regard to a given set of inputs, and the process is usually referred to as "learning" or "training.". Normally, the learning process is run on very large datasets, and the weights are adjusted according to a specific optimization algorithm. **Figure 1.3** illustrates the architecture of biological brain networks. The layered structure of artificial neural networks and the connections between neurons are shown in **Figure 1.4**. The neural network training process flowchart is simply shown in **Figure 1.5** as illustrated. As a result, ANNs gain the ability to make accurate predictions to new data samples.

Artificial neural networks have their origins in work by Warren McCulloch and Walter Pitts around the 1940s when they tried to express mathematically the working principles of neurons in the human brain. McCulloch and Pitts showed that nerve cells could be modeled by simple nonlinear functions and proved these models could perform basic computer operations. In the 1950s, Frank Rosenblatt worked out the first practical artificial neural network algorithm: Perceptron, which was a single layer neural network model. The Perceptron is a very simple learning algorithm used to solve classification problems. Today, it comprises the bases of the now more complex artificial neural network models.

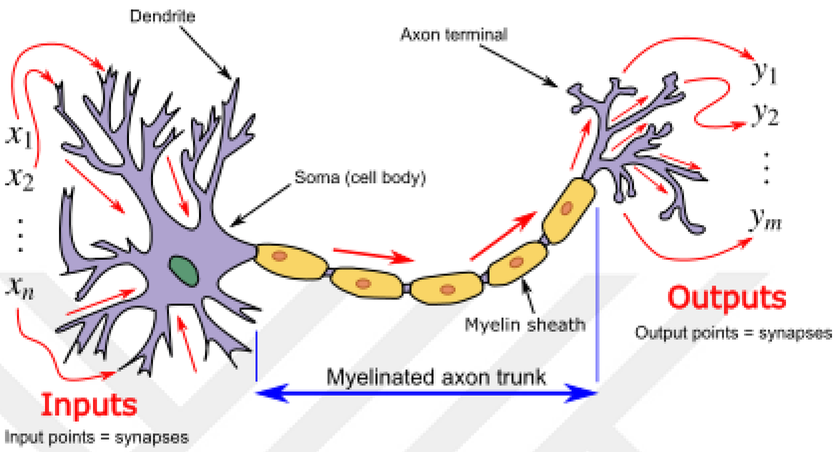

Figure 1.3: The neuron and myelinated axon function by transmitting signals from the dendrites to the axon terminals. Neural communication takes place in the form of sudden electrical fluctuations through action potentials, also known as 'spikes' [21].

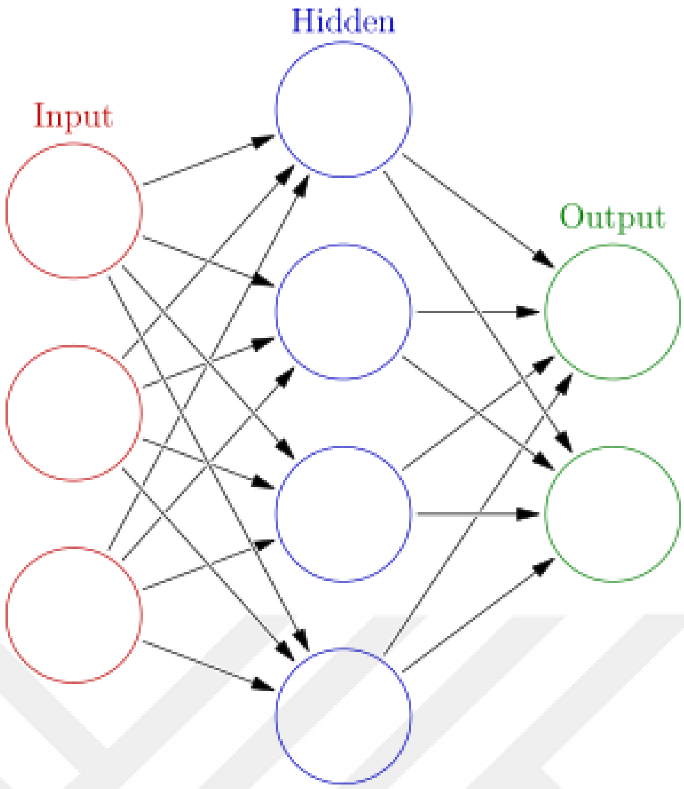

Figure 1.4: Neural network model with color-coded layer structure [22].

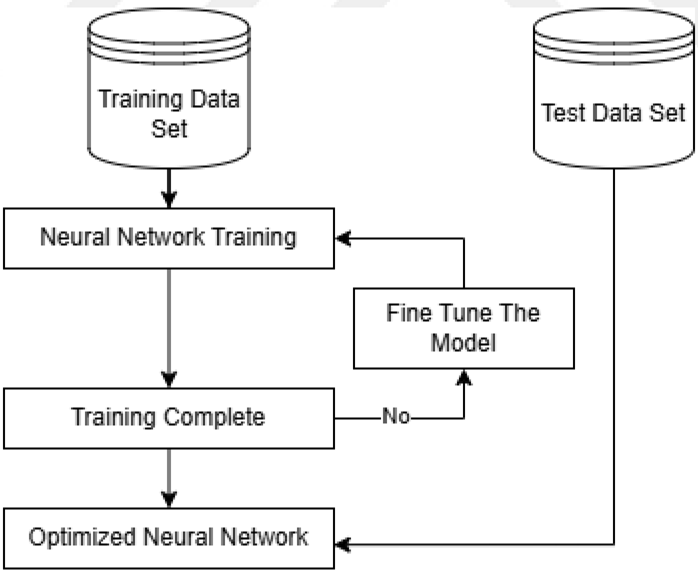

Figure 1.5: Basically, neural network training flowchart.

Important developments in artificial neural networks took place in the 1980s and 1990s. It was during this period that multilayer perceptrons along with the back-propagation algorithm gave the neural network the "strength" to solve complex problems. Back propagation is the process of adjustment of weights of the network by back propagation of the errors, hence enabling one to train deeper and more complex networks. Since the

2000s, when large data sets and high computing power became available, ANNs with more than two hidden layers are popular under the name deep learning. Deep learning spawned quite extraordinary successes in image recognition, natural language processing, and game playing. These accomplishments paved the way for the general usage of ANNs in many fields today.

Application areas of artificial neural networks in the present day are inducing revolutionary changes in a wide array of sectors, including but not limited to health, finance, automotive, and entertainment. ANNs have been applied in the health sector in areas such as cancer diagnosis within medical image processing systems and genetic analyses for disease risk prediction, plus in the construction of individually-tailored treatment plans for patients by analyzing their data. ANNs play important roles in the financial sector, including stock forecasting, fraud detection, and using algorithmic trading strategies. Deep learning capabilities of ANNs are utilized in developing autonomous vehicles for the automotive industry. In the entertainment industry, ANNs are applied in recommendation systems, audio, and image processing technologies, and game artificial intelligence.

Other important milestones in this development process of Artificial Neural Networks include works by different researchers like Geoffrey Hinton, Yann LeCun, and Yoshua Bengio. In 2006, deep belief networks, which really opened the doors to deep learning, were first introduced by Hinton and his team members. One more pioneer was Yann LeCun, whose works on Convolutional Neural Networks brought outstanding results in image recognition and processing. Bengio's contributions are marked by the advancement of optimization in deep learning algorithms and natural language processing. For their contributions in the domain of artificial neural networks and deep learning, these researchers have been awarded the Turing Prize in 2018.

In recent years, transfer learning, generative adversarial networks (GAN), and natural language processing models have enabled more advanced applications of artificial neural networks. Transfer learning allows for fine-tuning a model trained for one task to then be used for another task, hence high performance with limited data. On the other hand, GANs are such an ingenious approach wherein two networks are pitted against each other, hence yielding realistic data generation. In the event of the last decade, more so in the preceding years, a few developments have been done on human-like text generation and language understanding using transformer-based models, particularly the large-scale language models like BERT and GPT-3, in the field of natural language processing. These developments continue to increase the capacity of artificial neural networks to solve some complex problems of great variety, hence helping them qualify at the frontline in future technological developments.

1.2.3.2. Convolutional neural networks

Convolutional Neural Networks (CNN) is a kind of neural network which is widely used among deep learning architectures, especially in image and signal processing [23]. CNNs can effectively capture local features in images and use these features in high-level tasks. As a result, they do incredibly well on tasks like object identification, semantic segmentation and image classification.

The basic principle of a CNN is to apply the convolution process for the extraction of local features of the image. The working of the convolution process occurs by applying a filter, which acts upon an image based on the sliding window application principle. This filter will learn features in certain regions of the image. Convolutional layers can use more than one filter in order to learn different attributes of the image. Typically, a CNN architecture will include convolution layers, fully connected layers and pooling layers in succession A simple illustration of a CNN is shown in **Figure 1.6**.

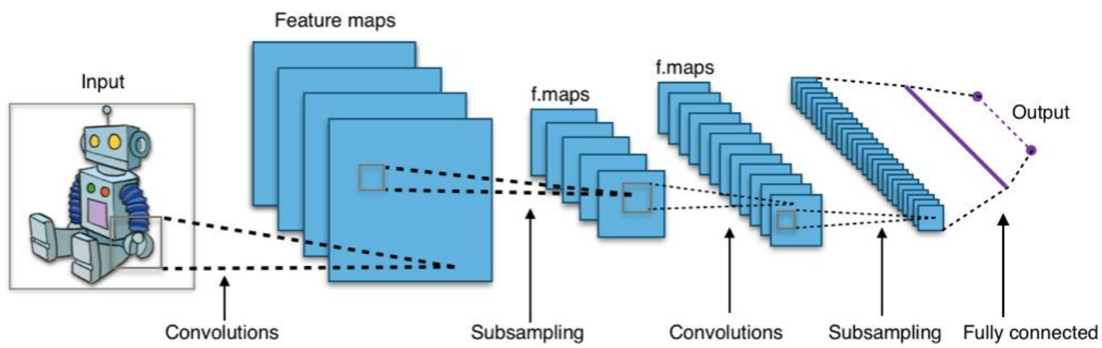

Figure 1.6: Typical Convolutional Neural Network (CNN) architecture [24].

The convolution layers can catch local features of the image. These layers filter on the image according to the principle of the sliding window and each filter learns features in some area of the image. After the convolution layers come the pooling layers, which reduce the feature maps' extent and so reduce computational cost; this enables the network to learn larger regions of the image. Fully connected layers then transform the feature maps back to a vector for final classification or regression tasks.

CNNs are widely used especially in the field of image processing. They can successfully perform many tasks such as image classification, object detection, semantic segmentation, image synthesis and super resolution. In addition, CNNs are also used in other fields such as audio processing, natural language processing and bioinformatics. The ability of CNNs to capture local features is very useful in feature extraction of data in these areas.

1.2.3.3. Residual neural network

Properly designed convolutional neural networks can efficiently capture local features extracted from any images and hence have reached high accuracy rates for image classification, objection detection, etc. Increasing the depth of convolutional neural networks can further enhance the performance of the network. However, increasing the depth brings about the problem of difficulty in training the network. To this regard, Residual Network was proposed [25]. ResNet adds a connection type called "skip connection" to Convolutional Neural Networks, solving optimization problems arising from depth. **Figure 1.7** shows a residual block in a deep residual network. With ResNet's strong positive bias weights, it behaves like an unfolding motorway network. It allows deep learning models with hundreds of layers to be easily trained and approach better accuracy as they go deeper.

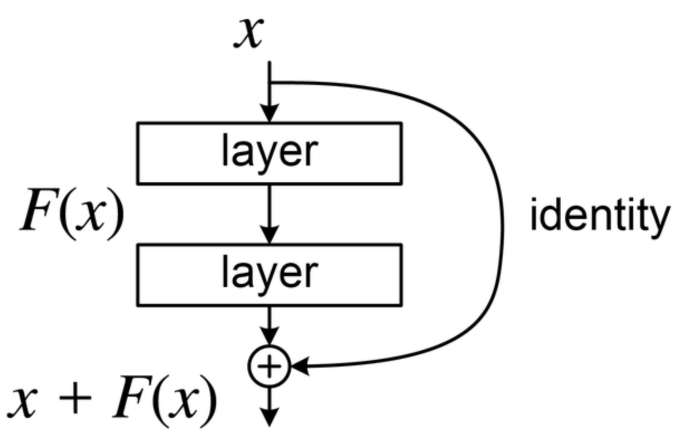

Figure 1.7: A basic building block used in Deep Residual Networks is the Residual Block. This block contains a residual link that bypasses two sequential layers [26].

1.3. Contributions to Literature

In this thesis, a simulator based on Active Electronically Scanned Array (AESA) radar architecture is used to create a realistic radar simulation environment. The simulator is capable of generating High Resolution Range Profile (HRRP) data for a total of 10 targets belonging to different categories. In this way, the performance of the developed target recognition algorithms can be evaluated on a diverse and comprehensive dataset representing real-world scenarios.

Two different target models were used for each target category in the study and thousands of HRRP data were generated for each target model under different angle, distance and noise conditions. Thus, the diversity of the data set was increased and it was aimed to increase the generalization ability of the deep learning model to be used in later stages.

While automatic target detection is performed from high-resolution range profiles, in military operations, it is of operational importance to determine the possible viewpoint of the detected target due to its position relative to the radar. In order to obtain information about the target's viewpoint, segment detection models were trained separately for each target class and the outputs of these models were analyzed using template matching techniques. Thus, as a result of the processing of data obtained from radar images, the possible horizontal viewpoint of the target with respect to the radar can be determined. This approach provides more detailed information about the targets in operational planning and execution processes and provides critical input to decision makers.

Using the generated HRRP data, a Convolutional Neural Network (CNN) architecture is trained. CNNs show very successful performance especially in image processing and object recognition problems. The designed CNN architecture aims to accurately classify and detect the targets in the test data by learning the patterns in the HRRP data. During the training phase, some of the data set was used to train the model, while the remaining part was reserved for testing purposes.

After the training was completed, the performance of the CNN model was evaluated on the test data set. At this stage, the success of the model in accurately classifying the targets was analyzed using criteria such as classification accuracy, sensitivity and precision. In addition, the effects of different noise conditions and angle/distance variations on the model performance were also analyzed. Thus, this thesis aims to develop an effective target detection and classification system by combining AESA radar technology and deep learning approaches.

The pioneering nature of this thesis and the new perspectives it brings to the literature can be summarized as follows:

- High Resolution Range Profile (HRRP) data were generated using a simulator based on the Active Electronically Scanned Array (AESA) radar architecture.
- A total of 10 target models in 5 different categories were used and a large data set was created for each target model. In this way, the generalization capability of the trained model was increased and it was aimed to successfully detect different target types.
- The performance of the trained Convolutional Neural Network (CNN) model was tested under different noise conditions and angle/distance variations.
- A new method is proposed to estimate the viewpoint of targets from radar signals. The proposed method uses a segment detection model and a template matching technique to determine the possible horizontal viewpoint of the target with respect to the radar

CHAPTER 2

2. THEORETICAL PART

Nowadays, aircraft radars form an important part of aerospace and defense. In particular, ground target classification and estimation of their orientation angles are of high significance for strategic decision making. This corresponding capability of aircraft radars has been increasingly utilized not only in military operations but also in a host of civilian applications. Modern airborne radar systems can detect, track, and classify ground target motion and simultaneously process this information for presentation to the operator. All of this actually starts with the processing of radar signal returns that get reflected from targets, and sophisticated algorithms are used to extract precise information about the type and orientation of targets. The objective of the study is the review of existing methods for classification and orientation estimation of ground targets by aircraft radars and an evaluation of state-of-the-art approaches in this area.

While classical radars were capable of detecting only the presence and placing of objects on the ground, modern radar technologies together with AI-supported algorithms give the capability of identifying the type and even orientation of targets. Basically, such radar systems scan targets by using radio waves and then analyze the frequency, phase, and amplitude characteristics of the signals that reflected from the targets. For instance, Doppler shifts in radar echoes may provide information for speed and orientation estimation of moving targets. It can be combined with classification algorithms to classify the target as either a vehicle, building, or another object. More specifically, this study will review the deep learning methods applied in the processing of radar signals and analyze how they have an impact on the accurate classification and orientation estimation of ground targets. These will lead to more accurate and reliable future radar systems.

In the sub-sections, data generation, high-resolution range profile and target recognition methods and related concepts will be analyzed in detail. Details of the theoretical foundations, mathematical models and algorithms will be presented, and application examples will reinforce the topics.

2.1. Generating Range Profiles of Radar Targets

The physical representation of the range profile makes more sense when it is presented as a function of range or distance rather than of time. This can also be represented so that the range axis more or less coincides with the X-axis. This will give a more physically descriptive distribution of the signals reflected from the scattering centers of the radar target along the range. This is because it appears that the range profile is the unique radar signature of a given target in range space. This representation will prove to be critical in recognizing and classifying of targets.

The range profile becomes more physically meaningful when it is presented against distance rather than against time. The range axis is then expressed as **(2.1)**;

$$r = c.t \tag{2.1}$$

Where r is range, c is the speed of the electromagnetic (EM) wave and t is the time [18]. For example, suppose a target has K point scatterers along the x-axis and each of these points is located at a different position x_i. In this case, the backscattered electric field of the far field can be approximately expressed as the vector sum of the reflected contributions from each point target:

$$E^S(f) \cong \sum_{i=1}^{K} A_i \cdot \exp(-j2k \cdot x_i) = \sum_{i=1}^{K} A_i \cdot \exp\left(-j2\pi\left(\frac{2f}{c}\right) \cdot x_i\right) \tag{2.2}$$

In **(2.2)**, c represents the speed of light, A_i is the backscattered field amplitude of the point scattered at point x_i and $k = 2\pi f/c$ is the corresponding wave number for frequency f. The exponential number "2" describes the bidirectional propagation between radar and point scatterers. Under the assumption that the backscattered field is collected in the far field along the -x direction and that the phase center of the scene is taken as x = 0, the sign of the argument of the exponential term must agree with the sign of the x_i points [18]. In line with this approach, the range profile can be obtained by taking the inverse Fourier transform (IFT) of the frequency diversity field with respect to $((2f/c := \alpha))$, as shown in **(2.3)**;

$$E^S(x) = \mathcal{F}_\alpha^{-1}\{E_s(f)\} = \int_{-\infty}^{\infty}\left[\sum_{i=1}^{K} A_i \cdot \exp(-j2\pi\alpha \cdot x_i)\right]\exp(j2\pi\alpha \cdot x)\, d\alpha \qquad \textbf{(2.3)}$$

In **(2.3)**, $\mathcal{F}_\alpha^{-1}$ denotes the inverse Fourier transform (IFT) operation with respect to the variable α. In the equation given above, both the summing and integral operators are linear; therefore, they can be substituted as follows;

$$E^S(x) = \sum_{i=1}^{K} A_i \cdot \int_{-\infty}^{\infty}\exp\big(j2\pi\alpha \cdot (x - x_i)\big)\, d\alpha \qquad \textbf{(2.4)}$$

The integral in **(2.4)** then becomes the $\delta(\cdot)$ pulse (or Dirac delta) function, as shown below:

$$E^S(x) = \sum_{i=1}^{K} A_i \cdot \delta(x - x_i) \qquad \textbf{(2.5)}$$

In **(2.5)**, $E^S(x)$ represents the range profile information as a function of distance x. Therefore, point scatterers located at different x_i positions can be precisely positioned on the range axis by means of their respective backscattering amplitudes A_i [20].

In order to generate high-resolution range profiles, the RASES software will be utilized, which will be described in detail in the following sections.

2.1.1. Radar target signature estimation software

Nowadays, considering the advancement of technologies, the detectability of the platforms by any electromagnetic scanning device is considered as one of the vital attributes. In this context, Radar Cross Section estimation acts as the critical parameter for estimating the extent to which a platform reflects radar signals and hence, the ease by which a platform can be detected using radar. One of the most important tools in this area of study is the RASES software, developed by TÜBİTAK, which performs the required calculations [27].

RASES has implemented three approaches for RCS calculation: physical optics, bounced ray and physical diffraction methods. The physical optics technique models the reflection and refraction of an electromagnetic wave from surfaces and is customarily used, relatively speaking, in the analysis of smooth surfaces. The ricochet beam method, which assumes the reflection of the electromagnetic waves from surfaces corresponds to the reflection of light rays, is very useful in analysis related to angular and irregular surfaces.

Diffractions from edges and corners are considered in quite the same way under the physical diffraction method. Thus, RCS calculation has been implemented in the three methods, and complex geometry of platforms can be taken into account by software. It will bring to the fore the detectability of the platform from radar systems and take necessary precautions. Since this kind of software is very important in areas such as the defense industry, aviation, and space technologies, it plays a big role in the design process and optimization of platforms.

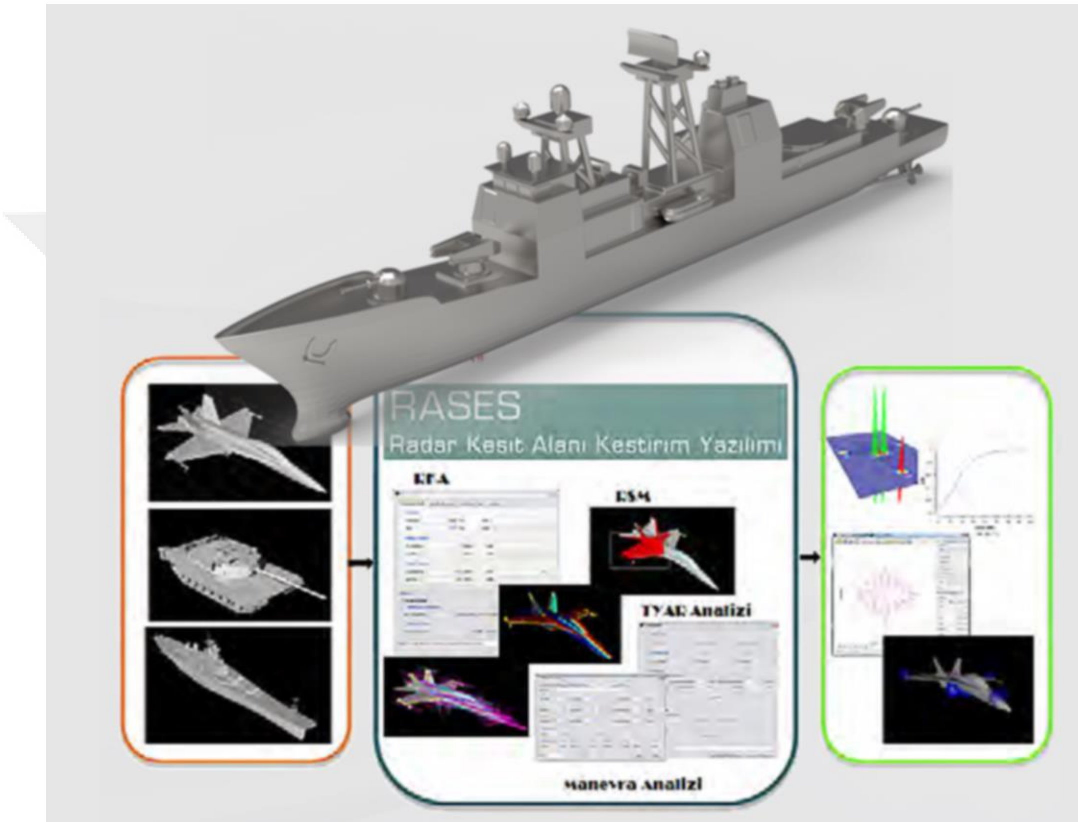

Figure 2.1: RASES Software GUI [27].

RASES can calculate the RCS of platforms covered with various materials, not only limited to the shape of the platform. The important competences offered by RASES are as follows:

- High frequency Radar Cross Section (RCS) calculation of platforms: RASES can calculate the RCS of platforms with high accuracy using electromagnetic simulation techniques. These calculations can be performed at different frequencies and from different viewpoints.
- RCS calculation of platforms covered with various materials: RASES can calculate the RCS not only by taking into account the shape of the platforms, but

also the effect of the materials covering them on the RCS. This feature makes it possible to perform realistic and reliable RCS calculations.

- Determination of forward and cross range profiles: RASES can calculate the RCS of platforms not only from a single point, but also from different distances and angles. This provides detailed information about the RCS profiles of the platforms and how they are detected by the radar.

These features are effectively used in RCS analyses for estimating and optimizing the electromagnetic visibility of the platform.

High-resolution radar range profile generation is an important process in developing radar systems, as well as in target detection improvement. Basically, a process using RASES software undergoes three steps. On the first step, a detailed 3D model of the target has to be input into the software. The electromagnetic scattering characteristics are then calculated for this model. Again, numerical electromagnetic techniques, such as the Method of Moments or Physical Optics, can be used here. Finally, in the last step, the computed data of the electromagnetic scattering is used to formulate a radar range profile, which essentially provides the distribution of a radar cross-section of the target along the dimension of range. This methodology enables realist radar range profiles to be generated and provides useful data for the design of radar systems, target identification algorithms, and electronic warfare applications. The steps are represented in **Figure 2.2**.

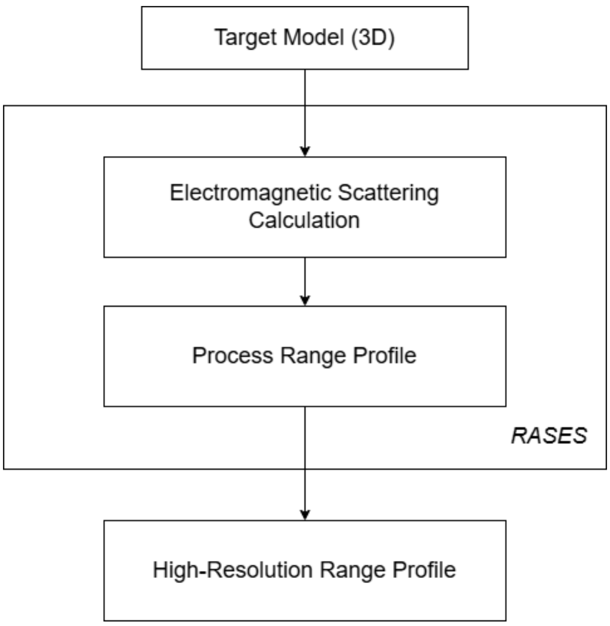

Figure 2.2: Structure of the target classification.

2.2. A Deep Learning Based Approach for Air-to-Ground Target Classification

Air-to-ground target classification is a difficult task both in military and civilian realms. The data that has been gathered by unmanned aerial vehicles, reconnaissance aircraft, and other aerial sensors would require proper identification of potential threats or targets. It is postulated that traditional machine learning methods are less successful when processing and classifying complex data. For this purpose, this study introduces a novel approach for air-to-ground target classification, which is a deep learning methodology. Deep neural network models are capable of learning complex patterns from large volumes of data automatically and generalizing well. This study proposes a deep learning-based approach that enables accurate type and horizontal orientation angle prediction for air-to-ground targets.

The approach proposed in this study consists of three steps as shown in **Figure 2.4**. In the first phase, the deep learning-based main model classifier takes the targets' profile data as input. This classifier consists of and ResNet architectures shown in **Figure 2.3**. The CNN architecture provides the ideal structure for learning and features extraction, while ResNet architecture gives an upper performance since it resolves the problems faced during training in the deep networks. At this step, the base model classifier is able to identify different types of targets (e.g., aircraft, helicopter, unmanned aerial vehicle, etc.) with high accuracy.

In the second step, the types of targets detected by the main model classifier are then passed on to sub-classifier networks specifically designed to predict horizontal orientation angles of targets. The sub-classifier networks are all optimized for one target type or another and can predict horizontal orientation angles of targets with quite high accuracy. This will lead to the follow-up objective of generating a customized prediction model for each target type, on the basis that various target types could possess different geometrical characteristics.

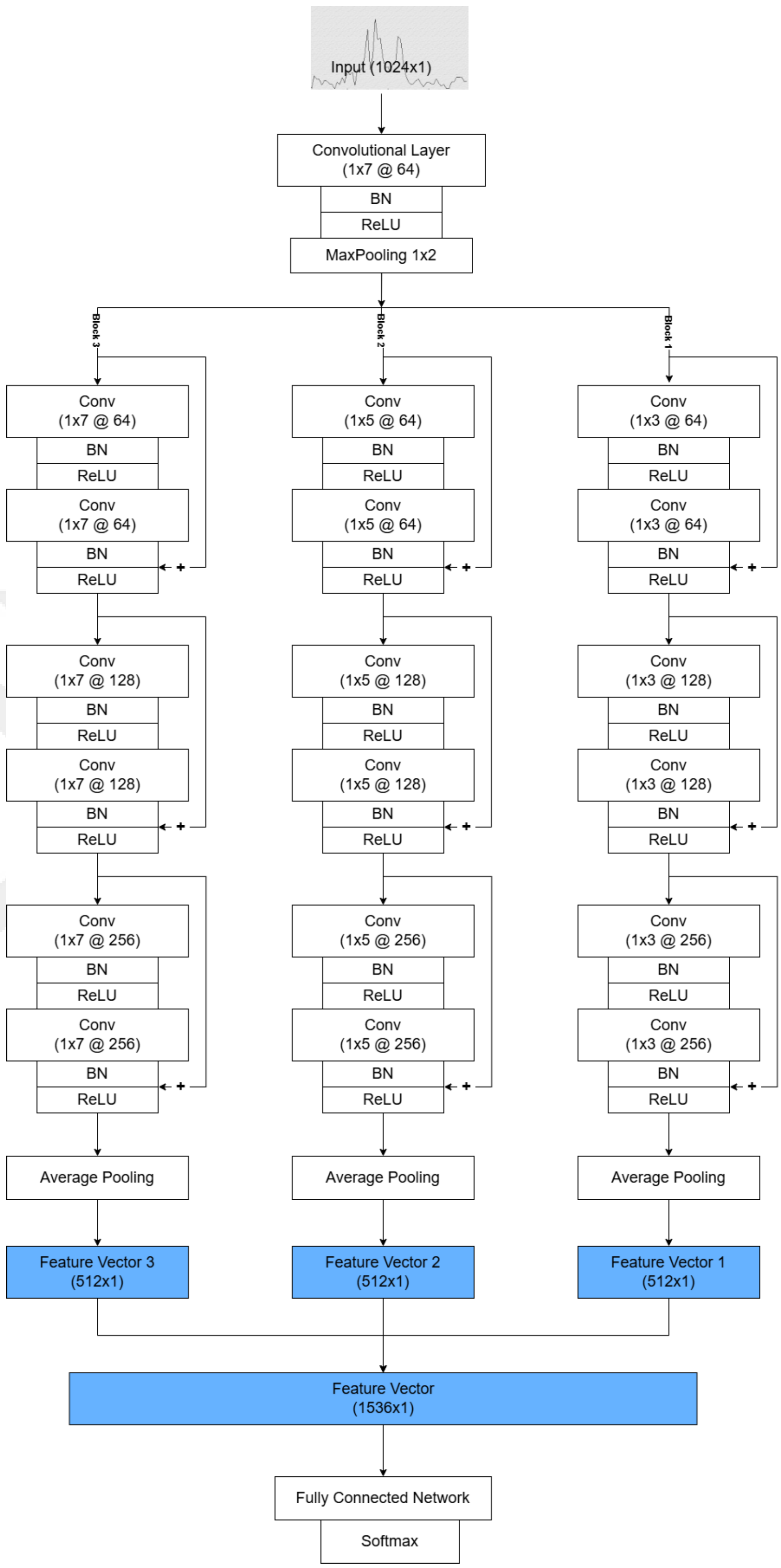

Figure 2.3: Structure of the target classification network. The architecture consists of three sequential convolutional neural network blocks with different kernel sizes (1×3, 1×5 and 1×7). In each CNN sub-block, a residual learning mechanism is implemented to reduce the overlearning problem.

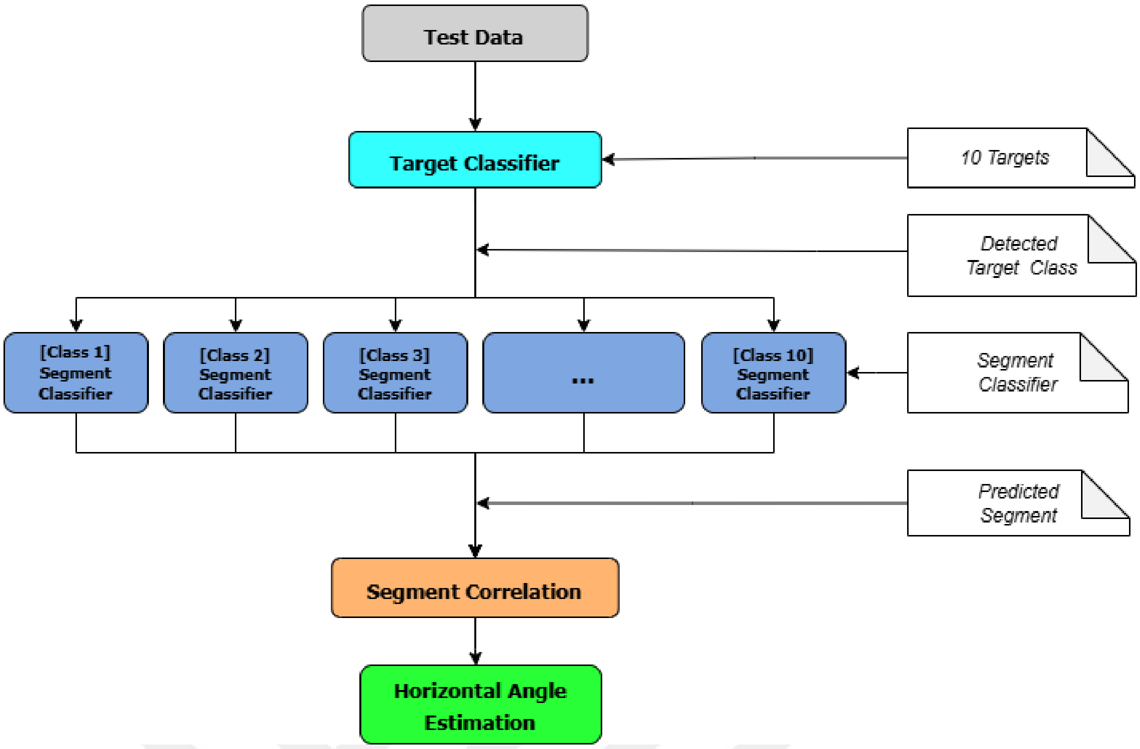

Figure 2.4: Estimation of horizontal orientation angles together with the class of targets

The final step combines the results of the prediction by the main model classifier and subclassifier networks with respect to estimating both the type and horizontal orientation angles of the targets. Therefore, the defense system will know what the targets are and in which direction they are moving to take necessary measures.

The proposed approach provides an innovative solution to the problems of air-to-ground target classification and orientation estimation by utilizing the power of deep learning. This approach can increase the effectiveness of defense systems, enabling faster and more accurate responses to threats.

2.2.1. Architecture of deep learning model

Traditional approaches are based on hand-crafted features with shallow-learning algorithms, whereas deep learning models, particularly convolutional neural networks, have recently achieved very promising results in this field. In this study, a residual network and a multiscale kernel-based CNN architecture are used for target classification from high-resolution range profiles.

Basically, this work presents the use of an artificial neural network architecture to classify the target from high-resolution radar range profiles. This model has been created using three major blocks (Block1, Block2, Block3) each using multi-scale convolutional layers so as to capture features at different scales. Each block is thus composed of convolutional layers with kernels of different sizes, Batch Normalization layers, ReLU activation functions, and residual connections. The input to the model is a radar range profile of size 1x1024. In these models, the first layer is a convolutional layer with 64 kernels of size 1x7 followed by BN, ReLU, and a maximum pooling layer of size 1x2. Since local and global features are powerful in understanding complex target signatures, this structure helps the network learn them effectively. In addition, the residual connections enable the network to be deeper without degradation of performance in learning more complex features.

One convolutional block is an architectural unit, built by a combination of convolutional layers with three different core sizes: 1x3, 1x5, and 1x7. All these core sizes are used to extract features at different scales. Additionally, they use these cores in conjunction with different expansion factors to perceive different frequency components. Each convolutional layer is followed by batch normalization with BN and a nonlinear activation function, which is a ReLU.

Another important component in the architecture is the residual connections. This adds the input of a convolution block to its output whereby the network can go deeper while learning more complex features without degradation in performance. The redundant connections accelerate the training of the network by making the back residual of gradients easier.

Finally, the network is end with a fully connected network where the output from the three convolution blocks is combined before being fed into a softmax layer. This means that the output from the network will be a softmax output representing a probability distribution for each of the target classes, thus enabling the network to make a prediction of the most likely class.

The architecture has demonstrated good performance in the task of target classification from high-resolution range profiles, due to its modular architecture, which makes it easily adaptable for different datasets and tasks. Besides, the multiscale cores and residual links provide the network with the ability to learn complicated target signatures. Proposed architecture has huge potential to improve performance of high-resolution systems in enhancing situation awareness in different applications.

2.2.2. Horizontal angle estimation with segment classification

In this part of the thesis, we will explain step-by-step how the target class identification, segmentation and horizontal angle estimation are performed. This process is designed to ensure accurate target classification and precise angle estimation on a segment-by-segment basis. The steps of determining the class of a particular target, applying the segment detection model and then using the segment data will be discussed in detail in this chapter.

In the first step, a target classifier is used to determine whether each target belongs to a particular class. By analyzing various features and data samples, the classifier determines which class the target belongs to with high accuracy. This is an important step where classification algorithms and machine learning techniques are used. The classification process is critical for the accurate processing of the target in the subsequent segment detection and horizontal angle estimation steps.

After the classification process is completed, the segment detection model of the detected target class is activated. The segmentation representation is shown in **Figure 2.5**. The segment interval is set as 20 degrees for each target and each segment is separated by N = 10 degrees. This segmentation is necessary for a more precise determination of the horizontal angle of the target. The segment detection model expresses the probability values in which segment the target is located and these probability values are used to estimate the horizontal angle of the target more accurately.

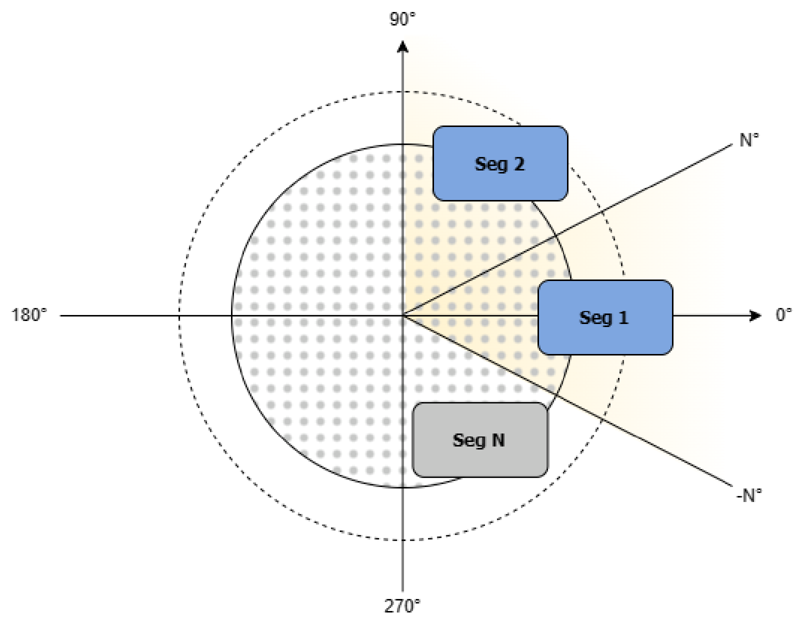

Figure 2.5: An illustration of dividing the horizontal axis into segments

Once the probability values obtained from the segment detection model have determined the probable segment of the target, a template matching technique is used to obtain a more accurate angle determination. Template matching aims to determine the true horizontal angle of the target with high accuracy by analyzing all data within a given segment. This technique attempts to determine the most probable angle of the target by measuring the correlation between the data. Correlation-based template matching provides high accuracy, especially with noisy data, and is an effective method to determine the true position of the target.

The implementation of the above-mentioned steps has led to significant success in the target classification and segment detection processes. Experiments and tests have shown that this method provides high accuracy rates in accurately classifying targets and accurately estimating their horizontal angles. Setting the segment range as 20 degrees and using the segment detection model and template matching technique together provided significant advantages in determining the horizontal angles of the targets.

CHAPTER 3

3. EXPERIMENTAL WORKS

In this chapter, experimental studies on target classification and horizontal angle estimation using deep learning models from high-resolution radar range profiles will be discussed in detail. The main objective of the study is to evaluate the effectiveness of deep learning techniques to improve the target recognition and positioning capabilities of advanced radar systems. In this context, radar range profile data for 10 different targets were generated using a specially designed simulator to obtain realistic radar data.

The experimental process includes data generation, data preprocessing, training and evaluation phases. The deep learning model used was aimed to perform in both target classification and horizontal angle estimation tasks. In this section, the data set, training strategies and performance metrics used will be explained in detail and the results obtained will be analyzed comprehensively.

3.1. Range Profile Data Validation

The validation of the data is always an important step in the data processing or analysis steps. Especially in applications like high resolution range profiling, it is extremely important that the returned data are accurate. Ambiguous or vague information can result in improper decision making, ineffective decision making and total-blankets and consequently undesirable effects. That is why it is essential to implement the data validation process that excludes the possibility of obtaining inaccurate data results during the data analysis.

In the present study, test scene was developed in order to ensure the accuracy of the HRRP data generation procedure. Five distinct cube objects were arranged on the X-axis plane to conduct the test scene for the generation of high-resolution range profiles. This artificial environment was created to mimick the real-world conditions and see how the data in the set behaves depending on the distances. Data generation was carried out by looking in parallel to the X-axis and in parallel to the X-axis sideways. A view of this example scene is shown in **Figure 3.1**. This approach allows data to be collected from different angles and vantage points so that the comprehensiveness and consistency of the data can be assessed.

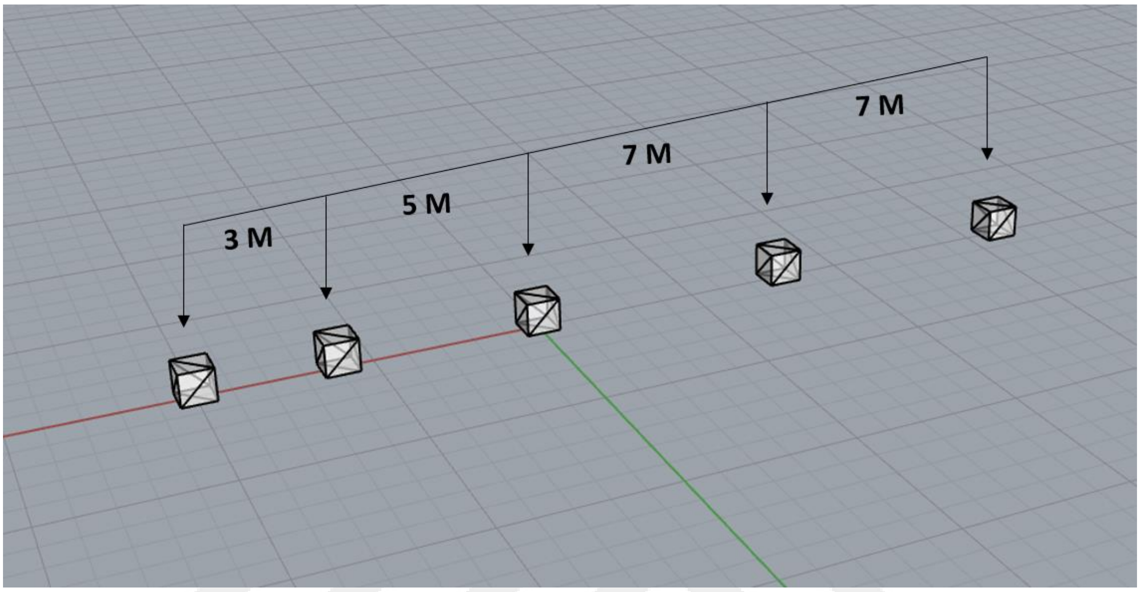

Figure 3.1: Test scene with cube-shaped objects at different distances.

Weak, narrow and sharp is what we would expect to be obtained when the target is facing the radar system from the side. This is because target returns to the radar's coverage area is very small and most of the returns originate from a limited span. The symbolism and structure of the profile along the lateral plan that is comparatively less complicated is eliminated. On the other hand, if the target independently addresses the radar system, the profile becomes less expressed and more even, with a maximum of expressing the amplitude. Since there are reflections from all sides of the target, more detail and structural features are noticed in the profile. In this case the estimates regarding the size and the distribution of the target could be more accurate.

The results of the measurement conducted with the help of the test protocol within our study at different horizontal and vertical angles are provided in details in the following figure of merit, **Figure 3.2**. In this case, it can be appreciated that through this graphical representation it is possible to show the dispersion of the data points in space and how they are associated with the variations of the angular coordinate. One of the most encouraging outcomes of the results is the high resemblance of the values captured at symmetrical points.

However, it can also be observed that this distribution is symmetrical which can be interpreted as a sign of reliable and accurate measurements in the given environment. The variation of measured values from different angle confirms our result and verifies the reliability in our technique of experimentation and measurements.

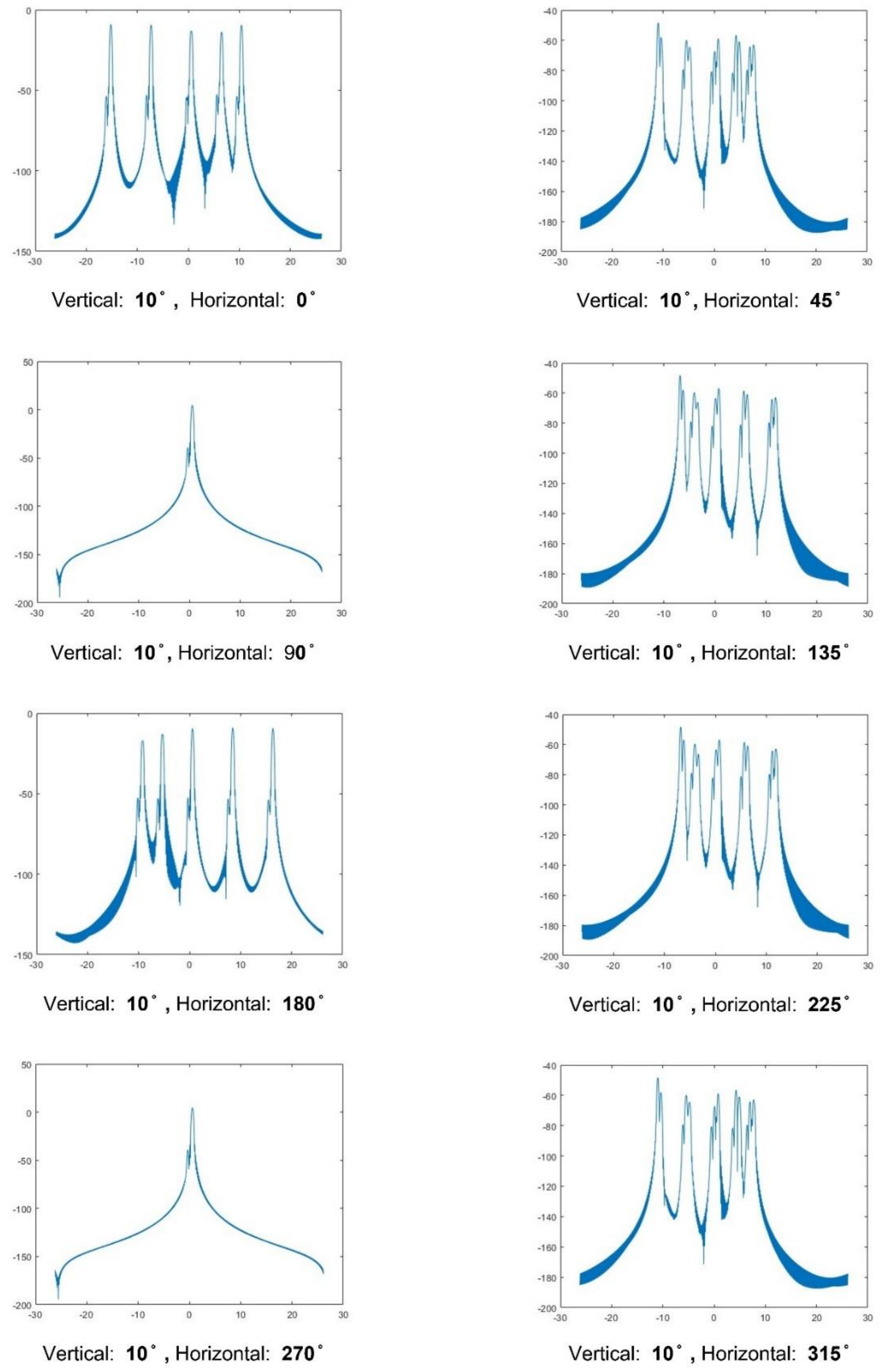

Figure 3.2: The range profile data of the test scene obtained from different horizontal and vertical angles.

3.2. Target Selection and Radar Range Profile Data Set Generation Process

In the creation of the dataset, five different categories were chosen, considering the most common targets that are usually encountered in military applications: helicopter, tank, military land vehicle, truck, and military building. The bottom line for the choice of these categories is to have data that is varied and closest to real-world scenarios.

For each type, two different 3D models have been selected, which can best demonstrate what that type is. These models have specifically been handpicked to reflect the characteristics of their categories very nicely. There were models of rotors of different configuration for helicopters, with various armor and weapon systems models for tanks, models with varying mobility and protection levels for military land vehicles, those having different load capacity and design features for trucks, and, in the case of military buildings, models with different structural designs and materials.

Range profile data for the selected 3D models were generated using the RASES software. The RASES software simulates target recognition and tracking functions for radar systems and makes an overview of the range profiles for various targets. This software calculates reflections and returns of radar signals on targets; hence, we are able to get the range profiles of each target.

This generated dataset is a rich resource in terms of using it to train machine and deep learning algorithms. These data can be used to improve target detection and classification systems, primarily ATR systems. This dataset can even further be utilized to establish a benchmark in the performance of various sensor systems.

Thus, the dataset developed within the framework of this work contains range profile information obtained using 3D models and RASES software for five types of military objectives. Thus, the work provides a detailed set of data capable of becoming the basis for further research in the field of military target detection and classification. In future researches, the collection of the target categories and environment conditions should be increased to enhance the future military target detection systems. Rendered images of the 3D models used are given in **Figure 3.3** and some generated range profile data given in **Figure 3.4** and **Figure 3.5**.

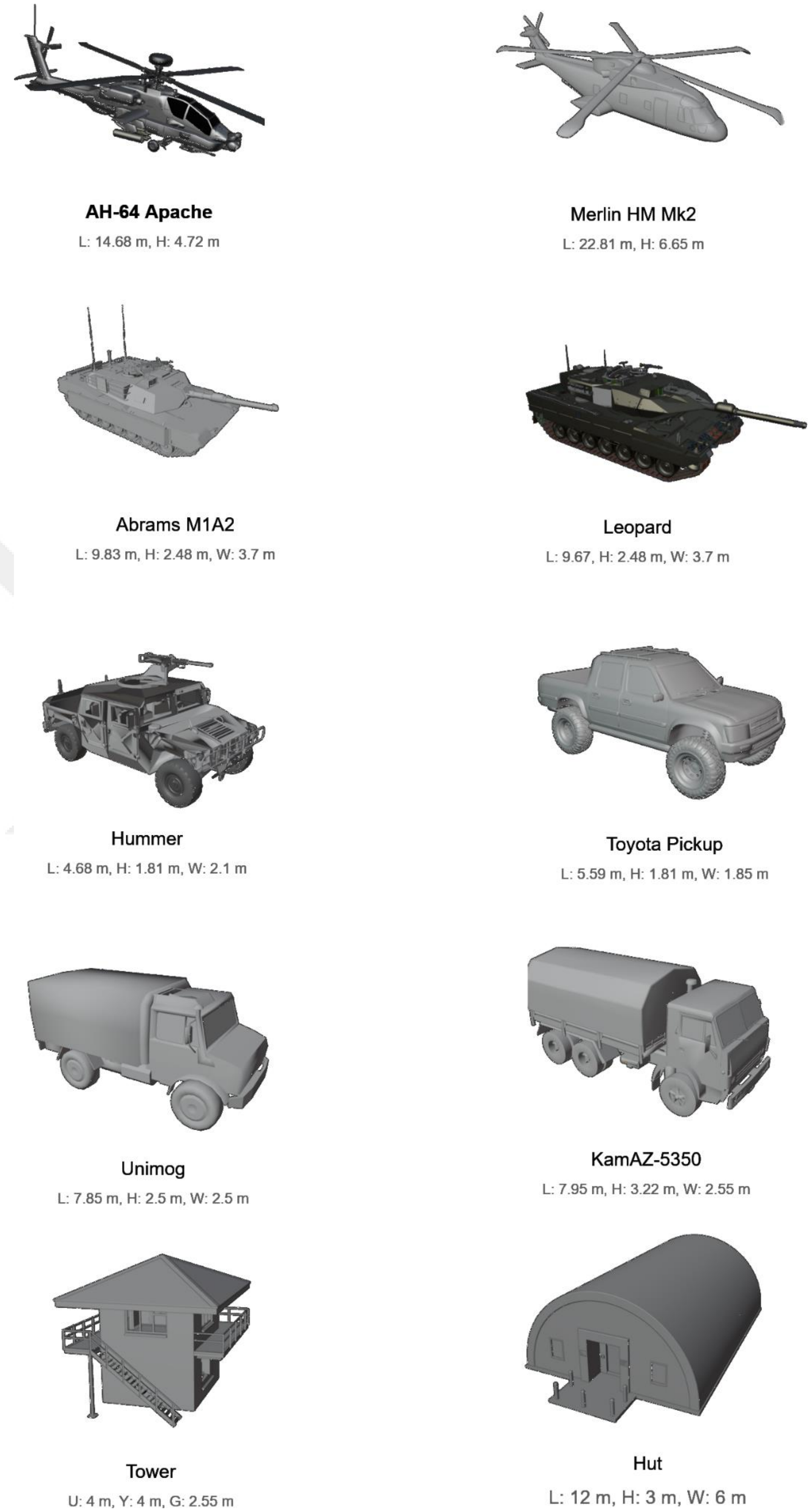

Figure 3.3: Display of 3D models selected to generate the dataset.

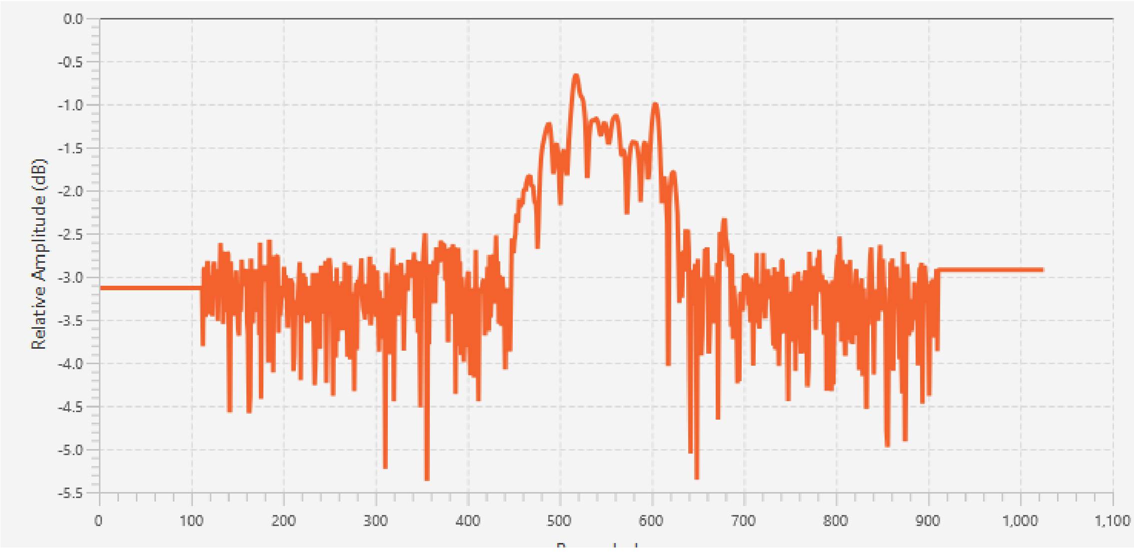

Figure 3.4: Range profile data generated for AH64 helicopter model at 116° horizontally and 10° vertically angle.

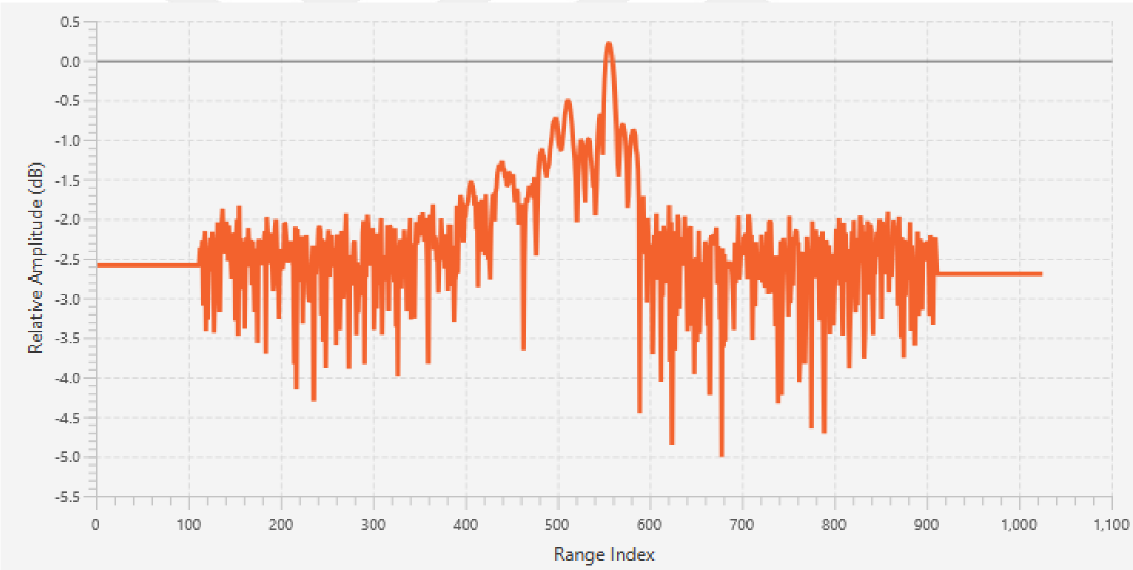

Figure 3.5: Range profile data generated for Leopard tank model at 246° horizontally and 5° vertically angle.

3.3. Reproduction of Data with Different Noise Levels

The dataset was created by duplicating the Range Profile data at several instances of Signal-to-Noise Ratio. SNR of 1 dB, 5 dB, 10 dB, 15 dB, 20 dB, 25 dB and 30 dB were selected. SNR is the ratio between the power of radar signal to that of noise, which affects the performance of radar systems. The low values of SNR represent the case when the signal is weak in comparison with the noise, and high values of SNR represent the domination of the signal over the noise.

Basically, replication of data at different SNR values is done to test the performance of such data on a deep learning network. Deep learning algorithms are capable of identifying and learning complex data-patterns from huge and heterogeneous datasets. This study uses range profile data with different SNR values to quantify performance variations in the deep learning network with respect to noise levels.

The performance of the deep learning network is tested with range profile data obtained at different SNR levels. The performance of the deep learning network for a variety of values of SNR could have a number of important implications. One can answer at which SNR level the model begins to perform acceptably. For example, it has been shown that low levels of SNR—for example, 1 dB and 5 dB—will degrade the performance of the deep learning network in target recognition and tracking, whereas at high levels—in particular, 25 dB and 30 dB—exhibitions show great improvements. At mid-point levels of SNR, such as 10 dB, 15 dB, and 20 dB, gradually improving performances are displayed. On the other hand, one could gauge the performance impact of rising SNR. The gain to be expected from improved hardware or new signal processing techniques could also be estimated.

As a result, the range profile data at different SNR values appear to be very crucial in providing insight into the deep learning algorithms' performance. Second, the architectures of the deep learning networks and data augmentation strategies can significantly improve the radar system's adaptability to real-world situations. It will therefore lead to massive benefits concerning the implementation of radar technology and AI algorithms in military and civil uses.

CHAPTER 4

4. RESULTS AND DISCUSSION

The deep network model developed for the radar range profile is based on a two-stage structure. During this first stage of training, the model returned two major outputs: unique detection of the class and the determination of the category to which the class belongs. This dual output structure will give a fuller and more detailed classification of the radar targets. While unique class detection provides the specific characteristics of the target, category detection informs about the general characteristics of the target. This approach is bound to greatly enhance the target identification potential of radar systems. The show-related outcomes have been discussed in **Section 4.1**.

The second stage of the model focuses on estimating the orientation angle of the target. This part plays an important role when one wants to establish an understanding of the dynamic behavior of radar targets. The estimation of the orientation angle gives very important information with regard to the maneuverability of the target, the direction of movement, and potential intentions if estimated accurately. Results related to this are discussed in **Section 4.2**.

4.1. Target Classification Results at Different SNR Levels

In this section, the effectiveness of target detection performance at various signal-to-noise ratio (SNR) levels will be discussed in detail.

- Results for 1 dB SNR:

When the overall accuracy (55.52%), F1 score (0.5516), recall (0.5544) and precision (0.5514) in this confusion matrix obtained for the SNR 1db dataset are evaluated, we can say that the overall performance of the model is moderate. This indicates that the model performs well in certain classes but struggles in others.

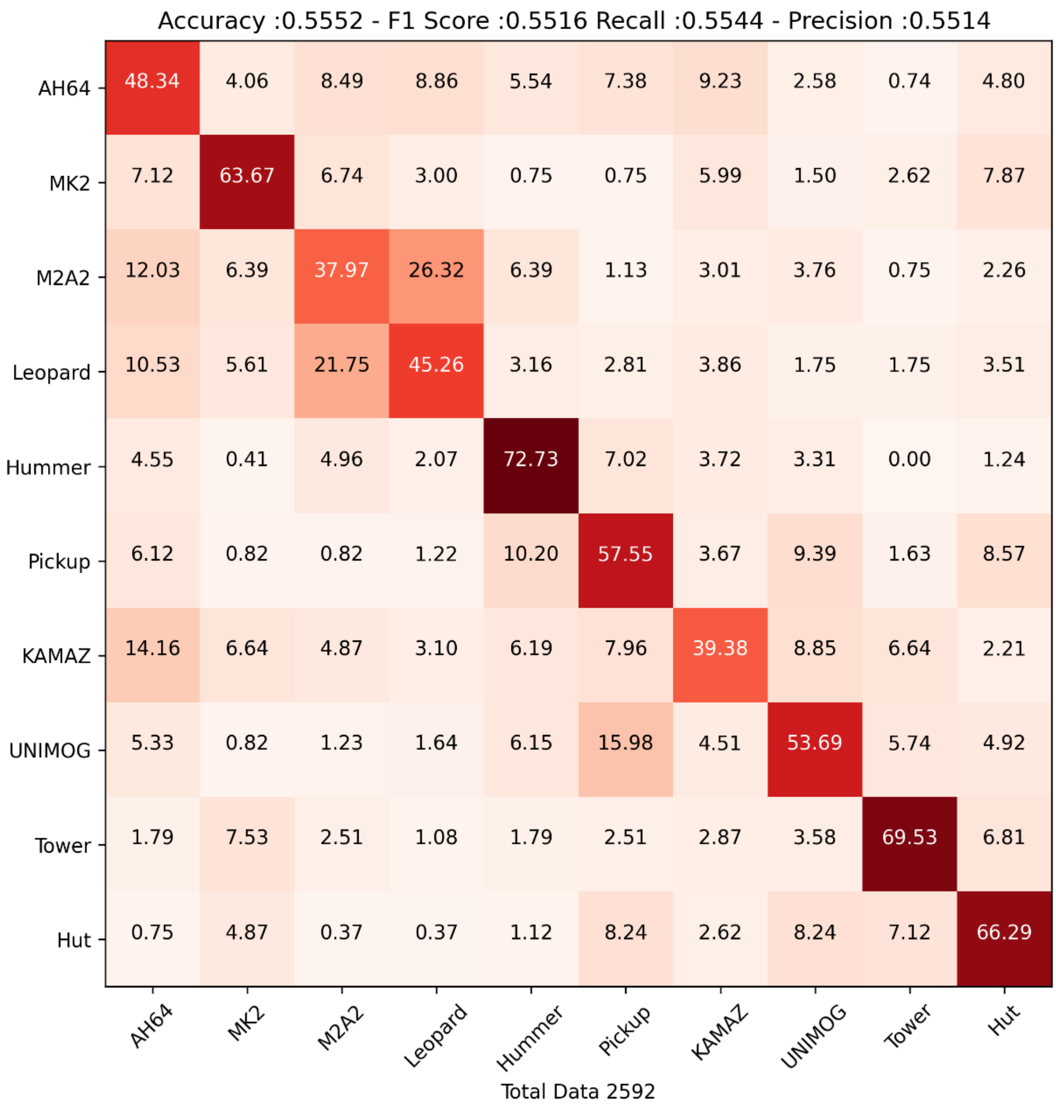

Figure 4.1: Confusion matrix of the SNR 1 dB dataset for target classification results.

AH64: The accuracy rate for this class is 48.34% and the rate of confusion with other classes is quite high. In particular, significant confusion was observed with M2A2 and KAMAZ classes.

MK2: This class performs relatively better than the other classes with an accuracy of 63.67%. However, the confusion with AH64 and M2A2 is noteworthy.

M2A2: It is a very mixed class with an accuracy rate of 37.97%. There are serious confusions with Leopard and AH64.

Leopard: This class shows a moderate performance with an accuracy of 45.26%. There is confusion with AH64 and M2A2.

Hummer: With an accuracy rate of 72.73%, the model is one of the most successful classes. However, confusion was observed with Pickup and UNIMOG.

Pickup: It performs well with an accuracy of 57.55%. There is some confusion with Hummer and KAMAZ.

KAMAZ: It performs at a moderate level with an accuracy of 39.38%. Confusion with AH64 and Pickup is notable.

UNIMOG: Good performance with an accuracy of 53.69%. Confusion was observed with KAMAZ and Pickup.

Tower: It is a successful class with an accuracy rate of 69.53%. However, there are confusions with MK2 and Hummer.

Hut: It performs well with an accuracy rate of 66.29%. Confusion was observed with KAMAZ and MK2.

The values in the matrix show how much the classes are confused with each other. Low accuracy rates and high confusion rates indicate that the model has difficulty in distinguishing between these classes. In particular, classes such as AH64 and KAMAZ are highly confused with other classes, indicating that the model has difficulty in correctly identifying these classes.

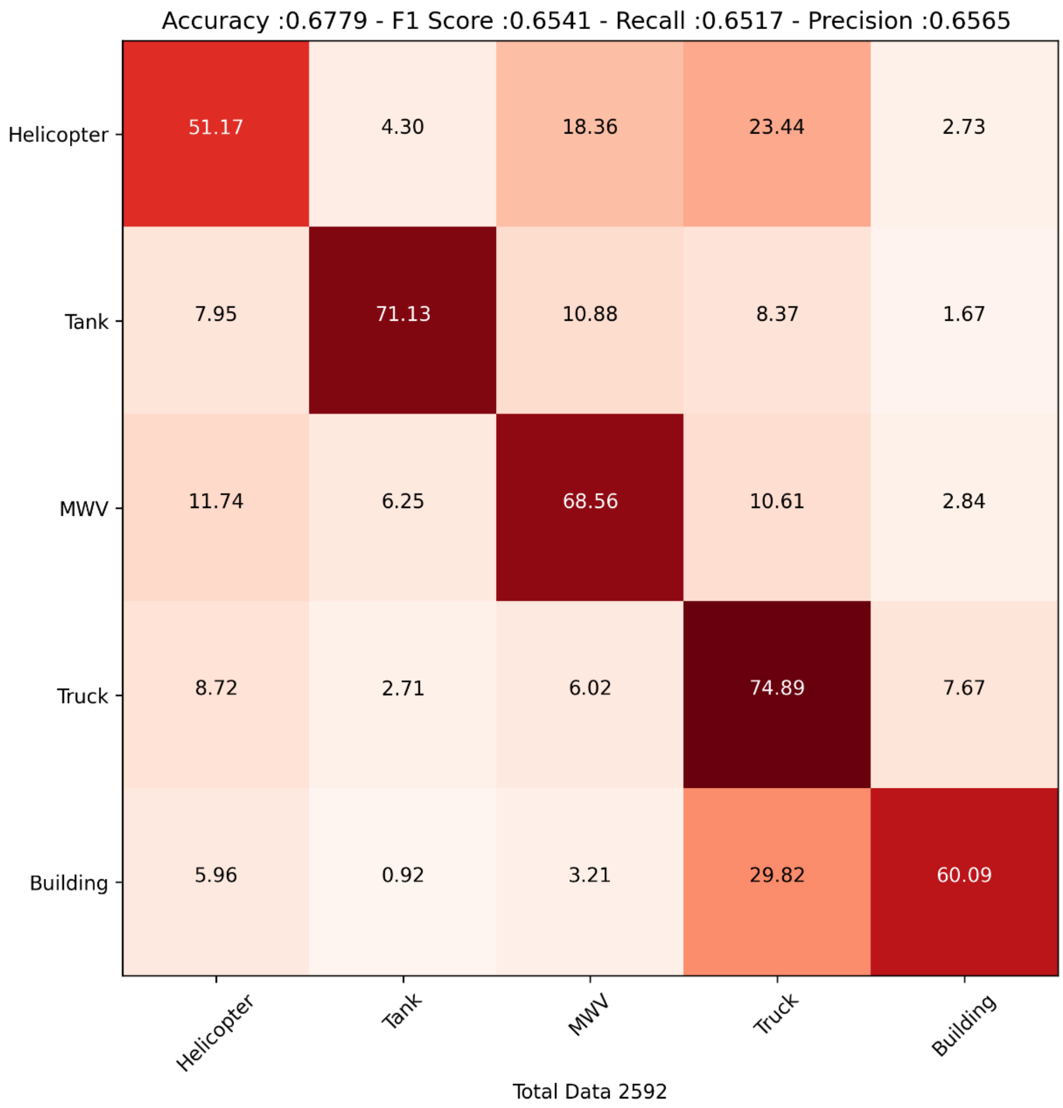

Figure 4.2: Confusion matrix of the SNR 1 dB dataset for the results of the target categories.

In general, the training result for the data set with 1 dB noise added shows that the model performs well in some classes, but has significant difficulties in others.

- Results for 10 dB SNR:

These metrics show that the model works with an overall accuracy of 72%, and the sensitivity and precision rates are similarly around 72%. The F1 Score is a summary of the overall performance of the model and is determined as 71.87%.

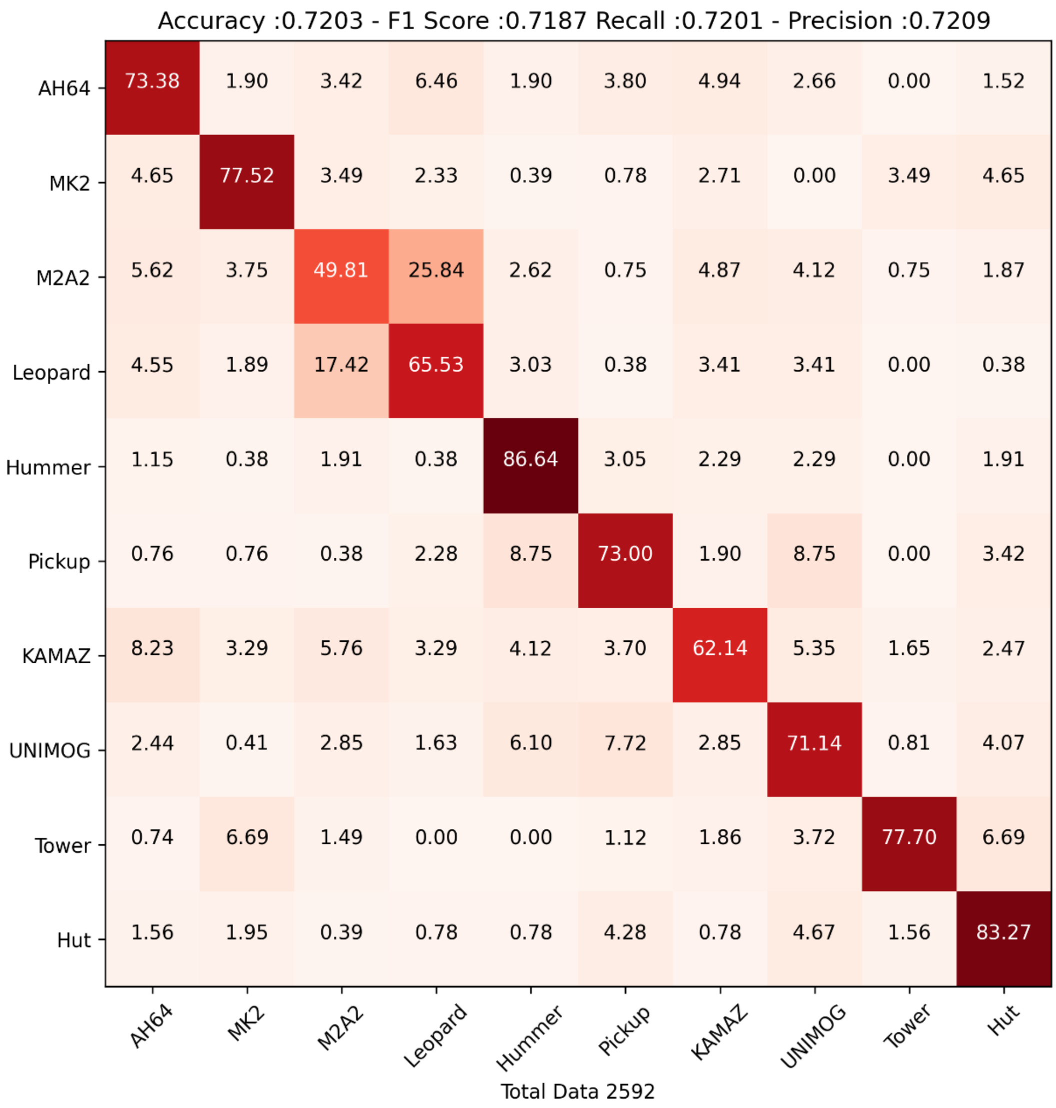

Figure 4.3: Confusion matrix of the SNR 10 dB dataset for target classification results.

The Hummer class is generally correctly classified, but there is some confusion with Pickup and UNIMOG. The Pickup class has some misclassifications with Hummer and Hut. The KAMAZ class showed confusion with UNIMOG and AH64. The UNIMOG class has some errors with the KAMAZ and Tower classes.

This confusion matrix and performance metrics show that the model performs well in general, but there is confusion between some classes. In particular, the model needs to be improved for better separation of M2A2, Leopard, KAMAZ and UNIMOG classes.

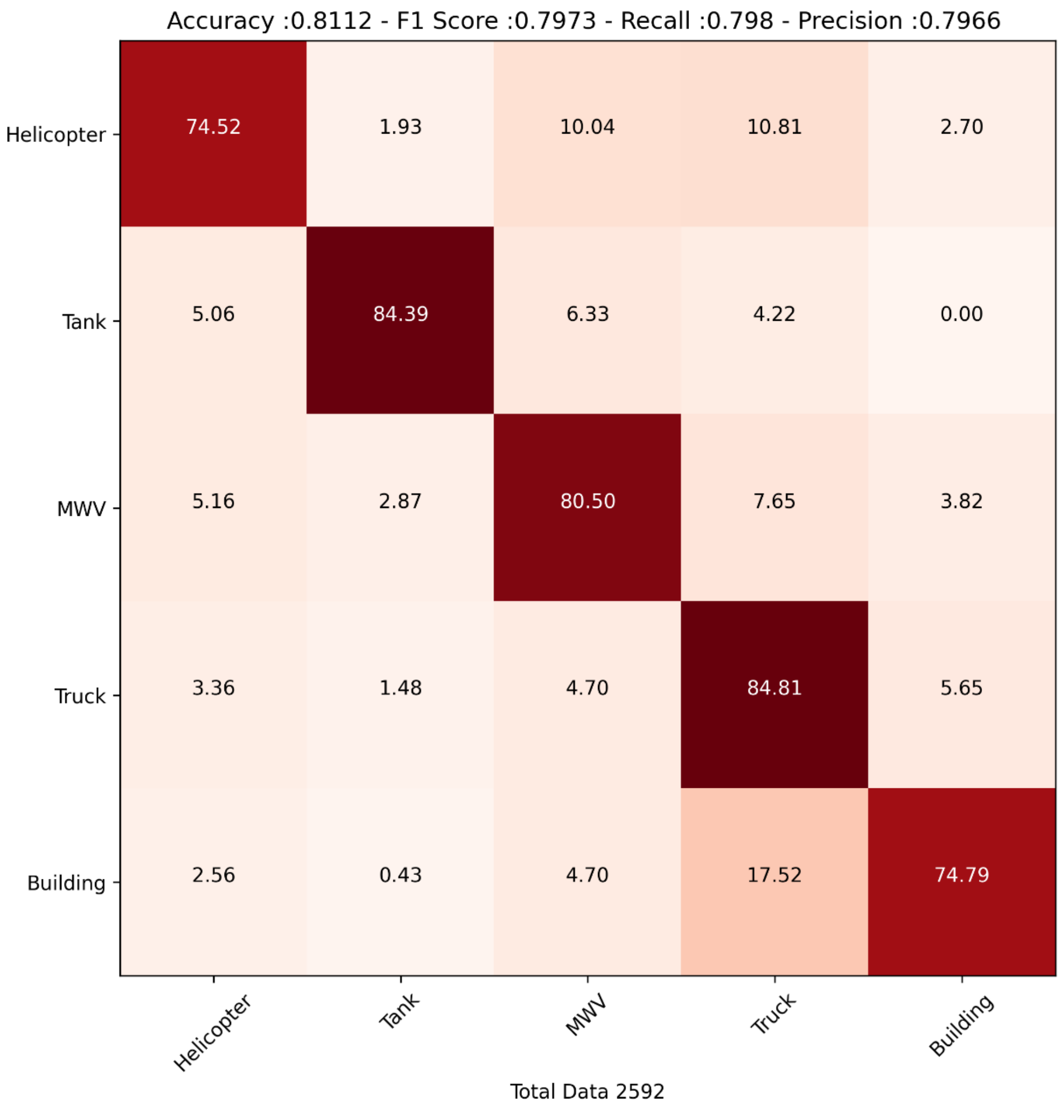

Figure 4.4: Confusion matrix of the SNR 1 dB dataset for the results of the target categories.

- Results for 30 dB SNR:

The overall accuracy of the model is 89.39%, F1 score is 89.31%, recall is 89.4% and precision is 89.36%. This indicates an overall high performance of the model.

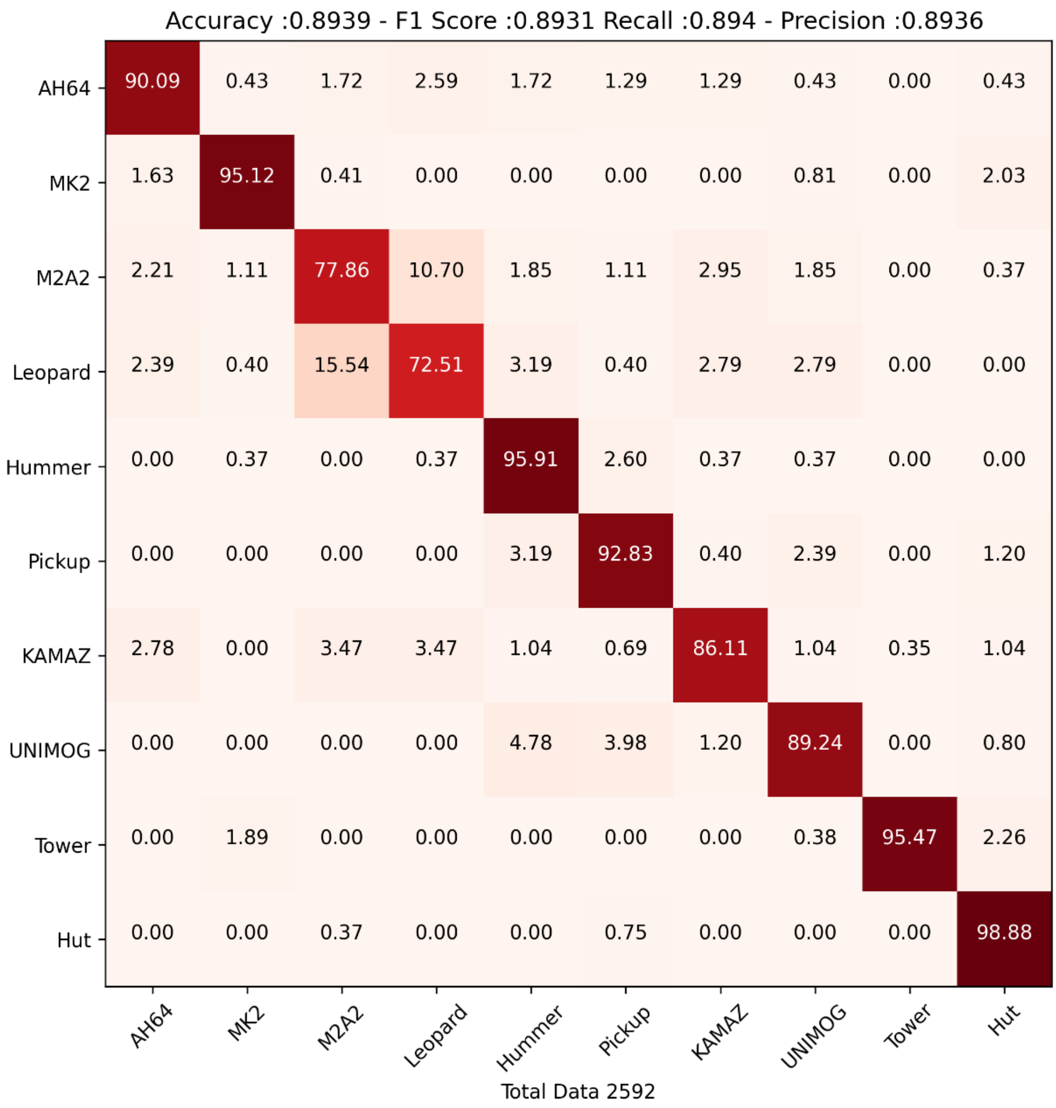

Figure 4.5: Confusion matrix of the SNR 30 dB dataset for target classification results.

It is observed that the model has significant confusion between some classes. For example, there is 15.54 percent confusion between the M2A2 and Leopard classes. There are generally low confusion rates between other classes.

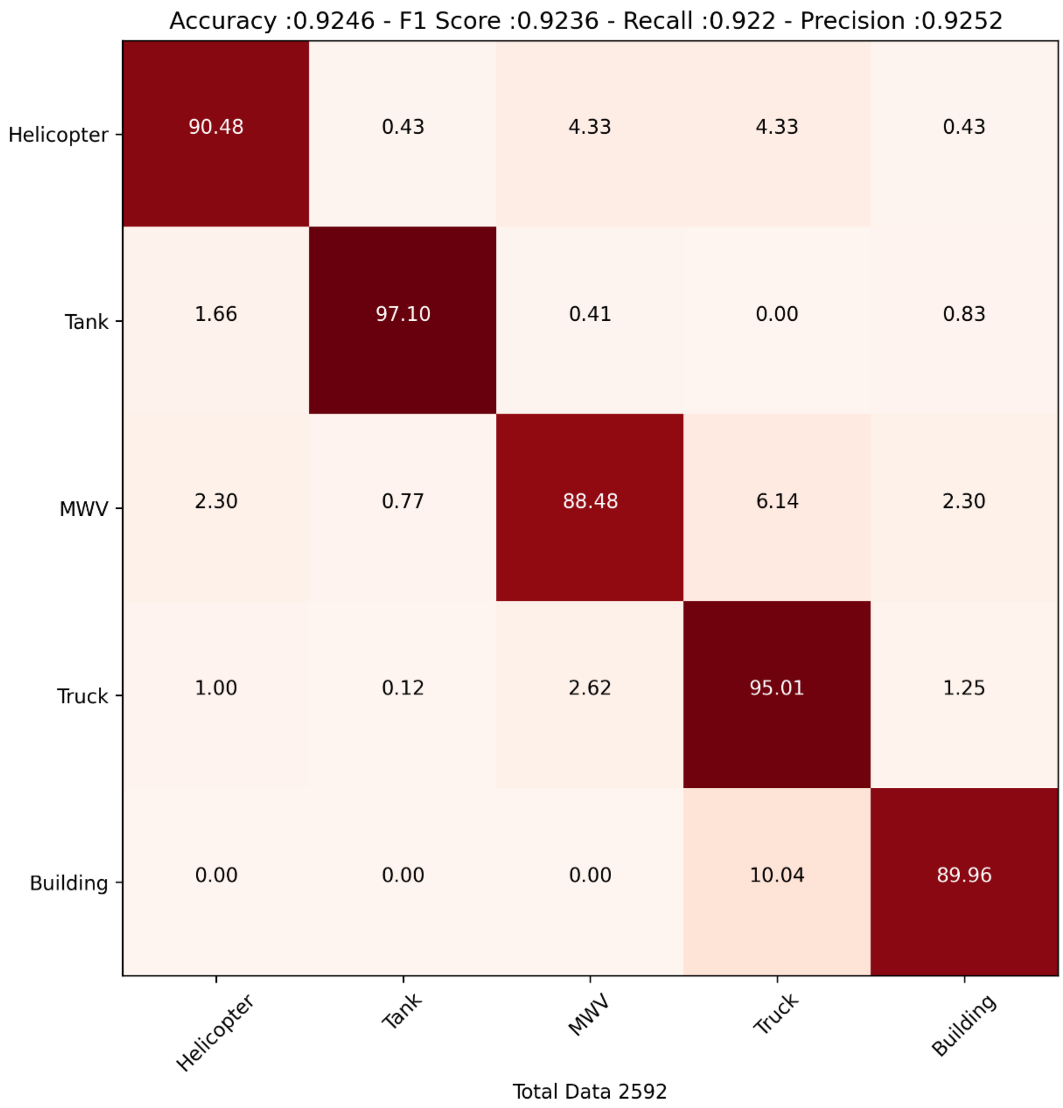

Figure 4.6: Confusion matrix of the SNR 30 dB dataset for the results of the target categories.

The target classification performance of the deep learning model used in the study was analyzed depending on the Signal-to-Noise Ratio (SNR) values in the data set. The results obtained show that the accuracy of the model increases significantly with the increase in SNR value. This situation reveals that high SNR values make the signals in the data set clearer and more distinct, thus allowing the model to make more accurate predictions in the classification process. At low SNR values, noise becomes dominant over the signal, making it difficult for the model to learn distinctive features and reducing accuracy rates. These findings emphasize that SNR is a critical parameter that directly affects the performance of deep learning models. Model classification performance according to SNR value is shown in **Figure 4.7**.

Table 4.1: Model accuracy table by SNR value

SNR (dB)	Accuracy (%)
1	55.5
5	59.9
10	72.0
15	80.8
20	85.3
25	87.5
30	89.3

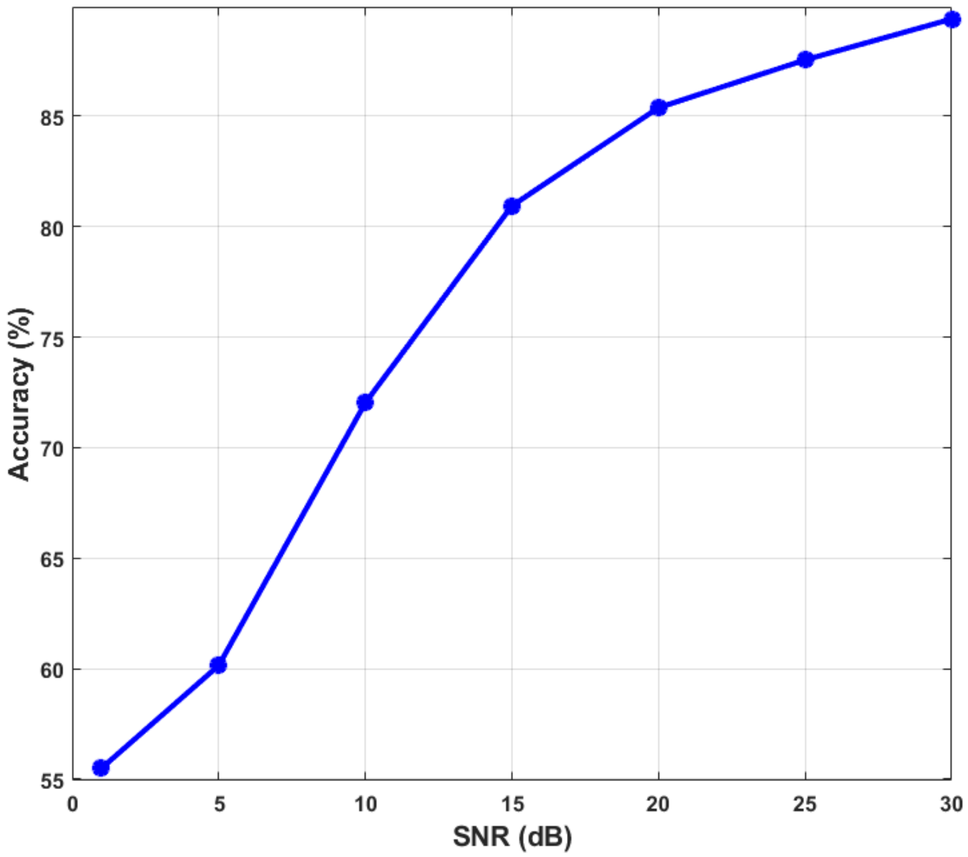

Figure 4.7: Graph of the change of model accuracy according to SNR value.

The results of the data generated with other SNR values are given in Appendix A.

In this study, two helicopter model that is not included in the dataset were used to test the performance of the deep learning network. For this purpose, the Bell UH- 1 and Mil Mi-24 helicopter models that show in **Figure 4.8** and **Figure 4.9** were used. Totally 3240 range profile data generated for each from different horizontal and vertical angles. The performance results of the deep learning network were analyzed using these data.

Figure 4.8: CAD model of UH-1 helicopter.

Figure 4.9: CAD model of Mi-24 helicopter.

For the UH-1 helicopter model, 1503 of 3240 generated high-resolution range profiles were correctly labeled helicopters by used deep learning network. So that network had an accuracy of 46.3%.

As another conclusion, the network correctly identified 2269 data as helicopter for Mi-24 model with a success rate of 70%. These results show us deep learning model used by this study is useful for a model that has never seen of this type.

4.2. Heading Angle Estimation Result

In this section, the orientation angle estimation results of an example helicopter class, AH-64 Apache, using a 30 dB SNR data set are presented.

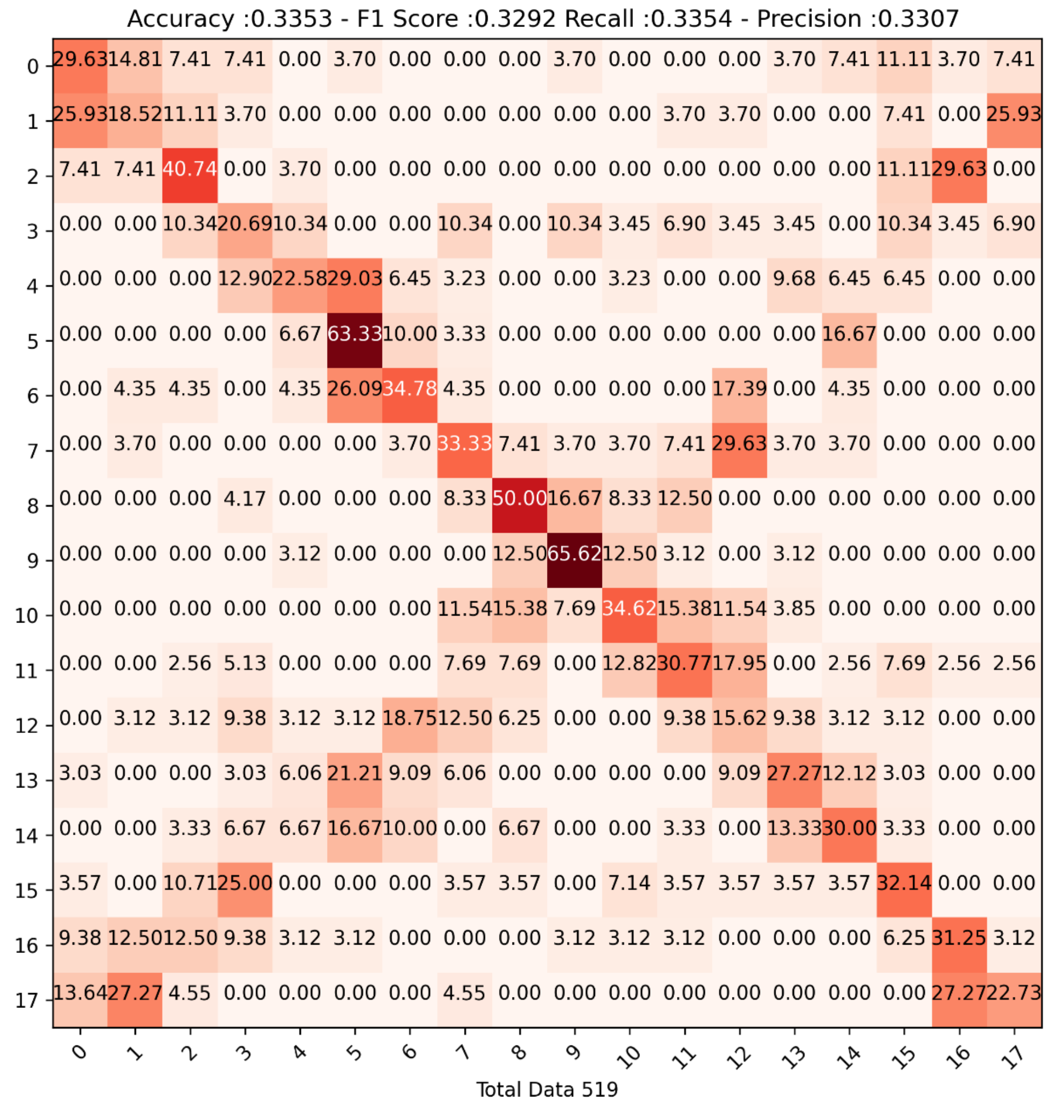

Figure 4.10: Confusion matrix of the heading angle estimation.

The confusion matrix shown in **Figure 4.10** shows the performance of the segment estimation model. The segments are numbered from 0 to 17 and the values in each cell are given as a percentage. Each cell in the matrix shows the proportion of the true class in the row corresponding to the predicted segment in the column.

The overall accuracy, F1 score, sensitivity and precision are low, indicating that the model needs to be improved. Improvements can be made to the dataset and the model to determine which classes the model confuses and to eliminate these confusions. Retraining the model with more data can be considered. In future studies, in general, the data set and the model should be carefully analyzed and necessary improvements should be made to improve the performance of the model.

The target data obtained from the radar range profile is provided as input to a deep learning algorithm for angle segmentation. This algorithm outputs a segment number in order to determine the segment range to which the horizontal angle of the target corresponds. Subsequently, a correlation analysis is performed between the radar range profile of the detected target and the range profile data of the identified segment. As a result of this analysis, the peak of the signal is identified, so that the target's orientation angle can be determined with greater precision. A visual example of the application of this methodology is shown in **Figure 4.11**.

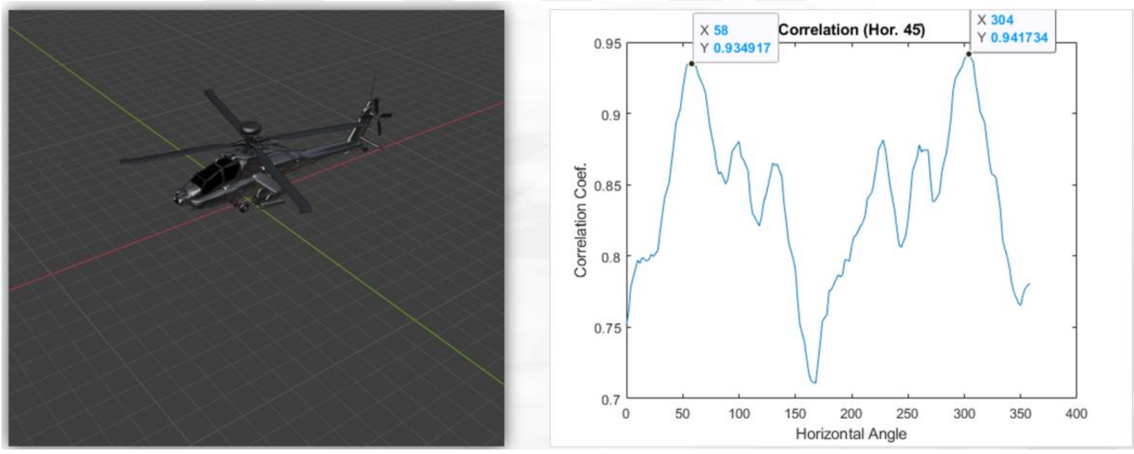

Figure 4.11: The result of the correlation of the helicopter model with the values in the segment.

4.3. Investigation of Architectures with Different Block Numbers

In this study, the architectures of the proposed model that contain two and four multi-scale residual blocks were also investigated. From the results, it was observed that the two-block architecture is not as good as the three-block architecture in terms of effectiveness. This means that if there are fewer blocks, then the negative impact on the classification accuracy is also fewer and the model is unable to learn deep features properly. The architectures of the two multi-scale residual blocks shown in **Figure 4.12**. However, the four-block architecture provided better outcomes and enhanced the classification performance as compared to the three-block architecture. This proves that with more number of blocks, the capacity and performance of the model is enhanced but at the same time it increases the computational cost. The architectures of the two multi-scale residual blocks shown in **Figure 4.13**. These findings show that, based on the results of the target classification problem, the number of parallel multi-scale residual blocks has a significant effect.

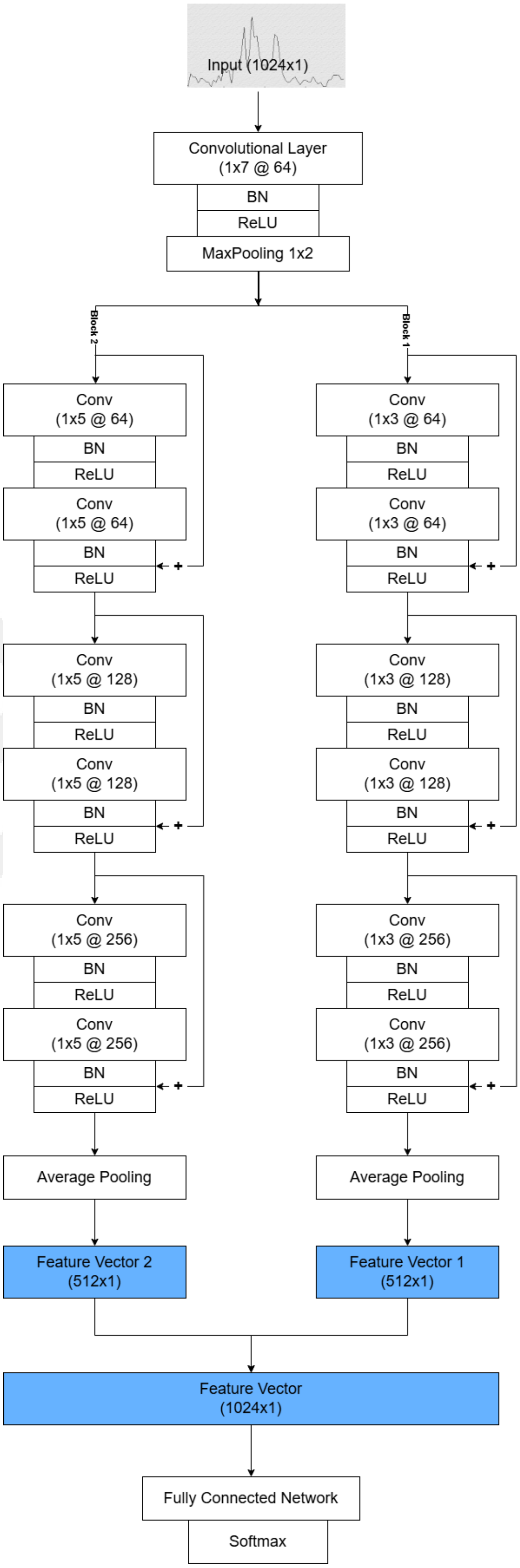

Figure 4.12: The architectures of the two multi-scale residual blocks.

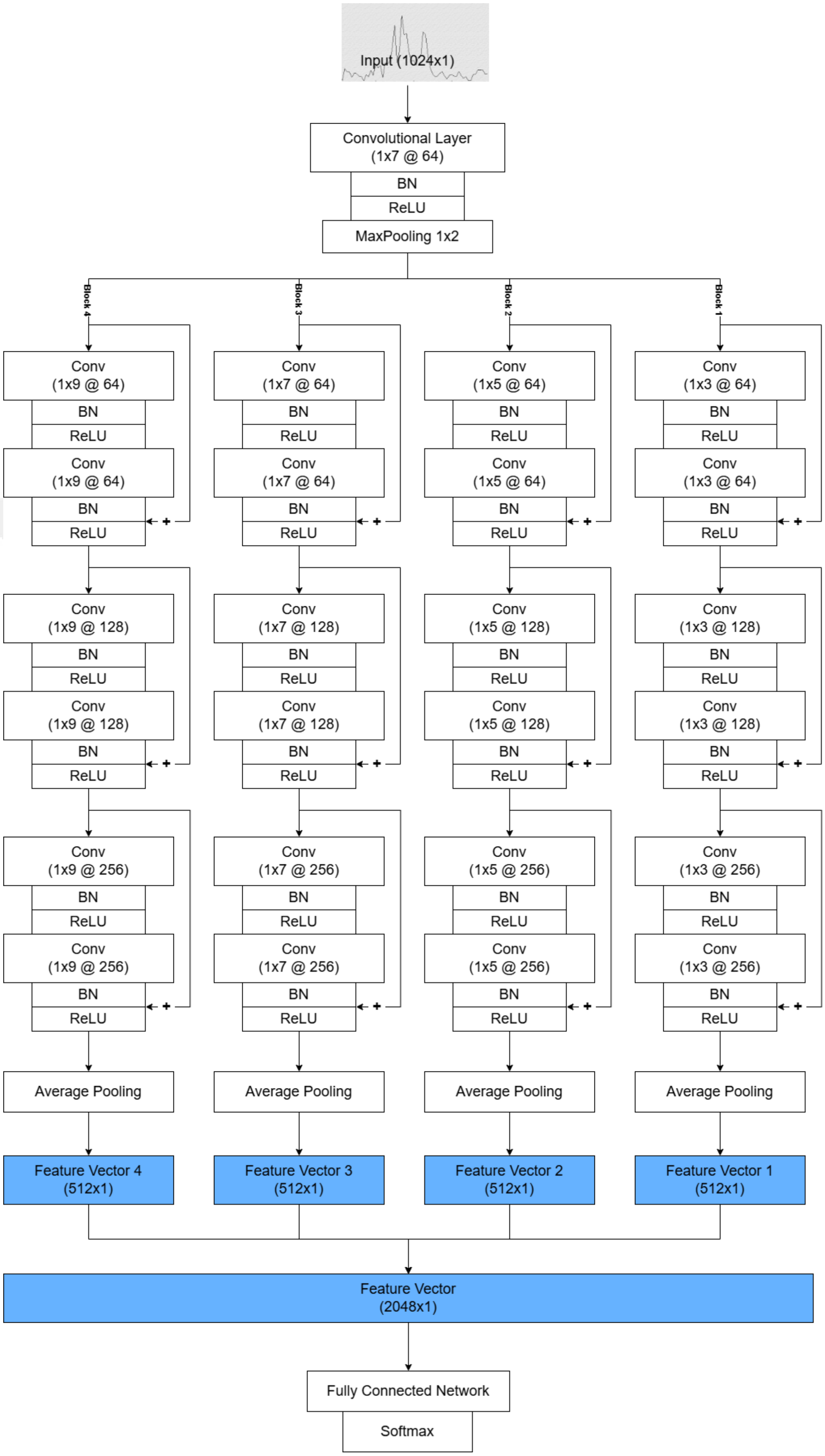

Figure 4.13: The architectures of the four multi-scale residual blocks.

CHAPTER 5

5. CONCLUSIONS AND FUTURE WORK

The problem that is considered in this work is the ground target classification employing high range resolution radar systems. The main research goal is to propose a novel approach for identifying objects and recognizing their clusters and calculating horizontal angles in air-land operations. To that, a detailed analysis is made with the help of the simulation data extracted from the radar simulator.

The framework of the study is derived based on the mechanisms of handling range profiled data using deep learning approaches. This approach offers a more advanced and flexible solution compared to traditional radar signal processing methods. Radar signals analysis and the identification of fine details in the detected signals show high performance caused by deep learning algorithms. Targets in this study were classified using high-resolution range profiles that was provided by radar data and the deep learning algorithms employed in this study include neural networks.

High-resolution range profile data was used to evaluate auto-detection performance. High-precision characteristic feature-based reflection from the target shall help in classifying it more accurately. Deep learning models have been processed for extracting information on target type and orientation.

Another important aspect of the work involves the use of trained segment models in discrimination at different angles for various object classes. These play a very important role when computing any horizontal angle aimed at a target. Horizontal angle information of this kind is very important in understanding the relationships of targets with respect to spatiality and assessing the potential levels of threats.

In these results, the proposed method has high accuracy and precision. This can provide a very good advantage in that it allows effective execution of the air-ground missions.

This increased accuracy rate increases the reliability of the operational decisions because it reduces false positive and false negative results.

In summary, this research has set forth the development of a new approach for target classification and estimation of their horizontal angles in air-ground missions. The accuracy and sensitivity that were found by the proposed methodology insinuate its potential to play an important role in future military and civilian applications. The results of the present study are an important contribution toward developing radar-based technologies for target detection and classification.

In the future, it shall be necessary to test this methodology on real-world scenarios, and performance assessment of the said system under varying environmental conditions. Further development and optimization will pave the way for better enhancements in the real-time applications for the model. These results greatly enhance radars and artificial intelligence applications.

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APPENDIX A

- Results of SNR 5 dB Data Set

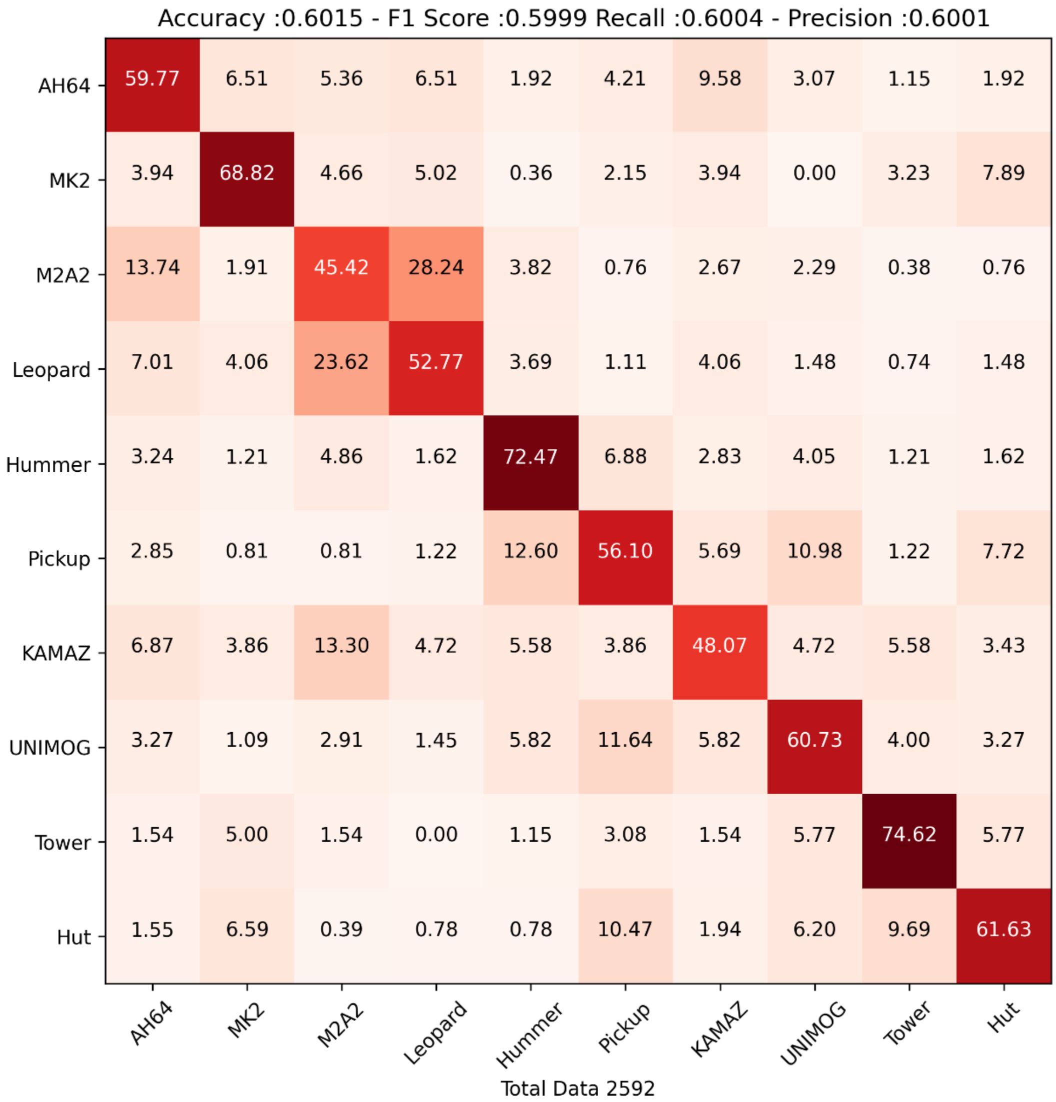

Figure 5.1: Confusion matrix of the SNR 5 dB dataset for target classification results.

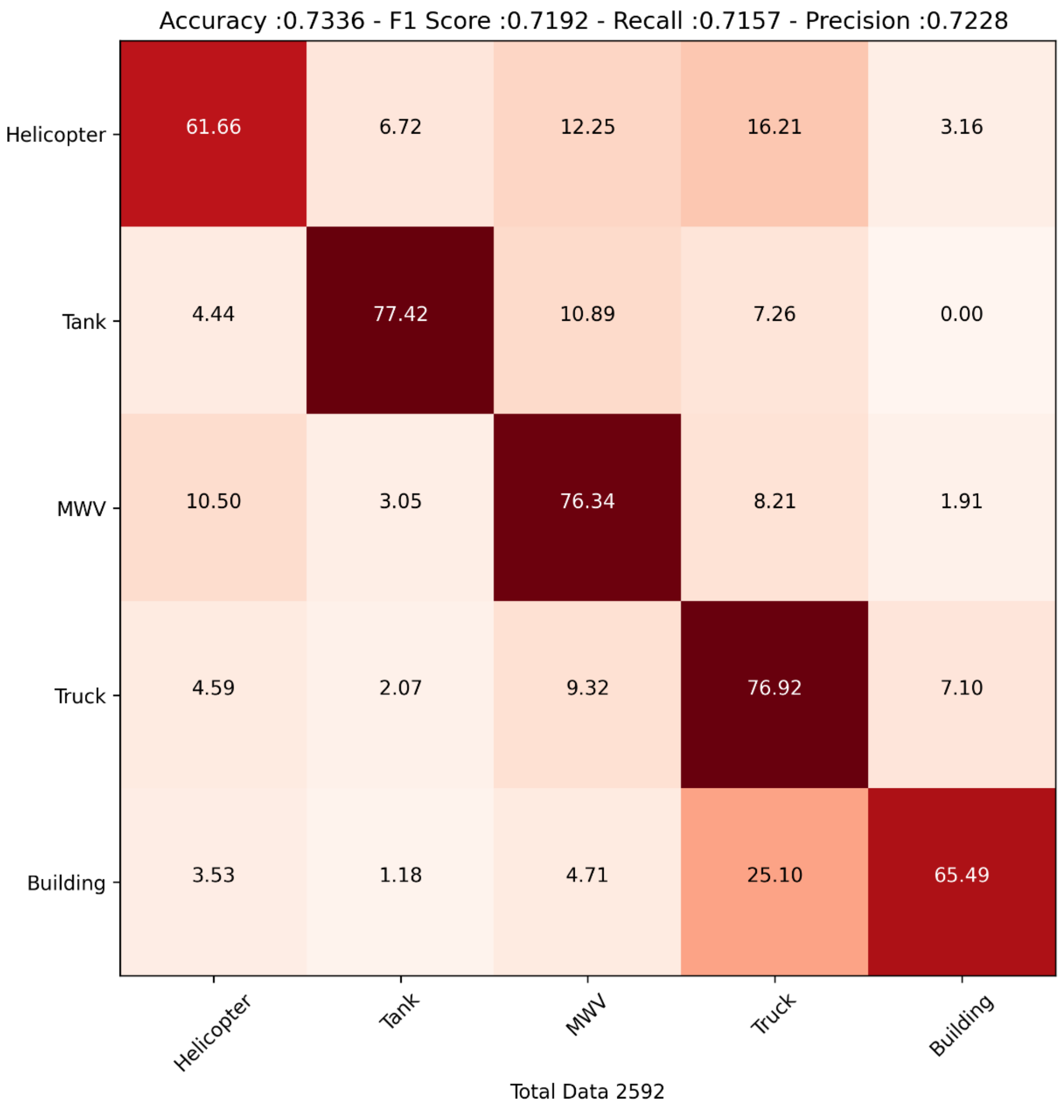

Figure 5.2: Confusion matrix of the SNR 5 dB dataset for the results of the target categories.

- Results of SNR 10 dB Data Set

Figure 5.3: Confusion matrix of the SNR 10 dB dataset for target classification results.

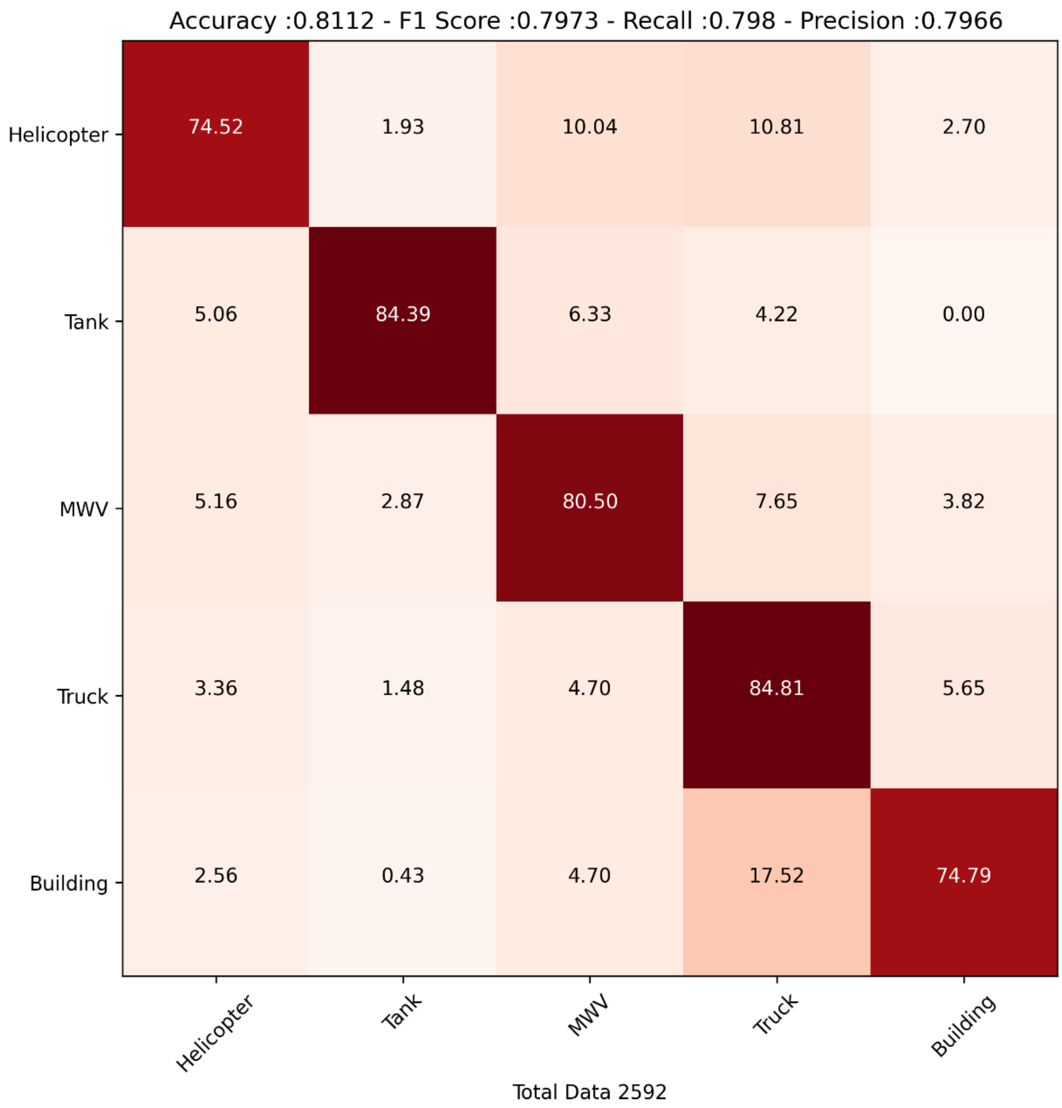

Figure 5.4: Confusion matrix of the SNR 10 dB dataset for the results of the target categories.

- Results of SNR 20 dB Data Set

Figure 5.5: Confusion matrix of the SNR 20 dB dataset for target classification results.

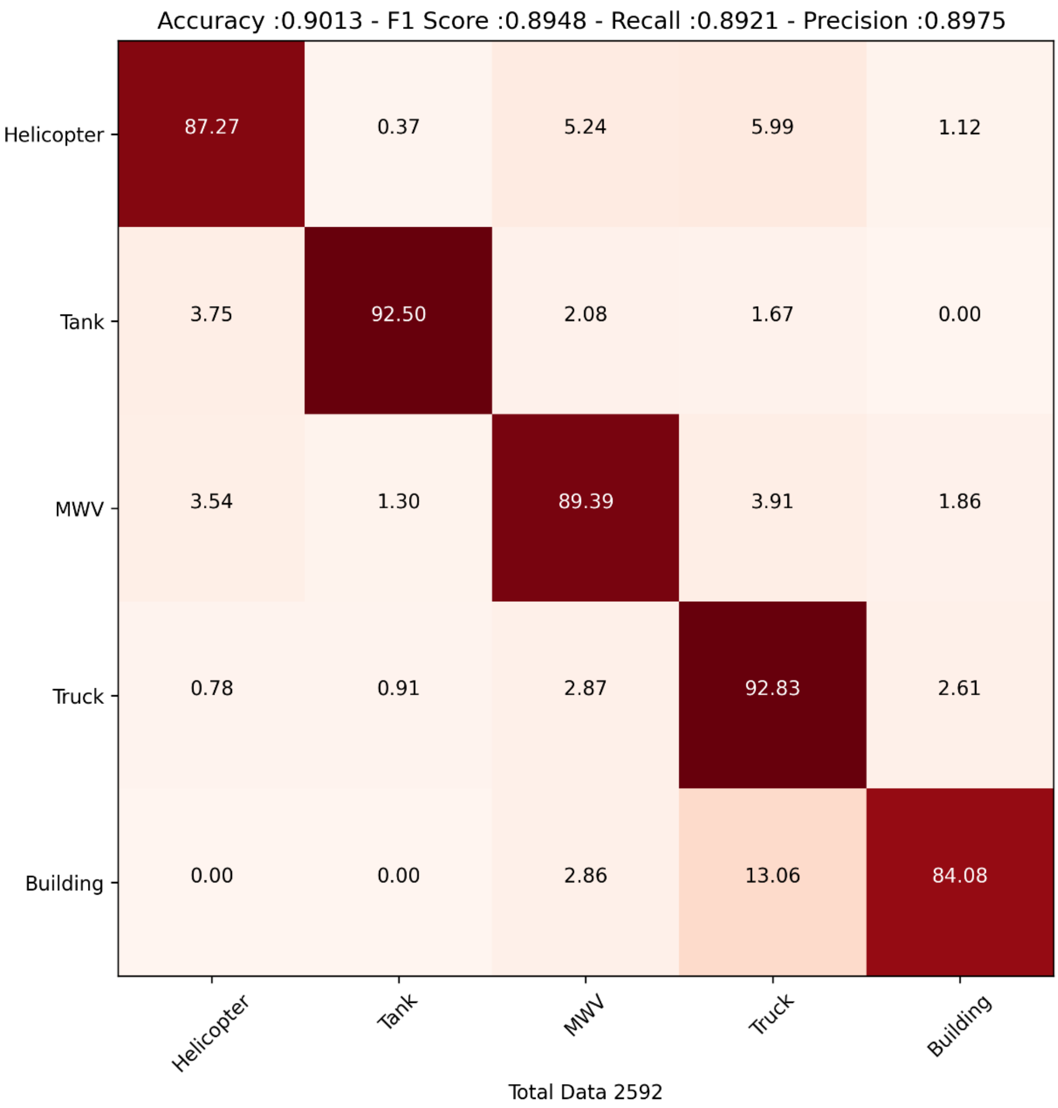

Figure 5.6: Confusion matrix of the SNR 20 dB dataset for the results of the target categories.

- Results of SNR 25 dB Data Set

Figure 5.7: Confusion matrix of the SNR 25 dB dataset for target classification results.

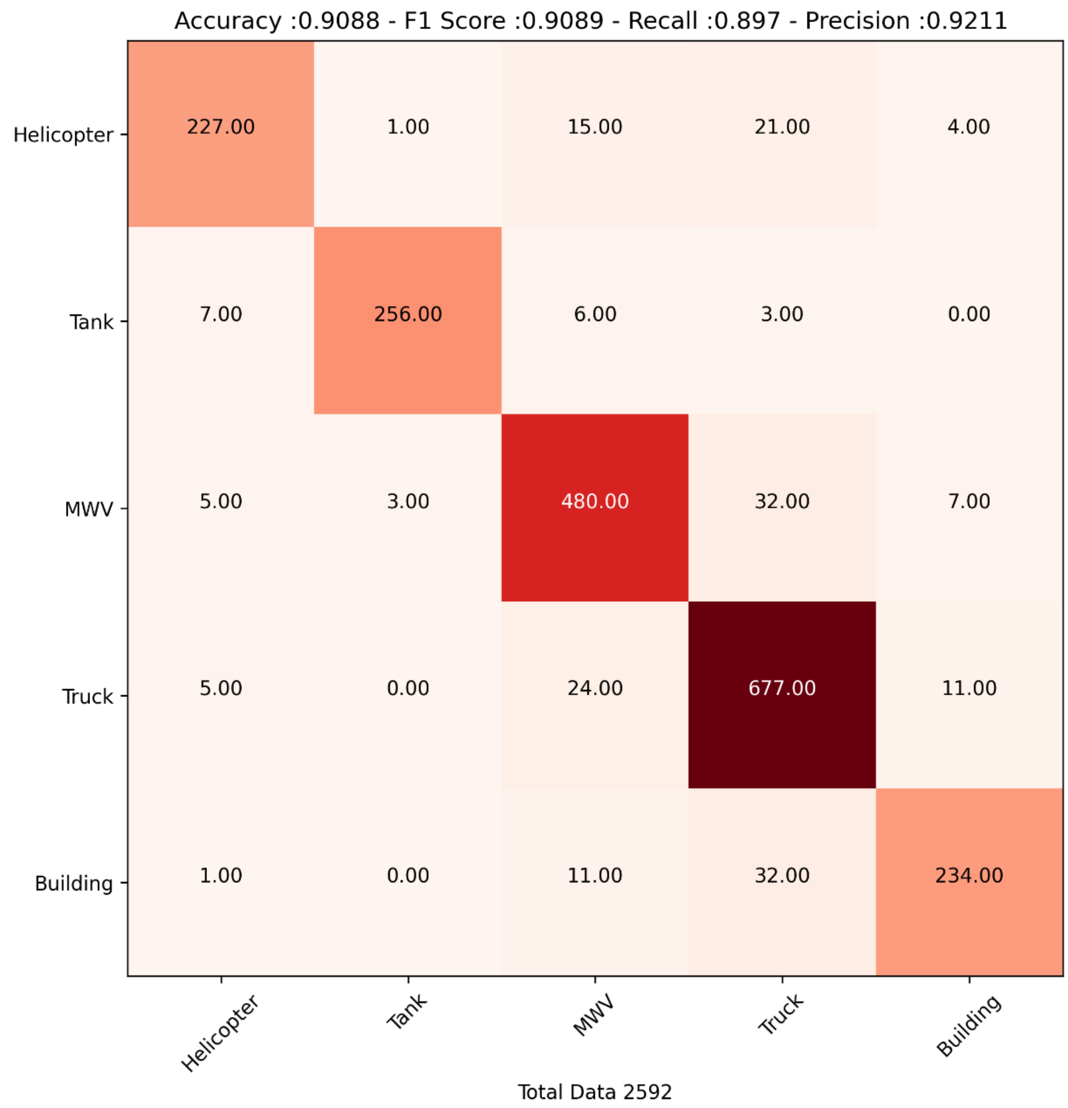

Figure 5.8: Confusion matrix of the SNR 25 dB dataset for the results of the target categories.

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