ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

IMPROVED HELICOPTER CLASSIFICATION
VIA
DEEP LEARNING AND OVERLAPPED RANGE-DOPPLER MAPS

M.Sc. THESIS

Deniz Can ACER

Electronics and Communication Engineering Department

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JANUARY 2023

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

DERİN ÖĞRENME VE ÖRTÜŞEN MENZİL-DOPPLER GÖRÜNTÜLERİ İLE GELİŞTİRİLMİŞ HELİKOPTER SINIFLANDIRMASI

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Deniz Can ACER, a M.Sc. student of ITU Graduate School student ID 504191270, successfully defended the thesis entitled "IMPROVED HELICOPTER CLASSIFICATION VIA DEEP LEARNING AND OVERLAPPED RANGE-DOPPLER MAPS", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my family,

FOREWORD

I want to express my sincere gratitude to my supervisor Prof. Dr. Işın Erer, for her guidance and support throughout this graduate program.

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ABBREVIATIONS

RD	**:** Range-Doppler Map
GRU	**:** Gated Recurrent Unit
LSTM	**:** Long-short Term Memory
HRRP	**:** High Resolution Range Profiling
MCC	**:** Matthew's Correlation Coefficient

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**IMPROVED HELICOPTER CLASSIFICATION
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SUMMARY

Radar target classification is the process of identifying and categorizing objects based on their radar echoes. This is an important task in a variety of fields, including air defense, air traffic control.

One of the main reasons why radar target classification is important is because it allows for the effective detection and tracking of objects. This is particularly important in military defense, where it is necessary to be able to identify and track enemy targets. By accurately classifying radar targets, it is possible to determine the type and number of objects that are present, which can inform decision making and allow for the development of effective countermeasures.

There are several different methods that have been developed for radar target classification, which can be broadly grouped into five categories based on the input used by the classification algorithms. These categories include micro-doppler signatures, High Resolution Range Profiling, image-based approaches, kinematic feature-based approaches (such as RCS, velocity, and position), and RD maps (Range-Doppler maps). Additionally, the outputs of these approaches can also be combined using probabilistic methods.

In this thesis, we focus on RD maps and propose a method for classifying helicopter targets using radar data and a 2D overlapping range-Doppler map approach with a GRU network. Range-Doppler (RD) maps are a commonly used tool in radar target classification, as they provide information about the range and velocity of a target. RD maps are created by taking the Fourier transform of the radar echo signal and plotting the resulting data in a two-dimensional grid. The range of the target is represented on the x-axis and the velocity of the target is represented on the y-axis, and the amplitude can be seen in the z-axis.

There are several advantages to using RD maps for radar target classification. One of the main benefits is that they provide detailed information about the movement and characteristics of a target. This can be particularly useful when trying to distinguish between different types of targets, as different targets will have unique RD map signatures. For example, a helicopter will have a different RD map signature than a car or a plane, which allows for accurate classification of the target.

Recurrent neural networks (RNNs) are a type of neural network that are particularly well-suited for processing sequential data. One type of RNN, known as a gated recurrent unit (GRU), is particularly effective at handling smaller datasets. GRUs have

a simpler structure compared to other types of RNNs, such as long short-term memory (LSTM) networks.They are able to effectively capture long-term dependencies in the data, which is often a challenge when working with smaller datasets. This is because smaller datasets often have less data available to learn from, which can make it difficult for the model to learn complex patterns in the data. By allowing the model to capture long-term dependencies, they are able to better capture the underlying structure of the data, which can help to improve the performance of the model. Moreover, like LSTMs, they GRUs are able to handle variable-length input sequences which is suitable for radar classification since RD map sizes are not the same.

Moreover, the overlapped window is a method used in data processing and analysis, particularly in the field of deep learning. It involves dividing a dataset into smaller segments or "windows," and then overlaying these segments on top of one another, with some overlap between them. This overlap allows for the incorporation of additional context and information in the data, which can be useful for tasks such as classification and prediction. One of the main benefits of using overlapped windows is that it allows for the inclusion of more temporal or spatial information in the data. For example, in the field of natural language processing, an overlapped window approach can be used to process longer texts or sequences of words, allowing for the inclusion of more context and meaning in the analysis. In image processing, overlapped windows can be used to analyze images at different scales, incorporating information about the overall structure as well as fine details. Another advantage of overlapped windows is that they can improve the robustness and generalizability of the model being used. By incorporating more information and context in the analysis, the model is able to better handle variations and deviations in the data, leading to better performance on unseen or out-of-sample data. This can be particularly useful in cases where the dataset is small or imbalanced, as is often the case in real-world applications. Furthermore, overlapped windows are often used in time series analysis and other tasks that involve sequential data. The idea is to divide the data into overlapping segments or "windows" of a fixed size, and then use these windows as input to a deep learning model. Thus, it can improve the accuracy of the classification, as more of the relevant information about the target is retained. Additionally, the use of overlapping windows allows for the classification of RD maps regardless of the range resolution, as the window size can be adjusted to fit the size of the targets. This makes the method highly flexible and adaptable to different scenarios.

We demonstrate that this approach is effective in accurately identifying different types of helicopters using various radar systems. The use of an overlapped window model allows for the incorporation of spatial information in the data, while the GRU network is able to handle smaller datasets and preserve more of the relevant information about the target. Our results indicate that the proposed method outperforms traditional approaches in terms of accuracy and robustness. This method is highly flexible and adaptable to different scenarios, as it is able to classify radar data of varying sizes. The overlapped multicell GRU method for radar target classification was found to have the highest helicopter classification accuracy on data from radars A and B, respectively, in the first experiment. In the second experiment, it also achieved a better helicopter classification accuracy. Moreover, evaluation metrics such as the F1 score and Mathew Correlation Coefficient (MCC) were also calculated, and the results are in the same direction as accuracies. Overall, the overlapped multicell GRU method was found to perform better compared to the other methods tested.

DERİN ÖĞRENME VE ÖRTÜŞEN MENZİL-DOPPLER GÖRÜNTÜLERİ İLE GELİŞTİRİLMİŞ HELİKOPTER SINIFLANDIRMASI

ÖZET

Radar hedef sınıflandırması, nesneleri radar yankılarına göre tanımlama ve sınıflandırma etme işlemidir. Bu, hava savunması, hava trafik kontrolü dahil olmak üzere çeşitli alanlarda önemli bir görevdir.

Radar hedef sınıflandırmasının önemli olmasının ana nedenlerinden biri, nesnelerin etkili bir şekilde algılanmasına ve izlenmesine izin vermesidir. Bu, düşman hedeflerini tespit edip takip edebilmenin gerekli olduğu askeri savunmada özellikle önemlidir. Radar hedeflerini doğru bir şekilde sınıflandırarak, karar vermeyi bilgilendirebilecek ve etkili karşı önlemlerin geliştirilmesine izin verebilecek mevcut nesnelerin türünü ve sayısını belirlemek mümkündür.

Radar hedef sınıflandırmasının önemli olmasının bir başka nedeni de, radar sistemlerinin doğruluğunu ve güvenilirliğini artırmaya yardımcı olabilmesidir. Nesneleri doğru bir şekilde tanımlayıp sınıflandırarak, radar sistemleri iletilen bir sonraki darbenin özelliklerini uyarlayabilir ve seçebilir, bu da sistemin genel performansını artırabilir.

Radar hedef sınıflandırması için geliştirilmiş birkaç farklı yöntem vardır ve bunlar, sınıflandırma algoritmaları tarafından kullanılan girdiye dayalı olarak geniş bir şekilde beş kategoride gruplandırılabilir. Bu kategoriler arasında mikro-doppler imzaları, Yüksek Çözünürlüklü Menzil Profili Oluşturma, görüntü tabanlı yaklaşımlar, kinematik özellik tabanlı yaklaşımlar (RCS, hız ve konum gibi) ve RD haritaları (Menzil-Doppler haritaları) bulunur. Ek olarak, bu yaklaşımların çıktıları da olasılıksal yöntemler kullanılarak birleştirilebilir.

Mikro-Doppler, bir helikopter rotorunun bıçakları veya bir uçağın kanatçıkları gibi bir hedef içindeki küçük hareketli parçaların veya titreşen yapıların Doppler kaymasını tanımlamak için kullanılan bir terimdir. Bu küçük hareketler, hedef hakkında ek bilgi elde etmek için kullanılabilen radar dönüş sinyalinde ince modülasyonlara neden olabilir. Bir hedefin mikro-Doppler imzasını analiz ederek, hedefin sınıflandırılmasına yardımcı olabilecek mevcut hareketli parçaların veya yapıların tipini ve sayısını belirlemek mümkündür.

Yüksek Çözünürlüklü Menzil Profili oluşturmaya dayalı başka çalışmalar da var. Yüksek menzilli çözünürlüklü radar (HRRP), yüksek çözünürlüklü menzil profili olarak bilinen bir nesnenin tek boyutlu imzasını elde etmek için kullanılan bir tekniktir. Bu imza, hedefin bir radar darbesine verdiği zaman alanı yanıtının bir temsilidir ve sinyalin genliği, belirli bir zaman gecikmesinde geri dönüşün gücü hakkında bilgi

sağlayarak her bir yüksek çözünürlüklü menzil hücresinde ölçülür. HRRP, menzil profili imzalarının farklı özelliklerinden dolayı radar hedeflerinin sınıflandırılmasında kullanışlıdır.

Bunun dışında görüntü sınıflandırma yaklaşımları genellikle Sentetik Açıklıklı Radar (SAR) veya ISAR'a dayalıdır. SAR görüntüleri, artan çözünürlüklü tek bir görüntü oluşturmak için farklı konumlardan iletilen çoklu darbelerden gelen sinyalleri birleştiren sentetik açıklık adı verilen bir teknik kullanılarak geri gönderilen radar sinyallerinin işlenmesiyle üretilir. Ortaya çıkan görüntü bir fotoğrafa benzer, ancak görünür ışık yerine radar sinyalleri kullanılarak oluşturulur. Özellikle MSTAR veri setine dayalı birçok hedef sınıflandırma çalışması bulunmaktadır.

Kinematik özelliklerse, bir nesnenin hareketi veya hareketi ile ilgili özellikleri veya özellikleri ifade eder. Radar alanında, kinematik özellikler, radar teknolojisi kullanılarak tespit edilip analiz edilebilen bir hedefin hareketinin veya hareketinin özelliklerine bağlıdır. Bu özellikler, hareket özelliklerine göre farklı tipteki hedefleri tanımlamak ve sınıflandırmak için radar tabanlı otomatik hedef tanıma (ATR) sistemlerinde kullanılabilir. Kinematik özellikler, özellik çıkarma algoritmaları ve makine öğrenme teknikleri dahil olmak üzere çeşitli yöntemler kullanılarak radar verilerinden çıkarılabilir.

Menzil-Doppler (RD) haritaları, bir hedefin menzili ve hızı hakkında bilgi sağladıkları için radar hedef sınıflandırmasında yaygın olarak kullanılan bir araçtır. RD haritaları, radar yankı sinyalinin Fourier dönüşümü alınarak ve elde edilen verilerin iki boyutlu bir grafikte çizilmesiyle oluşturulur. Hedefin menzili x ekseninde temsil edilir ve hedefin hızı y ekseninde temsil edilir ve genlik z ekseninde görülebilir.

Radar hedef sınıflandırması için RD haritalarını kullanmanın çeşitli avantajları vardır. Başlıca faydalarından biri, bir hedefin hareketi ve özellikleri hakkında ayrıntılı bilgi sağlamasıdır. Farklı hedefler benzersiz RD harita imzalarına sahip olacağından, bu özellikle farklı hedef türleri arasında ayrım yapmaya çalışırken faydalı olabilir. Örneğin, bir helikopter, bir araba veya uçaktan farklı bir RD görüntüsüne sahip olacak ve bu, hedefin doğru bir şekilde sınıflandırılmasına izin verecektir. Bu tezde, RD haritalarına odaklanıyoruz ve radar verilerini ve bir GRU ağı ile 2B örtüşen menzil-Doppler harita yaklaşımını kullanarak helikopter hedeflerini sınıflandırmak için bir yöntem öneriyoruz.

Tekrarlayan sinir ağları (RNN'ler), dizi verileri işlemek için özellikle uygun olan bir sinir ağı türüdür. Geçitli tekrarlayan birim (GRU) olarak bilinen bir tür RNN, daha küçük veri kümelerini işlemede özellikle etkilidir. GRU'lar, uzun kısa süreli bellek (LSTM) ağları gibi diğer RNN türlerine kıyasla daha basit bir yapıya sahiptir. Verilerdeki uzun vadeli bağımlılıkları etkili bir şekilde yakalayabilirler ki bu genellikle daha küçük veri kümeleriyle çalışırken bir zorluktur. Bunun nedeni, daha küçük veri kümelerinin genellikle öğrenilebilecek daha az veriye sahip olmasıdır, bu da modelin verilerdeki karmaşık kalıpları öğrenmesini zorlaştırabilir. Modelin uzun vadeli bağımlılıkları yakalamasına izin vererek, modelin performansını iyileştirmeye yardımcı olabilecek verilerin temel yapısını daha iyi yakalayabilirler. Ayrıca, LSTM'ler gibi, GRU'lar da, RD harita boyutları aynı olmadığından, radar sınıflandırması için uygun olan değişken uzunluktaki girdi dizilerini işleyebilir.

Ayrıca örtüşen pencere, özellikle derin öğrenme alanında veri işleme ve analizde kullanılan bir yöntemdir. Bir veri kümesini daha küçük parçalara veya "pencerelere" bölmeyi ve ardından bu bölümleri aralarında bir miktar örtüşme olacak şekilde üst üste bindirmeyi içerir. Bu örtüşme, sınıflandırma ve tahmin gibi görevler için yararlı olabilecek ek bağlam ve bilgilerin verilere dahil edilmesini sağlar.

Örtüşen pencereleri kullanmanın ana faydalarından biri, verilere daha fazla zamansal veya uzamsal bilginin dahil edilmesine izin vermesidir. Örneğin, doğal dil işleme alanında, daha uzun metinleri veya kelime dizilerini işlemek için örtüşen bir pencere yaklaşımı kullanılabilir ve bu da analize daha fazla bağlam ve anlamın dahil edilmesini sağlar . Görüntü işlemede, üst üste binen pencereler, görüntüleri farklı ölçeklerde analiz etmek için kullanılabilir ve ince ayrıntıların yanı sıra genel yapı hakkındaki bilgileri de içerir.

Örtüşen pencerelerin diğer bir avantajı, kullanılan modelin sağlamlığını ve genellenebilirliğini geliştirebilmesidir. Model, analize daha fazla bilgi ve bağlam dahil ederek verilerdeki varyasyonları ve sapmaları daha iyi işleyebilir ve bu da görünmeyen veya örneklem dışı verilerde daha iyi performans sağlar. Bu, gerçek dünya uygulamalarında sıklıkla olduğu gibi, veri kümesinin küçük veya dengesiz olduğu durumlarda özellikle yararlı olabilir.

Ayrıca, örtüşen pencereler genellikle zaman serisi analizinde ve sıralı verileri içeren diğer görevlerde kullanılır. Buradaki fikir, verileri örtüşen bölümlere veya sabit boyutta "pencerelere" bölmek ve ardından bu pencereleri bir derin öğrenme modeline girdi olarak kullanmaktır. Böylece, hedefle ilgili daha fazla ilgili bilgi tutulduğu için sınıflandırmanın doğruluğunu artırabilir. Ek olarak, örtüşen pencerelerin kullanımı, pencere boyutu hedeflerin boyutuna uyacak şekilde ayarlanabildiğinden, menzil çözünürlüğünden bağımsız olarak RD haritalarının sınıflandırılmasına izin verir. Bu, yöntemi oldukça esnek ve farklı senaryolara uyarlanabilir hale getirir.

Bu yaklaşımın, çeşitli radar sistemlerini kullanarak farklı helikopter tiplerini doğru bir şekilde tanımlamada etkili olduğunu gösteriyoruz. Örtüşen bir pencere modelinin kullanılması, uzamsal bilgilerin verilere dahil edilmesine izin verirken, GRU ağı daha küçük veri kümelerini işleyebilir ve hedefle ilgili daha fazla ilgili bilgiyi koruyabilir. Sonuçlarımız, önerilen yöntemin doğruluk ve sağlamlık açısından geleneksel yaklaşımlardan daha iyi performans sergilediğini göstermiştir. Bu yöntem, farklı boyutlardaki radar verilerini sınıflandırabildiği için oldukça esnektir ve farklı senaryolara uyarlanabilir.

Radar hedefi sınıflandırması için örtüşen çok hücreli GRU yönteminin, ilk deneyde Radar A ve B'den gelen verilerde sırasıyla yüzde 96,3 ve yüzde 96,13 ile en yüksek helikopter sınıflandırma doğruluğuna sahip olduğu bulunmuştur. İkinci deneyde ayrıca yüzde 93,72'lik bir helikopter sınıflandırma doğruluğu ve yüzde 99,37'lik bir gürültü ve kargaşa doğruluğu elde edilmiştir. F1 puanı ve Mathew Korelasyon Katsayısı (MCC) gibi değerlendirme metrikleri de hesaplanmıştır ve sırasıyla 0,942961037 ve 0,935928076 olarak bulunmuştur. Genel olarak, örtüşen çok hücreli GRU yönteminin, test edilen diğer yöntemlere kıyasla daha iyi performans gösterdiği bulunmuştur.

Bu bulguların, önerilen yaklaşımın radar hedeflerinin doğru bir şekilde tanımlanması ve sınıflandırılması için umut verici bir yöntem olduğunu öne sürdükleri için, radar hedefi sınıflandırma alanı için önemli çıkarımları vardır. Önerilen yöntem, radar sistemlerinin performansını önemli ölçüde iyileştirme ve radar verilerine dayanan çeşitli uygulamaların yeteneklerini geliştirme potansiyeline sahiptir.

1. INTRODUCTION

Radar target classification is the process of identifying and categorizing objects based on their radar echoes. The classification of different types of radar targets has become increasingly important as a result of the increasing variety and capabilities of these targets [3]. Radar sensors play a crucial role in this process, as they are capable of withstand a wide range of weather and lighting conditions [3]. Radar systems operate by transmitting electromagnetic waves through a medium that [3] may contain targets of interest and then analyzing the delayed and Doppler-shifted echoes that are received information about reflected surfaces or targets [5].

There are several different methods that have been developed for radar target classification. In general, we can examine them into five categories by considering input of the classification algorithms, such as micro-doppler signatures, High Resolution Range Profiling, image based approaches, kinematic feature based approaches (such as RCS, velocity, position) and RD maps (Range-Doppler maps). Moreover, outputs of these approaches also may be fuse together with probabilistic methods like [6].

It has been common practice in earlier approaches to utilize theoretical models of radar echoes and characteristic Doppler spectra in order to study the characteristics of these echoes [3]. In [7], they proposed the idea of rotating objects such as propeller blades, rotor blades, jet engine cause modulation in return signal. Then, they tried to analyse the theoratical return signal from aircraft propeller blades. They make assumptions about how propeller blades act and based on six main variables, which are number of blades, distance of the blade roots from the center of rotation, distance of the blade tips from the center of rotation, wavelength of transmitted signal, angle between the plane of rotation and the line of sight from the radar to the center of rotation, and frequency of rotation. By performing simulations, they showed that there is a distinguishable feature that could be used in classification. However, these approaches require high signal-to-noise ratios and very long time-on-target [4]. In [8] they did a similar analysis for jet engine modulation and proposed a method based on the recurring modulation of the echo [3].

In [9], they proposed a method based on the helicopter rotor hub model. Then, they acquire data from an S-band surveillance coastal radar with a Russian MI-2 helicopter. They showed that helicopter echo can be distinguished. However, their observation time is high (tens of miliseconds). A high SNR and very long time-on-target [9] are required [3]. Thus, performance decreases with low flight altitude and velocity.

Then, on the basis of these, the micro-doppler concept is introduced [10]. Microdoppler signatures consist of induced vibrating and rotating of parts of a target [10].

In [7], they used an X-band radar and collected data from vibrating reflector, helicopter body, and rotor blades. With the analysis and the experiment, they showed that microdoppler signatures can be useful for detection and classification of targets.

In [11], they use the micro-doppler signatures for target classification and compare the Bayes linear, k-nearest neighbor, and support vector machine algorithms.

Other then using the Doppler effect for classification, there are other works based on High Resolution Range Profiling [12] [13] [14]. High-range resolution radar (HRRP) is a technique used to obtain a one-dimensional signature of an object, known as a high-resolution range profile. This signature is a representation of the time domain response of the target to a radar pulse, and the amplitude of the signal is measured in each high-resolution range cell, providing information about the strength of the return at a particular time delay [12]. HRRP is useful for classification of radar targets due to the distinct characteristics of their range profile signatures.

In [13], they a method for non-cooperative target recognition (NCTR) in air missile defense systems using a combination of moving target detection (MTD) and high range resolution (HRR) profiling. The MTD processing is used to detect moving targets in low elevation search mode, while HRR profiling is used to generate range profiles for automatic target recognition (ATR). The use of this method allows for early NCTR decisions to be made for all detected targets and for the extraction of additional target features that can improve overall target recognition performance. The simulation results show that the MTD and HRR profiling algorithms are effective at detecting and recognizing different types of targets, including theater ballistic missiles and air breathing targets.

In [15], they collected data with an X band radar with a large bandwidth (with a stepped frequency waveform, a sweep bandwidth of 256 MHz) in a range from 110 degree to 160 degree. Boeing 727 and Boeing 737 aircrafts are used for this experiment, and with a bayesian classifier they showed classification from a wide range of aspects is possible.

In [16], they use a C-band radar with pulse repetition frequency of 400 Hz, signal bandwidth of 400 MHz, and collect data from An-26 (medium-sized propeller), Cessna (small-sized jet) and Yark-42 (large-sized jet). Then, with their proposed deep learning model which is deep nested neural network, they achieve classification rates above 90 percent for these air crafts.

Then, image classification approach is generally based on Synthetic Aperture Radar (SAR). SAR images are produced by processing the returned radar signals using a technique called synthetic aperture, which combines the signals from multiple pulses transmitted from different positions to create a single image with increased resolution. The resulting image is similar to a photograph, but it is created using radar signals rather than visible light. There are many target classification works expecially based on MSTAR dataset [17].

In [17], a deep learning method for synthetic aperture radar (SAR) image classification with limited labeled training data is proposed. The method utilizes contrastive learning and pseudo-labels to enhance the representation ability of the backbone networks and improve the classification accuracy. The proposed method consists of two separate networks trained independently by minimizing a contrastive loss, followed by connection to two classification heads for image classification. The networks are then optimized using a cross-training strategy, in which pseudo-labels generated by one network are used to fine-tune the other network. With the classification results, they showed effectiveness of this method.

Kinematic features refer to characteristics or features that relate to the motion or movement of an object [18]. In the field of radar, kinematic features may refer to characteristics of a target's movement or motion that can be detected and analyzed using radar technology. These features may be used in radar-based automatic target recognition (ATR) systems to identify and classify different types of targets based on their motion characteristics. Kinematic features can be extracted from radar data using various methods, including feature extraction algorithms and machine learning techniques [18] [19].

In [18], they proposed a binary classifier for the identification of drones based on trajectory analysis using radar detections. The classification approach utilizes kinematic features and Random Forests, and is designed for real-time use with an adaptive sliding window procedure. The classifier was tested using experimental data from a holographic radar and achieved an accuracy of over 95 percent. The study also addressed the challenges of imbalanced datasets in drone classification.

In [19], they proposed a method for classifying micro-Unmanned Aerial Vehicles (UAVs) and non-UAV targets using Track-While-Scan radar data, with the aim of improving the ability to detect and classify UAVs in air defense systems. The proposed approach explores the use of predefined kinematic and radiofrequency features and extracted features using Principle Component Analysis and an Autoencoder, a deep learning method for unsupervised learning. Different classification methods including Linear SVM, Gaussian SVM, Convolutional Neural Network, and Softmax Classifier are applied to the selected features and their performance is compared using a confusion matrix. The proposed approach is tested on real radar data and the results show that the CNN and Softmax Classifier outperform the other methods, with the CNN achieving the highest accuracy of 92.3 percent.

Then, Range-Doppler Maps (RD Maps) are also can be used for classification of targets [20]. They are consist of range and doppler information which are obtained by range gating and pulse compression in the coherent processing interval [5].The received echos are stacked together as a two-dimensional matrix that includes a single pulse along one axis (fast time, which contains information about the range) and similar pulses along the other axis (slow time, which contains information about the Doppler spectrum) [3]. The resulting matrix is a two-dimensional matrix [3]. By applying the Fourier transform along the slow-time axis, the resulting Range-Doppler map (RD map) can be used to classify targets based on their distinguishable range-Doppler properties, such as propeller size and shape [7] [3]. However, collecting and processing huge amount of data require high computational power. Therefore, RD maps are started to be used in classification With the advancement of computational power [3]. Moreover, deep learning-based algorithms achieve remarkable performance in classification tasks, such as the classification of radar targets with this increase.

RD-map classification cooking process using the CNN structure is proposed in [20]. They create a window that can contain the target's Doppler echo and use it for classification. They recorded RD maps of 6 different scenarios which are boiling pot, no pot, empty-pot, filled-pot, hand movements and combination of these with a 77 GHz chirp-sequence radar. The models were tested on a dataset of 18000 range-Doppler maps belonging to six different classes. The range-Doppler maps, which had 64 range and 64 velocity bins, were fed into the models. The first model achieved an accuracy of 96.86 percent on the test set, while the second model achieved an accuracy of 99.17 percent [20].

In [2], A new method for classifying helicopters in a single Range-Doppler map using a combination of a LSTM-based approach and a novel normalization technique has been proposed. The Doppler signature in each individual range row is treated as a separate sequence, normalized according to the radar parameters, and then input into an LSTM network [2]. LSTM has fewer parameters than CNNs. Moreover, it is able to handle data with varying resolutions and can classify data which is not used. An X-band pulse-Doppler radar is used for test and proposed method achieved 85.7 percent accuracy for helicopters and 98.1 percent accuracy for others [2]. The proposed method achieved 77.8 percent accuracy for helicopters and 99.8 percent accuracy for others in the other X band radar [2].

1.1 Contributions of the Thesis

In this thesis, there are two main contributions. The first contribution is the usage of overlapped data windows. With this method, information about the spatial size of the targets is also used. Thus, Doppler rows for different ranges are related to each other, and this can be used for classification of targets. This approach, called the RD-map overlapping method [3], has been shown to be effective in target classification tasks. The second contribution is the usage of computationally more efficient deep learning architectures such as LSTM with projected layer and GRUs. They are designed to be computationally efficient, particularly in the context of relatively smaller data sets commonly found in radar target classification. The effectiveness of the proposed method is evaluated using various metrics such as accuracy, F1 score, and Matthews Correlation Coefficient.

1.2 The Outline of the Thesis

The present thesis is focused on the problem of helicopter classification using Range-Doppler map, and specifically on the proposal of a 2D overlapping Range-Doppler map approach based on a Gated Recurrent Unit (GRU) network. The working principle of radars is first introduced in Chapter 2, while the proposed method is presented in detail in Chapter 3. The experimental setup, the data set used, and the obtained results are then discussed in Chapter 4. Finally, the conclusion and possible future research directions are addressed in Chapter 5.

2. BACKGROUND INFORMATION ON RADAR AND CLASSIFICATION

Radar is a technology that uses radio waves to detect and measure the distance of objects by emitting electromagnetic waves through a medium that could potentially contain the objects being desired [3]. The name "RADAR" is an acronym for "radio detection and ranging. Then, reflected energies, which are called echoes, provide information about reflected surfaces [21], [7]. In this section, the basic principles of radar will be introduced.

There can be many radar classes based on the feature used as the classifier. These can be waveform type, platform type, mission type, beamforming type, antenna type, power amplifier structure, and transmitter, receiver position, and count.

Depending on waveform type, radar systems can be divided into three categories, which are continuous wave (CW), pulsed, and hybrid radar systems (such as pulsed FMCW radar [22]). CW radars use sinus waveforms. If transmitted waveforms have a center frequency of f_0, echoes from stationary objects also have a center of f_0. Then, if objects are not stationary, their echoes will be shifted by f_d, which is the Doppler shift. By using it, the radial velocity of objects can be found accurately. However, the range cannot be determined without using additional methods such as frequency modulated continuous wave radars (FMCWs) [21]. However, two separate antennas are required due to the nature of continuous transmitting and receiving.

In pulsed radars, modulated/coded pulse waveforms are transmitted and received [5]. Doppler frequency can be found from sequential pulses or Doppler Filter Banks [5]. There are four vital properties of pulse radars. These are carrier frequency, pulse width, modulation, and pulse repetition interval. The carrier frequency affects the mission radar, such as ground penetrating radars [23] which use up to 3 GHz frequencies due to effective depth, or the over-the-horizon radar uses reflection from the ionosphere and is in the frequency range of 3–30 MHz. Pulse width is related to bandwidth, so it affects range resolution. Modulation can affect radar performance; for example, with pulse compression, the range resolution and SNR performance become better.

Finally, PRI affects the Doppler range ambiguity, which is explained in further detail, and transmitted power.

In addition, there are elemental properties of the information that the return signals carry. One of them is the distance to the reflected surface, or the range of the target, which can be found by the travel time, which is the duration taken for the transmitted signal to hit the surfaces and come back. The other is the velocity of the surfaces, which can be found by the change in the frequency of the return signal due to the Doppler effect [5] [21].

2.1 Range and Sampling Interval in Range

The slant range R is defined as the distance between the target and the radar antenna. It can be found by using the time delay between the transmitted and received echo.

$$R = \frac{ct_{delay}}{2} \tag{2.1}$$

The echo is demodulated by a coherent receiver and a baseband signal is acquired. Then, this signal is sampled with a frequency higher then or equal to Nyquist frequency, and stored in a form like in Figure 2.1. Each cube represents a single sample of the baseband signal. A total of N_r samples of baseband signal are called range bins, range, gates or range cells.

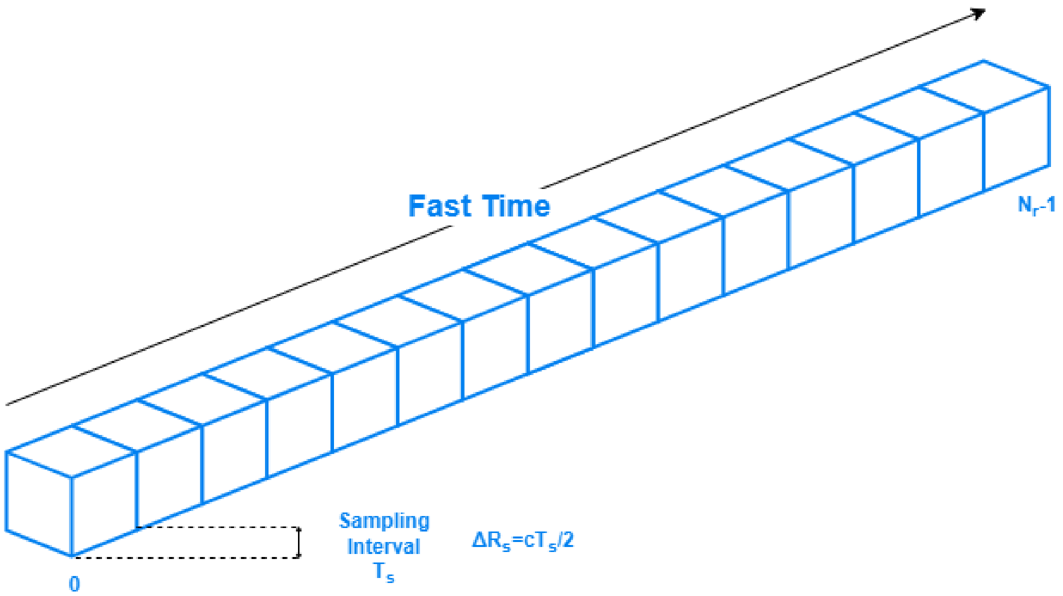

Figure 2.1 : Constructed range bins from echo

R_s is the sampling interval in the range and is proportional to T_s, which is the sampling interval. Moreover,

$$N_r = \frac{R_w}{R_s} \tag{2.2}$$

where R_w is the selected operating range window [24]. Thus, theoretically, the maximum N_r is $\frac{R_{unambigious} - R_{blind}}{R_s}$ where $R_{unambigious}$ is the unambiguous range which will be given in detail in the next sections, R_{blind} is the blind range, which is the minimum distance of the detectable target. Furthermore, $R_{blind} = \frac{c_0 \tau}{2}$ where τ is the pulse width.

2.2 Doppler and Doppler Resolution

Doppler can be defined as the frequency shift on the radar signal due to the relative movement between the transmitter and the illuminated object [25]. It is generally used to separate moving and stationary targets from each other [5]. Let us say that R_0 is the slant range at t_0, and radial velocity of the target is v. Then, we can define the range at any time as

$$R(t) = R_0 - v(t - t_0) \tag{2.3}$$

The signal received on the radar.

$$s_r(t) = s(t - \Delta(t) - t_0) \tag{2.4}$$

where the transmitted bandpass signal is s(t) and the total transmission signal travel time is $\Delta(t)$. For simplicity we can take t_0 as 0

$$\Delta(t) = \frac{2}{c}(R_0 - vt) \tag{2.5}$$

By using eqn. 2.5 and 2.4 we can write the received signal as

$$s_r(t) = s((1 + \frac{2v}{c})t - \frac{2R_0}{c}) \tag{2.6}$$

Then by defining the compression factor $\gamma = 1 + \frac{2v}{c}$, and defining a $\Delta t_0 = \frac{2R_0}{c}$, we can rewrite eqn. as

$$s_r = s(\gamma t - \Delta t_0) \tag{2.7}$$

It is a time-compressed version of the transmitted signal. If we take its Fourier transform, it's frequency domain spectrum will be expanded by γ. The spectrum of the received bandbass signal is centered at $\pm\gamma f_0$ instead of f_0. Then, the difference between these centers will give the Doppler shift f_d. Thus,

$$|f_d| = \frac{2v}{\lambda} \qquad \textbf{(2.8)}$$

This is the Doppler shift. Moroeover, f_d is positive for closing targets and negative for receding ones.

We can collect pulses as in a Figure 2.1 over a coherent processing interval (CPI) together into a matrix as seen in Figure 2.2.The DTFT of slow-time bins gives the Doppler spectrum. The CPI is equal to the $N_d PRI$. Thus, the Doppler resolution is

$$\Delta f_d = \frac{1}{N_d PRI} \qquad \textbf{(2.9)}$$

Then, the number of pulses (N_d) is

$$N_d = \frac{PRF}{\Delta f_d} \qquad \textbf{(2.10)}$$

As seen in eqn. 2.10, N_d is related to both PRF and Doppler resolution.

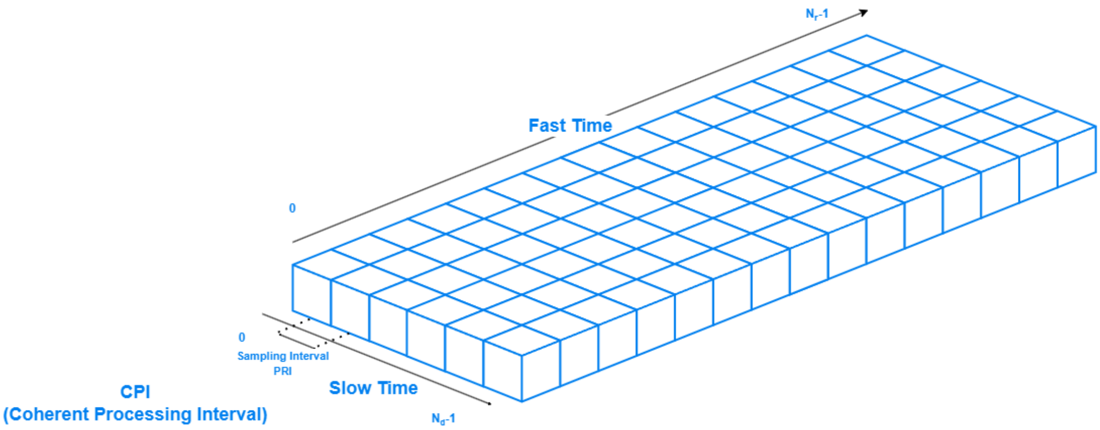

Figure 2.2 : Matrix of fast and slow time bins for a coherent processing interval

2.3 Range and Doppler Ambiguity

The radar systems generally use pulse trains with different Pulse Repetition Frequencies (PRF), which determines the rate at which pulses of radio frequency (RF) energy are transmitted [25]. These PRFs can be examined in three different categories with respect to their frequency levels [5]. These are low PRF, medium PRF, and high PRF. Radar systems transmit pulses with predetermined intervals. If an echo belong to the target 2, arrives the radar after the second pulse transmitted, we cannot know that it is an echo from the first pulse or the second one. Thus, range becomes ambiguous. Thus, unambiguous range can be defined as

$$R_{unamb} = \frac{c}{2PRF} \tag{2.11}$$

Respectively, for the Doppler shift, if we look into the frequency domain representation, maximum unambiguous Doppler frequency [24] difference can be defined as

$$f_{unamb} = \frac{PRF}{2} \tag{2.12}$$

Thus, a dilemma arises. In general, low PRF radars transmit pulses at a slower rate, which allows them to more accurately measure range to a target [5]. This is because the time delay between the transmitted pulse and the received echo is directly related to the range, and a longer time delay allows for more accurate range measurement. However, low PRF radars have poor performance in terms of Doppler velocity, as they cannot distinguish between targets moving at different velocities.

On the other hand, high PRF radars transmit pulses at a faster rate, which allows them to more accurately measure velocity [5]. However, high PRF radars have poor range resolution, as the time delay between the transmitted pulse and the received echo is shorter, which results in less accurate range measurement.

Medium PRF radars offer a trade-off between range and velocity resolution, but they also present ambiguous range and velocity measurements that must be resolved. To overcome this issue, radar systems often use multiple PRFs sequentially, switching between different PRFs to optimize range and velocity resolution for different scenarios [26].

2.4 Range-Doppler Map

The Range-Doppler map is a type of visual representation of radar data. It is used to display the range and velocity of objects detected by a radar system. The range of an object is represented by the distance between the radar and the object, while the Doppler shift of the radar signal reflects the object's velocity.

In radar systems, target classification refers to the process of identifying the type of object that is being detected by the radar. This can be done based on the characteristics of the radar return signal. The range-Doppler map can be used to help classify targets by displaying the range and velocity of the targets as a function of Doppler frequency shift. By analyzing the range and velocity information contained in the map, it is possible to classify objects based on their characteristics, such as size, shape, and material composition. This can be useful for detecting and tracking moving objects, such as aircraft or vehicles.

For example, different types of targets may have distinct patterns on the Range-Doppler map due to their unique range and velocity characteristics. For example, a high-speed airplane may produce a narrow, elongated pattern on the Range-Doppler map, while a slower vehicle may produce a more wide, diffuse pattern. By analyzing these patterns, it is possible to classify targets according to their type and characteristics [7].

To create a range-Doppler map, radar data is typically collected within a coherent processing interval (CPI) as seen in Figure 2.2. Then by performing fast Fourier transform (FFT) along with slow-time axis (CPI) range-doppler maps are acquired. This allows the range and velocity information to be extracted and displayed on a two-dimensional graph. The resulting map can be used to identify and classify objects based on their range and velocity information.

In the proposed part, we will be using collected range-Doppler maps. However, to see how a range-Doppler map is constructed in a more technical representation, let us consider an example. Let us say that a pulsed radar system where transmitted signal is $x(t)$ and assume there is a moving point target at a distance R_0 and with a velocity v. Let us define transmitted pulse signal as

$$x(t) = p_{rec}(t)cos(2\pi f_0 t + \theta(t)) \tag{2.13}$$

where $p_{rec}(t) = rect(\frac{t}{\tau})$, τ is the pulse width, f_0 is carrier frequency and $\theta(t)$ is the phase of the transmitted signal. Then, we can say that the received signal is

$$y(t) \sim x(t - \frac{2R_0}{c}) = p_{rec}(t - \frac{2R_0}{c})cos(2\pi f_0 t + \theta(t) - \frac{4\pi R_0 f_0}{c}) \tag{2.14}$$

By using an I-Q demodulator, and low-pass filter we will get in-phase and quadrature components of signal. For in-phase channel

$$\begin{aligned} &p_{rec}(t - t')cos(2\pi f_0 t + \theta(t) - \theta')2cos(2\pi f_0 t) \\ &= p_{rec}(t - t')(cos(4\pi f_0 t + \theta(t) - \theta') + cos(\theta(t) - \theta')) \end{aligned} \tag{2.15}$$

where $\theta' = \frac{4\pi R_0 f_0}{c}$ and $t' = \frac{2R_0}{c}$. Then by low-pass filtering, we will get $p_{rec}(t - t')cos(\theta(t) - \theta')$. Similarly, for the quadrature channel, using $2sin(2\pi f_0 t)$ and low-pass filtering, we will get $p_{rec}(t - t')sin(\theta(t) - \theta')$. The combination of these channels can be written as $p_{rec}(t - t')e^{j(\theta(t) - \theta')}$. Now, let us say, we will transmit N_d pulses within a CPI ($p_{rec}(t) = \sum_{n=0}^{N_d-1} rect(\frac{t-nT}{\tau})$ where T is equal to PRI) as seen in Figure 2.3.

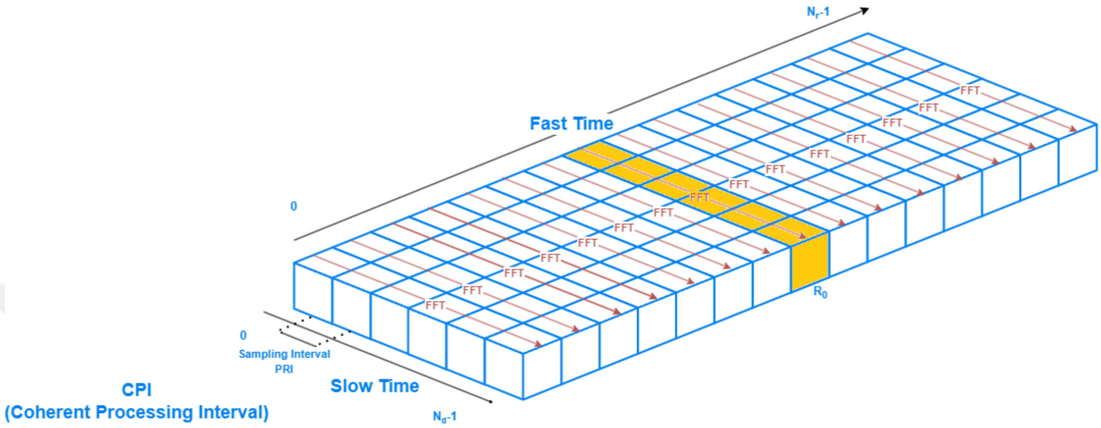

Figure 2.3 : Creation of range Doppler map

We can write the received baseband signal as

$$y[m] = p_{rec}(mT - t')e^{j(\theta(mT) - \frac{4\pi f_0}{c}(R_0 - vmT))} \tag{2.16}$$

where m is pulse number within an interval of $0 \leq m \leq N_d - 1$ and T is equal to PRI. Then, by performing DFT or FFT with K points where $K \geq N_d$ along with the slow-time axis, we will get a Doppler bin. By performing FFT through all, we will get the range Doppler map.

2.5 LSTM based Target Classification with RD maps

LSTM (Long Short-Term Memory) networks are a type of Recurrent Neural Network (RNN) that are designed to extract relevant features from sequential data. RNNs are a variation of neural networks that are designed to process data where the sequence of the data is important. They achieve this by using the output of each neuron at a previous time step and combining it with the new input data at the current time step [27] in order to extract relevant features from the data. Essentially, RNNs maintain an internal memory that encodes relevant information about the input sequence and updates this memory as new data is received.

However, RNNs can struggle to retain relevant information when processing lengthy sequences due to the vanishing gradient problem [28]. This occurs when the information propagated to the beginning of the sequence becomes smaller as the sequence length increases, which hinders the learning capabilities of RNNs. To address this issue, LSTM networks were developed [1].

LSTM networks are structured with a number of "gates" that control the flow of information within the network. These gates allow LSTMs to selectively retain or discard information in the internal memory, which helps to prevent the vanishing gradient problem [1]. LSTMs also have an internal memory called the hidden state, which is updated with data from the most recent time step. This hidden state is used to store relevant information about the input sequence, and it is updated as new data is received. The working principle of each gate is as follows:

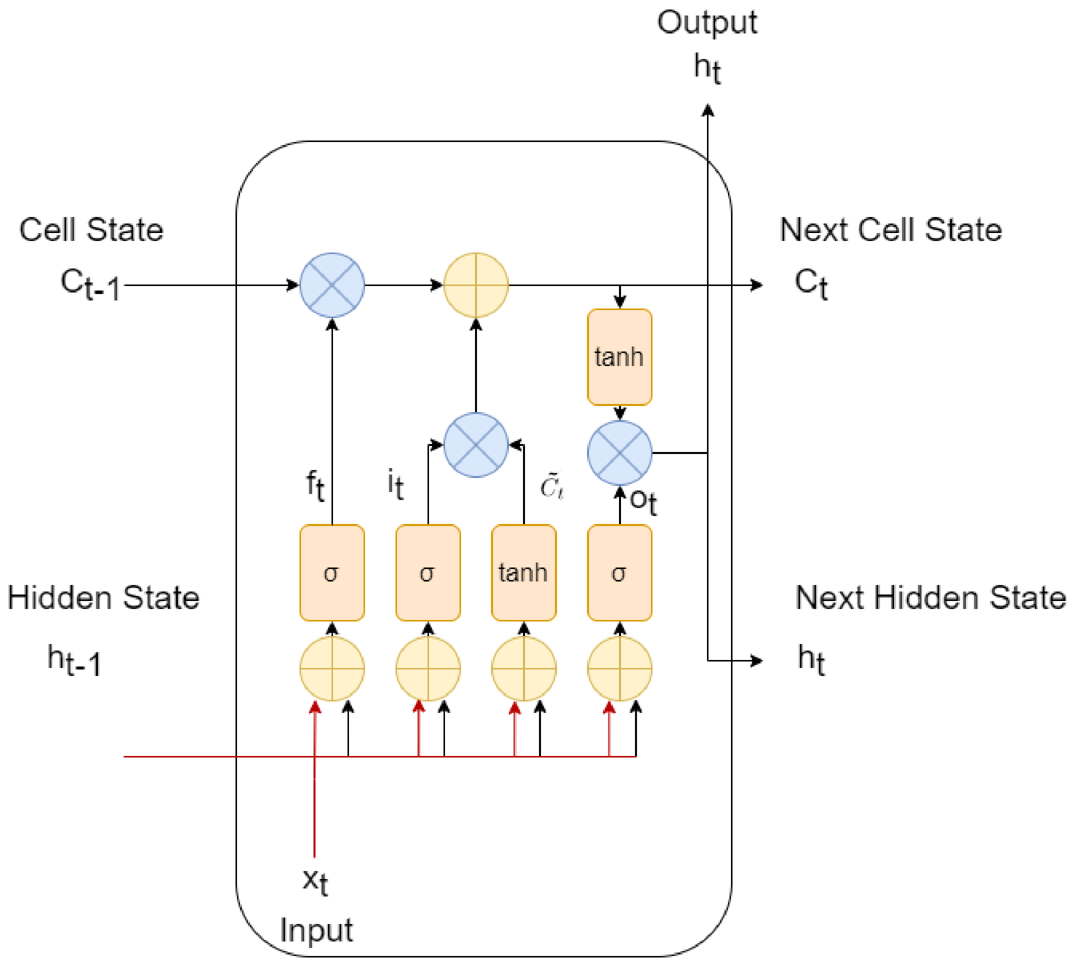

Figure 2.4 : Simplified LSTM structure based on [1]

Mathematical expression of Figure 2.4 is as follows,

Algorithm 1 LSTM [1], [29], [25]

Forget Gate [3] $f_t = \sigma(x_t W_f + h_{t-1} U_f + b_f)$
Input/update gate's activation vector [3] $i_t = \sigma(x_t W_i + h_{t-1} U_i + b_i)$
Output Gate [3] $o_t = \sigma(x_t W_o + h_{t-1} U_o + b_o)$
Cell Input Activation Vector [3] $\tilde{C_t} = tan[(x_t W_C + h_{t-1} U_c + b_c)]$
Cell State Vector [3] $C_t = \sigma(f_t \times W_C + i_t \times \tilde{C_t})$
Current Hidden State [3] $h_t = tanh(C_t) \times o_t$

where W, U and b are weight matrices and bias vector paramaters that will be utilized in training and x_t is input vector and [3] [25]. In Figure 2.4, bias parameters are not shown for simplicity.

The input gate is responsible for controlling the flow of information into the internal memory of the LSTM cell. It is implemented as a sigmoid neural network layer that takes the previous hidden state and the current input data as input and produces a value between 0 and 1 for each element in the internal memory. A value of 0 indicates that the element should be discarded, while a value of 1 indicates that it should be stored in the internal memory. The input gate determines which pieces of the current input data should be retained and which should be discarded. Then, the forget gate is responsible for controlling the flow of information out of the internal memory of the LSTM cell. It is implemented in a similar manner to the input gate, using a sigmoid neural network layer that takes the previous hidden state and the current input data as input and produces a value between 0 and 1 for each element in the internal memory. A value of 0 indicates that the element should be forgotten, while a value of 1 indicates that it should be retained in the internal memory. The forget gate determines which pieces of the previous internal state should be retained and which should be discarded. Finally, the output gate is responsible for controlling the flow of information out of the LSTM cell. It is implemented as a sigmoid neural network layer that takes the previous hidden state and the current input data as input and produces a value between 0 and 1 for each element in the internal memory. A value of 0 indicates that the element should not be used to compute the output of the LSTM cell at the current time step, while a value of 1 indicates that it should be used. The output gate determines which pieces of the internal state should be used to compute the output of the LSTM cell at the current time step.

The ARIN [2] (Adam-trained Radar Independent Network) structure, which was introduced in a previous study, allows for the algorithm to be trained on various combinations of range and Doppler bin sizes, enabling it to make real-time decisions compared to CNN-based methods thanks to its LSTM structure [3]. An innovative normalization method has also been introduced that uses radar-specific parameters to better generalize the data, taking into account the noise floor levels and the maximum potential level of the radar signal [3].

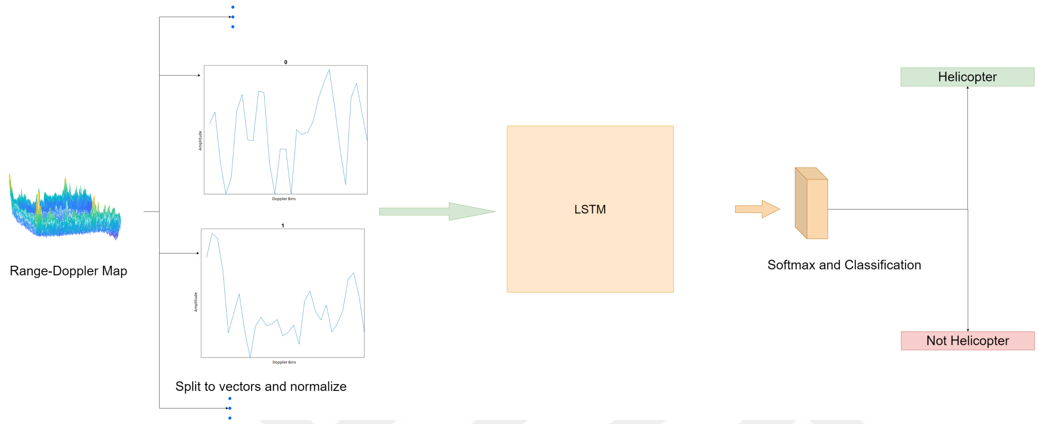

Figure 2.5 : Overall ARIN structure (Only Doppler signature is used, range information is lost) [2]

Overall ARIN structure can be seen in Figure 2.5. At first $RD_{map}(t_m, w) \in \mathbb{C}^{N_a x Nr}$ is divided into N_a vectors. Thus as input, we have N_a Doppler vectors, and no range information. Following splitting the data, we will normalize the vectors, divide the data into training and test sets, and train the LSTM (Long Short-Term Memory) network. Then, with the learned Doppler information, classification is performed.

3. PROPOSED METHOD

3.1 Overlapped Window Model

An overlapped window model involves dividing the Range-Doppler map into a series of smaller windows and then moving the window through the data in a sliding fashion to extract features from different parts of the data. This can be a useful approach if we want to capture local features or patterns within the data that may not be visible on a global scale. In this case, we want to capture Doppler and range related features from RD maps.

Different targets can have different configurations of scattering centers, which can result in different Doppler characteristics [3]. In the approach mentioned above , $RD_{map}(t_m, w) \in \mathbb{C}^{N_d \times Nr}$ is divided into N_r columns, and only Doppler characteristics across independent range columns, N_r times $RD_{map}(t_m, w) \in \mathbb{C}^{N_d \times 1}$, are used to classify targets. However, the targets have different spatial sizes, so they take different spaces on the range axis.

Let us define RD map for practical applications to explain the overlapped method. As seen in RD map creation subsection, a $N_d \times N_r$ matrix is obtained. N_d and N_r values are changing according to the pulse configuration of radars. By adding this information and redefining time (t_m) and Doppler shift (w) by r and d, and taking its transpose for just graphical interpretations,

$$M(s)_{r,d} = RD^{s}_{map}(t_m, w) \tag{3.1}$$

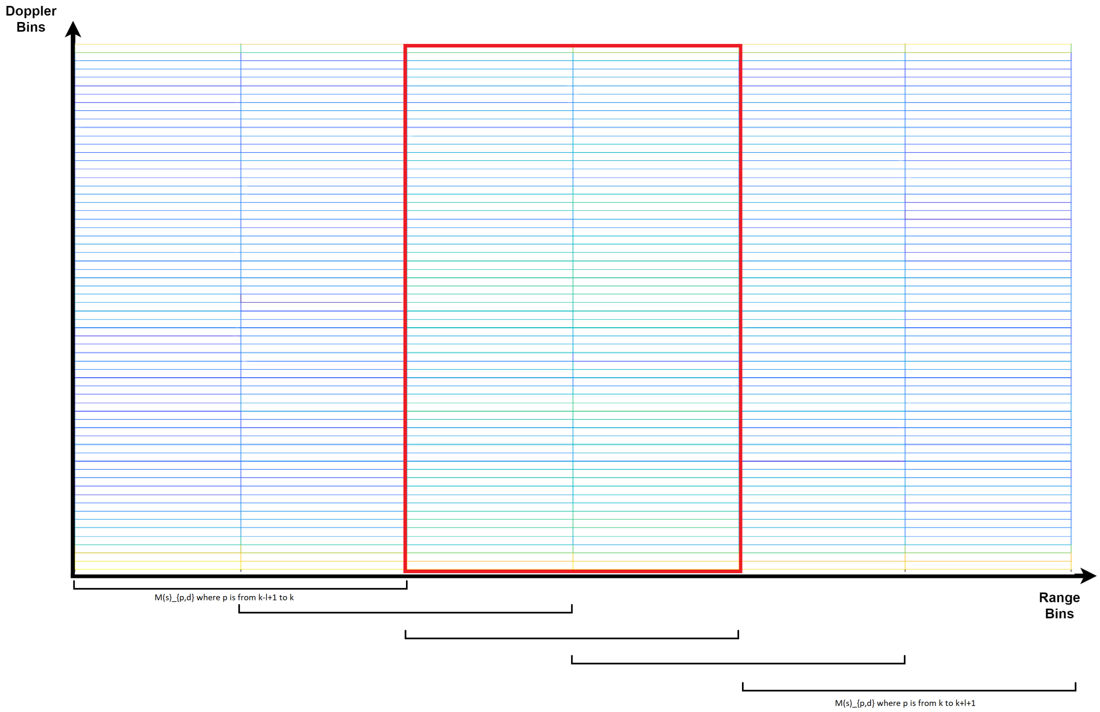

Figure 3.1 : Proposed Windowed Data (The area between the red lines shows target) [3]

$M(s)_{r,d}$ is RD map where s is the sample number, r is the range indices from 1 to the range size of the related sample, and d is the Doppler indices from 1 to the length of the Doppler bin count as in [3]. As depicted in Figure 3.1, the analysis of the RD map through the use of overlapping windows offers a wealth of information regarding the spatial size of the target, and it is anticipated that this information will enhance the classification accuracy rate [3].

3.2 Gated Recurrent Units

Gated Recurrent Units are a special type of Recurrent Neural Networks (RNNs), and have similar but different structures to those of LSTM. Key Differences Between Long-Short-Term Memory (LSTM) Networks and Gated Recurrent Units (GRUs) are:

- Structure: LSTM networks have a more complex structure than GRUs, with three different types of gates (input, output, and forget) that control the flow of information through the network [4]. The input gate controls the flow of information into the network, the output gate controls the flow of information out of the network, and the forget gate controls the retention of information within the network [30]. This allows LSTM networks to selectively retain or discard information over time, which makes them particularly effective at learning long-term dependencies in the data. In contrast, GRUs have a simplified structure with two gates that control the flow of information (update and reset). The update gate determines which information from the previous time step should be retained and the reset gate determines which information should be discarded. This allows GRUs to selectively retain or discard information over time, but to a lesser extent than LSTMs.

- Training time: LSTM networks can take longer to train than GRUs due to their more complex structure. This is because LSTMs have a larger number of parameters and require more computations to update the gates, which can slow down the training process. However, LSTM networks may also be more effective at learning long-term dependencies in the data, as they are able to selectively retain or discard information over time.

- Memory requirements: LSTM networks have a larger number of parameters than GRUs, which can result in higher memory requirements during training. This is because LSTMs require more memory to store the weights and biases for the three gates, as well as the hidden state. This can be an issue for large-scale tasks or when training on GPUs with limited memory.

- Generalization ability: Some research has suggested that GRUs may have better generalization ability than LSTMs, meaning that they may perform better on unseen data.

Let us look at the GRU structure in Figure 3.2

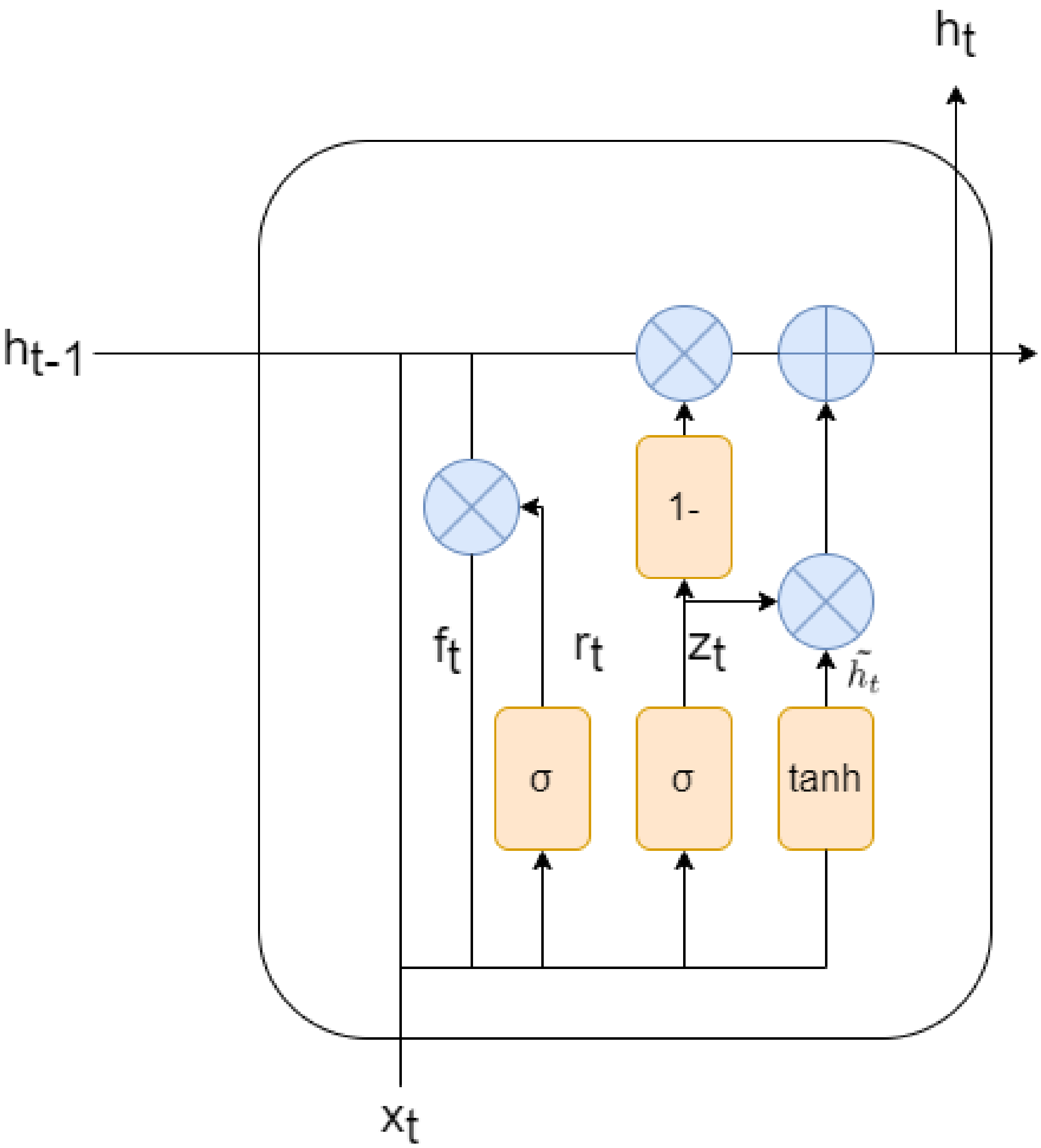

Figure 3.2 : GRU internal structure based on [4]

If we write mathematical expression of it we will see

Algorithm 2 GRU [3] [25]

Update Gate [3] $z_t = \sigma(x_t W^z + h_{t-1} U^z + b_z)$
Reset Gate [3] $r_t = \sigma(x_t W^r + h_{t-1} U^r + b_r)$
Candidate Hidden State [3] $\tilde{h_t} = tanh(r_t \times h_{t-1} U + x_t W + b_c)$
Hidden State [3] $h_t = (1 - z_t) \times \tilde{h_t} + z_t \times h_{t-1}$

where W^z, W^r and W are the weight matrices for the related input vector; U^z, U^r and U are the weight matrices of the previous time step; and b_r, b_z and b are the corresponding biases.

3.3 LSTM with Projected Layer

The key difference between the projected LSTM and the original LSTM is the way the hidden state is computed. In the original LSTM, the hidden state is computed using the following equation [1]:

$$hiddenstate_t = f_t * hiddenstate_{t-1} + i_t * cellstate_t \quad \textbf{(3.2)}$$

where f_t is the forget gate, i_t is the input gate, and $cellstate_t$ is the cell state.

In the projected LSTM, the hidden state is computed using a different equation:

$$hiddenstate_t = f_t * hiddenstate_{t-1} + i_t * projection(cellstate_t) \quad \textbf{(3.3)}$$

where projection, $cellstate_t$,is a projection of the cell state.

Thus, projection layers are a type of deep learning layer that allows compression by reducing the number of unknown parameters. It is a type of deep learning layer that will reduce the number of stored learning parameters [31], and thanks to this the training speed of the model is increased.

According to [32] , the projected LSTM is similar to the original LSTM in terms of its ability to learn long-term dependencies in the data, but it has a more efficient structure that allows it to be trained and used more efficiently on large-scale tasks or on heterogeneous systems. Thus, it might give better results in target classification.

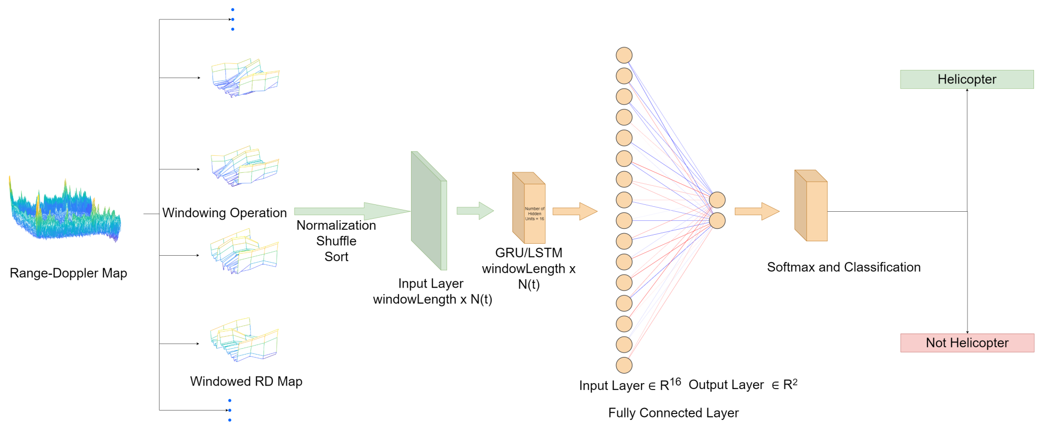

Figure 3.3 : Representation of overall algorithm proposed

A general outline of the proposed method to use GRU/LSTM for classification using range-Doppler maps can be seen in Figure 3.3, and summarized as

- Data acquisition and preprocessing: The first step in the algorithm is to acquire the RD maps for each radar target and store them in a dataset. After the RD maps are acquired, we transform the data into a format suitable for input to the GRU network.

- Overlapped Window extraction: To enable the use of overlapped windows in the classification process, the RD maps data are divided into multiple overlapping windows along Range axis. Each window consists of a contiguous segment of the RD map with a fixed size, and the windows overlap by a certain percentage.

- Data normalization: The training and test sets are then normalized to have zero mean and unit variance. This is done to improve the stability and convergence of the network during training, and to ensure that the input data has a consistent scale. Clipping normalization technique is used which will be explained in the Experimental Results chapter.

- Data splitting: They are shuffled, sorted and split into training and test sets. The training set is used to train the GRU network, while the test set is used to evaluate the performance of the trained network on unseen data. The size of the training and test sets may vary depending on the size of the dataset and the desired balance between training and testing.

- Training: The GRU network is then trained on the training set using an optimization algorithm, such as Adam(A Method for Stochastic Optimization) or a stochastic gradient descent, to learn the relationships between the RD map windows and the corresponding class labels. The training process involves iteratively updating the weights of the network using backpropagation and the optimization algorithm, with the goal of minimizing the error between the predicted class labels and the true class labels. The network is trained until the performance on the training set reaches a satisfactory level or the performance on the validation set stops improving.

- Evaluation: Once the network is trained, it is evaluated on the test set to measure its performance on unseen data. This can be done using performance metrics such as accuracy, F1 score and Matthew Correlation Coefficient. The performance metrics provide a quantitative measure of the network's ability to correctly classify the RD map windows into the correct class labels.

- Fine-tuning: If the performance on the test set is not satisfactory, the network can be fine-tuned by adjusting its hyperparameters, adding or removing layers, or using a different optimization algorithm. The fine-tuned network can then be re-trained and reevaluated in the test set.

Overall, this is a detailed version of the example algorithm for using an GRU network for classification of radar targets using RD maps with overlapped windows. It can also be applied with any RNN based structure.

4. EXPERIMENTAL RESULTS

4.1 Dataset Preparation

4.1.1 Data Acquisition

Two X band radars used in the data acquisition part, for convenience, they will be mentioned as radar A, B in following sections. There are two datesets acquired from radar A, B [3]. In radar A, while a helicopter with 2 pals was approaching with a speed of around 50 m/s, RD maps are collected [3] [2]. 64 RD maps are collected as different dimensional matrices. In radar B [3], RD maps are collected while a helicopter is in the process of approaching and departing from the radar system. 86 RD maps were acquired [3] as different dimensional matrices as in the radar A [3]. Different PRI values were used for the reasons mentioned in "Background Information on Radar" chapter.

Using helicopter GPS data, the range of t on the RD map is determined at each time, selected as helicopter, and everything else determined as noise & clutter. The collected data contain different elevation channels. The channel which has higher power on helicopter range is selected.

In the end, data collection for radar A yielded 188 data entries for helicopters and 80,277 data entries for noise and clutter, while radar B yielded 390 data points for helicopters and 98,124 data entries for noise and clutter [3]. To visualize, example data from radar A can be seen in Figure 4.1.(Range bin count, doppler bin count and amplitude of signals are removed for confidentiality reasons.)

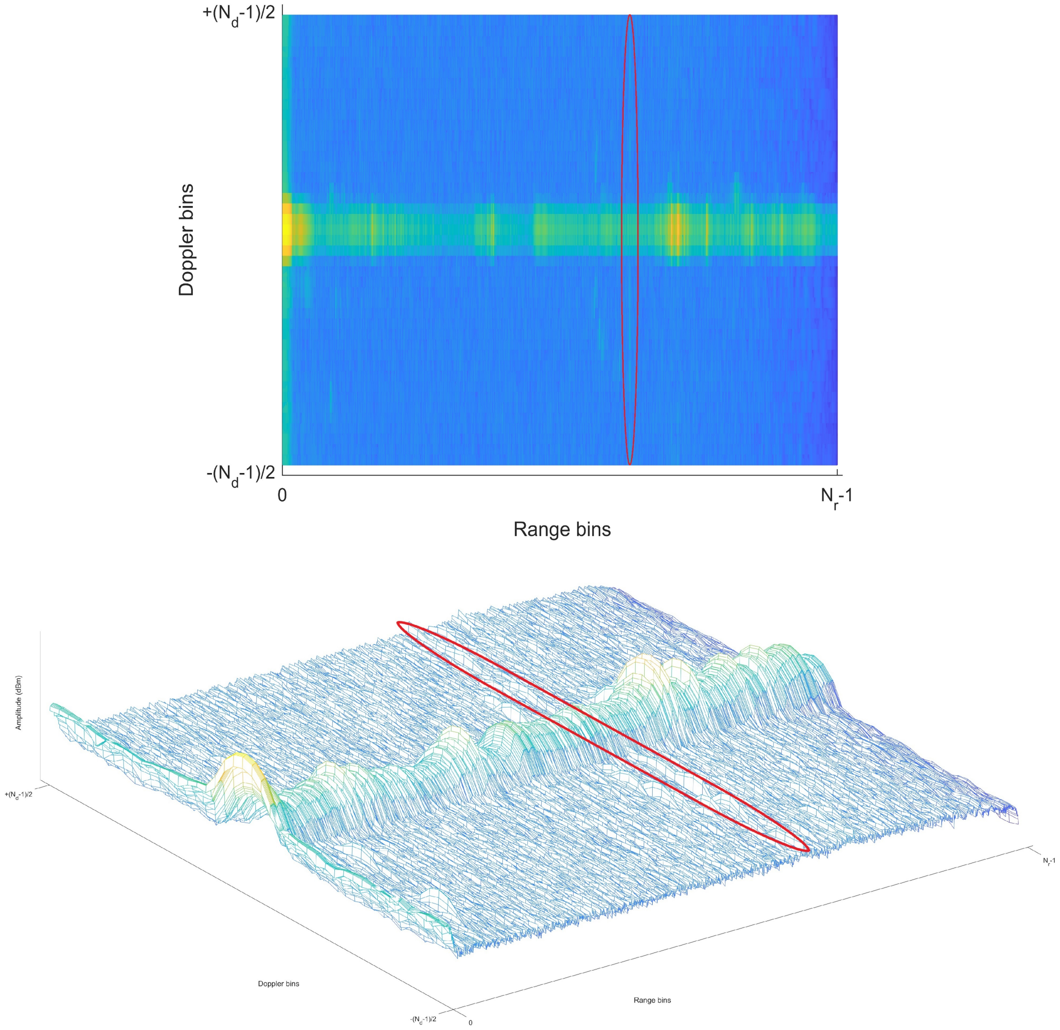

Figure 4.1 : Example Raw Data from radar A (Red contour shows helicopter echo everything else is accepted as clutter+noise)

4.1.2 Data Augmentation

Data augmentation is a technique that is used to generate additional data samples for a deep learning or machine learning dataset. It is often used when the dataset is imbalanced, meaning that the number of samples in one class significantly outnumbers the number of samples in the other class. For example, in a dataset of images of plants, there may be many more images of one type of trees than there are of another type (such as grass). This can create an imbalanced dataset, with a disproportionate number of samples in each class.

This can be a problem because deep learning algorithms are typically designed to learn from a balanced dataset, where the number of samples in each class is roughly equal. When the dataset is imbalanced, the algorithm may have difficulty learning to accurately classify the minority class, leading to poor performance on that class. In RD map classification problem, desired target which is helicopter covers less space than the noise & clutter, and this will be always the case. Thus, we need to augment the desired data, helicopter data.

As seen in Figure 4.1, there are high amplitude levels in first four and last three Doppler bins due to clutter. Moreover, there are also high amplitude clutters which is very close to the radar, and we removed the we also removed the first 50 range bins due that. Then, for proposed overlapped window model, data is splited to overlapped windows.

Then, we used circular shift to increase helicopter data [3]. Along Doppler axis, the data is moved one unit each time [3]. In radar A, a total of 14,320 pieces of data for helicopters and 84,032 pieces of data for noise and clutter were collected, and radar B produced 8,065 pieces of data for helicopters and 95,691 pieces of data for noise and clutter [3]. Example of windowed data for helicopter and noise & clutter can be seen in Figure 4.2. In general, the length of the helicopters are in the range of 8.5 m to 30.3 m [33]. Taking this fact into account, the window length is selected as three.

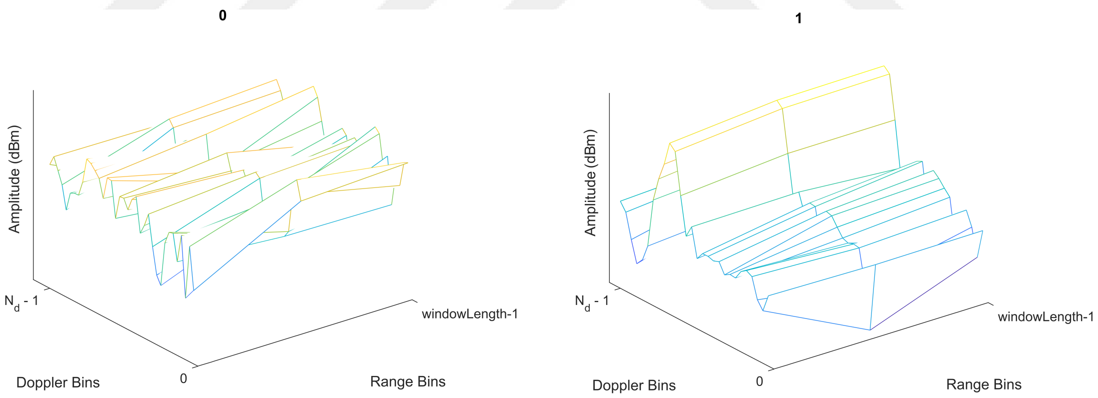

Figure 4.2 : Example windowed noise (left) and helicopter(right) data from radar B (The window length is chosen as three, so RD map dimensions are $3 \times N_d$)

For single cell model, overlapping window size can be considered as one. Thus, there is no overlapping window and the other processes stay same. Example single cell helicopter and noise &clutter data can be seen in Figure 4.3.

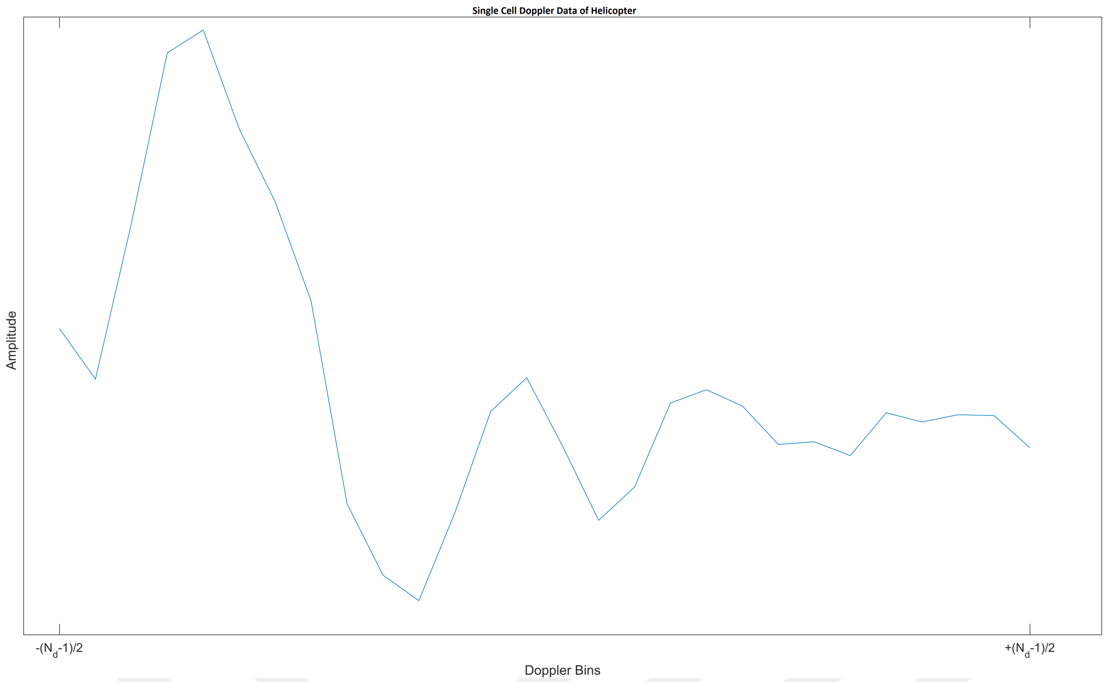

Figure 4.3 : Example single cell Doppler data of helicopter from radar A according to [2]

4.1.3 Data Normalization

Clipping normalization is a technique that is often used to pre-process data for use in deep learning. It involves scaling the data to a fixed range, such as between 0 and 1 or between -1 and 1, by clipping the values that fall outside of this range. It can reduce the effect of outliers in the data. Outliers are data points that fall significantly outside the range of the majority of the data and can have a disproportionate influence on the model if they are not handled properly. By clipping values that fall outside the fixed range, outliers can be effectively removed from the dataset, reducing their influence on the model.

We have been analyzing the dataset using amplitude (dB) plots up until now, and expect from deep networks to extract information from them. Therefore, the input to the subsequent clipping function is these RD map plots. Scaling the plots does not alter the shape of structures, as long as they are plotted between their minimum and maximum values with a fixed resolution.

If the values of the features in machine learning algorithms are close to each other, the algorithm is likely to train more efficiently and quickly compared to a dataset where the data points or feature values have large differences. When the data has data points that are far apart from each other, scaling is a technique used to bring them closer together. In other words, scaling makes the data points more generalized so that the distance between them is reduced. Machine learning models learn from the data by mapping data points from input to output. However, the distribution of data points can vary for each feature of the data. A larger difference between the data points of the input variables increases the uncertainty in the model's results.

Clipping normalization technique used in [2] is used. Predetermined radar-based minimum and maximum values for RD map are determined. If there are greater values then maximum, they are clipped to the max value. Then, if there are smaller values then minimum, they are clipped to the minimum. After that all the data map to the interval of zero and one. The clipping function can be defined as

$$clip(x) = \begin{cases} 1, & \text{if x} \geq RD_{max} \\ \frac{x}{RD_{max}-RD_{min}} & \text{if } RD_{min} < \text{x} < RD_{max} \\ 0, & \text{if x} \leq RD_{min} \end{cases} \quad \textbf{(4.1)}$$

where RD_{min} and RD_{max} are predetermined minimum and maximum radar amplitudes. Window size is arranged according to helicopter size, so it is hard to see the difference between raw RD map and clipped normalized one. Therefore, raw and normalized RD map from raw data for helicopter and noise & clutter can be seen in Figure 4.4, red contour shows helicopter echo.

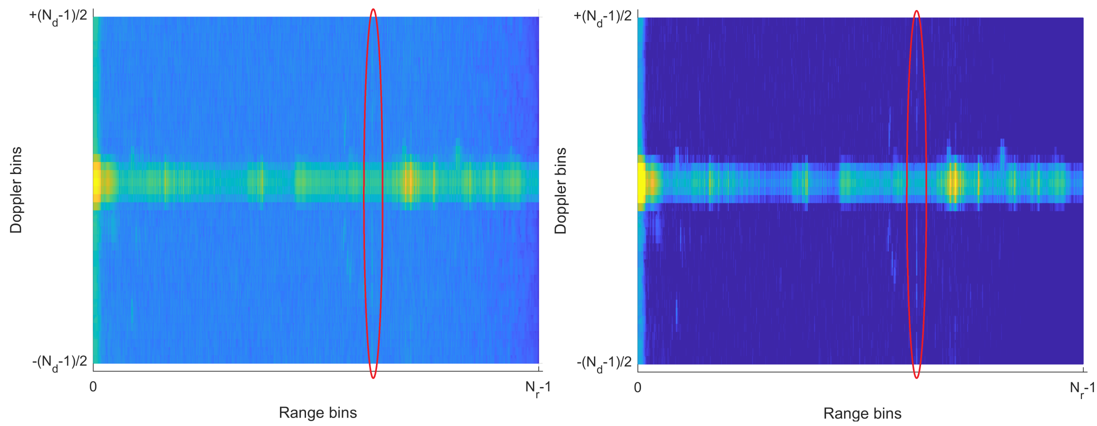

Figure 4.4 : (a.) Example raw data from radar A (left) and (b.) Example normalized data from radar A (right)

As seen the features become more distinct, and free from small variations around noise level. Variations on noise level become more stable, so network can better learn both noise and helicopter features. Thus, we can say that it can improve the generalizability of the model. Generalization refers to the ability of a model to make accurate predictions on unseen data and is an important factor in the performance of deep learning algorithms. By encouraging the model to learn more robust features that are not sensitive to small variations in the data, clipping normalization can improve the model's generalization ability and lead to better performance on unseen data.

4.2 Training Configurations

The ADAM (Adaptive Moment Estimation) algorithm is a stochastic gradient descent (SGD) algorithm that is designed to adaptively tune the learning rates of the model's parameters during training [34]. The Adam algorithm was employed with a learning rate drop interval of 20, a learning rate drop factor of 0.9, and an initial learning rate of 0.01 [3]. MATLAB 2022B and its Deep Learning Toolbox used for the designing and performing simulations. Maintaining the same Doppler length for each batch avoids the need for padding [2] [3]. This information is used to determine the size of the mini-batch [3]. A training option 'best-validation-loss' is selected. 1000 is selected as number of maximum epochs. However, since the best-validation-option is selected, at the end of 1000 epochs the network parameters are chosen as when the validation performance is best. The Nvidia Quadro T2000, RTX4000, and a high-performance computing system equipped with 12 Nvidia Titan X graphics cards were utilized for training purposes [3].

4.3 Layer Configurations

In GRU, LSTM like structures, the number of hidden units is a vital hyperparameter that determines the capacity of the network. The hidden size determines the number of memory cells available to the network to store and process information and plays a critical role in the ability of the network to learn and make predictions [29]. Generally speaking, a larger hidden size allows the LSTM network to capture and process more complex patterns in the data, which can improve its performance [29]. However, it is important to find the right balance, as a hidden size that is too large may lead to overfitting, while a hidden size that is too small may limit the ability of the network to learn from the data [35].

There are few approaches to select the number of hidden units. One option is starting with small network sizes then increase the network size until performance improves. Another option is grid search which is a technique for hyperparameter optimization that involves systematically searching through a defined range of hyperparameter values to find the optimal combination that gives the best performance on the model but it is computationally expensive. Since there is enough computational power for training, grid search is performed. Training and validation performances by using radar A dataset and 9 percent validation set are compared. It is found that when layer size is 16, network is achieved the best results.

By comparing training and validation performances and without increasing the computational load too much (Since the algorithm will be implemented on a real radar which has limited computational capability), optimum GRU layer size is chosen as 16.

4.4 Number of Total Learnables Comparison

The number of learnable parameters in a deep learning model refers to the number of weights and biases that are trained during the model fitting process. These parameters are typically stored in tensors, which are multi-dimensional arrays that can be modified during training. The total number of learnable parameters in a model is determined by the model architecture and the number of layers, as well as the size of the input data and the number of units in each layer.

In a deep learning model, they can have a significant impact on its implementation on hardware, as models with more parameters require more memory and computational resources to train and evaluate. For example, models with a large number of learnable parameters may require more memory to store the weights and biases, and may also require more time to train on a given dataset. This can be a challenge when implementing deep learning models on hardware with limited memory or processing power, such as on embedded devices or mobile devices. In radar applications, computational efficiency is important because of the nature of the problem. Thus, a network with million learnables is not suitable there. As suggested in [2], smaller network model is required. Single-Cell Model with LSTM (ARIN [2] has 338 total learnables. Therefore, we proposed applicable network models compared to CNN.

The overlapped LSTM with projection layer network has a total of 16 hidden units and 552 learnable parameters, making it an efficient and suitable choice for hardware implementation. In comparison, the overlapped LSTM network has 16 hidden units and 1.3k total learnable parameters, while the overlapped GRU network has 16 hidden units and 994 total learnable parameters. These architectures are also well-suited for hardware implementation, as they have a relatively low number of learnable parameters compared to some other deep learning models. When implementing these models on hardware, it is important to consider the available memory and computational resources, as well as the desired level of accuracy and performance. By carefully designing the model architecture and selecting an appropriate hardware platform, it is possible to achieve high performance and efficiency in the implementation of these overlapped networks

4.5 Performance Evaluation Metrics

As previously mentioned, the dataset is imbalanced. Despite attempts to balance it, there remains a discrepancy. Perfect datasets do not exist, so we must accept the imbalanced nature of this dataset. However, if we try to evaluate models just by accuracies, misleading results might occur. In imbalanced datasets, the distribution of classes is skewed, with one class (the majority class) having significantly more examples than the other class (the minority class). In such situations, using accuracy as the sole performance metric can be misleading, because accuracy does not take into account the class distribution in the data.

For example, consider a binary classification problem with a dataset that is 90 percent negative examples and 10 percent positive examples. If the model always predicts the negative class, it will achieve an accuracy of 90 percent, even though it is not making any correct predictions for the positive class. This can be misleading, as the model's performance on the positive class (which is the minority class) is not reflected in the accuracy metric.

To get a more complete picture of the model's performance in imbalanced datasets, it is important to use other performance evaluation metrics, such as the Matthews Correlation Coefficient (MCC) [36] and the F1 score, which take into account the balance of the classes in the data and provide a more detailed view of the model's performance [37]. These metrics are more sensitive to the class distribution in the data and can provide a more accurate assessment of the model's performance on the minority class.

MCC calculated as [36]:

$$MCC = \frac{(TP*TN - FP*FN)}{\sqrt{(TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}} \tag{4.2}$$

F1 score calculated as [37]

$$\frac{TP}{TP+0.5(FP+FN)} \tag{4.3}$$

where TP is true positive, TN is true negative, FP is false positive and FN is false negative in both equations.

4.6 Accuracy Comparisons

The performance of various recurrent neural network (RNN)-based methods for classifying radar targets was evaluated through two experiments using data from radars A and B. The first experiment aimed to assess the impact of incorporating spatial information of the target in the classification process, and compared the proposed overlapped multicell GRU method with the single cell LSTM model. The second experiment examined the generalizability of the model by using two different configurations of training and validation data.

The results of the first experiment, presented in Table 4.2, showed that the overlapped multicell GRU method achieved the highest helicopter classification accuracy with a difference of 9.05 percent and 34.27 percent on the data from radars A and B, respectively, compared to Single Cell LSTM. On the other hand, the single cell LSTM method achieved the highest noise and clutter classification accuracies of **98.87** percent and **99.99** percent on the data from radars A and B, respectively, but at the cost of lower target classification accuracy. In order to fully evaluate the performance of the various methods, it is necessary to consider additional evaluation metrics such as the F1 score and the Mathew Correlation Coefficient (MCC). The overlapped multicell LSTM method achieved a better F1 score with a difference of **0.000296163** and an MCC of **0.000242014** compared to the overlapped multicell GRU method. However,

Table 4.1 : Single Doppler bin and multi Doppler bin performance evaluation by utilizing radar A dataset

Model	Using 9% Test Set on Radar A		All Data on Radar B		F1 Score	MCC
	Helicopter Accuracy	Noise+Clutter Accuracy	Helicopter Accuracy	Noise+Clutter Accuracy		
Single Cell LSTM(based on ARIN [2])	87.25	**98.87**	61.86	**99.99**	0.856	0.845
Single Cell GRU	95.87	98.35	72.07	99.94	0.901	0.890
Overlapped Multi Cell LSTM	94.79	98.51	94.36	99.9	**0.943**	**0.934**
Overlapped Multi Cell Projected LSTM	95.48	98.12	94.37	99.2	0.925	0.916
Overlapped Multi Cell GRU	**96.3**	98.05	**96.13**	99.86	0.943	0.936

Table 4.2 : Performance evaluation of proposed methods utilizing common dataset

Model	Test Set on Radar A+B		F1 Score	MCC
	Helicopter Accuracy	Noise+Clutter Accuracy		
Overlapped Multi Cell LSTM	92.85	99.25	0.934	0.926
Overlapped LSTM with Projected Layer	89.11	99.01	0.904	0.893
Overlapped Multi Cell GRU	**93.72**	**99.37**	**0.943**	**0.936**

the differences between the two methods are small and both perform well on the imbalanced dataset.

In the second experiment, a dataset containing data from both radars A and B was created, and a 9 percent validation ratio was used as in the first experiment. The results, presented in Table 4.1, showed that the overlapped multicell GRU method achieved a helicopter classification accuracy of **93.72** percent and a noise and clutter accuracy of **99.37** percent. The F1 score and MCC were also calculated and found to be higher with a difference of **0.009** and **0.010**, respectively compared to the overlapped multi cell LSTM. By considering all of the evaluation metrics, it can be concluded that the overlapped multicell GRU method performs better overall compared to the other methods tested.

Therefore, the proposed overlapped multicell GRU/LSTM method demonstrated strong performance in both experiments, with particularly high helicopter classification accuracy and robustness when considering classes in both radars A and B. This suggests that use of an overlapped window model in combination with a GRU/LSTM network is a promising approach for radar target classification.

5. CONCLUSIONS AND RECOMMENDATIONS

In this thesis, we have presented a novel approach for classifying helicopter targets using RD map data and overlapped window GRU networks. By applying an overlapped approach that also takes advantage of utilizing the range information [3] of the target and a GRU-based network, which is particularly well-suited for handling smaller datasets, we have developed a classification algorithm that is more generalizable and robust. Through a series of experiments, we have shown that this method is effective at accurately identifying helicopter targets with different radars. One of the key contributions of our work is the use of overlapped window GRU networks, which enable the incorporation of spatial information in the data. This is a significant advancement over previous methods, which have typically relied on single-cell models.

The first experiment demonstrate that the overlapped window approach outperforms these previous methods in terms of accuracy and robustness. Moreover, the usage of overlapped data windows make the usage of RNN based methods in a environment, where coherent processing interval, and pulse configurations are continuously changing, possible. Without this window model, to able to use spatial information of targets with a deep learning network, RD maps need to be cropped or truncated. This means a possible beneficial data loss. Overlapped data window also contributes the solution of this problem.

The usage of LSTM with projected layer and GRUs provide computationally more efficient structure then other RNNs and this makes the real-time implementation possible with lower memory requirements. Another advantage of using these networks for radar target classification is that they do not require the data to be cropped or truncated in order to be processed. In contrast, convolutional neural networks (CNNs) often require the input data to be of a fixed size, which can result in the loss of valuable information. The use of these allows for the classification of radar data without the need to crop or truncate the data, which can be particularly useful when dealing with targets that have complex shapes or structures. This can help to improve the accuracy and robustness of the classification, as more of the relevant information about the target is preserved. Additionally, the use of these networks allows for the classification of radar data regardless of the size of the range-Doppler (RD) map. In our algorithm, both window size and range bins count can be changed. This is because RNNs are able to process data of variable length, whereas CNNs typically require the input data to be of a fixed size. This means that the proposed algorithm is applicable to a wide range of RD map sizes making it highly flexible and adaptable to different scenarios. The final advantage is that they are more suitable for smaller datasets since radar target classification is a problem where collecting data about desired target is time consuming and costly.

In future work, it would be interesting to extend the scope of the method to include a greater variety of target types, such as fixed-wing aircraft and ground vehicles, and to move beyond binary classification to a multi-class classification setting. Additionally, by implementing the method in a 3D neural network with a similar overlapping approach, we may be able to further improve the reliability and accuracy of the algorithm. These developments would significantly enhance the capabilities and applicability of the proposed method for a wide range of radar types. Moreover, by using clutter reduction methods like using robust principal component analysis or singular value decomposition, we might further increase the performance of algorithms.

Another direction for future research is to investigate the use of the 2D overlapping window model with GRU in combination with other target classification methods commonly used in radar systems. By integrating the strengths of multiple approaches, it may be possible to achieve even higher accuracy and robustness in radar target classification tasks. One approach that could be particularly useful to consider is the incorporation of kinematic properties such as velocity, altitude, and radar cross-section (RCS) into the classification process. These properties can provide valuable information about the nature and behavior of the target, and could be used in conjunction with the 2D overlapping window model to more accurately distinguish between different types of targets.

For example, it might be possible to use the 2D overlapping window model with GRU to extract features related to the shape and structure of the target, and then use kinematic properties such as velocity and altitude to further refine the classification. This could be especially useful in situations where the target data is limited or noisy, as the additional information provided by the kinematic properties could help to improve the accuracy of the classification.

Overall, combining the 2D overlapping window model with GRU with other target classification methods has the potential to significantly advance the field of radar target classification, and could lead to the development of more reliable and efficient radar-based systems for a variety of applications.

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