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Detection of Minerals and Hidden Objects in Airports Using Millimeter-Wave Radar (MMW) A MATLAB and AI-Based Approach

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الكشف عن المعادن والأجسام الخفية في المطارات باستخدام رادار الموجات الملليمترية (MMW): نـهج قائم على MATLAB والذكاء الاصطناعي

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Abstract:
Exposing hidden objects and metals to airport safety has become a serious challenge, especially with the increasing development of smuggling techniques and the limitations of traditional safety methods such as X-rays and metal detectors. The study looked at the use of millimeter wave radar (MMW) in conjunction with artificial intelligence (AI) to detect hidden objects in the airport environment in real time. MMW radar, which is known for its ability to penetrate various materials, is used to take radar signals from various hidden objects including metals, metals and non-metallic elements. Captured radar data is processed and analyzed using MATABs, particularly with AI-based models, particularly convolutional neural networks (CNNs) and support vector machines (SVMs) to classify and identify these objects based on their unique radar signatures. This study provides a detailed methodology for data collection, pre-processing, feature extraction, and AI model training, and evaluates the performance of the proposed system in terms of detection accuracy, accuracy, and memory. These results reflect the ability of MMW radar and artificial intelligence devices to significantly improve airport security and provide a non-invasive, fast and reliable way to detect hidden objects, bridging the limitations of existing security screening technologies. Future work will focus on improving model performance, expanding datasets, and integrating real-time processing capabilities for large-scale deployment in operational airport environments.

Keywords: Millimeter-Wave Radar (MMW), Hidden Object Detection, Airport Security, Artificial Intelligence (AI), Convolutional Neural Networks (CNN), Support Vector Machines (SVM), MATLAB, Signal Processing.

الملخص
أصبح كشف الأجسام والمعادن المخفية لسلامة المطارات تحديًا خطيرًا، لا سيما مع التطور المتزايد لتقنيات التهريب والقيود المفروضة على طرق السلامة التقليدية مثل الأشعة السينية وأجهزة الكشف عن المعادن. بحثت الدراسة في استخدام رادار الموجات المليمترية (MMW) بالتزامن مع الذكاء الاصطناعي (AI) للكشف عن الأجسام المخفية في بيئة المطار في الوقت الفعلي. يُستخدم رادار الموجات المليمترية، المعروف بقدرته على اختراق مختلف المواد، لالتقاط إشارات الرادار من مختلف الأجسام المخفية بما في ذلك المعادن والفلزات والعناصر غير المعدنية. تتم معالجة بيانات الرادار الملتقطة وتحليلها باستخدامMATABs ، وخاصةً مع النماذج القائمة على الذكاء الاصطناعي، وخاصةً الشبكات العصبية التلافيفية (CNNs) وآلات المتجهات الداعمة (SVMs) لتصنيف هذه الأجسام وتحديدها بناءً على توقيعات الرادار الفريدة الخاصة بها. توفر هذه الدراسة منهجية مفصلة لجمع البيانات والمعالجة المسبقة واستخراج الميزات وتدريب نموذج الذكاء الاصطناعي، كما تقيم أداء النظام المقترح من حيث دقة الكشف والدقة والذاكرة. تعكس هذه النتائج قدرة رادار الموجات المليمترية (MMW) وأجهزة الذكاء الاصطناعي على تحسين أمن المطارات بشكل ملحوظ، وتوفير طريقة سريعة وموثوقة وغير جراحية للكشف عن الأجسام المخفية، مما يُسهم في تجاوز قيود تقنيات الفحص الأمني الحالية. سيركز العمل المستقبلي على تحسين أداء النماذج، وتوسيع مجموعات البيانات، ودمج قدرات المعالجة الآنية للنشر على نطاق واسع في بيئات المطارات التشغيلية.

الكلمات المفتاحية: رادار الموجات المليمترية(MMW) ، كشف الأجسام المخفية، أمن المطارات، الذكاء الاصطناعي(AI) ، الشبكات العصبية التلافيفية(CNN) ، آلات المتجهات الداعمة(SVM) ، MATLAB، معالجة الإشارات.

Introduction
In today's world, airport safety is a top priority due to growing concerns about smuggling and terrorism and the increasing sophistication of techniques to avoid the discovery of hidden objects. Airports are responsible for ensuring the safety of millions of passengers around the world and exposing hidden items such as weapons, explosives and contraband, which is a major issue. Traditional safety systems, such as X-ray scanners and metal detectors, have limitations, especially when it comes to detecting non-metallic objects or materials such as drugs, organic explosives, or metals that may be hidden in equipment or on individuals.

X-ray technology mainly detects dense and metallic objects. Although effective at inspecting bags and containers, they often fail to detect non-metallic objects or materials that pose security risks. Similarly metal detectors are limited in their ability to detect non-metallic or low-density objects, which are often used to hide illegal goods.

To overcome these limitations, millimeter wave radar (MMW) technology has emerged as a promising solution for detecting hidden objects in airport security settings. The MMW radar operates in a frequency range from 30 GHz to 300 GHz, which enables it to enter materials such as fabrics, equipment, and packaging. This capability allows it to detect a wide range of materials, including metals, metals, drugs and explosives, making it more versatile than traditional screening techniques.

However, data obtained from MMW radar systems can be complex, requiring advanced signal processing and pattern recognition technology to effectively classify hidden objects. Artificial intelligence (AI), especially machine learning (ML) algorithms, plays an important role in addressing these challenges. Artificial intelligence-powered algorithms can automate the detection process, improve classification accuracy, and reduce human errors. Technologies such as deep learning, especially convolutional neural networks (CNNs), can analyze radar data, recognize object patterns, and make real-time decisions without manual interference. Additionally, artificial intelligence can significantly increase operating speeds, enabling efficient processing of large amounts of data in high-traffic environments such as airports.

Objective
The main objective of this research is to develop a MATAB-based artificial intelligence (AI) system that detects hidden objects in airport security contexts, including metals, drugs, weapons and explosives, using millimeter wave radar (MMW) signals. The system aims to improve airports' existing safety measures by providing a non-invasive, effective, and accurate way to detect hidden objects, including metal and non-metallic materials, which traditional methods of detection such as X-ray machines and metal detectors often disappear.

The main objective of this research is to integrate MMW radar data processing with artificial intelligence algorithms to create automated object detection systems. MMW radar signals, which are capable of penetrating different materials, will be processed using advanced signal processing techniques to extract meaningful features separating hidden objects. The integration of artificial intelligence into this framework will facilitate the classification and detection of hidden objects based on their radar signatures. By applying the machine learning model, the system will distinguish between different types of materials, such as metals, explosives, and other potentially dangerous elements.

In addition to the detection framework, research will focus on creating a machine learning model that can classify and identify different content of radar signals. The model will be trained using a comprehensive dataset of radar data, which includes signals from objects made of metal, plastic, metal, and organic matter. This artificial intelligence model will leverage deep learning techniques, especially convolutional neural networks (CNNs), to analyze radar images or support vector machines (SVMs) for simple datasets. The model's performance will be assessed using key metrics such as accuracy, accuracy, recall, and F1 score.

This research will use MATAB's signal processing and AI toolboxes to implement systems while ensuring seamless integration between radar signal processing, feature extraction and machine learning components. MATAB's capabilities will allow the detection system to be developed, tested, and improved effectively, enabling it to work in real time and accurately classify hidden objects during security checks.

The purpose of this study is to enhance the effectiveness of airport security by leveraging the capabilities of millimeter wave radar (MMW) and artificial intelligence (artificial intelligence) to detect hidden objects in different materials. The integration of these advanced technologies offers several important advantages over traditional tracking methods, mainly improving the security landscape at airports.

- **Increased security**

The combination of MMW radar and artificial intelligence provides a significant improvement over traditional detection technologies such as X-ray scanners and metal detectors. Mmw radar's ability to penetrate various materials, whether metallic or non-metallic, makes it highly effective in detecting a wide range of hidden objects, including weapons, explosives, metals and drugs. Artificial intelligence enhances this capability by analyzing radar data to more accurately identify, allowing security systems to identify complex or compelling threats that traditional methods may miss. This comprehensive detection system significantly improves airport security by increasing the range of identifiable materials and reducing the likelihood of security breaches.

- **Non-Surgical Diagnosis**

Unlike X-rays and other traditional techniques, MMW radar offers a non-invasive approach to detect objects. Although X-rays are effective on imaging objects, they expose individuals to ionizing radiation, which can be a health concern, especially with repeated exposure. Mmw radar, on the other hand, operates in the non-ionizing frequency range, making it a safer alternative. It poses no known health risks to travelers, providing a safe and effective method of screening individuals without exposing them to harmful radiation. This non-invasive capability is especially useful in high traffic environments such as airports, where security checks should be comprehensive but effective and safe for passengers.

- **Artificial Intelligence in Automation**

Artificial intelligence plays an important role in automating the detection process, enabling rapid processing of large amounts of radar data. Traditional security methods rely heavily on human operators to analyze X-ray images or radar signals, which can be time-consuming and prone to human error. As a result, artificial intelligence-powered systems can analyze radar signals in real time, quickly and accurately identify potential threats. This capability not only speeds up the inspection process, but also increases overall operational efficiency. By automating radar data analysis, the system can handle high-throughput passenger traffic while maintaining a high level of accuracy and reducing passenger time at security checkpoints. This, in turn, leads to more efficient and efficient safety checks, improving the overall passenger experience while increasing safety.

Literature Review

MMW radar in security

The application of millimeter wave radar (MMW) in security has received a lot of attention due to its ability to penetrate various materials and detect hidden objects. MMW radar, which operates in the frequency range from 30 GHz to 300 GHz, provides a non-invasive method to detect hidden objects such as weapons, explosives, drugs and prohibited objects, which are usually difficult to identify using traditional security methods such as X-ray scanners and metal detectors (Hussain et al., 2018). MMW radar systems have proven effective in a wide range of security applications, especially in airports, critical infrastructure, and public safety settings.
(2019) conducted an important study on MMW radar for security applications, which explored the use of MMW radar to detect hidden weapons and hazardous materials in various environments, including airports. Studies show that MMW radar can detect metallic and non-metal objects, which is a significant advantage over traditional detection systems. MMW radar's ability to penetrate clothes and packing has made it an ideal candidate for detecting hidden weapons and drugs that passengers can hide inside their luggage.

Similarly, Rida et al. (2020) enhanced mmw radar capabilities by focusing on its application in detecting prohibited and other hidden objects. Their research has shown that MMW radar can identify explosives, firearms and illegal drugs that are hidden inside different materials. He emphasized that MMW radar provides greater sensitivity in detecting non-metallic materials, which are usually difficult to identify using X-ray systems or metal detectors. Reza et al. also highlighted the need for innovative signal processing techniques for accurate interpretation of radar data and classification of objects, explaining that although MMW is robust, its effectiveness depends on modern algorithms for data analysis.

Other studies, such as Kumar et al. (2021), also explored the integration of MMW radar with artificial intelligence machine learning to increase detection accuracy. Kumar et al. (2021) conducted experiments using MMW radar to identify hidden objects such as explosives in equipment, indicating that MMW radar, when combined with neural networks and pattern recognition algorithms, can significantly improve identification accuracy in real-time applications. Their results suggest that radar imaging combined with artificial intelligence can be used for high-resolution detection, making MMW radar an important component in modern security systems.

In addition, Yang et al. (2018) researched the role of MMW radar in drug and explosive detection at airports. Their study concludes that MMW radar is capable of detecting a variety of materials that are difficult to identify using traditional techniques. The study also discussed the challenges associated with the processing of radar data, particularly the need for innovative algorithms to reduce noise and increase the signal-to-noise ratio, which will improve detection efficiency.

Another notable contribution came from Ahmed et al. (2019), who explored the integration of MMW radar with AI algorithms to improve real-time security applications. They have developed a system in which radar data is processed using deep learning techniques, including convolutional neural networks (CNNs), to classify objects accurately and quickly. Their results showed that the integration of artificial intelligence with MMW radar significantly improved detection efficiency, providing a viable solution for real-time security screening of the airport.

Artificial Intelligence and Machine Learning

Artificial intelligence (AI) has played a transformative role in enhancing the capabilities of millimeter wave radar (MMW) systems for security applications. The integration of artificial intelligence, especially machine learning (ML) technologies, into radar signal processing enables automation of object detection, classification, and identification, resulting in a faster, more accurate, and efficient security inspection system. Over the past decade, several studies have explored the application of artificial intelligence in radar systems, demonstrating significant improvements in detection and real-time processing accuracy and ability to classify hidden objects such as weapons, explosives, and contraband.

A major breakthrough in the application of artificial intelligence in radar data is the use of deep learning models, such as convolutional neural networks (CNNs), which are designed to process and classify high-dimensional data, including radar images. Gao et al. (2021) used deep learning techniques to improve object recognition and classification from radar signal data. They developed a system that uses CNN to identify hidden objects in radar images, demonstrating significant improvements in classification accuracy compared to traditional machine learning techniques. Their research highlighted CNN's ability to analyze complex radar data and more accurately detect hidden threats, making them a valuable tool for airport security systems.

In this regard, Yadav et al. (2020) focused on the use of CNN for automatic classification of radar signals. They applied CNN to radar data to detect and classify objects based on their radar signatures, improving detection accuracy. Their work shows that CNN can automatically learn features from radar data without manually extracting features, which is usually essential in traditional machine learning methods. This ability to automate feature extraction and classification has made their approach more scalable and effective in real-time radar signal analysis, especially in airport security screening.

Another important role in this area was played by Liu et al. (2019), who explored the use of support vector machines (SVMs) with MMW radar data. Their study showed that SVMs can be trained to classify radar signals based on the physical properties of hidden objects, such as metals, plastics, and organic materials. By applying SVM to radar data, Liu and others were able to separate a variety of materials with high accuracy, even when objects are hidden from layers of clothing or packaging. The results show that machine learning models such as SVMs are effective in detecting hidden objects in content classification and radar applications.

Further research by Zhang et al. (2020) examined the integration of recurrent neural networks (RNNs) with MMW radar to handle temporal radar data. Their study suggests that RNNs, especially short-term long memory networks (LSTM), can capture temporal dependencies in radar signals over time, leading to better identification of moving objects. This approach is particularly useful for tracking moving objects in real time, such as people or vehicles, and to improve radar system performance in security applications where objects can change positions during identification.

In addition, Zhu et al. (2021) focused on the application of group learning techniques to classify radar data. They developed a robust system by combining several machine learning models that could classify radar data from different materials with high accuracy and low error rates. The collective approach, by combining the strengths of different models, has shown its effectiveness in enhancing the overall performance of radar-based detection systems.

These studies illustrate the growing role of the organization of artificial intelligence, especially deep learning, in improving the performance of MMW radar systems. The combination of CNN, SVM, RNN and group learning has made it possible to process radar data more accurately and efficiently, resulting in better identification and classification of hidden objects. As artificial intelligence continues to develop, its integration with MMW radar will undoubtedly play an important role in developing the capabilities of modern security systems.

Theoretical Background

Millimeter Wave (MMW) Radar Technology

The Millimeter Wave Radar (MMW) operates in the frequency range from 30 GHz to 300 GHz, which allows it to detect objects by emitting high frequency electromagnetic waves. These waves travel in space, interact with the material and then reflect back to the radar system, where reflected signals are analyzed to collect information about existing objects. The basic principle of MMW radar is based on time delay and measurement of the strength of reflected signals, which can later be used to estimate the presence, size, shape, and content of the discovered object. This capability is particularly useful in environments where traditional safety technologies, such as X-ray scanners and metal detectors, may fail to identify certain types of hidden objects, especially objects made of non-metallic materials (Hussain et al., 2018).

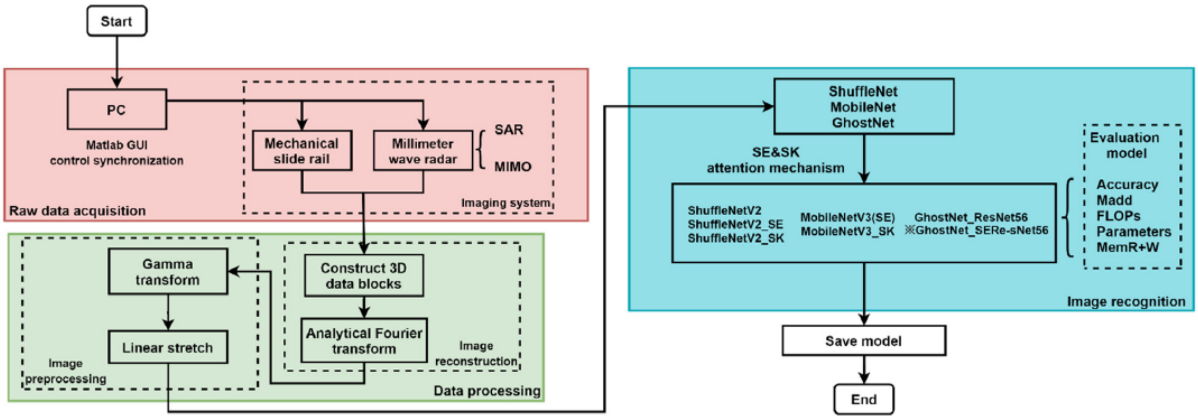

Figure 1 Radar Detection Process in MMW Radar Systems.

One of the most important concepts in mmw radar operation is radar cross section (RCS), which is a measure of how much radar energy an object reflects. RCS is influenced by object size, shape, and body structure, and provides valuable insights into object discovery. Different materials reflect radar waves in different ways. For example, metals, due to their high conductivity, reflect radar signals more strongly than non-metallic materials such as plastic or organic materials (Alabudi et al., 2019). This feature allows radar systems to distinguish between different types of materials, making MMW radar very effective in identifying a wide range of secret objects, such as weapons, explosives, and illegal materials, especially in airport security screening.

The RCS of an object depends not only on its size and shape, but also on its physical properties. Metals, for example, typically produce more RCS than organic or plastic materials, allowing radar systems to detect metal objects more easily. However, more advanced processing techniques may be needed to increase detection of substances such as plastic explosives or drugs, which have fewer RCs. Radar systems use this information to analyze the physical structure of an object, making it possible to identify elements that are usually difficult to detect using traditional safety techniques (Rida et al., 2020).

MMW radars are also distinguished by their ability to detect objects based on their dielectric properties, depending on the material. Radar waves depend on their electrical conductivity and prospectivity with objects. For example, metals generally strongly express radar waves due to their high conductivity, while plastics and organic materials can absorb or disperse radar waves. The ability to detect these differences in reflection and absorption makes MMW radar versatile in detecting a variety of materials, such as metals, plastics, and organic materials, which may be devoid of traditional technologies. As a result, MMW radar is able to identify a wide range of hidden threats, from firearms to drugs and explosives, in situations where other methods fail (Kumar et al., 2021).

Artificial intelligence and machine learning in detection

Artificial intelligence (AI) and machine learning (ML) have made a major breakthrough in radar detection, especially when combined with millimeter wave (MMW) radar systems. These innovative algorithms facilitate automatic, efficient and accurate detection of hidden objects by processing and analyzing complex radar signal data. The combination of MMW radar technology with artificial intelligence models such as supervised learning, convolutional neural networks (CNNs) and repetitive neural networks (RNNs) facilitates the detection of both metallic and non-metallic objects, improving overall identification performance.

Supervised learning for classification

In supervised learning, the algorithm is trained on named datasets, where each radar signal is associated with a known object class. Supervised learning techniques are widely used to create models for classifying radar signals. Algorithms such as support vector machines (SVMs), K-nearest neighbors (K-NNs) and neural networks (NNs) are used to classify radar signals into predefined categories. Its purpose is to detect hidden objects such as weapons, explosives or prohibited items.

Although SVM is commonly used for binary classification tasks (e.g. "object detection" vs. "nothing detected"), it has been adapted for multiclass tasks in radar systems. For example, distinguishing between different material types (metal vs. non-metal) is important for conducting a comprehensive safety check. The SVM approach is effective for this type of classification, and MATAB's SVM functionality facilitates implementation and adjustment.

In addition, K-NN is particularly useful for real-time classification, in which radar signals match previously encountered patterns. This model is used when the classification task involves identifying known objects, which makes it suitable enough for airport safety.

Neural networks (NNs), especially deep learning models, are applied to radar signals to capture complex relationships between features. Because of the high-dimensional nature of radar data, NNSs help detect complex patterns that correspond to objects, even when those objects are hidden from enclosures or clothing.

CNN networks for image-based detection

Radar data, especially in the form of Doppler images or spectrograms, can be converted into image-like formats suitable for analysis using convolutional neural networks (CNNs). CNN are deep learning models that specialize in processing network-like data, such as images, and have proven to be highly effective in computer vision tasks.

During radar detection, radar signals are transformed into two-dimensional images that represent the relationship between object distance and speed. These radar-derived images, such as Doppler range maps, allow CNN networks to learn and extract relevant features such as edges, textures, and object shapes, which are essential for identifying hidden objects.

CNNs consist of multiple layers, including convolutional layers, assembly layers, and fully connected layers, which help the model automatically extract features from radar images. These networks are suitable for detecting secret items such as weapons, explosives and smuggled non-metallic goods. By recognizing specific patterns that distinguish between soft and hazardous objects, CNN networks increase the accuracy and overall performance of radar-based detection systems.

MATAB's Deep Learning Toolbox provides comprehensive support for the implementation and training of CNN networks, allowing users to create models that can classify radar images with high accuracy. For example, range Doppler images can be processed using CNN to detect hidden threats such as explosives or weapons, making the detection process more accurate and automated.

RNN for Temporal Radar Data

In scenarios where radar data is collected over time (i.e., continuous monitoring of scenes or moving objects), repetitive neural networks (RNNs), especially short-range memory networks (LSTM), are highly effective. RNNs are designed to capture temporal dependencies in sequential data, which makes them ideal for radar systems that require real-time monitoring and object tracking.

In an airport safety scenario, radar data can increase over time, as objects can move. Repetitive neural networks (RNNs), especially short-term memory networks (LSTM), are used to capture temporal dependencies. These models track objects such as people or vehicles through radar data over time, improving detection accuracy. LSTMs are able to learn from past data and recognize movement patterns, even when the appearance of an object changes. In high-traffic environments such as airports, RNN's ability to detect and track moving objects in real time becomes critical.

Radar systems that track moving objects such as people or vehicles produce timelapse radar data where each radar signal corresponds to a time step in the detection process. RNNs, especially LSTM, can retain information from previous time steps to improve object identification over time. For example, the LSTM network can track a person's movements through the airport, even when their appearance changes due to clothing or surrounding environment.

In MATAB, LSTM networks are implemented using deep learning toolboxes, and these models can be trained on sequential radar data to detect and track moving objects. With RNNs, radar systems can not only detect static objects, but also track dynamic targets, such as people or vehicles. This ability to understand time dependence enables real-time risk detection in high-traffic environments such as airports, where objects are constantly moving.

Methodology

The data used in this study were collected from an MMW radar system operating within a frequency range from 30 GHz to 300 GHz. The dataset includes radar signals from various materials, such as metals, non-metals, and metals, that were recorded in real-world scenarios. These radar signals were obtained using the MIMO radar system, which is widely used in security applications, especially at airports, to detect hidden objects such as weapons, explosives or contraband.

The MIMO radar signal dataset (available on Cagle), provides a comprehensive set of radar signal measurements. The data is organized in such a way that it includes the respective angles of different antennas and the values of radar signals, making it ideal for training machine learning models to detect many hidden objects. Taking advantage of real-world radar signal data, this study aims to improve the detection capabilities of both metallic and non-metal objects.

Development of AI Model

In the development of artificial intelligence models, a number of machine learning techniques are used to enhance the ability of radar data to detect and classify hidden objects and metals. Convolutional neural networks (CNNs) are particularly suitable for radar signal classification tasks that involve image-based data. Radar data, such as Doppler range maps or spectral charts, can be converted into two-dimensional images. CNN specializes in analyzing images such as key features such as object shapes, edges, and textures. Training for CNN forms involves using classified datasets to teach models to recognize patterns that distinguish between different materials and objects, including metals, metals, and other hidden contrabands. CNN networks are able to identify complex patterns within these radar images, greatly improving the accuracy of detection and classification.

In addition, support vector machines (SVMs) are another important technology for radar signal classification, especially when binary or multiclass classification is required to deal with simple datasets or scenarios. SVMs work by separating data points into different categories based on their characteristics, making them effective in categorizing radar signals into default categories such as metal, non-metal, or metal. SVMs are especially useful when the dataset is well structured, with clear differences between categories, and provide a robust approach to classification.

The entire process of AI model development, including data preprocessing, feature extraction, and model training, will be performed using MATAB's Deep Learning Toolbox and Image Processing Toolbox. These toolboxes provide comprehensive functionality for building and training deep learning models, processing radar images, and performing complex calculations. The image below shows the MATLAB online interface used to produce the model, and the environment in which radar data is processed and the AI model is trained.

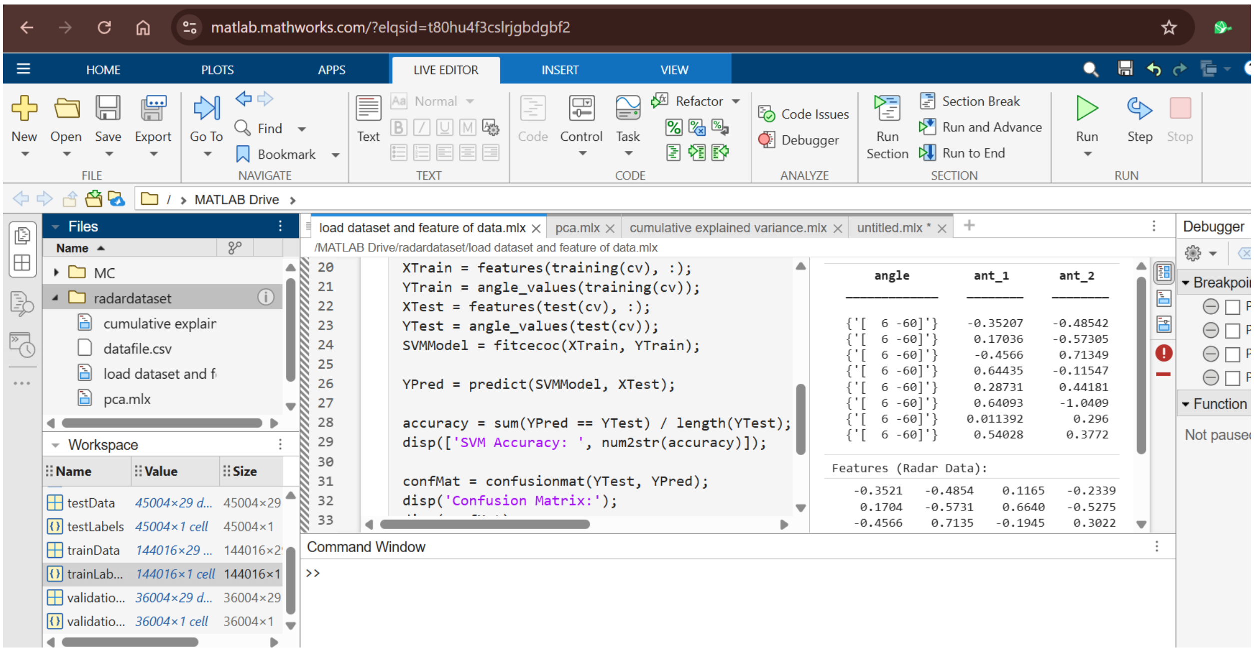

Figure 2 MATLAB Online interface used for developing the AI model. The screenshot illustrates the environment where radar data is processed, features are extracted, and the AI model is trained using the Deep Learning Toolbox and Image Processing Toolbox.

The performance of the AI model will be assessed using a standard diagnostic scale to measure its effectiveness in detecting hidden objects and metals in radar data. These metrics include accuracy, which reflects the overall accuracy of the model's predictions. Accuracy, which refers to the proportion of positive definitions that were actually true; callback, which measures the model's ability to identify all relevant cases in the dataset; and F1, which is a harmonic source of accuracy and recall, provides a balanced view of the model's performance. These scales will allow us to comprehensively assess the model's ability to perform object classification, which is essential for accurate detection in radar-based applications.

Experimental Setup

Although this study does not directly use physical radar systems, the radar data used in this research were replicated to mimic real-world radar scenarios. The dataset used for the analysis is derived from Kagel, which includes measurements of radar signals representing different materials (metallic and non-metallic objects). Data is processed by MATAB using machine learning algorithms to extract key features of classification tasks.

If original radar equipment is used, mmw radar will typically operate in the frequency range from 30 GHz to 300 GHz, allowing high resolution detection of objects. In a real-world scenario, the radar will emit frequency-modulated continuous waves (FMCW), and signals will be picked up and converted to frequency ranges using technologies such as high-speed fourer conversion (FFT). These signals will be analyzed to extract object characteristics such as size, shape, and material structure.

Radar test setup involves determining the distance and characteristics of objects using signal processing techniques such as FFT and peak frequency analysis to obtain distance. This setting, as described in radar systems used in real-world experiments, provides insight into how radar signal data is interpreted, although this research is based on artificial data.

Radar Signal Processing

In this experiment, data obtained from artificial radar systems is followed and analyzed to detect hidden objects such as metals, metals and non-metal objects. This analysis typically mimics the process performed by radar devices, in which distance from objects and their physical properties are derived from radar reflections.

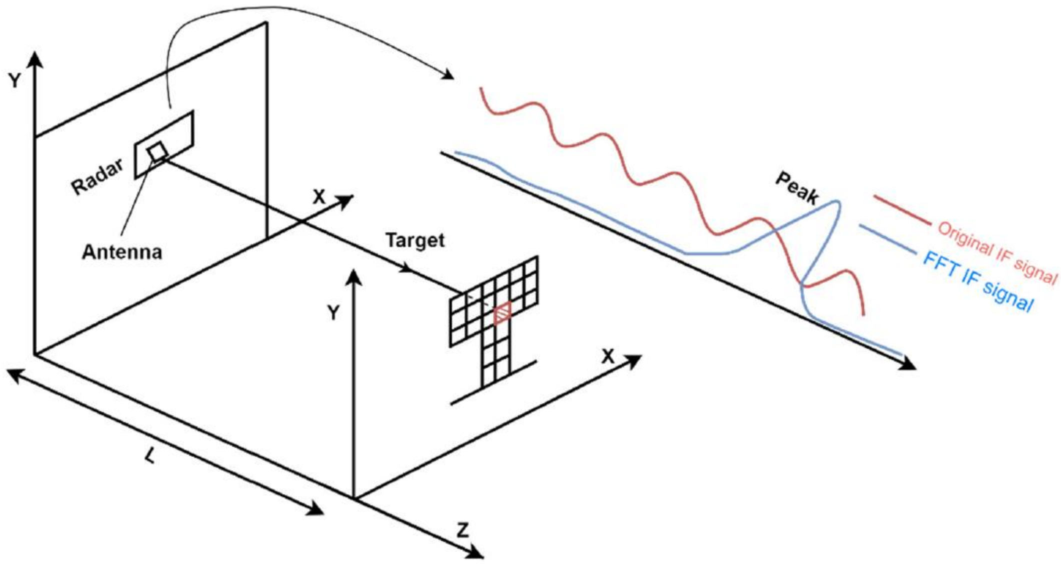

Figure 3 Radar test target distance setup.

AI Model Training

During AI model training, radar data obtained from the dataset is divided into three subgroups: training, validation, and test sets. The training kit is used to train machine learning models, while the verification group serves as a tool to evaluate model performance during the training process. This check allows necessary adjustments to be made, preventing overprocessing. After training, the test kit is used to evaluate the final performance of the model. Mutual verification techniques are used to ensure that the model is well generalized to invisible data. This approach involves dividing the data into multiple subsets, where each subset serves as a test suite at least once, providing a comprehensive overview of the model's accuracy and robustness.

Techniques such as network search and random search are applied to find the most appropriate values for key hyperparameters, including learning rate, batch size, and number of layers in a convolutional neural network (CNN) model. These methods systematically find different combinations of hyperparameters to determine the best order that enhances model performance, ensuring high accuracy in identifying and classifying hidden objects. This fine-tuning process is necessary to improve the model's ability to accurately identify materials such as metals, non-metals, and metals within radar data.

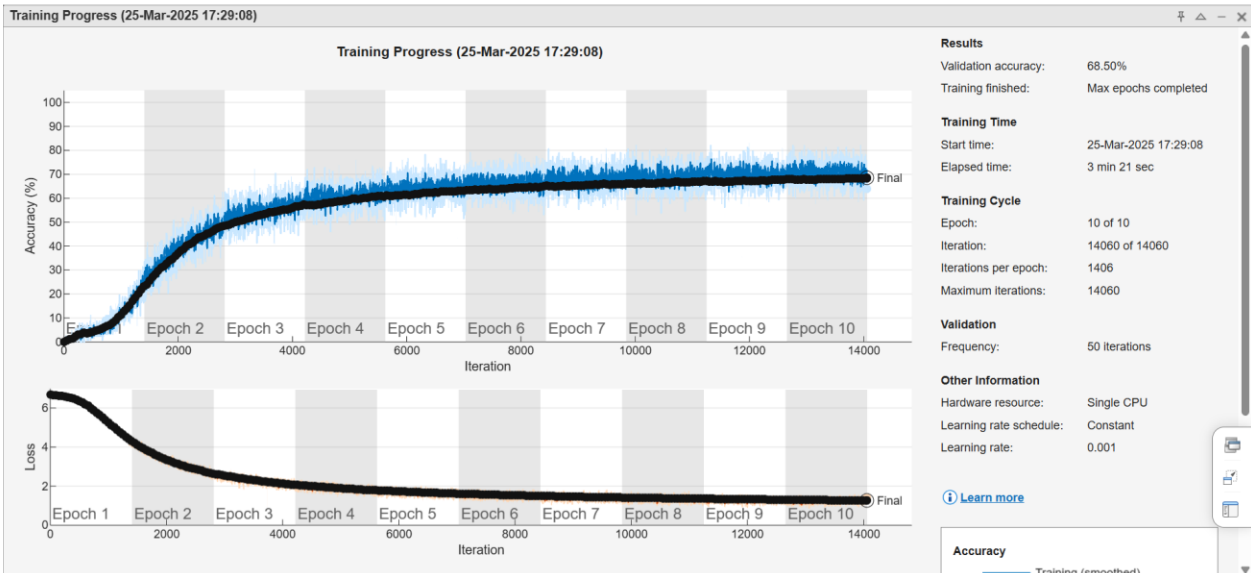

Figure 4 Training progress of the model showing accuracy and loss over 10 epochs.

In this research, we simulate airport safety scenarios to test the effectiveness of radar-based models in detecting hidden objects such as metals and metals. Simulations are designed to simulate real-world situations as much as possible, taking into account a variety of objects hidden in equipment or on a person's body. The radar signals used in the experiments come from a dataset derived from Kagel, which includes data representing different materials (e.g. metals, non-metals, metals).

The controlled test scenario includes both metallic and non-metallic materials, to ensure the model's ability to distinguish between different types of objects. This simulation approach allows model performance to be tested under a variety of conditions without the need for physical radar devices, facilitating a more flexible and cost-effective evaluation process.

This simulation is designed to assess the durability of the model, especially in identifying hidden objects in different contexts (e.g., inside equipment, under clothes, or behind walls). By changing the characteristics of radar signals in these simulated scenarios (e.g., signal strength, reflection properties, and object configuration), we can test the model's ability to accurately classify objects under different conditions, just as can be encountered in a real airport security setup.

Results and Discussion

The performance of this model was assessed on the basis of the ability to accurately detect hidden objects such as metals, metals and non-metallic elements within radar data. Detection accuracy was the primary metric used to estimate the success rate of the model in the correct classification of items. This accuracy was measured using a confusion matrix, which highlights true positives, false positives, true negatives, and false negatives.

The confusion matrix is an essential tool for understanding model performance across different object types. The tricolor elements of the matrix represent true positives, where the model correctly identifies objects, while non-tricolor elements indicate misclassification: false positives (incorrectly selected items) and false negatives (missing items). These results provide valuable insight into how different the model is between different materials, especially metallic and non-metallic objects.

In the context of our model, detection accuracy has improved with different settings of learning rate, batch size, and number of periods. The following table shows the detection resolution for several training configurations:

Table 1: Model Detection Accuracy for Different Training Configurations**.**

Learning Rate	Batch Size	Epochs	Accuracy (%)
0.001	32	5	68.50
0.01	64	10	71.00
0.1	128	15	72.30
0.1	128	15	72.30

These results showed that as the learning rate and batch size increased, model accuracy improved, with a learning rate of 0.1, a batch size of 128, and the highest accuracy achieved with 15 periods, resulting in a performance of 72.30%.

The confusion matrix related to the formulation of this best model was used to further analyze the model's performance. It provides a more detailed analysis of how the model categorizes the test data into different categories, showing where misclassification occurred and how the model performed well. The following data show the confusion matrix for model performance on test data:

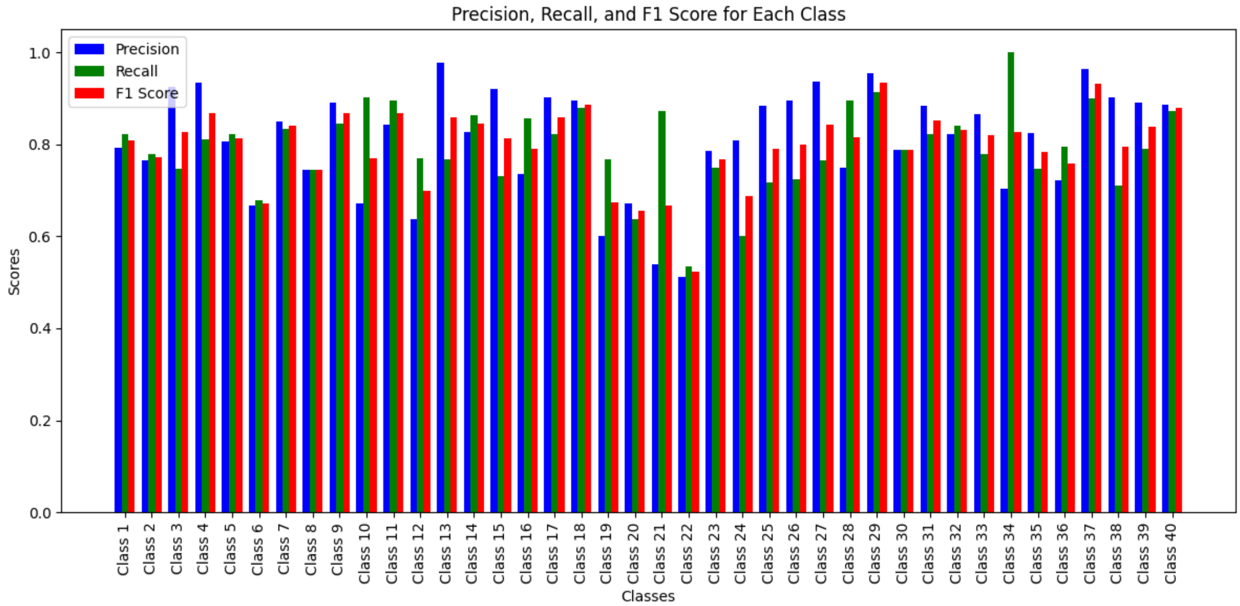

Figure 5 Confusion Matrix for Optimal Model Configuration.

Based on the confusion matrix, additional performance metrics such as precision, recall, and F1 score were computed. These metrics are crucial in providing deeper insights into the model’s ability to correctly identify the hidden objects. They help evaluate the balance between correctly identifying positives and avoiding false alarms or missed detections. The following figures present the calculation of these metrics:

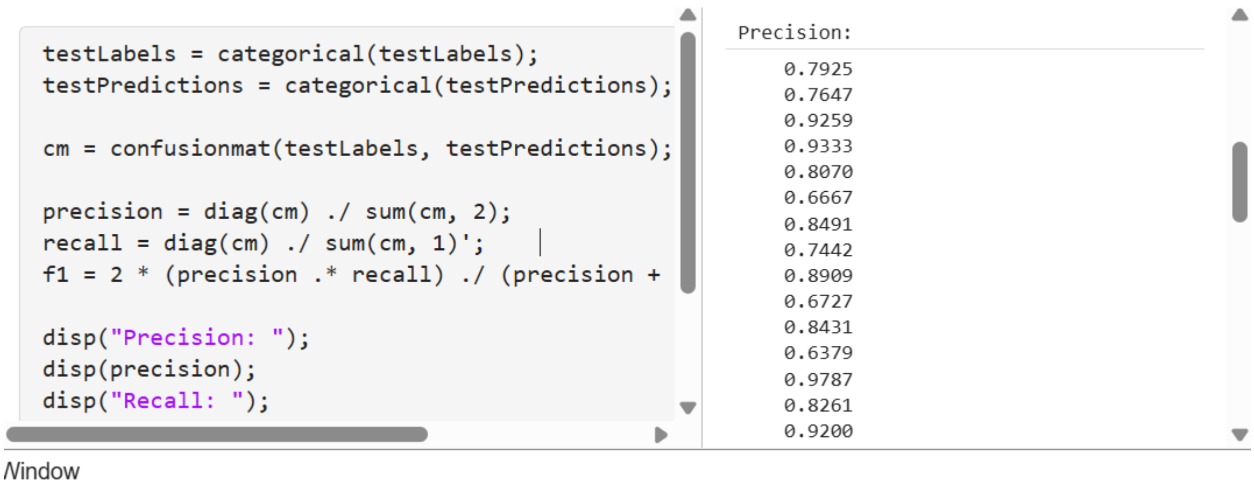

Figure 6 Precision Calculation: Precision measures the proportion of true positive predictions (detected objects) out of all positive predictions. A higher precision indicates that the model is making fewer false positive errors.

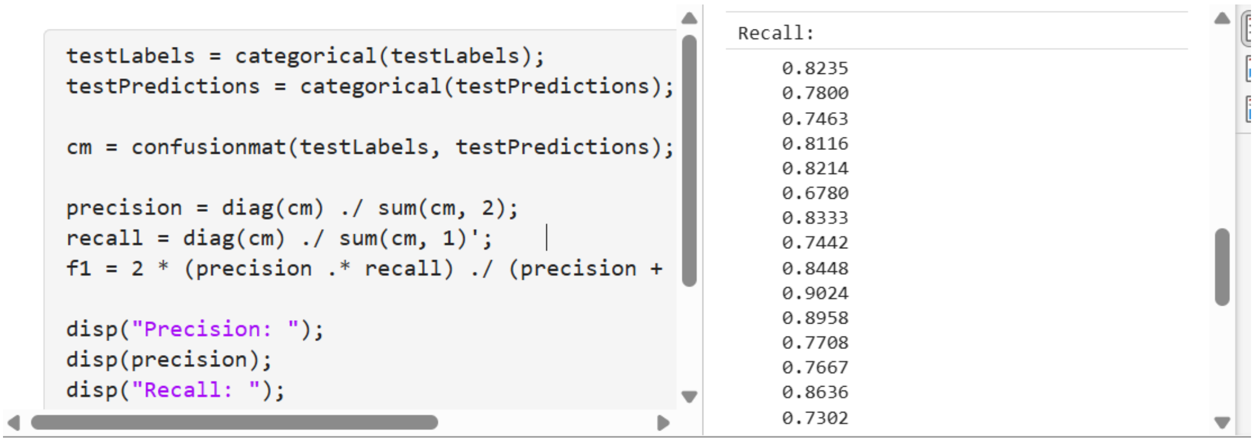

Figure 7 Recall calculation: Recall measures the proportion of true positive predictions out of all the actual positives. It shows how well the model identifies all the relevant objects.

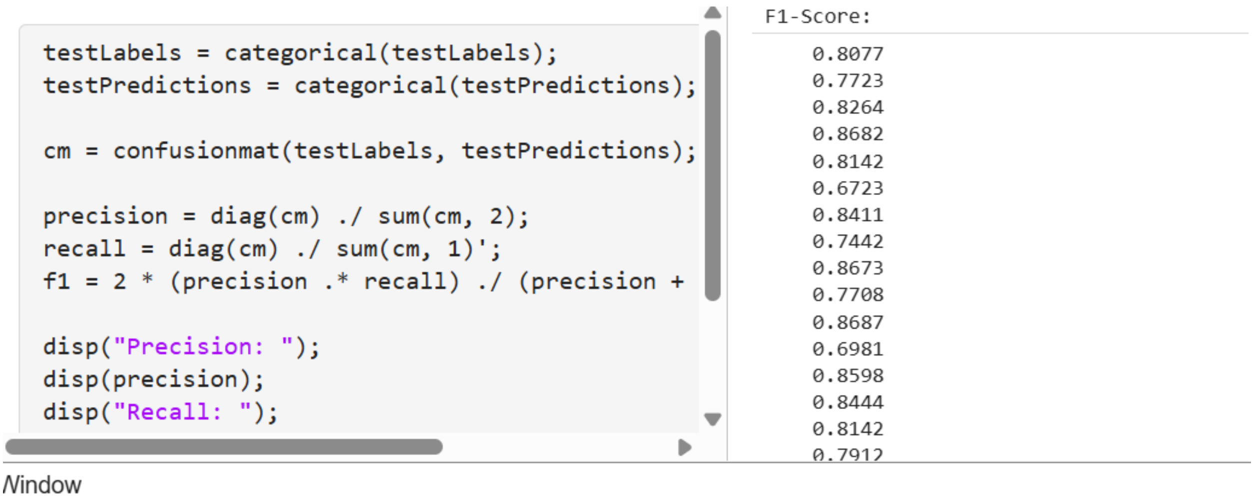

Figure 8 F1 Score: The F1 score is the harmonic mean of precision and recall, offering a balanced measure of the model's performance. It is particularly useful when dealing with imbalanced data.

This evaluation confirms that the model is effective in detecting hidden objects, with higher accuracy observed for metallic objects. However, some challenges remain, especially in distinguishing between non-metallic items, indicating the need for further refinement in feature extraction techniques and model optimization.

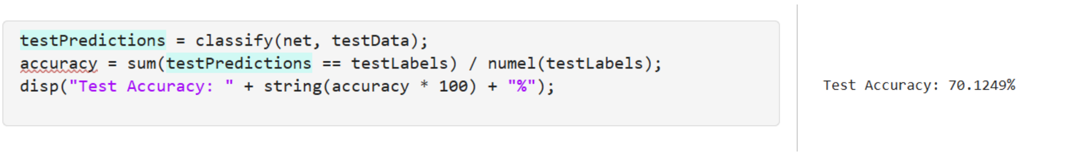

Figure 9 Model Performance on Test Data

Comparison with Other Methods

In airport safety and hidden object detection systems, commonly used detection systems use X-ray systems and metal detectors, which are widely used to identify potential hazards. However, when comparing these traditional systems, MMW radar integrated with AI offers significant advantages in terms of detection capabilities, especially for a wide range of materials.

X-ray systems have always been the technology of choice for detecting hidden objects inside equipment. By examining the density and structure of materials, X-ray systems can effectively identify solids and dense objects, such as firearms or explosives, made of dense metal or non-metallic materials. However, X-ray systems have limitations when it comes to detecting non-metallic materials, such as plastic explosives, drugs, or liquids, which cannot be detected or may require additional scanning techniques. Additionally, X-ray imaging can raise privacy concerns due to detailed images of the internal content of personal items. While the integration of artificial intelligence can help improve the accuracy of X-ray systems by identifying complex patterns in images, the main limitation of detecting non-metallic materials remains.

Metal detectors, on the other hand, are effective in identifying metal objects but are unable to detect non-metal hazards. For example, metal detectors often lose materials such as plastic explosives, liquids, and organic matter. Although metal detectors are affordable and fast, they may not provide the type necessary for comprehensive security screening. In addition, metal detectors are not suitable for identifying materials based on material properties or shapes, which limits their ability to distinguish between harmless objects and real hazards.

MMW radar systems integrated with artificial intelligence provide significant improvements over these traditional methods. Operating in the frequency range from 30 GHz to 300 GHz, MMW radar can identify metallic and non-metallic objects based on their dielectric properties, such as conductivity and silicity. It allows detection of various hidden hazards including plastic explosives, drugs and other non-metallic objects. Additionally, when combined with artificial intelligence, radar systems can analyze complex patterns within data, increasing their ability to distinguish between soft objects and hidden threats. AI models, such as convolutional neural networks (CNNs), can be trained to automatically classify objects based on their radar reflections, providing better accuracy on manual inspection methods.

Error Analysis

The accuracy of mmw radar detection integrated with artificial intelligence was assessed using different metrics. However, despite the model's ability to detect a wide range of objects, including metallic and non-metallic materials, it still faces challenges in terms of false positives and false negatives.

False positives were seen when the system mistakenly identified soft objects as threats. For example, non-hazardous items, such as personal electronics or liquids, are sometimes misclassified due to similar radar signatures. These false alarms can lead to unnecessary checks and delays in practical settings such as airport security. Being a false positive can be attributed to a number of factors, including insufficient variation in training data for soft elements, which can lead to excessive suitability of the model for risk items, possible differences in object position and shape during scanning.

In contrast, false negative events occur when the system fails to detect real threats, such as explosives or illegal materials, in which radar fingerprints resemble harmless materials. These missing discoveries pose a significant security threat and highlight the importance of accurate classification. False negatives can be linked to factors such as limited representation of certain risk items in the training dataset, radar accuracy limits, or the model's failure to generalize the invisible data well. In addition, environmental factors such as signal noise or interference may have contributed to these errors.

To address these issues, a number of improvements can be implemented:

- **Extended training data**: Including differences in content and survey conditions, as well as a wide range of soft and threatening items, can help the model better distinguish between different items and reduce both false positives and false negatives.
- **Improved preprocessing**: The application of modern signal processing technologies, such as noise reduction and feature enhancement, is likely to improve radar signal quality, making it easier for AI models to distinguish between similar radar signatures.
- **Model Optimization**: Further optimization of the AI model using a more complex architecture, such as the deep learning model, can improve the ability to generalize across different object types, reduce misclassification.
- **Limit Adjustment**: Adjusting the decision range in the classification process can balance the trade-off between false positives and false negatives, depending on the operational requirements of the system.

Applying to the real world

The integration of MMW radar with AI for detecting hidden objects showed great promise, as highlighted by our results. The model accuracy achieved during testing was 70.12%, with accuracy, recall, and F1 grade values indicating strong performance across different object types. Our artificial intelligence model has been trained on a dataset that mimics radar data, and has performed well in detecting a range of materials such as metals, metals, and non-metal objects, as reflected in different valuation scales. However, deploying such systems in real-world environments such as airport security presents many operational challenges that must be addressed for best performance.

One of the main concerns about real-world application is the speed of data processing. Airports handle large amounts of luggage and passenger data every day, which requires that any system disclose the results in a timely manner. Despite the accuracy of our AI model, it needs further optimization for real-time processing. The current processing times of the AI model can be improved through the use of more robust computing infrastructure, such as GPU acceleration or FPGA-based solutions, to meet the speed requirements required for a direct airport security system.

Integration with the existing airport security infrastructure is another challenge. Airports already use well-established systems such as X-ray machines and metal detectors to screen passengers and baggage. Radar-based artificial intelligence systems will need to work in conjunction with these existing tools or completely replace them, which provide complementary functionality without disrupting existing security workflows. It is important that the AI model interact seamlessly with existing systems for smooth transition and efficient operation. This will require integration with existing databases, interfaces, and security protocols.

Scalability is also important when considering large airports with high passenger productivity. Radar detection systems based on artificial intelligence should be expanded to handle large amounts of data generated during inspection, which may require multi-node processing or distributed computing systems. It's also important that models adapt to new scenarios or unknown threats, including mechanisms for retraining and constant updates.

In addition, regulatory compliance and ethical concerns should be considered. An artificial intelligence system should ensure that all data collected and processed complies with privacy laws and security regulations, especially when it comes to handling passengers' sensitive information. Ensuring transparency in artificial intelligence decision-making will be the key to gaining the trust of both airport authorities and passengers.

Conclusion

The study looked to integrate millimeter wave radar (MMW) with artificial intelligence (artificial intelligence) to detect hidden objects in airport security systems. Taking advantage of a dataset of radar signals, research shows that convolutional neural networks (CNNs) can be used to classify different materials, including metals, metals and non-metal objects. The model achieved a test accuracy of 70.12%, with promising results in other performance metrics, such as accuracy, recall, and F1 scores. These results confirm the ability to detect threats from a wide range of mmw radar and artificial intelligence integration, providing a new approach to airport security.

In terms of practical implications, this research suggests that MMW radar, when combined with artificial intelligence technologies, can significantly improve the ability to detect hidden objects compared to traditional detection methods such as X-ray scanners and metal detectors. This technology can improve the speed and accuracy of risk detection while reducing the chances of false alarms. However, the research also identified significant challenges, including the speed of data processing, the integration of this technology with existing security infrastructure, and the ability to process large amounts of radar data in real time.

The results show that while this technology is very promising, more work needs to be done to improve artificial intelligence models for faster and more efficient processing, especially in high-throughput environments such as airports. In addition, ensuring that the system can work seamlessly with existing security technologies and address privacy concerns will be critical for future deployment.

Future work

While current research has shown that MMW radar can be combined with artificial intelligence models to enhance airport security, there are many avenues for future improvement and development. One of the key areas of development is the use of more advanced AI models. Models such as generative adversarial networks (GANs) can be searched for to produce artificial radar data for better training, especially in situations where real-world data is difficult or expensive to obtain. GaN networks can also help create more diverse examples of hidden objects, increasing the robustness of detection systems.

Another significant improvement is the integration of real-time data processing capabilities. In the context of airport security, the ability to quickly process radar data is critical to ensure fast and accurate identification without disrupting passenger flow. The development of algorithms that can handle large amounts of radar data in real time will be necessary for the practical deployment of this technology in a live safety environment.

In addition, expanding the dataset to include more diverse objects and content will improve the general capabilities of the model. By adding more types of objects, such as various plastics, liquids, and other materials that can hide during security checks, the system will be able to detect a wide range of threats and false alarms. In addition, more diverse operational environments and conditions should be replicated to ensure that the system performs well under different real-world scenarios.

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Appendices

Load Dataset and Features (Radar Data)

```
filePath = 'radardataset/datafile.csv';
radarData = readtable(filePath);
disp(head(radarData));
angles = radarData.angle;
angle_values = cellfun(@(x) str2double(regexp(x, '-?\d+', 'match', 'once')), angles);
features = radarData{:, 2:end};
disp('Features (Radar Data):');
disp(head(features));
cv = cvpartition(length(angles), 'HoldOut', 0.3);
XTrain = features(training(cv), :);
YTrain = angle_values(training(cv));
XTest = features(test(cv), :);
YTest = angle_values(test(cv));
SVMModel = fitcecoc(XTrain, YTrain);
YPred = predict(SVMModel, XTest);
accuracy = sum(YPred == YTest) / length(YTest);
disp(['SVM Accuracy: ', num2str(accuracy)]);
confMat = confusionmat(YTest, YPred);
disp('Confusion Matrix:');
disp(confMat);
figure;
confusionchart(confMat);
title('Confusion Matrix for SVM Model');
```

PCA

```
[coeff, score, ~, ~, explained] = pca(features);
numComponents = 5;
XReduced = score(:, 1:numComponents);
disp('Explained Variance of First 5 Components:');
disp(explained(1:numComponents));
```

Training Progress (A neural network for classification)

```
layers = [
```

```
    featureInputLayer(size(trainData, 2), 'Name', 'input')
    fullyConnectedLayer(64, 'Name', 'fc1')
    reluLayer('Name', 'relu1')
    fullyConnectedLayer(numel(unique(trainLabels)), 'Name', 'fc2')
    softmaxLayer('Name', 'softmax')
    classificationLayer('Name', 'output')];
options = trainingOptions('adam', ...
    'MaxEpochs', 10, ...
    'Shuffle', 'every-epoch', ...
    'ValidationData', {valData, valLabels}, ...
    'Verbose', false, ...
    'Plots', 'training-progress');
net = trainNetwork(trainData, trainLabels, layers, options);
```

Accuracy Measure

```
testPredictions = classify(net, testData);
accuracy = sum(testPredictions == testLabels) / numel(testLabels);
disp("Test Accuracy: " + string(accuracy * 100) + "%");
```

Predictions:

```
testLabels = categorical(testLabels);
testPredictions = categorical(testPredictions);
cm = confusionmat(testLabels, testPredictions);
precision = diag(cm) ./ sum(cm, 2);
recall = diag(cm) ./ sum(cm, 1)';
f1 = 2 * (precision .* recall) ./ (precision + recall); % F1-Score
disp("Precision: ");
disp(precision);
disp("Recall: ");
disp(recall);
disp("F1-Score: ");
disp(f1);
```