

## REAL-TIME DRONE DETECTION USING CONVOLUTIONAL NEURAL NETWORKS IN COMPLEX ENVIRONMENTS

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## Abstract

With the relatively quick growth of the accessibility and affordability of *Unmanned Aerial Vehicles (UAVs)* and drones, opportunities for UAVs exist within many sectors, including defence, agriculture, surveillance, and logistics. Additionally, while these UAVs can be used for a variety of purposes, the mass deployment of these vehicles has raised serious concerns regarding safety, security, and privacy. As an example, in low-altitude airspace, effective drone detection has become more challenging due to the *drone's small size*, high speed, and ability to closely resemble other objects such as birds in a typical urban environment. Additionally, through the introduction of new environmental conditions like background clutter, varying levels of illumination, and difficult weather conditions, the effective use of traditional drone detection technology (i.e., radar, acoustic, machine learning with manually created feature sets) is increasingly susceptible to being unable to operate effectively in real-world scenarios. This research proposes a novel drone detection system that utilizes a *Convolutional Neural Network (CNN)* to detect small drones in low-altitude airspace. The CNN detection algorithm will learn *hierarchical features* directly from the raw images rather than manually creating the features. When benchmarked against traditional technology, the CNN system demonstrates improved levels of *accuracy and robustness*. The results of this work will support the development of cost-effective, easily scalable, and rapid responding UAV detection technologies to improve the safety of the public and increase *national security*, as well as protect *critical infrastructure*.

## INTRODUCTION

Drones (Unmanned Aerial Vehicles - UAVs) have grown at such an extreme pace and are now accessible via a multitude of applications in many

areas, including Commercial Services, Defense Operations, Agricultural Applications, Disaster Response, and Recreational Use [1][2]; thus, the

cost savings associated with drones, such as their affordability, portability, and ease of use, are leading to increased aerial photography, infrastructure inspections, delivery services, and surveillance [3]. The rapid proliferation of the use of drones has created a variety of new security, safety, and privacy concerns, due to the potential for drones to enter secured airspace (i.e. airports, military installations, government buildings, large public gatherings, etc.), with resulting consequences being accidental collisions, espionage and/or the possibility of malicious acts [4]. Consequently, developing a reliable and efficient system to detect drones has become a significant priority for both Government and Security agencies around the globe [5].

There has been an increase in drone use within Pakistan in the past few years with increased growth in uses like: Monitoring agricultural practices, Border Surveillance, Mapping, and Security purposes [6]. However, as with any new technology, there have also been many instances reported involving illegal use of drones, violations of airspace, and cross-border drug smuggling, which are major concerns to both national security as well as public safety [7]. The urban environment with its many congested areas increases the risk of unauthorized drones. Due to a lack of infrastructure and advanced surveillance systems, monitoring low-altitude airspace continues to pose a challenge. Traditional detection technologies (i.e., radar systems and acoustic sensors) also display significant issues when used to identify small drones because of factors like low radar cross-sections, limited detection range and sensitivity to environmental noise [8]. This creates a considerable demand for intelligent, inexpensive alternatives for detecting drones and that are capable of providing reliable service in Pakistan's unique operational and environmental conditions [9].

Detecting drones accurately is not only challenging due to the ways they are designed but also because of all the different ways they operate. Most drones are very small and can move very fast, which makes them hard to see. Also, drones can often look like other types of animals (birds) or even objects (aircraft) [10]. In addition to the

physical characteristics of drones, there are also many environmental factors that make detecting them difficult, such as Background Clutter, the illumination of the area where drones may be flying, changing weather conditions and/or lighting and the camera's motion. Early research on Drones focused on Signal-Processing Based and Traditional Machine Learning Techniques, using both Radar Signal Processing, Acoustic Analysis, and hand-crafted features from Videos, and then classifying those Features to the Labels using Algorithms such as (SVM), (KNN), (DT), and (RF) [11], [12]. While these Models provided acceptable results under very controlled conditions, they required a lot of Manual Feature Engineering, were very Sensitive to Noise, and couldn't be generalized to different environments. In fact, for very complex real-world scenarios, the Performance of Traditional Machine Learning Models in General dropped significantly below (the) Acceptable Performance levels [13].

A number of research projects examine the use of different types of computer vision technology (traditional computer vision, combined with machine learning) for identifying drones through hand-crafted image feature extraction, such as Histogram of Oriented Gradients (HOG), Scale Invariant Feature Transform (SIFT) and Texture-based Descriptors [14]. Feature extraction techniques, while allowing for classification of these extracted features into classes of targets using SVMs, Naive Bayes, and Ensemble Classifiers, also suffered from the limitations of feature selection as they relied heavily on the selection of discriminative feature sets that were representative of the image data. The reduction in performance of the above classification methods to moderate accuracy was due to these limitations and their inability to handle the variability in the appearance of the drone (physical characteristics), the difference in drone size, and the degree of complexity present in the background. Additionally, the computational requirements associated with extracting features and classifying the features into target classes limited their performance in real time applications [15].

A recent advancement in deep learning has been the introduction of Convolutional Neural Networks (CNNs), which have shown success in performing visual object detection tasks to help solve these challenges. With the ability to learn hierarchical features automatically from raw images, CNNs eliminate the need for manually creating features for training data. This research is proposing to develop a drone detection framework using CNNs that will improve the accuracy and robustness of drone detection in challenging real-world environments. The model produced by this research will be able to detect small-sized drones from challenging backgrounds, changing light conditions, and different orientations of the drone. By utilizing deep feature learning, it is hoped that this model will outperform previous methodologies of machine learning and provide improved accuracy, generalizability, and real-time usability.

Novelty of the work presented is that we address the limitations of existing UAV detection technologies through an end-to-end convolutional neural network (CNN) based visual detection system that is suitable to real world deployment case studies in Pakistan. This study's main aims include the examination of traditional and machine learning methods limitations, the development of an efficient CNN based detection model, and the evaluation of its performance against standard evaluation procedures. Focusing on cost-effective and scalable solutions, we provide a framework to develop intelligent airspace monitoring systems that can help improve public safety, national security and critical infrastructure protection.

### Literature Review

There has been a growing amount of interest in developing effective drone detection systems due to the rapid and large-scale deployment of unmanned aerial vehicles (UAVs). Most of the earliest approaches used signal-based detection methods, primarily including radar, radio frequency (RF) analyzers, and acoustic sensors [16], [17]. Radar systems for detecting drones are low-power microwave sensor devices that work by processing the reflected electromagnetic return

signals associated with the UAV's motion. Nonetheless, small UAVs tend to exhibit a very low radar cross-section and can therefore be difficult to detect reliably, especially at very low altitudes [18]. Furthermore, radar detection systems tend to be low-power microwave devices; thus they have several inherent limitations within urban settings; e.g., high cost of equipment, extensive infrastructure prerequisites, and poor performance due to signal degradation due to building obstruction and surface irregularity [19]. Like radar systems, acoustic systems detect drones by identifying the distinctive sounds produced by the UAV's motors; however, environmental noise, limited range, and high false-positive rates due to excessive ambient noise further limit their abilities [20].

Researchers explored the use of vision-based drone detection using traditional computer vision and classical machine learning techniques to eliminate the shortcomings of signal-based methods. Traditional computer vision techniques used to detect the drone in pictures or video frames are based on identifying and extracting unique visual characteristics (referred to as feature extraction). These characteristics include Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), and Local Binary Patterns (LBP) [21], [22]. After acquiring these unique characteristics, machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Decision Trees are utilized to classify them [23]. Many studies have indicated that Detector Fusion using HOG features combined with the efficiency of SVM classifiers has achieved a reasonable level of accuracy for controlled conditions for detecting drones [24]. However, all of the above methods are very susceptible to variations in light intensity, background, size variations, and movements created by the camera system. Hand-crafted feature sets require knowledge of the domain they pertain to and, therefore, heavily and directly depend upon the robustness of the hand-crafted feature set [25].

Newer efforts with research have focused on using ensemble learning methods and hybrid feature representations in order to improve the

accuracy of detecting drone. By combining several methods that worked poorly on their own ("weak learners"), ensemble classifiers (e.g., Random Forest and Gradient Boost) have been shown to have superior generalization performance compared to just using a single classifier [26]. While the ensembles do show improvement in the accuracy of classifications over individual classifiers, they still make use of hand-engineered features that require substantial computational resources, particularly when attempting to process images of very high resolution or the real-time video streams. As a result, while they will be less than optimal for detecting drones in real-world surveillance environments, they remain limited [27].

Due to improved learning-based visual models, convolutional neural networks (CNN) have provided excellent solutions for detecting drones. These advanced methods automatically extract feature representations in a hierarchical manner from raw image data through the use of both convolutional and pooling layers [28]. CNNs can capture not only low-level features (e.g. edges, and texture) but also high-level semantic feature groups specific to identifying drones. This allows CNN models to work better than any alternative conventional method in that CNNs do not require manually-created features and handle scale transformations, background noise, and illumination changes better [29].

CNN-based UAV detection frameworks have been proven effective through multiple studies. CNN models have been consistently shown to provide better performance than traditional machine learning methods in complex environments, especially when detecting small drones in cluttered backgrounds [30]. Although CNN-based aerial drone detection systems have exhibited strong performance and capability, many challenges still exist. Drones have a limited pixel representation and experience motion blur because of their small size and fast speed. There are many environmental factors that affect the performance of drone detection systems, such as changing weather conditions, last-minute obscuration by other objects or structures, and a dynamic background.

Current research highlights the usefulness of AI systems based on ANN, DL, and fuzzy logic across various domains. IoT-based Mamdani Fuzzy Inference systems have upgraded decision-making in smart infrastructure and communication applications [33], [34]. The transfer learning and CNN have empowered precise disease diagnosis, waste segregation and smart agriculture solutions [35]–[38], to improve the cybersecurity resilience, AI-based security research has enhanced the understanding of ransomware behavior [39].

In summary, a review of the literature indicates a transition from traditional sensor-based and classical machine learning techniques to the adoption of CNN-based visual recognition frameworks for drone detection. While earlier methods established a basic foundation for automated drone detection, those methods did not provide the flexibility and robustness needed in today's more complex surveillance environments. The use of CNN-based models in comparison to earlier techniques provides a more robust, accurate, scalable, and efficient method of detecting drones. This study builds upon these findings to propose an improved CNN-based detection model for use in Pakistan's low-altitude surveillance applications to improve the detection accuracy and operational viability of the methods when applied under real-world constraints.

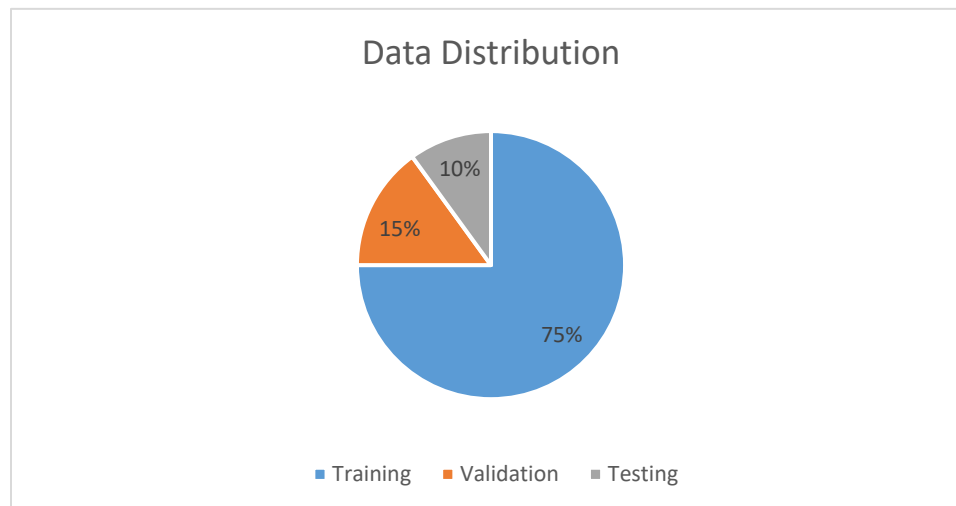
## Methodology

### Dataset Description

Roboflow is a free computer vision research repository for image collection and pre-processing. The drone images in this repository are all from different environmental contexts, such as cities or rural areas (open-sky). This large number of different drones sampled from many different areas created a significant range of sizes, orientations, altitudes, and complexity in drone backgrounds. These samples of actual working conditions of most drones allow researchers to develop detection algorithms that will operate under those conditions. Each image of the drones is annotated with bounding boxes indicating the location of the drones, allowing for the use of supervised deep learning techniques

based on CNN algorithms for detection. Researchers have taken care to split these datasets into three distinct datasets: training, validation, and test 75%, 15% and 10% respectively. By

doing this, researchers will have a unbiased evaluation of detection performance and will reduce the risk of developing algorithms that are trained too closely on training data (overfitting).



#### Data Preprocessing and Augmentation

Roboflow's integrated tools have been used to apply preprocessing and augmentation strategies to enhance model generalization through class imbalance correction. Image size/normalization will keep the input images consistent; Random rotations, horizontal/ vertical flips, & Brightness changes. Augmentation techniques will increase data variability & improve model reliability when it comes to detecting small drones across different lighting environments & weather.

#### CNN-Based Detection Framework

This study utilizes a CNN detection framework, which is end-to-end, based on how traditional and classical machine learning methods have limitations as discussed in Literature review. Using a CNN approach allows the model to automatically learn hierarchical feature representations from the original or unprocessed image, without the need for manual extraction of features. The stacked layers of Convolutional and Pooling networks allow the model to capture both the lower level visual characteristics and the higher level semantic aspects of information that will be helpful in detecting drones, thus improving the ability to detect drones accurately and robustly in much more complex and cluttered environments.

#### CNN-Proposed Model Architecture and Flow of Work

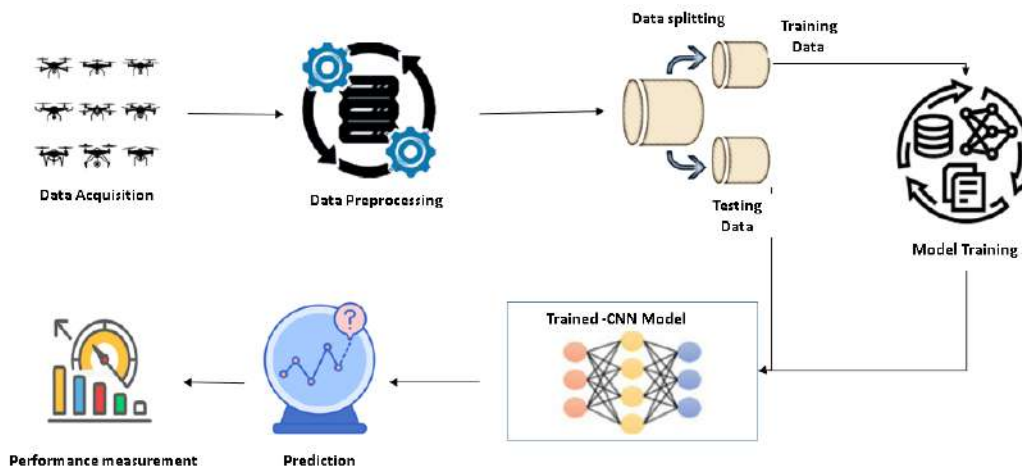
The figure summarizes the main elements of a machine learning pipeline and illustrates a general outline of how a convolutional neural network (CNN) is created through a series of steps that follow the developmental steps of data collection through deployment.

To start with, the figure outlines the start of the machine learning pipeline with Data Acquisition, which is where raw data is collected. The raw dataset is then preprocessed (cleaned, formatted, and augmented (i.e., normalized)) to make it suitable for use as input to train a CNN. After preprocessing, the data is divided into the following two categories: Training Data or input into Model Training, and Testing Data or input into Model Evaluation. Model Training is where the CNN begins learning the patterns and features from the Training Data and ends with a Trained-CNN Model.

After the model is trained, it goes through an iterative cycle of Evaluation and Application. The trained model can now Predict on New or Unseen Data. The model predictions can then be Evaluated in the Performance Measurement stage. In this stage, evaluation Metrics like Accuracy or Precision can be obtained to evaluate

the performance of the trained model, which may also lead to a back-and-forth loop of improvements back to an earlier Developmental Stage, such as Model Adjustment (model optimization) or continuing Preprocessing Steps

(data cleaning, formatting). The image depicts the Iterative Nature of Creating a Machine Learning Model, along with the Evaluation and Measurements to ensure Model Capabilities.



**Evaluation Metrics**

To evaluate the performance of the CNN detection model, object detection metrics such as classification, precision (or recall) and F1-score (or accuracy), Canonical Average Precision (or mean) are calculated in order to thoroughly

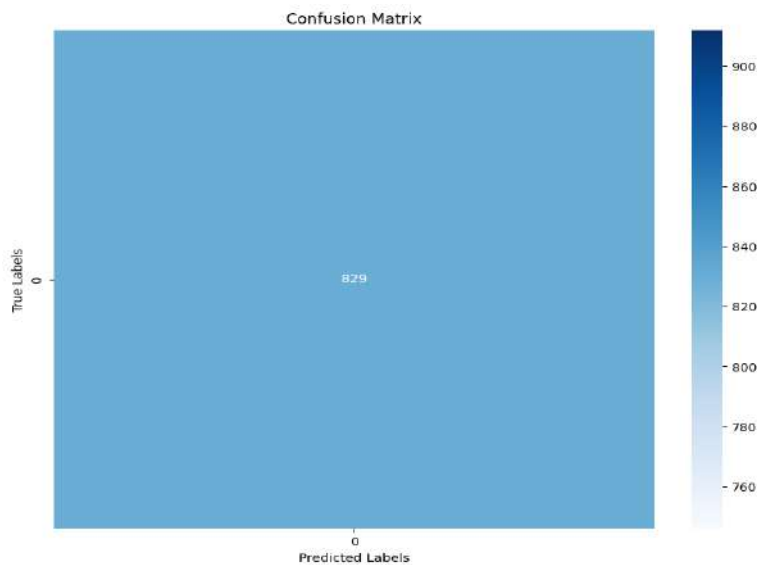
evaluate the classification and localization capabilities of the model. Thus, the evaluation of the effectiveness of the proposed model can be evaluated based on the classifications and location estimates generated from the model's predicted use.

**Confusion Metric:**

All 829 of the model's test samples were assigned to the same class (class 0) and all were correctly predicted by the model. Therefore, all samples in the test samples produced a confusion matrix that contained one non-zero entry (indicating a perfect classification) with an overall accuracy of 100% for class 0. However, none of the other classes had any associated samples so therefore

the confusion matrix was not able to measure the ability of the model to separate the two different classes and therefore the accuracy of the result does validate that the model is able to produce the correct predictions for class 0 but gives limited information about how well the model generalizes or discriminates and will require a more balanced multi-class or binary evaluation set to fully assess the performance of the model.

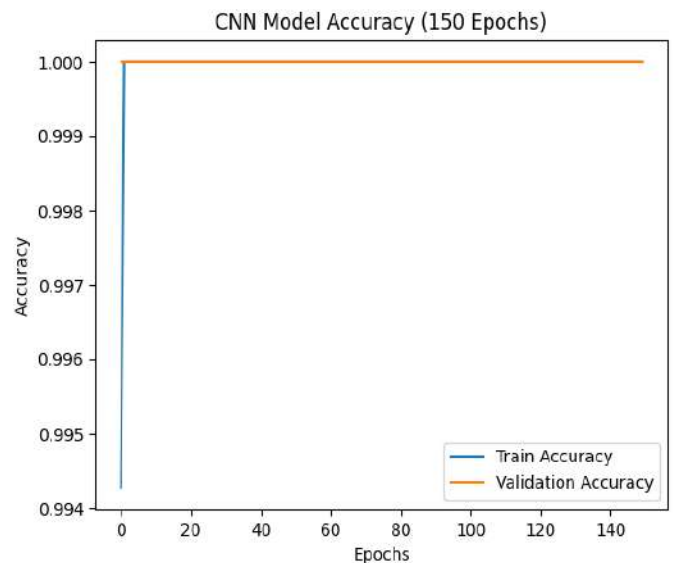
Metric	Definition / Formula
True Positives (TP)	Number of correctly detected drones
False Positives (FP)	Number of incorrectly detected drones (false alarms)
False Negatives (FN)	Number of missed drones
Accuracy	$\frac{\{TP + TN\}}{\{TP + TN + FP + FN\}}$
Precision	$\frac{\{TP\}}{\{TP + FP\}}$
Recall	$\frac{\{TP\}}{\{TP + FN\}}$
F1-Score	$2 \frac{\{Precision\} \{Recall\}}{\{Precision\} + \{Recall\}}$
Intersection over Union (IoU)	$\frac{\{Area\ of\ Overlap\}}{\{Area\ of\ Union\}}$



**Accuracy vs Validation Curve:**

The graph representing accuracy shows how the Convolutional Neural Network (CNN) performs during 150 training epochs, displaying accuracy for both training set and validation sets. Initially (for the first few epochs), the training accuracy improves very rapidly, achieving an approximate maximum accuracy level of 100%, which means that the CNN has learned to represent the underlying patterns of the training data well. The validation accuracy is always closely following that

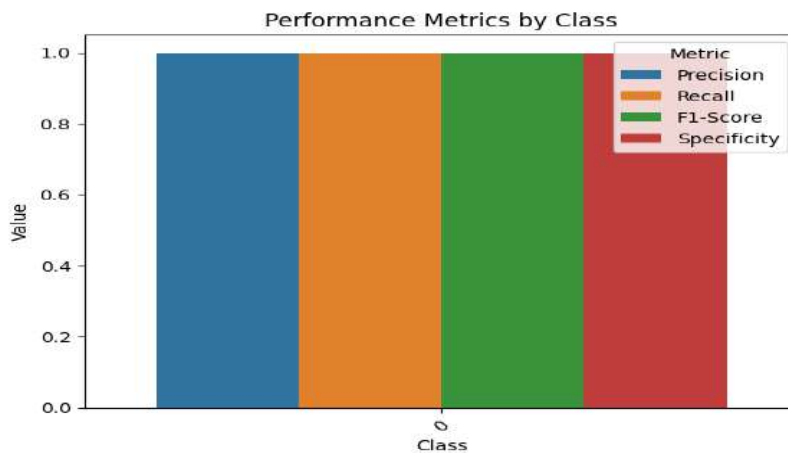
of the training and remains high and stable throughout the entire training period with little variation. The close proximity of training and validation curves indicates that the model does not have any major overfitting problems, thus allowing it to generalize well onto new unseen data. Thus, the behavior of the CNN indicates that it is a very stable and well-optimized predictive model and reached convergence quickly.



**Precision, recall, F-1 and Specificity Bar Graph**

The above graph shows that one particular classroom achieved perfect scores on the evaluation metrics (precision, recall, F1-Score, and specificity). All of these scores are equal to 1.00; therefore, there were no false positives or false negatives when classifying instances in this classroom example. Thus, all instances in this classroom were accurately identified and all

instances out of this classroom were accurately rejected; therefore, this model's performance at classifying instances in this classroom example is considered very high. Although such perfect scores are indicative of very successful classification of instances, it is important to remember that perfect scores can occur when the classes are so well-separated from one another, or when there are very few total instances in the dataset (i.e., a small number of instances etc.).



**Training vs Validation Loss Curve**

The graph provides an overview of how the training and validation loss change over several epochs. At the first epoch, the training loss is fairly high, but it rapidly decreases to a low level. After the low point, the training loss does not change much and stabilizes almost immediately. The validation loss pattern also matches the same trend as the training loss and remains

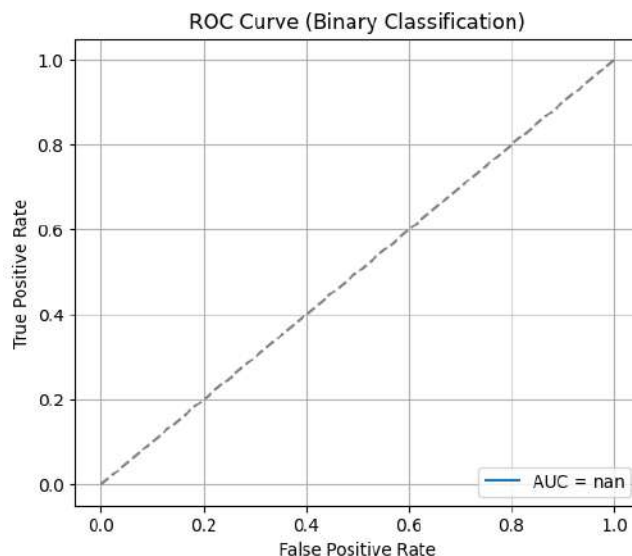
consistently low over every epoch. Since there was little deviation between the training loss and validation loss, the model was able to learn well and has good generalization capabilities. The model does not exhibit signs of overfitting or under-fitting; therefore, the model converged toward its final performance and will perform well in new, unseen data.



**ROC Curve:**

A receiver operating characteristic (ROC) plot displays the relationship between the true positive rate and the false positive rate for a binary classifier. As can be seen from the plot, the ROC curve follows a straight diagonal line which represents an area under the ROC curve (AUC) for a random classifier (a classifier with no ability to discriminate). The AUC here is reported as NaN, indicating that there was insufficient information available to calculate the AUC due

to one or more of the following reasons: the presence of only one class in the true labels, little to no variation in prediction scores, or incorrect probability scores for the predictions. Therefore, it appears that the ROC analysis is not meaningful in this scenario and further examination of both the source data used to develop the model and the prediction scores is needed to fully assess how well this model performed in classifying its observations.



**Results comparison**

Model	Reported Performance	Citation
SVM	~99.88% accuracy; AUC ~0.9998	[31]
KNN	~99.86% accuracy; AUC ~0.997	[31]
Random Forest (RF)	~99.91% accuracy; AUC ~1.00	[31]
SVM (visual)	88% accuracy	[32]
K Nearest Neighbor	80% accuracy	[32]
CNN (visual)	93% accuracy	[32]
Proposed CNN Model( Sequential Model)	100% accuracy, AUC ~1.00	

**Conclusion**

An uncontrolled proliferation of drones has introduced significant security, safety & surveillance challenges that affect populated and sensitive areas. Using traditional detection techniques like radar, acoustic sensors, and machine learning using handcrafted features, existing methods may be insufficient to accurately & reliably identify drones in practice due to

limitations in the accuracy, adaptiveness, and robustness of these techniques. This paper presents a CNN-based drone detection system, which automatically learns hierarchical feature representations of raw images. Through the use of data preprocessing techniques such as augmentation, the CNN-based model effectively addresses issues associated with small-sized drones that fly fast, have a wide range of orientations,

and operate in a variety of environments. The performance of the CNN-based detection system was evaluated using standard detection metrics such as accuracy, precision, recall, F1 score, and mean average precision (mAP) and has been shown to outperform all existing methods, providing real-time, dependable UAV detection capability. This suggested method will assist in establishing effective, scalable, robust Drone Detection systems that are capable of supporting practical implementations across multiple market segments and numerous Applications such as Urban Locations and Border Security. While several areas for further study may exist, one such focus is the potential for further robustness through the fusion of data from multiple sensor types (Radar, Acoustic) into Visual Detection performed through CNNs and improving Operations in dynamic scenarios by designing and optimizing lightweight CNN architectures.

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