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Automatic Detection of Foreign Object Debris on Runways

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Abstract: Foreign object debris can easily damage aircraft engines as well as injure personnel in an airport environment. Airfield Inspectors routinely inspect runways for the presence of FOD items, which differ in material, shape and colour using conventional and automated methods. The major shortcoming of the current method is their inability to detect all types of foreign objects in an accurate and timely manner. For removal from the airport runways in this study, we address this shortcoming, that is the lack of accuracy and timelines in the detection by developing an object detection framework to detect FOD for quick removal from the airports. The proposed FOD detection framework consists of unmanned aerial system for inspecting and collecting data from the airfields data processing and augmentation technique to counter the issue of learning on limited types of foreign objects, whether conditions and airport surface materials that are present in the data sets. A computer vision based object detection model to attain high accuracy and faster inference time force range and develop various models, including the you only look once object detector family of models in this framework.

Keywords: Convolution Neural Network (CNN), FOD Detection, Raspberry Pi.

I. INTRODUCTION

Foreign object debris (FOD) poses a significant threat to aviation safety, potentially damaging aircraft and leading to accidents. Manual FOD inspection is time-consuming, prone to human error, and often ineffective. This work aims to develop and implement an automated system for detecting and identifying FOD on airport runways using deep learning and computer vision technologies. High-accuracy FOD detection: Deep learning models trained on a large dataset of runway images with diverse FOD objects will achieve significantly higher accuracy compared to manual inspection.

Real-time performance: The system will operate in real-time, continuously scanning runways and immediately notifying airport personnel about detected FOD. Enhanced efficiency: Automated FOD detection will eliminate the need for dedicated inspection personnel, saving time and resources. Improved safety: Timely detection and removal of FOD will significantly reduce the risk of FOD-related accidents, enhance aviation safety, scalability and adaptability: The system will be designed to be easily scalable for implementation at airports of various sizes and configurations.

II. LITERATURE REVIEW

This section throws light on the Literature Survey carried out for this work to design an Automatic Detection of FOD on Runways.

[1] This work presents a runway FOD detection system leveraging AI-powered computer vision. The authors propose a model that processes runway imagery to detect a wide variety of debris under realistic lighting and background conditions. Using convolutional neural networks (CNNs), the system emphasizes robust feature extraction and real-time performance. The evaluation demonstrates high detection accuracy across multiple debris types and runway environments, highlighting the potential for scalable AI deployment in airport safety systems. [2] This paper applies the anchor-free YOLOX object detector to runway FOD detection. It adapts the decoupled head and novel label assignment strategy (SimOTA) of YOLOX to improve small object recognition and localization under challenging runway textures. The model achieves improved average precision (AP) rates relative to traditional YOLO variants, while also maintaining high inference speeds conducive to real-time runway monitoring. [3] This study develops a radar-based FOD detection algorithm for millimeter-wave (mmWave) surveillance radar. It tackles the challenges of target weak echoes and complex ground clutter by modeling the radar signal and clutter characteristics under long-range (> 660 m) conditions. The proposed automatic detection algorithm improves the detection of small debris beyond ranges achievable by traditional radar systems. [4] This work presents design of detection system based on synthetic aperture radar (SAR) with arc-scanning geometry. Their approach enhances spatial resolution and detection range while suppressing clutter through SAR image formation.

This system is capable of detecting debris under various environmental conditions, including poor visibility.[5]This paper focuses on classification rather than only detection, this work uses deep convolutional neural networks to identify debris materials, especially metal objects that pose high risks. The network is trained to distinguish metallic FOD from non-metallic debris using visual appearance cues. [6]This survey provides a broad overview of FOD detection research up to 2020. It covers conventional sensor-based inspection methods, optical machine vision systems, radar modalities (including mmWave and SAR), and emerging AI-based detection frameworks. The authors review challenges such as limited datasets, small target detection, and operating environments

Proposed system Captures detailed images of the runway periodically Automates FOD detection, covering larger areas and potentially achieving higher accuracy than manual methods. Faster detection and removal of FOD minimizes the risk of aircraft damage and accidents.

III.METHODOLOGY

The following is a detailed methodology for an Automatic Detection of Foreign Object Debris on Runways.

A. Hardware Setup

Figure 1 shows the block diagram of the proposed system.

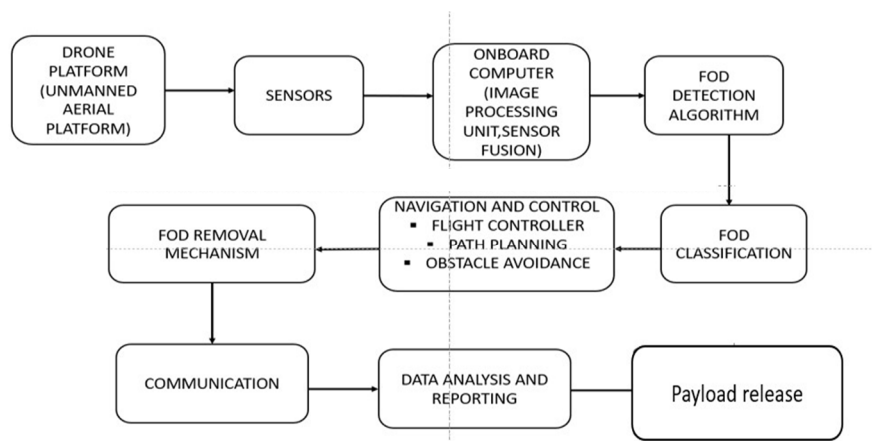


Figure 1 Block Diagram

Drone Platform (Unmanned Aerial Platform):A drone operates above the runway (typically within 30 m altitude), covering the runway surface efficiently and flexibly.

Sensors: The drone is equipped with RGB cameras are used to continuously scan runway surfaces for detecting debris

On-board Computer (Image Processing Unit, Sensor Fusion): Captured sensor data is sent to an on-board processing unit. This module carries out:

- Image processing to detect anomalies against the runway background.
- Detection algorithms-CNN-based detectors are trained to identify foreign objects like screws, bolts, plastic bottles, or metal fragments

FOD Detection Algorithm: Uses AI models (YOLOX) specifically trained on FOD datasets. These models are designed for detecting small objects under various atmospheric conditions in real-time inference.

FOD Classification: Once an object is detected, the classification module distinguishes between debris types (e.g., metal and non-metal)using CNN-based networks classification models, particularly, detection of higher risk items like metallic debris.

Navigation and Control: The drone's flight controller oversees:

- Path planning to systematically cover the runway,
- Obstacle avoidance to ensure safe navigation,
- Autonomous maneuvering to position over detected debris zones.

FOD Removal Mechanism: Uses grippers for debris pickup,

Communication: Wireless data links transmit detection and classification results to ground control systems or monitoring stations.

Data Analysis and Reporting: Collected data is used for: Real-time situational awareness, Statistical analysis, and for Generating reports and operational logs.

Payload Release: The drone releases debris into collection bags.

Otherwise the drone releases GPS-beacons to indicate the location of detected debris for human or vehicle crews.

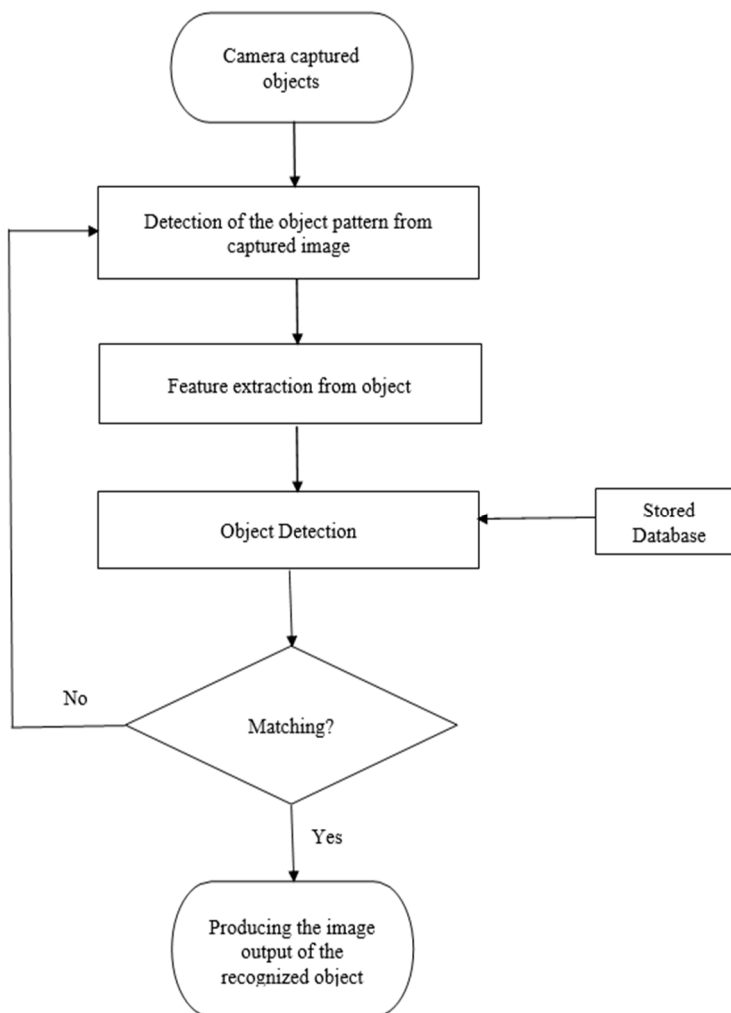


Figure 2 Flowchart of the Software system

Figure 2 shows the flowchart of the object detection

- 1) Capturing the object: The first step is to capture the object with a camera. This means taking a picture of the object.
- 2) Detecting the object pattern: The second step is to detect the object pattern from the captured image. This involves finding the specific shapes and colors that make up the object in the image.
- 3) Extracting features: The third step is to extract features from the object. These features are like fingerprints that help the computer identify the object. They might include things like the size, shape, and color of the object.
- 4) Matching the object with a database: The extracted features are then matched against a database of known objects. This database is like a giant collection of fingerprints of all the objects that the system has been trained to recognize.
- 5) Recognizing the object: If there is a match, the object is recognized. The system then outputs an image of the recognized object. If there is no match, the system may not be able to recognize the object.

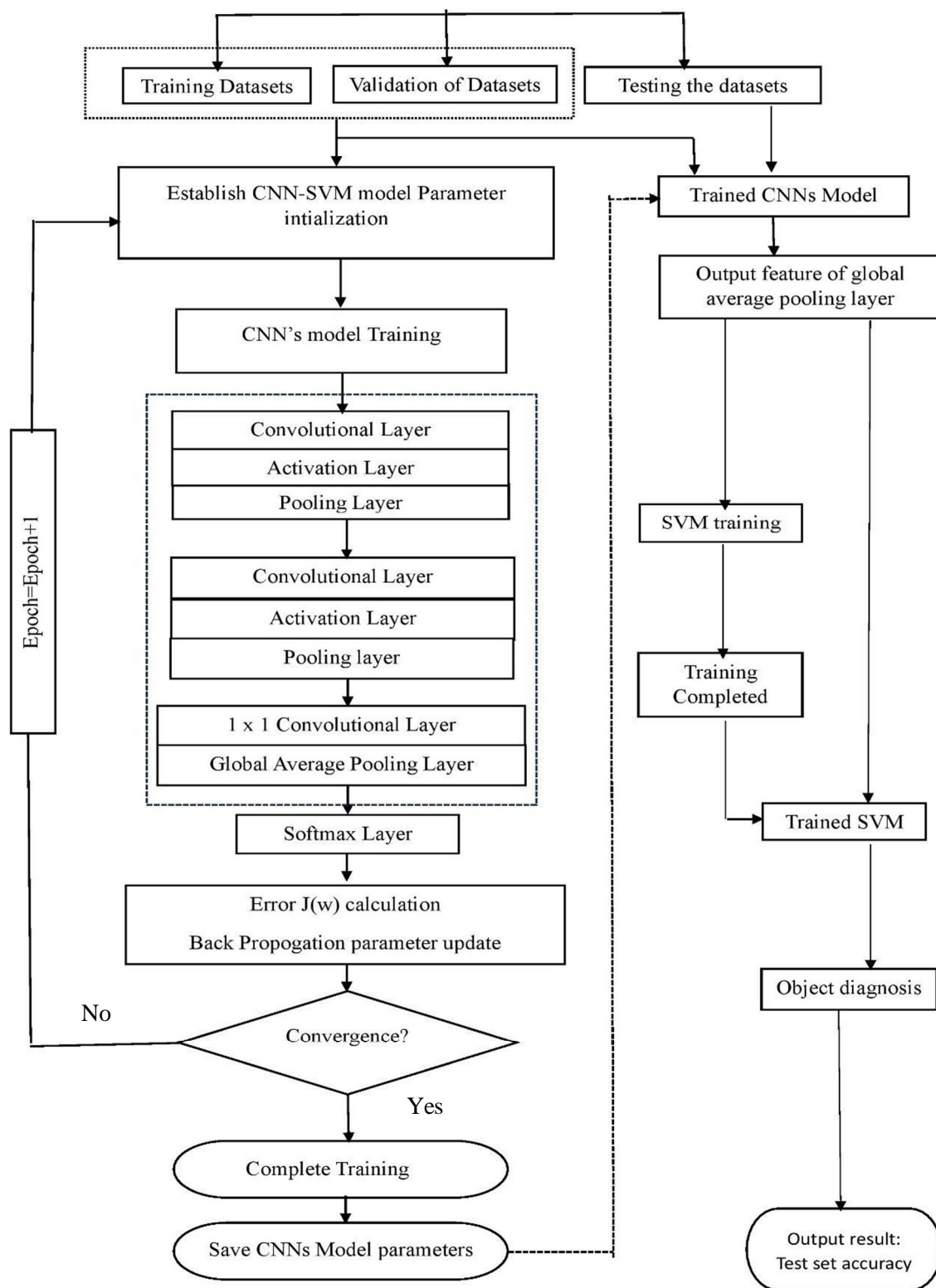


Figure 3 Flowchart of the algorithm

The figure 3 shows the flowchart of the hybrid algorithm. Firstly train CNN with convolutional layers, global pooling, until convergence. Extract GAP features, then train using SVM classifier on them. Then evaluate on test data for final accuracy.

IV. IMPLEMENTATION

A. Collection of Dataset

A comprehensive dataset comprising images of nuts, bolts and stones has been meticulously curated for this study. These images as shown in Figure 4 encompass diverse backgrounds and orientations, ensuring the model's robust detection capabilities. To guarantee the dataset's authenticity and reliability, the images are sourced from reputable and validated platforms known for their extensive collection of foreign object debris.



Figure 4 Collection of Datasets for FOD

Specifically, a substantial dataset is compiled for each FOD category, covering various backgrounds and viewing angles essential for training the model effectively. The dataset is meticulously obtained from the Kaggle.com website and live footage from airports, which is a renowned source for diverse datasets. The purpose of this dataset is to facilitate the practice of various image processing techniques, enhancing the overall robustness of the model. The dataset used in this research consists of the following particulars:

- Number of classes: 3 [Metal parts, stones and FOD(plastic, wooden pieces)]
- Number of images: 4000
- Image shape range: (100, 100) to (4992, 3328)

By incorporating this dataset into the research, the study benefits from a rich collection of images encompassing various classes of FOD having different sizes and shapes, essential for training and evaluating the model's detection capabilities.

B. Feature Extraction

The FOD image input is fed into the FOD detection system, in which it is pre-processed, then features are extracted. Then the extracted features are fed to softmax classifier which is the last part of CNN.

The input image is pre-processed and converted to grey scale image to find the Threshold value based on input image.

Next the system performs the task of detecting the type of FOD. The image is fed into system to find out edges and after sharpening the edges, the features are extracted and then fed into classifiers which are trained based on the available dataset to detect the FOD.



V. RESULTS

A. Experimental Results

In the expansion of the FOD detection system, this study successfully integrated the capability to accurately identify FOD, including metal parts, stones and rubber. The robustness of the Convolutional Neural Network (CNN) model has been rigorously tested across a dynamic and challenging conditions. It was observed that even if the image is slightly blurred, the system sustains an accuracy rate of over 75% in identifying these FOD. The overall performance shows an impressive accuracy rate of 80% and above for these FOD' detection.

A series of trials were conducted to validate the model's performance, during which the system consistently recognized and classified FOD with moderate precision. For instance, in a test image, the model confidently identified a nuts with an accuracy of 87%, as indicated by the bounding box and confidence score overlay. Similar tests on bolts and stones yielded comparable results, corroborating the model's adeptness at handling the intricate patterns and varied weather conditions associated in the airports.

The proposed CNN model has been trained on 4000 images. The model takes input images of sizes 320 x 320. The pixel values of the range 0-255 are converted into -1 to 1 range during preprocessing. The prototype model is as shown in figure 5 and Visual results of the detected image are shown in Figure 6.

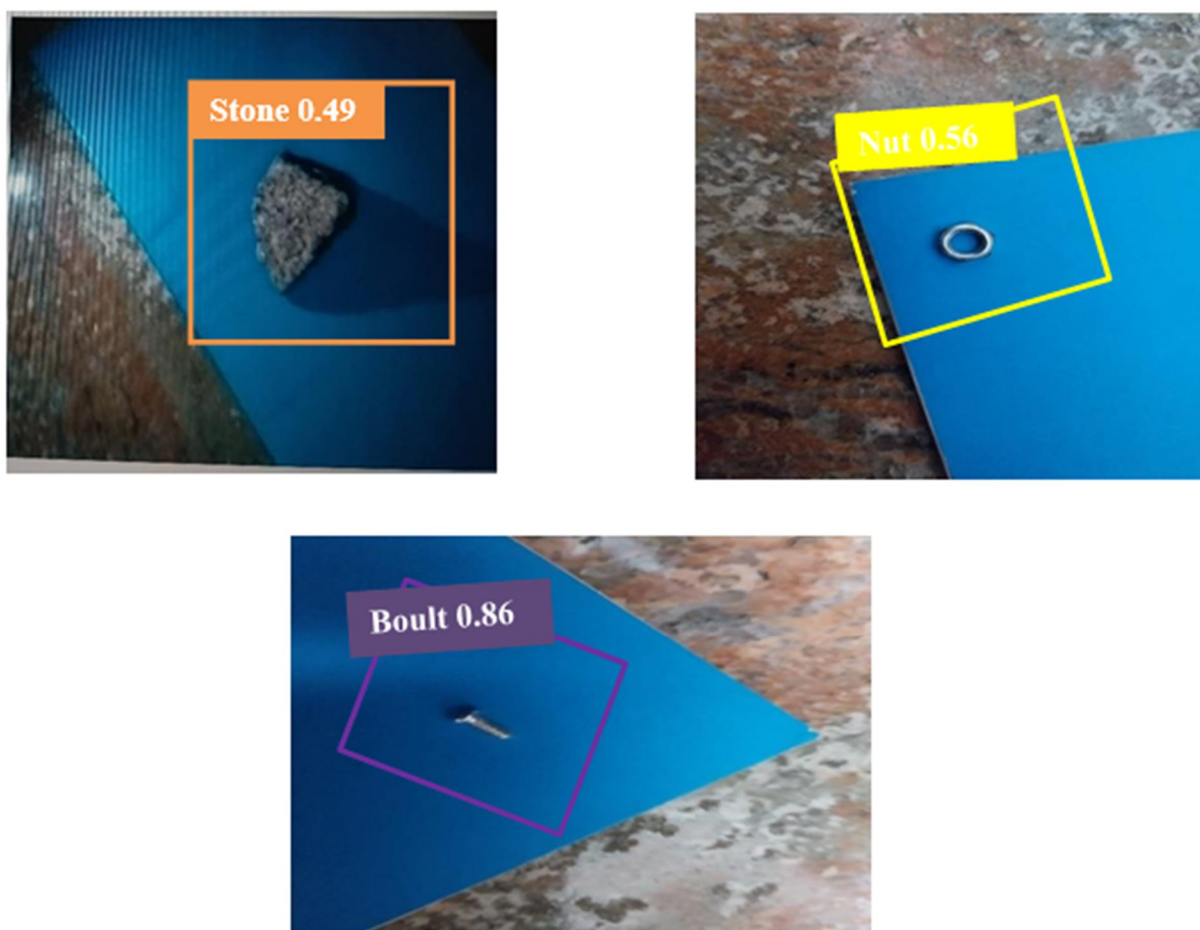


Figure 5 The Prototype

Figure 6 Visual results of detected images

B. Quantitative Analysis of Model Convergence

This research quantitatively evaluates the convergence behavior of the proposed FOD detection model through a series of graphs metrics over the training epochs.

- 1) *Confidence Curve*: Figure 7 depicts the confidence curve, which quantifies the model's confidence in predicting the correct FOD categories.

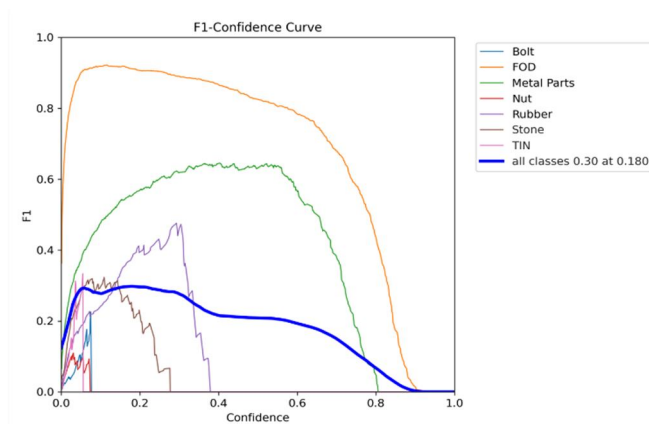


Figure 7 Confidence Curve

- 2) *Precision Recall Curve*: Figure 8 depicts the precision recall curve, which quantifies the model's precision in predicting the correct FOD categories.

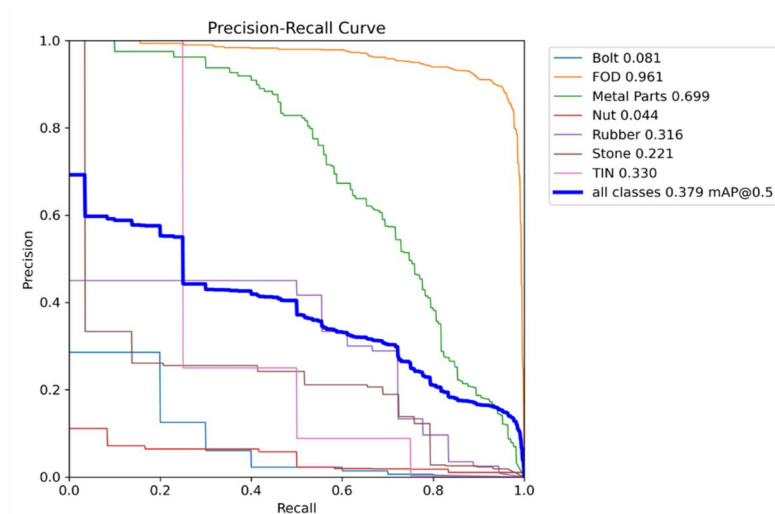


Figure 8 Precision Recall Curve

VI. CONCLUSIONS

The presence of a large number of foreign objects (in various colors, shapes, and materials) in an airport environment makes it infeasible to train an object detection model on all types of FOD items that could be found on runways. This characteristic makes the FOD items a set of unbounded target objects and this problem non-trivial. The data augmentation component in the proposed FOD detection framework is able to counter the issue of training on limited types of foreign objects, weather conditions, and surface materials and attain higher FOD detection accuracy.

It is important to detect foreign objects, irrespective of identifying their types, to reduce the chance of damage or injury in an airport environment. By assigning a single class to this set of foreign objects in the training data, we demonstrated that our framework with the computer vision model is able to learn the inherent features within the internal filters and detect previously unseen objects with a high accuracy. The CNN model trained on the data set of FOD images obtained after applying the augmentation techniques on the original images captured by the UAS outperforms all the other modeling approaches in the object detection accuracy performance metrics. The proposed FOD detection framework with the CNN model has the highest average precision value, recall rate, and precision rate among all other models.



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