IJARETY

International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 3, May-June 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE
SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

DOI:10.15680/IJARETY.2025.1203077

Automatic Detection and Predictive Geo-location of Foreign Object Debris on Airport Runway

Mr. A. Rajesh[1], Ms. V. Anusha[2], Ms. Y. Akshitha[3], Ms. T. Bhavani[4]

Associate Professor, Department of Computer Science & Engineering, Guru Nanak Institute of Technology, India[1]

Student, Department of Computer Science & Engineering, Guru Nanak Institute of Technology, India[2]

Student, Department of Computer Science & Engineering, Guru Nanak Institute of Technology, India[3]

Student, Department of Computer Science & Engineering, Guru Nanak Institute of Technology, India[4]

ABSTRACT: Foreign Object Debris (FOD) on airport runways can lead to serious risks for aircraft, especially because such debris is often small and hard to detect in bad weather. This project introduces a smart detection system using YOLOv8, a modern object detection model. We enhance it further using a geolocation predictor built with machine learning. The system combines deep learning with attention mechanisms to better recognize small items. Experiments show that this model works better than earlier versions like YOLOv5, YOLOX, and YOLOv7, and it maintains high accuracy even in tough conditions. The geolocation model also accurately predicts the debris location, which helps make airport runways safer. Foreign Object Debris (FOD) on airport runways can lead to serious risks for aircraft, especially because such debris is often small and hard to detect in bad weather. This project introduces a smart detection system using YOLOv8, a modern object detection model. We enhance it further using a geolocation predictor built with machine learning.

KEY WORDS: Long Short-Term Memory (LSTM), LIAR dataset and LIAR2, Recurrent neural network (RNN) , Natural language processing (NLP), CNN-BiLSTM (Convolutional Neural Network - Bidirectional Long Short-Term Memory), GloVe, Preprocessing, Word Embeddings, Data Collection, Data Loading, Text Preprocessing, Word2Vec Embedding, H5 Format, NumPy, Pandas, Matplotlib, Scikit-learn, Generative Adversarial Networks (GANs) or Synthetic Minority Oversampling Technique (SMOT).

I. INTRODUCTION:

Foreign Object Debris (FOD) on airport runways can cause serious harm to aircraft parts like engines and tires. Quick and accurate detection of such debris is necessary for safe and smooth airport operations. However, detecting FOD is difficult because the debris is usually small and can be missed easily, especially during low visibility.

Old methods like manual checks or sensors are not always reliable or efficient. With new technologies like drones and machine learning, we can now build automatic detection systems. In this project, we use YOLOv8 with Swin Transformer to improve the detection of small objects. We train the model using drone images from different conditions and add a geolocation model to find the exact position of the debris. Tests show that our system works better than older models and is useful for real-life airport safety.

The primary objective of this project is to develop an advanced FOD (Foreign Object Debris) detection system that uses the YOLOv8 object detection algorithm enhanced by Swin Transformer for accurately identifying small debris on airport runways. In addition to detection, the system integrates a machine learning-based regression model to predict the geo-location of the debris for efficient removal. The goal is to achieve high precision, real-time performance, and adaptability to diverse weather and environmental conditions. The system's performance will be evaluated through ablation studies and comparative assessments with existing models like YOLOv5, YOLOX, and YOLOv7, showcasing improvements in Mean Average Precision (mAP) and overall detection accuracy.Finally, the project will demonstrate the practical application of the proposed FOD detection system in real-world airport environments, emphasizing its real-time detection capabilities and accuracy across diverse conditions.

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203077

II. LITERATURE SURVEY

Title: Semi-automatic crack width measurement using an OrthoBoundary algorithm,
Author: Z. Li, Y. Miao, M. E. Torbaghan, H. Zhang, and J. Zhang
Year: 2024.
Description: Evaluation of pavements' crack severity levels currently relies heavily on width measurement, which necessitates the development of a rapid, and high-accurate, automatic measurement approach for complex pavement cracks. This paper presents an OrthoBoundary algorithm that leverages the crack boundary and skeleton directions to determine crack propagation. Comparative analysis has been conducted between OrthoBoundary and Area-Length, Skeleton Shortest Distance (SSD), Edge Shortest Distance (ESD), and Orthogonal Projection (OP) methods. Results indicate that the OrthoBoundary algorithm achieves an average accuracy of 90.10%, outperforming the Area-Length (86.60%), SSD (76.01%), ESD (87.24%), and OP (88.07%) methods. Notably, the OrthoBoundary algorithm also exhibits processing speeds approximately 120 times faster than other considered methods while demonstrating improved robustness and user-friendliness. It has significant potential to quantify and assess the severity of pavement cracks.

Title: An automated 3D crack severity assessment using surface data for improving flexible pavement maintenance strategies.
Author: Z. Li, M. E. Torbaghan, T. Zhang, X. Qin, W. Li, Y. Li, and J. Zhang
Year: 2024
Description: Evaluation of crack severity in flexible pavements predominantly centers around the analysis of cracks surface characteristics. However, this study highlights the critical importance of 3D crack parameters, including volume and depth, for comprehensive assessment. The objective here is to develop an autonomous crack severity assessment, by predicting the vertical parameters of cracks exclusively from their surface properties. To achieve this, a dataset of 3D parameters comprising 200 cracks from eight flexible pavements was acquired, and both linear and nonlinear correlations were conducted among these 3D parameters. Subsequently, five single-output and one multi-output machine learning models were developed to explore the potential of utilizing surface parameters to predict the vertical parameters of cracks. The outcomes validated the effectiveness of two specific methods, namely, Artificial Neural Network and Extreme Gradient Boosting models, in predicting crack volume based on surface parameters, with R2 scores of 0.832 and 0.748, respectively.

Title: Improved small foreign object debris detection network based on YOLOv5,
Author: H. Zhang, W. Fu, D. Li, X. Wang, and T. Xu
Year: 2024
Description: In response to the challenges of detecting foreign object debris (FOD) on airport runways, where the objects are small in size and have indistinct features leading to false detections and missed detections, significant improvements were made to the YOLOv5 algorithm. First, the original YOLOv5-n model was optimized by incorporating multi-scale fusion and detection enhancements. To improve detection speed and reduce parameters, the detection head for large objects was removed. Second, the C3 module in the backbone network was replaced with the C2f module, resulting in enhanced gradient flow and improved feature representation capabilities. Additionally, the spatial pyramid pooling-fast (SPPF) module in the backbone network was refined to expand the receptive field and enhance the model's perception of dependencies between targets and backgrounds. Furthermore, the coordinate attention (CA) mechanism was introduced in the neck layer to further enhance the model's perception of small FOD items.

Title: Airport runway foreign object debris (FOD) detection based on YOLOX architecture
Author: J. Taupik, T. Alamsyah, A. Wulandari, E. U. Armin, and A. Hikmaturokhman
Year: 2023**.**
Description: A modified YOLOv8 FOD object detection algorithm is proposed to address the issue of foreign object debris (FOD) target size being too small on airport runways. Add space to depth convolution to eliminate the negative impact of convolution and pooling operations on small targets; Introducing lightweight and efficient convolutional attention modules to focus on key features of the network from both spatial and depth dimensions; Improve multi-scale feature fusion to effectively improve the detection accuracy of small targets; Use weighted bounding box fusion algorithm to improve the accuracy of bounding boxes and the overall detection performance of the model. The experimental results show that the improved YOLOv8 object detection algorithm achieves 94% mAP50 and 93% mAP50-90 while meeting real-time requirements, effectively solving the problems of false detection, missed detection, and low positioning accuracy in FOD detection tasks.

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203077

III. EXISTING SYSTEM

Current approaches for Foreign Object Debris (FOD) detection on airport runways mainly rely on traditional computer vision techniques and various deep learning models. Among the most used models for object detection are the YOLO (You Only Look Once) family of algorithms, such as YOLOv5, YOLOX, and YOLOv7. These models have shown considerable success in real-time object detection tasks due to their speed and accuracy. However, they face limitations when it comes to detecting small objects, such as FOD, especially under challenging conditions like low visibility or complex weather.

Additionally, many existing systems struggle to maintain detection performance with varying input data, resulting in a decline in accuracy when exposed to diverse environmental scenarios. Furthermore, while these systems can identify objects, they often lack a robust mechanism for geolocation prediction of FOD, which is critical for efficient removal and maintenance operations.

EXISTING SYSTEM DISADVANTAGES:

- Limited Handling of Small Objects
- High Computational Demand for Larger Models
- Increased Model Size and Complexity
- Overfitting on Small Datasets

IV. PROPOSED SYSTEM

The proposed system addresses the challenges of detecting and removing Foreign Object Debris (FOD) on airport runways, particularly focusing on small object detection and overcoming the effects of adverse weather conditions. The system utilizes an advanced FOD detection model that combines YOLOv8, enhanced by Swin Transformer (ST), to improve detection performance. The model is trained on a large-scale dataset collected by an Unmanned Aerial Vehicle (UAV), which consists of 74,737 images across 21 distinct object types, covering a wide range of FOD scenarios. YOLOv8, known for its high accuracy and efficiency, is further augmented by the Swin Transformer, which introduces a self-attention mechanism to capture long-range dependencies and contextual information, thereby improving the detection of small and complex objects in diverse environments. YOLOv8 is employed for its advanced capabilities in object detection, particularly for small objects like FOD. The integration of Swin Transformer enhances YOLOv8's performance by providing more precise feature extraction and handling complex, cluttered environments more effectively

PROPOSED SYSTEM ADVANTAGES:

- Superior Small Object Detection.
- Improved Accuracy and Robustness
- Improved Handling of Cluttered Backgrounds
- Better Integration of Attention Mechanisms

V. SYSTEM ARCHITECTURE

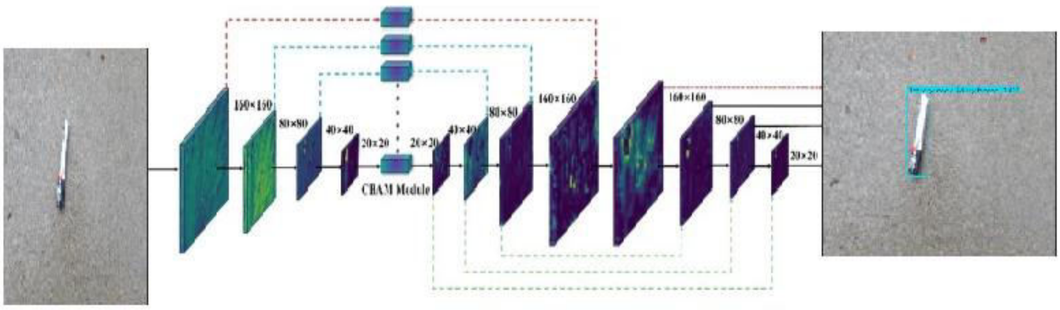

Fig 1: System Architecture

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |
|| Volume 12, Issue 3, May-June 2025 ||
DOI:10.15680/IJARETY.2025.1203077

This system architecture diagram shows the workflow of detecting foreign objects on airport runways using a deep learning model. It starts with an input image, which is passed through several convolutional layers to extract important features. A CBAM (Convolutional Block Attention Module) is used in between to help the model focus on the most relevant parts of the image. The features are refined further through more layers. Finally, the model outputs the same image as the object detected and labeled with a bounding box and confidence score.

VI. METHODOLGY

Module Names:
This project has the following modules:
- Data Collection
- Data Preprocessing
- Feature Extraction
- Model Training
- Model Evaluation
- Object Detection

Module Explanation:
1) Data Collection:
Gathering the raw data needed for training a model. In object detection, this involves collecting labeled images or videos where the objects of interest are annotated with bounding boxes.

2) Data Preprocessing:
Cleaning and transforming the collected data into a format suitable for model training. This includes Resizing images to the model's input size, Normalizing pixel values, Data augmentation (e.g., flipping, rotation, etc.) to improve model robustness.

3) Feature Extraction:
In object detection, feature extraction refers to using a neural network or another technique to extract relevant features from the images. CNNs (Convolutional Neural Networks) are typically used for this purpose.

4) Model Training:
Training machine learning or deep learning model on the processed data. In object detection, this involves training a model to predict both the class and bounding box of objects in images.

5) Model Evaluation:
After training, the model is evaluated on a separate test dataset to measure its performance. Common evaluation metrics for object detection include Precision, Recall: Measures the accuracy of the predictions, mAP (mean Average Precision): A popular metric for evaluating the performance of object detection models.

6) Object Detection:
The final task where the trained model is used to detect objects in new, unseen images or video streams. The model outputs bounding boxes around detected objects along with class labels.

VII. TECHNIQUES OR ALGORITHMS

Existing Technique (Yolov5, Yolov7):
YOLOv5 (You Only Look Once version 5) is a real-time object detection algorithm that improves upon the earlier YOLO versions, introducing optimizations for speed and accuracy. Developed by Ultralytics, YOLOv5 is a flexible and efficient model designed for a wide range of object detection tasks, including small object detection. YOLOv5 is notable for its simplicity, ease of use, and modular architecture. The model uses convolutional neural networks (CNNs) for feature extraction and a single-stage approach to directly predict bounding boxes, object classes, and confidence scores for each object in an image.

YOLOv7 is an advanced version of the YOLO (You Only Look Once) object detection algorithm, offering significant improvements in both speed and accuracy over its predecessors. YOLOv7, developed by the YOLO community, is

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203077

optimized for high-performance detection, especially in environments where high accuracy is required for detecting small or overlapping objects.

Proposed Technique (Yolov8):

YOLOv8 is the latest iteration of the YOLO (You Only Look Once) family of algorithms designed for real-time object detection. YOLOv8 builds upon the improvements of previous versions (YOLOv5, YOLOv7) and incorporates new innovations to further enhance accuracy, efficiency, and versatility. YOLOv8 is developed with a focus on small object detection, better generalization, and adaptability to diverse environments, making it highly effective in real-world applications, including complex scenarios like FOD detection on airport runways.

YOLOv8 integrates the latest advancements in deep learning, including novel optimizations for both extraction and object localization.

Combines convolutional layers with attention mechanisms like the self-attention found in transformer-based models, enhancing its ability to detect objects in challenging conditions.

YOLOv8 is designed to run efficiently on both high-performance systems and edge devices, providing faster inference without sacrificing detection accuracy.

The proposed technique utilizes the YOLOv8 object detection algorithm enhanced with the Swin Transformer to improve the accuracy and efficiency of detecting small foreign object debris (FOD) on airport runways. YOLOv8 is chosen for its real-time detection capabilities and superior performance in small object recognition. The integration of the Swin Transformer introduces a self-attention mechanism that captures long-range dependencies and contextual information, making the detection more robust in complex environments. The system is trained on a large UAV-captured dataset to ensure adaptability to real-world scenarios. In addition to object detection, a machine learning-based regression model is implemented to predict the precise geo-location of the detected debris. This dual approach enables both accurate detection and efficient localization, helping airport authorities take prompt action. The use of the Swin Transformer also enhances feature extraction by focusing on the most relevant image regions, reducing false detections. The proposed model shows significant improvement in Mean Average Precision (mAP) compared to previous versions like YOLOv5 and YOLOv7. Overall, the technique ensures high performance even under challenging conditions such as low visibility, cluttered backgrounds, and varying runway surfaces.

VIII. EXPERIMENTAL RESULTS

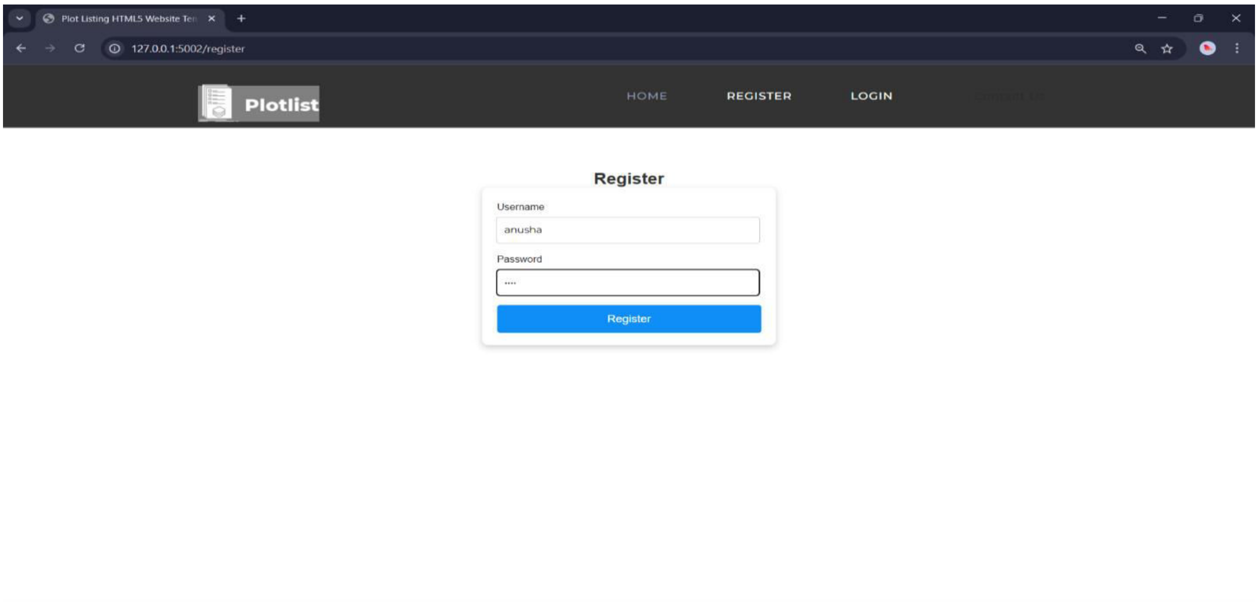

Fig 2: Home Page

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203077

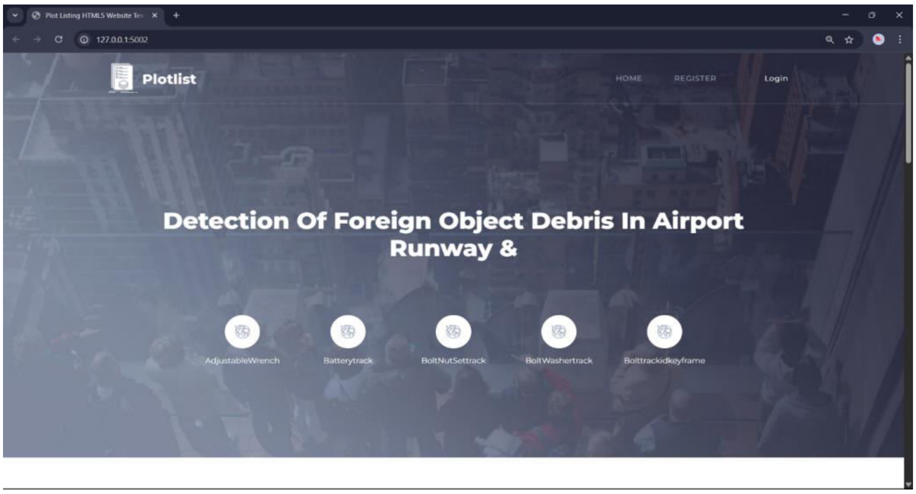

Fig 3: Register Page

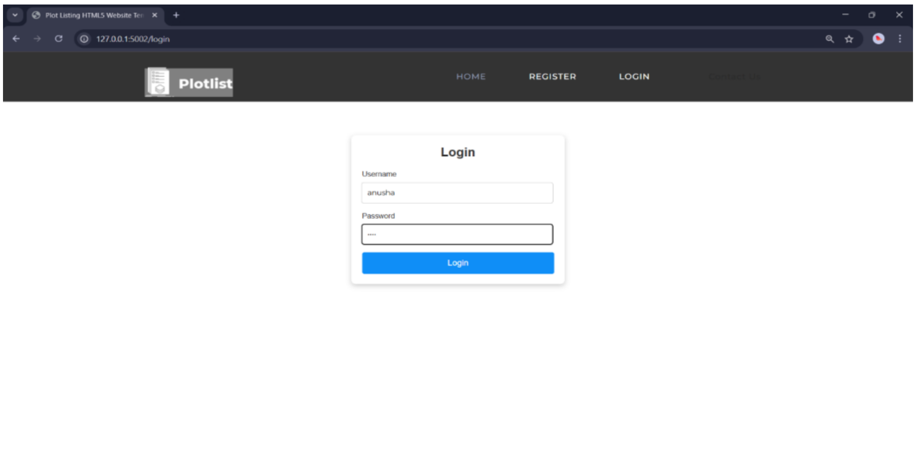

Fig 4: Login Page

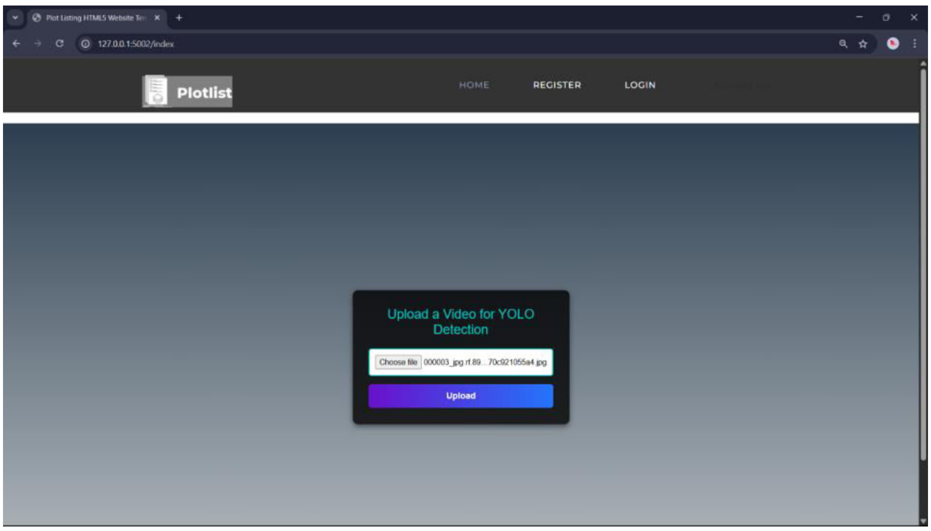

Fig 5: Upload Video for Detection

International Journal of Advanced Research in Education and TechnologY(IJARETY)

IJARETY

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203077

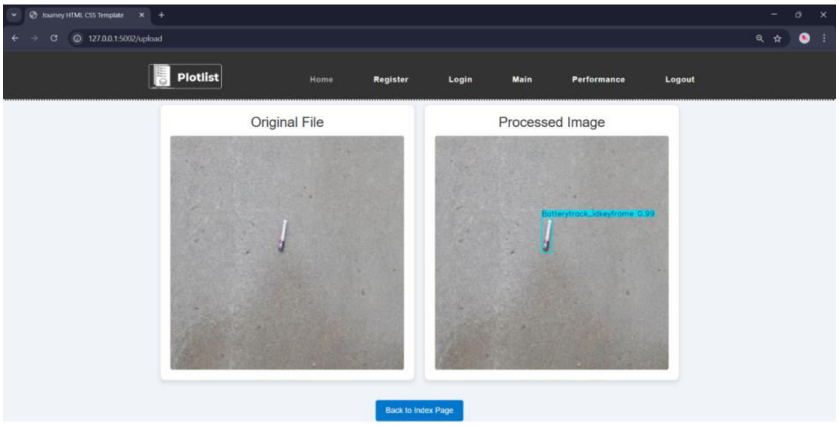

Fig 6: Detection Output – Original vs Processed

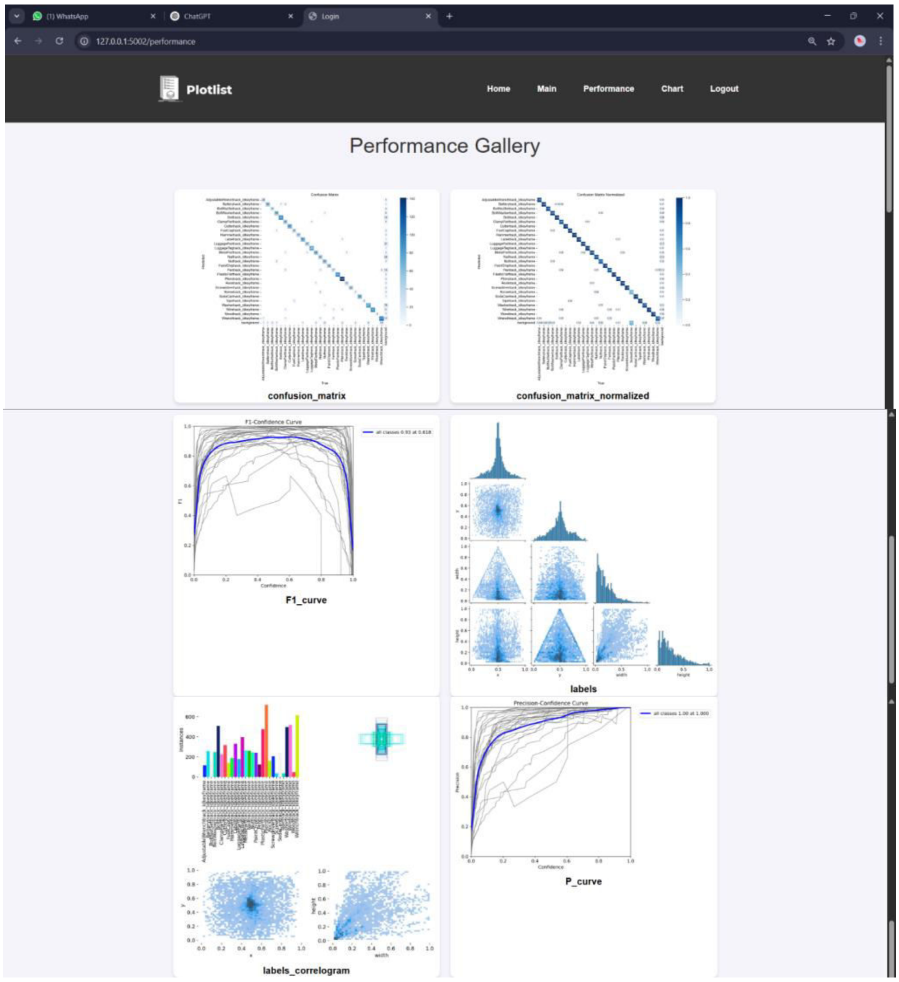

Fig 7: Confusion Matrix, Normalized Confusion Matrix, F1 Score Curve, Labels Scatter Plot (Correlogram), Class-wise Bar Chart and Box Plot, Precision Curve

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203077

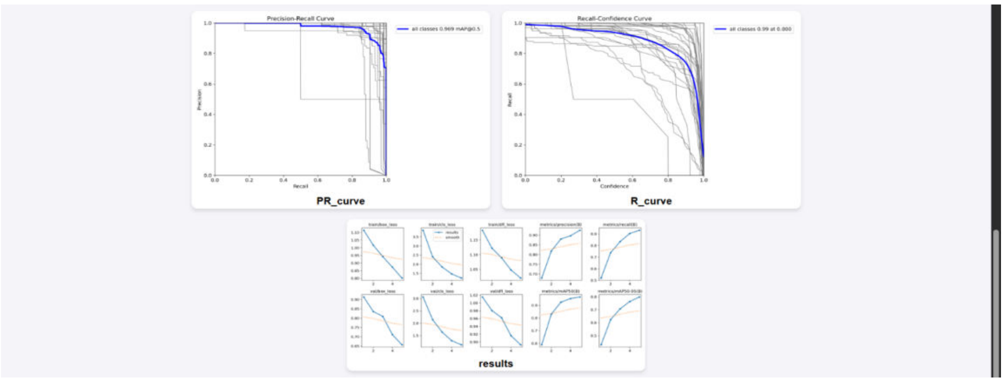

Fig 8: Recall Curve, Precision-Recall (PR) Curve, Model Results Summary Charts

IX. CONCLUSION

In conclusion, this study proposes a novel FOD detection algorithm utilizing the ST-Enhanced YOLOv5 model, combined with advanced feature extraction techniques and a geolocation prediction model based on machine learning regression algorithms. The system demonstrated notable improvements in detection accuracy, as evidenced by the ablation tests and comparative analysis with existing models like YOLOv5, YOLOX, and YOLOv7. The proposed model achieved significant enhancements in the Mean Average Precision (mAP) metrics, especially in small object detection, and showed robustness across various input data resolutions. Furthermore, the FNN regression model proved to be highly effective in predicting the geolocation of detected FOD with impressive accuracy, highlighting the potential of machine learning-based regression techniques for real-time applications. While the model's performance is promising, future work should focus on expanding its capability to handle extreme weather conditions and integrating the detection and geolocation prediction components into specialized software to meet the practical needs of airport authorities. Overall, the study presents a promising approach to improving FOD detection and removal, contributing to enhanced safety and efficiency on airport runways.

X. FUTURE ENHANCEMENTS

Although the proposed model demonstrates significant improvements in FOD detection and geo location prediction, there are still areas for future enhancement. One limitation of the current study is that it does not fully address the impact of extreme weather conditions such as rain, snow, and fog, which can severely affect the accuracy of object detection on airport runways. Future research should focus on enhancing the model's robustness under these challenging weather scenarios to ensure reliable FOD detection in all environmental conditions. Additionally, integrating the current FOD detection and geo location prediction techniques into specialized software for airport authorities could further improve operational efficiency. This software would be designed to promptly identify and eliminate FOD, minimizing safety hazards and reducing flight delays. Future work should also aim to optimize the real-time performance of the system, enabling faster processing and more accurate detection to meet the needs of dynamic airport environments.

REFERENCES

[1] M. Noroozi and A. Shah, ''Towards optimal foreign object debris detection in an airport environment,'' Expert Syst. Appl., vol. 213, Mar. 2023, Art. no. 118829.
[2] S. Song, X. Qin, J. Brengman, C. Bartone, and J. Liu, ''Holistic FOD detection via surface map and YOLO networks,'' in Proc. IEEE 33rd Int. Workshop Mach. Learn. Signal Process. (MLSP), vol. 10, Sep. 2023, pp. 1–6.
[3] S. M. Zainab, K. Khan, A. Fazil, and M. Zakwan, ''Foreign object debris (FOD) classification through material recognition using deep convolutional neural network with focus on metal,'' IEEE Access, vol. 11, pp. 10925–10934, 2023.
[4] Y. Wang, Q. Song, J. Wang, B. Du, and P. Wang, ''A correction method to systematic phase drift of a high resolution radar for foreign object debris detection,'' Remote Sens., vol. 14, no. 8, p. 1787, Apr. 2022.
[5] Y. Wang, Q. Song, J. Wang, and H. Yu, ''Airport runway foreign object debris detection system based on arc-scanning SAR technology,'' IEEE Trans. Geosci. Remote Sens., vol. 60, 2022, Art. no. 5221416.
[6] Z. Li, Y. Miao, M. E. Torbaghan, H. Zhang, and J. Zhang, ''Semi-automatic crack width measurement using an OrthoBoundary algorithm,'' Autom. Construct., vol. 158, Feb. 2024, Art. no. 105251.

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |
|| Volume 12, Issue 3, May-June 2025 ||
DOI:10.15680/IJARETY.2025.1203077
[7] Z. Li, M. E. Torbaghan, T. Zhang, X. Qin, W. Li, Y. Li, and J. Zhang, ''An automated 3D crack severity assessment using surface data for improving flexible pavement maintenance strategies,'' IEEE Trans. Intell. Transp. Syst., vol. 25, no. 9, pp. 12490–12503, Sep. 2024.
[8] K. Hu, D. Cui, Y. Zhang, C. Cao, F. Xiao, and G. Huang,''Classification of foreign object debris using integrated visual features and extreme learning machine,'' in Proc. 2nd CCF Chin. Conf. Comput. Vis. (CCCV), Tianjin, China, 2017, pp. 3–13
[9] Y. Jing, H. Zheng, C. Lin, W. Zheng, K. Dong, and X. Li, ''Foreign object debris detection for optical imaging sensors based on random forest,''Sensors, vol. 22, no. 7, p. 2463, Mar. 2022.
[10] X. Cao, G. Gong, M. Liu, and J. Qi, ''Foreign object debris detection on airfield pavement using region based convolution neural network,'' in Proc.Int. Conf. Digit. Image Comput., Techn. Appl. (DICTA), Gold Coast, QLD,Australia, Nov. 2016, pp. 1–6.
[11] A. Alshammari and R. C. Chabaan, ''SPPN-RN101: Spatial pyramid pooling network with ResNet101-based foreign object debris detection in airports,'' Mathematics, vol. 11, no. 4, p. 841, Feb. 2023.
[12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ''ImageNet classification with deep convolutional neural networks,'' Commun. ACM, vol. 60, no. 6, pp. 84–90, May 2017.
[13] K. He, X. Zhang, S. Ren, and J. Sun, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR),Seattle, WA, USA, Jun. 2016, pp. 770–778.
[14] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, ''Rethinking the inception architecture for computer vision,'' in Proc. IEEE Conf.Comput. Vis. Pattern Recognit. (CVPR), Seattle, WA, USA, Jun. 2016, pp. 2818–2826.
[15] R. Saleem and H. Mahmood, ''Design and analysis of a 25 GHz frequency modulated continuous wave radar for foreign object debris detection,'' in Proc. IEEE Student Conf. Res. Develop. (SCOReD), Batu Pahat, Malaysia, Sep. 2020, pp. 154–158.
[16] J. Taupik, T. Alamsyah, A. Wulandari, E. U. Armin, and A. Hikmaturokhman, ''Airport runway foreign object debris (FOD) detection based on YOLOX architecture,'' in Proc. Int. Conf. Comput. Sci., Inf. Technol. Eng. (ICCoSITE), Feb. 2023, pp. 40–43.
[17] S. Öztürk and A. E. Kuzucuoğlu, ''A multi-robot coordination approach for autonomous runway foreign object debris (FOD) clearance,'' Robot. Auto. Syst., vol. 75, pp. 244–259, Jan. 2016.
[18] Y. Jing, H. Zheng, W. Zheng, and K. Dong, ''A pixel-wise foreign object debris detection method based on multi-scale feature inpainting,'' Aerospace, vol. 9, no. 9, p. 480, Aug. 2022.
[19] H. Xu, Z. Han, S. Feng, H. Zhou, and Y. Fang, ''Foreign object debris material recognition based on convolutional neural networks,'' EURASIP J. Image Video Process., vol. 2018, no. 1, pp. 1–10, Dec. 2018.
[20] M. Ren, W. Wan, Z. Yu, and Y. Zhao, ''Bidirectional YOLO: Improved YOLO for foreign object debris detection on airport runways,'' J. Electron. Imag., vol. 31, no. 6, Dec. 2022, Art. no. 063047.
[21] T. Munyer, P.-C. Huang, C. Huang, and X. Zhong, ''FOD-A: A dataset for foreign object debris in airports,'' 2021, arXiv:2110.03072.
[22] T. Munyer, D. Brinkman, C. Huang, and X. Zhong, ''Integrative use of computer vision and unmanned aircraft technologies in public inspection:
Foreign object debris image collection,'' in Proc. 22nd Annu. Int. Conf. Digit. Government Res., Jun. 2021, pp. 437–443.
[23] H. Zhang, W. Fu, D. Li, X. Wang, and T. Xu, ''Improved small foreign object debris detection network based on YOLOv5,'' J. Real-Time Image Process., vol. 21, no. 1, p. 21, Feb. 2024.
[24] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, ''Microsoft COCO: Common objects in context,'' in Proc. 13th Eur. Conf. Comput. Vis. (ECCV), Zurich, Switzerland, Sep. 2014, pp. 740–755.
[25] Y.-K. Lai, ''Foreign object debris detection method based on fractional Fourier transform for millimeter-wave radar,'' J. Appl. Remote Sens., vol. 14, no. 1, Feb. 2020, Art. no. 016508.
[26] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, ''You only look once: Unified, real-time object detection,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Seattle, WA, USA, Jun. 2016, pp. 779–788.
[27] Z. He, G. Chen, S. Wang, Y. Zhang, and L. Guo, ''Detection of foreign object debris on night airport runway fusion with self-attentional feature embedding,'' Opt. Precis. Eng., vol. 30, no. 13, pp. 1591–1605, 2022.
[28] C.-Y. Wang, H.-Y. M. Liao, Y.-H. Wu, P.-Y. Chen, J.-W. Hsieh, and I.-H. Yeh, ''CSPNet: A new backbone that can enhance learning capability of CNN,'' in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW), Jun. 2020, pp. 1571–1580.
[29] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, and B. Guo, ''Swin transformer: Hierarchical vision transformer using shifted windows,'' in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), Oct. 2021, pp. 9992–10002.
[30] S. H. Woo, J. Park, J. Y. Lee, and I. S. Kweon, ''CBAM: Convolutional block attention module,'' in Proc. 15th Eur. Conf. Comput. Vis. (ECCV), Munich, Germany, Sep. 2018, pp. 3–19.

IJARETY

International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152

www.ijarety.in editor.ijarety@gmail.com