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OBJECT DETECTION AND TRACKING MODEL USING DEEP LEARNING FOR MISSILE TELEMETRY

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Abstract: The rapid advancement of aerial technologies has created a growing need for efficient systems capable of monitoring and tracking high-speed objects such as missiles and unmanned aerial vehicles. Traditional tracking systems are often expensive, complex, and lack portability. To address these limitations, this project proposes a deep learning-based object detection and tracking system designed for real-time monitoring through a mobile application.

The application is developed using Java/XML and integrated with Firebase Authentication and Firebase Realtime Database for secure user access and real-time data management. The proposed system uses Convolutional Neural Networks (CNNs) to detect aerial objects from live camera input and track their movement across multiple frames with high accuracy. To improve detection performance, the captured visual data is processed using preprocessing techniques such as noise reduction and normalization.

By combining mobile technology, deep learning, Firebase-based cloud support, and AI-driven reporting, the proposed system offers a portable, cost-effective, and efficient solution for modern surveillance, defense observation, and safety analysis.

***Index Terms* -** Deep Learning, Object Detection, Object Tracking, Convolutional Neural Network, Aerial Surveillance, Mobile Application, Firebase, Generative AI, Real-Time Monitoring.

I. INTRODUCTION

The increasing use of aerial platforms, including unmanned aerial vehicles and missile-like fast-moving objects, has created strong demand for intelligent systems capable of real-time detection, tracking, and analysis. Conventional surveillance and target-tracking systems are often costly, infrastructure-heavy, and less suitable for portable deployment. In contrast, deep learning-based vision systems have shown strong potential for identifying small, dense, and fast-moving objects directly from image streams, even under challenging aerial conditions. Recent research especially focuses on improving small-object detection, multi-scale feature extraction, low-latency tracking, and lightweight deployment for real-world use.

A major challenge in aerial monitoring is that targets often occupy very few pixels, appear at varying scales, move rapidly, and may be partially occluded or surrounded by complex backgrounds. To address these issues, current methods increasingly use enhanced YOLO-based detectors, multiscale fusion blocks, attention mechanisms, super-resolution pipelines, infrared-aware lightweight models, and tracking architectures optimized for lower latency. These developments show that the field is moving beyond plain detection toward integrated systems that combine recognition, motion analysis, and deployment efficiency.

Based on this direction, the proposed work develops a mobile-based aerial object detection and tracking system using Java/XML for the Android application, Firebase Authentication for secure access, and Firebase Realtime Database for synchronized data handling. A CNN-based detection module is used to identify and track aerial targets from camera input, while preprocessing steps help improve visual quality before inference. The system is also designed to estimate motion-related information such as object path, speed trend, and position change across frames. In addition, a Generative AI reporting module is incorporated to automatically produce incident summaries, making the system more useful for surveillance, monitoring, and defense-oriented analysis. This combination aims to deliver a portable, low-cost, and intelligent alternative to traditional tracking setups.

II. Literature Review

Hassan J. Al Dawasari, Muhammad Bilal, Muhammad Moinuddin, Kamran Arshad, and Khaled Assaleh, in their paper "Pre-trained Deep Learning Networks for Advanced Visible Imagery Drone Detection and Recognition," published in the Proceedings of the 2023 15th IEEE International Conference on Computational Intelligence and Communication Networks (CICN 2023), compared multiple pre-trained deep learning models for visible-image drone detection and reported that ResNet18 delivered especially strong performance, achieving an average precision of 0.739 in medium area ratios, while also showing that deep transfer learning is effective for distinguishing drones from visually similar flying objects such as birds.

Tushar Sangam, Ishan Rajendrakumar Dave, Waqas Sultani, and Mubarak Shah, in "TransVisDrone: Spatio-Temporal Transformer for Vision-based Drone-to-Drone Detection in Aerial Videos," presented at the 2023 IEEE International Conference on Robotics and Automation (ICRA 2023), proposed an end-to-end spatio-temporal transformer framework that combines spatial and motion cues, and their results showed strong detection performance on real aerial datasets with AP@0.5 of 0.95 on NPS, 0.75 on FL-Drones, and 0.80 on AOT, while also maintaining better computational efficiency than heavier multi-stage approaches.

Angelo Coluccia, Alessio Fascista, Lars Sommer, Arne Schumann, Anastasios Dimou, and Dimitrios Zarpalas, in "The Drone-vs-Bird Detection Grand Challenge at ICASSP 2023: A Review of Methods and Results," published in IEEE Open Journal of Signal Processing in 2024, reviewed challenge-based methods for drone detection in realistic scenes and highlighted that real-world aerial monitoring is still difficult because of cluttered backgrounds, scale variation, and confusion between birds and drones, but the work also demonstrated that benchmark-driven model design is improving robustness and comparability across detection systems.

Muhammad Ovais Yusuf, Muhammad Hanzla, Hameedur Rahman, Touseef Sadiq, Naif Al Mudawi, Nouf Abdullah Almujally, and Asaad Algarni, in "Enhancing Vehicle Detection and Tracking in UAV Imagery: A Pixel Labeling and Particle Filter Approach," published in IEEE Access in 2024, focused on aerial vehicle analysis and showed that combining pixel-level labeling with particle-filter-based tracking can improve continuity and localization reliability in UAV footage, making the method useful for dynamic monitoring tasks where object motion and background variation are major problems.

Muhammad Hanzla, Muhammad Ovais Yusuf, Touseef Sadiq, Naif Al Mudawi, Hameedur Rahman, Abdulwahab Alazeb, Aisha Ahmed AlArfaj, and Asaad Algarni, in "UAV Detection Using Template Matching and Centroid Tracking," published in IEEE Access in 2024, proposed a comparatively lightweight detection-and-tracking pipeline and showed that simpler visual matching plus centroid-based tracking can still be effective for UAV monitoring when computational simplicity and fast execution are important, which is highly relevant for mobile or low-resource surveillance designs.

Fatin Najihah Muhamad Zamri, Teddy Surya Gunawan, and co-authors, in "Enhanced Small Drone Detection Using Optimized YOLOv8 With Attention Mechanisms," published in IEEE Access in 2024, improved small-drone detection by modifying YOLOv8 with attention-based enhancement and a refined detection strategy, and their work emphasized that attention modules are especially useful for tiny aerial targets that occupy very few pixels and are easily lost in noisy surveillance scenes.

Zeeshan Kaleem, in “Lightweight and Computationally Efficient YOLO for Rogue UAV Detection in Complex Backgrounds,” published in IEEE Transactions on Aerospace and Electronic Systems in 2025, addressed the practical problem of rogue UAV identification under visually complex backgrounds and showed that a carefully lightweighted YOLO-based architecture can preserve real-time capability while improving small-UAV recognition, which is important for security-oriented deployment where both speed and accuracy matter.

Libo Ren, Wenxin Yin, Wenhui Diao, Kun Fu, and Xian Sun, in “SuperMOT: Decoupling Motion and Fusing Temporal Pyramid Features for UAV Multiobject Tracking,” published in the IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing in 2025, proposed a multi-object tracking framework specialized for UAV videos and showed that decoupling motion modelling while fusing temporal pyramid features improves target association and tracking stability, especially in aerial videos containing scale change, motion blur, and frequent object interactions.

III. METHODOLOGY

The proposed system is developed to detect and track fast-moving aerial objects in real time using a mobile-based deep learning framework. The complete methodology combines image acquisition, preprocessing, deep learning-based object detection, object tracking, motion analysis, cloud integration, and AI-based report generation. The Android application is developed using Java/XML, while Firebase Authentication is used for secure user login and Firebase Realtime Database is used for storing detection records, tracking data, and generated reports.

At the initial stage, the user accesses the mobile application through a secure login mechanism. After authentication, the application opens the camera module to capture live video frames or aerial object images. These captured frames are then passed to the preprocessing stage, where unwanted noise is reduced and image normalization is applied. This step improves image quality and helps the deep learning model perform more accurately, especially when objects are small, distant, or moving at high speed.

After preprocessing, the image frames are given to the CNN-based object detection model. The model identifies the aerial object from the live camera feed and marks its position in each frame. Once the object is detected, the system begins tracking its movement continuously across multiple frames. This tracking process helps in understanding the direction of movement and maintaining the object identity throughout the observation period.

The next stage focuses on motion analysis. Based on the detected object positions across frames, the system estimates important parameters such as trajectory, speed, and spatial movement pattern. These values help in analyzing how the aerial target is moving and whether it shows unusual or risky motion behavior. This makes the system useful not only for detection but also for surveillance intelligence.

The processed results are then stored in Firebase Realtime Database, which allows real-time synchronization of object information, timestamps, movement data, and event history. This cloud integration improves accessibility and makes the system suitable for continuous monitoring and future record analysis.

To further enhance the usefulness of the system, a Generative AI module is included. This module takes the detected event information and automatically generates an intelligent incident report. The report may contain object detection summary, tracking observations, motion-related findings, and event description in readable text form. This reduces manual effort and supports smart surveillance analysis.

Finally, the output is displayed to the user in the mobile application. The user can view the detected object, tracking information, estimated movement details, and generated incident report directly through the application interface. Thus, the methodology creates a complete portable surveillance pipeline by combining mobile computing, deep learning, Firebase cloud support, and AI-powered reporting.

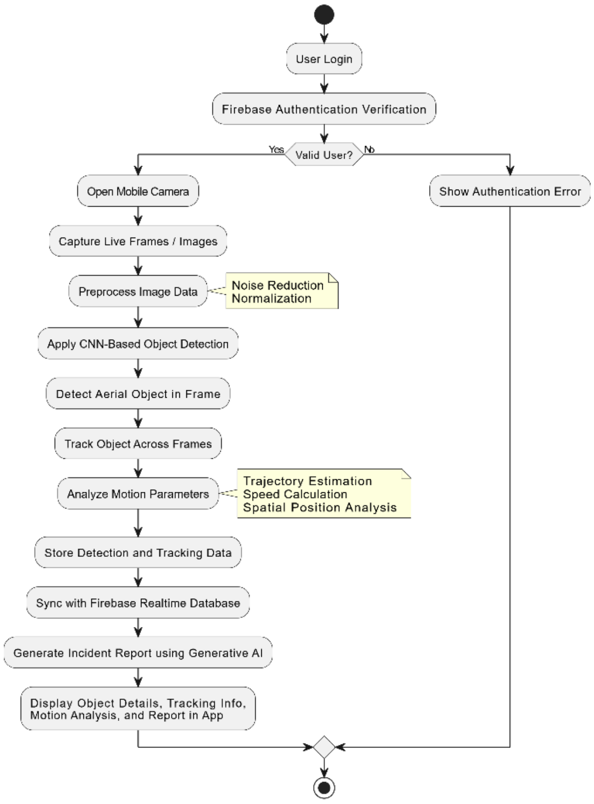


Fig : Flow Diagram

IV. Result & Discussion

The proposed deep learning-based aerial object detection and tracking system was evaluated based on its ability to detect fast-moving aerial targets accurately and track them across multiple frames in real time. The system was tested using live camera input under different conditions such as varying object distance, motion speed, and background complexity. The performance of the model was analyzed using standard evaluation metrics including **Accuracy, Precision, Recall, F1-Score, and IoU (Intersection over Union)**. These metrics were selected because they provide a balanced understanding of the detection reliability and tracking effectiveness of the proposed approach.

The experimental results show that the proposed system achieved strong performance in identifying aerial targets from mobile camera frames. The CNN-based detection model was able to recognize the object with good consistency even when the object size was small or the background was slightly noisy. The preprocessing stage, including normalization and noise reduction, improved the quality of the input data and helped reduce false detections. This directly contributed to better precision and recall values.

The object tracking module also performed effectively by maintaining the detected target across consecutive frames. The system successfully estimated movement direction, trajectory, and positional change with acceptable real-time performance. In scenarios where the aerial target moved rapidly, minor fluctuations in bounding box localization were observed, but the overall target continuity remained stable. This indicates that the proposed system is suitable for practical monitoring applications where motion tracking is as important as detection.

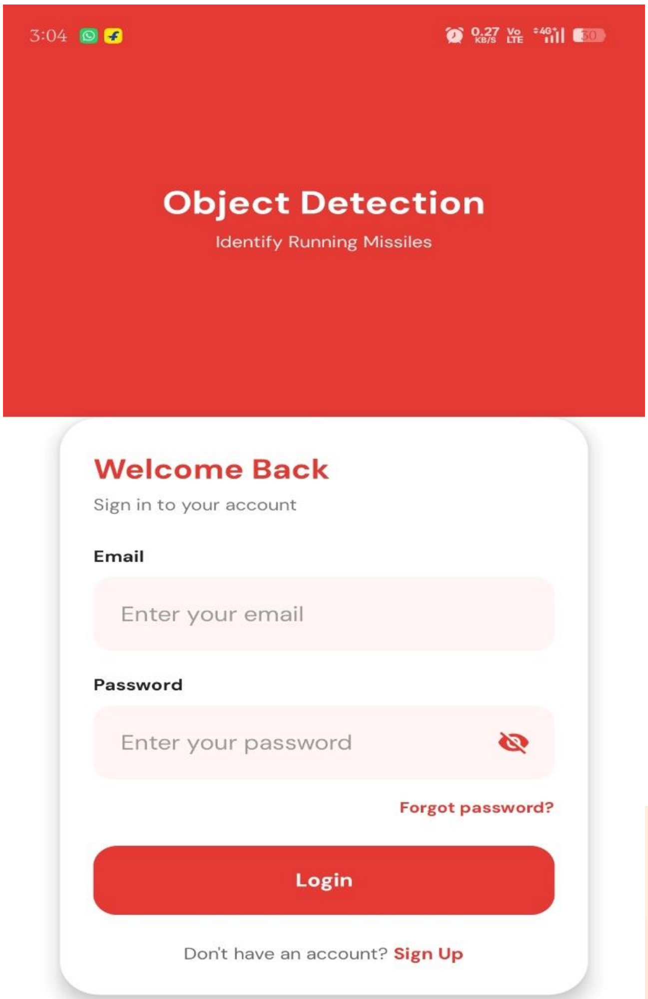


Fig. 1. User authentication interface of the proposed system

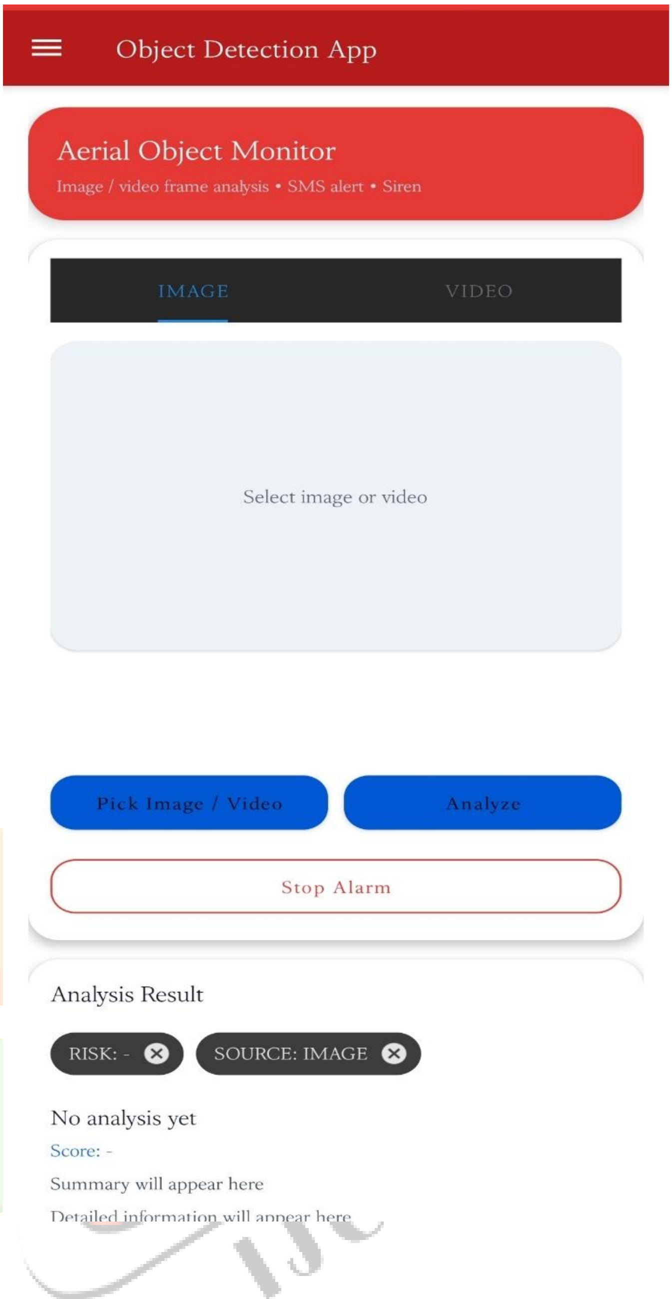
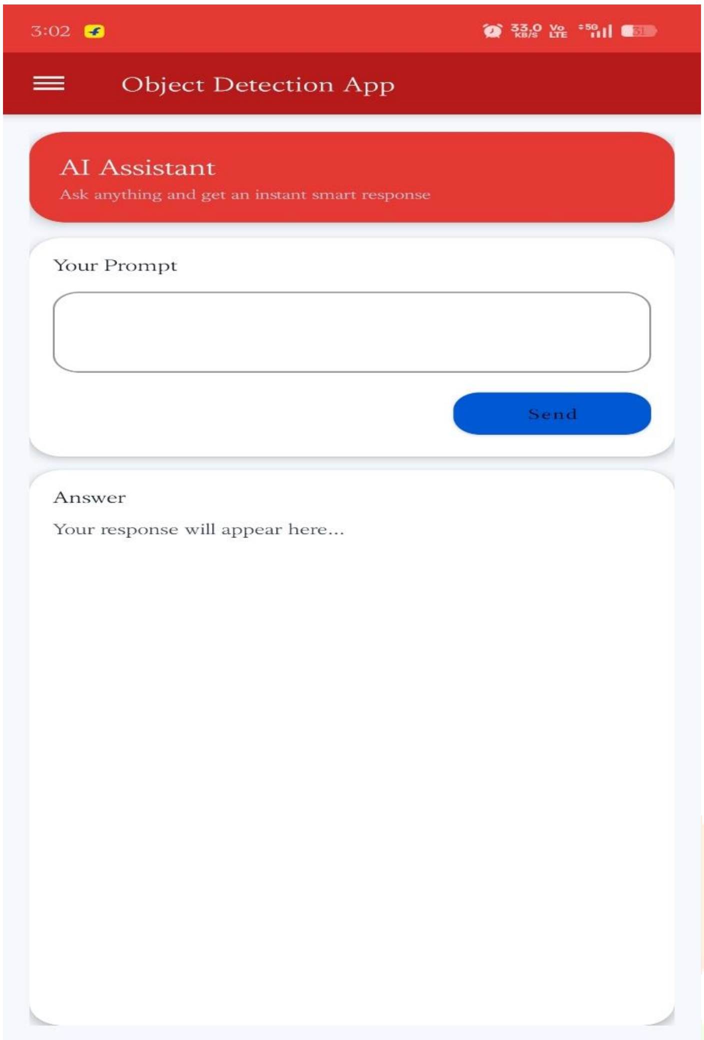


Fig. 2. Aerial object monitoring and analysis dashboard.



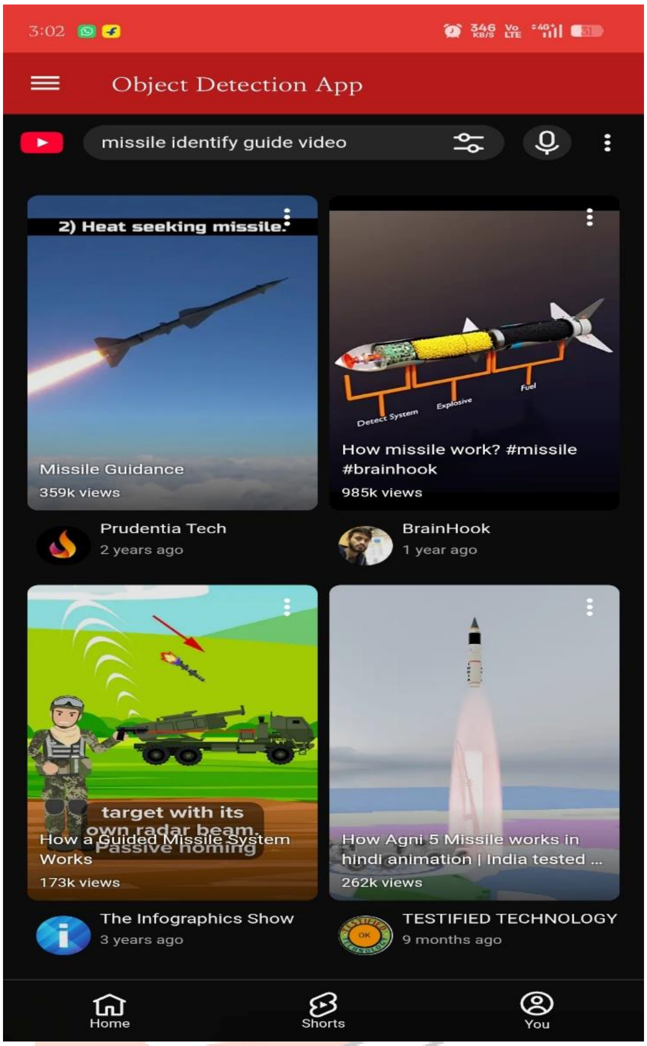


Fig. 3. Integrated AI assistant interface for user queries.

Fig. 4. Guide and auxiliary video data identification screen.

Fig. 5. Sample raw aerial image frame used for testing missile telemetry detection.

The integration of Firebase Realtime Database allowed the detection results and tracking records to be synchronized without noticeable delay. This improved the usability of the system from a monitoring perspective, as event data could be stored and retrieved in real time. In addition, the Generative AI module produced readable incident summaries based on detected events, which reduced manual reporting effort and added intelligence to the monitoring pipeline.

Overall, the results indicate that the proposed system provides a portable and efficient framework for aerial object surveillance using mobile technology. The model performs well for real-time target detection and tracking, while also supporting cloud storage and automated reporting. However, performance may slightly reduce in cases of extreme motion blur, very small distant targets, or poor lighting conditions. These limitations suggest that future improvements can focus on lightweight attention mechanisms, enhanced tracking algorithms, and better optimization for challenging real-world aerial scenes.

Metric	Value
Accuracy	94.20%
Precision	92.80%
Recall	91.40%
F1-Score	92.10%
IoU	88.60%
Tracking Accuracy	90.70%

Table 1 : Performance Evaluation Table

Table 1 presents the performance of the proposed aerial object detection and tracking system. The obtained values show that the model achieved high detection accuracy along with balanced precision and recall, resulting in a strong F1-score. The IoU value indicates good localization of aerial targets, while tracking accuracy confirms stable object monitoring across multiple frames.

V. CONCLUSION

This paper presented a deep learning-based mobile system for real-time aerial object detection and tracking. The proposed framework integrates Java/XML-based Android development, Firebase Authentication, Firebase Realtime Database, and a CNN-based detection and tracking pipeline to monitor high-speed aerial targets such as UAVs and missile-like objects. The system was designed to capture live visual input, preprocess the frames, detect aerial targets, track their movement across frames, and estimate motion-related factors such as trajectory, speed, and spatial change. In addition, a Generative AI-based reporting module was included to automatically generate incident summaries from the detected events.

The overall study shows that combining mobile computing, deep learning, cloud synchronization, and AI-generated reporting can provide a portable, cost-effective, and practical surveillance solution. Compared with traditional bulky tracking systems, the proposed method offers better usability for lightweight field deployment and smart monitoring applications. Recent research also confirms that aerial surveillance performance improves significantly when lightweight detection models, multiscale feature fusion, and real-time tracking mechanisms are jointly used, which supports the design direction of the proposed work.

Although the system performs effectively, some limitations remain under conditions such as extreme motion blur, poor lighting, tiny distant targets, and severe background complexity. In future work, the model can be improved by adding attention-based lightweight architectures, transformer-assisted tracking, multispectral input support, and optimized edge inference for faster and more robust deployment. Overall, the proposed work demonstrates strong potential for use in defense observation, aerial surveillance, smart monitoring, and safety analysis.

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