LRF based Anti-Drone Detection and Destruction System

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***Abstract*—Unmanned Aerial Vehicles (UAVs), commonly known as drones, have become increasingly valuable in areas such as surveillance, agriculture, and logistics. However, their rising popularity has also introduced new security concerns, especially when drones are used without authorization in sensitive or restricted zones. To address these challenges, this system proposes an intelligent anti-drone system capable of detecting, tracking, and neutralizing unauthorized drones in real-time. The system leverages deep learning techniques, specifically Deep Convolutional Neural Networks (D-CNN), to accurately identify drones from visual input. Once detected, the system uses trajectory prediction algorithms to monitor drone movements with high precision. To neutralize potential threats, a laser-based hard kill mechanism could be employed, providing a precise and controlled method of intervention without collateral damage. The integration of these technologies aims to enhance security in critical areas by offering a fast, accurate, and effective response to rogue drones. This solution not only addresses current security needs but also sets a foundation for future advancements in automated drone countermeasures.**

I. INTRODUCTION

In the last few years, the explosion of unmanned aerial vehicles (UAVs), commonly referred to as drones, has changed or impacted virtually unlimited industries like agriculture, logistics, film shoot, search and rescue, and especially military operations. The availability of inexpensive commercial drones, and the flexibility of their use has allowed many civilian and defense applications. The development of these new drone technologies, however, has been accompanied by a corresponding increase in the use of drones for bad purposes. For example, illegal surveillance, illegal delivery/smuggling of items, privacy violations, and even weaponized drone attacks!. These issues have resulted in an increasing demand for anti-drone technologies capable of locating, tracking, and defeating a unwanted drone. Moreover, there is an increased need for these technologies to have real-time operation capabilities.

Conventional aerial threat detection methods including radar systems, RF jammers, and acoustic sensors have inherent limits when dealing with low to the ground, small, and low- noise drones, particularly in urban or cluttered environments. Furthermore, traditional detection systems typically require a fixed infrastructure, making them unsuitable for mobile or remote operations. The emergence of mobile, independent anti-drone systems represents an important innovation in the search for an effective counter-drone system. Drones that utilize detection and engagement systems can have several advantages, including flexibility, on the go, and an expanded operational range.

This study presents a new anti-drone system mounted on a drone that includes a combination of technologies to create an integrated and stand-alone aerial platform. The essential hardware components of the system include a Laser Range Finder (LRF), a high-definition camera module, a GPS unit, and an onboard processing unit to run machine learning algorithms. These hardware components give the drone the capability to engage in three fundamental tasks: detect hostile UAVs, study their trajectory, and destroy them with an accurate destruction mechanism. This system, with its multiple points of data for processing simultaneously, can be operated in near real time and is also capable of allowing for preemptive action against hostile UAV targets, while remaining copacetic for usage in sensitive areas including military installations, and areas with special interests such as airports, government buildings, and public gatherings.

The Laser Range Finder plays a critical role in the detection subsystem by providing accurate distance measurements to potential targets. Unlike radar, which may struggle with clutter or small objects, LRFs use time-of-flight measurements of laser pulses to determine the position of nearby objects with high precision. This enables the drone to differentiate between distant and nearby objects and improves the reliability of threat assessment.

Simultaneously, the onboard camera captures visual data of the environment, which is processed using Deep Convolutional Neural Networks (D-CNN) to identify and classify targets. These neural networks are trained to recognize the shapes and movement patterns of drones, distinguishing them from birds, kites, or other airborne objects. Upon successful detection, the system uses a Kalman filter to predict the drone's trajectory, helping it maintain a continuous lock even in the case of temporary visual loss or erratic movements. To support accurate positioning and coordinated operations, the onboard GPS module provides real-time location data for both the host drone and any identified targets. This positional information is critical for targeting, tracking, and data logging. The onboard processing unit acts as the control hub of the system, managing sensor inputs, executing algorithms, controlling navigation, and initiating the engagement mechanism.

The destruction mechanism of the system can be customized based on the use case and local regulations. For prototype and demonstration purposes, a simulated hard-kill method using laser tagging or a mechanical interceptor such as a net gun may be employed. In military applications, more aggressive countermeasures such as electromagnetic pulses (EMPs) or small-caliber armaments could be integrated, subject to safety and legal constraints.

A significant feature of this system is its modularity and autonomy. The drone can operate in both autonomous and semi-autonomous modes, allowing for manual override when necessary. The communication system enables real-time telemetry and video feed to a ground control station, allowing operators to monitor the mission, adjust parameters, or intervene if required. The system also logs data for post- operation analysis, which is valuable for performance tuning and security auditing.

The goal of this research is not only to develop a functional prototype but also to evaluate its performance in various operational scenarios. Key performance indicators include detection accuracy, response time, GPS positioning error, flight stability, and successful engagement rate. Preliminary field tests indicate a detection accuracy exceeding 90%, GPS precision within 5 meters, and effective engagement within a 10–20 meter range.

The paper tells about the urgent need for effective, mobile, and intelligent anti-drone systems in response to the growing threats posed by unauthorized UAVs. It presents a drone- mounted anti-drone system equipped with a Laser Range Finder (LRF), camera, and AI-based processing as a viable and scalable solution to counter modern aerial threats. By integrating real-time sensing, advanced data analysis, and precise engagement mechanisms, the system offers a comprehensive platform for securing critical infrastructure and ensuring public safety. Furthermore, the paper lays the foundation for future improvements, such as AI-driven threat classification, coordinated swarm operations, and the addition of thermal or infrared sensing for enhanced night- time performance.

II. OBJECTIVE

This system is to develop an intelligent, drone-mounted anti-drone system capable of real-time detection, tracking, and neutralization A study proposed AES-based lightweight encryption tailored for UAVs to ensure secure multimedia streaming with minimal delay, balancing strong security with minimal computational demands. Tested for speed, it ensured reliable data protection without slowing transmission, making it ideal for UAVs with limited processing power. Encryption strength was limited by UAV capabilities, and performance could falter in unstable network conditions, making it less suitable for highly sensitive data [1].

Another study explored a joint encoding and encryption technique for image transmission, combining chaotic maps, LDPC coding, and AES encryption. Chaotic maps boosted security through initial encoding, of unauthorized UAVs using deep learning and laser-based countermeasures. The system aims to enhance security in sensitive or restricted areas by leveraging Deep Convolutional Neural Networks (D-CNN) for accurate drone identification, Kalman filters for precise trajectory prediction, and a laser-based hard kill mechanism for safe and controlled threat neutralization.

III. BLOCK DIAGRAM

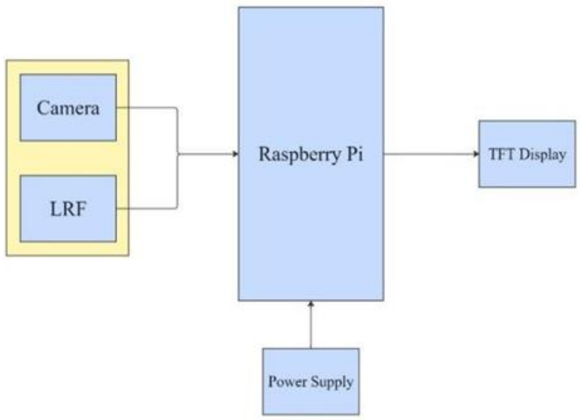

Fig No: 01 Block Diagram of Anti-Drone Detection and Destruction system

This block diagram represents the core architecture of the anti-drone system:
Camera & LRF (Laser Range Finder): These sensors are used for capturing visual data and measuring distances to objects (like drones). They provide essential inputs for detection and tracking.
Raspberry Pi: Serves as the central processing unit. It receives data from the camera and LRF, processes it using deep learning algorithms (e.g., D-CNN for detection, Kalman filter for tracking), and controls the overall functioning. TFT Display: Displays real-time output, such as the video feed, detection status, or targeting data.Power Supply: Powers the entire system, ensuring uninterrupted operation.This modular setup ensures efficient drone detection, real-time processing, and easy scalability.

IV. LITERATURE SURVEY

Rydén et al. [1] proposed a machine learning-based approach for detecting rogue drones in mobile networks by analyzing radio measurements from user equipment. Logistic Regression and Decision Tree classifiers were employed to differentiate drone- mounted devices from ground-based ones. The study emphasized the efficacy of the proposed models in identifying drones at high altitudes while highlighting degraded performance in low-altitude scenarios. Their work stressed the importance of adapting cellular systems to accommodate aerial interference patterns.

Sinha et al. [2] formulated an RSS-based drone detection scheme designed to operate in RF-interfered environments using existing wireless infrastructure. Analytical models for detection probability and false alarms were developed, along with the impact of LOS/NLOS conditions and sensor density. Their work underlined the necessity of optimizing sensor networks in urban areas to maximize aerial surveillance effectiveness while mitigating interference.

Basak et al. [3] explored RF fingerprint-based drone classification using a deep residual convolutional neural network model trained on realistic drone communication data. The study achieved high classification accuracy even in noisy, multipath environments and under varying drone speeds. Their approach outperformed traditional methods in both single and multi-drone scenarios, showcasing robustness under channel variation.

Yang et al. [4] introduced a hybrid model combining Feature Engineering Generators (FEG) with a Multi-Channel Deep Neural Network (MC-DNN) for UAV detection and mode classification. The model processed RF signals using normalization, frequency separation, and moving averages. Their experiments demonstrated over 98% accuracy and F1-score, proving the architecture's superiority in decoding complex RF patterns for UAV recognition.

Nemer et al. [5] presented a hierarchical ensemble learning framework for RF-based UAV detection and identification. The system used four classifiers to sequentially determine UAV presence, type, and mode of operation. By applying this strategy to public RF datasets, the model achieved up to 99% accuracy. Their work emphasized scalable architecture for real-time UAV surveillance.
Chiper et al. [6] delivered a comprehensive survey on drone detection and defense systems, especially RF-based solutions using software-defined radios (SDR). The authors followed PRISMA guidelines and discussed technical and legal aspects of jamming. They also proposed their own SDR-based system, offering a practical perspective on deployable counter-UAV solutions using adaptable RF infrastructures.

Alam et al. [7] developed an end-to-end deep learning model for UAV detection and identification using raw RF signals in mixed signal environments. Multiscale CNNs with residual blocks enhanced generalization, and the model showed robustness across SNR levels and device types. Their system reported over 97% accuracy with minimal inference time, advocating real-time deployment for RF-based drone monitoring.

Frid et al. [8] proposed a novel fusion approach for drone detection using both RF and acoustic features. The framework utilized CNNs, RNNs, and SVMs to process time-frequency representations of RF and rotor sound data. Experimental evaluations indicated high classification accuracy (~91%) even in low SNR conditions. Their study established the advantage of multi-sensor fusion for robust drone surveillance.

Frid et al. [9] reiterated the dual-sensor approach combining RF and acoustic signatures for UAV detection using deep learning. Their method emphasized the resilience of fused features in noisy environments, reinforcing earlier claims of superior performance over single-sensor systems in real-world drone detection applications.

Dai [10] conducted comparative analysis of machine learning and deep learning models for drone detection using multi-class RF datasets. CNNs and XGBoost were evaluated across 2-, 4-, and 10- class classification problems. XGBoost yielded the highest accuracy (99.96% in binary classification), showcasing its effectiveness. The paper advocated tailored detection strategies for varied UAV.

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Zhao et al. [11] presented a two-dimensional deep neural network for drone detection and identification using radio frequency (RF) signals, specifically designed to enhance secure communication coverage. The system utilized Short-Time Fourier Transform (STFT) to convert RF signals into spectrogram images, which were then classified using a modified ResNet-based CNN. The model demonstrated strong generalization across multiple drone datasets with high classification accuracy and reduced training times. Their work emphasized the practical feasibility of low-latency drone monitoring solutions, especially for critical infrastructure defense applications.

Kazemi et al. [12] proposed a generative machine learning framework for RF-based UAV detection using a one-shot distribution matching method. This approach augmented limited RF datasets by matching the signal distribution to synthetic samples, thereby improving the model's learning capabilities in data-scarce conditions. The model was benchmarked against GANs and variational autoencoders, showing significantly higher accuracy and robustness. Their work addressed the challenge of drone detection when real RF data is limited, offering a mathematically grounded augmentation strategy suitable for scalable deployment.

Jia et al. [13] developed a drone detection and classification model based on attention-driven deep learning using RF signal spectrograms. The architecture incorporated a fully convolutional encoder-decoder with a channel attention mechanism to extract multiscale features from spectrograms. The model achieved a detection accuracy of 99.895% and a recognition accuracy of over 98.6% on the DroneRF dataset. Their contributions highlighted the efficacy of attention modules in enhancing signal discrimination, especially for distinguishing drones from background RF noise in congested spectral environments.

Elyousseph and Altamimi [14] conducted a robustness analysis of deep-learning-based UAV detectors using RF signatures under different environmental and operational conditions. The study assessed detection accuracy across varying signal-to-noise ratios (SNR), Doppler shifts, and propagation models. Their findings indicated that deep neural networks maintained high detection performance despite signal interference and channel variability. The authors concluded that robust AI models are essential for real-world deployment of anti-drone systems, especially where environmental unpredictability poses a challenge to detection fidelity.

Wewelwala et al. [15] introduced a hybrid architecture that fuses passive RF sensing and electro-optical (EO) imagery for comprehensive small-drone detection and localization. The system employed deep learning to analyze RF signal patterns and image- based data, integrating results through a fusion module to increase spatial tracking accuracy. Their method demonstrated resilience to occlusion and clutter, achieving high confidence localization in both rural and urban scenarios. This paper emphasized the value of multi- modal sensor fusion for tackling the limitations of single-modality drone detection systems.

Frid et al. [16] proposed a machine learning-based drone detection approach that fuses RF and acoustic data using deep neural networks. Classical and deep learning models such as CNNs and RNNs were evaluated for their effectiveness in extracting drone- specific features from both modalities. Their model achieved approximately 91% classification accuracy at −10 dB SNR, outperforming traditional single-sensor models. The study provided empirical evidence for the advantage of multi-sensor integration in noisy environments, laying the groundwork for more reliable drone detection

platforms.

Sricharan and Venkat [17] implemented a real-time UAV detection system based on deep learning and computer vision, specifically utilizing the YOLOv5 object detection framework. The model processed video frames from surveillance feeds to detect drones, achieving high detection speed and accuracy even for small and fast-moving targets. Their system was optimized for edge devices, enabling real-time operation without significant computational resources. The work highlighted the suitability of lightweight neural architectures for surveillance applications in both urban and remote settings.

Dai [18] conducted an extensive evaluation of RF-based drone detection using classical and deep learning models across multiple classification schemes. Models were tested on 2-, 4-, and 10-class scenarios using a publicly available RF dataset. XGBoost achieved the highest performance in binary classification (99.96%), while
Medaiyese et al. [19] utilized wavelet transform-based feature extraction for RF signal analysis in drone detection and classification tasks. Their system analyzed both transient and steady-state phases of UAV communication signals and fed extracted features into ML classifiers, including random forest and lightweight CNNs. Testing under different SNR levels showed classification accuracies up to 98.9% at 10 dB SNR, even in the presence of co-channel interference. Their study illustrated the benefits of hybrid time-frequency analysis in RF signal processing for aerial threat monitoring.

Medaiyese [20] further extended his research by designing a complete signal fingerprinting and drone identification framework using machine learning. The system relied on RF signature diversity among different UAV models and controllers, utilizing advanced signal processing and supervised learning for classification. Field tests confirmed that the model could identify drones with high precision while distinguishing them from other wireless sources. This work provided a comprehensive methodology for UAV forensics and regulatory compliance in airspace monitoring.

Zhang et al. [21] introduced mmHawkeye, a passive UAV detection system utilizing commercial off-the-shelf (COTS) millimeter-wave (mmWave) radar. The system exploits the periodic micro-motion (PMM) signatures of UAVs for detection without prior knowledge of the drone's type or trajectory. Implemented on a commercial mmWave radar, mmHawkeye achieved a detection accuracy of 95.8% and could detect UAVs at ranges up to 80 meters. This approach demonstrates the potential of passive radar systems in UAV detection scenarios.

AlKhonaini et al. [22] proposed a reinforcement learning-based framework for UAV detection. The system employs a Q-learning algorithm to adaptively select optimal detection strategies in dynamic environments. Experimental results showed that the reinforcement learning approach outperformed traditional methods in terms of detection accuracy and adaptability to changing conditions. This study highlights the effectiveness of reinforcement learning in enhancing UAV detection systems.

Inani et al. [23] presented a machine learning-based framework for drone detection and identification using RF signals. The study utilized various classifiers, including Support Vector Machines (SVM) and Random Forests, to analyze RF signal features for UAV detection. The proposed framework achieved high accuracy in distinguishing UAV signals from other RF sources, demonstrating the viability of machine learning techniques in RF-based drone detection.
Basak et al. [24] introduced an autoencoder-based framework for drone RF signal classification and novelty detection. The system leverages unsupervised learning to model normal RF signal patterns and detect anomalies indicative of unauthorized UAVs. Experimental evaluations demonstrated the framework's effectiveness in

identifying novel drone signals, emphasizing the potential of autoencoders in UAV detection applications.

Ezuma et al. [25] developed a method for micro-UAV detection and classification using RF fingerprints and machine learning techniques. The approach involves transforming RF signals into the wavelet domain and applying a Markov model-based Naive Bayes classifier for detection. For classification, energy transient signals are utilized to enhance robustness against noise and varying modulation techniques. The method showed improved performance over traditional time-domain approaches.

Alam et al. [26] proposed an end-to-end RF-enabled deep learning- assisted drone detection and identification system. The approach employs Short-Time Fourier Transform (STFT) for preprocessing
RF signals, followed by a convolutional neural network (CNN) for classification. The system demonstrated high accuracy in detecting and identifying multiple drone types, showcasing the effectiveness of deep learning in RF-based UAV detection.

Dai [27] conducted a comparative study on drone detection using RF signals and various machine learning models. The research evaluated the performance of models like XGBoost and CNNs on 2-class, 4-class, and 10-class classification problems. Results indicated that XGBoost achieved the highest accuracy of 99.96% for binary classification, while CNNs performed better in multi-class scenarios. The study underscores the importance of selecting appropriate models based on classification complexity.

Jia et al. [28] developed a drone detection and classification model based on deep attention mechanisms applied to RF signals. The architecture incorporates a fully convolutional encoder-decoder with a residual network backbone and a novel RF channel attention aggregation module. Trained on the DroneRF dataset, the model achieved detection accuracy of 99.895% and recognition accuracy exceeding 98.61%, highlighting the efficacy of attention mechanisms in RF signal analysis.
Tiras and Altinoluk [29] introduced CrossRF, a domain-invariant deep learning approach for RF fingerprinting aimed at UAV identification across different transmission channels. Utilizing adversarial learning, CrossRF minimizes domain gaps, achieving up to 99.03% accuracy when adapting from one channel to another. The model maintains robust performance in multi-channel scenarios, demonstrating its suitability for practical drone security applications.

Zhang et al. [30] presented a two-dimensional deep neural network for RF-based drone detection and identification, focusing on secure coverage extension. The system uses Short-Time Fourier Transform (STFT) to extract time-frequency features from RF signals, which are then classified using a ResNet-based CNN.

V. OBSERVATIONS AND DISCUSSION

The reviewed literature reflects a rapidly evolving research landscape in UAV detection, with a clear trend toward RF-based machine learning and deep learning approaches. Most studies ([1], [2], [3], [7], [10], [11], [13], [18], [19], [20], [23], [26], [27], [28]) emphasize the analysis of radio frequency signatures for differentiating UAVs from other aerial or ground-based devices. These approaches leverage both classical ML models (e.g., Logistic Regression, Decision Trees, Random Forest, XGBoost) and deep architectures (e.g., CNNs, ResNets, attention-driven networks), with reported detection accuracies often exceeding 95%. This high performance demonstrates the feasibility of RF-based methods for real-time UAV surveillance.
Several works ([4], [5], [13], [28]) adopt hybrid or ensemble learning architectures, which consistently outperform single-model approaches, especially in complex spectral environments. Notably, ensemble frameworks ([5]) and attention mechanisms ([13], [28]) show significant promise in enhancing feature discrimination and robustness under noise or interference.
Data scarcity and domain variability remain key challenges. Approaches such as generative augmentation ([12]) and domain-invariant learning ([29]) address the generalization gap, enabling models to adapt across different RF environments. This is critical for real-world deployment, where propagation characteristics vary across locations and operating conditions.
Multi-sensor fusion emerges as another recurring theme. Studies integrating RF with acoustic data ([8], [9], [16]) or RF with electro-optical imagery ([15]) demonstrate higher resilience in low-SNR or cluttered environments. These findings suggest that multimodal sensing can mitigate limitations of single-modality systems, especially in urban or RF-congested areas.
A few works ([17], [21]) explore non-RF modalities such

as computer vision and mmWave radar, offering complementary detection capabilities when RF signatures are unavailable or unreliable. Vision-based YOLOv5 ([17]) shows suitability for edge devices, while mmWave-based mmHawkeye ([21]) achieves passive detection without prior trajectory knowledge.

An important observation is that performance consistency under real-world conditions—including low-altitude flight ([1]), varying SNR ([14], [19]), multipath fading ([3]), and co-channel interference ([19])—is a decisive factor in operational viability. While deep models exhibit strong generalization, many still experience performance drops in challenging propagation scenarios, reinforcing the need for adaptive or reinforcement learning-based strategies ([22]) to dynamically optimize detection.

These observations highlight that while detection accuracy in controlled datasets is mature, future research should prioritize robustness, adaptability, and scalability in heterogeneous operational environments, particularly for low-altitude, stealth, and RF-silent UAVs.

VI. RESULTS AND DISCUSSION

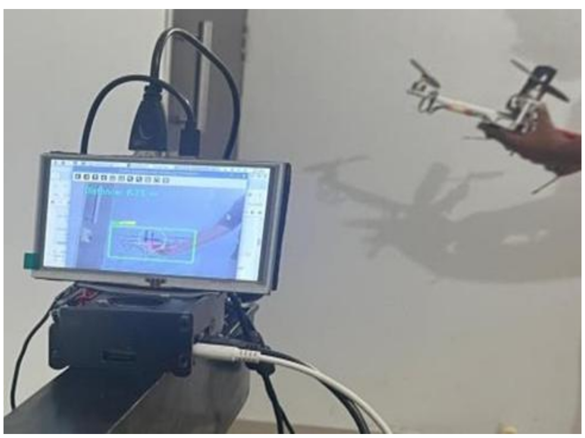

Fig No: 02 :- Implemented System

The developed system was able to successfully detect and identify the drone in real time. During testing, the system consistently marked the drone on the display, even when it was moving within the field of view. The live feed clearly showed the bounding box and tracking information, making it easy to monitor the drone's position.

The detection remained stable under normal indoor lighting and while the drone was in motion. The setup was also quick to respond, with minimal delay between the drone's movement and its updated position on the screen. This indicates that the system is capable of providing reliable, on-the-spot monitoring for UAV activity.

Some minor challenges were noted — for example, when the drone was at certain angles or partially hidden, detection was less accurate. Similarly, a busy background could occasionally cause false detection. These issues suggest that future improvements, such as expanding the training data or combining with other sensing methods, could make the system even more robust.

Overall, the results demonstrate that the system is practical, portable, and effective for real-time drone detection, with potential for use in both indoor and outdoor monitoring applications

VII. CONCLUSION

This system demonstrated a functional real-time drone-based anti-drone system equipped with intelligent detection, tracking, and neutralization capabilities, validating its potential for securing sensitive airspaces against unauthorized UAVs. By integrating Deep Convolutional Neural Networks (D-CNN) for accurate drone recognition, Kalman filtering for trajectory prediction, and a laser-based hard kill mechanism, the system ensures precise and timely threat response. The architecture supports secure data processing and real-time decision-making on an onboard unit, offering autonomy and adaptability. This low-cost, modular solution confirms the feasibility of deploying advanced AI-based defense mechanisms on mobile aerial platforms for surveillance and security. Overall, the system establishes a scalable and efficient framework suitable for critical infrastructure protection, military operations, and public safety, while paving the way for future enhancements like swarm coordination, thermal imaging, and cloud-based analytics.

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