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AEWACS: Airborne Early Warning and Control System Using Pulse-Doppler Radar

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Abstract: This project presents the design and development of a compact Airborne Early Warning and Control System (AEWACS) using Pulse Doppler Radar for real-time drone detection and classification. Conventional AEWACS platforms used in defense systems are large and expensive, making them unsuitable for smaller and mobile applications. To address this limitation, the proposed system uses the Texas Instruments IWR6843 mmWave radar, operating in the 65 GHz frequency band, to transmit and receive electromagnetic signals. The reflected signals are analyzed using Doppler shift principles to estimate target range, velocity, and motion characteristics. Signal processing techniques are used to separate moving targets from background clutter. The processed radar data is then provided to a machine learning model trained to classify drones and birds. The system is designed to be compact, energy-efficient, and modular, allowing future integration with UAV platforms. This approach enables a cost-effective and flexible solution for applications such as border surveillance, infrastructure protection, and public safety monitoring.
Keywords: Pulse Doppler Radar, AEWACS, mmWave Radar, CNN, Range-Doppler Map, CFAR Detection

I. INTRODUCTION

The use of drones and UAVs has increased rapidly in recent years because they are used in many fields such as surveillance, agriculture, delivery services, and disaster management. However, drones can also create security risks if they are used for illegal activities like unauthorized surveillance or entering restricted areas. Because of this, drone detection systems have become very important.Traditional radar systems are designed to detect large aircraft and may not detect small drones effectively due to their small size and low flight altitude. To solve this problem, compact radar systems are being developed to detect smaller aerial targets.

In this project, a compact AEWACS system using Pulse Doppler radar is developed. The system uses the TI IWR6843 mmWave radar sensor, along with signal processing and machine learning techniques, to detect and classify aerial targets such as drones and birds.

II. RELATED WORK

Several research works have explored radar-based techniques for detecting small aerial targets such as drones. Bertocco et al. introduced a method that detects drones by analyzing micro-Doppler signatures generated by rotating propellers. Although effective for identifying known drones, this approach depends on prior knowledge of specific vibration patterns.Gao et al. examined the use of passive radar systems based on broadcast signals like DVB-T for drone detection. Their multistatic architecture allows detection without dedicated transmitters, reducing system cost. However, the performance of passive radar systems is strongly influenced by environmental conditions and synchronization between receivers.Machine learning approaches have also been applied for UAV detection. Taha and Shoufan reviewed various machine learning methods and showed that CNN-based models can effectively classify radar signatures using Range–Doppler maps, enabling differentiation between drones and birds.

III. SYSTEM ARCHITECTURE

The overall architecture of the proposed radar detection system is shown in Fig. 1.

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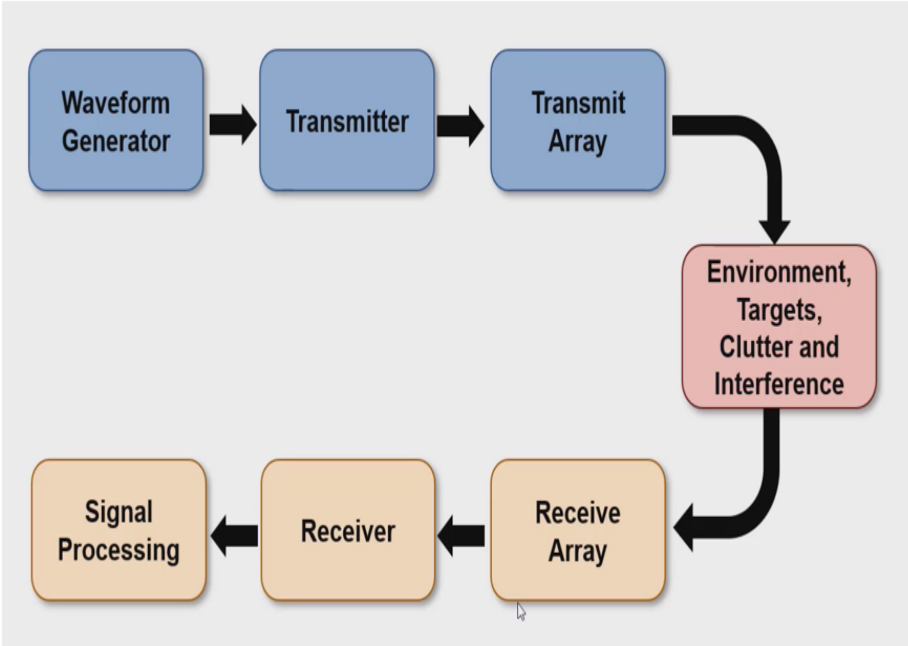

Fig. 1 End-to-End Radar System Architecture

The overall architecture of the proposed AEWACS radar detection system is illustrated in Fig. 1. The system consists of several key components, including a waveform generator, radar transmitter, transmit antenna array, receive antenna array, receiver module, and a signal processing unit. These components operate together to detect and analyze radar signals reflected from aerial targets.The waveform generator produces frequency-modulated chirp signals, which are transmitted through the radar transmitter and the transmit antenna array. These signals propagate through the surrounding environment and interact with objects such as drones, birds, or other aerial obstacles. When the transmitted radar waves encounter a target, part of the signal is reflected back toward the radar system.The receive antenna array captures the reflected signals and sends them to the receiver module. The receiver then processes the signals using digital signal processing techniques to extract important target parameters such as range, velocity, and direction of motion. The processed data is further used to generate Range–Doppler maps, which provide a visual representation of the movement characteristics of detected targets

IV. SIGNAL PROCESSING METHODS

A. FFT Processing

The Fast Fourier Transform (FFT) is used in radar systems to convert received signals from the time domain to the frequency domain. In the proposed system, FFT is applied to radar data to analyze its frequency components and detect Doppler shifts caused by moving targets.When a radar signal reflects from a moving object, its frequency changes due to the Doppler effect. By applying FFT, the system identifies frequency peaks that correspond to moving targets. These peaks provide information about the velocity of the object and help differentiate moving targets from stationary background clutter.

B. CFAR Detection

CFAR (Constant False Alarm Rate) is used to detect targets in radar data while minimizing false detections caused by noise. Instead of using a fixed threshold, CFAR calculates a dynamic threshold based on the average noise level of surrounding radar cells. If the signal strength of a cell exceeds this threshold, it is considered a potential target.In this system, the Cell Averaging CFAR (CA-CFAR) method is used. It estimates the noise power from neighboring cells and multiplies it by a scaling factor to determine the detection threshold. This adaptive approach allows reliable target detection even when noise levels vary.

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V. SYNTHETIC DATA GENERATION

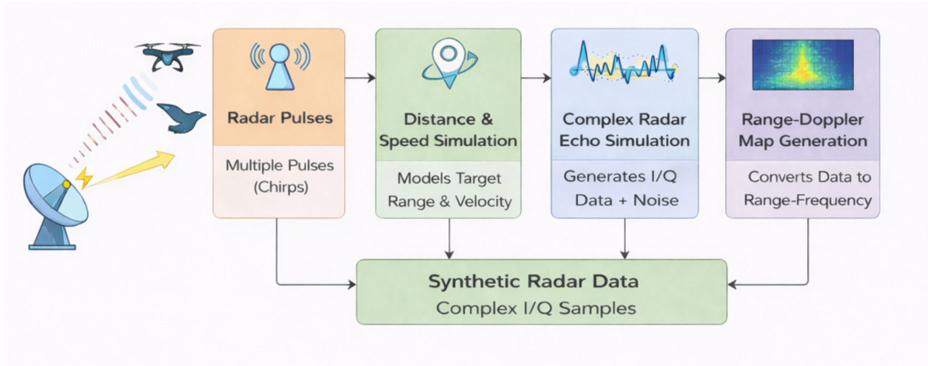

Fig. 2 Synthetic Radar Data Generation

Obtaining real radar datasets for drone detection is often difficult due to equipment limitations and safety concerns. To address this issue, synthetic radar data generation techniques are used in this project. Synthetic radar data allows the simulation of radar signals reflected from aerial targets such as drones and birds under controlled conditions.The synthetic data generation process begins with the simulation of radar chirp signals that represent the transmitted waveform of an FMCW radar system. Target parameters such as distance and velocity are defined to simulate the motion of aerial objects. These parameters are used to generate complex radar echoes that include both signal reflections and environmental noise.The simulated radar echoes are processed to produce complex in-phase and quadrature (I/Q) samples. These samples are then transformed into Range-Doppler maps using FFT processing. The generated Range-Doppler maps serve as input data for training the machine learning model.

VI. DATASET

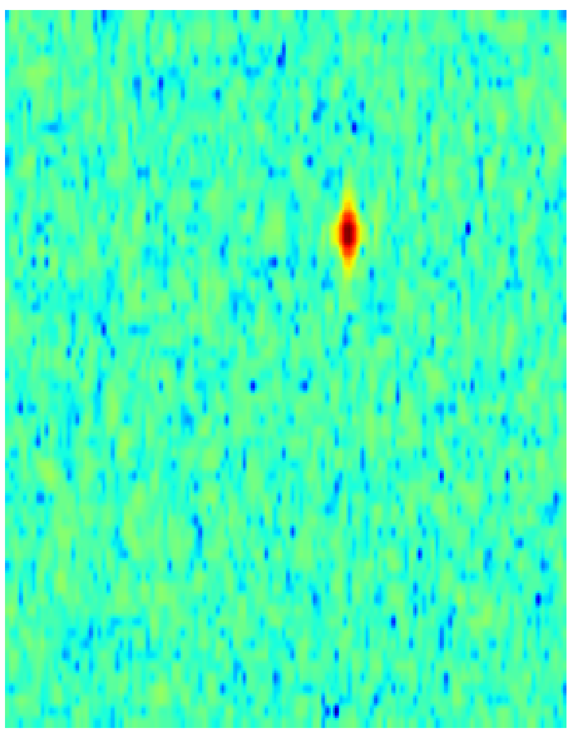

Fig. 3 Range-Doppler Map of Bird

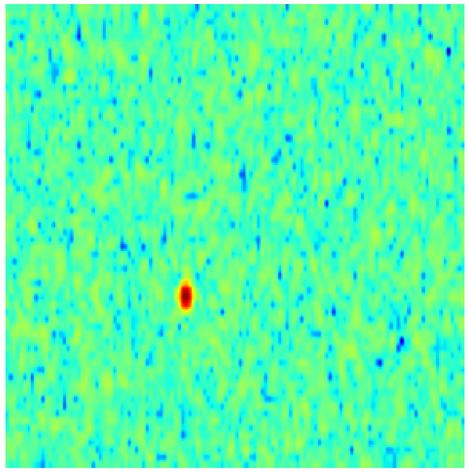

Fig. 4 Range-Doppler Map of Drone

VII. MACHINE LEARNING MODEL

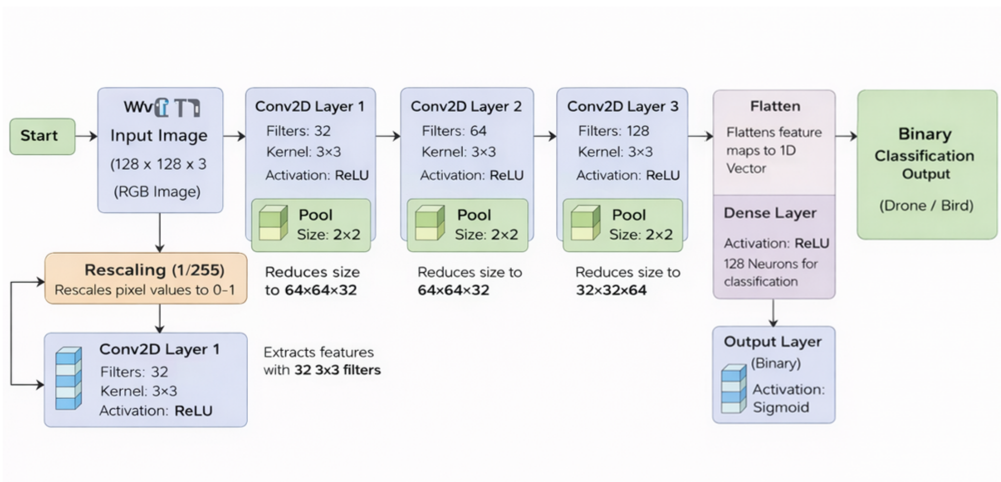

Fig. 5 CNN Architecture

To automatically classify aerial targets detected by the radar system, a Convolutional Neural Network (CNN) model is used. CNNs are widely used in image processing and pattern recognition tasks due to their ability to extract spatial features from input data. In this project, the CNN model analyzes Range-Doppler maps to identify patterns associated with drones and birds.The CNN architecture consists of multiple convolutional layers followed by pooling layers that gradually extract higher-level features from the input images. The convolutional layers apply multiple filters to detect patterns such as edges, shapes, and motion signatures within the radar images. Pooling layers reduce the spatial dimensions of the feature maps while preserving important features.After feature extraction, the flattened feature vector is passed through dense layers for classification. The final output layer uses a sigmoid activation function to perform binary classification between drone and bird targets.

VIII. RESULTS

Dataset statistics:
Total dataset: 2000 images
Training dataset: 1600 images
Testing dataset: 400 images
Classes: Bird, Drone

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Accuracy:
Bird – 86.5%
Drone – 82.5%
Overall – 84.5%

The performance of the proposed radar detection system was evaluated using a dataset consisting of 2000 synthetic Range-Doppler images. The dataset was divided into training and testing subsets to evaluate the performance of the CNN model. A total of 1600 images were used for training, while 400 images were used for testing.The classification results indicate that the CNN model achieved an accuracy of 86.5% for bird detection and 82.5% for drone detection. The overall classification accuracy of the system was 84.5%. These results demonstrate that the proposed system can effectively distinguish drones from birds using radar signatures

IX. OUTPUT INTERFACE

Fig. 6 Radar Detection Interface

The radar detection system includes a graphical user interface that visualizes detected objects on a radar display. The interface displays target positions on a circular radar screen and provides additional information such as range, velocity, and classification results.The interface also includes a detection panel that summarizes the number of detected objects and their classification categories such as drone, bird, or unknown. This visualization helps users quickly interpret radar data and monitor aerial activity in real time.

X. HARDWARE IMPLEMENTATION

Fig. 7 Hardware Prototype using TI IWR6843 Radar Board

The hardware prototype uses the TI IWR6843AOP mmWave radar module operating in the 57–64 GHz frequency band. The radar board integrates transmitter and receiver antennas along with onboard signal processing capability. The module is mounted on a custom stand and connected to a laptop via USB for power and data communication. The radar data is processed using signal processing algorithms to generate Range-Doppler maps and perform object classification.

XI. CONCLUSION

This paper presented the design and implementation of a compact AEWACS system for drone detection using Pulse-Doppler radar and machine learning techniques. Synthetic radar datasets were generated to simulate aerial targets and train a CNN model for object classification. Signal processing techniques such as FFT and CFAR were used to detect moving targets and generate Range-Doppler maps. Experimental results demonstrated that the proposed system achieved an overall classification accuracy of 84.5%. The hardware prototype implemented using the TI IWR6843 radar module successfully validated the radar detection pipeline. The proposed approach demonstrates the potential of integrating radar sensing and machine learning for compact airborne surveillance systems

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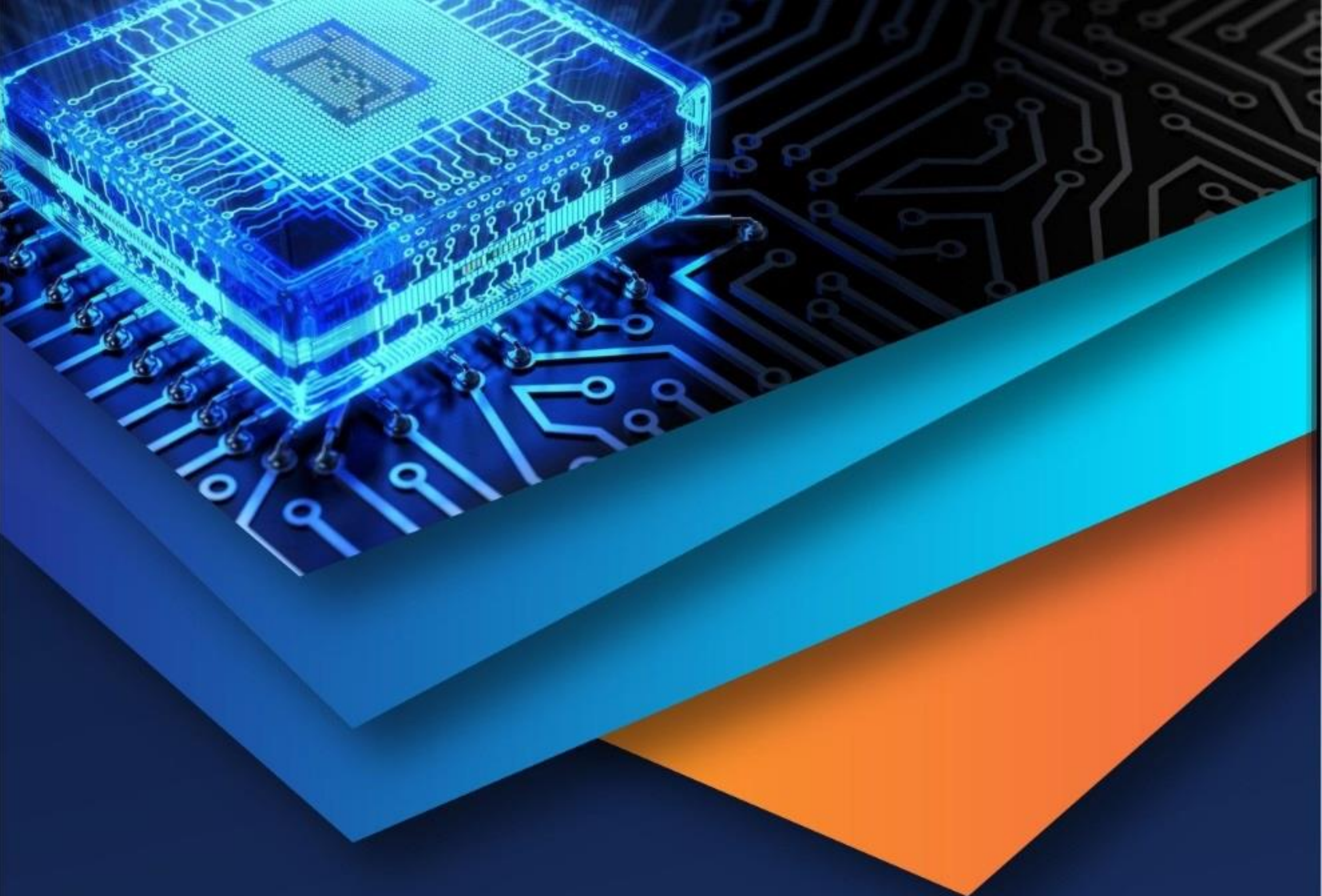

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