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REAL-TIME AIR-BORNE TARGET CLASSIFICATION USING KINEMATICS DATA FOR COASTAL SURVEILLANCE RADAR

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Abstract—
Aircraft target classification is an important component of modern defense and surveillance systems. This paper presents a machine learning-based framework for real-time aircraft classification using kinematic trajectory parameters. The proposed system utilizes statistical and temporal feature extraction methods combined with supervised learning algorithms. Experimental evaluation demonstrates strong classification accuracy and real-time operational capability suitable for coastal surveillance radar systems. The system processes real-time trajectory data containing parameters such as height, resultant velocity, resultant acceleration, and Automatic Gain Control (AGC) values received through UDP-based communication. A sliding window mechanism is employed to extract meaningful statistical and temporal features from continuous time-series data. Multiple machine learning algorithms including Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, Gradient Boosting, and XGBoost were trained and comparatively evaluated. Among all models, the Random Forest classifier achieved the best performance with high classification accuracy and robustness. The proposed framework also integrates an interactive visualization dashboard for real-time monitoring, analytics, and prediction reporting. The developed system demonstrates low-latency prediction capability, making it suitable for operational deployment in defense monitoring and coastal surveillance applications. Furthermore, the proposed methodology provides scalability, reliability, and improved decision-making support for intelligent real-time airborne target recognition systems for coastal region.

***Keywords*—** Aircraft Classification, Machine Learning, Random Forest, Kinematic Data, Radar Systems, UDP Communication, Real-Time Classification, Coastal Surveillance Radar, Target Recognition, Feature Engineering, Time-Series Analysis, Supervised Learning, Airborne Target Detection, Defense Systems, Data Preprocessing, Trajectory Analysis, Streamlit Dashboard, Statistical Feature Extraction, Radar Signal Processing, Artificial Intelligence.

I. INTRODUCTION

Aircraft target classification has become one of the most significant research domains in modern defense systems and surveillance technologies. The rapid increase in airborne activities, UAV deployments, and advanced radar systems has generated a demand for intelligent real-time classification mechanisms capable of identifying multiple aircraft categories accurately and efficiently.

Traditional aircraft recognition systems depended heavily on radar cross-section analysis, Doppler signatures, and manual operator interpretation. However, these methods often fail in noisy environments, stealth conditions, and electronic warfare scenarios. Kinematic trajectory analysis provides a more reliable alternative because aircraft movement patterns are inherently linked to their physical capabilities and mission profiles.
This paper proposes a machine learning-based framework capable of processing real-time kinematic trajectory data and classifying airborne targets into multiple aircraft categories. The system integrates feature engineering, preprocessing, supervised learning algorithms, and real-time UDP communication into a unified operational pipeline.

The proposed framework demonstrates strong classification accuracy, low latency prediction, and operational suitability for defense and coastal surveillance systems.

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II. LITERATURE REVIEW

Researchers across defense and machine learning domains have explored various approaches for airborne target recognition. Traditional methods include radar cross-section analysis, inverse synthetic aperture radar imaging, and Doppler frequency-based classification.
Machine learning approaches have significantly improved classification performance. Support Vector Machines were initially utilized for binary classification problems such as distinguishing birds from aircraft. Neural Networks and Deep Learning techniques later enabled temporal sequence modeling and improved trajectory analysis.
Random Forest algorithms gained popularity due to their robustness, reduced overfitting, and strong performance on multidimensional datasets. Ensemble methods such as Gradient Boosting and XGBoost further enhanced prediction accuracy.
Despite these advancements, many existing systems suffer from high computational complexity, insufficient feature engineering strategies, poor scalability, and lack of real-time deployment capability. This work addresses these limitations through optimized feature extraction and operational deployment mechanisms.

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III. DATASET DESCRIPTION AND FEATURE ENGINEERING

The dataset used in this research consists of real-time aircraft kinematic trajectory data acquired through radar systems and simulated operational environments. The dataset contains trajectory measurements including height, resultant velocity, resultant acceleration, and Automatic Gain Control values.

A sliding window mechanism was implemented to capture temporal dynamics from sequential trajectory data. Each window generates statistical and temporal features including mean, standard deviation, median, minimum, maximum, range, rate mean, and rate standard deviation.

Feature engineering plays a critical role in improving classification performance. Statistical features capture steady-state behavior while derivative-based temporal features capture maneuvering dynamics. Consensus ranking methods including ANOVA F-test, Mutual Information, Random Forest Importance, and XGBoost Importance were used for feature selection.

The final selected feature vector contained the most discriminative features capable of distinguishing among multiple aircraft classes with high accuracy.
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IV. PROPOSED METHODOLOGY

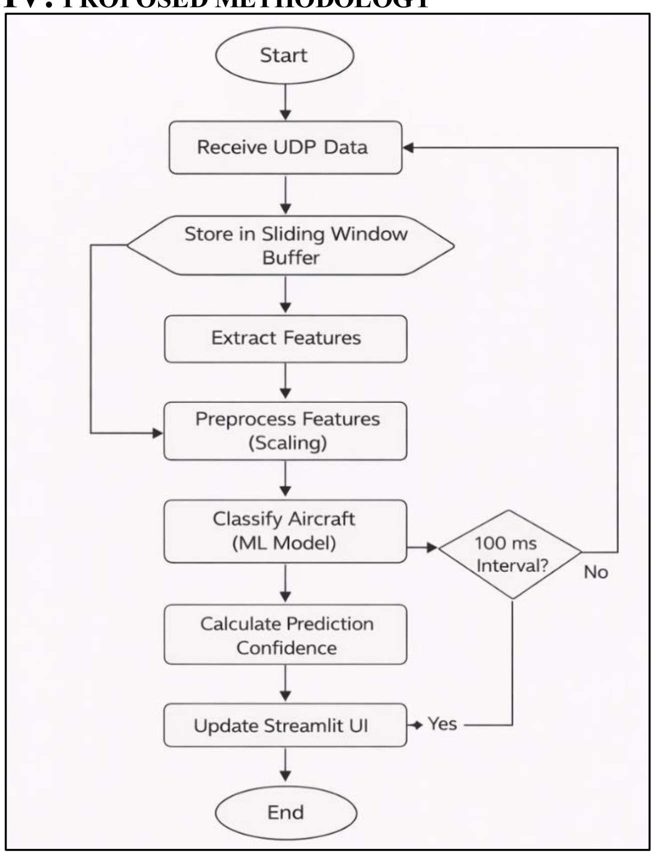

Fig. 1: System Flowchart

The proposed system follows a multi-stage machine learning pipeline consisting of data acquisition, preprocessing, feature extraction, classification, and visualization

Real-time UDP socket communication is used to receive binary trajectory packets from radar systems. Incoming packets are decoded and structured into tabular format using Python-based processing modules. Sliding window segmentation is applied to the time-series trajectory data. Feature extraction algorithms generate statistical and temporal descriptors from each window. Feature normalization is performed using StandardScaler to ensure uniform feature distribution. Multiple supervised learning models were evaluated including Logistic Regression, K-Nearest Neighbors, Support Vector Machines, Decision Trees, Random Forest, Gradient Boosting, and XGBoost. Random Forest demonstrated the best overall performance and was selected for deployment. The methodology also integrates probability estimation, majority voting mechanisms, and confidence score computation for robust operational predictions.

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V. SYSTEM IMPLEMENTATION

The implementation was developed using Python and integrated with multiple libraries including NumPy, Pandas, Scikit-learn, Matplotlib, Streamlit, and XGBoost. The system architecture contains multiple modules including UDP Receiver, Data Structurer, Feature Engineering Engine, Preprocessing Unit, Classification Engine, and Visualization Dashboard.

The Streamlit-based graphical interface enables real-time data visualization, prediction monitoring, confusion matrix analysis, ROC curve generation, and report downloading functionality.

The UDP module receives binary packets at 10 Hz frequency and processes them asynchronously using thread-safe queues. The classification engine performs real-time prediction using the trained Random Forest model.

The deployed framework successfully demonstrates operational capability with low latency and high classification accuracy.
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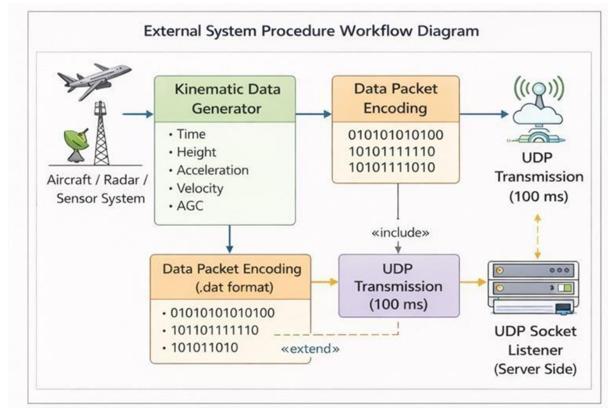

Fig. 2: External System Workflow

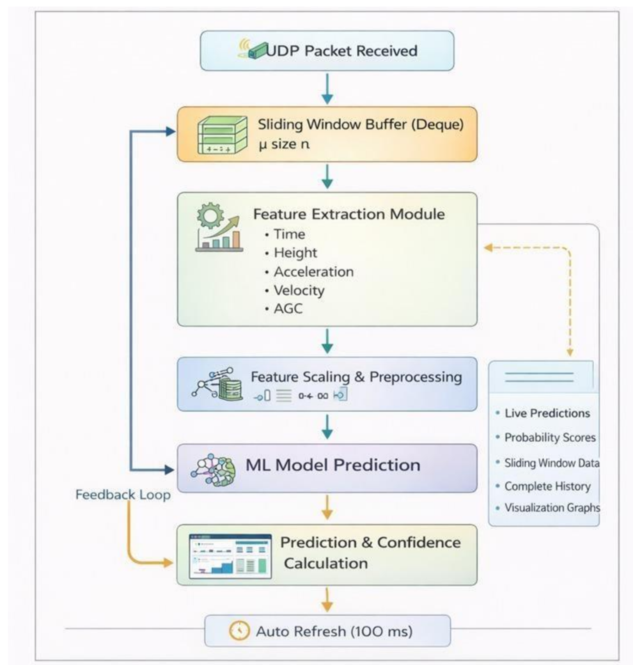

Fig. 3: Internal System Workflow

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VI. RESULTS AND PERFORMANCE ANALYSIS

Experimental evaluation demonstrated that the Random Forest classifier achieved superior performance compared to other machine learning algorithms.

Fig. 4: System Evaluation Result

The Random Forest model achieved approximately 95.8% classification accuracy with strong precision, recall, and F1-score metrics. Gradient Boosting and XGBoost also demonstrated strong performance, while Decision Trees suffered from overfitting. Cross-validation analysis confirmed strong model generalization capability across multiple folds. Confusion matrix analysis revealed accurate classification across all aircraft categories with minimal inter-class confusion.

Real-time UDP testing confirmed the operational suitability of the framework. The classification system maintained low prediction latency while processing continuous streams of trajectory data.

The experimental results validate the effectiveness of statistical and temporal kinematic features for aircraft target classification.

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VII. CONCLUSION AND FUTURE SCOPE

This research proposed a real-time airborne target classification framework using machine learning and kinematic trajectory analysis. The proposed system successfully integrated feature engineering, supervised learning algorithms, and UDP-based real-time processing into a unified operational platform.

The Random Forest classifier demonstrated excellent performance with high accuracy and robust generalization capability. The system effectively classified multiple aircraft categories using motion-based behavioral signatures.

Future enhancements may include integration of deep learning architectures such as LSTM and Transformer models for advanced sequence learning. Additional improvements may focus on anomaly detection, multi-modal sensor fusion, explainable AI, and cloud-based deployment.

The proposed framework provides a scalable and reliable solution suitable for modern defense surveillance and radar-based target recognition applications.

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