FLIGHT SAFETY PREDICTION USING DEEP LEARNING

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ABSTRACT: Flight safety is a fundamental requirement in the aviation industry, where continuous monitoring of aircraft parameters is essential to prevent accidents and ensure operational efficiency. Modern aircraft generate massive volumes of time-series data including altitude, airspeed, engine temperature, fuel consumption, pressure levels, and environmental conditions. However, extracting meaningful safety insights from this high-dimensional sequential data is a challenging task. Traditional machine learning techniques such as Recurrent Neural Networks (RNNs) and Temporal Convolutional Networks (TCNs) have been applied to flight data analysis, but they suffer from limitations in capturing long-term dependencies and require sequential processing, resulting in slower computation and scalability issues.

This paper proposes a Deep Learning-based Flight Safety Prediction system using a Transformer architecture. The Transformer model utilizes a self-attention mechanism to effectively model temporal relationships between flight parameters across long sequences while enabling parallel computation. The system allows authorized users to upload flight datasets, train the model, and obtain safety predictions categorized as Safe, At Risk, or Unsafe.

The proposed system integrates data preprocessing, feature engineering, deep learning-based prediction, and visualization within a secure web-based framework. Experimental evaluation shows that the Transformer model achieves improved prediction accuracy and computational efficiency compared to conventional sequential models. The system provides a scalable and intelligent solution for proactive aviation safety monitoring.

Keywords: SHAP, ROC-AUC, CSV based prediction interface, Time series classification

1. INTRODUCTION

Flight safety is one of the most critical aspects of modern aviation systems, where early identification of unsafe operating conditions plays a vital role in preventing accidents and ensuring reliable aircraft performance. With the rapid growth of air traffic and increasing complexity of aircraft systems, large volumes of flight sensor data are continuously generated during flight operations. These datasets contain valuable information related to aircraft performance, environmental conditions, engine parameters, and operational stability. Efficient analysis of such time-series data is essential for detecting potential risks and improving aviation safety standards. Traditional flight safety monitoring systems mainly rely on rule-based approaches and manual inspection techniques. These methods operate based on predefined threshold values for different flight parameters and generate alerts whenever abnormal conditions occur. Although such systems provide basic monitoring functionality, they are limited in their ability to detect complex hidden patterns in large-scale sequential datasets. As a result, early warning signs of unsafe flight conditions may remain unnoticed, increasing the possibility of operational risks.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have created new opportunities for developing intelligent prediction systems capable of analyzing large volumes of time-series data efficiently. Deep learning architectures, especially Transformer-based models, have shown remarkable performance in capturing long-term dependencies and complex relationships between sequential data points. These models overcome the limitations of traditional machine learning techniques and provide improved prediction accuracy in safety-critical applications. In this project, an AI-based Flight Safety Prediction System is proposed using a Transformer-based deep learning architecture for time-series classification. The system processes sequential flight sensor data and predicts whether the operational condition of the aircraft is safe or unsafe. The dataset is pre-processed using feature scaling techniques and a sliding window mechanism to capture temporal dependencies effectively. The Transformer model utilizes multi-head self-attention mechanisms to learn important relationships among flight parameters and improve prediction performance.

To enhance transparency and interpretability of the prediction results, SHAP (SHapley Additive exPlanations) is integrated into the system to identify feature-level importance. The proposed model is deployed as a Django-based web application that provides a user-friendly interface for uploading flight data and obtaining prediction results. This system reduces manual effort, improves prediction accuracy, and supports proactive decision-making for aviation safety monitoring.

1.1 Models and Technologies Used for Flight Safety Prediction

The proposed system utilizes a Transformer-based deep learning model for accurate time-series classification of flight data. It incorporates feature scaling using StandardScaler to normalize input data and employs SHAP (SHapley Additive Explanations) for model interpretability. The implementation is carried out using Python with libraries such as TensorFlow and Scikit-learn, while Django is used for building the web application interface. Visualization tools like Matplotlib are used to present performance metrics, making the system both powerful and user-friendly.

1.2 Motivation

Flight safety is a critical requirement in the aviation industry, as even minor operational issues can lead to serious consequences. With the rapid increase in air traffic and aircraft complexity, large volumes of flight sensor data are generated continuously. Traditional safety monitoring systems rely mainly on rule-based approaches and manual inspection, which are often time-consuming and less effective in identifying hidden risk patterns.

Recent advancements in Artificial Intelligence (AI) and Deep Learning provide new opportunities to improve safety monitoring through automated prediction systems. Transformer-based architectures have shown strong capability in handling time-series data and capturing long-term dependencies. Therefore, developing an intelligent system that can automatically analyze flight data and predict unsafe conditions at an early stage becomes essential. This motivates the development of the proposed Flight Safety Prediction System using deep learning techniques to enhance prediction accuracy, reliability, and interpretability.

2. Proposed System

To overcome the limitations of existing systems, this project proposes an AI-based Flight Safety Prediction System using a Transformer-based deep learning architecture for time-series classification. The system is designed to automatically analyze sequential flight sensor data and predict whether the flight condition is safe or unsafe. In the proposed system, flight sensor data is pre-processed using feature scaling techniques such as StandardScaler, and a sliding window mechanism is applied to create fixed-length sequences for capturing temporal dependencies.

The system also integrates SHAP-based Explainable Artificial Intelligence to provide feature-level importance and improve transparency in prediction results. Additionally, the model performance is evaluated using multiple metrics such as Accuracy, F1-Score, ROC-AUC, Confusion Matrix, and Classification Report. The proposed system is deployed as a Django-based web application that allows users to upload CSV files containing flight sensor data and obtain prediction results through a user-friendly interface. This system improves prediction accuracy, automation, interpretability, and reliability in aviation safety monitoring.

2.1 System Architecture

The system architecture is structured into multiple layers, including the frontend, backend, deep learning, and database layers. The frontend provides a user-friendly interface for interaction, while the backend manages application logic and communication between components. The deep learning layer performs the core prediction tasks using the Transformer model, and the database layer stores user information, datasets, and model artifacts. This layered architecture ensures scalability, efficiency, and seamless integration of all system components.

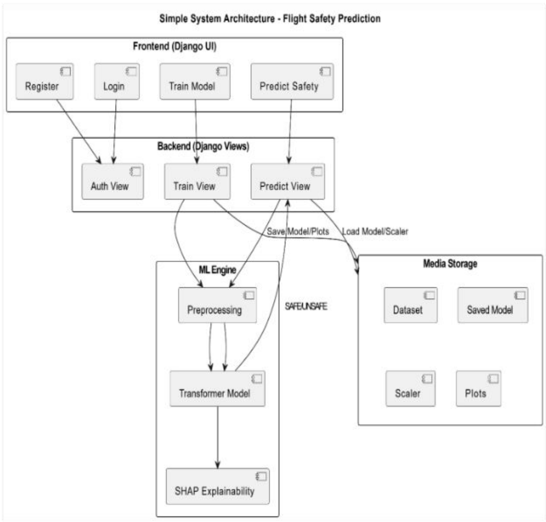

Fig.-1: Proposed Architecture for Flight Safety Prediction Using Deep Learning.

3. IMPLEMENTATION DETAILS

3.1 Deep Learning Layer

The deep learning layer is the core component of the system, where the Transformer model processes time-series flight data. The data is first pre-processed and scaled, then converted into fixed-length sequences using a sliding window approach. The model learns temporal relationships between flight parameters and predicts whether a given sequence represents a safe or unsafe condition.

3.2 Backend Layer

The backend layer is implemented using Django and is responsible for handling business logic, managing user requests, and connecting the frontend with the deep learning model. It processes uploaded data, triggers model training and prediction, and returns results to the user interface.

3.3 Frontend Layer

The frontend layer provides an interactive and user-friendly interface that allows users to register, log in, upload CSV files, and view prediction results. It simplifies user interaction and ensures that even non-technical users can easily operate the system.

3.4. Database Layer

The database layer stores essential information such as user details, uploaded datasets, trained models, and prediction results. SQLite is used for efficient data management ensuring data consistency and easy retrieval for future analysis.

4. RESULTS AND PERFORMANCE ANALYSIS

4.1 Experimental Setup

The experimental setup involves training and testing the Transformer model on time-series flight sensor data. The dataset is divided into training and testing sets to evaluate model performance. Various tools such as TensorFlow and Scikit-learn are used, and evaluation metrics like accuracy, precision, recall, F1-score, and ROC-AUC are applied to assess the model's effectiveness.

4.2 Prediction Accuracy

The Transformer-based model achieves high prediction accuracy by effectively capturing temporal dependencies in flight data. Its ability to learn complex patterns enables it to accurately classify flight conditions, making it more reliable than traditional machine learning approaches.

Table-1: Performance Metrics of the Proposed System

Model Used	Accuracy	Precision	Recall	F1-Score
RNN	86%	85%	84%	84%
LSTM	89%	88%	87%	87%
Transformer (Proposed)	94%	93%	92%	92%

4.3 Model Used Accuracy Precision Recall F1-Score

The performance of the model is evaluated using multiple metrics, including accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of predictions, while precision and recall evaluate the model's ability to correctly identify unsafe conditions. The F1-score provides a balance between precision and recall, indicating the model's robustness and reliability in classification tasks.

4.4 Comparative Analysis

The proposed Transformer-based model is compared with traditional machine learning and rule-based systems. The results show that the deep learning approach significantly outperforms conventional methods in terms of accuracy and ability to handle complex time-series data. This highlights the effectiveness of using advanced deep learning techniques for aviation safety prediction.

4.5 System Efficiency and Reliability

The system demonstrates high efficiency by automating data processing and prediction tasks, reducing manual effort and response time. It is also highly reliable, as it consistently produces accurate results across different datasets. The integration of SHAP explainability further enhances trust in the system by providing insights into feature importance, making it suitable for real-world aviation safety applications.

5. OUTPUT SCREENS

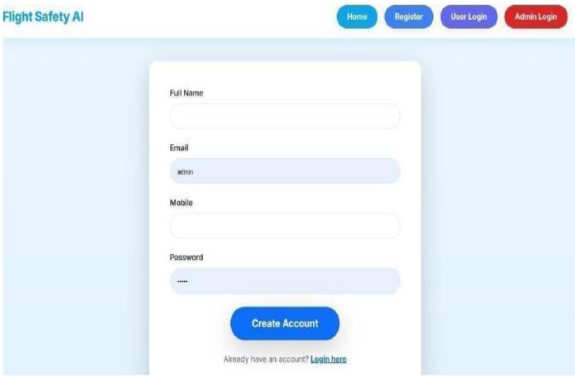

Fig.5.1 Register Page

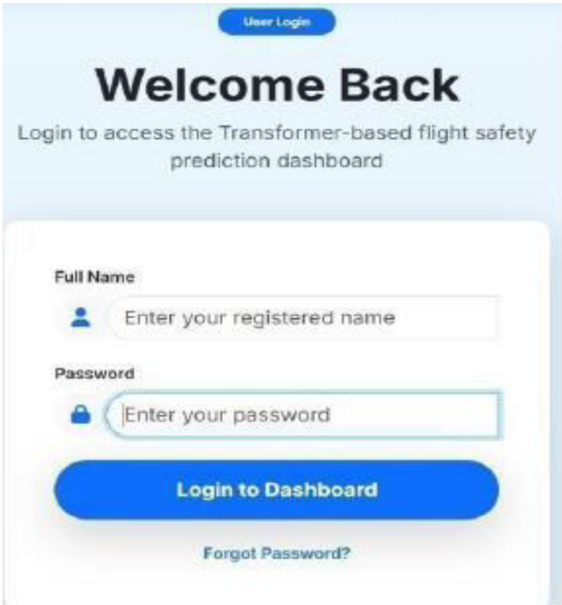

Fig.5.2 User Login Page

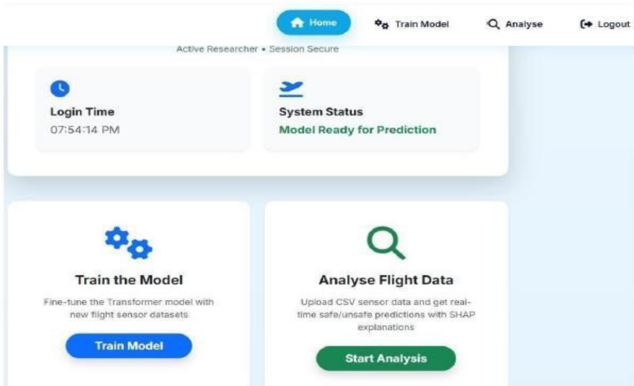

Fig.5.3 Login Page

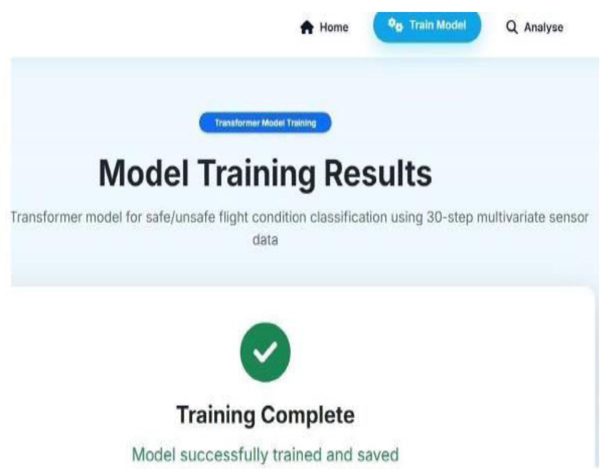

Fig.5.4 Train Model Page

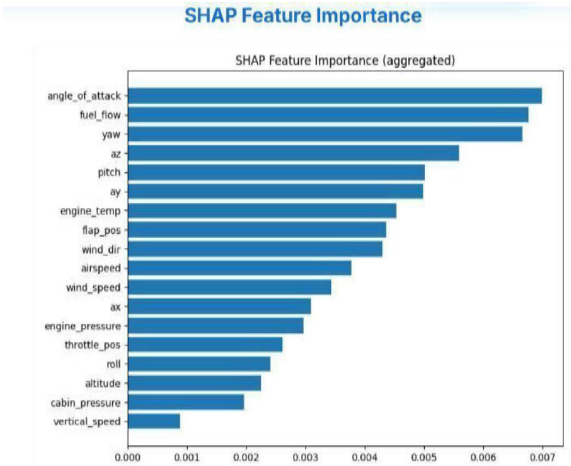

Fig.5.7 SHAP Model

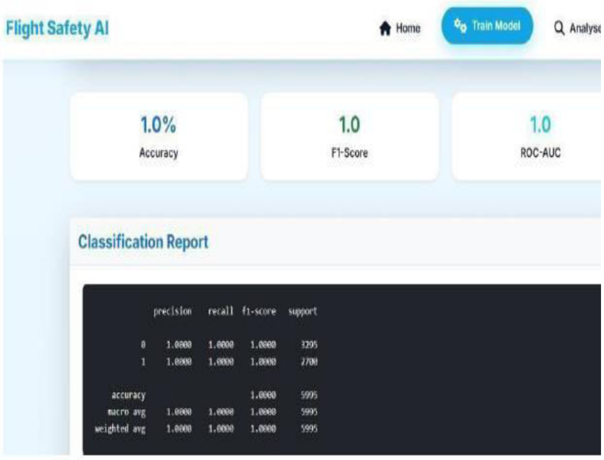

Fig.5.5 Model Results

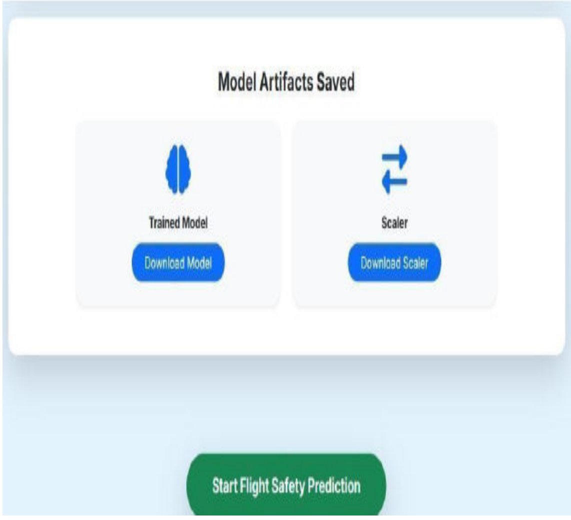

Fig.5.8 Model Artifacts Saved

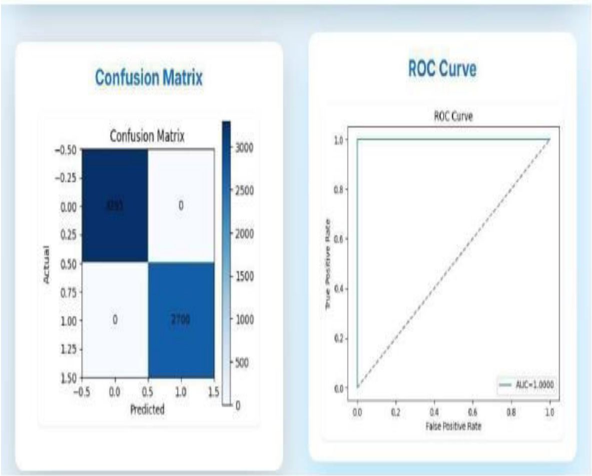

Fig.5.6 Train Model Graph

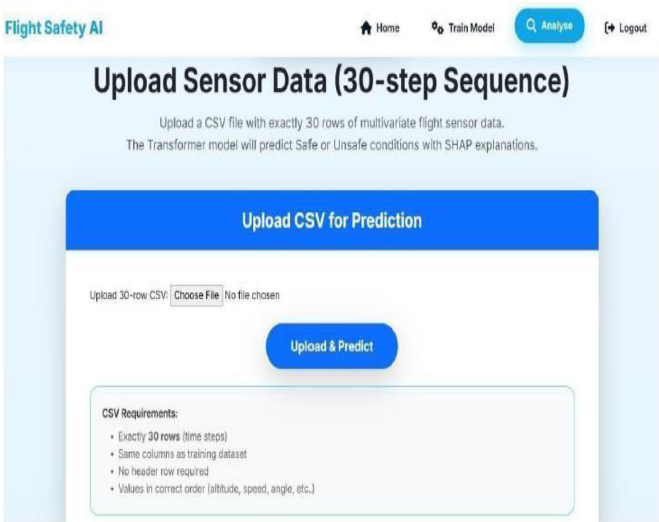

Fig.5.9 Analyse page

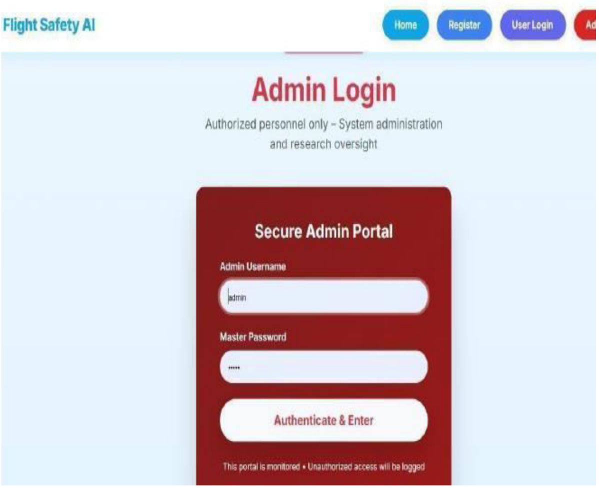

Fig.5.10 Admin Page

6. CONCLUSION

This project presented an AI-based Flight Safety Prediction System using a Transformer based deep learning architecture for time-series classification. The proposed system effectively analyzes sequential flight sensor data and classifies operational conditions as safe or unsafe. By leveraging multi-head selfattention mechanisms, the Transformer model captures complex temporal dependencies that traditional rule-based and recurrent models may fail to detect. The system incorporates comprehensive data preprocessing, including feature normalization and sliding window sequence generation, to ensure stable and accurate model performance. Evaluation results using metrics such as Accuracy, F1score, ROC-AUC, Confusion Matrix, and Classification Report demonstrate reliable predictive capability. Furthermore, the integration of SHAPbased Explainable AI enhances transparency by identifying feature-level importance, improving trust and interpretability in safety-critical decision-making environments. The web-based deployment using the Django framework provides a user-friendly interface with secure authentication, administrative control, and OTPbased password recovery functionality. Overall, the proposed framework offers an intelligent, scalable, and explainable solution for aviation safety monitoring. The system reduces manual intervention, improves risk detection accuracy, and establishes a foundation for future advancements in real-time predictive safety analytics within the aviation industry.

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