Modeling Delay Propagation and Status Transitions in Aviation Networks Using Hybrid Deep Neural Architectures

ABSTRACT

The aircraft industry serves as a backbone of modern global connectivity, facilitating rapid transport of passengers and goods. However, as the volume and complexity of air traffic increase, maintaining the operational efficiency of flights becomes progressively challenging. Flight status prediction—encompassing delays, cancellations, and diversions—is essential for optimizing airline operations, improving passenger experience, and minimizing economic losses. Despite the availability of historical flight data, existing prediction methods often rely on traditional machine learning or statistical models that struggle to handle the nonlinear, high-dimensional, and temporally dependent nature of aviation data. These limitations restrict their predictive accuracy and adaptability in dynamic operational environments. The primary aim of the proposed research is to develop a novel hybrid deep learning model for robust and accurate flight status prediction. Initially, a large and diverse dataset will be collected from publicly available repositories. The data will undergo extensive preprocessing, including cleaning, encoding, and normalization. Exploratory Data Analysis (EDA) will be performed to identify patterns and relationships that support effective feature engineering. A hybrid model architecture will be designed by combining temporal and spatial learning techniques, capturing complex dependencies across flights, airports, and operational variables. The model will be trained and evaluated using industry-standard performance metrics, such as precision, recall, F1-score, and AUC-ROC. The proposed system will support proactive decision-making, enable better resource allocation, and reduce the cascading effects of flight disruptions. Ultimately, this research aims to contribute to the development of intelligent and resilient air transportation systems, with significant benefits for airlines, airports, regulatory bodies, and society at large.

Keywords: *Flight status, hybrid deep learning, air traffic, cancellation, aviation, artificial intelligence*

1. INTRODUCTION

The aviation industry, a cornerstone of global connectivity and commerce, functions within a highly complex, time-sensitive ecosystem [1]. With the continual expansion of international mobility and rapid globalization, reliance on air transportation for passenger and cargo movement has become indispensable. This growing dependence demands rigorous standards for efficiency, punctuality, and operational reliability. Among the most critical aspects of air transport management is the ability to monitor, assess, and predict flight status — a multifaceted indicator that encompasses not only on-time performance but also delays, cancellations, diversions, and other disruptions that alter the planned state of a flight. Ensuring the accurate prediction of flight status has, therefore, emerged as a pressing necessity for aviation stakeholders across commercial, regulatory, and consumer domains.

Flight status, broadly defined as the real-time or forecasted operational state of an aircraft's schedule, plays a pivotal role in air traffic planning, gate allocation, passenger information systems, and crew management [2]. While delays remain the most frequently discussed manifestation of status disruptions, cancellations, diversions, and rescheduling events are equally consequential, often resulting in logistical bottlenecks and significant economic and reputational costs. These disruptions collectively affect millions of flights annually, leading to cascading operational inefficiencies, lost revenue, increased fuel usage, and widespread traveler dissatisfaction. More critically, irregular flight status undermines the overall resilience of the aviation network, especially at congested hubs or during peak travel seasons.

The challenge of predicting flight status is compounded by the numerous factors that contribute to deviations from scheduled operations [3]. These include meteorological phenomena such as thunderstorms, fog, and wind shear; airport-specific constraints like runway closures and gate congestion; airline-induced issues such as crew availability or maintenance delays; and broader systemic problems like airspace saturation or geopolitical disruptions. Unlike single-outcome modeling tasks, predicting flight status requires accounting for the multiclass nature of outcomes—distinguishing not just between delayed and on-time flights, but also identifying potential cancellations, diversions, or even early arrivals.

Traditional methods for estimating flight performance have largely relied on statistical and rule-based frameworks [4]. Linear regression, probabilistic classifiers, and time series models like Autoregressive Integrated Moving Average (ARIMA) have historically been employed to forecast flight delays or assess schedule adherence. While these techniques have offered basic insights into operational trends, their reliance on fixed assumptions (e.g., linearity, stationarity) and handcrafted features limit their efficacy in dynamic, real-time environments. Furthermore, their general design focuses on binary outcomes or point estimates, which are insufficient for modeling the multi-outcome structure inherent in-flight status prediction.

Moreover, legacy approaches struggle to adapt to evolving system conditions. For instance, a statistical model trained on pre-pandemic flight data may fail to generalize under postpandemic demand patterns, altered airline schedules, or changes in regulatory oversight. The increasing volume, velocity, and variety of aviation data further challenge these models, demanding predictive systems that are scalable, flexible, and capable of learning from diverse and temporally shifting data inputs.

Considering these limitations, researchers and industry practitioners have increasingly turned to artificial intelligence (AI) as a more robust approach to flight status prediction [5]. AI, particularly its subdomains of machine learning (ML) and deep learning (DL), enables the development of models that learn directly from data—extracting latent patterns, capturing nonlinear relationships, and adapting to real-time updates without the need for explicit rule design. ML models such as Random Forests, Support Vector Machines, and Gradient Boosting Machines have been effectively used to predict delay probabilities and identify key influencing features in aviation datasets. These models exhibit higher predictive accuracy than traditional techniques and offer partial transparency through feature importance metrics.

However, most classical ML algorithms operate under the assumption of independent and identically distributed (i.i.d.) inputs and are not inherently suited to capturing sequential dependencies or long-term temporal effects, which are fundamental to flight status outcomes. For instance, a diversion due to weather at one airport may lead to multiple cancellations in other cities later in the day. Such interdependencies necessitate models that can learn from the temporal and spatial propagation of operational disruptions, which traditional ML techniques alone are not equipped to do. Such complexities highlight the unique strengths of deep learning. Architectures such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs) are specifically designed to capture sequence-based information, making them well-suited for modeling time-dependent phenomena like evolving flight status. These models can account for patterns in prior flight events, weather trajectories, air traffic flow, and historical performance to forecast likely future outcomes. In addition, convolutional and attention-based networks have expanded the toolkit for processing multivariate time series, geospatial patterns, and unstructured inputs such as radar imagery or natural language weather reports.

DL models not only enhance prediction accuracy but also enable the generation of probabilistic outputs that inform confidence levels in status forecasts. This capability is particularly valuable for operational decision-making, where misclassification—such as failing to predict a cancellation or diversion—can trigger cascading disruptions across the flight network.

Furthermore, recent advancements in DL have introduced attention mechanisms and interpretability modules that allow for more transparent model outputs. These features are especially critical in safety-sensitive environments like aviation, where understanding the rationale behind predictions can improve trust and facilitate informed decision-making.

The integration of AI into aviation analytics represents a transformative shift in how flight status is monitored, predicted, and managed [6]. AI-powered models hold the potential to revolutionize operational workflows—not merely by anticipating disruptions, but by enabling intelligent responses. From dynamic crew scheduling and automated gate reassignments to real-time passenger notification and disruption recovery, AI can support a wide range of functions that depend on timely and accurate status forecasts. With the ability to integrate weather forecasts, real-time aircraft telemetry, historical operational patterns, and airport traffic conditions, AI systems can construct a comprehensive and contextualized view of flight performance. This facilitates proactive interventions that significantly improve efficiency, safety, and service reliability.

Furthermore, the integration of AI into aviation systems unlocks new possibilities for predictive maintenance, intelligent disruption management, and long-term infrastructure optimization. Continuously learning from dynamic operational data streams, AI systems can evolve into real-time, self-updating engines of insight that reflect the current state of the aviation network and forecast its short-term evolution. When embedded within decision-support frameworks, these models can assist controllers, dispatchers, and airline managers in crafting timely, data-driven, and context-aware responses to disruptions—thereby strengthening the resilience and adaptability of the entire air transportation ecosystem. Recognizing both the opportunities and transformative potential of AI, the proposed research will aim to overcome the shortcomings of traditional methods by developing a novel hybrid deep learning model specifically designed to improve the accuracy, robustness, and interpretability of flight status prediction.

2. RELATED WORKS

Yujie Yuan [7] proposed a hybrid DL model named 3DF-DSCL to enhance the accuracy of departure flight delay prediction. The study aimed to address the challenges of modeling complex spatial-temporal dynamics in airport operations using a combination of 3D Convolutional Neural Networks (3D-CNNs), Graph Convolutional Networks (GCNs), and Long Short-Term Memory networks (LSTMs). The model captured temporal sequences, spatial structures, and dynamic aircraft trajectories from multi-attribute datasets comprising

305,643 flights and meteorological records collected at Beijing Capital International Airport. The 3DF-DSCL model achieved a Mean Absolute Error (MAE) of 0.26, representing a 14.47% improvement over baseline models. While the model demonstrated high predictive accuracy, its application was limited to short-term data.

Hatipoğlu and Tosun [8] aimed to enhance flight delay prediction by evaluating ML models, including Logistic Regression, Naïve Bayes, Neural Networks, Random Forest, XGBoost, CatBoost, and LightGBM. The study incorporated Synthetic Minority Oversampling Technique (SMOTE) to address data imbalance and used SHAP for model interpretability. Bayesian optimization was applied for hyperparameter tuning, and the impact of weather data was tested across four experimental scenarios using a three-year dataset from a Turkish airport. XGBoost achieved the highest accuracy (80%) and recall (20–27%), outperforming other models. Weather data had limited influence on predictive accuracy, suggesting airport-specific factors played a more dominant role. A key limitation was the generalizability of the models, which required further refinement and more granular environmental data to improve real-world application.

Seongeun Kim and Eunil Park [9] conducted a study aimed at predicting flight takeoff delays using long-term weather and flight operation data from ICN, JFK, and MDW airports. The research employed various machine learning and deep learning models, including Decision Tree, Random Forest, Support Vector Machine, Logistic Regression, and Long Short-Term Memory (LSTM) networks. The models achieved high accuracy, with LSTM performing best for JFK (0.852) and MDW (0.785) at 2-hour intervals, while Random Forest excelled at ICN (0.749). For 48-hour predictions, similar accuracy patterns were observed. Despite strong performance, limitations included regional weather variability and missing features in the ICN dataset, which affected generalizability. The study highlighted the feasibility of real-time, long-range delay prediction using weather-informed AI models.

Min Dai [10] conducted a study aimed at improving the prediction of flight delays by introducing a clustering-based ensemble learning model. The methodology incorporated ANOVA and Forward Sequential Feature Selection (FSFS) to identify influential indicators, followed by DBSCAN clustering to segment large flight data into subgroups. Each cluster was modeled using a customized random forest, where individual trees were optimized and weighted using the Coyote Optimization Algorithm (COA), forming the COWRF model. The approach achieved an average accuracy of 97.2%, marking a 4.7% improvement over existing models. Performance gains included a 5.3% accuracy increase and 39.17% faster processing. Despite its success, the study acknowledged limitations in feature selection efficiency and the handling of uncertainty.

Silvestre *et al.* [11] proposed a deep learning approach employing LSTM networks to predict the estimated time of arrival (ETA) for flights landing at Adolfo Suárez-Madrid Barajas Airport in 2022. The model integrated 4D flight trajectories with destination airport weather data, including wind conditions, visibility, and temperature, as well as surveillance data from OpenSky. Terminal Aerodrome Forecast (TAF) reports were used to characterize weather forecasts. The method achieved a mean absolute error (MAE) of 2.5 minutes and a root mean squared error (RMSE) of 4.25 minutes, outperforming baseline models such as Random Forest, Gradient Boosting Machines, and AdaBoost.

Emran Biswas *et al.* [12] aimed to enhance the prediction of airline arrival delays by developing a superior deep learning-based model. The study focused on flight data from five major U.S. states using a Deep Feed Forward Regression Network (DFFRN) combined with an innovative Correlation-Based Feature Selection (CFS) algorithm. Key methods included extensive data preprocessing, spatio-temporal feature engineering, and the integration of geographical variables. One-hot encoding was applied to process categorical features effectively. The DFFRN model achieved an exceptional R^2 score of 99.916% and a test RMSE of 1.672, significantly outperforming conventional models. A noted limitation was the absence of weather-related variables.

Chaudhuri *et al.* [13] proposed a DL-based model called LATTICE (LSTM-Attention based Time-dependent Flight-delay Classifier) to classify real-time flight arrival status using weather data, flight information, and ADS-B-based trajectory data. The model integrated a full-sequenced LSTM network to extract temporal features and an attention mechanism for assigning weight to relevant inputs. A masking layer addressed varying trajectory lengths, enhancing robustness. Evaluated on 15,000 inbound flights to Changi Airport, the model achieved 91% accuracy and a 0.96 AUC, outperforming baseline methods. Inclusion of trajectory data improved prediction performance by 8–15%. The approach required ADS-B data post-departure, limiting pre-departure applicability.

Bisandu *et al.* [14] proposed a technique that modified a stacked autoencoder architecture to explore the relationship between space, time, and flight on-time performance. The study aimed to classify and predict flight delays using three variants of autoencoders: vanilla, logistic regression, and multilayer perceptron. The models were trained in a layer-wise greedy fashion, incorporating dropout and normalization techniques to improve robustness and generalizability. The deep vanilla autoencoder outperformed the others, achieving up to 78.51% accuracy, 99.36% recall, and 73.18% precision. The logistic regression and multilayer perceptron autoencoders showed comparatively lower performance.

Ergun and Tuna [15] conducted a machine learning-based study aimed at predicting flight irregularities, including delays and cancellations, to assist passengers in minimizing travel disruptions. The research utilized 2022 flight data from the U.S. Department of Transportation and weather data from NOAA, focusing on departures from JFK Airport. Several classification models were employed, including LightGBM, Logistic Regression, SVM, MLP, KNN, and Gaussian Naive Bayes, alongside SMOTE and undersampling techniques to address class imbalance. LightGBM demonstrated computational efficiency, while SVM achieved the highest accuracy. The final model achieved an F1-score of 56% and an AUC of 0.76.

Chaitanya *et al*. [16] aimed to improve airline delay prediction accuracy through hybrid and ensemble machine learning models. The study applied a range of individual classifiers and ensemble techniques—such as XGBoost and neural networks—on an airline dataset to classify delays. XGBoost achieved over 90% accuracy in certain scenarios, highlighting its effectiveness. However, the overall accuracy across models remained relatively consistent, with limited gains from ensemble strategies. The research reported an 11% improvement in prediction accuracy over the baseline, with neural networks performing best. A key limitation identified was the dataset itself, which lacked critical real-time variables like weather conditions and prior flight statuses. This absence imposed an upper bound on model performance, constraining the predictive power of even the most sophisticated algorithms.

Jingyi Qu *et al.* [17] proposed a flight delay regression prediction model based on Att-Conv-LSTM to enhance the accuracy of predicting specific delay durations. The study aimed to capture both temporal and spatial dependencies by integrating long short-term memory (LSTM) networks for temporal features, convolutional neural networks (CNN) for spatial attributes, and an attention mechanism to boost learning efficiency. Using data from four Chinese airports between September 2019 and October 2020, the model demonstrated a significant improvement—reducing prediction error by 11.41% over LSTM and 10.83% over Conv-LSTM. The results confirmed that incorporating meteorological data and optimizing sequence length to 10 enhanced prediction performance. However, longer sequences led to redundancy and reduced accuracy, highlighting the model's sensitivity to temporal window size.

Ayaydın *et al.* [18] conducted a study aimed at minimizing financial and operational disruptions caused by flight delays by forecasting flight status using machine learning and deep learning techniques. The methods employed included Deep Recurrent Neural Networks (DRNN), Long Short-Term Memory (LSTM), and Random Forest (RF). A real-world dataset containing 62,597 cleaned samples from 368 airports worldwide was used, with a classification focus on delay, cancellation, and diversion. LSTM achieved the highest recall rate of 96.50%, outperforming DRNN and RF. The LSTM also demonstrated a success rate of approximately 79% in classification tasks. Despite promising results, the study faced limitations such as model overfitting and an imbalanced dataset.

Ziming Wang *et al.* [19] aimed to predict flight delay distributions using machine learning techniques based on empirical data from Guangzhou Baiyun International Airport. The study applied LightGBM, Random Forest, and Multilayer Perceptron (MLP) algorithms to model delay distributions, testing Beta, Erlang, and Normal functions, with the Normal distribution proving most effective. The research achieved a prediction accuracy of 0.80 for departure delays at the 0.65 confidence level and arrival delays at the 0.50 confidence level. Results demonstrated the potential of the approach to support strategic decision-making for airport and airline operations. However, the study was limited by its exclusion of cancellation data, the complexity of modeling delay causes, and the lack of advanced loss functions tailored to enhance model precision.

Wang *et al.* [20] aimed to enhance flight delay prediction accuracy through a causal model integrating a Long Short-Term Memory network with an attention mechanism (LSTM-AM). The model considered both direct and indirect influencing factors to capture critical temporal patterns in delay prediction, using operational data from Beijing International Airport. A Pareto encoding technique was employed to reduce dimensionality and improve training efficiency. The model outperformed several baseline machine learning and deep learning methods, achieving a mean absolute error of approximately 8.15 minutes. The attention mechanism enabled better interpretation of delay causes, particularly for indirect, controllable factors. However, the study lacked analysis of inter-airport interactions or multi-airport terminal airspace dynamics.

Mamdouh *et al.* [21] proposed an approach called Flight Delay Path Previous-based Machine Learning (FDPP-ML) to enhance the prediction accuracy of flight delay minutes using only basic flight schedule features. The method restructured flight data into point-based paths and introduced two novel features—Previous Flight Delay (PFD) and Flight Time Duration (FTD)—to capture temporal dependencies. A range of machine and deep learning models, including RNN, LSTM, GRU, and ensemble methods, were employed with default parameters. The approach demonstrated up to 57% error reduction in MSE and 50% in MAE over traditional models, particularly in short-term (2-hour) forecast horizons. However, limitations included reliance on default hyperparameters, diminishing performance over longer horizons, and inefficiencies in real-time retraining.

3. RESEARCH GAP

The major limitations of the existing approaches include:

- Short-term models often miss long-range dependencies and delay propagation effects
- Regression and probabilistic methods struggle with non-linear, multi-factor relationships.
- Operations research models are complex, hard to scale, and not suitable for real-time use.
- Network-based models are highly data-intensive and computationally expensive.
- Machine learning needs large, clean datasets and struggles with data imbalance.
- Prediction drops significantly for underrepresented classes like diversions and cancellations.
- Classical ML models lack scalability with high-velocity aviation data streams.
- Static feature sets often ignore critical causal factors like prior delays and airport congestion.
- LSTM and RNN models rarely include attention or propagation mechanisms.
- CNNs can't handle non-Euclidean flight networks without data distortion.
- GCNs are shallow and insufficient for extracting deep spatial correlations.
- Deep models often lack interpretability, limiting adoption in safety-critical systems.
- Few models apply robust explainability tools like SHAP or attention scores.
- Real-time prediction frameworks remain underdeveloped and non-adaptive.
- Most models lack validation across diverse, real-world operational conditions.
- Broader flight statuses (cancellation, diversion) are often excluded from predictions.

- ❖ Quantum-enhanced models face integration challenges with classical systems.
- ❖ Delay propagation across flight networks is rarely modeled effectively.
- ❖ Sequential path dependencies (e.g., inherited delays) are often overlooked.
- ❖ Many models lack modularity and are hard to integrate into Airport operation control (AOC) systems.
- ❖ Practical deployment considerations like latency and data pipeline integration are often ignored.

4. MOTIVATION OF THE STUDY

The rapid evolution of global air transportation networks has intensified the demand for intelligent systems capable of supporting real-time operational decision making. With the continued rise in passenger volumes, complex scheduling dependencies, and increasing pressure on airport infrastructure, even minor deviations from planned flight operations can result in extensive cascading effects. Events such as delays, cancellations, and diversions introduce multifaceted challenges that impact airlines, airport authorities, passengers, and regulatory agencies alike. Addressing these challenges requires forecasting models that not only anticipate disruptions but also inform proactive strategies to mitigate their operational and financial consequences. Predictive systems, therefore, play a central role in improving the continuity, efficiency, and responsiveness of air traffic management.

This study focuses on developing a robust and scalable computational framework for flight status prediction, grounded in the integration of advanced learning algorithms with structured aviation datasets. The proposed approach will aim to classify flight outcomes using temporally and spatially relevant features derived from real-world operational contexts. Such an approach supports more accurate planning of airport resources, enhances gate and crew scheduling, and contributes to minimizing passenger inconvenience during irregular operations. Furthermore, the ability to generate timely and precise status forecasts enables airport control systems and airline operations centers to adapt to disruptions with greater agility and confidence. By advancing predictive capabilities through a data-driven architecture, this research is aligned with international priorities in aviation modernization and system resilience. It is expected to contribute to the next generation of intelligent aviation solutions that facilitate improved coordination among stakeholders, efficient resource utilization, and a more reliable passenger experience across diverse operational environments.

5. OBJECTIVES OF THE STUDY

The major objectives of the proposed study are:

- To develop a detailed conceptual and operational understanding of flight status prediction, including the classification of flight outcomes such as delays, cancellations, and diversions within complex air traffic systems.
- To systematically analyze the shortcomings of current predictive frameworks and identify gaps in temporal modeling, feature integration, and multiclass classification relevant to flight status forecasting.
- To apply rigorous data preprocessing techniques such as time normalization, outlier detection, categorical encoding, and missing value imputation to construct a high-quality, feature-enriched dataset from raw flight operation logs.
- To design and incorporate domain-specific features such as sequential delay inheritance, route-level congestion indices, and temporal indicators (e.g., departure peaks, weather-affected intervals) to enhance the model's responsiveness to operational dynamics.
- To systematically evaluate the performance of the trained model using separate validation and test sets, employing advanced evaluation metrics such as macro-averaged F1-score, AUC-ROC, precision-recall curves, and confusion matrix analysis.
- To benchmark the proposed hybrid model against established machine learning and deep learning baselines under various operational conditions and forecast horizons.
- To contribute to the development of intelligent aviation analytics that support proactive planning, efficient resource utilization, and enhanced situational awareness across the air transportation network.

6. SCOPE OF THE STUDY

Accurate prediction of flight status plays a pivotal role in maintaining the efficiency, reliability, and safety of modern air transportation systems. As global air traffic continues to expand and operational networks become increasingly complex, disruptions such as delays, cancellations, and diversions pose significant challenges to both aviation stakeholders and passengers. These disruptions are often the result of a combination of factors including airport congestion, airspace capacity constraints, aircraft routing dependencies, and notably, dynamic and sometimes severe weather conditions. Weather remains one of the most unpredictable and impactful influences on flight operations, affecting visibility, wind patterns, precipitation, and runway availability, thereby contributing to delay propagation across interconnected flight paths.

Developing predictive capabilities that incorporate such operational and environmental complexities is essential for real-time decision-making in high-density traffic environments. This research aims to support the advancement of flight status forecasting through the construction of intelligent learning systems that account for spatial-temporal patterns, sequential flight dependencies, and meteorological influences. By modeling outcomes such as delay, cancellation, and diversion using structured aviation data and weather-linked variables, the study seeks to enable proactive measures for airport gate assignments, crew scheduling, and disruption management. The integration of weather data further strengthens the realism and applicability of the predictive framework, ensuring its relevance under diverse operating conditions. Additionally, the findings hold substantial value in enhancing situational awareness within airline operations control centers and air traffic management systems. The research contributes to the broader vision of building resilient and adaptive aviation infrastructure capable of withstanding operational volatility while maintaining service quality, safety, and regulatory compliance in an increasingly data-driven air transport ecosystem.

7. PROPOSED METHODOLGY

The primary objective of the proposed study is to develop a novel hybrid deep learning model capable of accurately predicting flight status outcomes such as delays, cancellations, and diversions using structured historical flight data. The methodological approach will encompass structured phases, including dataset acquisition, data preprocessing, exploratory analysis, domain-informed feature engineering, model development, performance evaluation, and validation under operational constraints. Figure 1 displays the general block diagram of the suggested methodology.

The initial phase of the study will involve the collection of a comprehensive and diverse dataset from publicly available sources such as Kaggle, which consolidates flight operation records. The dataset will include attributes such as scheduled and actual departure times, arrival delays, origin-destination pairs, carrier codes, and weather-related variables where available. Data from a representative time frame will be used to capture a variety of seasonal and operational patterns, including periods of high congestion, adverse weather, and peak travel demand. A large and varied dataset will be essential for enabling the model to learn the temporal dynamics and operational variabilities that govern flight status outcomes.

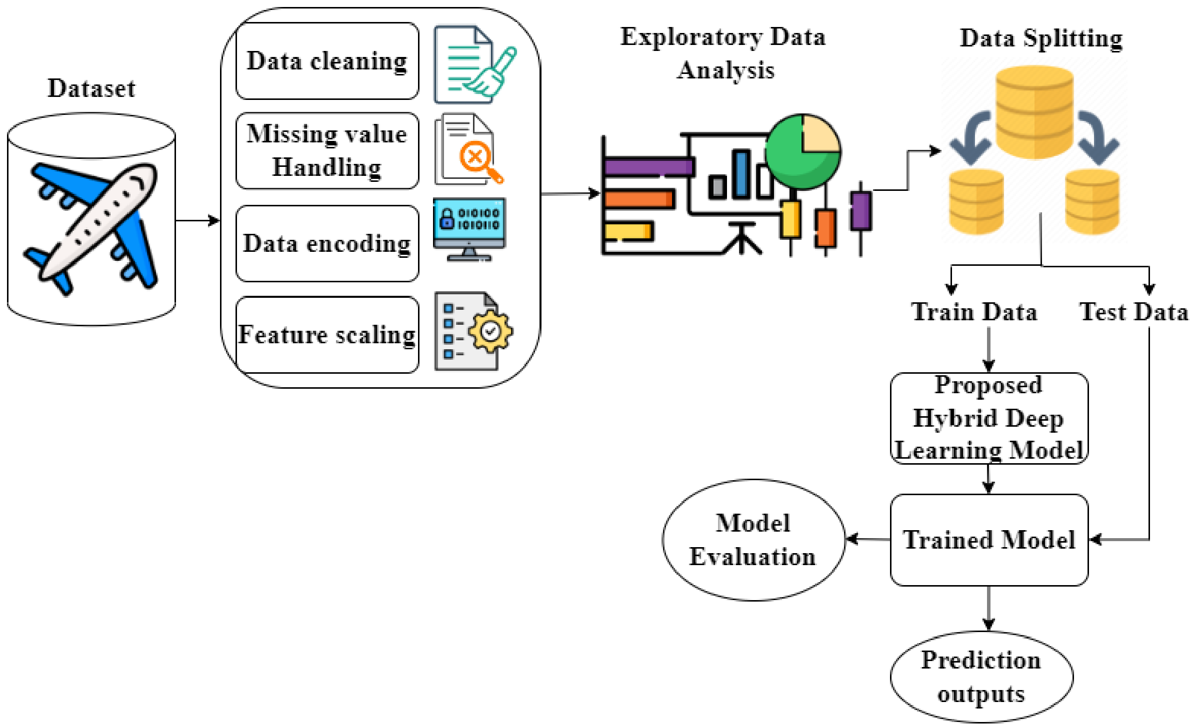

Fig.1. Block Diagram of Proposed Methodology for Flight status Prediction

In the data preprocessing phase, raw flight records will undergo cleaning to remove noise and ensure consistency. Columns that represent post-arrival data or are irrelevant for pre-departure predictions will be excluded to prevent data leakage. Missing values will be addressed using tailored strategies: columns with more than 50 percent missing data will be removed, while those with partial gaps will be imputed using statistical techniques. Categorical variables will be encoded using either one-hot encoding or label encoding, depending on model requirements, and numerical variables will be standardized using feature scaling techniques to ensure balanced input distributions. Following preprocessing, Exploratory Data Analysis (EDA) will be conducted to visualize and interpret patterns in the data. Visualization tools such as heatmaps, time-series plots, boxplots, and distribution graphs will be used to uncover correlations, seasonality, and delay tendencies across routes, airlines, and departure times. Insights from EDA will guide the selection of relevant features and highlight potential predictors of irregular operations.

The next phase will involve domain-informed feature engineering. Temporal features such as month, day of month, day of week, hour, quarter, and categorized departure time intervals will be extracted to capture flight timing effects. Additional engineered features will include sequential delay inheritance from previous flights, rolling averages of recent delays, route-specific congestion indices, and binary indicators for weekends and peak travel periods.

Weather-related features will be incorporated wherever available, including wind speed, visibility, and precipitation indicators, to capture environmental influences on flight performance. These engineered variables will provide a robust, high-resolution input space for model training.

The dataset will then be split into training and test sets using a standard ratio (e.g., 80:20) to evaluate model generalization on unseen data. A novel hybrid deep learning model will be designed. The training process will involve optimizing model weights to minimize a suitable loss function, using adaptive optimizers and cross-validation to tune hyperparameters such as learning rate, batch size, and number of epochs. The model will be trained to classify flight status outcomes into multiple categories using supervised learning strategies.

During the testing phase, the model will be evaluated on unseen data to assess its generalizability and robustness under varying operational scenarios. The final predictions will classify each flight into one of the predefined status categories. Performance will be assessed using comprehensive evaluation metrics including accuracy, precision, recall, F1-score, confusion matrix, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These metrics will provide insights into the model's ability to correctly identify all relevant flight outcomes while minimizing false predictions. Model performance will also be benchmarked against conventional machine learning and deep learning baselines to validate improvements in prediction accuracy and robustness.

Through this methodology, the proposed research aims to produce a high-performance, generalizable predictive system that can support real-time decision-making and disruption management in modern air transportation systems.

8. IMPLEMENTATION FEASIBILITY

The implementation of the proposed novel hybrid deep learning model will be carried out using the Python programming language on the Google Colaboratory (Colab) platform. Google Colab is a widely adopted, cloud-based environment designed to support interactive computing and collaborative machine learning development. It offers built-in support for essential data science libraries, including NumPy, pandas, scikit-learn, TensorFlow, and Keras, thereby facilitating seamless development and experimentation without the need for extensive local setup. One of Colab's most significant advantages is its provision of free access to GPU and TPU acceleration, which is especially beneficial for training deep learning models that require substantial computational resources. Furthermore, Colab's native integration with Google

Drive enables persistent storage, sharing of notebooks, and reproducibility of experiments in a collaborative setting. Given its accessibility, scalability, and rich ecosystem of tools, Google Colaboratory presents a robust and cost-effective platform for implementing, training, and evaluating the proposed model, ensuring feasibility within the scope of academic research and rapid prototyping.

REFERENCES

1. Samunderu, E. (2024). The Scope of the Global Aviation Industry. In The Economic Effects of Air Transport Market Liberalisation: A Perspective Analysis of the Single African Air Transport Market (SAATM) (pp. 1-116). Cham: Springer Nature Switzerland.

2. Degas, A., Islam, M. R., Hurter, C., Barua, S., Rahman, H., Poudel, M., ... & Arico, P. (2022). A survey on artificial intelligence (ai) and explainable ai in air traffic management: Current trends and development with future research trajectory. Applied Sciences, 12(3), 1295.

3. Abdelghany, K. F., Shah, S. S., Raina, S., & Abdelghany, A. F. (2004). A model for projecting flight delays during irregular operation conditions. Journal of Air Transport Management, 10(6), 385-394.

4. Olive, X., Sun, J., Lafage, A., & Basora, L. (2020, December). Detecting events in aircraft trajectories: rule-based and data-driven approaches. In Proceedings (Vol. 59, No. 1, p. 8). MDPI.

5. Geske, A. M., Herold, D. M., & Kummer, S. (2024). Artificial intelligence as a driver of efficiency in air passenger transport: A systematic literature review and future research avenues. Journal of the Air Transport Research Society, 100030.

6. Kabashkin, I., & Perekrestov, V. (2024). Ecosystem of aviation maintenance: transition from aircraft health monitoring to health management based on IoT and AI synergy. Applied Sciences, 14(11), 4394.

7. Yuan, Y., Wang, Y., & Lai, C. S. (2025). Multi-Attribute Data-Driven Flight Departure Delay Prediction for Airport System Using Deep Learning Method. Aerospace, 12(3), 246.

8. Hatıpoğlu, I., & Tosun, Ö. (2024). Predictive Modeling of Flight Delays at an Airport Using Machine Learning Methods. Applied Sciences, 14(13), 5472.
9. Kim, S., & Park, E. (2024). Prediction of flight departure delays caused by weather conditions adopting data-driven approaches. Journal of Big Data, 11(1), 11.
10. Dai, M. (2024). A hybrid machine learning-based model for predicting flight delay through aviation big data. Scientific Reports, 14(1), 4603.
11. Silvestre, J., Martínez-Prieto, M. A., Bregon, A., & Álvarez-Esteban, P. C. (2024). A deep learning-based approach for predicting in-flight estimated time of arrival. The Journal of Supercomputing, 80(12), 17212-17246.
12. Biswas, M. E., Sultana, T., Mandal, A. K., Golam Morshed, M., & Hossain, M. D. (2024). Spatio-Temporal Feature Engineering and Selection-Based Flight Arrival Delay Prediction Using Deep Feedforward Regression Network. Electronics, 13(24), 4910.
13. Chaudhuri, T., Zhang, S., & Zhang, Y. Attention-based Deep Learning Model for Flight Delay Prediction using Real-time Trajectory.
14. Bisandu, D. B., Soviani-Sitoiu, D. A., & Moulitsas, I. (2024). An enhanced deep autoencoder for flight delay prediction.
15. Ergün, E., & Tuna, S. (2024). Enhancing Travel Experience: Predicting Flight Delays for Informed Journey Planning. International Journal of Applied Methods in Electronics and Computers, 12(2), 40-47.
16. Chaitanya, G. S., Shaik, S., Visalakshi, P., & Rakshitha, G. (2024). Comparative study of ensemble machine learning techniques for airline delay prediction. IJECS, 6(1), 14-21.
17. Qu, J., Xiao, M., Yang, L., & Xie, W. (2023). Flight delay regression prediction model based on Att-Conv-LSTM. Entropy, 25(5), 770.
18. Mamdouh, M., Ezzat, M., & A. Hefny, H. (2023). A novel intelligent approach for flight delay prediction. Journal of Big Data, 10(1), 179.
19. Ayaydın, A., & Akcayol, M. A. (2022). Deep learning based forecasting of delay on flights. Bilişim Teknolojileri Dergisi, 15(3), 239-249.

20. Wang, Z., Liao, C., Hang, X., Li, L., Delahaye, D., & Hansen, M. (2022). Distribution prediction of strategic flight delays via machine learning methods. Sustainability, 14(22), 15180.

21. Wang, F., Bi, J., Xie, D., & Zhao, X. (2022). Flight delay forecasting and analysis of direct and indirect factors. IET Intelligent Transport Systems, 16(7), 890-907.