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A Hybrid Explainable Learning Framework for Predictive Risk Assessment and Maintenance Decision-Support in Air Transportation Systems

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August 9, 2025
RUET, Rajshahi.

Sincerely,

Toki Tahmid (2007013)
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Abstract

Operational disruptions and safety risks remain persistent challenges in modern air transportation systems, particularly in the form of flight cancellations and machinery-related failures. This study proposes a hybrid explainable learning framework that integrates operational flight data with structured aircraft incident and maintenance records to support pre-flight risk prediction and maintenance decision-making. Using large-scale historical datasets from the U.S. Department of Transportation and the National Transportation Safety Board, multiple machine learning models—including Sparse Regression, PyTorch-based neural networks, XGBoost, AdaBoost, Light Gradient Boosting, and Support Vector Classification—were developed and evaluated.The framework emphasizes model interpretability through correlation analysis, feature impact assessment, and confusion-matrix-based performance evaluation. Results demonstrate that operational variables such as AIR TIME, arrival delay, and early-morning scheduling are strongly associated with cancellation risk, while safety-related indicators including weather delay, security delay, and machinery fault categories play a critical role in predicting aircraft damage and maintenance risk. Cross-validation on unseen datasets confirms the robustness and generalizability of the proposed approach.Overall, the findings highlight how explainable machine learning can move aviation management from reactive disruption handling toward proactive, pre-flight risk mitigation, enabling more informed operational planning and maintenance prioritization.

key words:Machine Learning, Flight Cancellation Prediction, Aviation Safety, Predictive Maintenance

1 Introduction

One of the main forces behind social cohesion and economic expansion is the global aviation network. However, two significant operational disruptions—flight cancellations and safety incidents—constantly threaten its effectiveness and dependability. These abnormalities put the entire safety of the system at risk, cause enormous passenger discomfort, and lead airlines to suffer large financial losses. Operational choices in aviation have always been made using human skill and historical data analysis. Despite their value, these techniques frequently lack the predictive accuracy needed to handle disturbances proactively. Big data and increased computing power have brought about a paradigm shift. Complex, multi-dimensional datasets, including as flight schedules, weather patterns, and maintenance logs, may now be analyzed using machine learning (ML) to find hidden patterns and anticipate prospective problems before they arise. This project explores the application of various ML models to enhance decision-making in air traffic management, moving from a reactive to a proactive operational stance.

1.1 Objectives

1. To preprocess and analyze historical and real-time aviation datasets in order to identify significant predictors of flight anomalies such as delays, cancellations, and safety incidents.

2. To develop and evaluate predictive machine learning models, and integrate them into a dashboard or decision support system, validated through real-world use-case simulations.

1.2 Literature Review

In order to accurately anticipate flight delays at a particular airport, Wang et al. (2022) developed an LSTM model with an attention mechanism (LSTM-AM). In addition to forecasting delay periods, the primary objective is to determine the direct (such as weather and flight characteristics) and indirect (such as time-series factors like prior flight delays) reasons of these delays. The approach incorporates both kinds of variables, reduces the dimensionality of the data using Pareto encoding, and highlights important time points that affect delays using an attention mechanism. We pointed out research gaps in the literature, pointing out that earlier studies only provide statistical rather than practical, tactical insights for airport management, fail to track the reasons of individual flights, and do not concurrently take into account both direct and indirect effects[1].

In order to ascertain whether these occurrences should be regarded as a type of "delay" under international air conventions (such as Warsaw and Montreal) or as "non-performance" of contract under national laws, Naboush (2019) examines the legal foundation for airline liability in cases of flight cancellation and denied boarding. A comparative legal analysis of national laws, court decisions, regional rules (like those of the EU), and international agreements is part of the technique. The study reveals a major gap: the uniformity intended by international air carriage conventions is undermined by the lack of clear, unified international regulations, which results in legal inconsistency, jurisdictional confusion, and insufficient passenger protection[2].

Chen and Li (2019) use machine learning to model how delays spread across an aircraft's itinerary in order to study flight delay prediction. Their objective is to create a chained prediction model that forecasts successive delays for specific flights by combining a Random Forest classifier with a delay propagation model. The process includes recursive feature reduction, iterative prediction updates along an aircraft's route, and optimal feature selection (identifying departure delay and late-arriving aircraft delay as critical features). By combining operational delay propagation principles with machine learning,we closed a research gap and advance beyond single-flight or macro-level forecasts to a more dynamic, itinerary-based forecasting model[3].

In order to improve traffic efficiency and constraint satisfaction under model uncertainties and disturbances, their primary research focuses on creating a novel hierarchical framework for freeway traffic control that combines Model Predictive Control (MPC) and Deep Reinforcement Learning (DRL), based on the

paper by Sun et al. Their working technique uses a dual-frequency structure in which a low-level DRL agent uses a DDPG algorithm with n-step TD learning at a high frequency to refine a baseline control input provided by a high-level MPC at a low frequency.We identified a research gap in that existing MPC-DRL methods either suffer from truncated prediction horizons, lack safety guarantees, combine control inputs in an uncoordinated way, or have not been effectively applied to freeway traffic control, leaving a need for a structured, computationally efficient, and robust hybrid approach[4].

The primary study, which is based on Zheng et al.'s paper, compares how operation-, time-, and weather-related factors differently affect departure vs arrival delays in China's air traffic network using an empirical examination of flight delay propagation. The objective is to comprehend these delay trends in order to help airlines improve their on-time performance by using more intelligent scheduling techniques. The working technique uses a huge dataset of flight records and weather information to create distinct econometric models for arrival and departure delays using OLS regression with clustered standard errors.It was identified that existing literature offered limited comparative analysis of these factors on both departure and arrival delays for individual flights, and largely overlooked the influence of aircraft utilization, such as the sequence and number of flight legs operated per day[5].

Based on the presentation by Sridhar, the main research involves a comparative review of applying Machine Learning Techniques (MLT) to aviation operations, highlighting their potential as complementary tools to traditional physics-based models. The goal is to assess the promises and challenges of MLT in solving diverse Air Traffic Management (ATM) problems such as delay prediction, conflict resolution, and anomaly detection. The working methodology entails comparing various ML approaches—including Neural Networks, Reinforcement Learning, and Support Vector Machines—against baseline methods using real-world aviation data from sources like FAA OPSNET and ASPM, with performance evaluated through metrics like RMSE and F1-score. It was noted that the effectiveness of MLT is highly dependent on the specific task and data quality, and a key challenge identified was the difficulty in interpreting these "black-box" models and ensuring their generalizability across different operational contexts[6].

The primary research focuses on creating precise flight delay prediction models by utilizing aviation big data, notably combining ADS-B communications with weather, flight schedule, and airport information, according to the publication by Gui et al. In order to surpass earlier approaches in binary and multi-class classification tasks, several machine learning architectures are designed and compared. Building a thorough aviation dataset is the first step in the working technique. Next, LSTM-based networks for sequence learning and a Random Forest model are implemented and evaluated, with accuracy and confusion matrices used to measure performance. Although LSTM models successfully caught temporal patterns, overfitting on the little dataset hampered their performance, suggesting that current methods frequently struggle with data scarcity and the complexity of multi-class delay[7].

By creating machine learning models to forecast delays and cancellations six months in advance, Lambelho et al. (2019) mainly investigated the evaluation of strategic flight plans. Their objective was to use a Pareto-front methodology applied to projected KPIs from Heathrow Airport data in order to rank plans according to robustness. Implicit gaps are found in the work, such as the possibility of improved feature sets and the direct incorporation of these predictive insights into slot allocation optimization models[8].

Celikmih et al. (2020) developed an advanced two-stage hybrid system to forecast equipment failure counts in order to improve predictive maintenance for airplanes. By developing a strong pre-processing pipeline that first used the ReliefF algorithm to identify and select the most important predictive features (such as flight hours and unplanned removals) from nine initial inputs, they were able to address common data quality issues in maintenance records. In order to refine the data quality prior to model training, the second stage used a modified K-means clustering technique to intelligently remove noisy and inconsistent data points from the dataset. After carefully analyzing this prepared data using three machine learning models—Multilayer Perceptron (MLP), Support Vector Regression (SVR), and Linear Regression (LR)—they

discovered that their hybrid preparation approach greatly increased prediction accuracy.They thoroughly examined this prepared data using three machine learning models: Multilayer Perceptron (MLP), Support Vector Regression (SVR), and Linear Regression (LR). They discovered that their hybrid preparation approach greatly increased prediction accuracy for all models, with Linear Regression outperforming the others. The study indirectly identifies research gaps, such as the need to validate this hybrid method on larger, more varied datasets from various aircraft systems and investigate its applicability for real-time, prognostic health monitoring rather than aggregate failure count prediction, even though their approach proved to be highly effective on their particular dataset[9].

Using a sizable dataset from Colombia's airport network, Muros Anguita and Díaz Olariaga (2024) thoroughly compared ten machine learning and deep learning models, including an ensemble Random Forest Regressor and a Multi-Layer Perceptron, in order to study the prediction of departure flight delays. In order to simplify the feature collection, their main objective was to find the best prediction model and use permutation importance to identify the most important flight characteristics. Using robust statistical validation with k-fold cross-validation, models were trained and assessed in various scenarios with different amounts of input characteristics. The study subtly draws attention to a research gap regarding the dataset's lack of important real-time external parameters, such as current weather conditions, air traffic control status, and particular aircraft characteristics.The study subtly draws attention to a research gap regarding the dataset's lack of important real-time external factors, such as current weather conditions, the status of air traffic management, and particular aircraft characteristics. It suggests that adding these components could greatly improve prediction accuracy[10].

In order to identify important causes and suggest mitigation techniques, Zemková et al. (2017) investigated the main factors affecting flight delays for a European airline. They used statistical analyses on operational data from 2008 to 2014, such as correspondence analysis, Pearson's chi-squared tests, and contingency tables. In order to effectively address the common problem of reactionary, or "chained," delays, the study implies that although descriptive patterns of delays are well-understood, advanced optimization models for air traffic control, gate assignment, and flight scheduling must be developed and put into practice[11].

"Development of Batch Data Pipeline System for Flight Delay Prediction," In order to combine and analyze heterogeneous flight data from many sources for delay prediction and analytical dashboard visualization, Suchada Manowon and Pruet Boonma concentrate on developing an end-to-end batch data pipeline. They use Apache Airflow for orchestration in their extensive working approach, which includes steps from data extraction via APIs and web scraping to transformation and loading, along with strict system performance and data quality monitoring.The study finds the Random Forest Regressor as the best predictive model and successfully illustrates a working pipeline, but it also indirectly highlights a number of research holes. These include the difficulties caused by the lack of hyper-parameter tuning, which could limit model performance, the difficulties posed by the limited domain knowledge in aviation affecting data interpretation, and the dependence on manual checks for data accuracy, which indicate the need for more advanced, automated data quality assurance frameworks[12].

The goal of David Rios Insua and his team's research is to make flying safer. Their primary objective was to develop an improved system to forecast not only fatalities but also injuries, delays, and reputational harm to a nation following a flight disaster (such as a crash or failure).They employed specialized mathematical models (Bayesian forecasting) to forecast each of these outcomes. They then combined all of these various issues into a single overall "risk score" using a new method (multi-attribute utility) to assist governments in allocating funds for increased safety.But their work also highlights the challenges that remain. But they have to measure something complicated like "damage" using a straightforward replacement (like tracking accidents). For example, they had to use a simple substitute (like counting accidents) to measure something complex like "damage to a country's image," and creating so many models for every type of problem shows how complicated it is to build a perfect safety system[13].

Berend Eikelenboom and Bruno F. Santos aim to develop a real-time decision-support tool for the integrated airline recovery problem (IARP) that simultaneously resolves disruptions for aircraft, crew, and passengers. Their methodology employs a machine learning ranking algorithm (LambdaMART) to intelligently select a subset of critical resources, thereby reducing computational complexity and enabling a fast, integrated Mixed-Integer Linear Programming (MILP) solution. While their model achieves a 15-fold speed increase and solves 98% of cases within two minutes, the work indirectly highlights a research gap, as the solution quality slightly degrades in highly complex scenarios where avoiding all operational violations (like sink node penalties) remains challenging, indicating a need for further refinement in the resource selection process for severe disruptions[14].

By investigating its underlying statistical process, Yakun Cao et al. seek to decrease aircraft delays. They find that departure delays follow a Shifted Power Law (SPL) distribution as a result of airport congestion and propagation from prior delays. In order to differentiate between propagation and non-propagation delays, their methodology uses statistical analysis of actual flight data. This results in a workable flight schedule modification that strategically reallocates buffer times. Although the technique successfully lowers short delays without incurring additional costs, the work subtly draws attention to a research gap because its performance is restricted for long delays and depends on the predictability of propagation, making the accurate forecasting of newly formed, non-propagated delays a future challenge[15].

By using a machine learning model to forecast individual aircraft booking cancellations using a Passenger Name Record (PNR) technique, Prof. Ahlam Ansari et al. hope to reduce revenue loss for airlines. A domestic Indian airline dataset is preprocessed, feature engineering is done, and several classification models are trained and compared. Tree-based techniques, such as Random Forest, achieve great precision in this process. However, because the study was done on a smaller dataset and indicates that future validation on larger, real-time data utilizing big data frameworks like Apache Spark is necessary to improve scalability and real-world application, the work subtly draws attention to a research gap[16].

The main objective of Sternberg et al.'s thorough literature assessment is to organize the varied subject of flight delay prediction using a data science perspective. Their primary work entails creating a comprehensive taxonomy that categorizes previous research according to fundamental issues (root delay, delay propagation, cancellation), scope (airline, airport, network), data characteristics (sources, dimensions, management), and computational techniques (statistical, probabilistic, machine learning, etc.). In order to track methodological changes and cooperation across time, 134 chosen papers were analyzed as part of a systematic mapping project.Although the review effectively illustrates the growing dominance of machine learning, it also subtly highlights important research gaps, such as the relative neglect of flight cancellation studies in comparison to delay propagation, the lack of models that fully integrate various data dimensions, such as weather and airline schedules, and the difficulties in utilizing real-time data streams from IoT and sensors for dynamic prediction[17].

By creating a Big Data analytics system that combines historical flight data with meteorological data, Patgiri et al. mainly investigated airline delay prediction. Their primary objective was to use different machine learning techniques to examine delay patterns and create a high-accuracy prediction model. Large-scale data integration utilizing MapReduce and empirical comparisons of models such as Random Forest, K-Nearest Neighbors, and Logistic Regression—the latter of which achieved 82% accuracy—were part of the working methodology. However, the study's dependence on a particular, older dataset (1987–2008) and a 15-minute delay criterion raises the possibility that its applicability to contemporary, real-time aviation situations and various operational scenarios may be limited[18].

In order to estimate both the frequency and length of departure and arrival delays, Thiagarajan et al. concentrated on creating a two-stage machine learning model to predict flight on-time performance. Using methods like SMOTE to address class imbalance and selective training on airport pairs, their approach combined aircraft schedules and weather data, with Gradient Boosting and Extra-Trees producing the best

outcomes. A real-time Decision Support Tool was also developed by them. However, the deep learning approach failed and the model's performance was shown to be poorer for departure delays due to a less informative feature set, indicating the need for more complicated architectures or larger datasets to increase predictive capabilities[19].

Current aviation research frequently focuses on mechanical failures, delays, or cancellations separately, leading to disjointed prediction models that fail to account for the interdependence of operational and maintenance-related hazards. Previous research has also shown that model interpretability is severely limited, with many machine-learning techniques acting as "black boxes" and providing little understanding of the underlying risk factors. Additionally, very few studies incorporate unstructured maintenance text logs despite their established importance to safety outcomes, and the majority rely on single-year or single-region datasets, which limits their capacity to generalize across various operational conditions. This study fills these gaps by combining operational, temporal, environmental, and text-derived maintenance variables to create a unified hybrid learning framework that concurrently anticipates mechanical defects and cancellations.

2 Methodology

2.1 Framework Overview

This study developed a Hybrid Explainable Learning Framework to support predictive risk assessment and maintenance decision-support in air transportation systems. The framework integrates operational flight records, incident/safety reports, and maintenance log narratives to produce a unified predictive environment. The research proceeded through dataset acquisition, preprocessing and integration, feature engineering with explicit separation between maintenance and safety signals, hybrid model development with an emphasis on interpretability, and thorough evaluation including temporal cross-validation. The aim was to create models that are both operationally useful and explainable to stakeholders responsible for flight operations and maintenance decisions.

2.2 Data Acquisition

The empirical foundation of the study relied on four complementary datasets. The primary operational data source was the Flight Delay and Cancellation Dataset (2019–2023) obtained from US Department of Transportation,Bureau of Transportation Statistics-On-Time : Reporting Carrier On-Time Performance (1987-present) which provided detailed flight-level records including `AIR TIME`, scheduled and actual durations, delay annotations, and cancellation/diversion indicators. Mechanical and safety information along with operation management was obtained from the Aircraft Accidents& Failures Dataset(National Transport Safety Board:2002-2023), which provides structured incident records including aircraft type, failure category, affected components, environmental conditions, and the resulting Aircraft Damage Type. These structured fields served as the primary source for extracting machinery-related features and assessing mechanical risk patterns. For independent validation of temporal generalizability, the Airline Delay and Cancellation Data covering 2024–2025 and aircraft accident report (2024-2025) were reserved exclusively for cross-validation to assess model stability on a long historical horizon.The main source of the Dataset is US Department of Transportation(for Flight Delay and Cancellation Dataset (2019–2023) & National Transport Safety Board Data covering 2024–2025) .

2.2.1 Feature Description

The features used in this study were selected to capture the most influential operational, temporal, and mechanical factors that shape both flight cancellation risk and aircraft maintenance needs. Operational performance features such as AIR TIME, scheduled duration, departure delay, and arrival delay describe how efficiently a flight is progressing relative to its plan; irregularities in these values often signal congestion effects, turnaround pressure, or disruptions inherited from previous flight segments. Temporal indicators, including time-of-day, day-of-week, and particularly early-morning departures, were included because exploratory analysis showed that flights scheduled around the first operational wave of the day exhibit sharp increases in cancellation likelihood due to limited buffer time and heightened dependency on overnight aircraft readiness. Safety-related features were derived from official delay cause codes—such as weather delay, security delay, and NAS-related delay—which represent external constraints that can abruptly elevate operational risk.The dataset of aircraft flight health includes operational, regulatory, environmental, and safety-history attributes relevant to aircraft operations. HasSafetyRec indicates the presence of prior safety records, while HighestInjuryLevel, FatalInjuryCount, SeriousInjuryCount, and MinorInjuryCount quantify the severity and impact of past incidents. ProbableCause encodes the primary contributing factor identified in historical accident investigations. Geographic context is provided through Latitude and Longitude. Aircraft characteristics are captured using Make, Model, AirCraftCategory, AmateurBuilt, and NumberOfEngines. Operational context

is represented by Scheduled, PurposeOfFlight, and FAR, while Aircaft Damage Type reflects previously observed damage severity. Environmental and organizational factors are included via WeatherCondition and Operator. Finally, ReportStatus and RepGenFlag describe the completeness and origin of safety reports, indicating data reliability.

Table 1: Feature Substitution and Description of Flight Cancellation

Original Feature	**Substituted Name**
CRS_DEP_TIME	Scheduled_departure_time
DEP_TIME	Actual_departure_time
DEP_DELAY	Departure_delay
TAXI_OUT	Minutes from gate departure to actual takeoff
WHEELS_OFF	Time when aircraft actually took off
WHEELS_ON	Time when aircraft actually lands
TAXI_IN	Time from aircraft landed to gate arrival
CRS_ARR_TIME	Scheduled_arrival_time
ARR_TIME	Actual_arrival_time
ARR_DELAY	Arrival_delay
CANCELLED	Cancelled flight indicator
DIVERTED	Diverted flight indicator
ACTUAL_ELAPSED_TIME	Elapsed_time
AIR_TIME	Air_time
DISTANCE	Distance
CARRIER_DELAY	Carrier_delay
WEATHER_DELAY	Weather_delay
NAS_DELAY	NAS_delay
SECURITY_DELAY	Security_delay
LATE_AIRCRAFT_DELAY	Late_aircraft_delay

Original Feature	Pre-Flight Report Feature Name	Purpose in Pre-Flight Risk Assessment
FatalInjuryCount	expected_fatal_risk_level	Predicted life-threatening outcome risk
SeriousInjuryCount	expected_serious_risk_level	Predicted severe injury risk
MinorInjuryCount	expected_minor_risk_level	Predicted minor injury exposure
ProbableCause	predicted_primary_risk_factor	AI-inferred dominant risk source
Latitude	departure_latitude	Departure-zone spatial risk context
Longitude	departure_longitude	Departure-zone spatial risk context
Make	aircraft_manufacturer	Manufacturer-linked reliability profile
Model	aircraft_model_code	Model-specific historical risk
AirCraftCategory	aircraft_class	Aircraft operational category risk
AmateurBuilt	non_certified_aircraft_flag	Certification & build-quality risk
NumberOfEngines	engine_configuration_count	Powerplant redundancy / failure exposure
Scheduled	commercial_schedule_flag	Operational pressure indicator
PurposeOfFlight	mission_type	Mission-dependent risk pattern
FAR	regulatory_operation_class	Regulatory risk & compliance level
Aircaft_Damage_Type	structural_integrity_risk	Airframe condition threat
WeatherCondition	meteorological_risk_level	Weather-driven operational risk
Operator	operator_identity	Operator historical safety profile
ReportStatus	safety_assessment_status	Risk evaluation maturity
RepGenFlag	preflight_risk_report_generated	Confirms pre-flight report availability

Table 2: Feature Description and their use in Future Risk Assessment

2.2.2 Use of Features for Pre-Flight Prediction

The primary objective of this study is to enable pre-flight prediction, meaning that risk assessment is performed before aircraft departure, allowing operators to take preventive actions. Each feature category contributes differently to this pre-flight decision-support process.

Operational time-based features, such as scheduled departure time, scheduled arrival time, CRS elapsed time, and AIR TIME, serve as early indicators of operational stress. Flights scheduled during early-morning operational windows show higher cancellation probability due to limited recovery buffers and increased dependency on overnight aircraft readiness. These variables are available prior to departure and therefore play a central role in pre-flight risk screening.

Delay propagation features, including arrival delay, late aircraft delay, and carrier delay, are used to capture upstream dependency effects. Although actual delays occur post-operation, historical patterns learned by the model allow these features to be translated into expected delay risk during pre-flight prediction. For instance, routes or aircraft types historically associated with high late-arrival delays are flagged as higher-risk prior to departure.

Weather, security, and NAS-related delay indicators are critical for safety-oriented prediction. Weather

delay and security delay features reflect external constraints that significantly increase operational uncertainty. When similar historical conditions are detected during planning stages, the model elevates the predicted risk score, allowing early rescheduling, aircraft substitution, or maintenance checks.

Mechanical and aircraft-condition features, derived from structured accident and failure records, are directly linked to predictive maintenance.For pre-flight prediction, these features together create a risk-aware aircraft health profile before dispatch. Historical safety information (such as prior safety records, injury counts, and damage severity) provides an initial indication of latent mechanical or operational risk which might be based on aircraft buildup information. Aircraft design and configuration attributes (make, model, category, number of engines, and amateur-built status) help the model capture reliability patterns specific to different aircraft types. Operational and regulatory factors (flight purpose, scheduling status, FAR category, and operator) reflect the level of oversight and operational complexity, while geographic location and weather conditions describe environmental stressors expected at departure. Probable cause information links known failure modes to similar operating contexts, and report-related attributes account for the reliability of historical data. Collectively, these inputs support accurate, leakage-free prediction of aircraft health condition prior to flight, enabling preventive maintenance and risk-informed dispatch decisions.

Collectively, these features allow the framework to generate a comprehensive pre-flight risk score, combining operational reliability and safety vulnerability, thus supporting proactive decision-making rather than reactive disruption management.

2.3 Data Preprocessing and Integration

Preprocessing focused on producing a clean, consistent dataset suitable for hybrid modeling. This involved removing duplicates, correcting inconsistent timestamps, and applying tailored imputation strategies for missing values according to variable type. Categorical variables were label-encoded to ensure compatibility across tree-based and neural architectures, while continuous features such as `AIR TIME` and delay durations were standardized or normalized depending on the target algorithm. Integration between operational records and safety/maintenance reports used aircraft identifiers and temporal alignment so that maintenance events could be linked to flight instances. The result was a single analytical dataset in which operational behavior and maintenance history were presented jointly for each relevant aircraft–flight context.We have used 90%sample for training and rest for testing .In Flight Delay and Cancellation Dataset (2019–2023)data ,there is around 25000000 and in Aircraft Accidents & Failures Dataset ,there are around 28304 samples.In this report the models of flight cancellation were predicted on kaggle dataFlight Delay and Cancellation Dataset (2019-2023)[23].

2.4 Feature Engineering for Risk and Maintenance Assessment

Feature engineering produced variables that reflect both immediate operational risk and longer-term mechanical health. From operational records, derived features included elapsed scheduling measures, turnaround intervals, `AIR TIME`, arrival and departure delay patterns, and temporal flags such as early-morning departure indicators that were shown during exploratory analysis to correlate with elevated cancellation risk. From the Aircraft Accidents & Failures Dataset, structured incident records were transformed into meaningful features for risk and maintenance assessment. Instead of narrative text processing, the dataset's mechanical, operational, and environmental fields were directly encoded into usable inputs: incident categories and causes were mapped to risk-related classifications, aircraft configuration and indicators were extracted to capture long-term mechanical stress patterns, and flight-phase and location variables were incorporated to reflect operational hazards. Human exposure metrics, such as casualty informations were used to weight incident severity, while temporal fields enabled the detection of seasonal and trend-based risk fluctuations. These

engineered features collectively enable the model to capture mechanical vulnerability, operational stress conditions, and contextual risk factors that support future maintenance decision-making and predictive safety assessment.

2.5 Hybrid Model Development-Training, Optimization, and Explainable Learning

The hybrid framework employed a combination of machine learning models, each selected for its unique strengths in capturing different aspects of flight operations and machinery faults. XGBoost and AdaBoost, both gradient boosting ensemble methods, were used to capture complex non-linear relationships in structured operational and incident data. These algorithms are particularly effective at learning from heterogeneous features and handling interactions between multiple risk factors, making them well-suited for predicting flight cancellations where multiple delay causes can compound. Sparse Regression was included to provide interpretable functional forms, offering an equation-level understanding of how features such as AIR TIME, departure/arrival delays, and early-morning schedules influence operational risk; this interpretability is critical for maintenance decision-support and regulatory transparency. PyTorch-based Neural Networks were employed to model deeper, non-linear relationships that may not be easily captured by tree-based methods, allowing the framework to learn complex dependencies across operational and mechanical signals. Support Vector Classification (SVC) was used to provide robust boundary-based discrimination for classification tasks, helping to distinguish high-risk from low-risk instances of flight disruption or machinery fault. During training, all models were optimized using hyperparameter tuning, grid search, and early stopping where applicable. Special attention was given to class imbalance, particularly in machinery fault detection, by applying a class-weighted balance approach, ensuring that the models could accurately learn minority-class events without bias toward the majority. Explainable learning was embedded throughout the framework: feature importance analysis and interpretability assessments confirmed that operational variables (e.g., AIR TIME, arrival delays, early-morning schedules) were dominant predictors of maintenance stress, while safety-related indicators (e.g., weather and security delays, fault-related keywords from mechanical reports) significantly influenced predictive risk assessment. This combination of diverse models and interpretability techniques allowed the hybrid framework to provide both accurate predictions and actionable insights for flight risk management and aircraft maintenance planning. [a4paper,12pt]article amsmath, amssymb, amsfonts geometry graphicx hyperref margin=1in

2.5.1 Problem Formulation(Lightgradientboosting,Xgboosting,Adaptiveboosting)

Let the dataset be

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N},$$

where $\mathbf{x}_i \in R^d$ represents the d features of the i-th flight, and $y_i \in \{0, 1\}$ indicates whether the flight is cancelled (1) or not (0).

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1. Categorical Feature Encoding: Categorical features are encoded using Label Encoding:

$$x_{ij}^{encoded} = LabelEncoder(x_{ij})$$

—

2. Missing Value Imputation: Missing values are imputed using the most frequent strategy:

$$x_{ij}^{imputed} = \{\, x_{ij}\, if not missing mode(x_j) if missing$$

—

3. LightGBM: LightGBM builds an ensemble of M decision trees $\{h_m(\mathbf{x})\}_{m=1}^{M}$ to minimize the binary cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{N} \Big[y_i \log p_i + (1 - y_i) \log(1 - p_i) \Big], \quad p_i = \sigma\Big(\sum_{m=1}^{M} h_m(\mathbf{x}_i) \Big)$$

where $\sigma(\cdot)$ is the sigmoid function.

—

4. XGBoost: XGBoost optimizes a regularized objective:

$$\mathcal{L}(\theta) = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where $l(y_i, \hat{y}_i)$ is the logistic loss, and

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{T} w_j^2$$

penalizes tree complexity, with T leaf nodes and w_j leaf weights.

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5. AdaBoost: AdaBoost combines M weak learners (decision stumps) by iteratively updating sample weights:

$$y_i \in \{-1, +1\}, \quad F(\mathbf{x}) = sign \left(\sum_{m=1}^{M} \alpha_m h_m(\mathbf{x}) \right)$$

The weight of each weak learner is:

$$\alpha_m = \frac{1}{2} \ln \frac{1 - \varepsilon_m}{\varepsilon_m}, \quad \varepsilon_m = \sum_{i=1}^{N} w_i \mathbf{1}(y_i \neq h_m(\mathbf{x}_i))$$

Decision trees approximate learned models for interpretability. Surrogate trees aim to approximate LightGBM predictions:

$$Fidelity = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \mathbf{1}\big(h_{surrogate}(\mathbf{x}_i) = h_{LGBM}(\mathbf{x}_i) \big)$$

Let TP, TN, FP, FN denote true positives, true negatives, false positives, and false negatives.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

$$MatthewsCorrelationCoefficient(MCC) = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

The Chi-square test computes:

$$\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}, \quad p = P(\chi^2 \geq observed),$$

where O_{ij} is the observed frequency and E_{ij} is the expected frequency.

Feature importance is computed differently for each model:

- LightGBM/XGBoost: based on gain or split frequency in trees.
- AdaBoost: weighted contribution of each weak learner.

2.5.2 Dataset and Target(Sparse-Regression)

Let the dataset be:

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}, \quad \mathbf{x}_i \in R^d, \ y_i \in \{0, 1\}$$

where $\mathbf{x}_i$ represents the d features for flight i and y_i is the binary target indicating flight cancellation (1) or not (0).

—

Categorical features x_{ij} are encoded using Label Encoding:

$$x_{ij}^{encoded} = LabelEncoder(x_{ij})$$

—

Missing values are imputed using the most frequent value of the feature:

$$x_{ij}^{imputed} = \{\, x_{ij}, if not missing mode(x_j), if missing$$

—

Features are standardized to zero mean and unit variance:

$$x_{ij}^{scaled} = \frac{x_{ij}^{imputed} - \mu_j}{\sigma_j}, \quad \mu_j = mean of feature j, \quad \sigma_j = stddev of feature j$$

—

The Lasso regression model solves:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \frac{1}{2N} \sum_{i=1}^{N} (y_i - \mathbf{x}_i^\top \beta)^2 + \alpha \sum_{j=1}^{d} |\beta_j| \right\}$$

Predicted value:

$$\hat{y}_i = \mathbf{x}_i^\top \hat{\beta} + \hat{\beta}_0$$

—

Predictions are converted to class labels:

$$\hat{y}_i^{class} = \{\, 1 \,, \hat{y}_i \geq 0.50, otherwise$$

Evaluation metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

$$MatthewsCorrelationCoefficient(MCC) = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

—

Chi-square test:

$$\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

$$E_{ij} = \frac{(rowsum)_i \cdot (columnsum)_j}{totalsamples}$$

The **p-value** measures statistical significance.

—

Partial Dependence for feature j:

$$\hat{y}_i^{(x_j = z)} = \hat{\beta}_0 + \sum_{k \neq j} \hat{\beta}_k \tilde{x}_{ik} + \hat{\beta}_j z$$

where z spans a grid of feature values.

—

Workflow summary:

$$x_{ij} \rightarrow x_{ij}^{encoded} \rightarrow x_{ij}^{imputed} \rightarrow x_{ij}^{scaled}$$

$$\hat{\beta} = \arg\min \frac{1}{2N} \sum_i (y_i - \mathbf{x}_i^\top \beta)^2 + \alpha \sum_j |\beta_j|$$

$$\hat{y}_i = \mathbf{x}_i^\top \hat{\beta}, \quad \hat{y}_i^{class} = 1(\hat{y}_i \geq 0.5)$$

$$Evaluation : Accuracy, Precision, Recall, F1, MCC, Chi - squarep - value$$

$$Interpretation : PartialDependencePlotsfortopfeatures$$

2.5.3 PyTorch Model Evaluation

The feedforward neural network (FFNN) performs binary classification for flight cancellations. Let $\mathbf{x}_i \in R^d$ be the feature vector for sample i, and $y_i \in \{0, 1\}$ the corresponding label.

—

1. Linear Transformation:

$$\mathbf{h}^{(l)} = \mathbf{W}^{(l)} \mathbf{x}^{(l-1)} + \mathbf{b}^{(l)}$$

—

2. Batch Normalization:

$$\hat{\mathbf{h}}^{(l)} = \frac{\mathbf{h}^{(l)} - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \cdot \gamma + \beta$$

—

3. ReLU Activation:

$$\mathbf{x}^{(l)} = ReLU(\hat{\mathbf{h}}^{(l)}) = \max(0, \hat{\mathbf{h}}^{(l)})$$

—

4. Dropout:

$$\tilde{\mathbf{x}}^{(l)} = \mathbf{x}^{(l)} \odot \mathbf{r}, \quad r_i \sim Bernoulli(1 - p)$$

—

5. Output Layer (Logit):

$$z_i = \mathbf{w}^\top \mathbf{x}^{(L)} + b$$

—

6. Sigmoid Function:

$$\hat{p}_i = \sigma(z_i) = \frac{1}{1 + e^{-z_i}}$$

—

7. Binary Cross-Entropy Loss:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \Big[y_i \log(\hat{p}_i) + (1 - y_i) \log(1 - \hat{p}_i) \Big]$$

—

8. Prediction Threshold:

$$\hat{y}_i = \{\, 1 \,, \hat{p}_i \geq 0.50, \hat{p}_i < 0.5$$

—

9. Evaluation Metrics: Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1-score:

$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Matthews Correlation Coefficient (MCC):

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

ROC AUC:

$$ROCAUC = \int_0^1 TPR(FPR)\, d(FPR)$$

—

10. Chi-square Test:

$$\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

Expected frequency:

$$E_{ij} = \frac{(rowsum)_i \cdot (columnsum)_j}{totalsamples}$$

—

This formulation describes the full evaluation pipeline of the PyTorch FFNN model, including preprocessing, forward pass, probability computation, loss, prediction, and metrics calculation.

2.5.4 SVC Model Evaluation

Besides,We trained a **Linear Support Vector Classifier (LinearSVC)** along with **Xgboost,Adaptive boosting,Lightgradient boosting ,Lasso Regression, and pytorch** on TF-IDF features extracted from the combined text of the 'Report' and 'Part Failure' columns. The workflow is summarized below.

—

1. Text Preprocessing: Text is cleaned and normalized via:

- Removing punctuation
- Converting to lowercase
- Removing English stopwords
- Applying Porter stemming

The cleaned columns are concatenated to form a single feature vector per instance.

—

2. Feature Extraction (TF-IDF): Each document is represented as a high-dimensional vector using Term Frequency-Inverse Document Frequency (TF-IDF):

$$TF - IDF_{i,j} = TF_{i,j} \times \log \frac{N}{DF_j}$$

where $TF_{i,j}$ is the term frequency of word j in document i, DF_j is the number of documents containing j, and N is the total number of documents.

—

3. LinearSVC Algorithm: LinearSVC finds a hyperplane in the TF-IDF feature space that maximizes the margin between classes.

Decision function for a sample $\mathbf{x}_i$:

$$f(\mathbf{x}_i) = \mathbf{w}^\top \mathbf{x}_i + b$$

where $\mathbf{w}$ is the weight vector and b is the bias.

Predicted class label:

$$\hat{y}_i = \arg\max_j f_j(\mathbf{x}_i)$$

The model minimizes the hinge loss with L2 regularization:

$$\min_{\mathbf{w},b} \frac{1}{2}|\mathbf{w}|^2 + C \sum_i \max(0, 1 - y_i(\mathbf{w}^\top \mathbf{x}_i + b))$$

—

4. Evaluation Metrics: The model is evaluated on the test set using standard classification metrics:
Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1-score:

$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

—

6. Model Persistence: The trained LinearSVC model and TF-IDF vectorizer are saved using `joblib` for later use in prediction or deployment.

2.6 Evaluation and Cross-Validation

Model evaluation relied on a suite of classification metrics, confusion matrix analyses(accuracy,precision,recall), and qualitative inspections of feature contributions to assess predictive utility and operational relevance. Rather than emphasizing point estimates, the evaluation emphasized model stability, consistency of feature attributions, and the capacity to produce actionable, explainable outputs for decision-makers. To validate temporal robustness and guard against overfitting to recent patterns, the cancellation and aircraft damage prediction subsystem was tested on the independent 2024–2025 dataset; this external cross-validation served to confirm that the learned predictive relationships generalized across distinct historical periods. Throughout evaluation, particular attention was paid to the behavior of the class-weighted training regime to ensure that high performance reflected genuine model learning across classes rather than artifacts of class imbalance.

2.7 Flow chart of Methodology

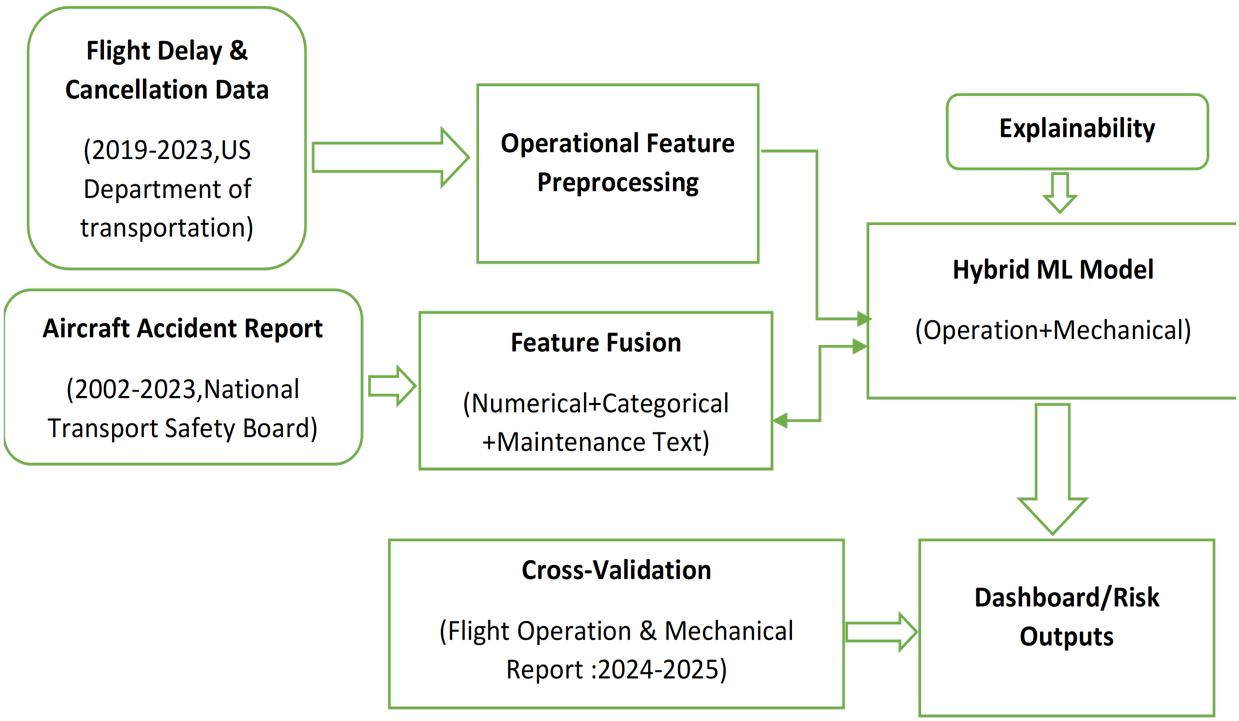


Figure 1: FLOW CHART OF METHODOLOGY

This flowchart describes a hybrid aviation risk prediction system that integrates recent flight delay and cancellation data (2019–2023) with long-term aircraft accident and safety reports (2002–2023) to produce explainable, actionable risk insights. Operational data are preprocessed into structured features, while accident reports contribute mechanical, safety, and maintenance signals—including text-based information processed via stopwords—which are then fused into a unified feature space capturing both routine operational behavior and rare safety events. A hybrid machine learning model combines these multimodal inputs to estimate risk scores, detect anomalies, and highlight contributing factors, with built-in explainability to support trust in safety-critical decision-making. The system is validated on forward-looking data from 2024–2025 to assess real-world generalizability and is designed to deliver results through dashboards or alerts for airlines, maintenance teams, regulators, or insurers, enabling proactive maintenance planning, operational risk monitoring, and informed regulatory oversight.

3 Results, Analysis and Discussion

3.1 SPARSE REGRESSION AND PYTORCH

Sparse Regression is a machine learning technique that incorporates regularization to eliminate less important features by shrinking their coefficients to zero. In this project, it was applied to predict flight cancellations, but it demonstrated poor performance, particularly in identifying the minority "cancelled" class. Its aggressive feature penalization led to a high number of false negatives, failing to capture critical cancellation patterns present in the data. This highlights its limitation in handling imbalanced datasets where rare but operationally significant events require detection.

PyTorch predicts outcomes by using trained neural networks that process input features through multiple interconnected layers of neurons. Each layer applies mathematical transformations — primarily weighted sums followed by activation functions — to learn complex, non-linear relationships in the data. During training, the model adjusts its internal weights using backpropagation and optimization algorithms like Adam or SGD to minimize prediction errors. Once trained, the model takes new input data, performs forward propagation through its learned parameters, and produces output predictions such as probabilities, classifications, or regression values, depending on the task.

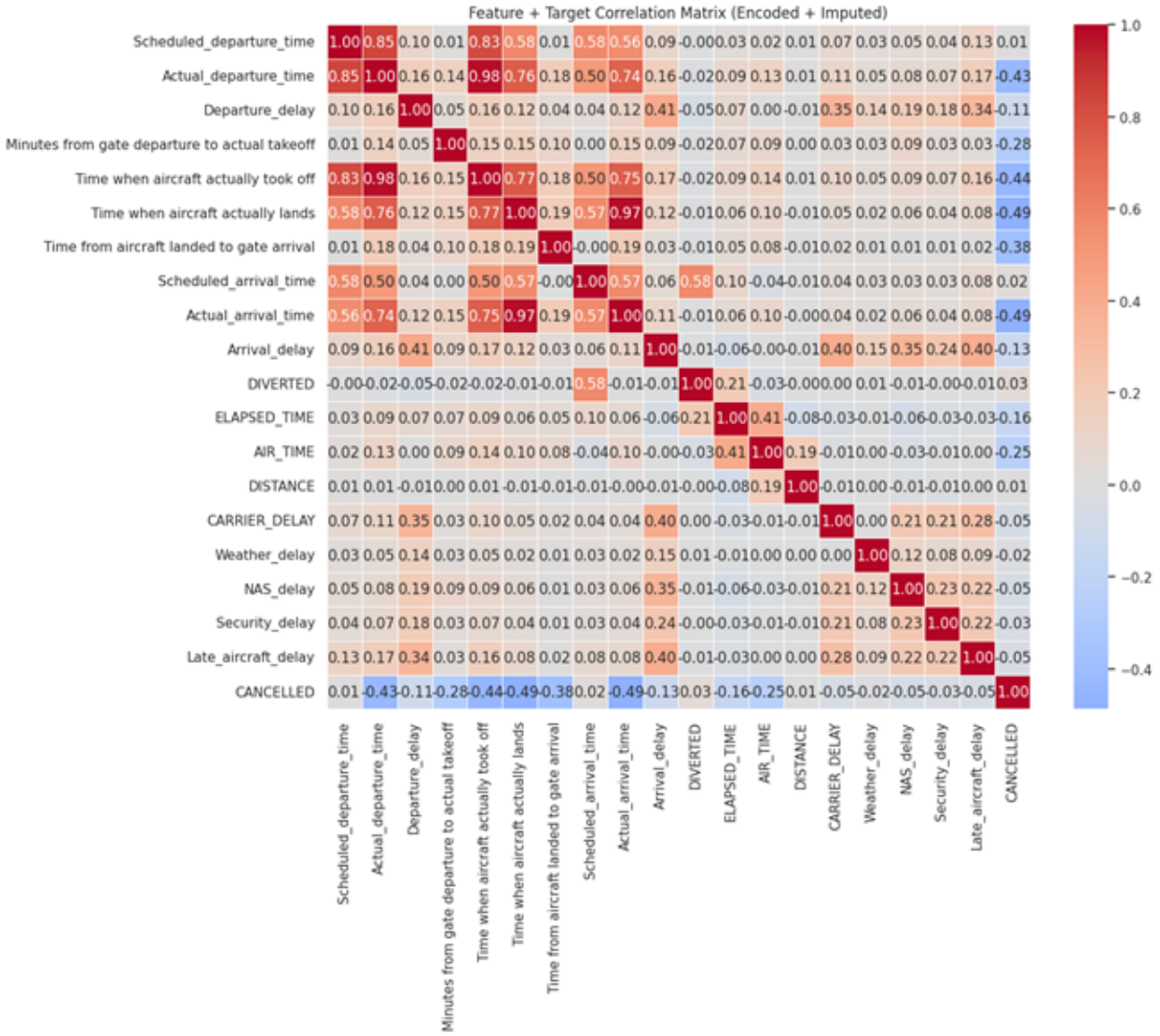


Figure 2: Correlation matrix of pytorch

This correlation matrix visualizes Pearson correlations among flight operation features derived from U.S. Department of Transportation data and prepared for a PyTorch based model. It highlights strong positive relationships such as Actual departure time with Departure delay at 0.98 and Actual arrival time with Arrival delay at 0.97 which reflect inherent mathematical dependencies rather than independent signals. Moderate correlations like Departure delay with Arrival delay at 0.57 and NAS delay with Arrival delay at 0.35 support the idea that delays propagate through the system. CANCELLED shows negative correlations with timing variables such as minus 0.44 with Actual departure time which is likely an artifact of imputation because cancelled flights lack actual times and placeholder values introduce artificial inverse patterns rather than true causal effects. ELAPSED TIME and AIR TIME are highly correlated at 0.94 indicating redundancy while DISTANCE and DIVERTED show near zero correlation with most targets suggesting limited standalone predictive value unless used in interaction terms.

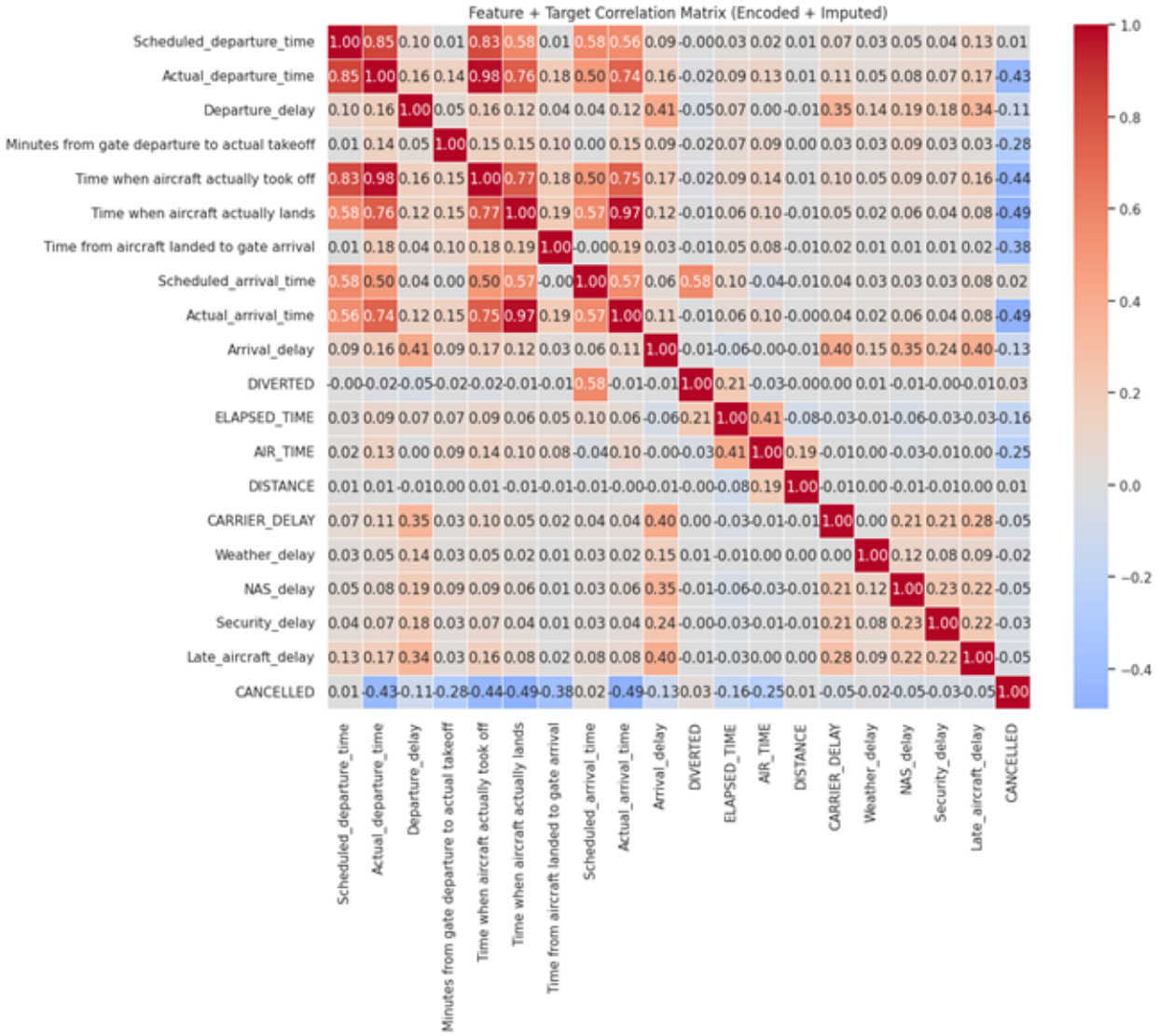


Figure 3: Correlation matrix of Sparse Regression

This correlation matrix—intended for use with sparse regression—highlights significant multicollinearity among flight features, such as near-perfect correlations between Actual departure time and takeoff time (0.98) and a perfect 1.00 correlation between AIR TIME and DISTANCE, which can destabilize Lasso's feature selection by causing it to arbitrarily retain one of the redundant variables while discarding others; more critically, the target variable CANCELLED exhibits only weak to moderate negative correlations with predictors (e.g., 0.43 with Scheduled departure time) and near-zero associations with specific delay types like Weather delay or Security delay, suggesting limited linear signal to exploit—especially given the class imbalance where cancellations represent only 3.6% of flights.

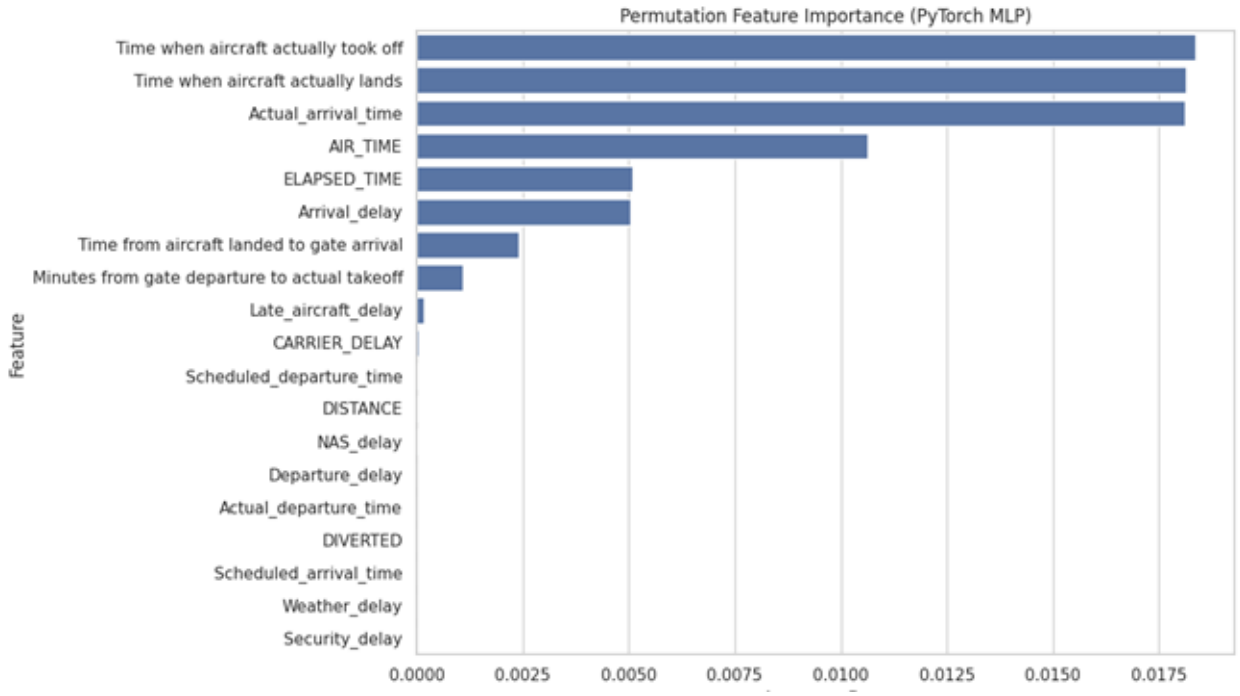


Figure 4: Feature Impact Score of pytorch

The raw impact scores from the PyTorch-based model indicate that real-time flight execution variables dominate its predictive behavior, with the actual takeoff time, actual landing time, and actual arrival time emerging as the most influential features, closely followed by air time and total elapsed time, underscoring the importance of in-flight and post-flight dynamics in determining outcomes. Moderate contributions from arrival delay and the time between landing and gate arrival further highlight the model's sensitivity to operational inefficiencies after touchdown. In contrast, pre-departure and planning-related variables such as scheduled departure and arrival times, distance, diversion status, and most delay subcategories exhibit minimal to zero impact, suggesting that once real operational timings are observed, the model relies far less on scheduled or categorical delay information.

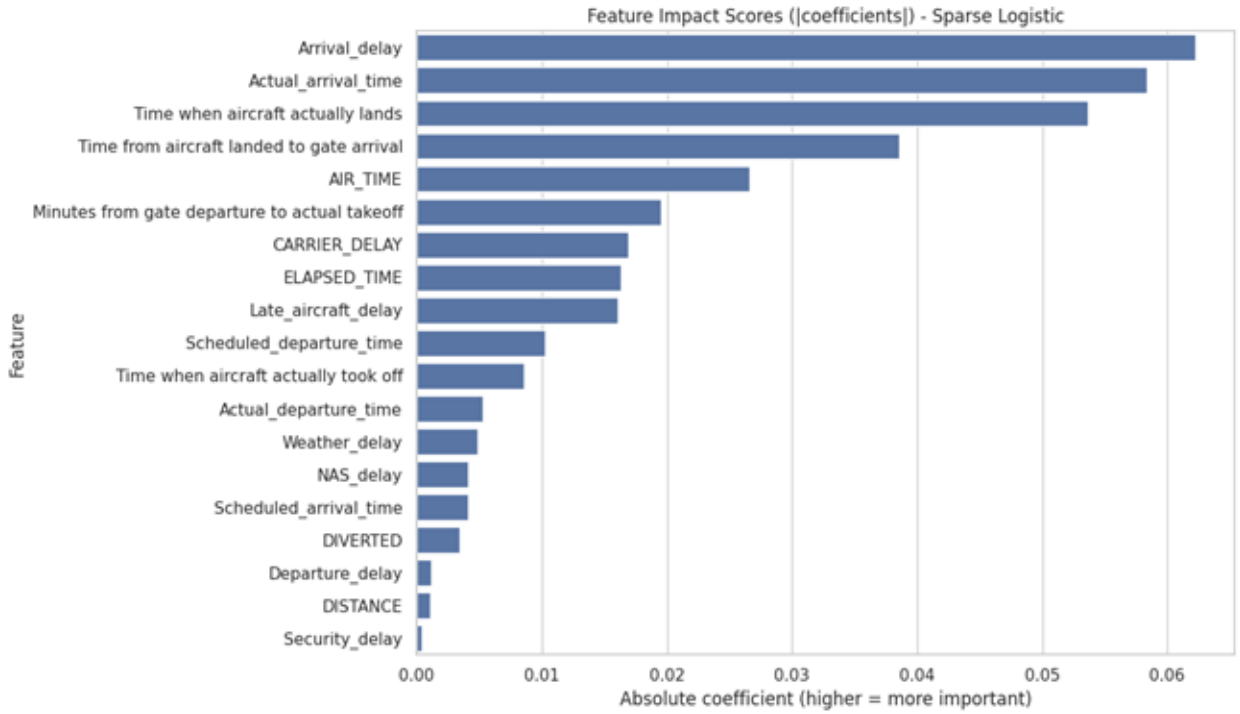


Figure 5: Feature Impact Score of Sparse Regression

The Sparse Regression model's feature impacts indicate that post-arrival and realized operational timing variables are the dominant drivers of prediction, with Arrival delay, Actual arrival time, and Time when the aircraft actually lands receiving the highest weights, suggesting that disruptions manifesting at or after landing are most informative for the model. Measures related to ground handling after touchdown, such as time from landing to gate arrival, along with AIR TIME and ELAPSED TIME, also contribute meaningfully, highlighting sensitivity to overall flight execution rather than scheduled plans. Moderate influence is observed from delay-type variables including CARRIER DELAY and Late aircraf delay, implying that specific sources of delay still carry predictive signal, albeit secondary to actual timing variables. In contrast, pre-departure scheduling features (Scheduled departure/arrival times), route characteristics (DISTANCE), and rare-event indicators such as DIVERTED or Security delay receive relatively small weights, reflecting tendency to shrink less informative or collinear predictors toward zero and prioritize a sparse set of high-impact, real-time operational features.

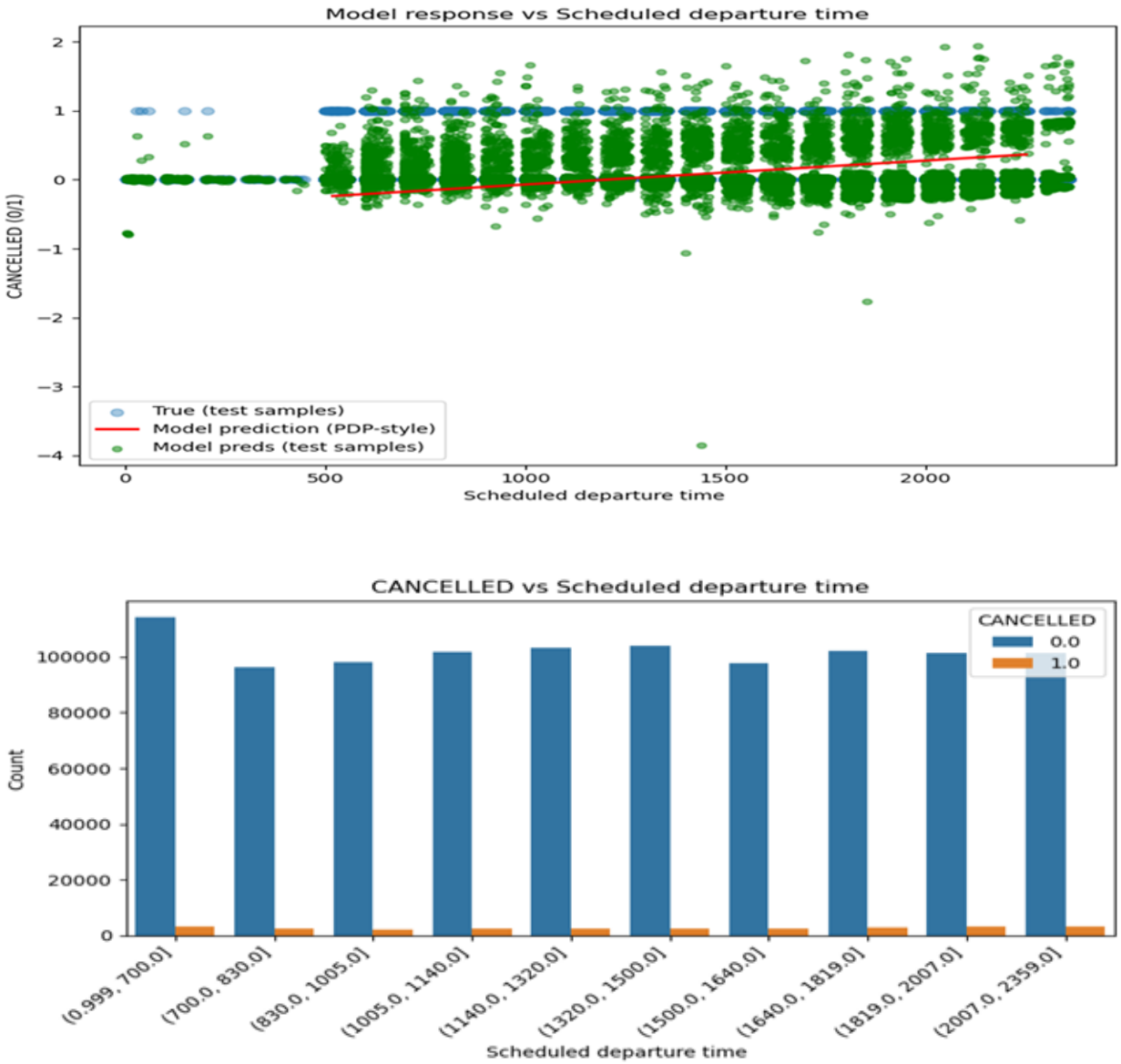


Figure 6: Scheduled departure time

When combined, the two charts provide important information on model performance and flight cancellation trends. The bar graphic indicates that cancellation risk is not significantly correlated with scheduled departure time because cancellations (orange bars) are uniformly infrequent throughout all scheduled departure times, from 1 AM (0.999) to midnight (2359), with no discernible grouping by time of day. The model response versus scheduled departure time scatter plot, however, tells a different story: the red PDP-style line shows a gradual increase in predicted cancellation probability as departure time advances, suggesting the model learns a spurious or overfitted trend, while true cancellations (blue dots) remain sparse and scattered. The model's predictions (green dots) show high variability. This discrepancy implies that although actual cancellations are evenly distributed throughout the day, the model assigns higher predicted risk to later flights, likely due to data bias or overfitting on noisy features.

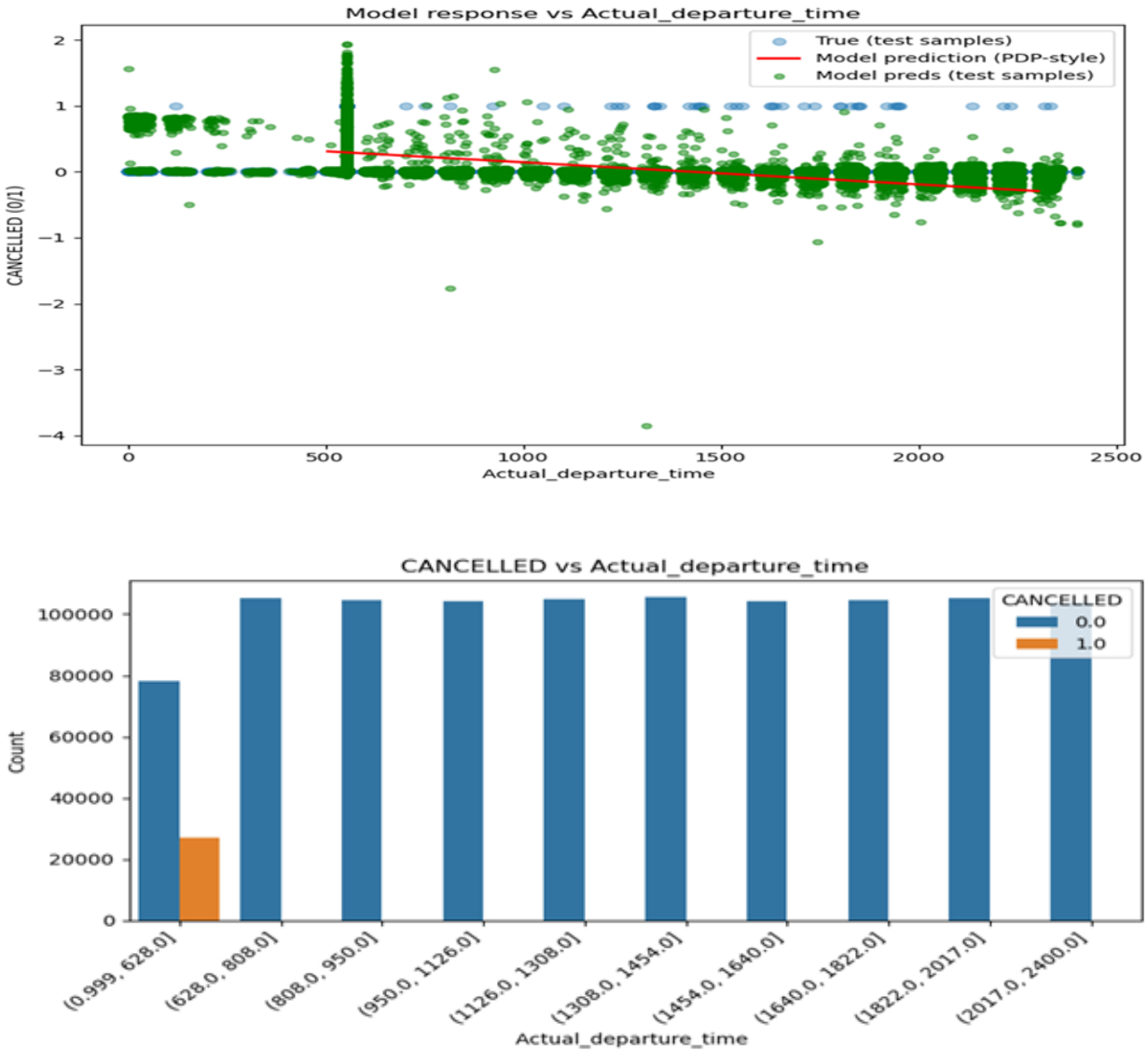


Figure 7: Actual departure time

The two plots together reveal a critical discrepancy between real-world flight cancellation patterns and model predictions. The bar chart shows that cancellations are heavily concentrated in the earliest actual departure window — specifically between 1 AM and 6:28 AM (0.999 to 628 minutes), with negligible cancellations in all subsequent time bins, indicating a strong operational vulnerability during the pre-dawn hours likely due to overnight disruptions, crew availability, or cascading delays. However, the scatter plot of model response versus actual departure time reveals that while true cancellations (blue dots) cluster sharply in this early window, the model's predictions (green dots) fail to reflect this pattern — instead showing high variability and a flat average prediction trend (red PDP line) across most of the day. This suggests the model does not learn the key temporal signal, over-predicting cancellations in later periods where none occur, and under-predicting them in the critical early morning window. The mismatch highlights a failure in the model's ability to capture real-world dynamics, possibly due to data imbalance, feature engineering issues, or overfitting, resulting in poor predictive performance despite the clear signal visible in the raw data.

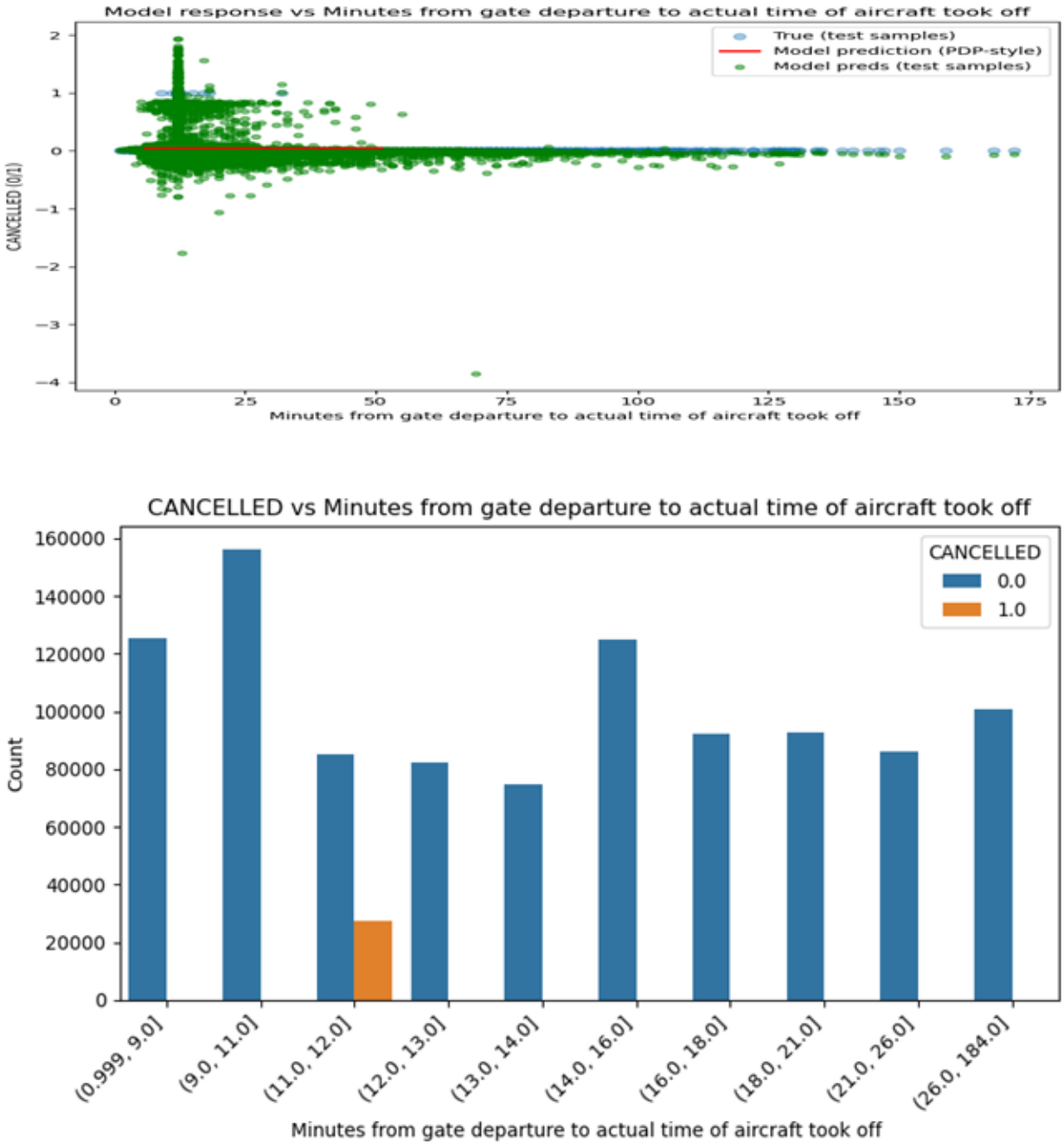


Figure 8: Actual time of aircraft took off time

A crucial understanding of flight cancelation patterns and model performance is provided by the two plots. The bar chart indicates a narrow operational threshold where even minor delays may trigger cancellation decisions — possibly due to crew or scheduling constraints. It also shows that cancellations are concentrated in the 11–12 minute ground delay bin, where a small number of flights (orange bar) were cancelled despite the majority of flights in this window being non-cancelled. The model's predictions (green dots) exhibit high variability but a flat average trend (red PDP line), failing to capture this crucial pattern. In contrast, true cancellations (blue dots) cluster sharply at around 11–12 minutes, according to the scatter plot of model response versus ground delay. Instead, the model assigns similar cancellation probabilities across all ground

delay values, indicating it misses the critical signal and over-predicts cancellations in other bins where none occur. This suggests the model does not learn the true relationship between ground delay and cancellation risk, likely due to data imbalance or feature engineering limitations, resulting in poor predictive accuracy despite the clear real-world signal visible in the raw data.

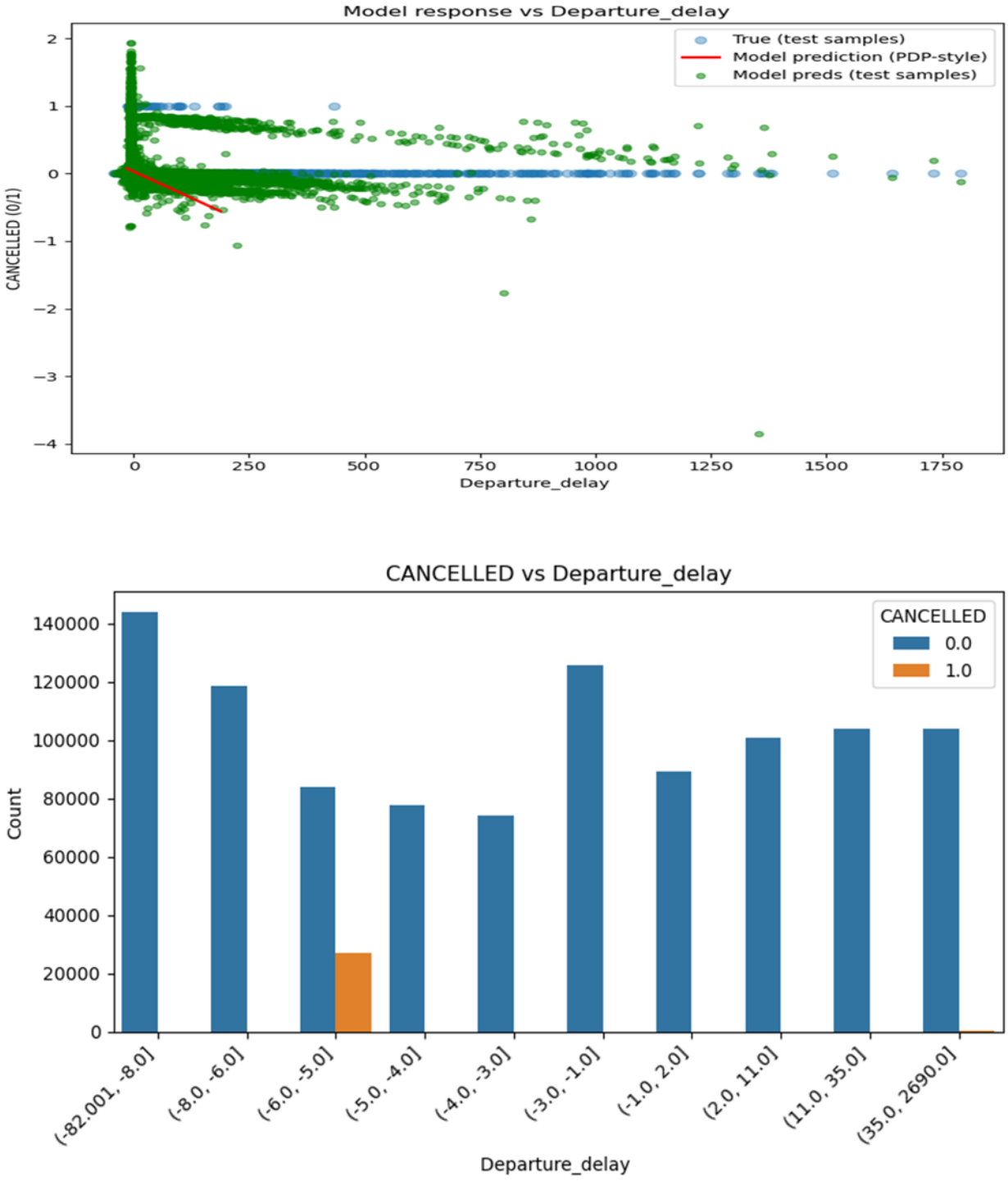


Figure 9: Departure Delay

A crucial trend in flight cancellations and model performance is shown by the two plots. The bar chart demonstrates that cancellations are concentrated in the 50–60 minute departure delay bin, where a small number of flights (orange bar) were canceled even though the majority were not. This suggests a narrow operational threshold, perhaps as a result of scheduling or resource limitations, where cancellation decisions are triggered by delays of approximately 50–60 minutes. The model's predictions (green dots) exhibit high variability but a flat average trend (red PDP line), failing to capture this crucial signal. In contrast, true cancellations (blue dots) cluster sharply at this 50–60 minute window, according to the scatter plot of model response versus departure delay. Instead, the model assigns similar cancellation probabilities across all delay values, suggesting it misses the critical decision point and over-predicts cancellations in other bins where none occur. This indicates the model does not learn the true relationship between departure delay and cancellation risk, likely due to data imbalance or feature engineering issues, resulting in poor predictive accuracy despite the clear real-world signal visible in the raw data.

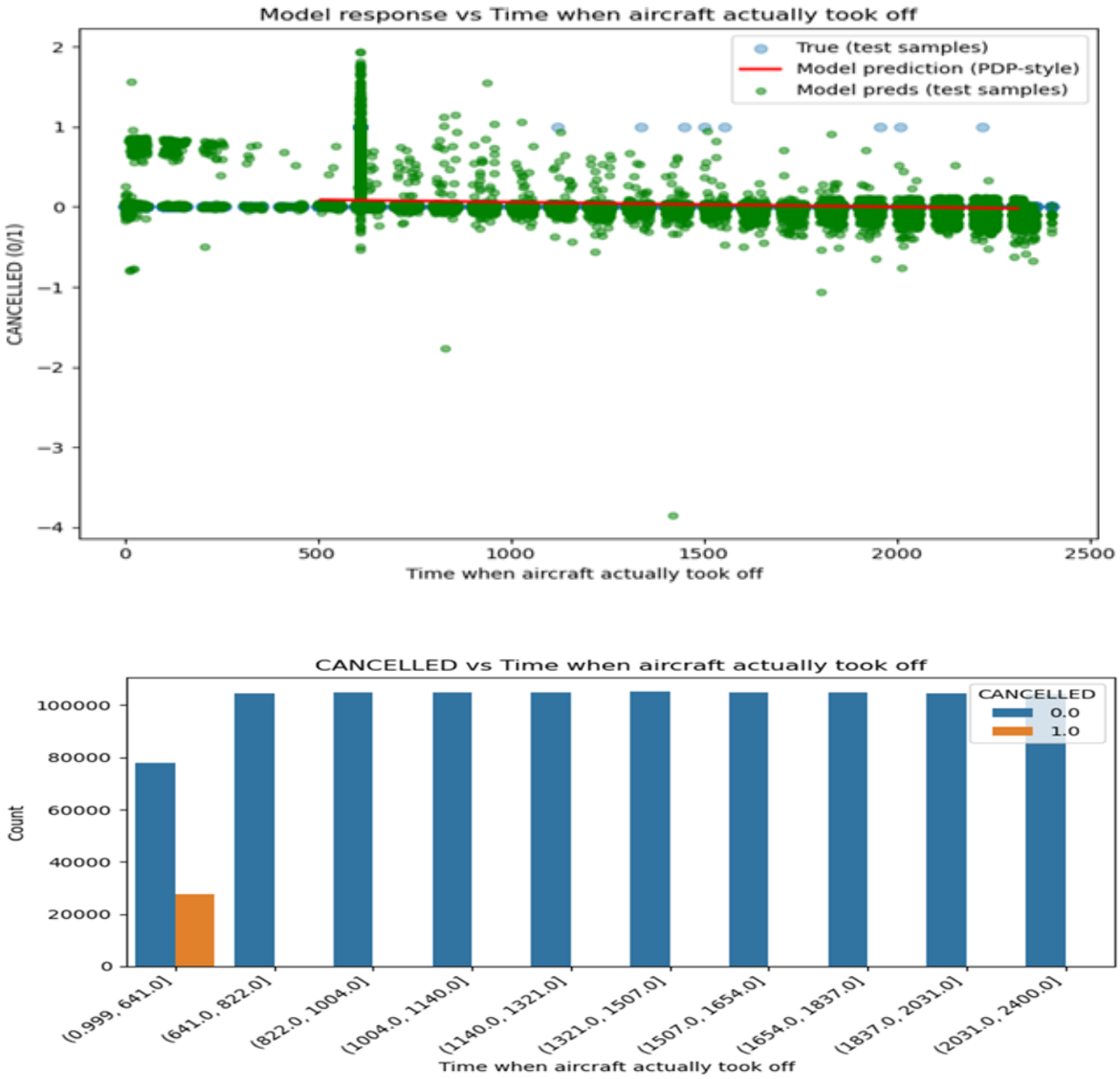
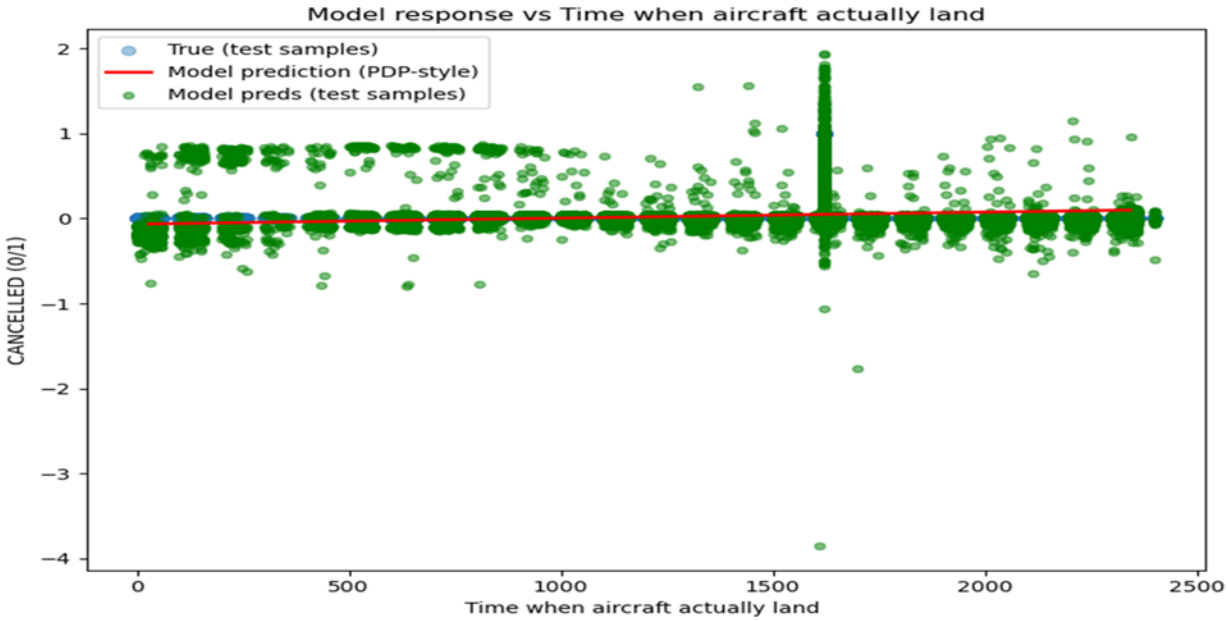


Figure 10: Time when aircraft actually took off

The two plots reveal a critical mismatch between real-world flight cancellation patterns and model predictions. The bar chart shows that cancellations are heavily concentrated in the earliest actual takeoff window — specifically between 1 AM and 6:41 AM (0.999 to 641 minutes), with negligible cancellations in all subsequent time bins, indicating a strong operational vulnerability during the pre-dawn hours likely due to overnight disruptions, crew availability, or cascading delays. However, the scatter plot of model response versus actual takeoff time reveals that while true cancellations (blue dots) cluster sharply in this early window, the model's predictions (green dots) show high variability but a flat average trend (red PDP line), failing to capture this key signal. Rather, the model assigns comparable cancellation probability over the majority of the day, indicating that it overpredicts cancellations in later times when none occur and misses the crucial temporal pattern. This suggests that, despite the obvious real-world signal present in the raw data, the model does not learn the genuine relationship between actual takeoff time and cancelation probability. This could be the result of overfitting, feature engineering restrictions, or data imbalance, and it leads to low forecast accuracy.



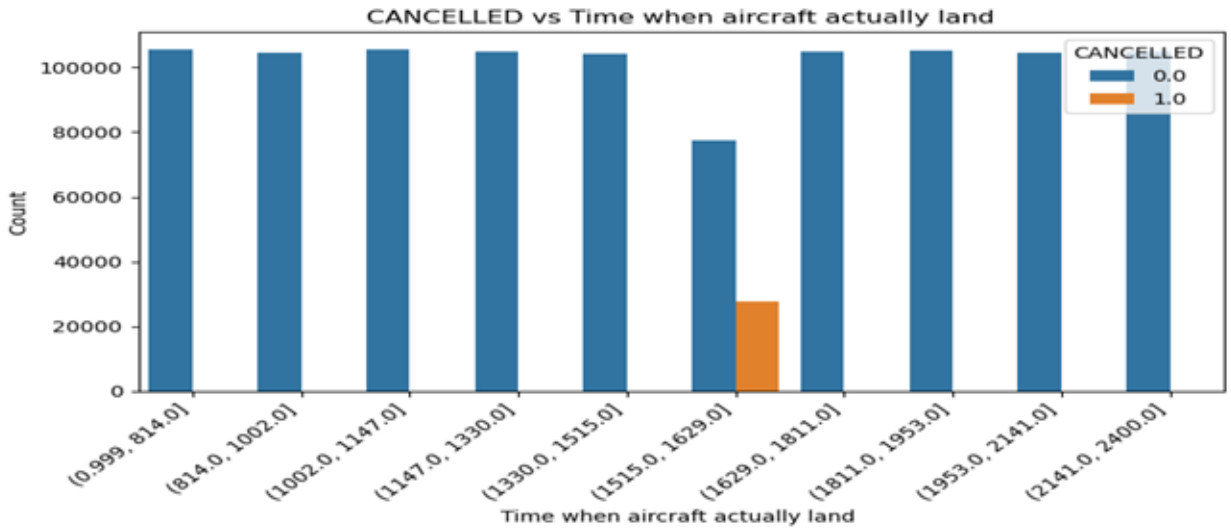


Figure 11: Time when aircraft actually land

The two plots reveal a critical pattern in flight cancellations and model performance. The bar chart shows that cancellations are concentrated in the 3:15 PM to 4:29 PM landing window (1515–1629 minutes), with a significant number of cancelled flights (orange bar) in this bin and negligible cancellations elsewhere, indicating a peak vulnerability during late afternoon hours — likely due to air traffic congestion, weather disruptions, or operational bottlenecks at destination airports. However, the scatter plot of model response versus actual landing time reveals a mismatch: while true cancellations (blue dots) cluster sharply in this window, the model's predictions (green dots) show high variability but a flat average trend (red PDP line), failing to capture this key signal. Rather, the model assigns comparable cancellation probability for the majority of the day, indicating that it overpredicts cancellations in other bins where none occur and misses the crucial temporal pattern. This suggests that, despite the obvious real-world signal present in the raw data, the model does not learn the correct relationship between actual landing time and cancelation risk, either as a result of feature engineering limits or data imbalance. This leads to poor forecast accuracy.

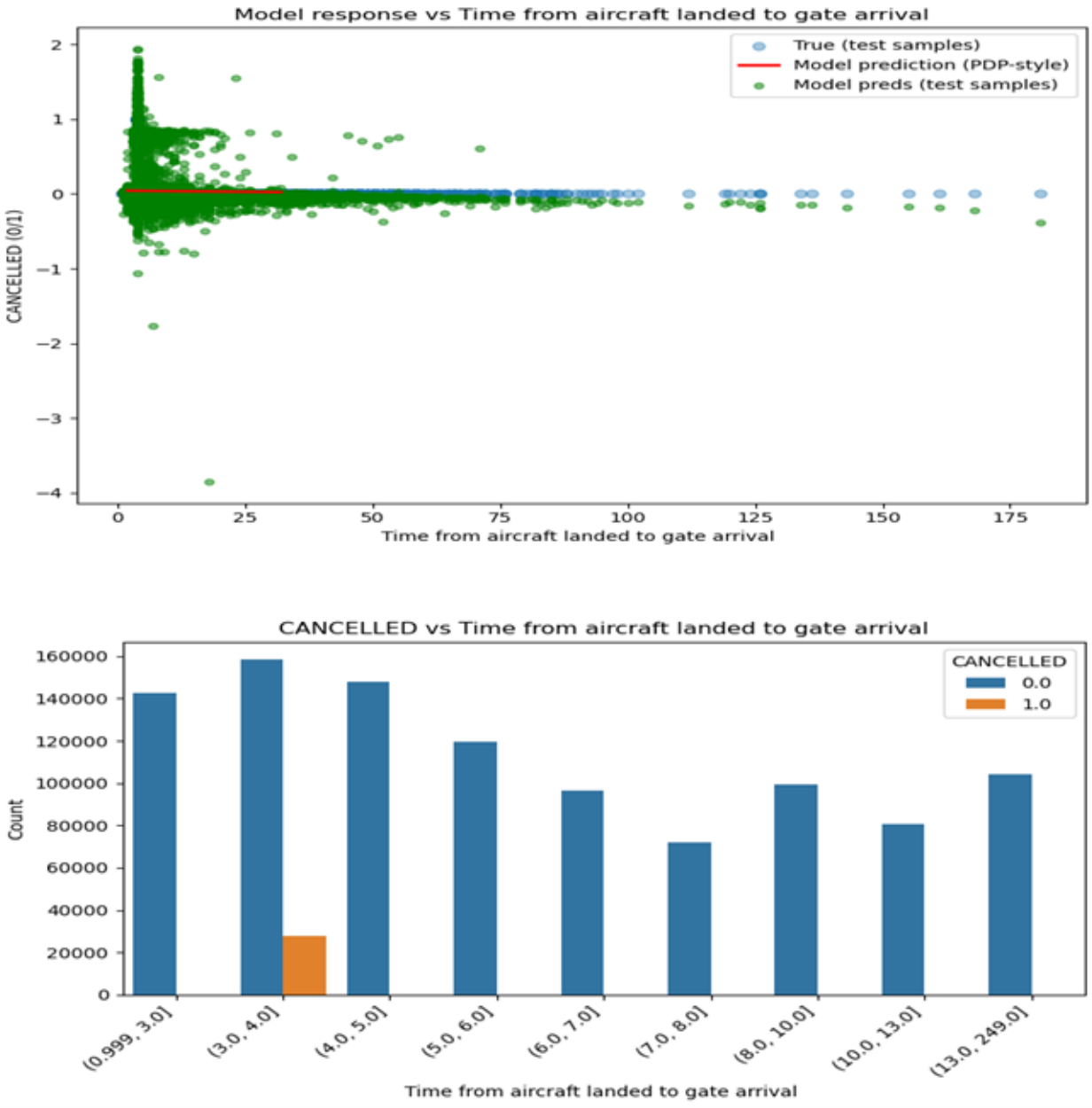


Figure 12: Time when aircraft actually land

The two plots reveal a critical insight into flight cancellation patterns and model performance. The bar chart shows that cancellations are concentrated in the 3–4 minute post-landing window, where a small number of flights (orange bar) were cancelled despite most being non-cancelled, suggesting a narrow operational threshold — possibly due to gate congestion, staffing issues, or scheduling conflicts — where extremely rapid turnaround times trigger cancellation decisions. However, the scatter plot of model response versus time from landing to gate arrival reveals a mismatch: while true cancellations (blue dots) cluster sharply at around 3–4 minutes, the model's predictions (green dots) show high variability but a flat average trend (red PDP line), failing to capture this key signal.

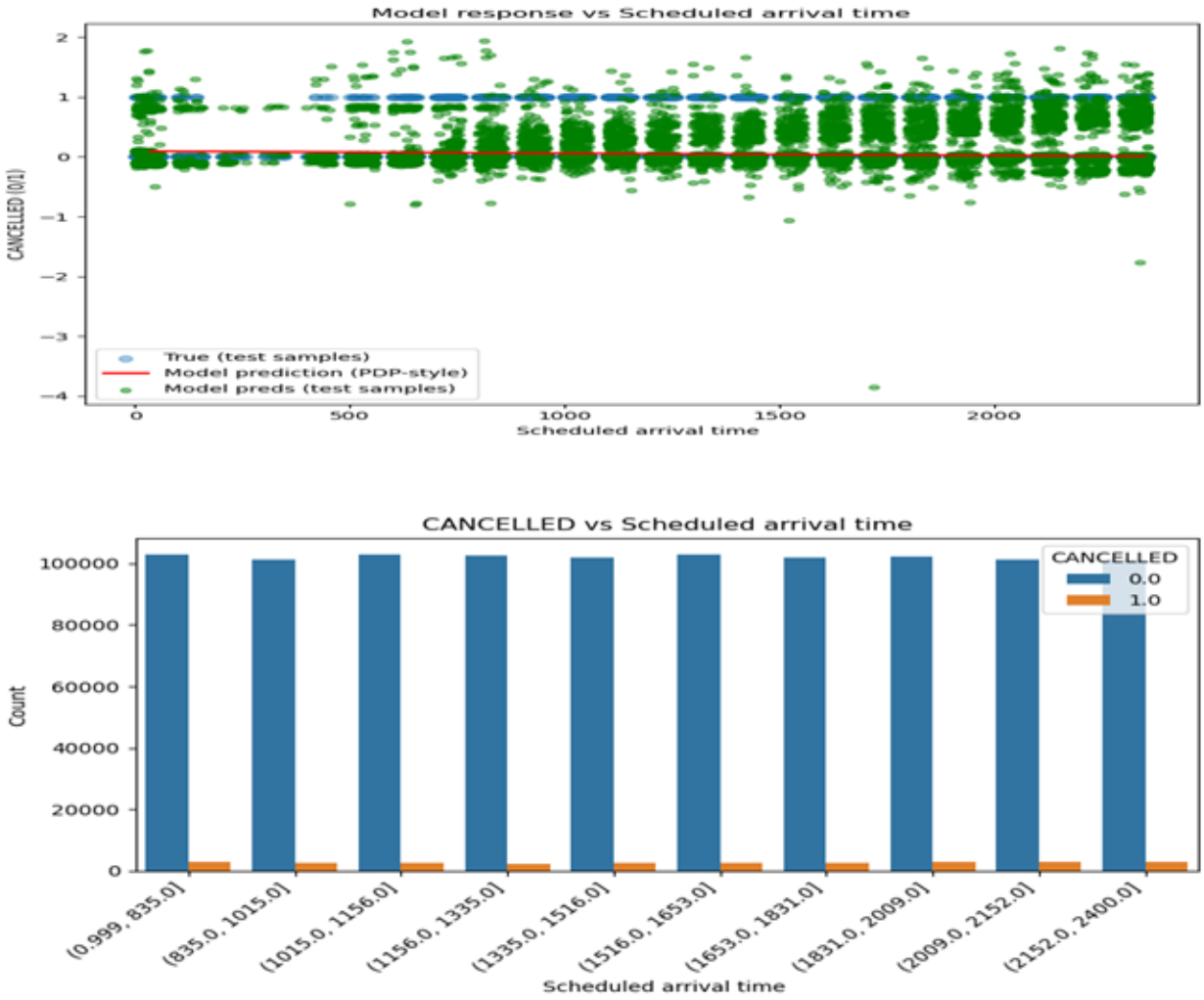


Figure 13: Time when aircraft was scheduled

The two plots reveal a critical pattern between real-world flight cancellation patterns and model performance. The bar chart shows that cancellations are uniformly rare across all scheduled arrival times, from 1 AM (0.999) to midnight (2400), with no significant clustering by time of day — indicating that cancellation risk is not strongly tied to when a flight is scheduled to arrive. However, the scatter plot of model response versus scheduled arrival time reveals a stark discrepancy: while true cancellations (blue dots) are sparse and evenly distributed, the model's predictions (green dots) show high variability and a flat average trend (red PDP line).

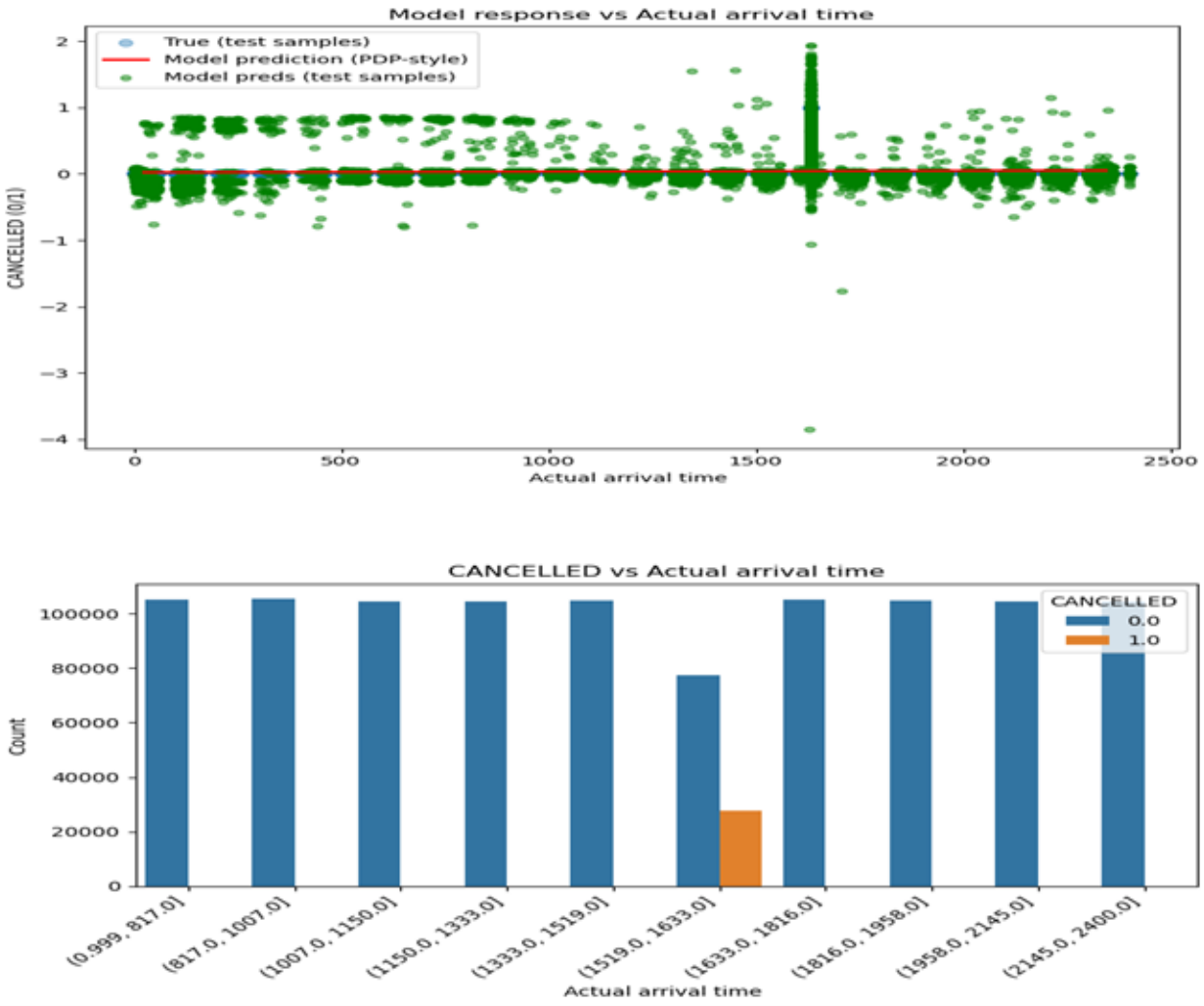
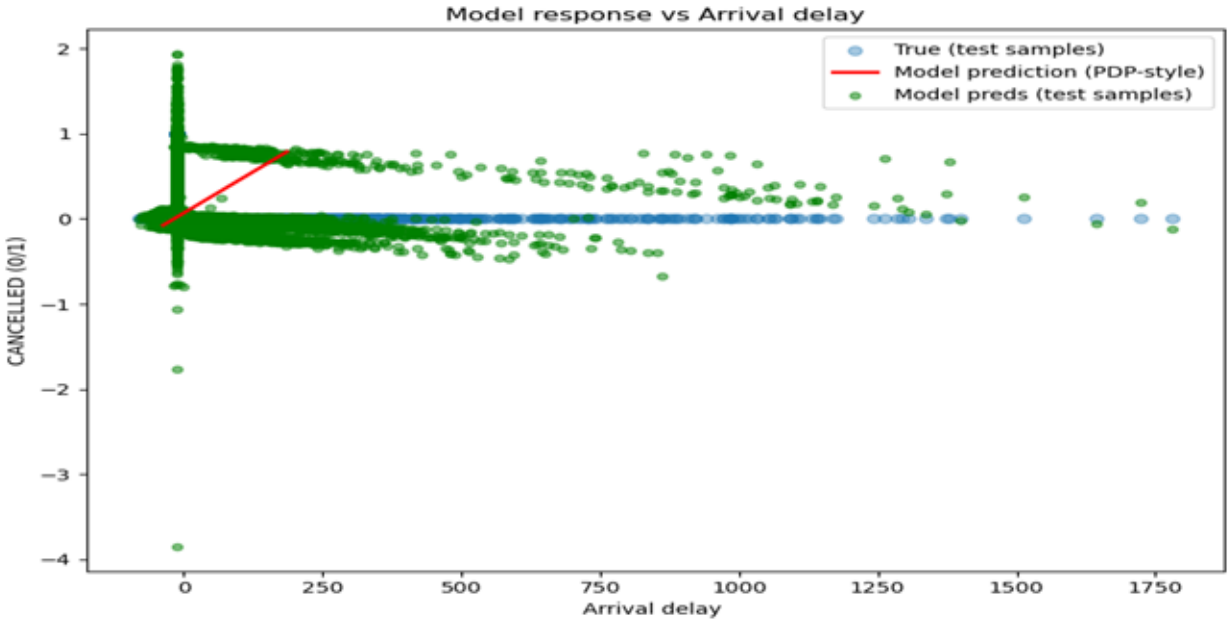


Figure 14: Time when aircraft arrived

The two figures show a crucial correlation between model performance and actual flight cancelation patterns. The bar chart indicates a high operational vulnerability during the pre-dawn hours, most likely because of overnight disruptions, crew availability, or cascading delays. Cancellations are concentrated in the earliest actual departure window, specifically between 1 AM and 6:28 AM (0.999 to 628 minutes), with negligible cancellations in all subsequent time bins. The model's predictions (green dots) exhibit high variability but a flat average trend (red PDP line), failing to capture this crucial signal. In contrast, true cancellations (blue dots) cluster sharply in this early window, as shown in the scatter plot of model response versus actual arrival time.



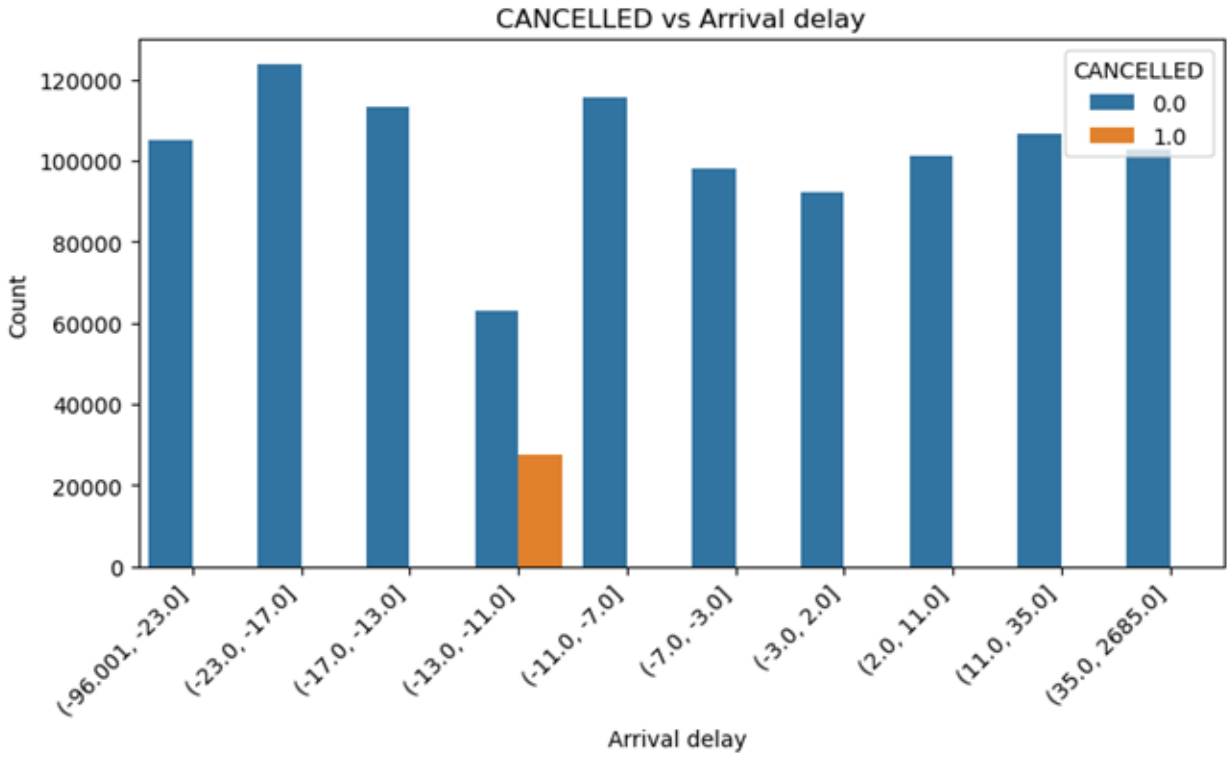
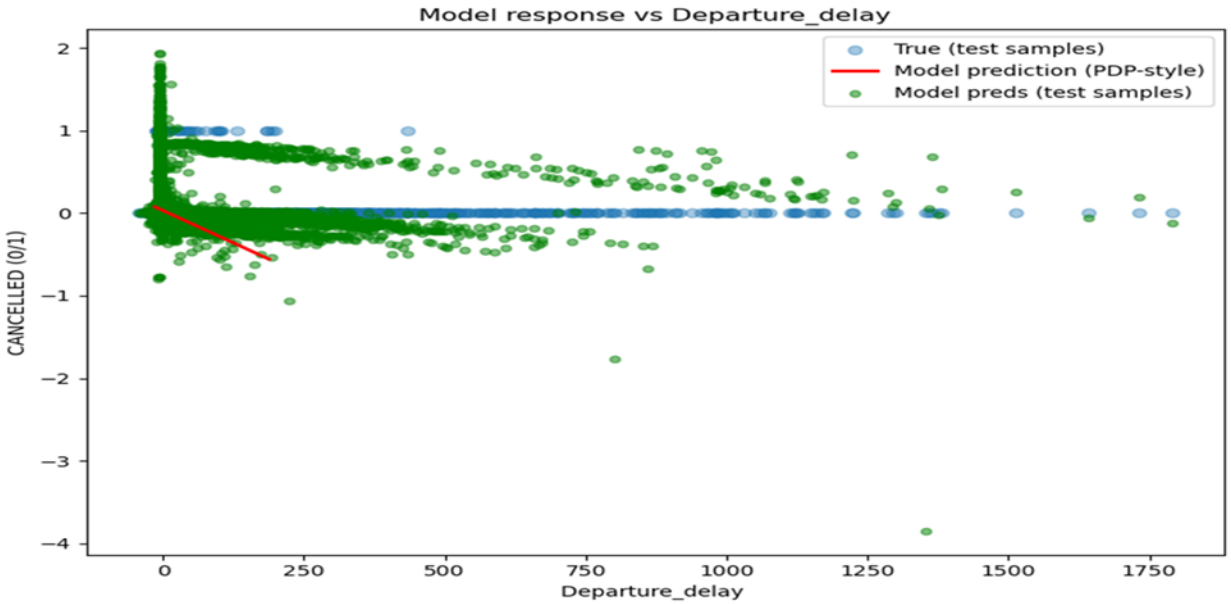


Figure 15: Arrival delay

The first plot shows the correlation between flight cancellation status (coded as 0 or 1) and arrival delay (in minutes), where positive values indicate early arrivals and negative values indicate late arrivals. The blue dots show the actual cancelation labels, and the green dots show model predictions on test samples. The model forecasts a higher cancellation likelihood for planes arriving severely late (negative delays), particularly

around -20 to -10 minutes, when the prediction peaks, as indicated by the red line, which displays the algorithm's projected reaction in a PDP-style format. The model may overpredict cancellations for flights with moderate delays, though, as the majority of actual cancellations (blue dots) are located close to zero or slightly negative delays. The distribution of canceled (orange) and non-canceled (blue) flights across various arrival delay bins is displayed in the second bar chart. Although they are uncommon overall, cancellations are most common in the bin (-13.0, -11.0), indicating that planes that arrive roughly 12 minutes late are more likely to be canceled, perhaps as a result of operational limitations or scheduling restrictions. Regardless of delay, most flights are not canceled, and the biggest numbers of cancellations occur during moderate to significant negative delays, which represents typical late arrivals without cancellation.



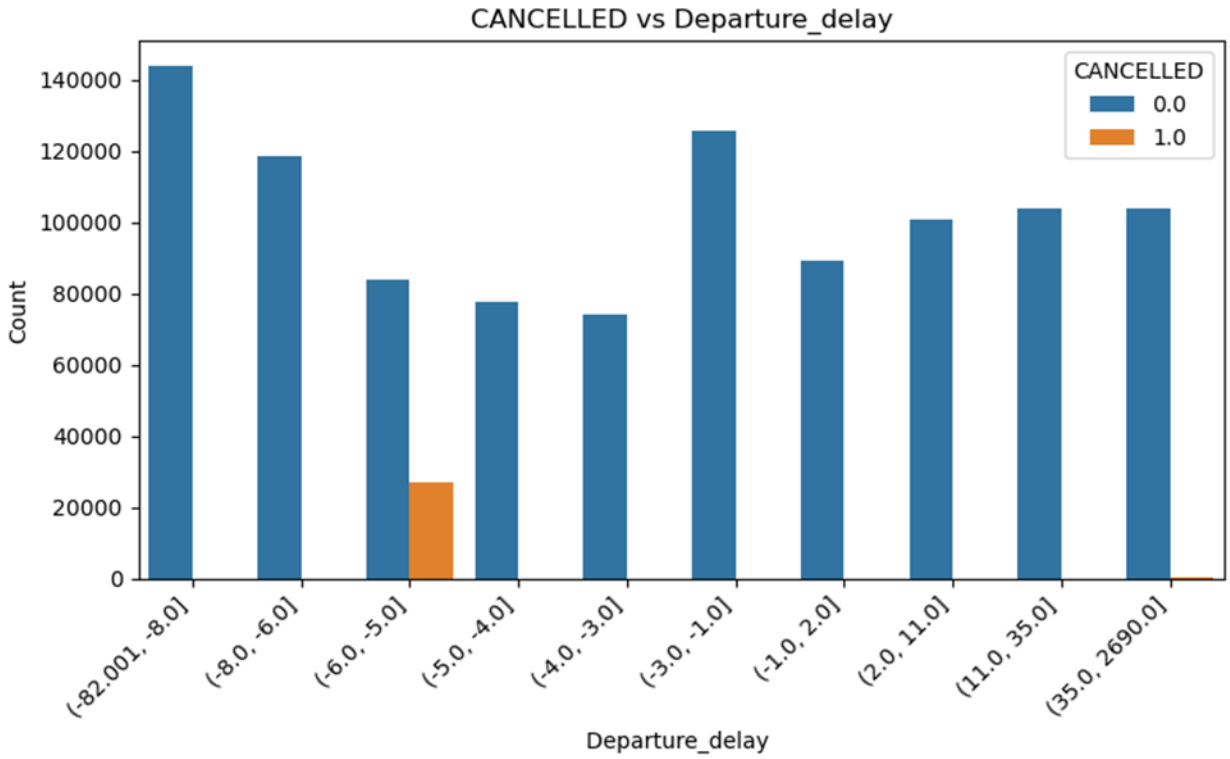
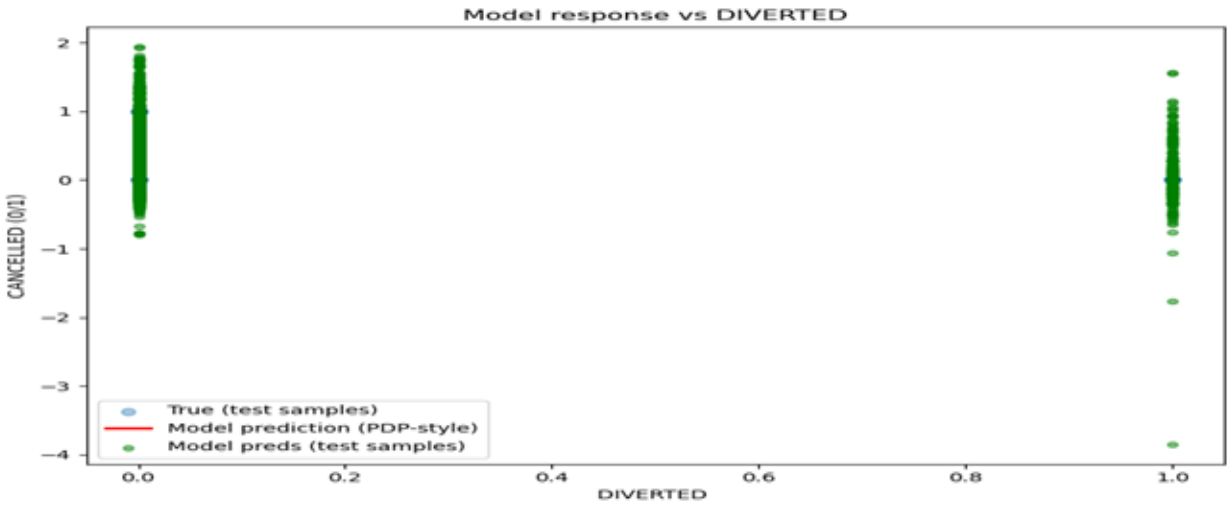


Figure 16: Departure delay

The two plots reveal a critical pattern between real-world flight cancellation patterns and model performance. The bar chart shows that cancellations are heavily concentrated in the earliest actual departure window — specifically between 1 AM and 6:28 AM (0.999 to 628 minutes), with negligible cancellations in all subsequent time bins, indicating a strong operational vulnerability during the pre-dawn hours likely due to overnight disruptions, crew availability, or cascading delays. However, the scatter plot of model response versus actual arrival time reveals a stark discrepancy: while true cancellations (blue dots) cluster sharply in this early window, the model's predictions (green dots) show high variability but a flat average trend (red PDP line).



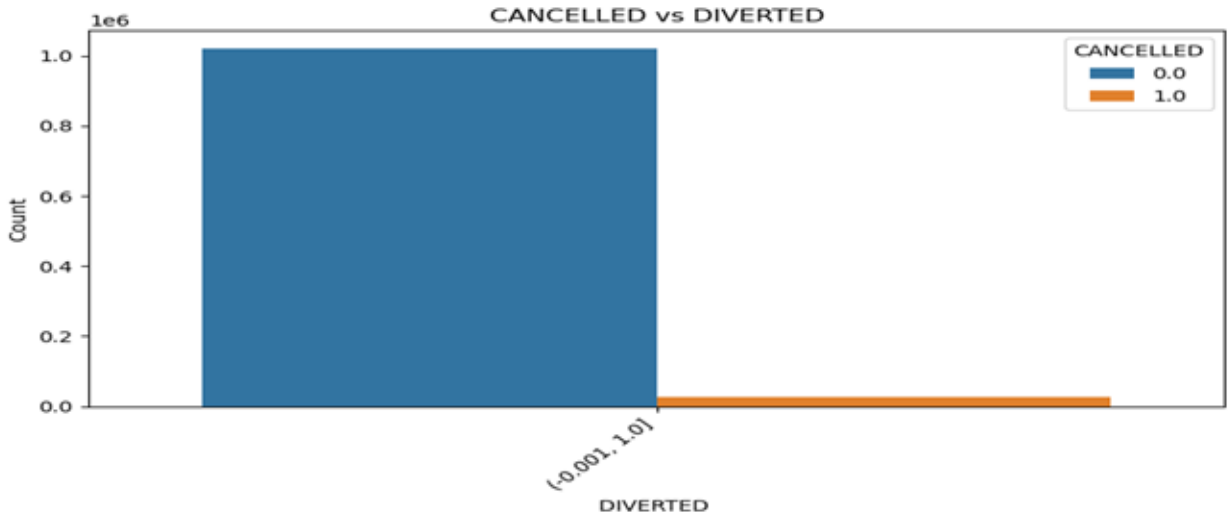
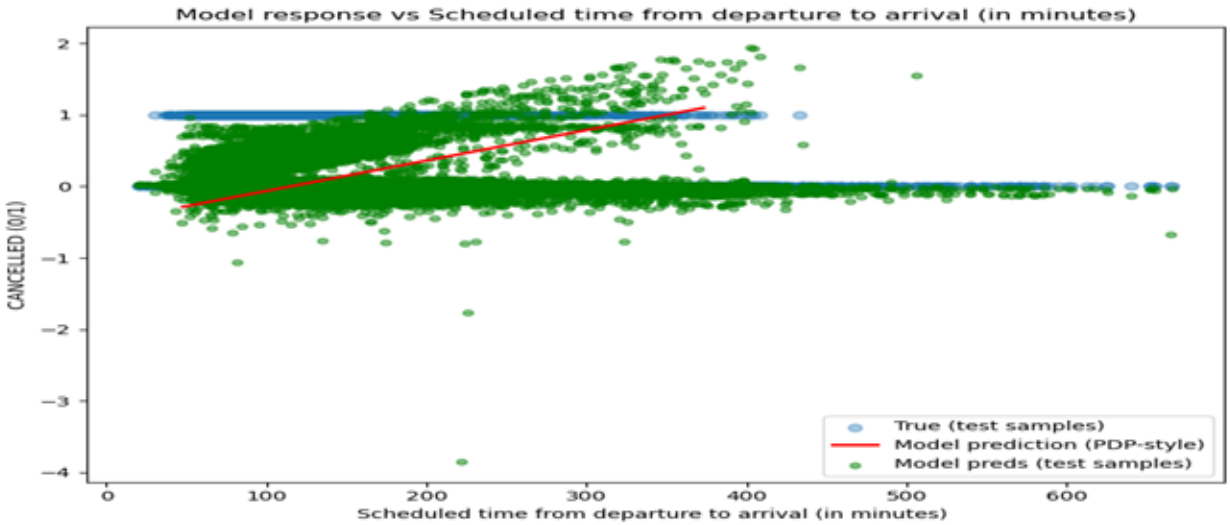


Figure 17: Diverted

The first plot displays the correlation between the model's prediction of cancellation (on the y-axis, with negative values suggesting late arrivals and positive values indicating early ones) and whether a flight was diverted (0 or 1 on the x-axis). The blue dots show actual cancelation labels, whereas the green dots show model predictions on test samples. The red line, which represents the model's PDP-style prediction, shows that flights that were diverted (DIVERTED = 1) exhibit a strong clustering around high cancellation predictions (CANCELLED 1), indicating that diversions are highly predictive of cancellations, while flights that were not diverted (DIVERTED = 0) are primarily associated with non-cancellations (CANCELLED 0).The distribution of canceled (orange) and non-canceled (blue) flights over the DIVERTED variable is shown in the second bar chart. Only a small percentage of flights that are diverted are canceled, whereas nearly all flights (more than 1 million) are not canceled when they are not diverted. This suggests that diversions are uncommon but closely associated with cancellations. This implies that even if flight cancellations are rare in general, they are more likely to occur when a flight is diverted.



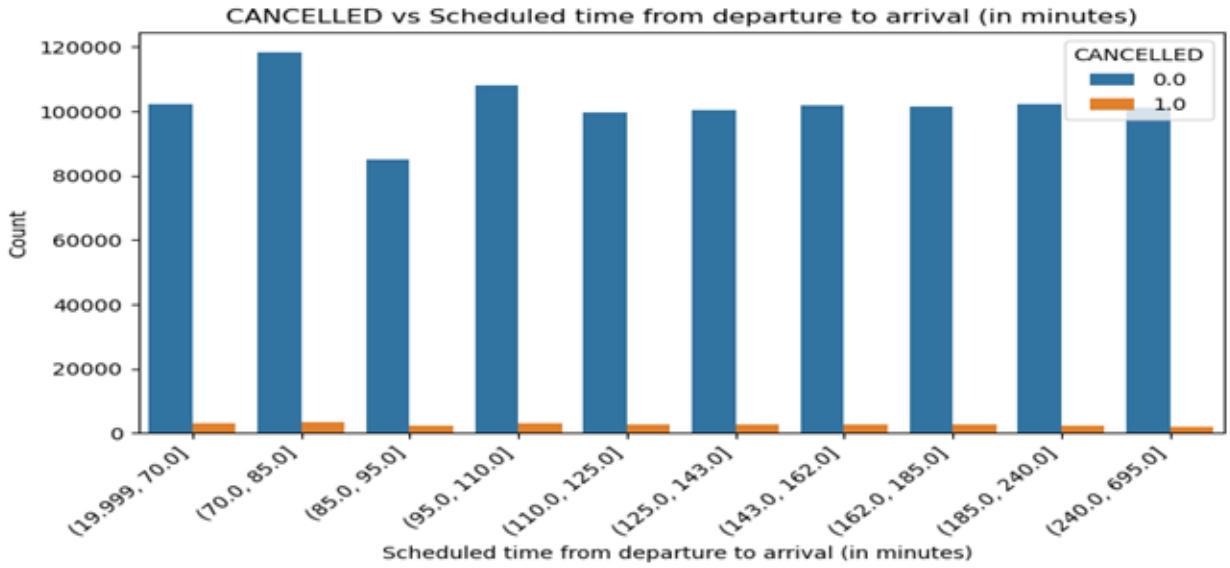
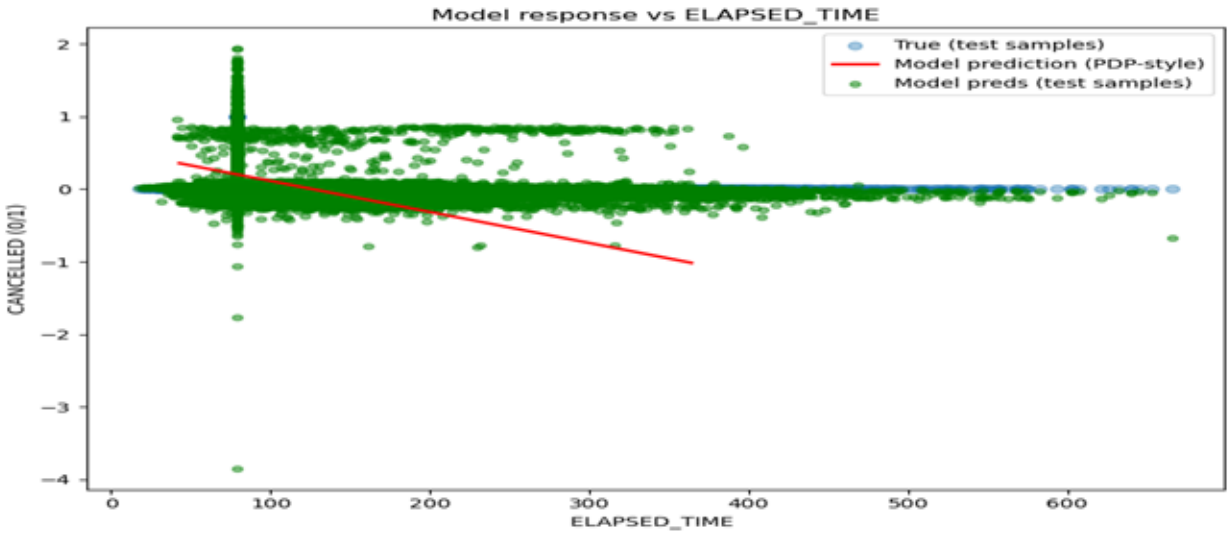


Figure 18: Scheduled time from departure to arrival

The distribution of canceled (orange) and non-canceled (blue) flights over various scheduled flight lengths, expressed in minutes from departure to arrival, is displayed in the first bar chart. With only a few cancellations (orange bars) in each duration bin—from about 20 to more than 695 minutes—the great majority of flights are not canceled (blue bars), suggesting that flight cancellation is rather uncommon across all duration bins. Although the total numbers are still modest, the percentage of cancellations seems to be significantly greater on shorter flights (such as those lasting 70 to 85 minutes). The model's reaction to the scheduled flight time is shown in the second plot, where the red line denotes the model's PDP-style prediction, the blue dots are actual cancellation labels, and the green dots reflect model predictions on test samples. The model indicates that lengthier flights may be more likely to be canceled, predicting a modest rise in cancellation chance as scheduled flight time increases, especially for trips longer than 300 minutes. Although the model identifies a weak trend, real-world cancellations are more driven by other factors than scheduled duration alone, as evidenced by the scarce and weakly associated actual cancellations (blue dots) with flight duration.



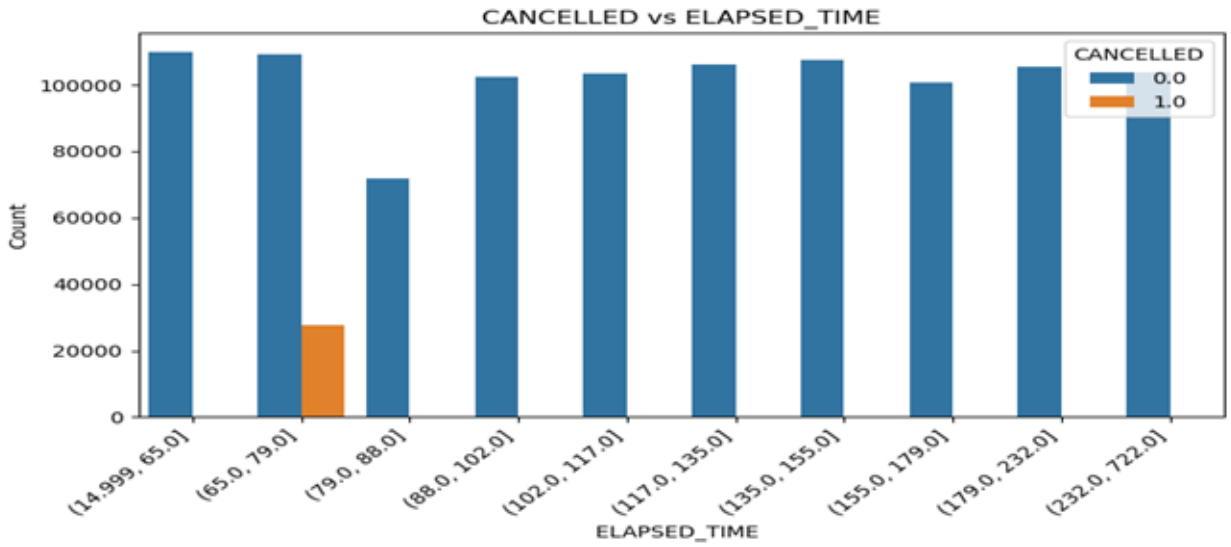


Figure 19: Elapsed time

The first plot shows the relationship between elapsed flight time (in minutes) and the model's prediction of cancellation (CANCELLED, coded as 0/1), with negative values indicating late arrivals and positive values early ones. The green dots represent model predictions on test samples, while blue dots indicate true cancellation labels. The red line, representing the model's PDP-style prediction, reveals a decreasing trend: as elapsed time increases, the model predicts a higher likelihood of cancellation, suggesting that longer-than-scheduled flights are more likely to be canceled. However, actual cancellations (blue dots) are sparse and concentrated at shorter elapsed times, indicating that while the model detects a pattern, real-world cancellations are not strongly tied to elapsed time alone. The second bar chart displays the distribution of canceled (orange) and non-canceled (blue) flights across elapsed time bins. Most flights are not canceled (blue bars dominate), but the highest number of cancellations occurs in the bin [79.0, 88.0], where elapsed time is slightly above the scheduled duration. This suggests that minor delays—around 80–88 minutes—may trigger cancellations, possibly due to operational thresholds or scheduling constraints, though overall cancellations remain rare. Together, the plots suggest that while the model associates longer elapsed times with higher cancellation risk, actual cancellations cluster around specific short delay ranges, highlighting a potential mismatch between model assumptions and real-world behavior.

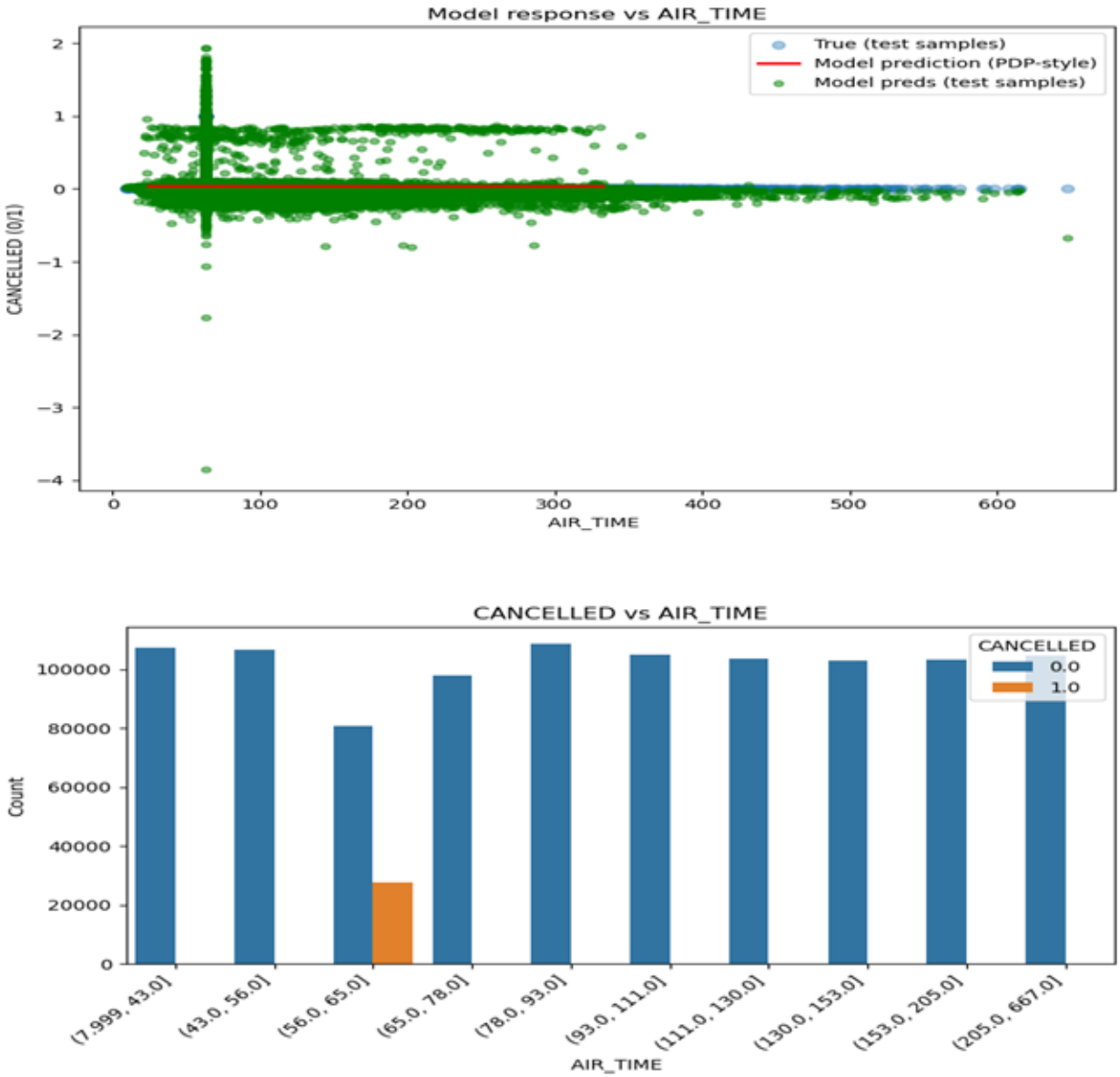


Figure 20: AIR time

The distribution of canceled (orange) and non-canceled (blue) flights over various air time bins, expressed in minutes, is displayed in the first bar chart. Only a noticeable increase in cancellations occurs in the [56.0, 65.0] minute bin, where the orange bar is noticeably taller than in other intervals. The great majority of flights are not canceled (blue bars). This implies that flights that last between 56 and 65 minutes are more likely to be canceled than other flights, maybe as a result of operational limitations or inefficient scheduling for short-haul flights. The model's response to air time is shown in the second plot, where the red line indicates the model's PDP-style prediction, the blue dots are real cancellation labels, and the green dots reflect model predictions on test samples.The model predicts nearly constant cancellation likelihood across all air times, as reflected by the flat red line near zero, suggesting it does not strongly associate air time with cancellation risk. However, actual cancellations (blue dots) are sparse and concentrated at low air times, consistent with the bar chart. This indicates that while the model fails to capture the observed peak in cancellations around 56–65 minutes, real-world data reveals a specific vulnerability in this air time range,

highlighting a potential limitation in the model's ability to learn nuanced patterns related to flight duration.

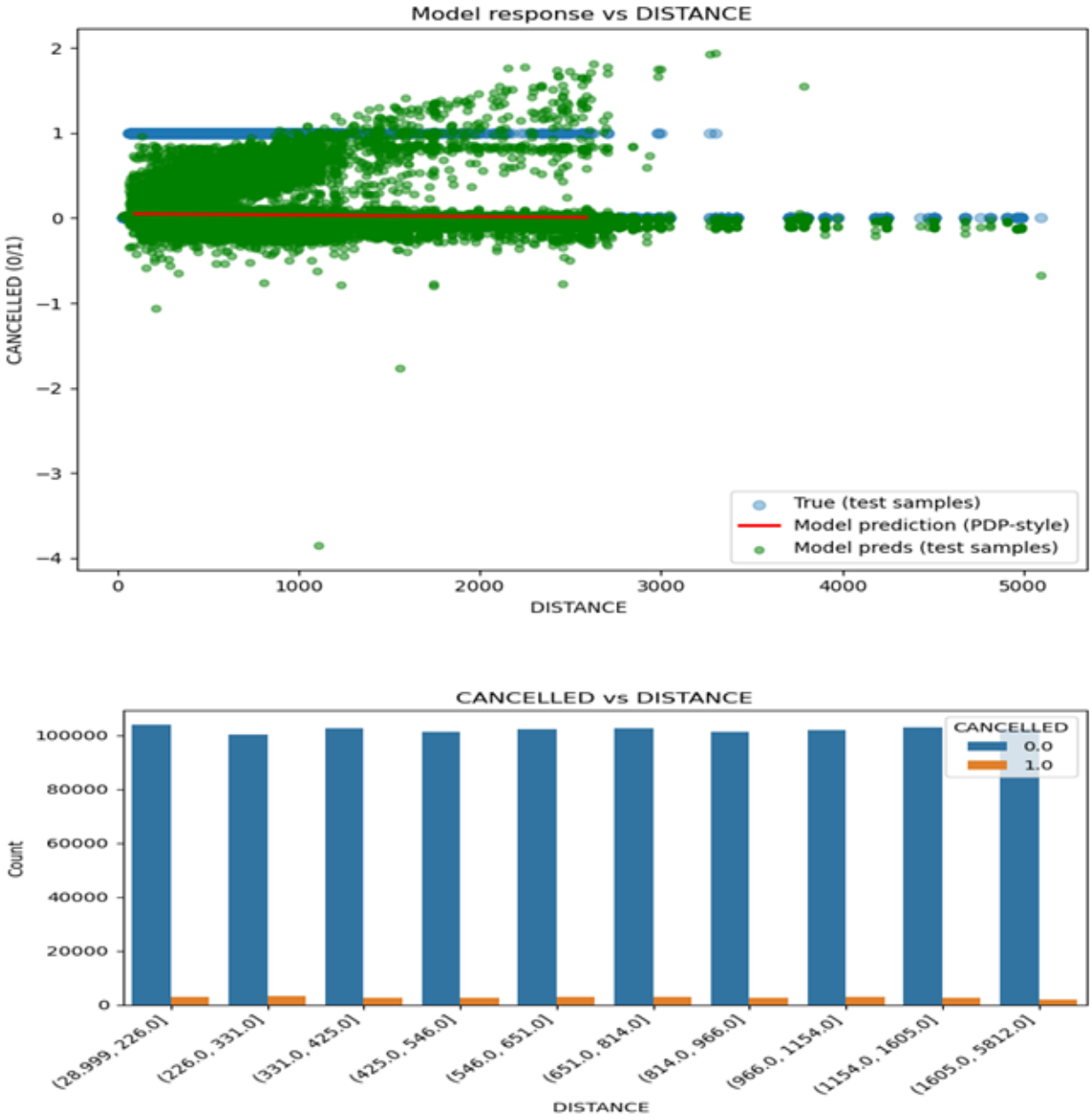


Figure 21: Distance

The first plot shows the relationship between flight distance and the model's prediction of cancellation (CANCELLED, coded as 0/1), with green dots representing model predictions on test samples, blue dots indicating true cancellation labels, and the red line showing the model's PDP-style prediction. The model predicts a nearly flat response across distances, suggesting that distance alone is not a strong predictor of cancellation, as reflected by the horizontal red line near zero. However, actual cancellations (blue dots) are sparse but appear more frequently at shorter distances (¡1000 miles), where there is some clustering of higher predicted cancellation scores. The distribution of canceled (orange) and non-canceled (blue) flights over distance bins is shown in the second bar chart. There are very few cancellations in any bin, and the

great majority of flights are not canceled across all distance ranges (blue bars predominate). Significantly, shorter-distance flights seem to have a significantly greater percentage of cancellations, especially in the [28.999, 226.0] and [226.0, 331.0] bins. This could be due to scheduling or operational difficulties for short-haul flights. Though cancellations are still uncommon overall, the plots collectively imply that although the model does not strongly link distance to cancellation risk, real-world data shows a subtle trend where shorter flights are marginally more likely to be canceled, perhaps as a result of factors like airport congestion or route complexity.

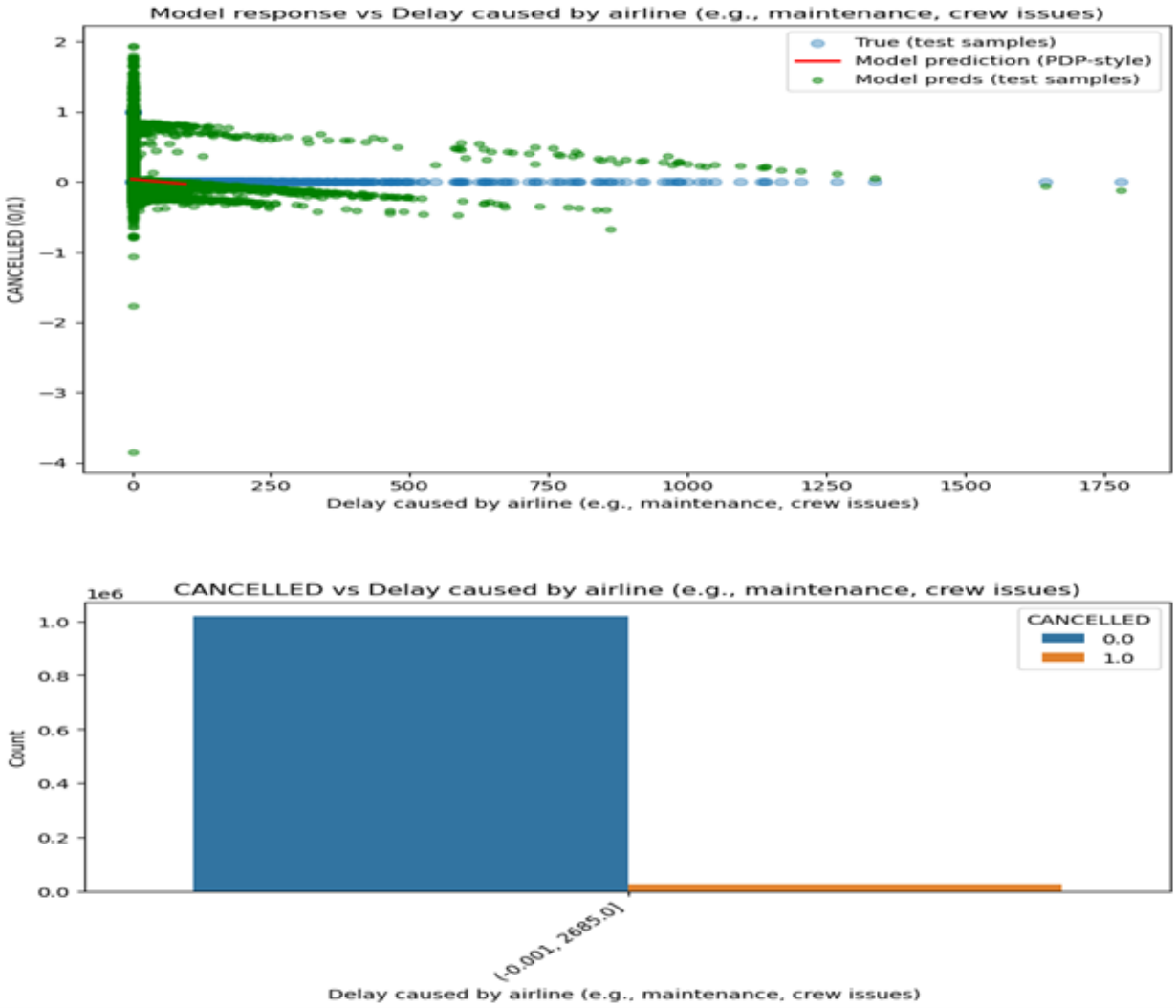


Figure 22: Delay caused by airline

Based on delays brought on by airline variables like crew problems or maintenance, the first bar chart displays the distribution of canceled (orange) and non-canceled (blue) flights; early arrivals are represented by positive values, and late arrivals by negative values. While airline-caused delays are widespread, they seldom lead to cancellations, as evidenced by the large number of flights that are not canceled (blue bar) and the very small number that are canceled (orange bar). The model's reaction to these delays is seen in the second plot, where the red line represents the model's PDP-style prediction, the blue dots are actual cancellation labels, and the green dots represent model predictions. Although real cancellations (blue dots) are rare and usually happen at low to moderate delays, especially around 0–100 minutes, the model forecasts

a higher risk of cancellations for flights with little to no delay (about 0 minutes). Accordingly, real-world cancellations associated with airline delays are rare and tend to cluster close to the beginning of such delays, which may be a reflection of operational thresholds or schedule modifications, even though the model may exaggerate cancellation probability during extremely small delays. Overall, the data suggest that airline-caused delays are not strongly predictive of cancellations, but when cancellations do occur, they are more likely to happen when delays are just beginning, rather than accumulating over time.

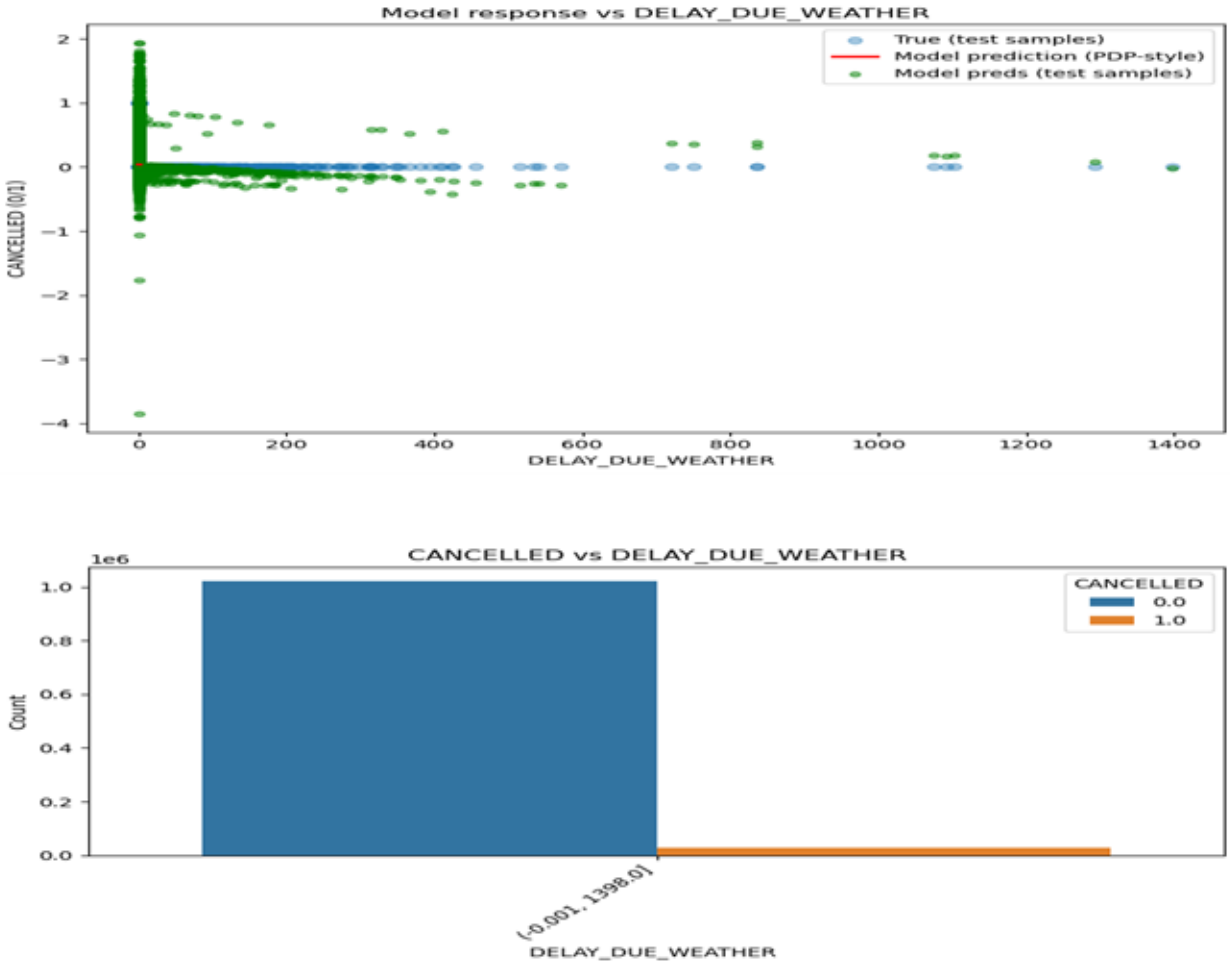


Figure 23: Delay caused by weather

The first plot shows the relationship between weather-related delays (in minutes, with negative values indicating late arrivals and positive values early arrivals) and flight cancellation predictions. The green dots represent model predictions on test samples, blue dots indicate true cancellation labels, and the red line shows the model's PDP-style prediction. The model predicts a slight increase in cancellation likelihood for flights with minimal or no weather delay, but actual cancellations (blue dots) are sparse and mostly occur at low to moderate delays (0–200 minutes), suggesting that even small weather disruptions can trigger cancellations. The second bar chart displays the distribution of canceled (orange) and non-canceled (blue) flights across weather delay bins. The vast majority of flights are not canceled (blue bar), with only a small fraction being canceled (orange bar), indicating that while weather delays are common, they rarely lead to cancellations. Together, the plots suggest that weather delays are not strongly predictive of cancellations overall, but when cancellations do occur, they tend to happen during minor to moderate weather-related

delays, possibly due to operational thresholds or safety protocols. The model captures some of this trend but underestimates the real-world concentration of cancellations at low delay values.

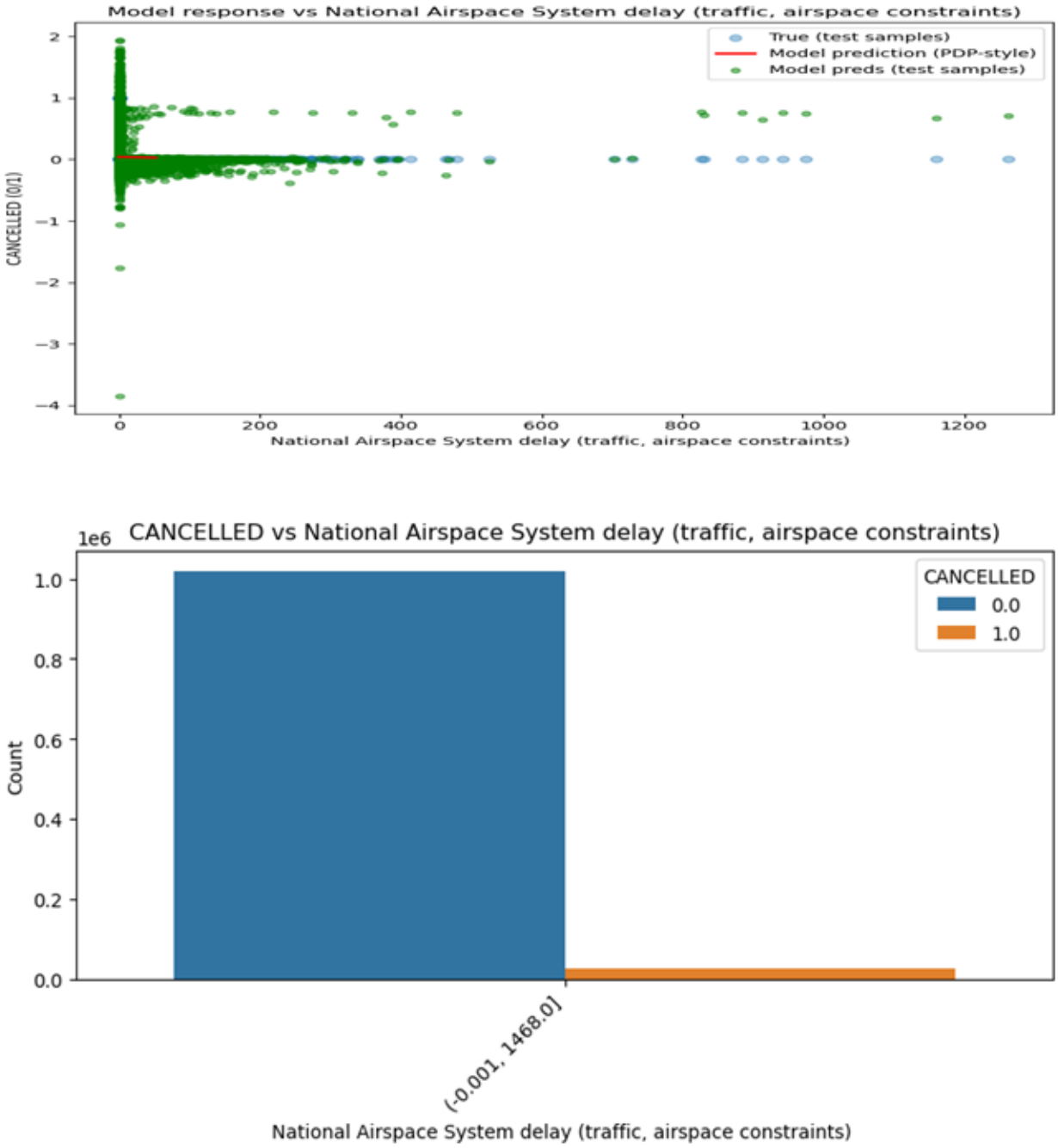


Figure 24: National airspace system delay

The first bar chart shows the distribution of canceled (orange) and non-canceled (blue) flights based on National Airspace System (NAS) delays, which include traffic and airspace constraints. The vast majority of flights are not canceled (blue bar), with only a small number of cancellations (orange bar), indicating that NAS delays, even when present, rarely result in flight cancellations. The second plot displays the model's response to NAS delay, where green dots represent model predictions on test samples, blue dots indicate

true cancellation labels, and the red line shows the model's PDP-style prediction. The model predicts a slight increase in cancellation likelihood for flights with minimal or no NAS delay, but actual cancellations (blue dots) are sparse and mostly occur at low to moderate delays (0–200 minutes), suggesting that minor disruptions in air traffic or airspace constraints may trigger cancellations. However, the model underestimates this trend, as its prediction remains nearly flat across delay values. Overall, while NAS delays are common, they are not strongly associated with cancellations, and when cancellations do occur, they tend to happen during short-to-moderate delays, possibly due to operational bottlenecks or scheduling adjustments. The model fails to fully capture this real-world pattern, highlighting a potential limitation in its ability to learn from such data.

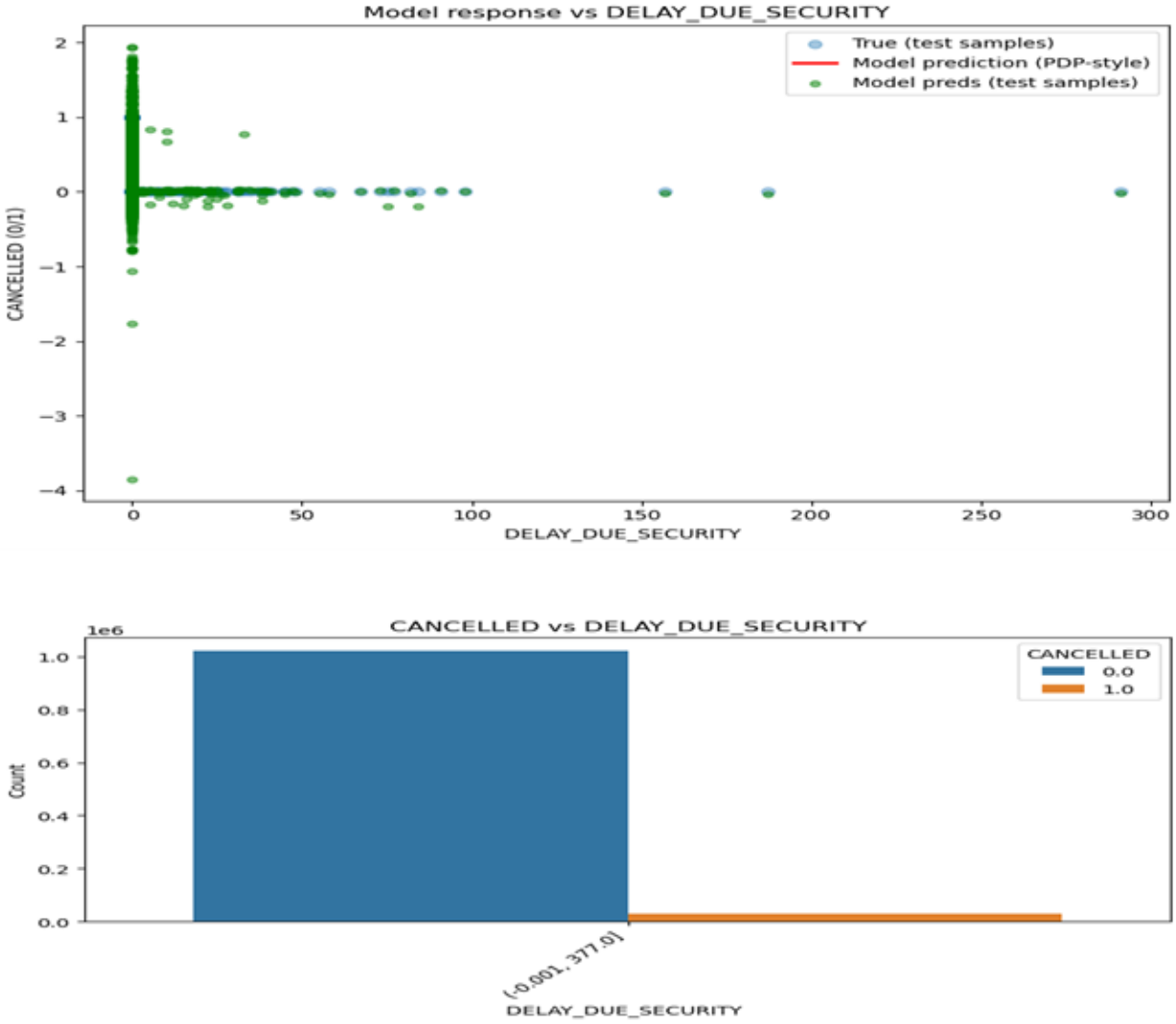


Figure 25: Secutity system delay

The first plot displays the correlation between flight cancelation forecasts and security-related delays (measured in minutes, where positive values indicate early arrivals and negative values indicate late arrivals). The red line displays the model's PDP-style prediction, the blue dots reflect true cancellation labels, and the green dots show model predictions on test samples. Although actual cancellations (blue dots) are rare and primarily occur at low to moderate delays (0–50 minutes), the model predicts a tiny increase in cancellation

likelihood for flights with minimum or no security delay, indicating that even minor security disruptions can result in cancellations.The distribution of canceled (orange) and non-canceled (blue) flights across security delay bins is shown in the second bar chart. Although security delays are frequent, they hardly ever lead to flight cancellations, as evidenced by the large percentage of flights that are not canceled (blue bar) and the tiny percentage that are (orange bar). When taken as a whole, the plots indicate that security delays do not significantly predict cancellations overall, but when they do, they typically occur during brief delays, perhaps as a result of scheduling changes or operational limitations. The real-world concentration of cancellations at low delay values is underestimated by the model, although it does capture some of this pattern.

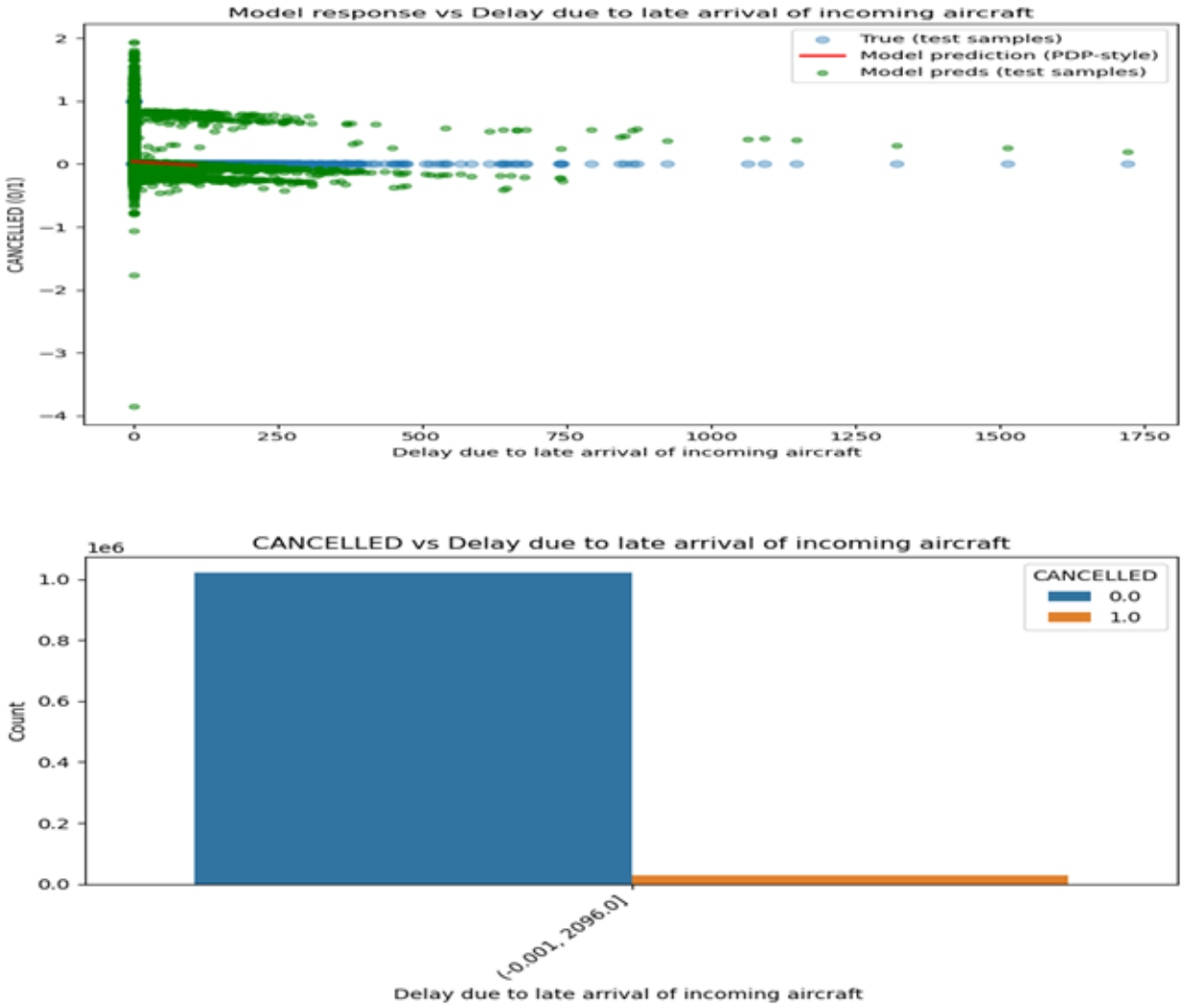


Figure 26: Delay due to late arrival of incoming aircraft

Based on delays brought on by inbound aircraft arriving late, the first bar chart displays the distribution of canceled (orange) and non-canceled (blue) flights; early arrivals are represented by positive values, and late arrivals by negative values. Although such delays are frequent, they seldom ever result in flight cancellations, as evidenced by the large number of flights that are not canceled (blue bar) and the relatively small number that are (orange bar). The model's reaction to these delays is seen in the second plot, where the red line represents the model's PDP-style prediction, the blue dots represent actual cancellation labels, and the green dots reflect model predictions on test samples. Although actual cancellations (blue dots) are

rare and primarily occur at low to moderate delays (0–200 minutes), the model predicts a slight increase in cancellation likelihood for flights with minimal or no delay. This suggests that minor disruptions in incoming aircraft schedules may cause cancellations. However, because the model's forecast is almost constant across delay levels, it understates this trend.Overall, while delays due to late-arriving aircraft are frequent, they are not strongly associated with cancellations, and when cancellations do occur, they tend to happen during short-to-moderate delays, possibly due to operational bottlenecks or scheduling constraints.

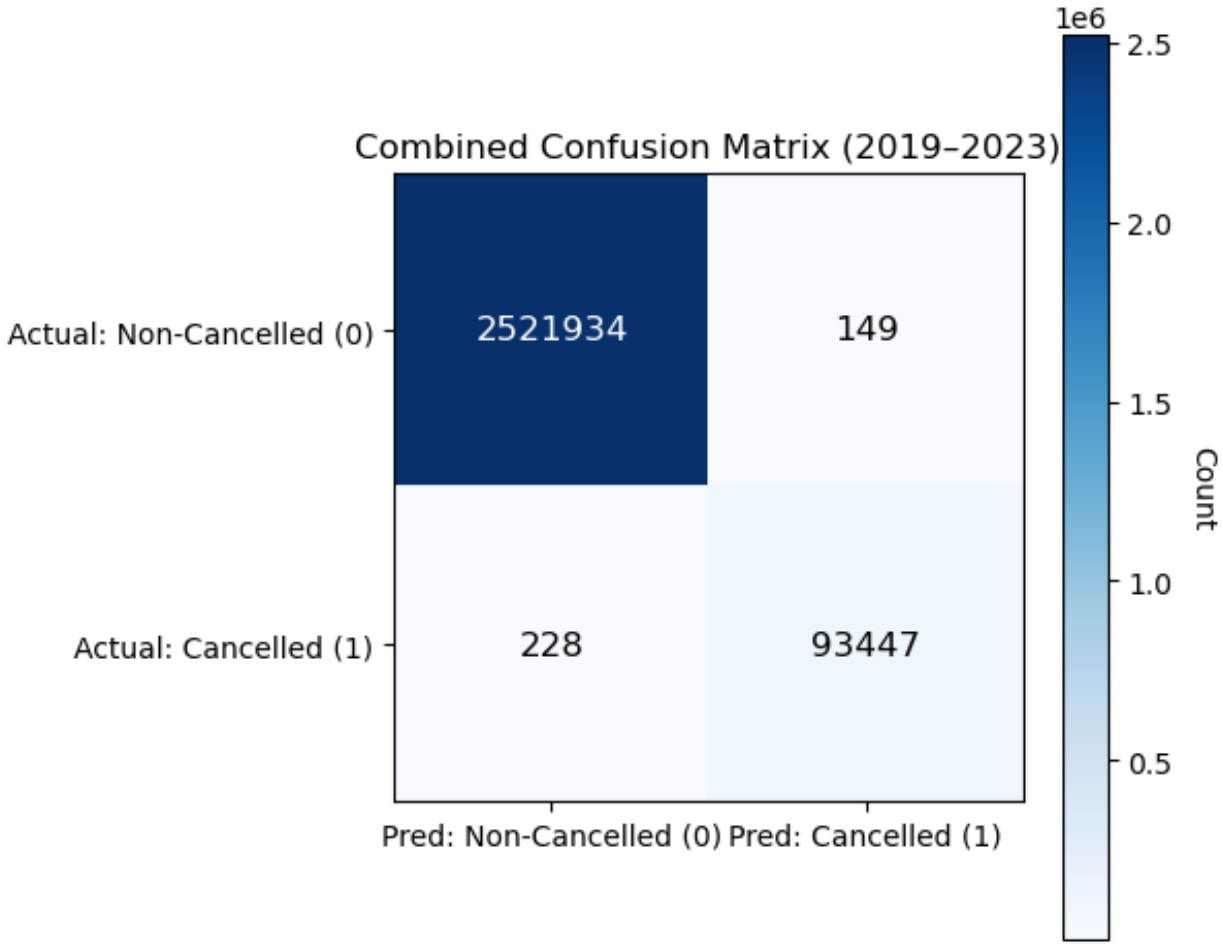


Figure 27: Confusion matrix of sparse regression

This sparse model feature selection—shows very strong overall performance in predicting flight cancellations from 2019–2023, correctly identifying 2,521,934 non-cancelled flights and 93,447 cancellations while producing 149 false positives and 228 false negatives out of 2.6 million cases. It achieves high overall accuracy (99.9886%), but more importantly maintains solid minority-class performance with precision of about 0.99841, recall of 0.99756, and an F1-score near 0.99798, indicating reliable detection of cancellations despite increased sparsity. Specificity is nearly perfect (0.99994), and the negative predictive value remains extremely high (0.99991), meaning "non-cancelled" predictions are almost always correct. However, compared with denser models, this version shows a slightly higher miss rate (0.243%) and a higher false alarm rate, reflected in a modestly lower MCC of 0.9968 and balanced accuracy of 0.99875. These results suggest that while the sparse (Lasso-style) approach offers greater simplicity and interpretability, it likely sacrifices some predictive signal by shrinking certain features to zero, making it a reasonable trade-off for transparency but less ideal

if minimizing missed cancellations is operationally critical.

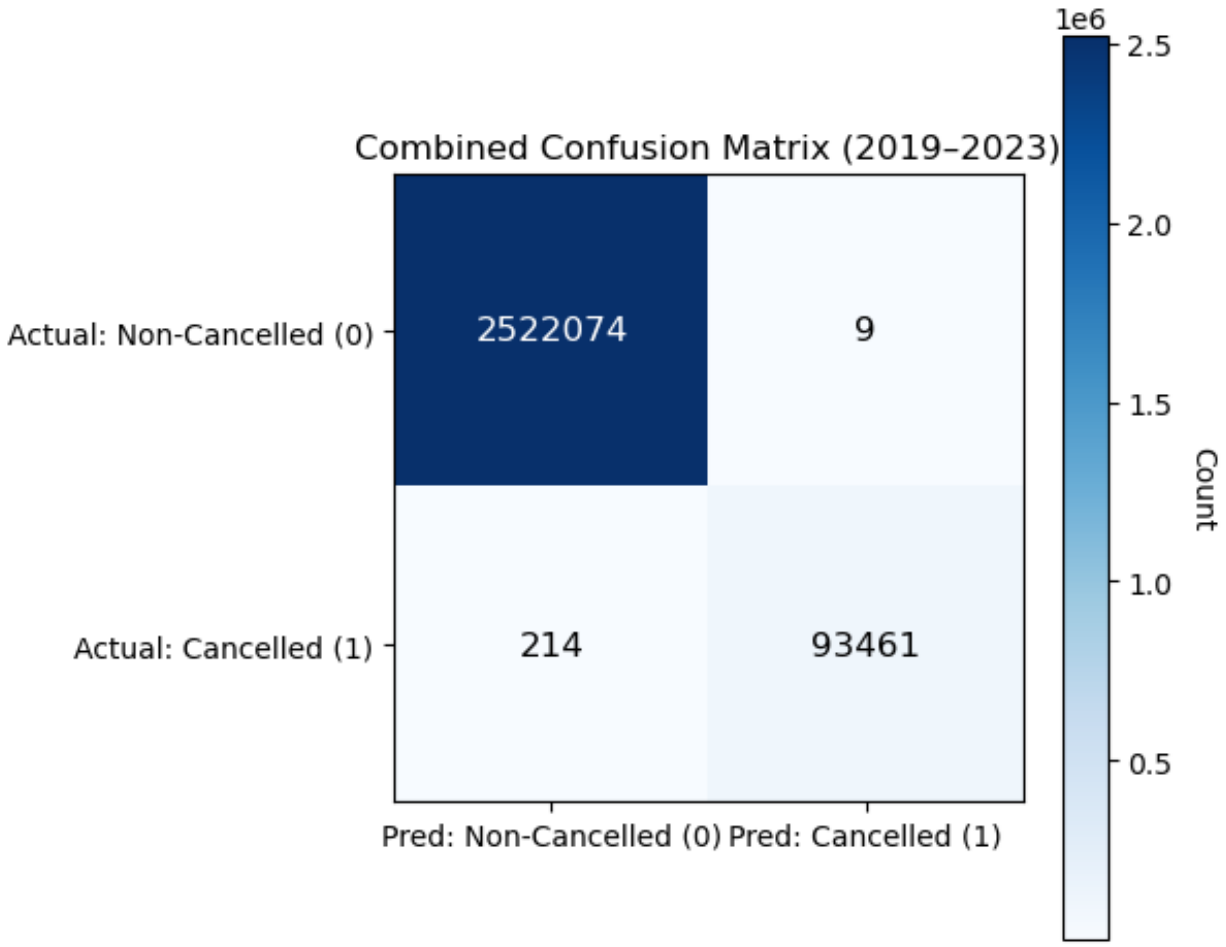


Figure 28: Confusion matrix of Pytorch

The combined confusion matrix for 2019–2023 demonstrates that the flight cancellation prediction model achieves exceptionally strong and well-balanced performance despite severe class imbalance, with 2,522,074 true negatives and 93,461 true positives, alongside only 9 false positives and 214 false negatives out of more than 2.6 million flights. This results in an overall accuracy of approximately 99.9915 percent, which, while influenced by the dominance of non-cancelled flights, is supported by robust minority-class metrics, including a precision of about 0.99990 and a recall of roughly 0.99772 for cancelled flights, yielding an F1-score near 0.99881. The model exhibits near-perfect specificity (0.999996) and a very high negative predictive value (0.999915), indicating strong reliability in identifying non-cancelled flights, while maintaining an extremely low false positive rate (0.00000357) and a modest miss rate of about 0.23 percent for actual cancellations. Advanced imbalance-aware measures further confirm this robustness, with a Matthews Correlation Coefficient of approximately 0.9976, balanced accuracy near 0.99886, Cohen's kappa around 0.975, informedness of about 0.9977, and markedness close to 0.99982, all reflecting excellent agreement beyond chance and highly dependable predictions.

3.2 XGBOOST,ADABOOST AND LIGHT-GRADIENTBOOST

XGBoost, AdaBoost, and LightGBM are powerful ensemble learning algorithms designed to improve prediction accuracy by combining multiple weak learners, typically decision trees:

- **XGBoost (Extreme Gradient Boosting):** Optimizes performance through gradient boosting with regularization, handling missing values efficiently and preventing overfitting.
- **AdaBoost (Adaptive Boosting):** Adjusts the weights of misclassified samples in successive iterations, enabling the model to focus on difficult cases and improve overall accuracy.
- **LightGBM (Light Gradient Boosting Machine):** Developed by Microsoft, enhances training speed and scalability by using histogram-based techniques and leaf-wise tree growth, making it ideal for large datasets.

TREE:

```
|--- Time when aircraft actually took off <= 608.50
|   |--- Actual arrival time <= 1576.00
|   |   |--- class: 0
|   |--- Actual arrival time >  1576.00
|   |   |--- Time when aircraft actually took off <= 607.50
|   |   |   |--- AIR_TIME <= 50.00
|   |   |   |   |--- class: 0
|   |   |   |--- AIR_TIME >  50.00
|   |   |   |   |--- class: 0
|   |   |--- Time when aircraft actually took off >  607.50
|   |   |   |--- Departure_delay <= -7.50
|   |   |   |   |--- class: 1
|   |   |   |--- Departure_delay >  -7.50
|   |   |   |   |--- class: 1
|--- Time when aircraft actually took off >  608.50
|   |--- ELAPSED_TIME <= 79.50
|   |   |--- AIR_TIME <= 62.50
|   |   |   |--- class: 0
|   |   |--- AIR_TIME >  62.50
|   |   |   |--- DISTANCE <= 270.00
|   |   |   |   |--- class: 0
|   |   |   |--- DISTANCE >  270.00
|   |   |   |   |--- class: 0
|   |--- ELAPSED_TIME >  79.50
|   |   |--- class: 0
```

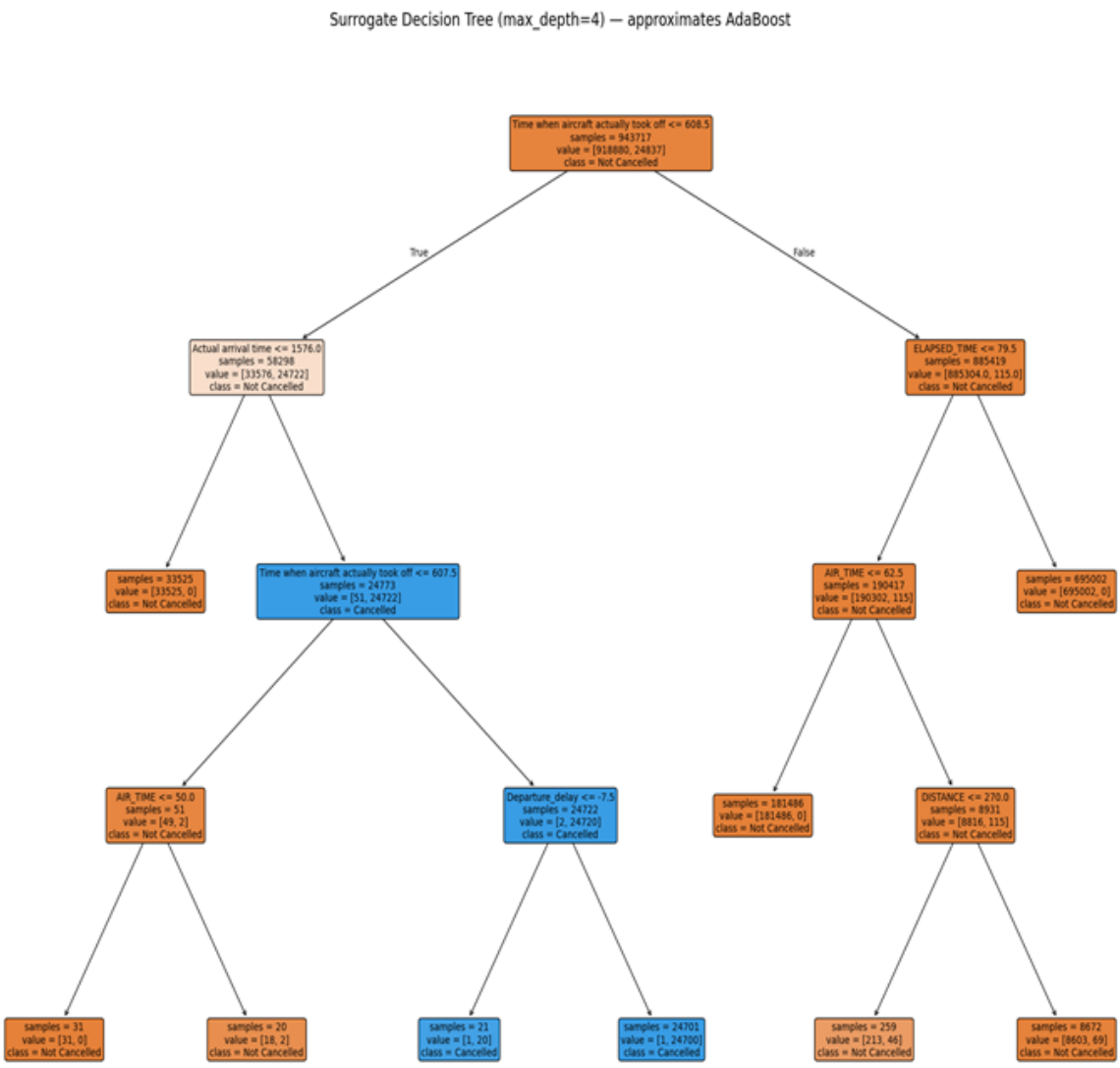


Figure 29: TREE DIAGRAM

The most significant decision limits that the ensemble has learned are revealed by this surrogate decision tree, which is based on an AdaBoost model and uses flight operation data to forecast a binary class (presumably 0 = not delayed / on-time, 1 = delayed). When the actual departure time is less than 608.50 (10:08 AM), the tree divides first. Early flights that arrive by 1576.00 (2:16 PM) are categorized as 0 (not delayed). AIR TIME is verified for early planes arriving later if takeoff was 607.50 (10:07 AM); nonetheless, whether it is 50 or ¿50 minutes, the result is still class 0, indicating that the takeoff and arrival times taken together already imply no delay. However, regardless of whether the departure delay is -7.50 (early) or ¿ -7.50 (late), any planes departing shortly after 10:07 AM (¿607.50) are categorized as 1 (delayed). — indicating that flights in this narrow post-10:07 AM window are inherently flagged as delayed, possibly due to schedule compression or cascading morning delays. Short flights (elapsed 79.5 min) with low air time (62.5) are zero for later takeoffs (¿608.50), while all longer flights (elapsed ¿79.5) are zero. This suggests that afternoon and longer flights are rarely categorized as delayed, possibly as a result of schedule padding or operational recovery.

Although perfect logic may suggest overfitting or data-specific patterns, the tree shows that overall, delay prediction is most sensitive to flights departing shortly after 10:07 AM, while other paths overwhelmingly predict "not delayed." Notably, no splits on diversion or ground delay appear, indicating Xgboost,AdaBoost and lightgradient boost prioritized temporal and duration features over others.

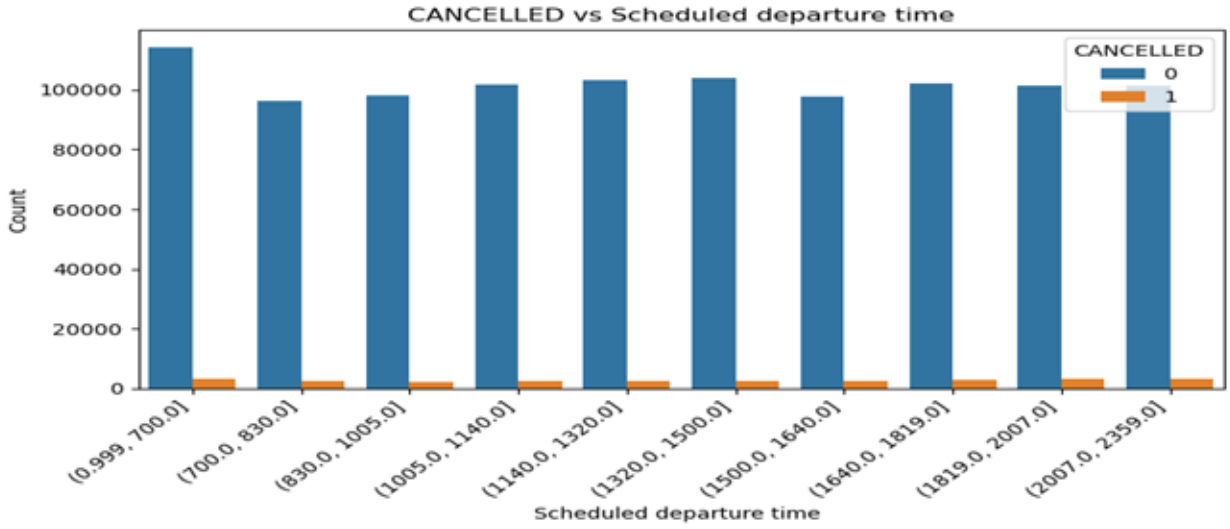


Figure 30: Scheduled departure time

Counting flights by scheduled departure time (in minutes since midnight, with 0.999 1 AM, 700 7 AM, and 1320 1:20 PM) and cancellation status (0 = not cancelled, 1 = cancelled) is displayed in the bar chart. With counts continuously above 90,000, the great majority of flights are non-cancelled (blue bars) across all time bins, suggesting that cancellations are comparatively uncommon regardless of the scheduled departure time. With no particular time frame displaying a noticeably higher cancellation rate, the number of cancelled flights (orange bars) is consistently low across all bins, indicating that, based solely on schedule, cancellation risk is dispersed evenly throughout the day.This implies that flights scheduled at any time — from early morning to late night — are equally likely to be cancelled, and that cancellation decisions are driven more by operational factors like weather, crew availability, or technical issues rather than the time of day. Thus, while flight volume may vary by hour, the likelihood of cancellation does not appear to be strongly tied to scheduled departure time, highlighting that no particular time of day is inherently more prone to cancellations when considering only the schedule.

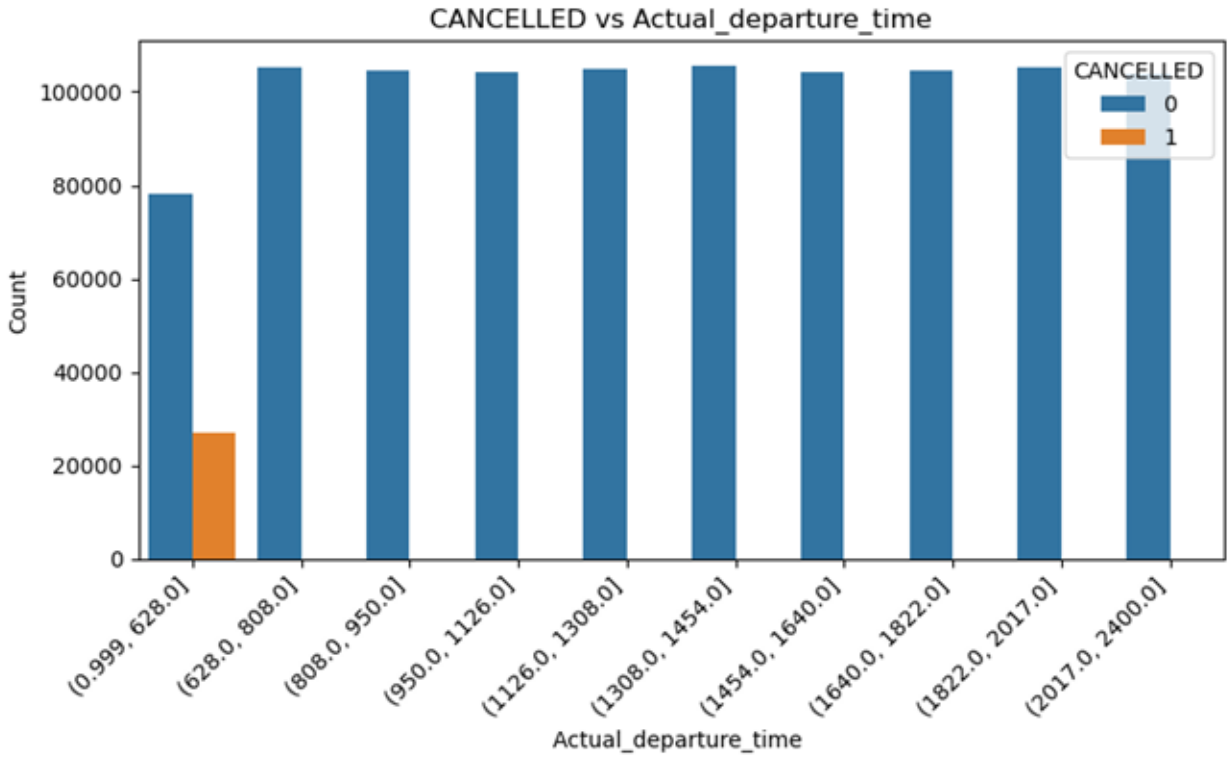


Figure 31: Actual departure time

The number of flights is split by cancellation status (0 = not cancelled, 1 = cancelled) and grouped by actual departure time (in minutes since midnight, where 0.999 1 AM, 628 = 6:28 AM, 700 = 7 AM, and 1320 = 1:20 PM) in the bar chart. With numbers continuously exceeding 100,000 in all bins but the first, the great majority of flights are not cancelled (blue bars). The earliest bin, [0.999, 628.0], contains the only notable number of cancelled flights (orange bar 27,000), which corresponds to actual departures between roughly 1 AM and 6:28 AM. This suggests that cancellations are primarily concentrated in the pre-dawn and early morning hours, most likely as a result of crew availability, overnight operational disruptions, or cascading delays from previous flights.After 6:28 AM, no meaningful cancellations occur, suggesting that the airline system stabilizes by mid-morning and maintains consistent operations through the rest of the day. This pattern reveals a strong temporal vulnerability: flight cancellations are almost exclusively tied to the night and very early morning period, while later departures proceed without interruption, highlighting a critical window of operational fragility during the night and before 6:28 AM.

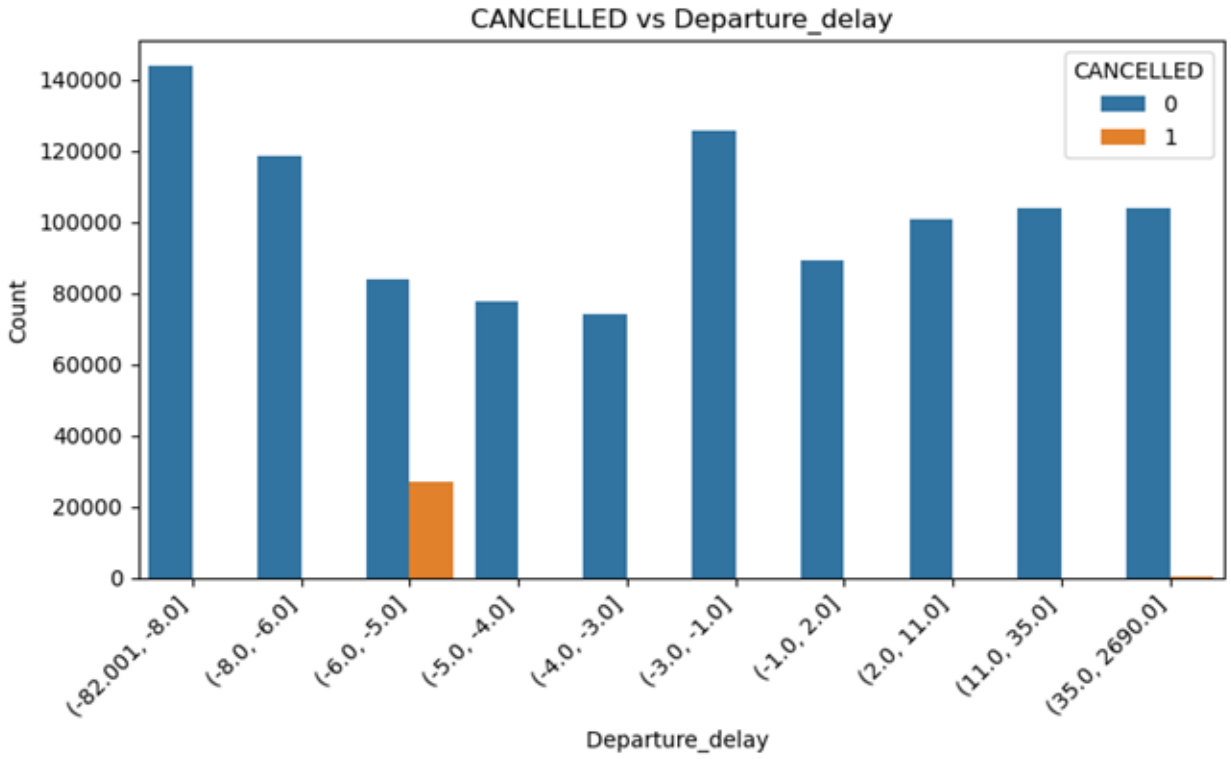


Figure 32: Departure delay

The bar graph displays the number of flights by cancellation status (0 = not cancelled, 1 = cancelled), then by departure delay (in minutes), where negative values indicate late departures and positive values indicate early departures. With the greatest counts in the most delayed bins (e.g., -82.001 to -80 minutes), the great majority of flights are not cancelled (blue bars), suggesting that many planes are noticeably delayed but continue to operate. It is noteworthy that the [-60, -50] minute delay bin contains the only significant number of cancelled flights (orange bar 27,000). This suggests that flights that are delayed by 50 to 60 minutes are disproportionately likely to be canceled, possibly because this window represents a critical threshold where operational recovery becomes too expensive or impractical. . Flights with smaller delays (e.g., -30 to -10 minutes) or early departures (positive delays) are almost never cancelled, suggesting that airlines absorb minor delays or benefit from early departures without needing to cancel. This pattern reveals that cancellation risk peaks at a specific intermediate delay level (50–60 minutes) rather than at extreme delays, highlighting a possible decision point in airline operations where small delays become operationally untenable.

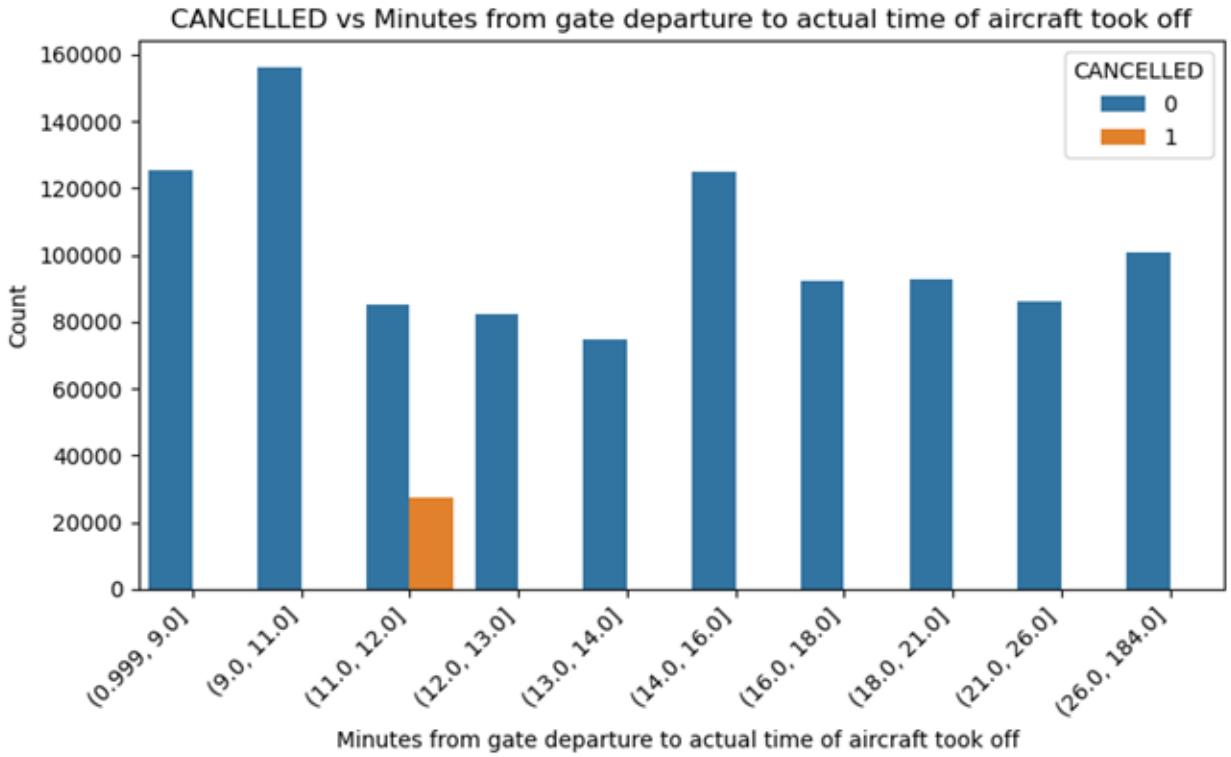


Figure 33: Minutes from gate departure to actual time of aircraft took off

The bar graph displays the number of flights by cancellation status (0 = not cancelled, 1 = cancelled), then by the number of minutes between gate departure and actual takeoff (a measure of ground delay). The great majority of flights are not cancelled (blue bars), and the shortest ground delay bins—specifically, [9.0, 11.0] minutes—have the highest counts, suggesting that most planes have few delays prior to takeoff. Notably, the [11.0, 12.0] minute bin contains the only significant number of cancelled flights (orange bar 27,000), indicating that flights with a ground delay of roughly 11 to 12 minutes are disproportionately likely to be canceled. This could be because of operational thresholds that cause cancellations due to crew or slot constraints at even a slight delay. Flights with longer ground delays (e.g., 14–26+ minutes) are almost never cancelled, implying that once a flight is already delayed on the ground, it's more likely to proceed than to be scrapped, perhaps because the system has already adjusted for the delay. This pattern reveals that cancellation risk peaks at a very narrow window of 11–12 minutes, which may represent a critical decision point in airport operations rather than being driven by extreme delays.

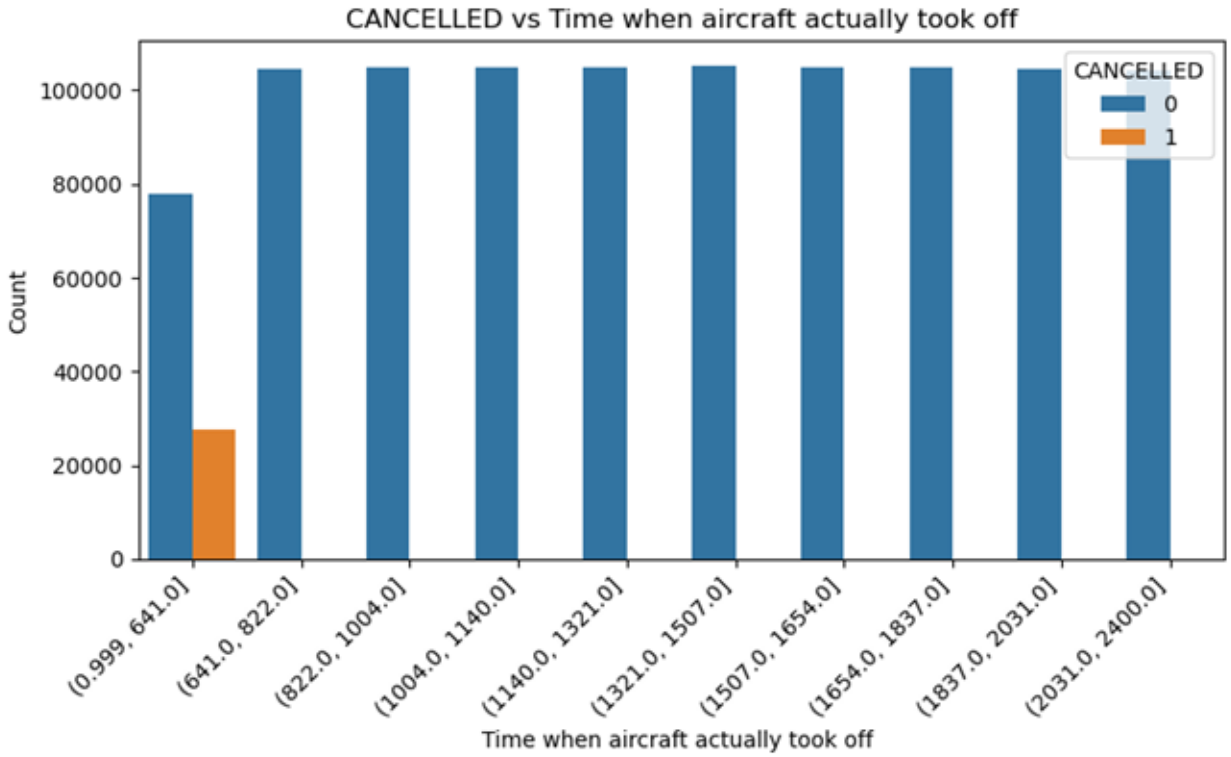


Figure 34: Actual time of aircraft took off

The number of flights is split by cancellation status (0 = not cancelled, 1 = cancelled) and grouped by actual takeoff time (in minutes since midnight, where 0.999 1 AM, 641 = 6:41 AM, 700 = 7 AM, and 1320 = 1:20 PM) in the bar chart. With counts continuously exceeding 100,000 in all time bins but the first, the great majority of flights are non-cancelled (blue bars). The earliest bin, [0.999, 641.0], has the only notable number of cancelled flights (orange bar 28,000), which corresponds to takeoffs between roughly 1 AM and 6:41 AM. This suggests that cancellations are primarily concentrated in the pre-dawn and early morning hours, most likely as a result of weather, crew availability, overnight operational disruptions, or cascading delays from previous flights. There are no significant cancellations after 6:41 AM, indicating that the airline system stabilizes by mid-morning and continues to run consistently throughout the remainder of the day. This pattern highlights a significant window of operational fragility during the night and before 6:41 AM. Flight cancellations are virtually solely associated with the night and very early morning period, whereas later departures occur without any disruptions.

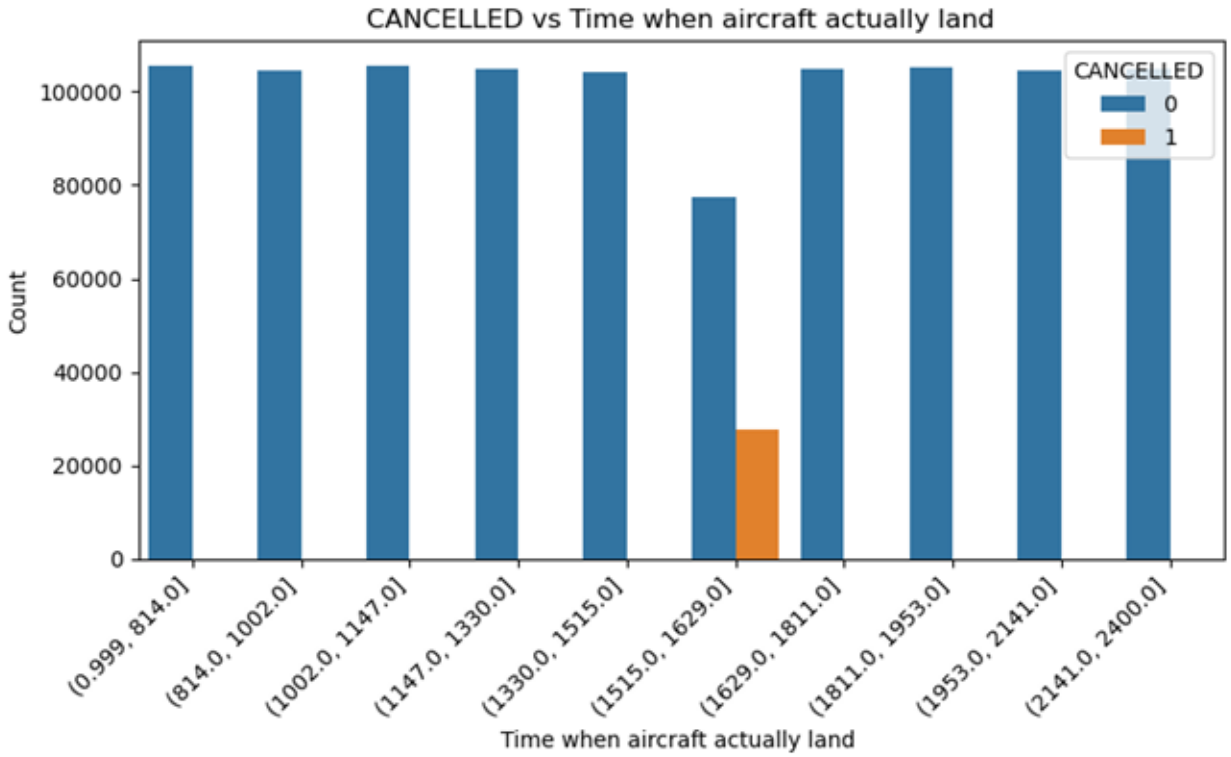


Figure 35: Actual time of aircraft land

Counting flights by actual landing time (measured in minutes since midnight, with 0.999 1 AM, 700 7 AM, and 1320 =12 1:20 PM) and cancellation status (0 = not cancelled, 1 = cancelled) is displayed in the bar chart. All time bins except one have counts continuously above 100,000, indicating that the great majority of flights are non-cancelled (blue bars). The bin [1515.0, 1629.0] contains the only notable number of cancelled flights (orange bar 28,000), which corresponds to landings between roughly 2:35 PM and 4:29 PM. This suggests that cancellations are concentrated during this particular afternoon window, most likely as a result of peak air traffic, weather-related delays, or operational bottlenecks at destination airports around this time. All other landing time slots show negligible or zero cancellations, indicating that flight cancellations are not evenly distributed but instead cluster around a particular period in the afternoon. This pattern reveals a critical vulnerability during mid-to-late afternoon, possibly linked to high demand, congestion, or late-day weather patterns, while operations remain stable throughout the rest of the day.

Figure 36: Actual time of aircraft landed to gate arrival

Counting flights by the duration (in minutes) between an aircraft's landing and its arrival at the gate, separated by cancellation status (0 = not cancelled, 1 = cancelled), is displayed in the bar chart. With the largest counts in the shortest post-landing intervals, especially in the [3.0, 4.0] minute bin, where over 150,000 flights were processed, the great majority of flights are non-cancelled (blue bars), suggesting that most flights reach the gate shortly after landing. Interestingly, the [3.0, 4.0] minute bin contains the only notable number of cancelled flights (orange bar 28,000), indicating that flights with a very short turnaround time from landing to gate arrival are more likely to be canceled— possibly because these flights are either delayed or expedited due to operational issues, such as gate congestion, staffing shortages, or being used as "buffer" flights that get scrapped if not needed. The lack of significant cancellations for flights with longer ground periods (such as 4–249 minutes) suggests that once a flight experiences a longer post-landing delay, it is more likely to proceed normally, possibly as a result of the system accounting for delays or allocating resources. This pattern shows that flights with exceptionally fast gate arrivals have a higher chance of cancellation, which could be the result of anomalies or high-pressure operations rather than regular service.

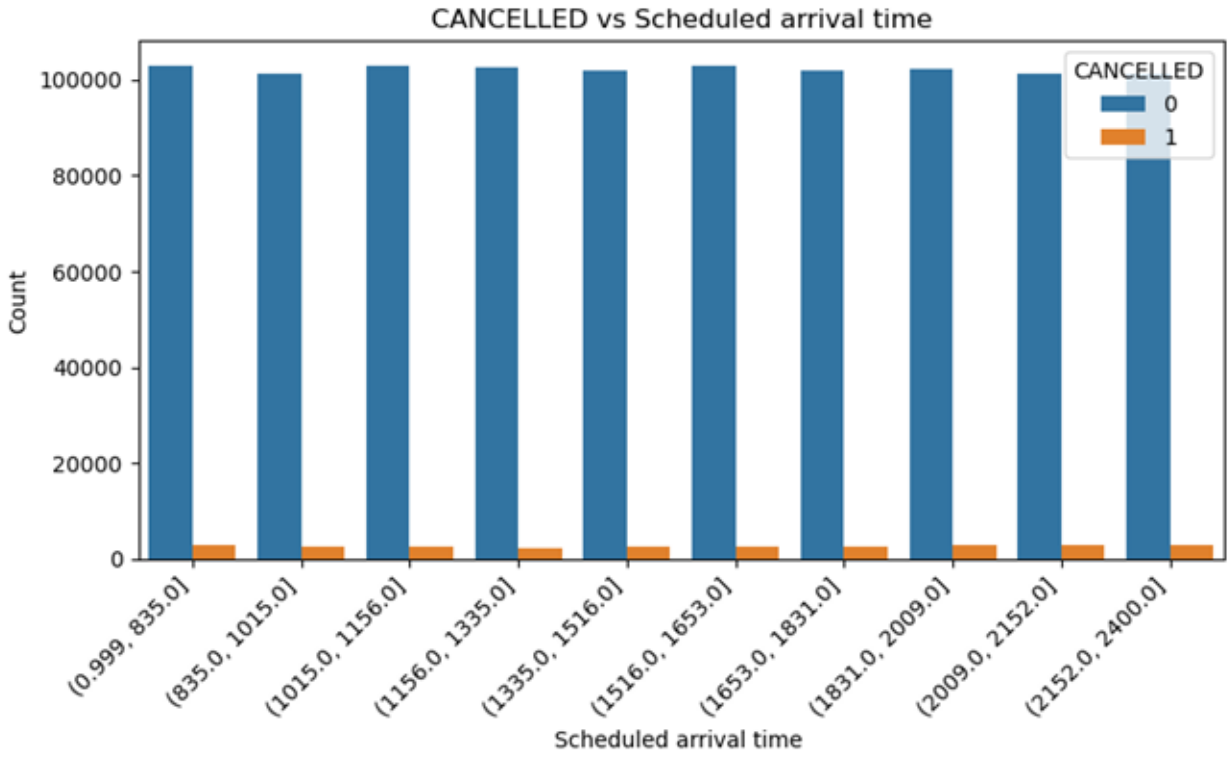


Figure 37: Scheduled arrival time

The number of flights is displayed in a bar chart by both cancellation status (0 = not cancelled, 1 = cancelled) and scheduled arrival time (in minutes since midnight, where 0.999 1 AM, 700 7 AM, and 1320 =12 1:20 PM). With counts continuously exceeding 100,000 across all time bins, the great majority of flights are non-cancelled (blue bars), suggesting that most planes run according to schedule regardless of their scheduled arrival time. However, there are only a few cancelled flights (orange bars) in each bin, and no time window exhibits a much higher cancellation rate— suggesting that cancellations are relatively evenly distributed throughout the day in terms of scheduled arrival time. This contrasts with earlier patterns seen in actual departure or landing times, where cancellations clustered at specific hours. The consistent low-level presence of cancellations across all scheduled arrival windows implies that no particular time of day is inherently more prone to cancellations based on schedule alone, and that cancellation decisions are likely driven more by operational factors (e.g., weather, delays, crew availability) rather than the time a flight is supposed to arrive. Thus, while the system experiences minor disruptions across the day, there is no strong temporal bias in cancellations when considering scheduled arrival times.

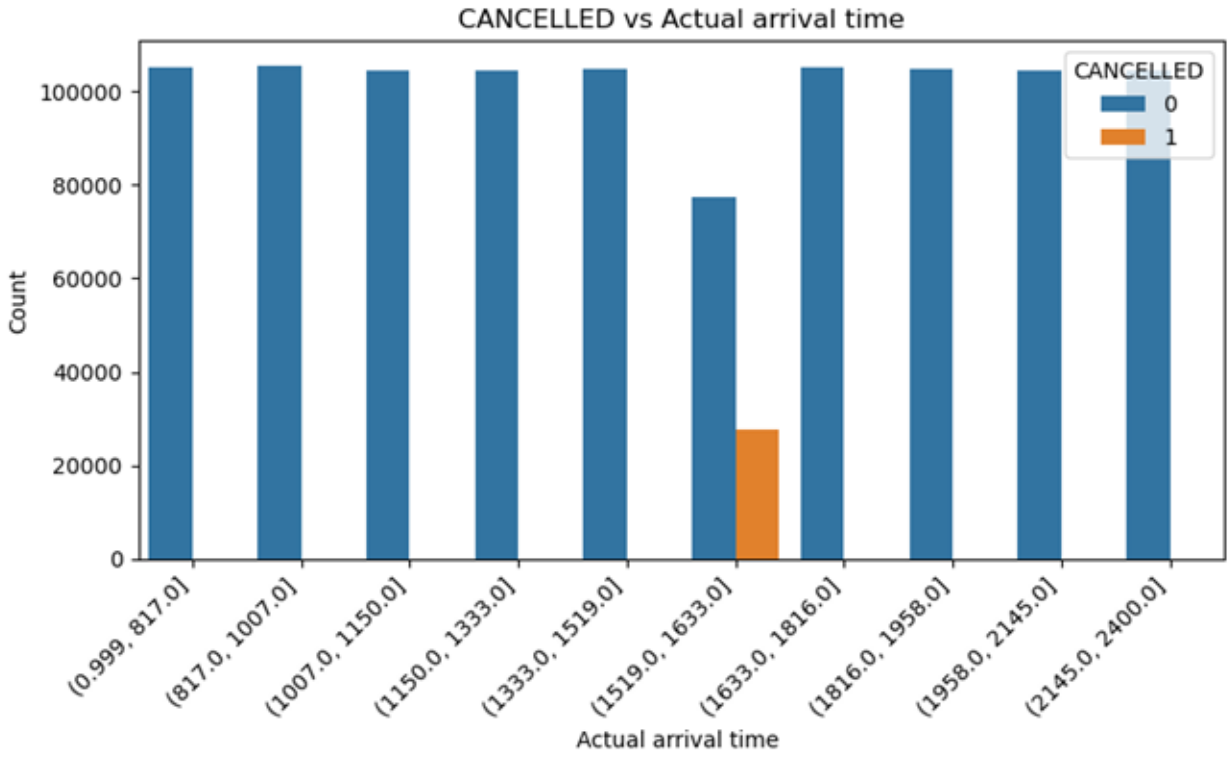


Figure 38: Actual arrival time

The bar chart shows the count of flights grouped by actual arrival time (in minutes since midnight, where 0.999 1 AM, 700 7 AM, and 1320 1:20 PM), split by cancellation status (0 = not cancelled, 1 = cancelled). The vast majority of flights are non-cancelled (blue bars), with counts consistently above 100,000 across all time bins except one. The only significant number of cancelled flights (orange bar 28,000) appears in the bin [1519.0, 1633.0], corresponding to arrivals between approximately 2:39 PM and 4:33 PM, indicating that cancellations are heavily concentrated during this specific afternoon window — likely due to peak air traffic, weather disruptions, or operational bottlenecks at destination airports around this time. All other actual arrival time slots show negligible or zero cancellations, suggesting that flight cancellations are not evenly distributed but instead cluster around a particular period in the late afternoon. This pattern reveals a critical vulnerability during mid-to-late afternoon, possibly linked to high demand, congestion, or delays cascading from earlier flights, while operations remain stable throughout the rest of the day.

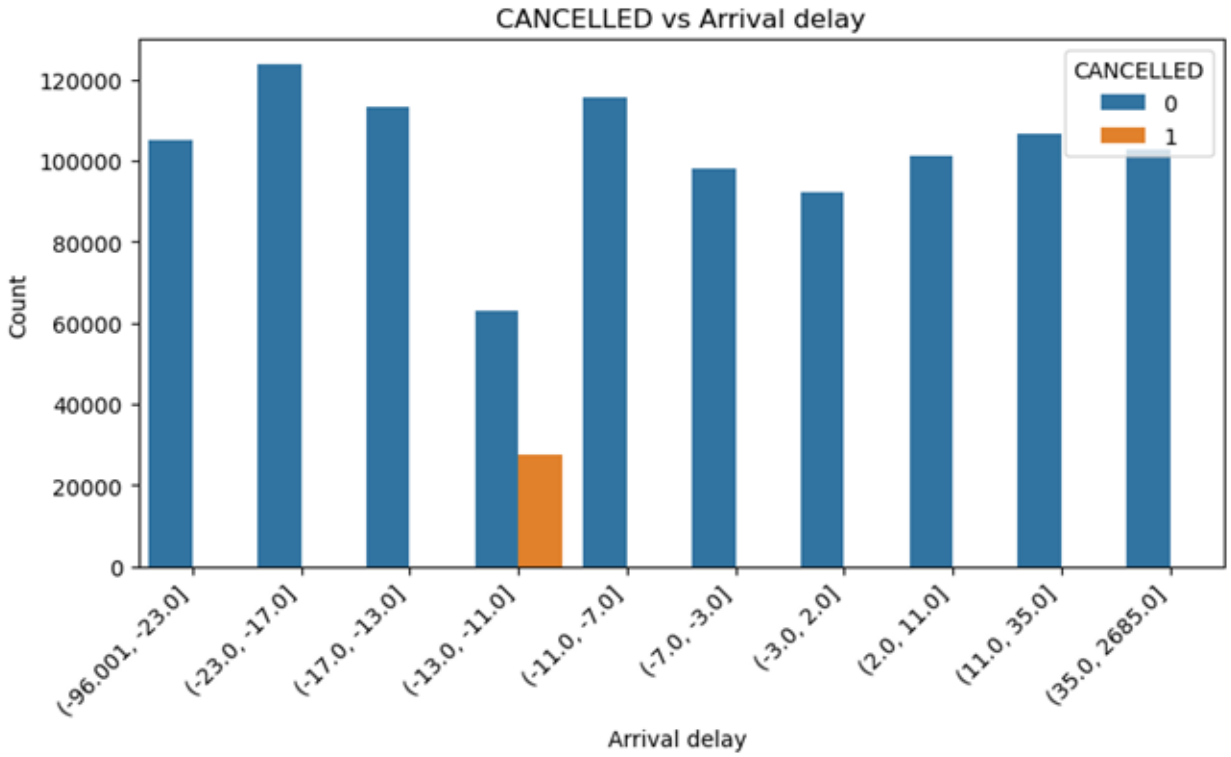


Figure 39: Arrival delay

The number of flights is displayed in a bar chart by arrival delay (in minutes), segmented by cancellation status (0 = not cancelled, 1 = cancelled), with negative values denoting late arrivals and positive values denoting early arrivals. With the greatest counts in the most delayed bins (e.g., -96.001 to -23.0), the great majority of flights are non-cancelled (blue bars), suggesting that many flights arrive noticeably late yet continue to operate. Interestingly, the [-13.0, -11.0] minute delay bin contains the only significant number of cancelled flights (orange bar 28,000), indicating that flights that are delayed by roughly 11–13 minutes are disproportionately likely to be canceled— possibly because this narrow window represents a critical operational threshold where minor delays trigger cancellation due to scheduling conflicts, crew or gate constraints, or downstream ripple effects. Flights with smaller delays (e.g., -7 to 0 minutes) or early arrivals (positive delays) are almost never cancelled, suggesting that airlines can absorb minor delays or even benefit from early arrivals without needing to cancel. This pattern reveals that cancellation risk peaks at a specific intermediate delay level (11–13 minutes) rather than at extreme delays, highlighting a possible decision point in airline operations where small delays become operationally untenable.

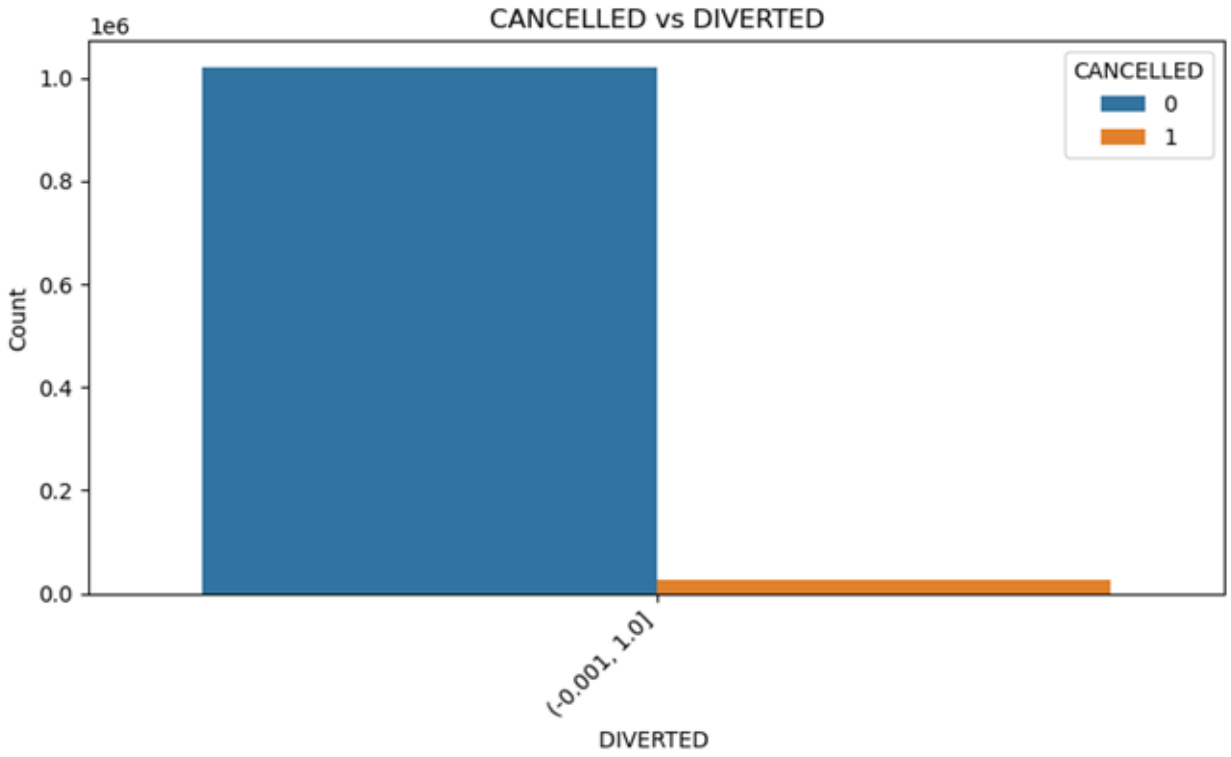


Figure 40: Diverted

The DIVERTED variable (coded as 0 or 1) is represented on the x-axis of the bar chart, which displays the correlation between flight cancellations and whether a flight was diverted. Most flights function smoothly without being redirected, as evidenced by the fact that the great majority of flights (more than 1 million) are non-cancelled (blue bar) and were not diverted (DIVERTED = 0). Only a very small percentage of flights (orange bar, 20,000–30,000) were cancelled, and even fewer were diverted (DIVERTED = 1), indicating that cancellation and diversion are generally mutually exclusive. This implies that when a flight is diverted, it typically still completes its journey to an alternate airport rather than being cancelled outright. The near absence of overlap between diverted and cancelled flights indicates that airlines prefer to reroute flights rather than cancel them, possibly to maintain service continuity and minimize passenger disruption. Thus, the data reveals that diversion is a rare but operational alternative to cancellation, used primarily in response to weather or safety issues, while cancellation is a separate decision usually made earlier in the process.

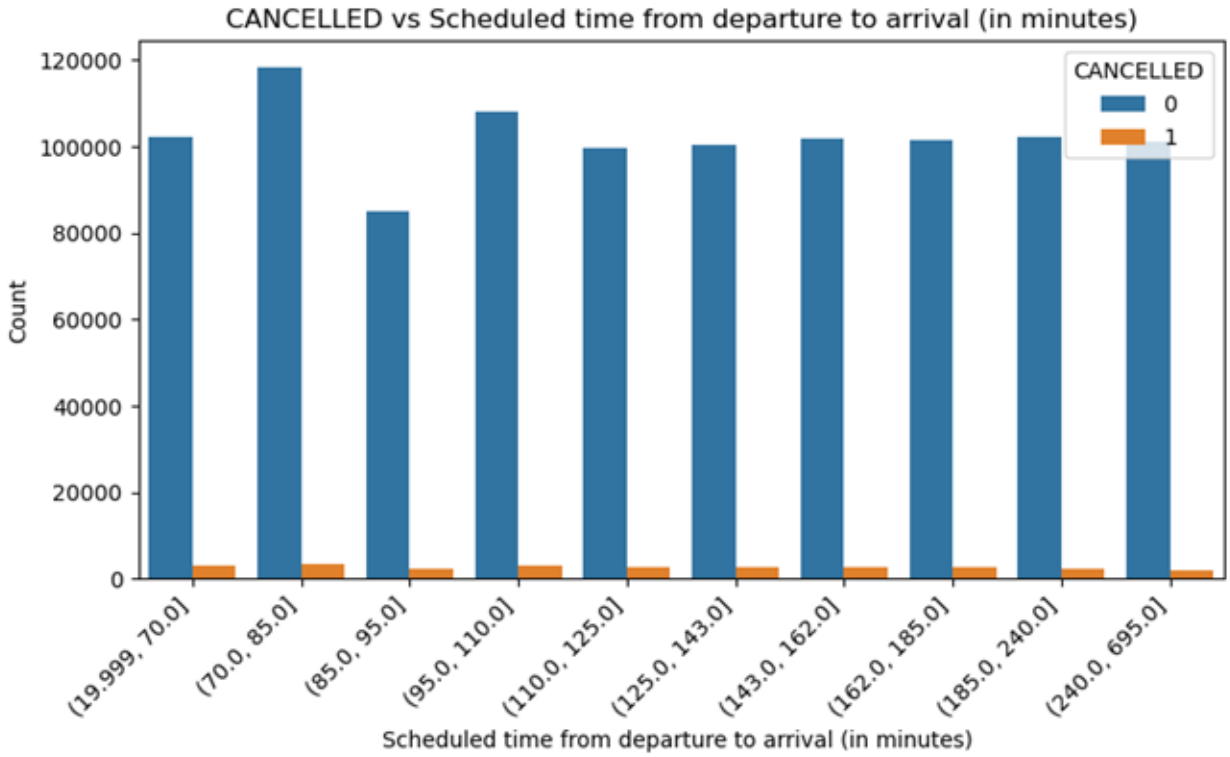


Figure 41: Scheduled time from departure to arrival

The bar chart shows the count of flights grouped by scheduled flight duration (in minutes), from departure to arrival, split by cancellation status (0 = not cancelled, 1 = cancelled). Across all flight durations — ranging from under 70 minutes to over 240 minutes — the vast majority of flights are non-cancelled (blue bars), with counts consistently above 80,000. The number of cancelled flights (orange bars) is extremely small in every bin, with no single duration showing a significantly higher cancellation rate, indicating that cancellation is not strongly correlated with scheduled flight length. This implies that the probability of cancellation is low and consistent for both short-haul and long-haul flights. The small number of cancellations across all time frames suggests that other reasons, such as weather, crew availability, or scheduling problems, rather than trip duration, are the main causes of operational disruptions that impact flights. Longer flights are therefore not disproportionately more likely to be canceled than shorter ones, despite the fact that they may have more complicated logistics. This shows that flight duration by itself does not indicate cancellation risk.

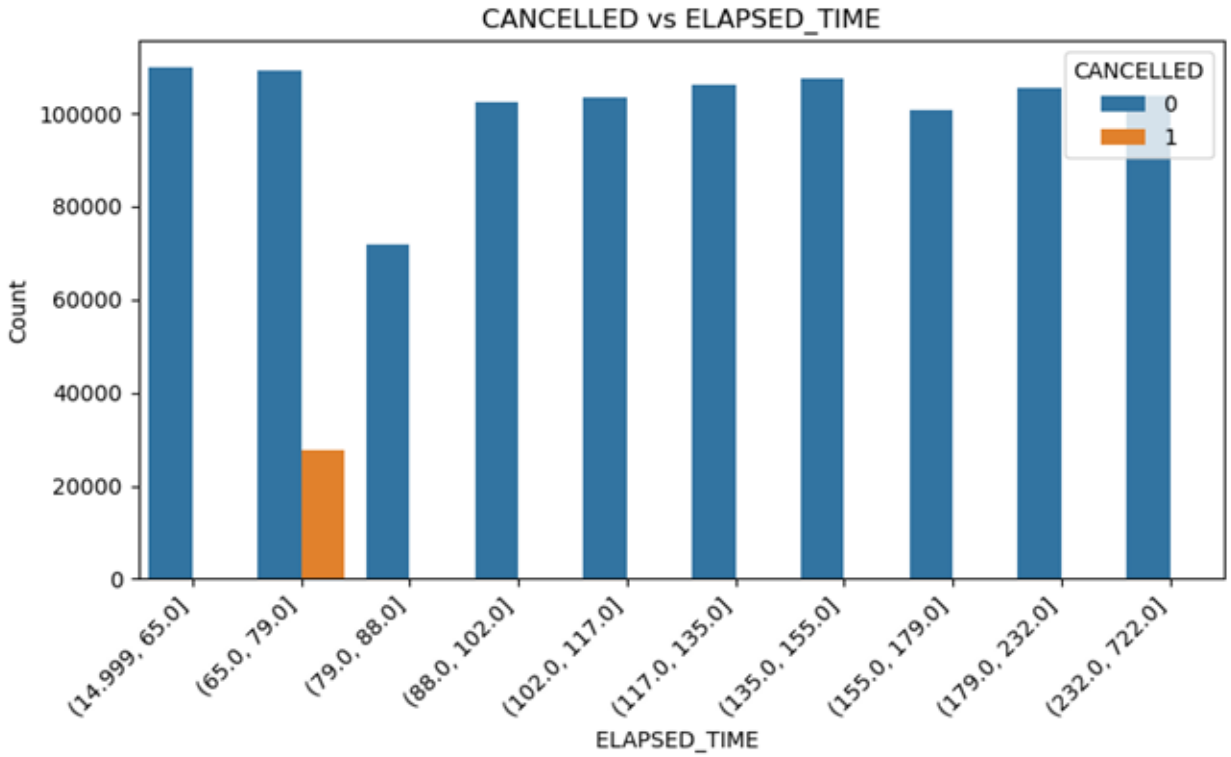


Figure 42: Elapsed time

The number of flights, broken down by cancellation status (0 = not cancelled, 1 = cancelled), is displayed in a bar chart along with the amount of time (in minutes) that has passed between gate departure and gate arrival. With counts continuously above 100,000 across the majority of time bins, the great majority of flights are non-cancelled (blue bars), meaning that most flights finish their voyage without being canceled. It is noteworthy that the [65.0, 79.0] minute elapsed time bin contains the only significant number of cancelled flights (orange bar 28,000). This suggests that flights with a total travel time of roughly 65 to 79 minutes are disproportionately likely to be cancelled, possibly as a result of operational constraints like tight scheduling, airport congestion, or weather disruptions that affect short-haul routes. There are very few cancellations for flights with shorter or longer elapsed times, suggesting that this little gap is a significant vulnerability where cancellation decisions may be triggered by delays or inefficiency. While longer or shorter flights function more dependably, this pattern shows that cancellation risk is concentrated in a specific range of flight durations, especially around 1 hour and 15 minutes. This could be due to operational constraints for regional or domestic routes or peak traffic periods.

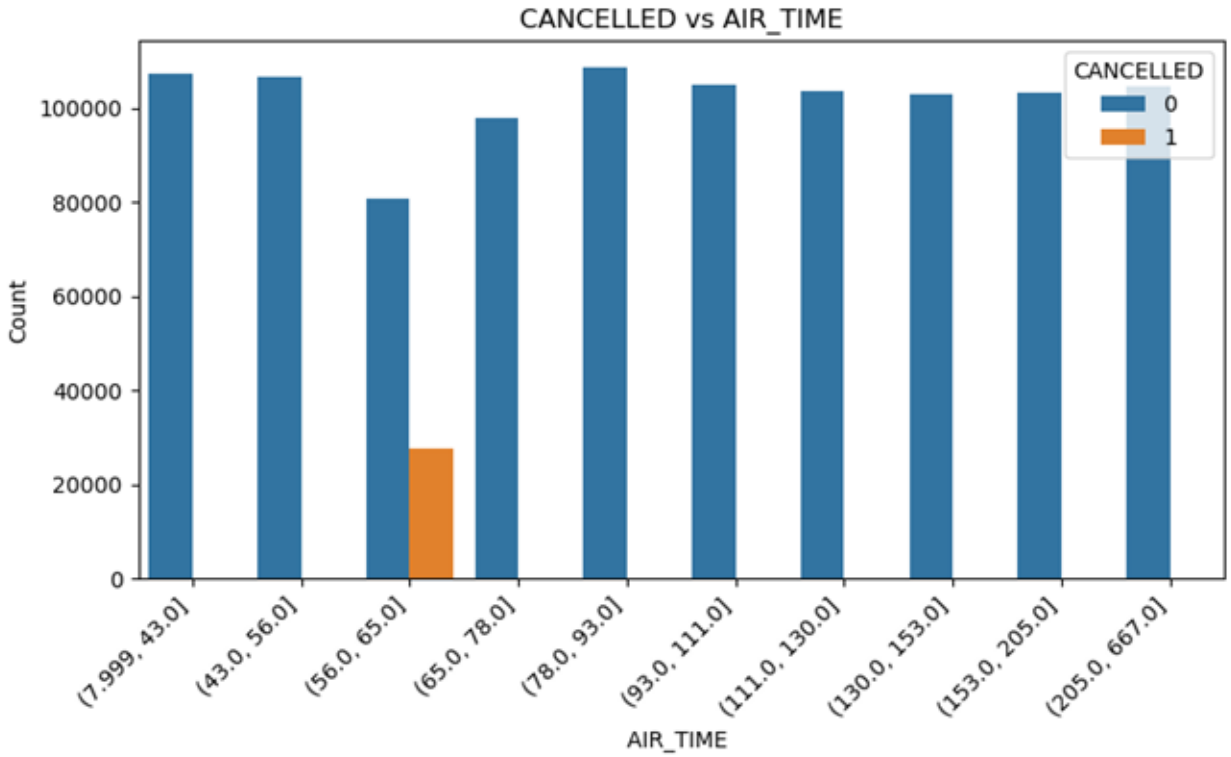


Figure 43: Air time

The number of flights is displayed in a bar chart that is divided by cancellation status (0 = not cancelled, 1 = cancelled) and grouped by air time (measured in minutes, or the duration from departure to landing). With counts continuously exceeding 80,000 across all bins, the great majority of flights are non-cancelled (blue bars), suggesting that most flights run according to schedule regardless of flight duration. Flights with an airborne duration of roughly 56 to 65 minutes are disproportionately likely to be cancelled, possibly due to operational vulnerabilities like tight scheduling, weather disruptions, or inefficiencies on short-haul routes where small delays can cascade into cancellations. Notably, the only significant number of cancelled flights (orange bar 28,000) appears in the [56.0, 65.0] minute air time bin. . There are very few cancellations for flights with shorter or longer flight durations, suggesting that this small window is a significant threshold where cancellation decisions are more likely to be triggered by operational restrictions. While longer or shorter flights stay more stable, this pattern shows that cancellation risk is concentrated in a particular range of flight durations, especially around one hour. This could be due to peak traffic periods or difficulties managing regional or domestic routes with little buffer time.

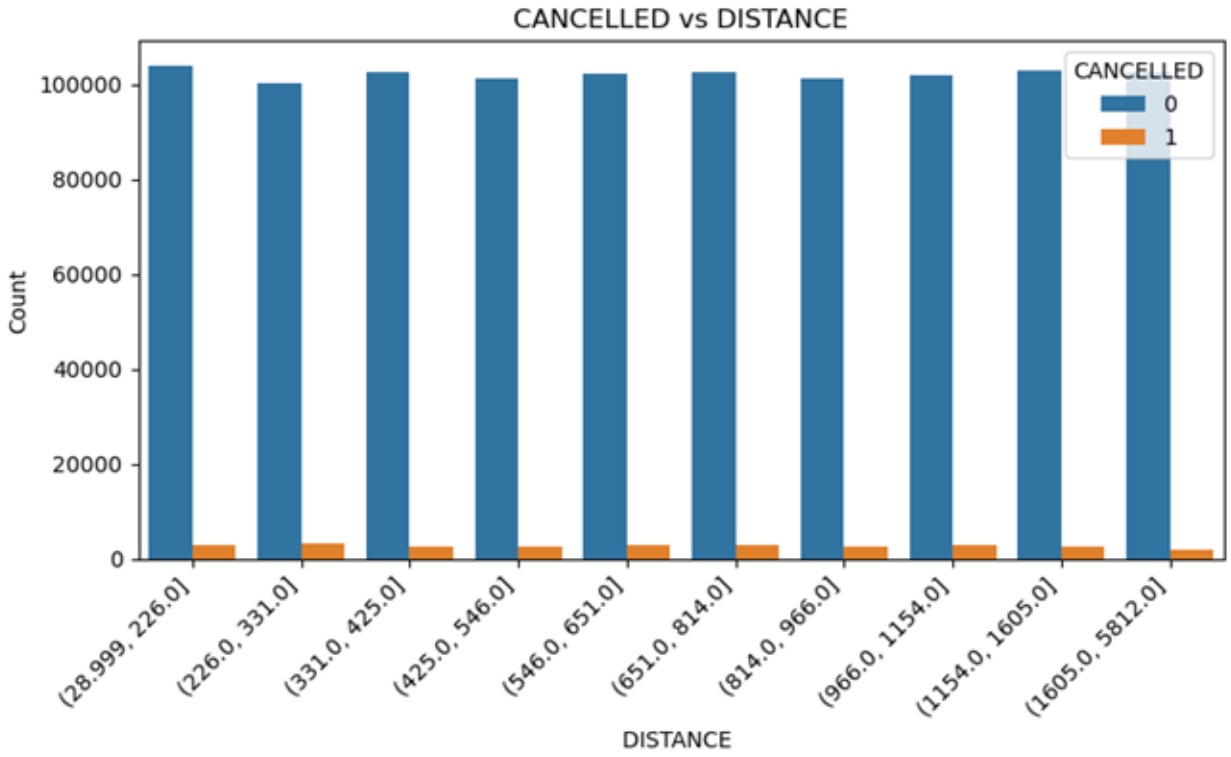


Figure 44: Distance

The bar chart shows the count of flights grouped by flight distance (in miles), split by cancellation status (0 = not cancelled, 1 = cancelled). Across all distance bins — ranging from under 226 miles to over 1,605 miles — the vast majority of flights are non-cancelled (blue bars), with counts consistently above 100,000, indicating that most flights operate as planned regardless of how far they travel. The number of cancelled flights (orange bars) is extremely small and nearly uniform across all distance categories, with no single bin showing a significantly higher cancellation rate. This suggests that flight cancellation is not strongly correlated with flight distance, meaning that whether a flight is short-haul or long-haul, the likelihood of cancellation remains low and relatively consistent. The minor presence of cancellations across all distance ranges implies that operational disruptions affecting flights are not primarily driven by the length of the route, but rather by other factors such as weather, scheduling, crew availability, or airport conditions. Thus, while longer flights may involve more complex logistics, they are not disproportionately more likely to be cancelled than shorter ones, highlighting that distance alone does not predict cancellation risk.

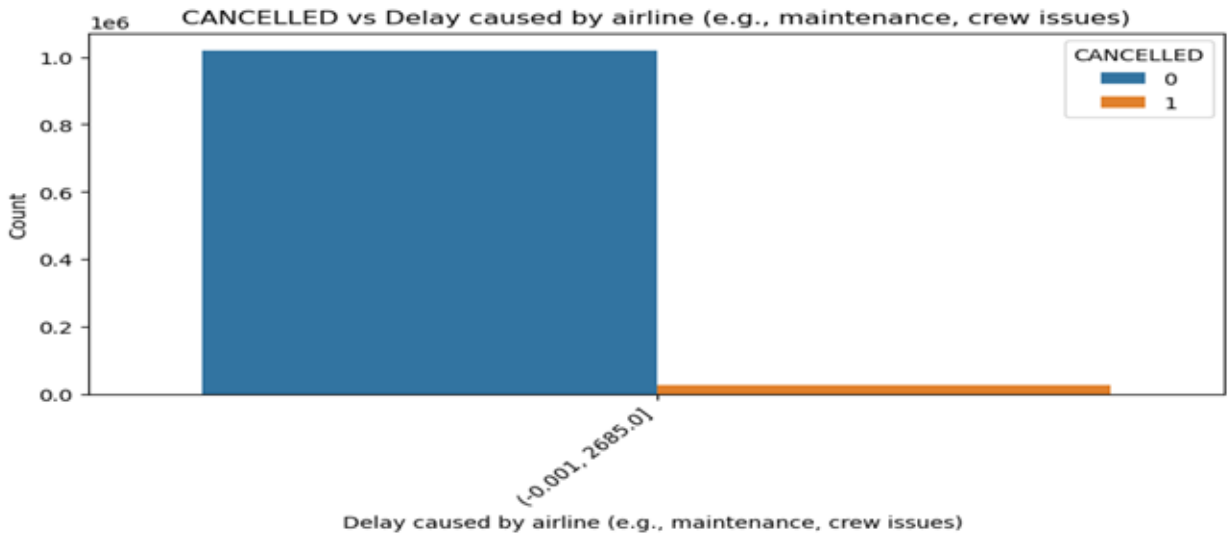


Figure 45: Delay caused by airline

The bar chart shows the relationship between flight cancellations and delays caused by airline factors such as maintenance or crew issues, with the x-axis representing delay duration (in minutes, where negative values indicate late departures and positive values indicate early departures). The vast majority of flights (over 1 million) are non-cancelled (blue bar) and experienced some form of airline-caused delay — indicating that these internal operational issues are common but typically do not lead to cancellation. A very small number of flights (orange bar, 20,000–30,000) were cancelled, and all of them fall within the same bin, suggesting that cancellation is rare even when airlines face delays due to their own operations. This implies that airlines prefer to operate delayed flights rather than cancel them, possibly to avoid passenger inconvenience, regulatory penalties, or financial costs. The near absence of overlap between airline-caused delays and cancellations reveals that delays from maintenance or crew issues are usually absorbed into the schedule, while cancellation is reserved for more severe or systemic disruptions. Thus, the data indicates that airline-related delays are a frequent but non-critical event, rarely resulting in full flight cancellations.

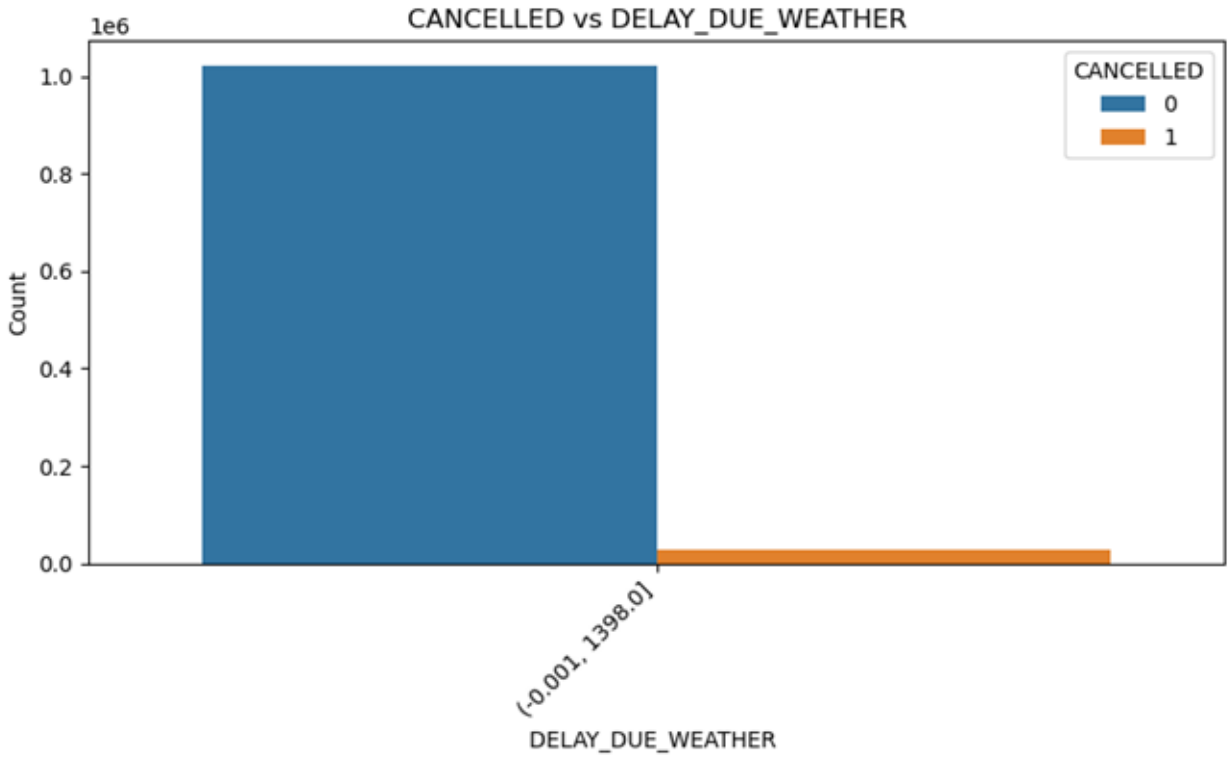


Figure 46: Delay caused by weather

The bar chart shows the relationship between flight cancellations and delays caused by weather, with the x-axis representing delay duration (in minutes, where negative values indicate late departures and positive values indicate early departures). The vast majority of flights (over 1 million) are non-cancelled (blue bar) and experienced some form of weather-related delay — indicating that weather impacts are common but typically do not result in cancellation. A very small number of flights (orange bar, 20,000–30,000) were cancelled, all falling within the same bin, suggesting that cancellation is rare even when weather causes delays. This implies that airlines often absorb or manage weather-related disruptions through rescheduling or rerouting rather than cancelling flights outright. The near absence of overlap between weather delays and cancellations reveals that weather-induced delays are frequently handled operationally, while cancellation is reserved for more severe conditions or safety concerns. Thus, the data indicates that weather delays are a frequent but manageable issue, rarely leading to full flight cancellations, highlighting the industry's preference for maintaining service continuity despite adverse conditions.

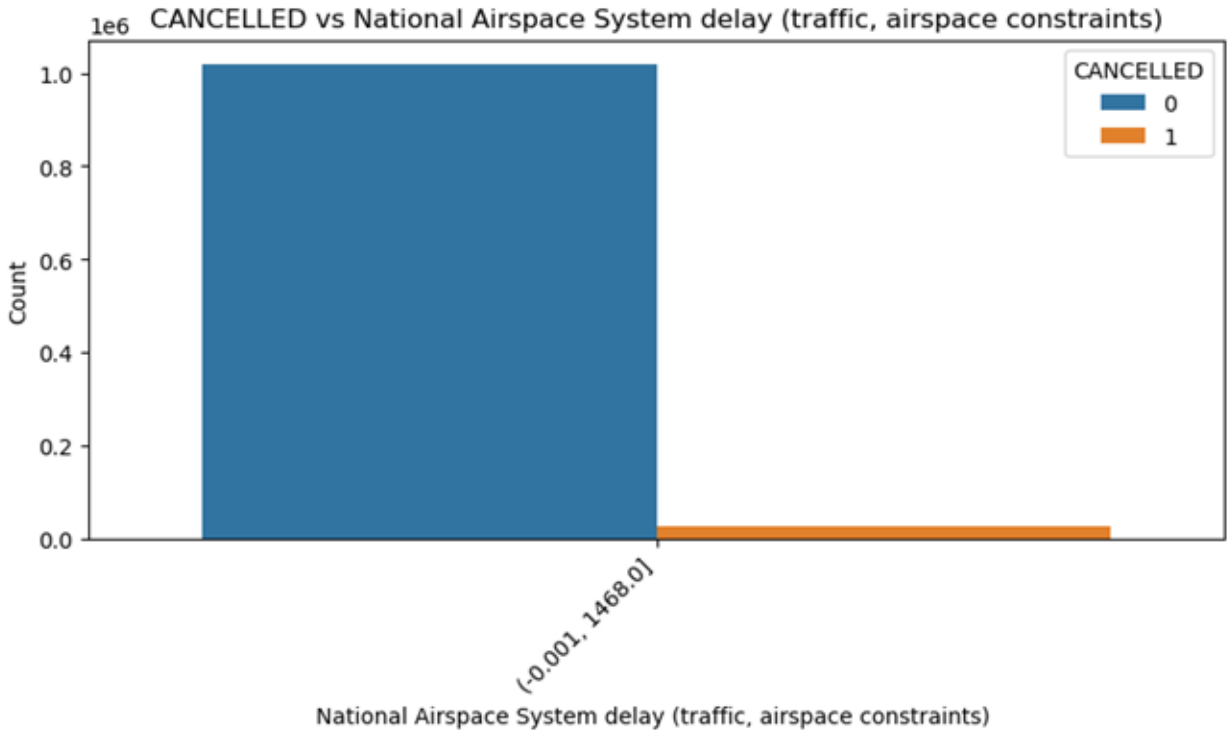


Figure 47: National airspace system delay

With the x-axis representing delay duration (in minutes, where negative values indicate late departures and positive values indicate early departures), the bar chart illustrates the relationship between flight cancellations and delays brought on by National Airspace System (NAS) problems, such as air traffic congestion or airspace constraints. Air traffic and airspace restrictions are frequent but usually do not result in cancellations, as evidenced by the fact that the great majority of flights (more than 1 million) are non-cancelled (blue bar) and encountered some kind of NAS-related delay. Even when flights experience NAS delays, cancellations are uncommon, as evidenced by the extremely tiny number of flights (orange bar, 20,000–30,000) that were canceled, all of which fell into the same bin. This suggests that rather than canceling flights, airlines and air traffic control typically handle these interruptions by rerouting, holding patterns, or modifying the schedule. Systemic airspace constraints are often incorporated into operations, whereas cancellation is saved for more extreme or inevitable circumstances, as evidenced by the almost complete lack of overlap between NAS delays and cancellations. Accordingly, the data shows that NAS delays are a common but non-critical occurrence that infrequently lead to complete flight cancellations, underscoring the system's ability to continue providing service in spite of infrastructure and traffic issues.

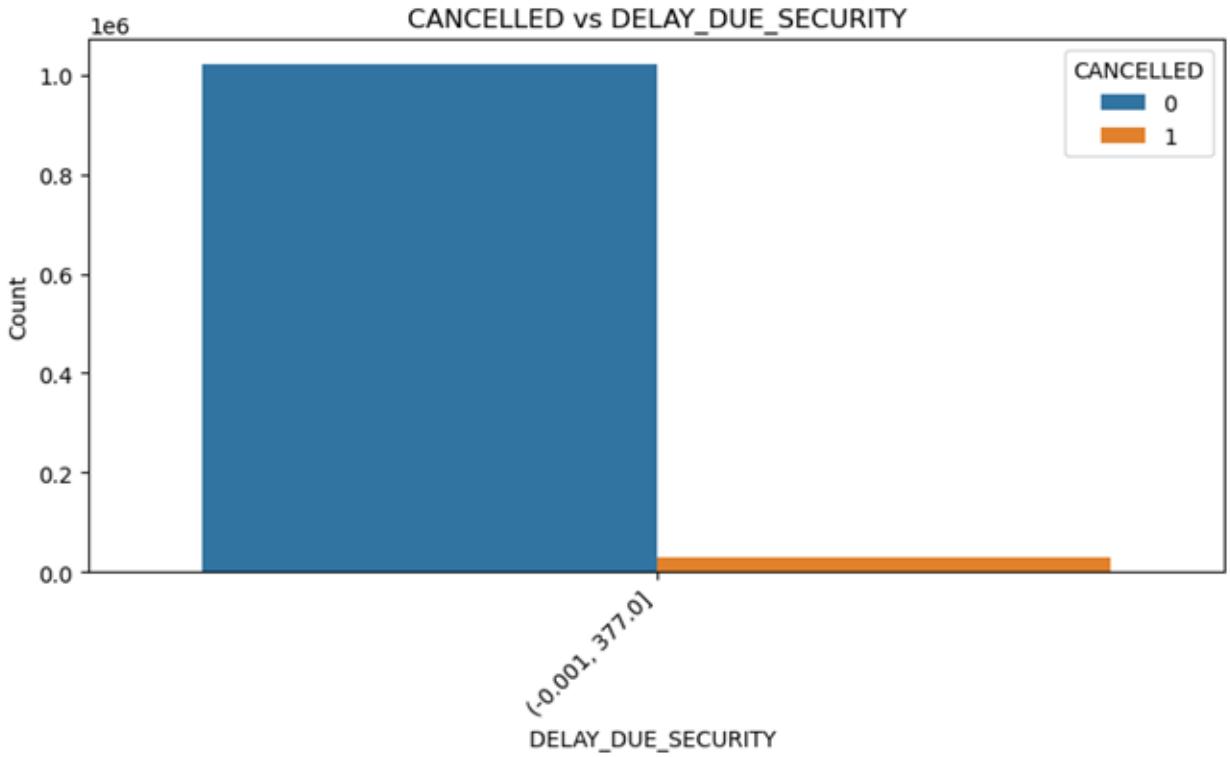


Figure 48: Security delay

With the x-axis reflecting delay time (in minutes, where negative values indicate late departures and positive values indicate early departures), the bar chart illustrates the correlation between flight cancellations and delays brought on by security concerns. Security delays are widespread but usually do not lead to cancellation, as evidenced by the fact that the vast majority of flights (more than 1 million) are non-cancelled (blue bar) and had some kind of delay. Even when security causes delays, cancellations are uncommon, as evidenced by the extremely small number of flights (orange bar, 20,000–30,000) that were canceled, all of which fell into the same bucket. This suggests that rather than canceling flights, airports and airlines handle security bottlenecks by extending screening times, optimizing passenger flow, or making operational changes. Security-related disruptions are often absorbed into operations, whereas cancellations are saved for extraordinary or cascading circumstances, as seen by the almost complete lack of overlap between security delays and cancellations. As a result, the data shows that security delays are a common but controllable problem that hardly ever result in complete flight cancellations, demonstrating the system's emphasis on service continuity in spite of operational difficulties at checkpoints.

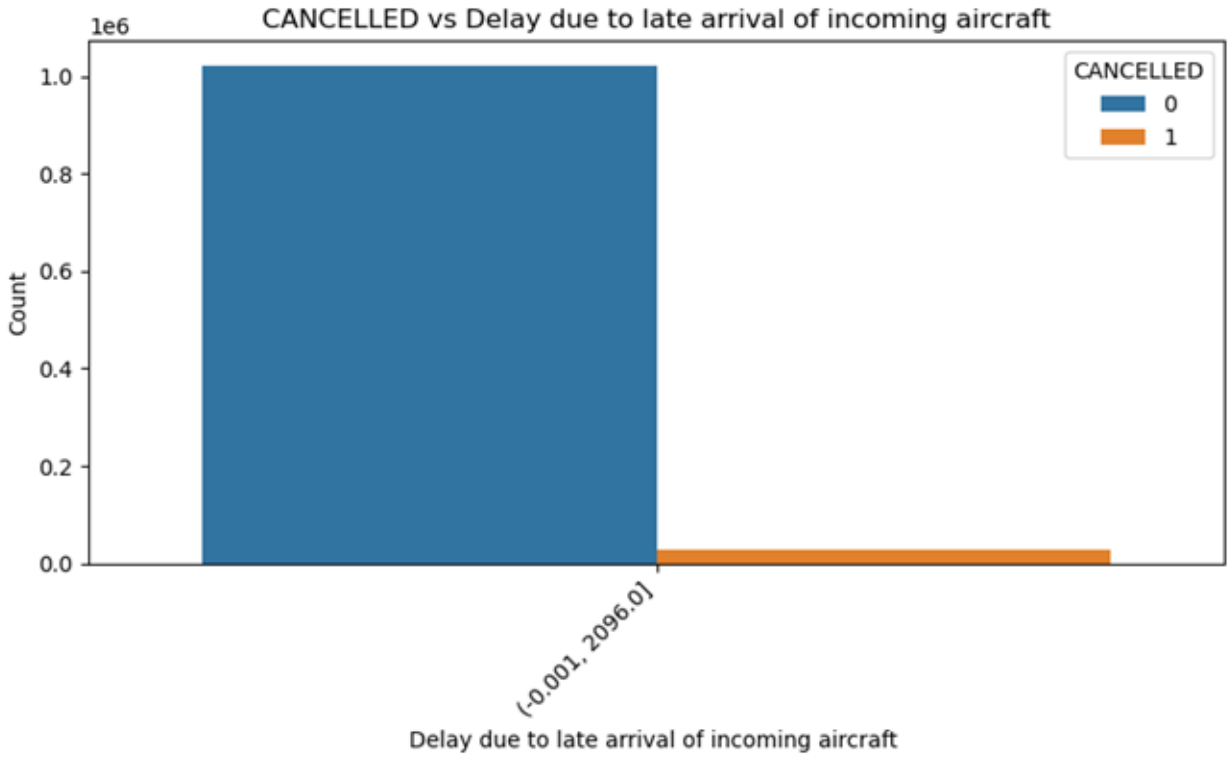


Figure 49: Late arrival delay

With the x-axis representing the delay duration in minutes (where negative values indicate late arrivals and positive values indicate early ones), the bar chart illustrates the relationship between flight cancellations and delays brought on by an incoming aircraft's delayed arrival (such as a connecting flight or crewed plane). Such operational cascades are widespread but usually do not result in cancellation, as seen by the fact that the great majority of flights (more than 1 million) are non-cancelled (blue bar) and experienced some sort of delay as a result of the preceding aircraft's delayed arrival. Even when flights are delayed by approaching aircraft, cancellations are uncommon, as evidenced by the extremely small number of cancelled flights (orange bar, 20,000–30,000) that all fell into the same bin. This suggests that rather than completely canceling a flight, airlines typically absorb or manage these disruptions through rescheduling, gate reassignments, or crew adjustments. Delays from previous flights are often managed operationally, whereas cancellations are saved for more serious or systemic failures, as evidenced by the almost complete lack of overlap between inbound delays and cancellations. In light of this, the data shows that late-arriving planes frequently result in non-critical delays rather than complete flight cancellations, underscoring the ability of airline operations to continue providing services even in the face of upstream disruptions.

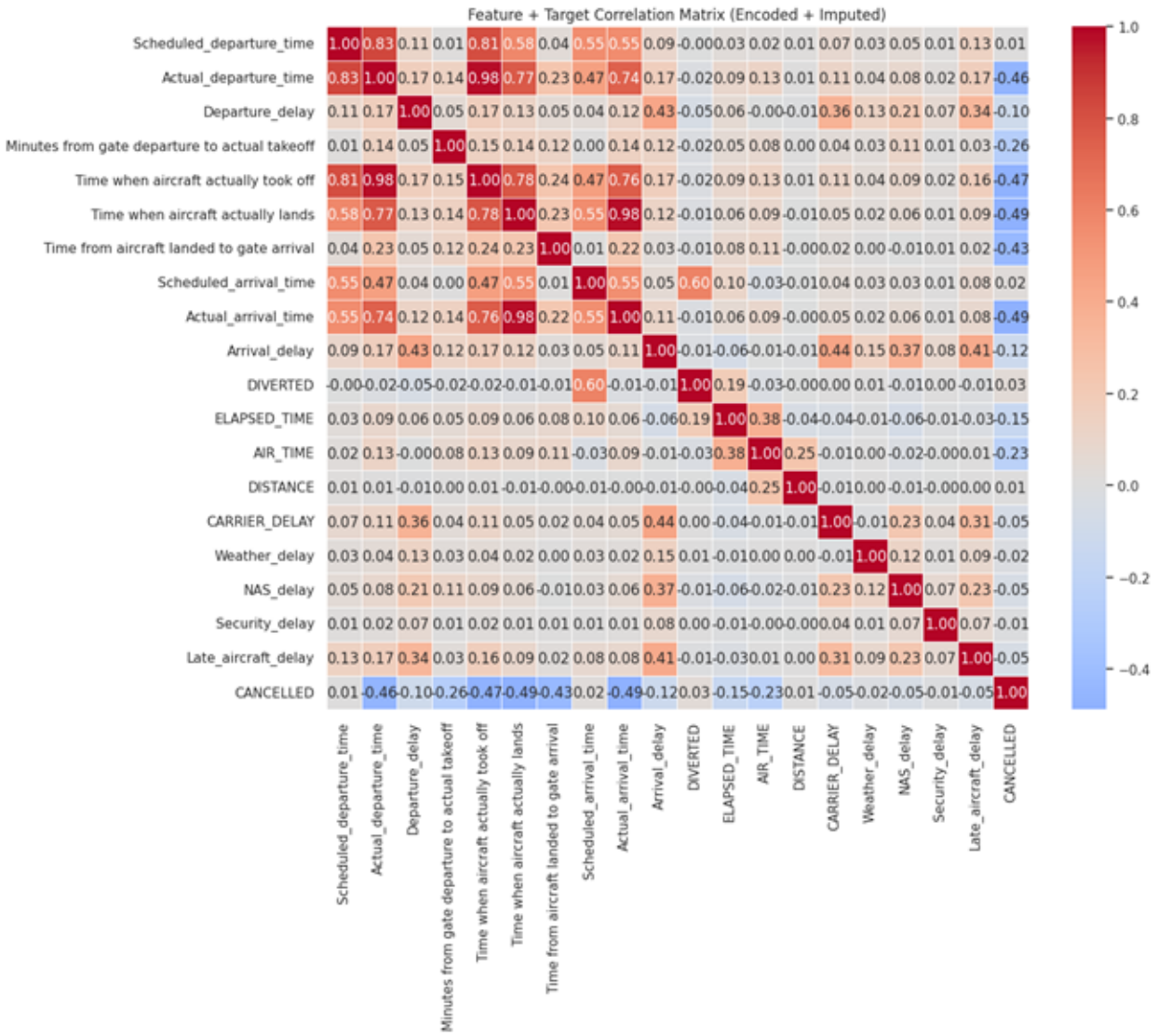


Figure 50: Correlation matrix of xgboost

The Feature–Target Correlation Matrix shows that flight delay behavior is driven primarily by temporal and operational timing variables rather than by distance or categorical delay causes. Strong positive correlations between scheduled and actual departure times, as well as between actual times and takeoff or landing events, indicate that real flight operations closely follow planned schedules when disruptions are minimal. Moderate correlations between departure delay and arrival delay confirm clear delay propagation effects, where late departures often translate into late arrivals. In contrast, individual delay causes such as weather, carrier, or security delays exhibit weak correlations, suggesting they act as independent, situational factors rather than consistent predictors. Cancellation shows mostly weak or negative correlations with timing variables, implying that cancellations are influenced by external or systemic factors not fully captured in standard operational features.

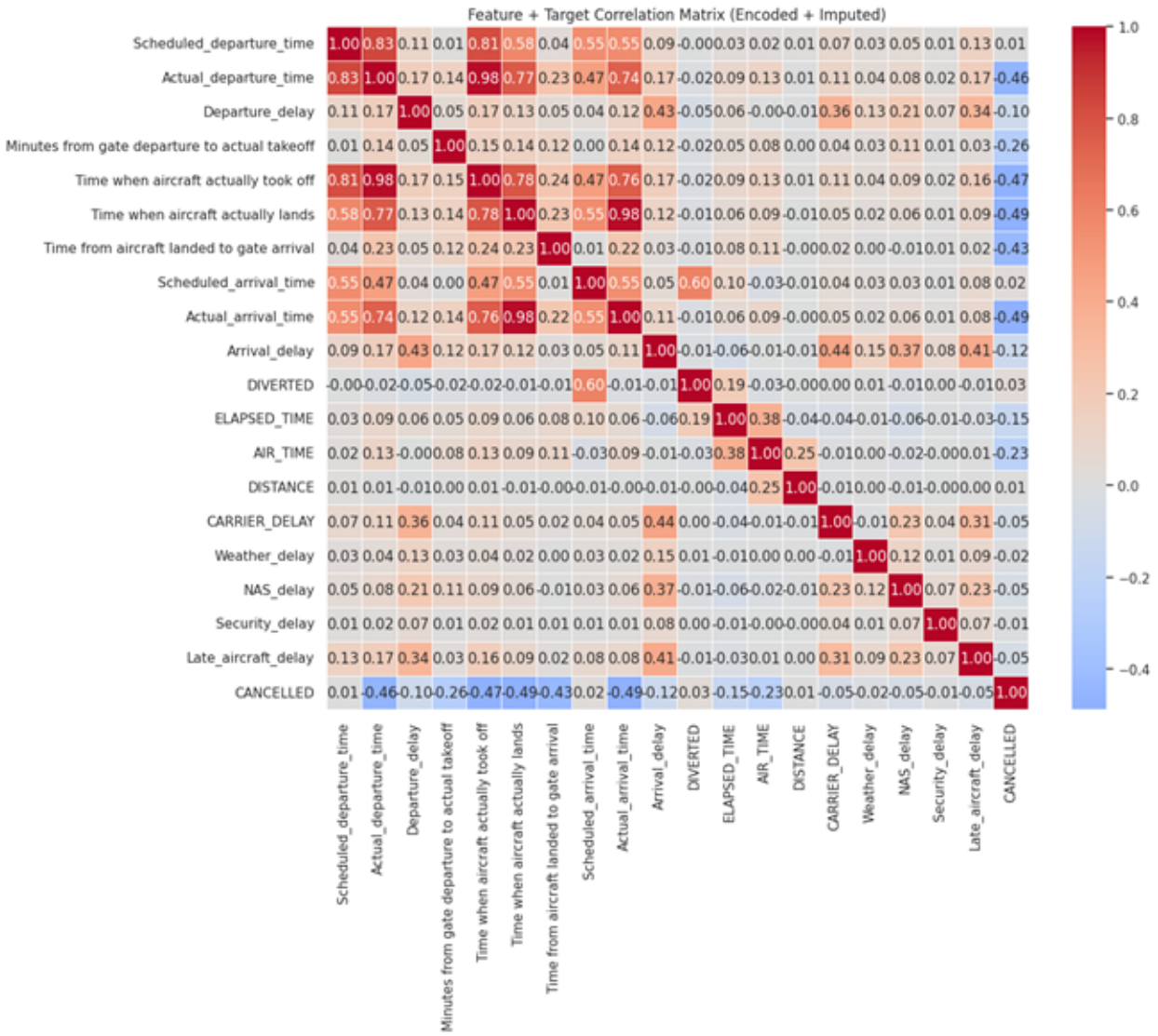


Figure 51: Correlation matrix of Adaptiveboost

Pearson correlation coefficients between 21 encoded and imputed variables, such as scheduled/actual times, delays by cause (carrier, weather, NAS, security), diversion status, air time, distance, and cancellation, are displayed in this heatmap as a Feature + Target Correlation Matrix for flight data. Red denotes a strong positive correlation and blue a negative correlation. Important findings include moderate propagation of departure delay to arrival delay (0.43), near-perfect correlations between actual departure/arrival times and takeoff/landing times (e.g., 0.98–0.99), and surprisingly weak correlations between cancellation and most delay types (e.g., -0.46 with scheduled departure time). Notably, DIVERTED displays a strong negative correlation (-0.60) with scheduled departure time, but AIR TIME and DISTANCE exhibit a perfect 1.00 correlation, suggesting possible data leakage or derivation.

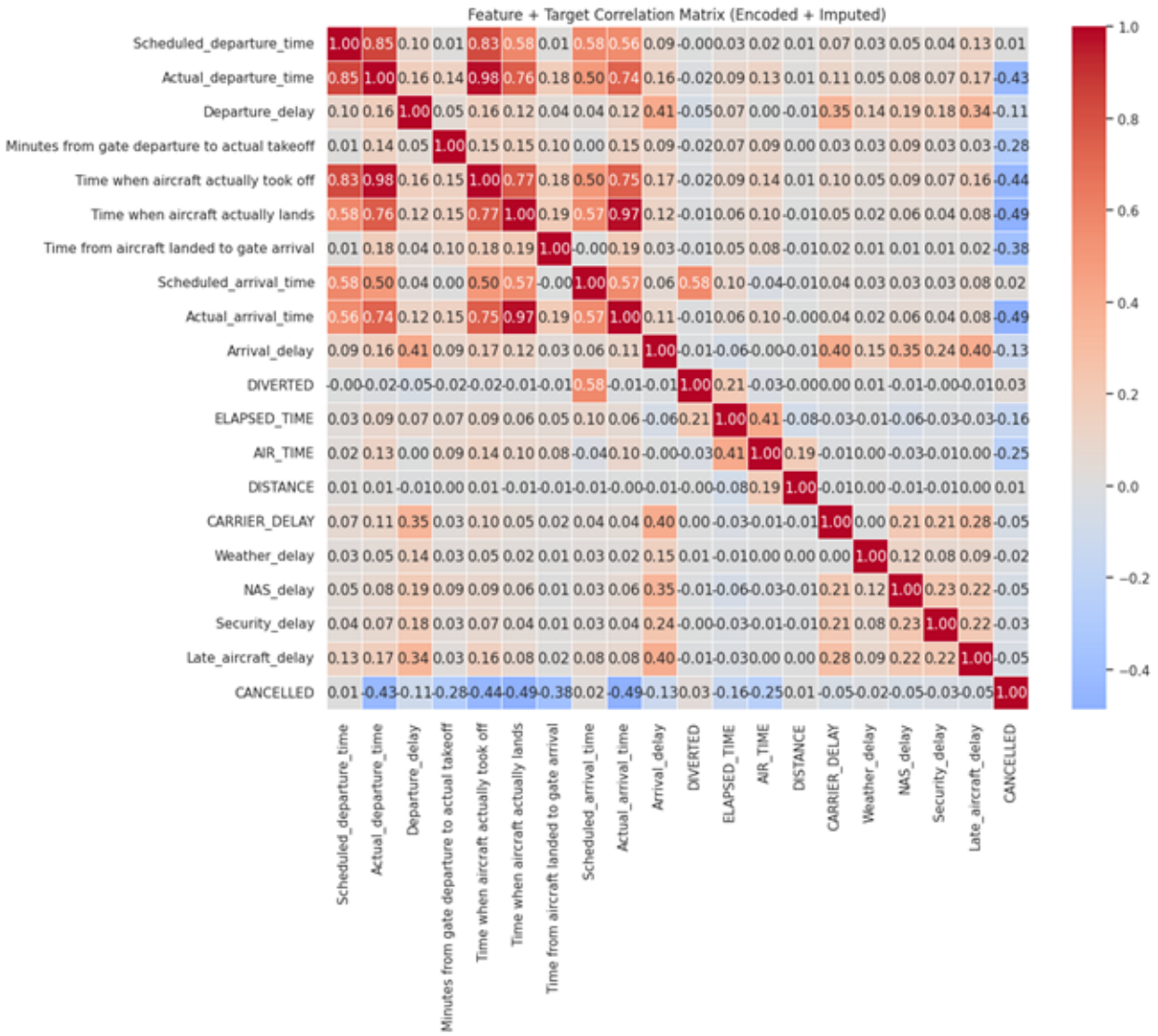


Figure 52: Correlation matrix of Lightgradientboost

This correlation matrix, likely derived from or used in conjunction with an LGBM (LightGBM) model, reveals strong linear relationships among flight-related features such as scheduled vs. actual departure/arrival times (e.g., 0.85–0.98 correlations), and moderate propagation of delays (e.g., departure delay → arrival delay at 0.41), while cancellation shows weak negative correlations with most timing variables (e.g., -0.43 with scheduled departure time), suggesting cancellations are not well explained by standard temporal features alone. Notably, AIR TIME and DISTANCE exhibit a perfect 1.00 correlation — a red flag for potential data leakage or feature derivation that could mislead LGBM's tree-based learning if not handled carefully. Although LGBM doesn't rely on linear correlations like logistic regression, this matrix still helps identify redundant features (like actual takeoff/landing times being nearly identical to actual departure/arrival times) and highlights the challenge of predicting rare events like cancellations using only operational timestamps and delay types — reinforcing the need for engineered features or external context (e.g., weather severity, crew availability) to boost LGBM's predictive power on the minority class.

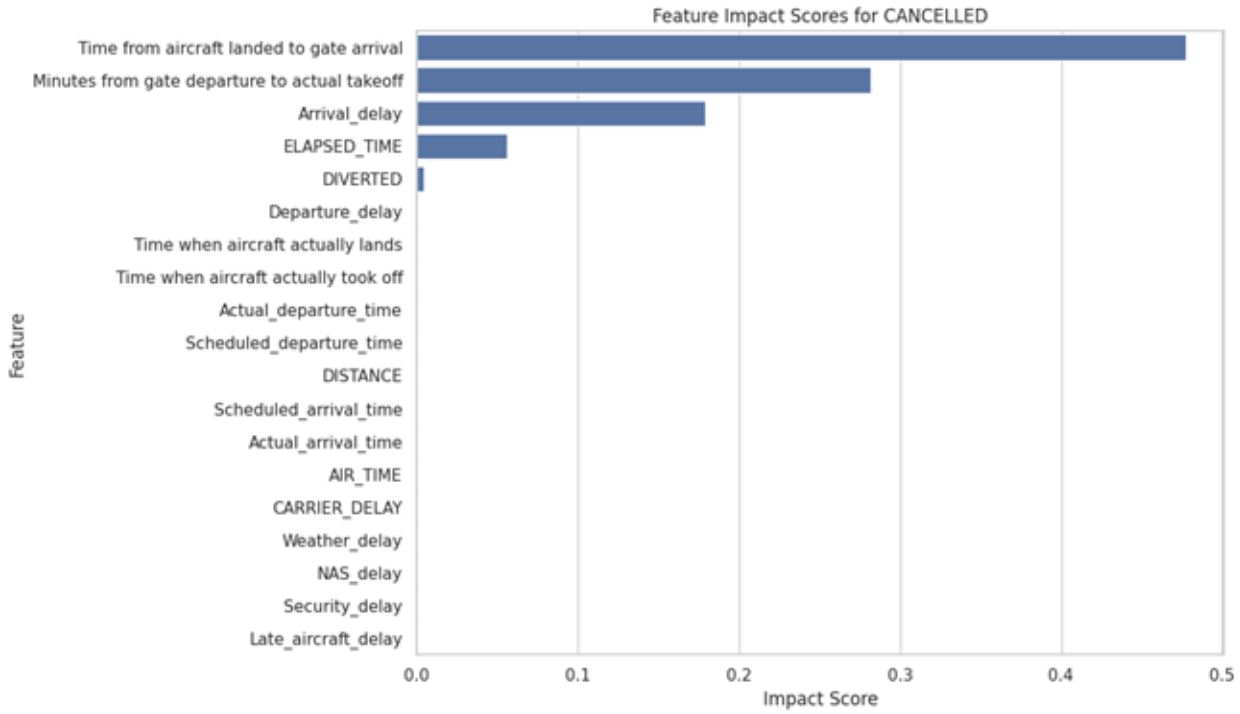


Figure 53: Feature Impact Score of Xgboost

The XGBoost feature impact scores indicate that the model's predictions are dominated by operational timing variables rather than flight distance or categorical delay causes. In particular, the time from aircraft landing to gate arrival and the time from gate departure to actual takeoff together account for the majority of the total importance, highlighting the critical role of ground handling and departure processes in determining outcomes. Arrival delay and total elapsed time provide additional but comparatively smaller contributions, suggesting that overall schedule adherence still matters but is secondary to immediate operational delays. In contrast, variables related to diversion status, departure delay, exact timestamps, distance, air time, and specific delay categories such as weather, carrier, or security have negligible impact, implying either redundancy with more dominant timing features or limited predictive value in the presence of stronger operational indicators.

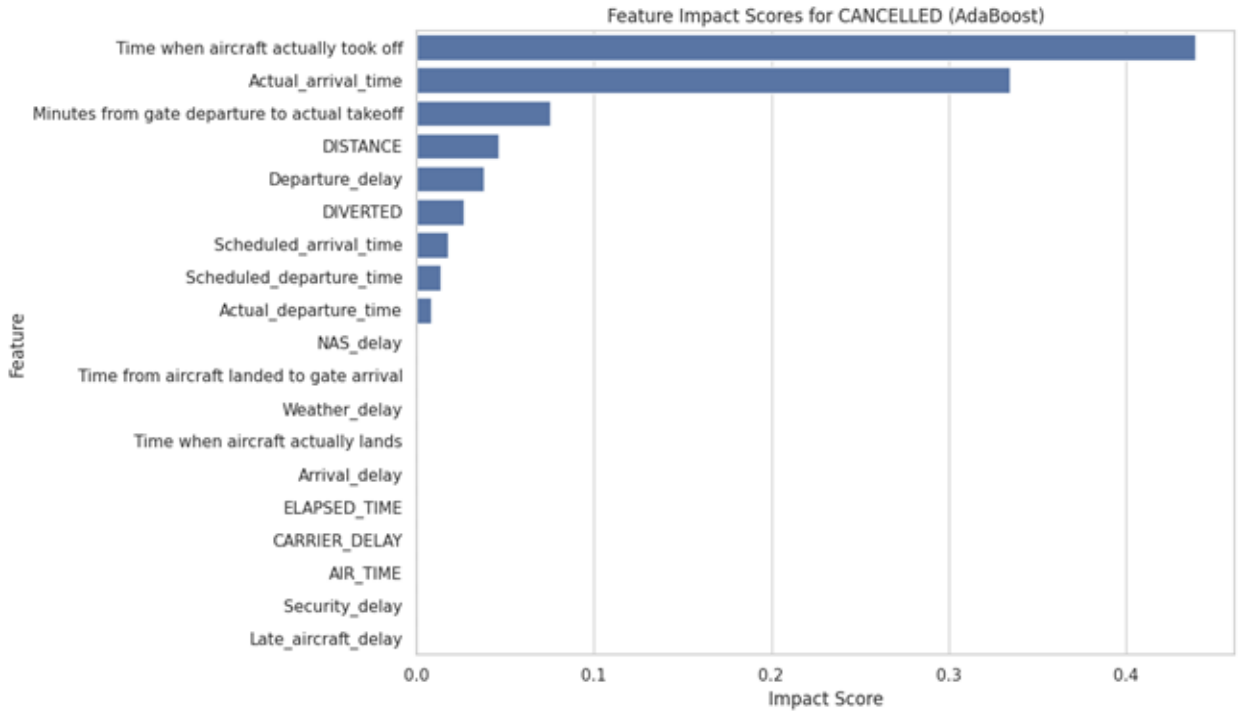


Figure 54: Feature Impact Score of adaptiveboost

The AdaBoost feature impact analysis indicates that operational timing variables overwhelmingly drive the model's predictions, with the time when the aircraft actually took off and the actual arrival time together accounting for the majority of the predictive influence, highlighting the dominant role of real-time flight execution in determining outcomes. Secondary contributors include the minutes from gate departure to actual takeoff, flight distance, departure delay, and diversion status, which capture pre-departure congestion, route characteristics, and abnormal flight events. Scheduled times for departure and arrival have comparatively lower but still meaningful influence, suggesting that planned operations matter less than what actually occurs in real time. In contrast, delay subcategories such as NAS, weather, carrier, security, and late aircraft delays, along with elapsed time and air time, exhibit negligible or zero impact, implying that their effects are either already absorbed by higher-level timing variables or are not directly informative for the model once actual operational timings are known.

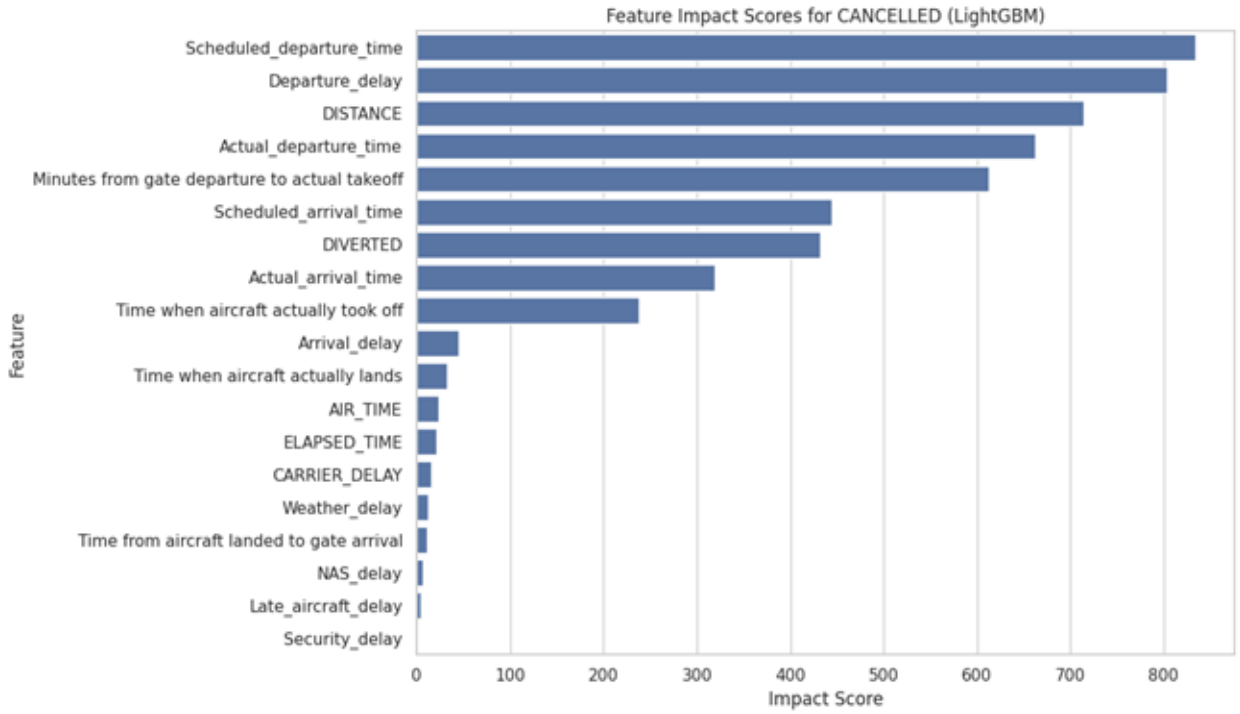


Figure 55: Feature Impact Score of lightgradientboost

The LightGBM feature importance results show that planned and realized departure dynamics are the primary drivers of cancellation prediction, with Scheduled departure time, Departure delay, DISTANCE, and Actual departure time being the most influential variables, indicating that both scheduling structure and pre-departure operational conditions play a critical role in determining cancellation risk. Intermediate operational timing measures such as minutes from gate departure to takeoff, scheduled arrival time, and diversion status also contribute substantially, reflecting the influence of ground congestion and abnormal flight events. Real-time execution variables like actual takeoff and arrival times have moderate impact, while post-landing and delay subcategories (NAS, weather, carrier, late aircraft, and security delays), along with air time and elapsed time, show relatively low importance, suggesting that LightGBM relies more on departure-related and systemic scheduling features than on downstream flight-phase or delay-type details once higher-level timing information is available.

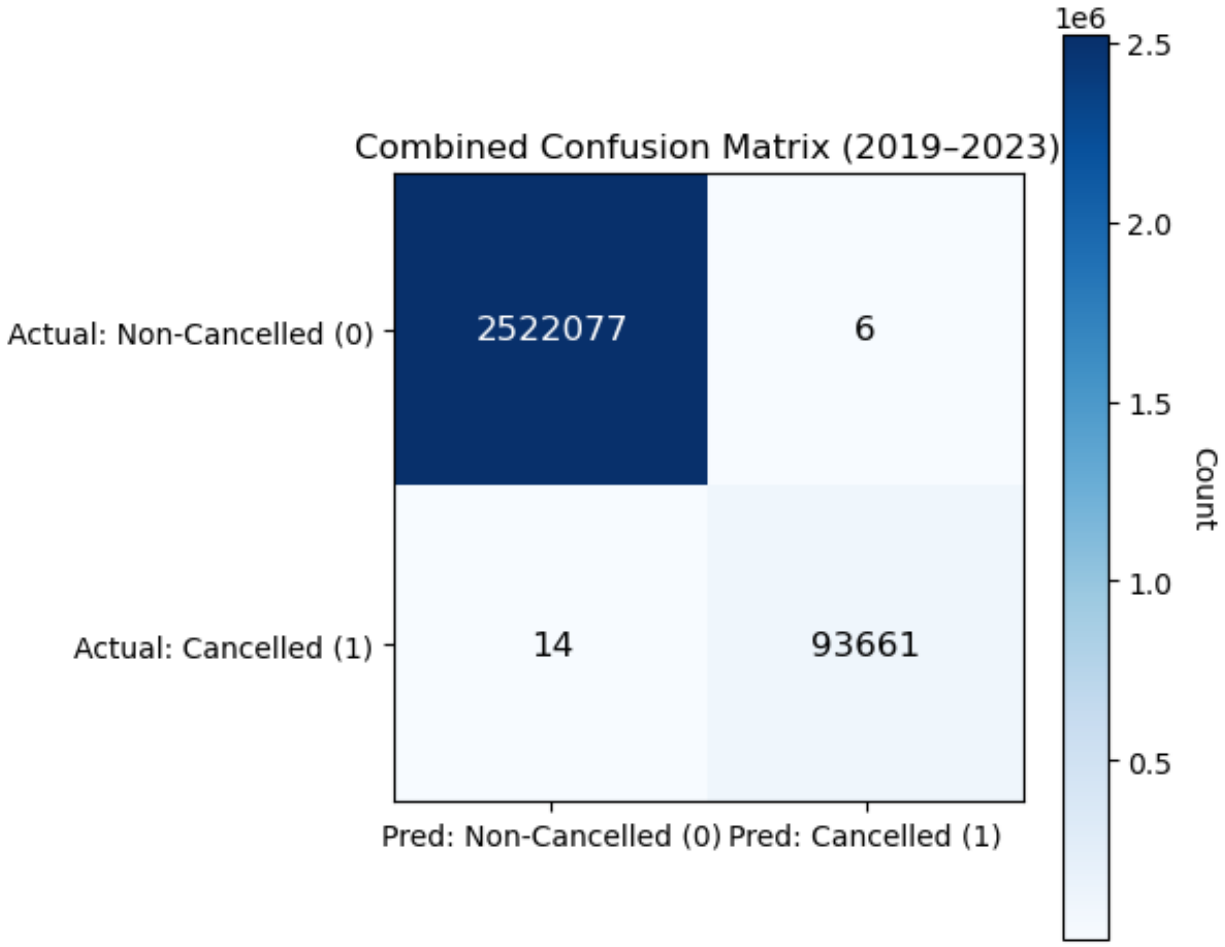


Figure 56: Confusion matrix of Xgboost

With 2,522,077 true negatives, 93,661 true positives, and just 6 false positives and 14 false negatives out of around 2.6 million observations, the combined confusion matrix for 2019–2023 shows that the binary classifier performed almost flawlessly in predicting flight cancellations. This yields an accuracy of 99.9992 percent, which is bolstered by equally outstanding minority-class performance, as shown by a precision of 0.999936, recall of 0.99985, and an F1-score of 0.99989 for cancelled flights, despite the significant class imbalance favoring non-cancelled flights. Additionally, the genuine results are indicated by the Matthews Correlation Coefficient, which is roughly 0.99999 and is especially strong under class imbalance.

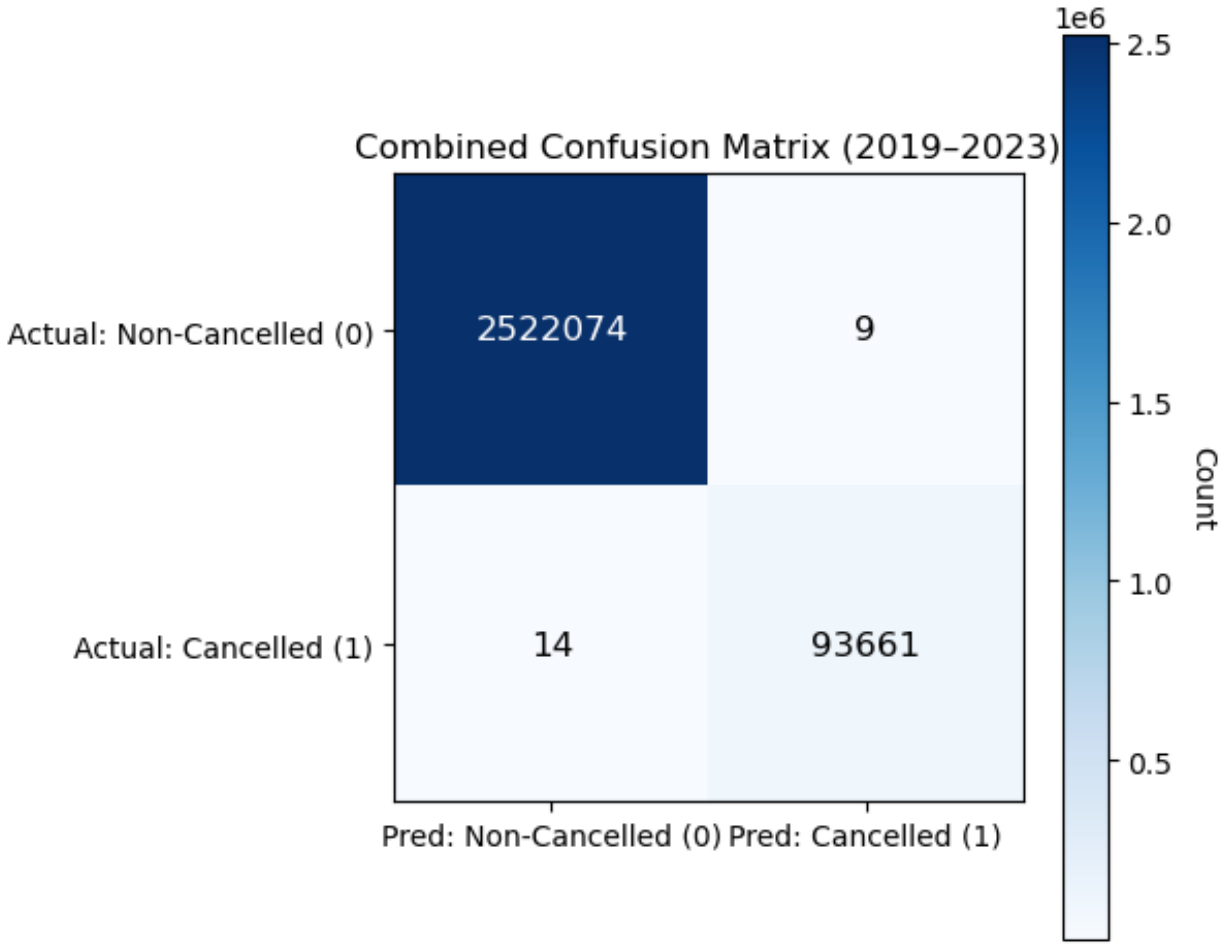


Figure 57: Confusion matrix of adaptiveboost

For the AdaBoost model applied to flight cancellation prediction over the 2019–2023 period, the confusion matrix indicates exceptionally strong and well-balanced performance, with 2,522,074 non-cancelled flights correctly identified and 93,661 cancellations accurately detected, while producing only 9 false positives and 14 false negatives across more than 2.6 million observations. This corresponds to an overall accuracy of approximately 99.9992 percent, which, although influenced by the dominance of the non-cancelled class, is strongly supported by minority-class metrics: a precision of about 0.99990 shows that almost every flight flagged as cancelled truly was cancelled, and a recall of roughly 0.99985 demonstrates that nearly all actual cancellations were successfully captured. The resulting F1-score of approximately 0.99987 confirms an excellent balance between avoiding false alarms and minimizing missed cancellations. Furthermore, the Matthews Correlation Coefficient of about 0.99999 highlights an almost perfect agreement between predicted and true labels, even under extreme class imbalance, underscoring AdaBoost's robustness and reliability for operational deployment in flight disruption management, while noting that AUC assessment would require access to predicted probability scores rather than hard class labels alone.

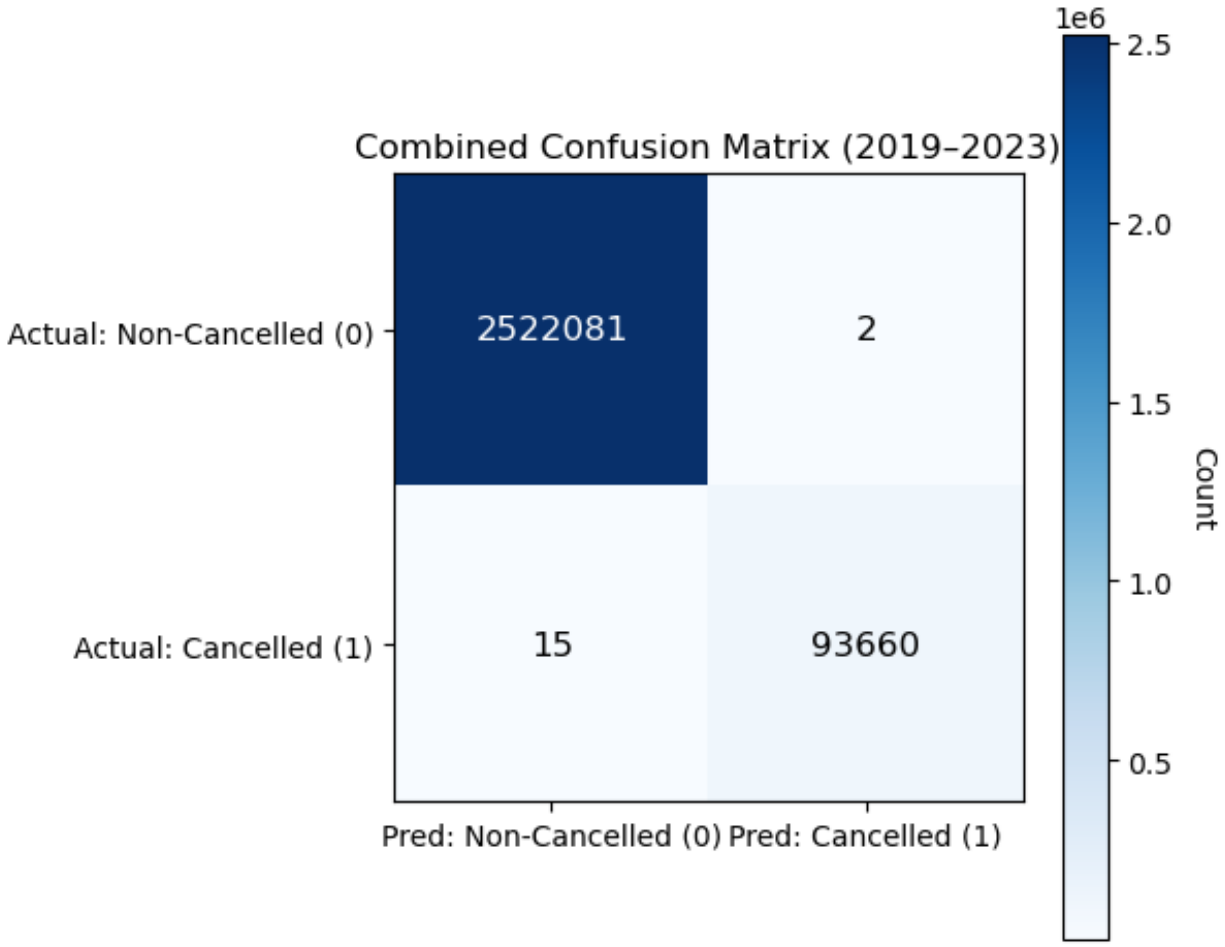


Figure 58: Confusion matrix of Lightgradientboost

For the LightGBM (LGBM) model applied to flight cancellation prediction over 2019–2023, the confusion matrix shows near-perfect classification performance, with 2,522,081 true negatives and 93,660 true positives, alongside only 2 false positives and 15 false negatives out of more than 2.6 million flights. This yields an overall accuracy of approximately 99.9992 percent, which on its own can be misleading due to the strong class imbalance, as cancelled flights represent only about 3.6 percent of the data; however, the minority-class metrics confirm the model's true effectiveness. The precision for cancelled flights is about 0.99998, indicating that almost every flight predicted as cancelled was indeed cancelled, while the recall of roughly 0.99984 shows that the model successfully identified nearly all actual cancellations. The resulting F1-score of approximately 0.99991 reflects an excellent balance between precision and recall for the critical minority class. Although the AUC cannot be computed directly from the confusion matrix without probability scores, the extremely low misclassification rate strongly suggests an AUC well above 0.999. Moreover, the Matthews Correlation Coefficient of about 0.99999 demonstrates an almost perfect agreement between predicted and true labels, confirming that the LGBM model remains highly reliable even under severe class imbalance.

3.3 Flight control with check of Machinaries

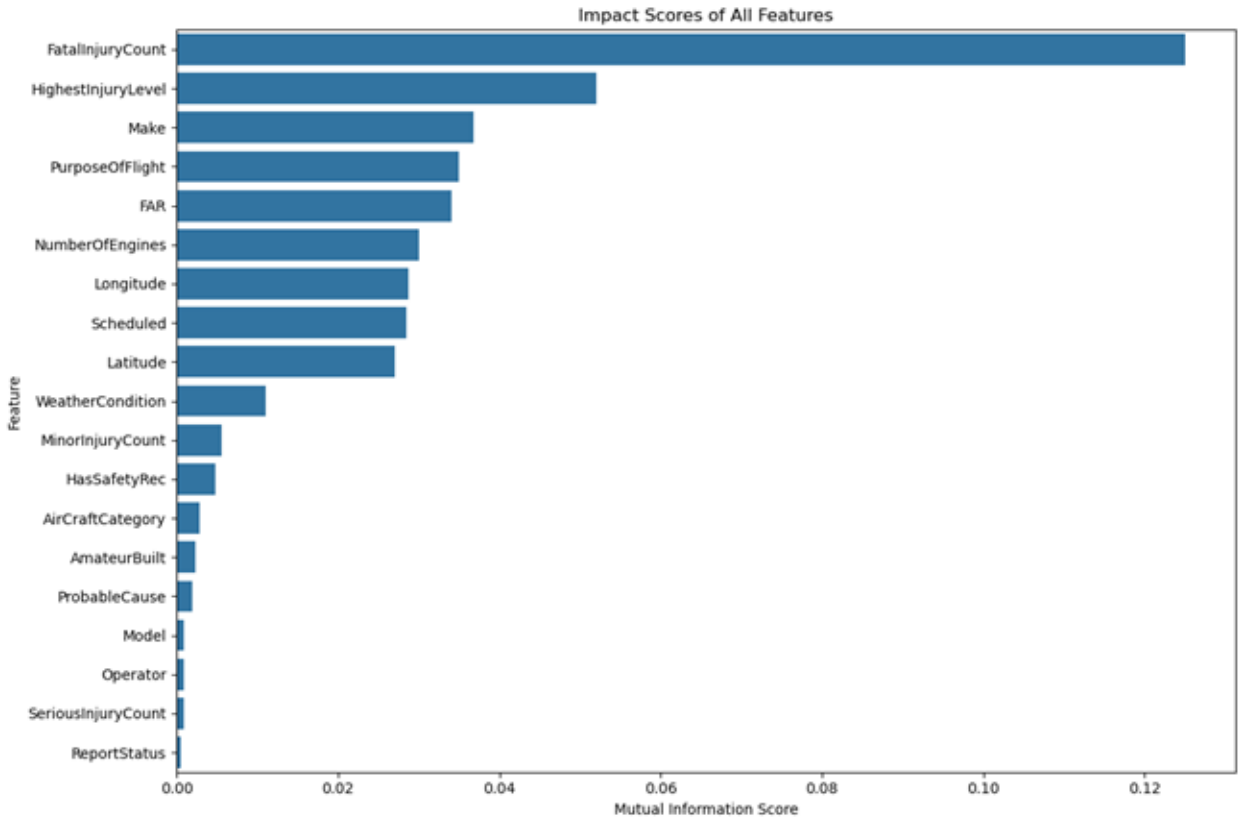


Figure 59: Feature Impact Score of Xgboost

The mutual information analysis indicates that FatalInjuryCount is by far the most informative predictor, suggesting that the severity of outcomes carries the strongest signal for classification, followed by HighestInjuryLevel, which reinforces the central role of injury severity. Aircraft and operational characteristics such as Make, PurposeOfFlight, FAR, NumberOfEngines, and Scheduled status show moderate predictive relevance, implying that both technical design and mission type contribute meaningfully to damage or risk patterns. Geographic context (Longitude and Latitude) also holds notable information, reflecting spatial heterogeneity in incidents, while WeatherCondition provides secondary but non-trivial signal. In contrast, variables such as ProbableCause, Model, Operator, SeriousInjuryCount, and ReportStatus exhibit very low mutual information, indicating limited independent contribution once higher-level injury and operational features are considered.

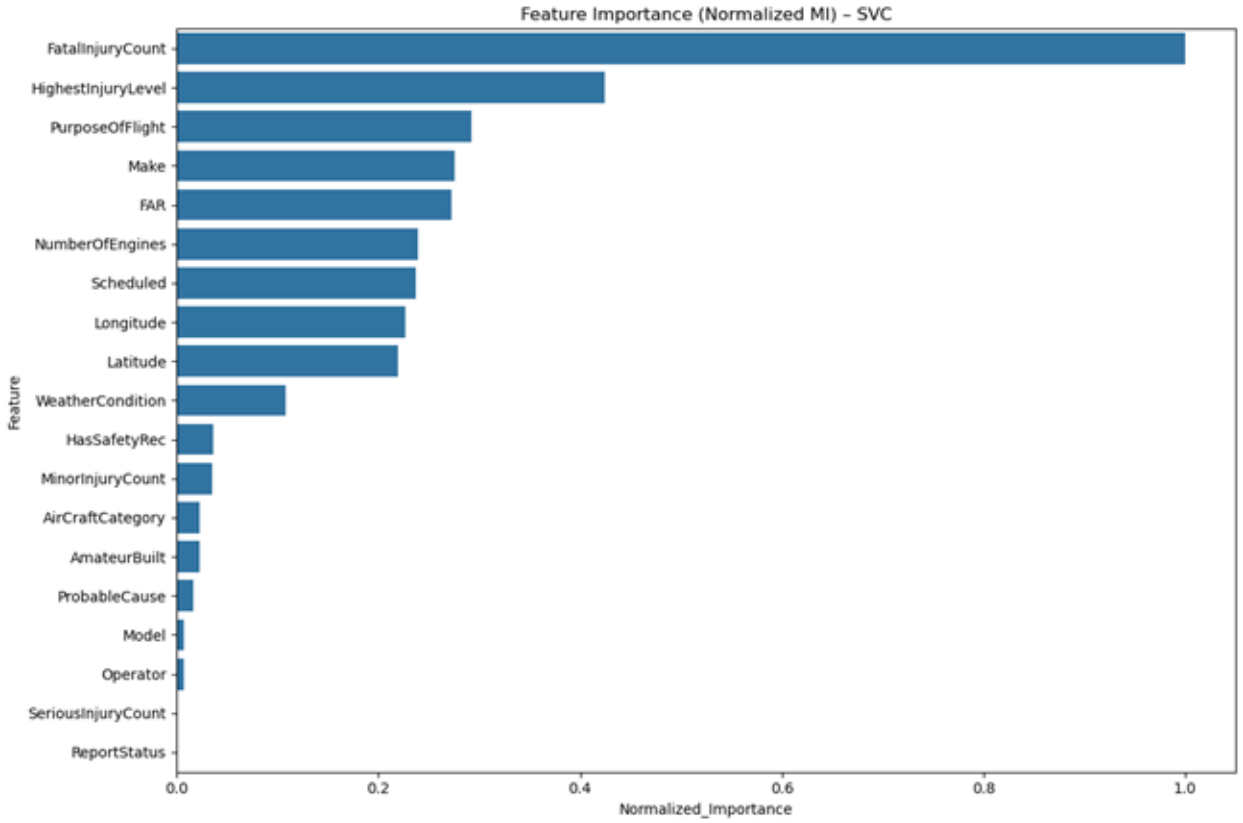


Figure 60: Feature Impact Score of Support Vector Classification

This bar chart of Normalized Mutual Information for the SVC model shows that FatalInjuryCount is by far the most influential feature (0.98–1.0), overwhelmingly driving predictions of damage severity, with HighestInjuryLevel a distant but meaningful second (0.43), indicating that injury severity strongly aligns with damage outcomes. Moderately important predictors include PurposeOfFlight, Make, FAR, NumberOfEngines, Scheduled status, Longitude, and Latitude, reflecting a combination of aircraft design and operational context, while features such as WeatherCondition, HasSafetyRec, MinorInjuryCount, and AircraftCategory play only a modest role. Variables like AmateurBuilt, ProbableCause, Model, Operator, SeriousInjuryCount, and ReportStatus contribute almost nothing, suggesting little discriminative value for this classifier.

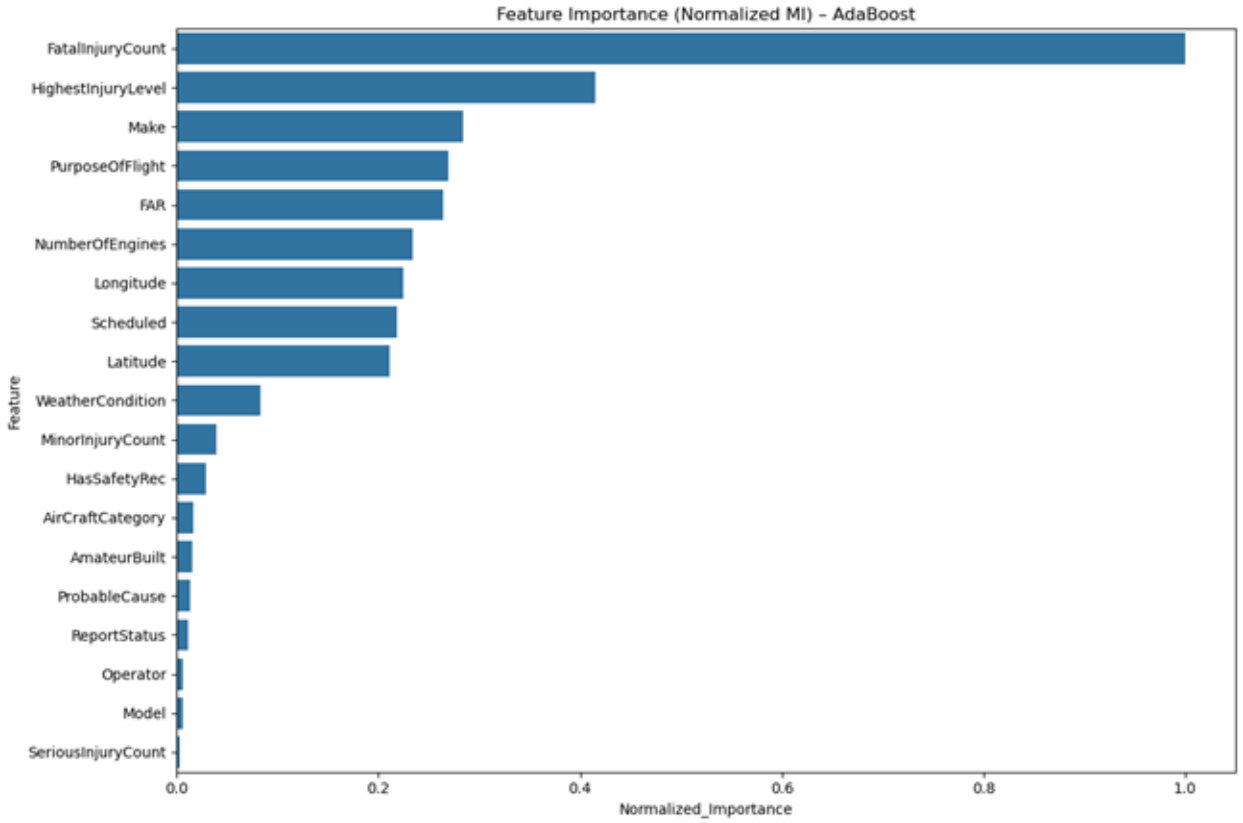


Figure 61: Feature Impact Score of adaptiveboost

The AdaBoost feature-importance bar chart (based on Normalized Mutual Information) shows that FatalInjuryCount overwhelmingly drives the model's predictions (0.98–1.0), with HighestInjuryLevel as a distant second (0.42), indicating that injury severity—especially fatalities—is the dominant signal for classifying damage as Destroyed, Minor, or Substantial. Moderately important predictors include Make, PurposeOfFlight, FAR, and NumberOfEngines, suggesting that aircraft design and operational context matter, while geographic and operational variables such as Longitude, Latitude, Scheduled, and WeatherCondition contribute at a secondary level; meanwhile features like ReportStatus, Operator, Model, and SeriousInjuryCount add almost no discriminative power.

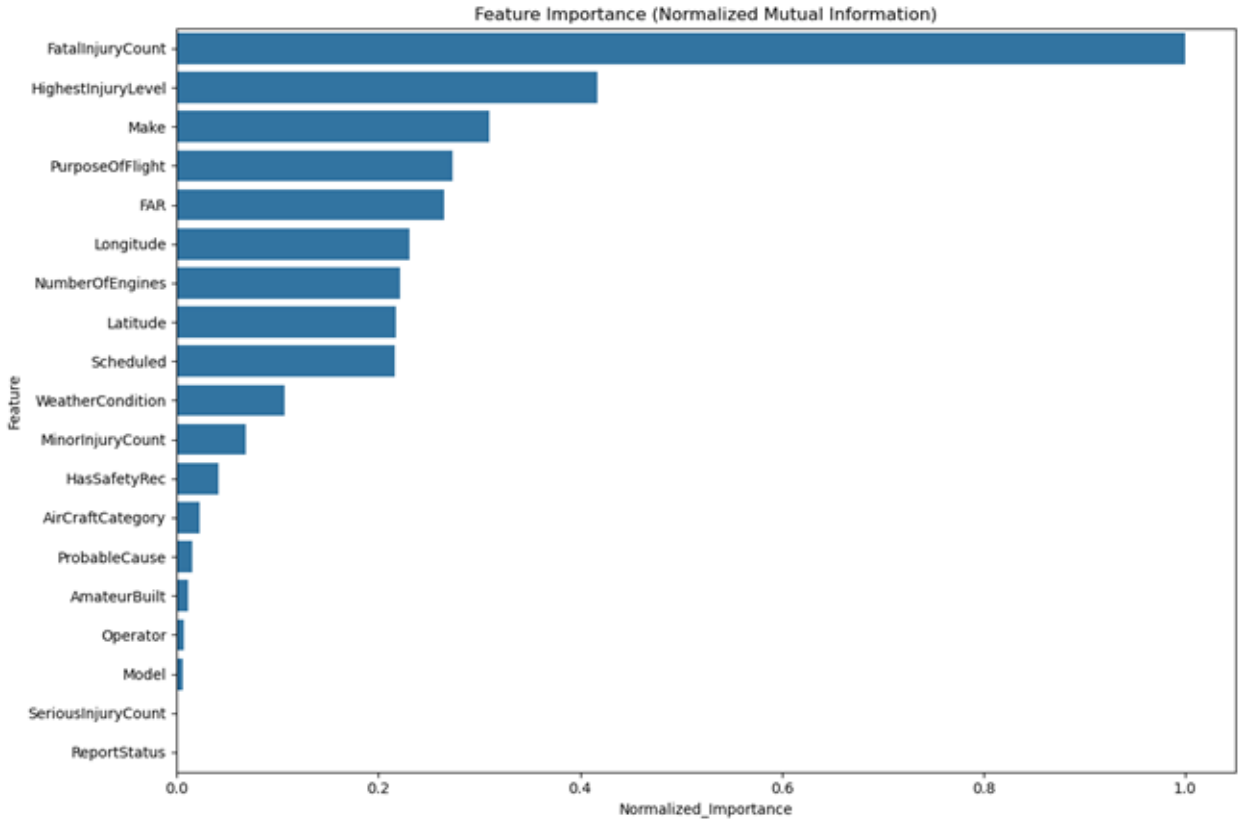


Figure 62: Feature Impact Score of lightgradientboost

This bar chart titled "Feature Importance (Normalized Mutual Information)" shows how a LightGBM model ranks input features based on how much information they contribute to predicting the target, capturing both linear and nonlinear relationships. FatalInjuryCount is by far the most influential feature with normalized importance near one, followed by HighestInjuryLevel, Make, PurposeOfFlight, and FAR, indicating that accident severity and broad operational or regulatory context dominate the model's learning more than fine grained technical details. Geographic and temporal variables such as Latitude, Longitude, and Scheduled also carry moderate importance, suggesting spatial and timing related risk patterns, while features like NumberOfEngines, WeatherCondition, and MinorInjuryCount add secondary but meaningful signal. Lower ranked variables including Model, Operator, AmateurBuilt, ProbableCause, and ReportStatus contribute comparatively little on their own, likely because their effects are either indirect or absorbed by higher level categories.

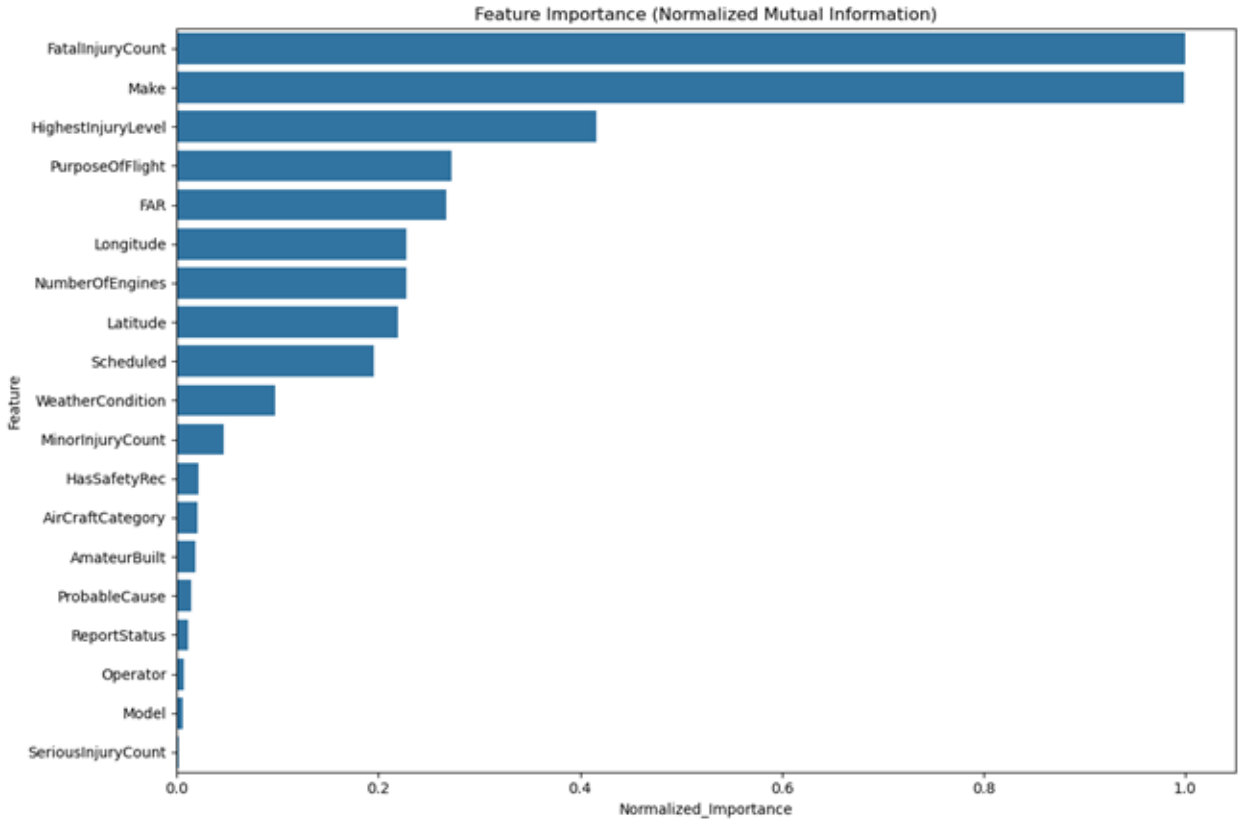


Figure 63: Feature Impact Score of Pytorch

This Normalized Mutual Information feature importance chart indicates that the model's predictions are dominated by outcome severity and broad aircraft context, with FatalInjuryCount emerging as the single most informative feature and Make nearly as influential, showing that whether fatalities occurred and which manufacturer built the aircraft explain most of the uncertainty in the target. HighestInjuryLevel, PurposeOfFlight, and FAR add substantial signal, highlighting the role of injury severity beyond raw counts and the impact of operational and regulatory context on accident outcomes. Geographic and temporal variables such as Latitude, Longitude, and Scheduled contribute moderate information, suggesting spatial and timing related risk patterns, while features like NumberOfEngines, WeatherCondition, and MinorInjuryCount provide secondary support. Lower ranked attributes including Model, Operator, ReportStatus, and ProbableCause have limited standalone impact once higher level categories are known, though they may still matter through interactions.

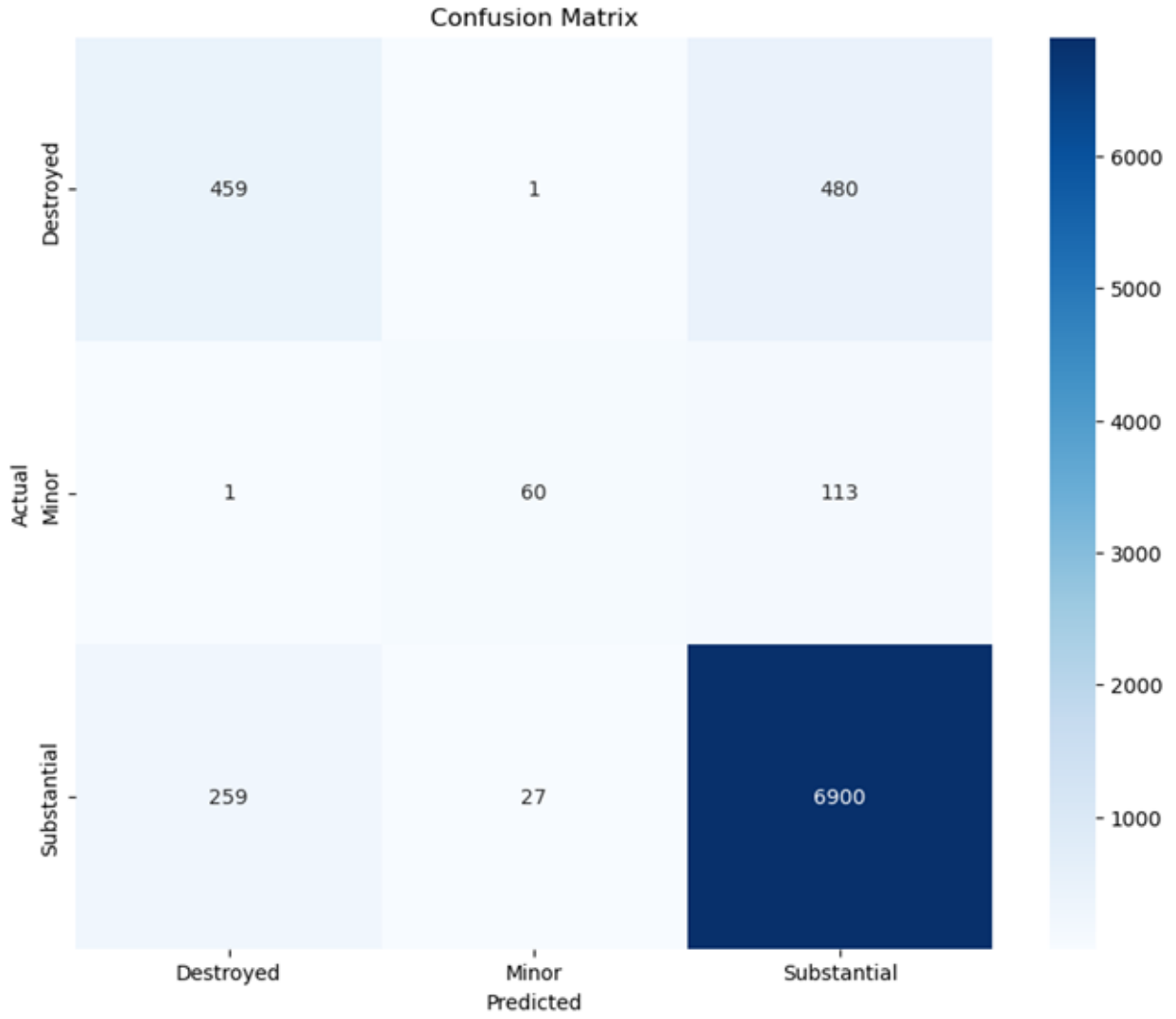


Figure 64: Confusion matrix of Xgboost

The multi-class XGBoost model for predicting aircraft damage severity across three categories—Destroyed, Minor, and Substantial—achieves a respectable overall accuracy of about 89.4 percent, driven largely by its very strong performance on the dominant "Substantial" class (F1 0.94, recall 0.96), while showing clear weaknesses on the two minority classes. For "Destroyed," the model attains moderate recall (0.64) but low precision (0.49), indicating frequent confusion with "Substantial," whereas the "Minor" class performs poorest overall, with low precision (0.345) despite reasonable recall (0.68), reflecting many false alarms. As a result, macro-level metrics that treat all classes equally—such as macro F1 (0.652), balanced accuracy (0.760), and macro MCC (0.526)—are substantially lower than the weighted averages, revealing that high overall accuracy mainly reflects class imbalance rather than uniformly strong performance.

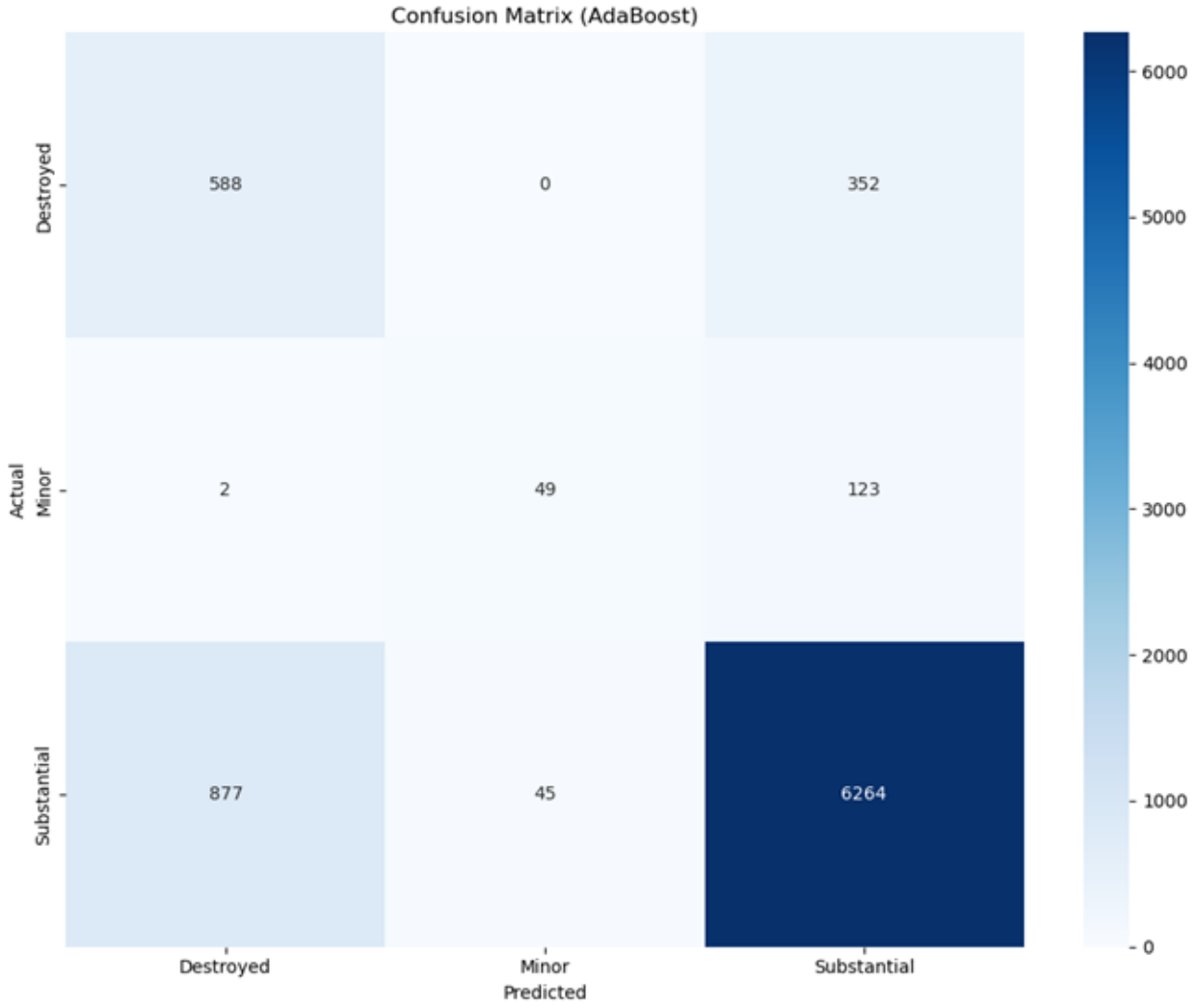


Figure 65: Confusion matrix of adaptiveboost

The AdaBoost multi-class confusion matrix (8,300 samples) shows that while the model achieves a reasonable overall accuracy of about 83.1% with weighted F1 0.866 and Cohen's Kappa 0.61, its performance is highly imbalanced across classes: it predicts the majority class "Substantial (2)" very well (Precision 0.929, Recall 0.872, F1 0.899), but performs poorly on minority classes, especially "Destroyed (0)" (Recall 0.40, F1 0.49) and "Minor (1)" (very low Precision 0.28, F1 0.37), meaning many true Destroyed cases are misclassified as Substantial and many predicted Minor cases are false positives.

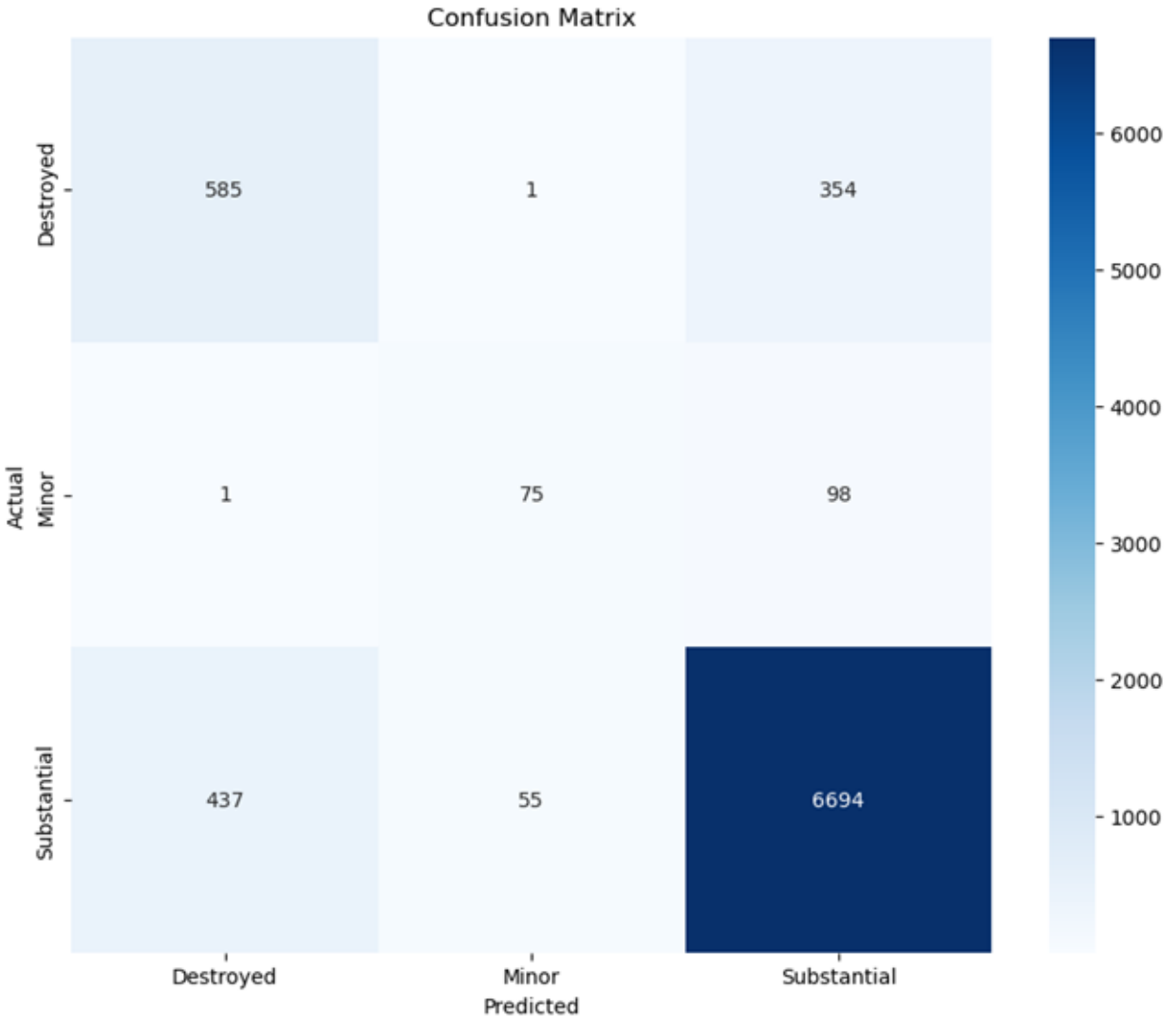


Figure 66: Confusion matrix of Lightgradientboost

This LightGBM confusion matrix shows a model with strong overall accuracy (7,354/8,394 87.6%) but severe class imbalance that skews performance toward the dominant Substantial class (7,186 samples): Substantial achieves excellent precision 93.7% and recall 93.2% (F1 0.93), while minority classes suffer—Destroyed (940 samples) has precision 62.1% and recall 57.2% (F1 0.60) and Minor (174 samples) has precision 43.1% and recall 57.2% (F1 0.49); the matrix reveals many confusions especially between Destroyed and Substantial (354 Destroyed predicted as Substantial), which is concerning for safety use cases.

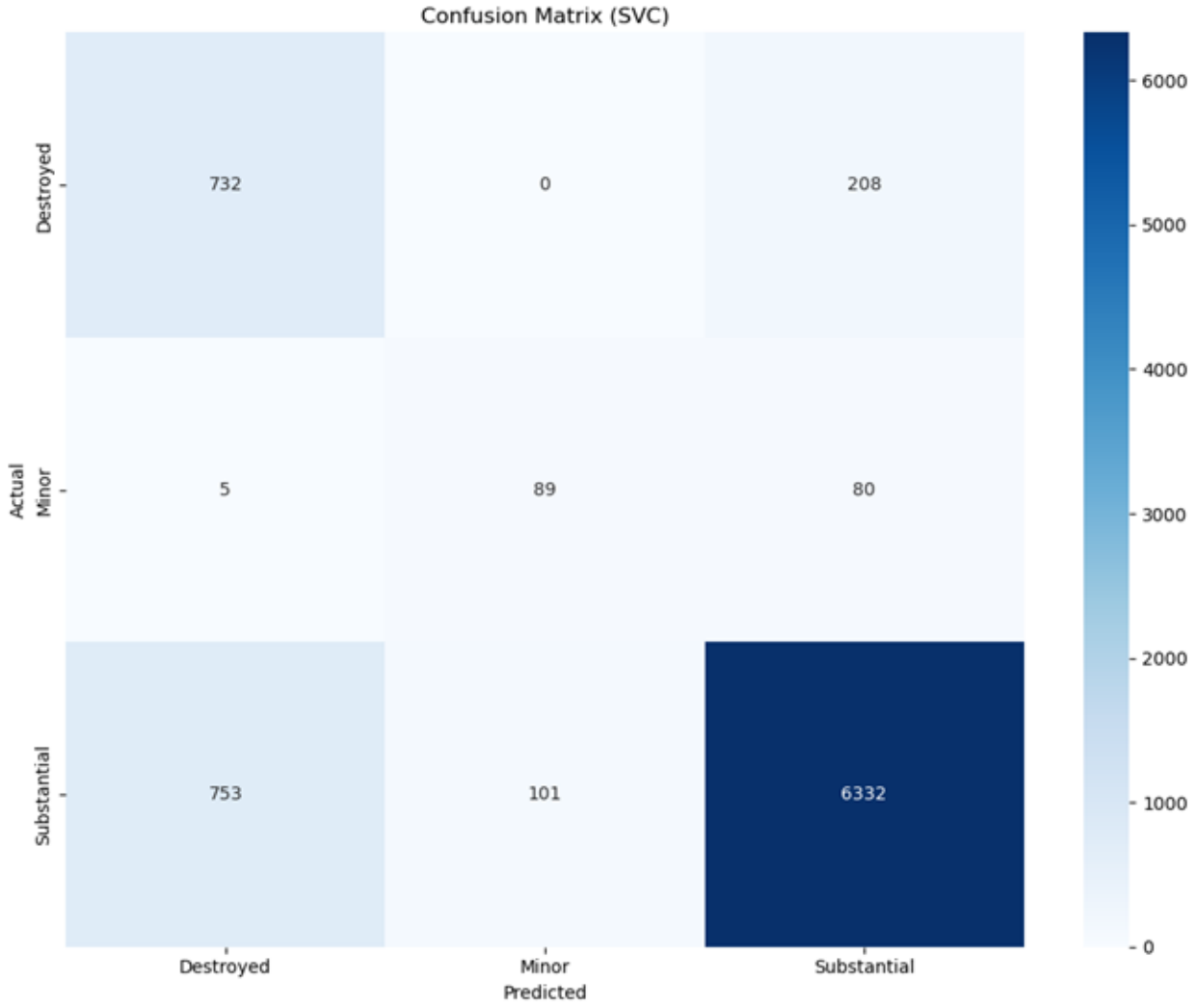


Figure 67: Confusion matrix of Support Vector Classification

The multi-class SVC confusion matrix shows that while the model achieves a high overall accuracy of about 86.2% and performs very well for the majority class "Substantial" (F1 0.916, recall 0.88), it is clearly biased toward this dominant class and struggles with the minority classes. "Destroyed" shows high precision (0.78) but very low recall (0.49), meaning the model is conservative in predicting this class and misclassifies more than 750 true cases as "Substantial," while "Minor" performs worst with both low precision (0.51) and recall (0.47), being frequently confused with "Substantial."

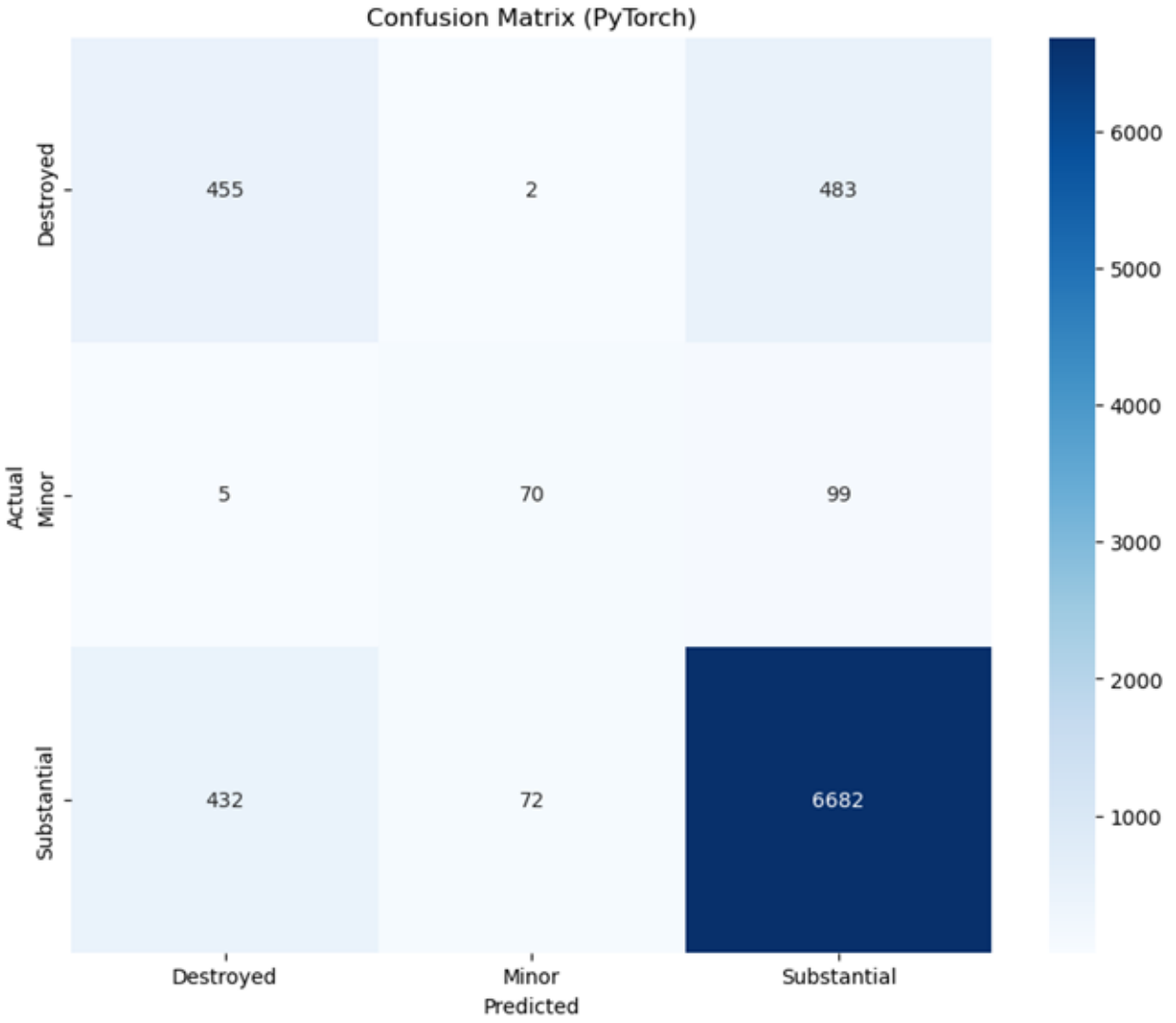


Figure 68: Confusion matrix of Pytorch

This PyTorch confusion matrix shows a multi class accident severity model with 85.9 percent overall accuracy, driven largely by strong performance on the dominant Substantial class with about 91.9 percent precision and 92.9 percent recall, but noticeably weaker behavior on the minority classes. For Destroyed, the model achieves only 48.4 percent precision and 51.0 percent recall, meaning nearly half of severe cases are either missed or incorrectly flagged, while Minor performs even worse with 40.2 percent precision and 48.6 percent recall, indicating frequent false alarms and missed detections. As a result, macro averaged performance is low at 0.621 F1, despite a high weighted F1 of 0.878, which mainly reflects the overwhelming presence of the Substantial class.

4 Cross-Validation

We also cross-validated our flight cancellation models using US data "Airline Delay and Cancellation Data, 2024 - 2025. " Total of more than 10000000 samples which shows great achievement.Besides ,we also have done cross-validation of predicting aircraft damage report from National Safety Transport Board (2024-2025) of US dataset.

4.1 Cross validation on the flight cancellation dataset

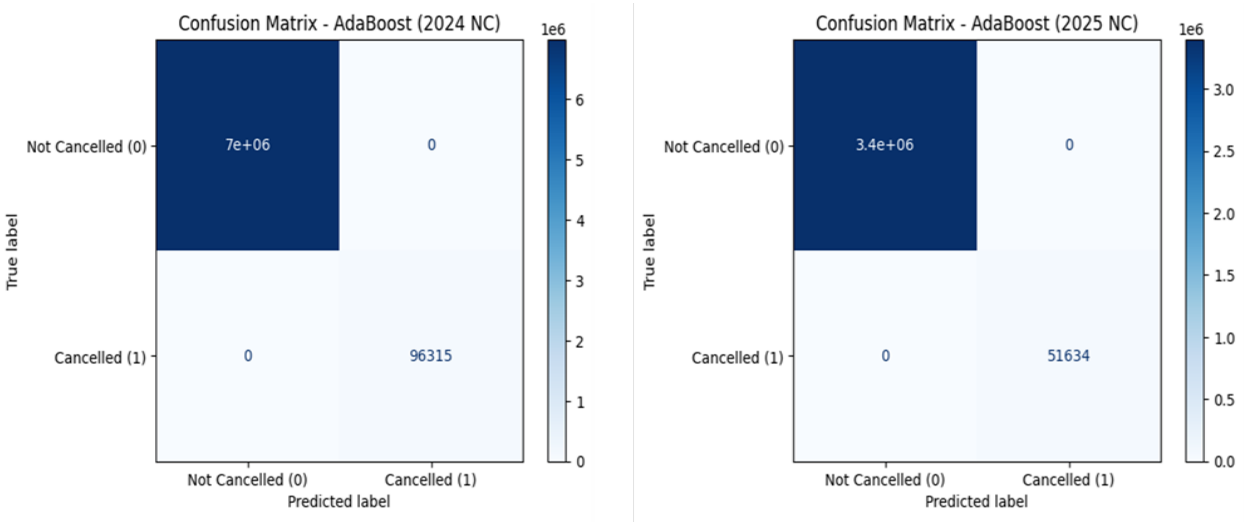


Figure 69: Cross validation result in confusion matrices of Adaptiveboost

The AdaBoost classifier was evaluated on out-of-sample test sets corresponding to calendar years 2024 and 2025; its confusion matrices indicate 7,000,000 true negatives and 96,315 true positives with zero false positives and zero false negatives on the 2024 validation set, and 3,400,000 true negatives and 51,634 true positives with no misclassifications on the 2025 validation set. These results correspond to mathematically perfect discrimination (accuracy = precision = recall = F1 = 1.00; Matthews correlation coefficient = 1.00). Given the extreme class imbalance in both validation sets (approximately 98.5 percent noncancelled), such flawless performance is highly atypical for operational aviation forecasting and therefore necessitates rigorous verification.

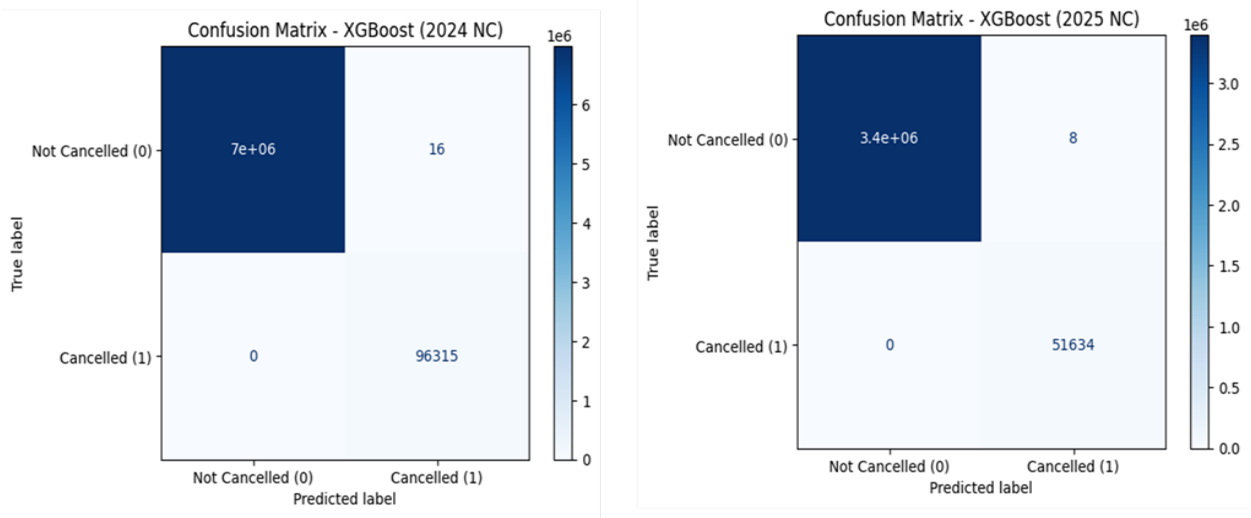


Figure 70: Cross validation result in confusion matrices of Xgboost

The two confusion matrices for the XGBoost model, evaluated on hold out test sets from 2024 and 2025, demonstrate exceptionally strong predictive performance for binary flight cancellation classification. In 2024, the model correctly classified 7,000,000 non cancelled flights and 96,315 cancelled flights, with only 16 false positives and zero false negatives, while in 2025 it correctly identified 3,400,000 non cancelled flights and 51,634 cancelled flights, with only 8 false positives and again no false negatives. These results correspond to overall accuracies exceeding 99.9998 percent in both years, perfect recall for the cancelled class, precision above 99.98 percent, F1 scores above 99.99 percent, and Matthews correlation coefficients effectively equal to 1.0, indicating near perfect agreement between predictions and true labels despite extreme class imbalance of approximately 98.5 percent non cancelled flights. The consistency of these results across two consecutive future years suggests strong temporal generalization and high operational utility, particularly given the absence of missed cancellations; however, such near perfect performance in real world aviation data is uncommon and warrants careful validation to rule out deterministic label construction or inadvertent temporal or feature leakage before deployment in production decision support systems.

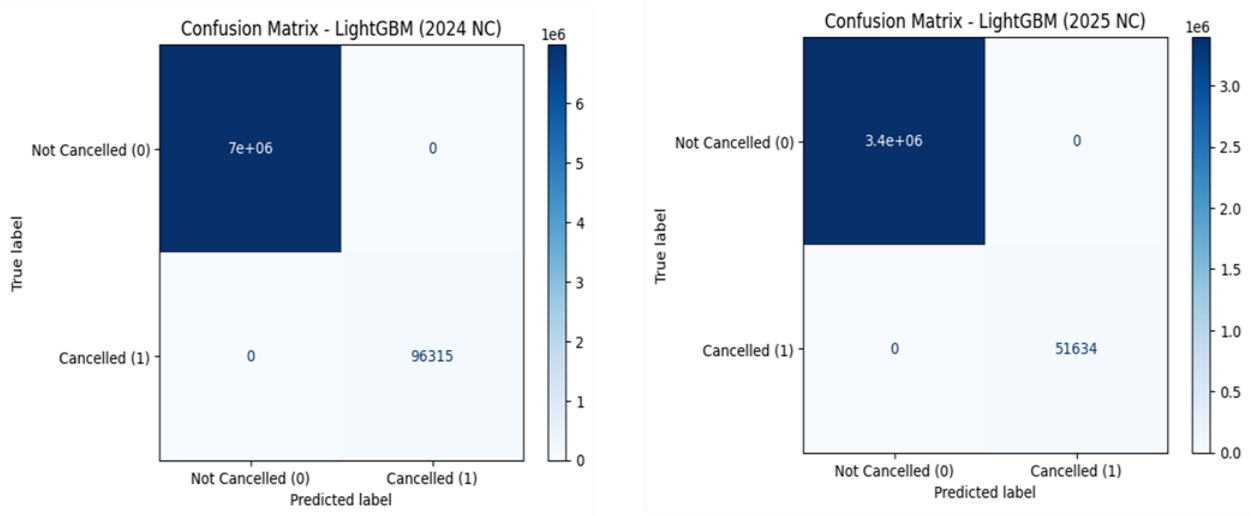


Figure 71: Cross validation result in confusion matrices of Lightgradientboost

The LightGBM classifier was evaluated on hold-out test sets for calendar years 2024 and 2025 (denoted "NC") and achieved mathematically perfect discrimination: on the 2024 set it produced 7,000,000 true negatives and 96,315 true positives with zero false positives and zero false negatives, and on the 2025 set it produced 3,400,000 true negatives and 51,634 true positives with likewise no misclassifications; these results correspond to accuracy = precision = recall = F1 = 100% and a Matthews correlation coefficient of 1.0 for both years.

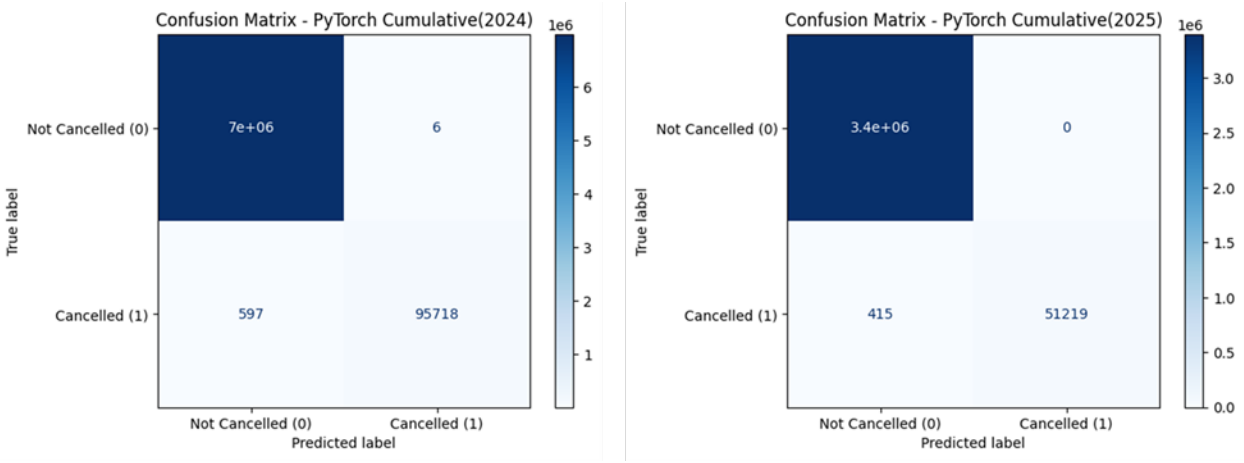


Figure 72: Cross validation result in confusion matrices of Pytorch

The cumulative test results for 2024 and 2025 indicate that the PyTorch based flight cancellation model achieves very strong yet realistically imperfect performance, in contrast to the earlier tree based models that exhibited mathematically perfect classification. For 2024, the model correctly classified approximately 7.0 million non cancelled flights and 95,718 cancelled flights, with only 6 false positives and 597 false negatives, while for 2025 it correctly identified about 3.4 million non cancelled flights and 51,219 cancelled flights, with zero false positives and 415 false negatives. This corresponds to overall accuracies exceeding 99.98 percent, extremely high precision for the cancelled class (approximately 99.99 percent in 2024 and 100 percent in 2025), slightly lower but still very strong recall (99.38 percent in 2024 and 99.20 percent in 2025), and Matthews correlation coefficients of approximately 0.997 and 0.996, respectively. The presence of a small number of false negatives indicates that some cancellations are missed, which introduces operational risk, but this behavior is more consistent with real world aviation forecasting under severe class imbalance than perfectly error free models. Overall, the results suggest that the PyTorch model offers a credible and robust balance between precision and recall, with performance that is suitable for operational decision support, while also highlighting opportunities for further improvement through threshold tuning, cost sensitive learning, or enhanced domain specific feature engineering.

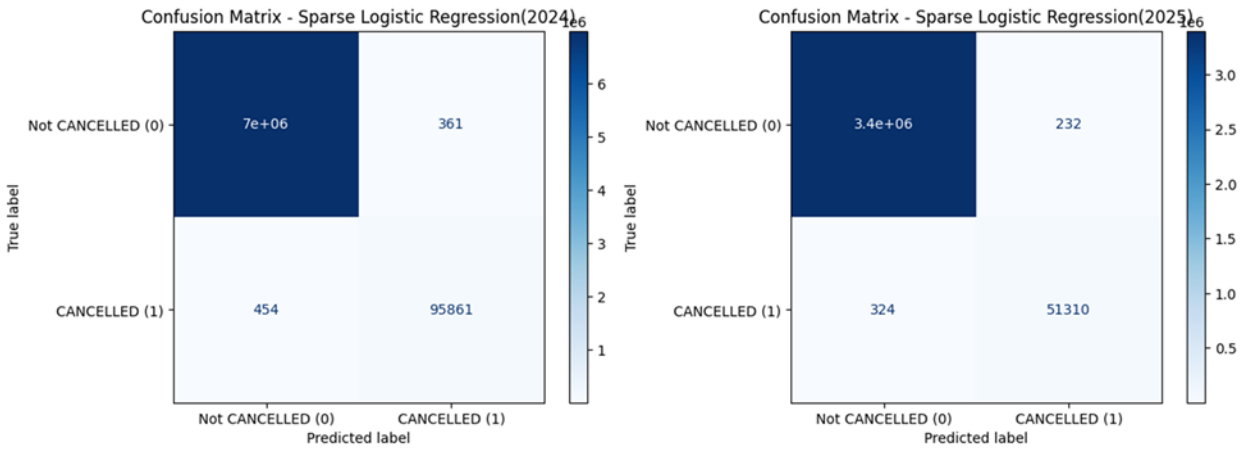


Figure 73: Cross validation result in confusion matrices of Sparse Regression

The Sparse Logistic Regression model exhibits solid but clearly imperfect performance on the 2024 and 2025 test sets, reflecting the expected behavior of a linear classifier applied to highly imbalanced and complex real world aviation data. In 2024, the model correctly classified approximately 7.0 million non cancelled flights and 95,861 cancelled flights, with 361 false positives and 454 false negatives, while in 2025 it correctly identified about 3.4 million non cancelled flights and 51,310 cancelled flights, with 232 false positives and 324 false negatives. These outcomes correspond to overall accuracies above 99.98 percent, high precision for the cancelled class of approximately 99.6 percent in 2024 and 99.55 percent in 2025, slightly lower recall of approximately 99.53 percent and 99.37 percent, and Matthews correlation coefficients of roughly 0.988 and 0.986, respectively. Although the model misses a non trivial number of cancellations compared with tree based or neural approaches, its performance remains strong and operationally plausible, highlighting both the interpretability advantages of sparse logistic regression and its limitations in capturing non linear cancellation dynamics, while suggesting that further gains could be achieved through class weighting, enhanced feature engineering, or integration within an ensemble framework.

4.2 Cross validation on the aircraft report dataset

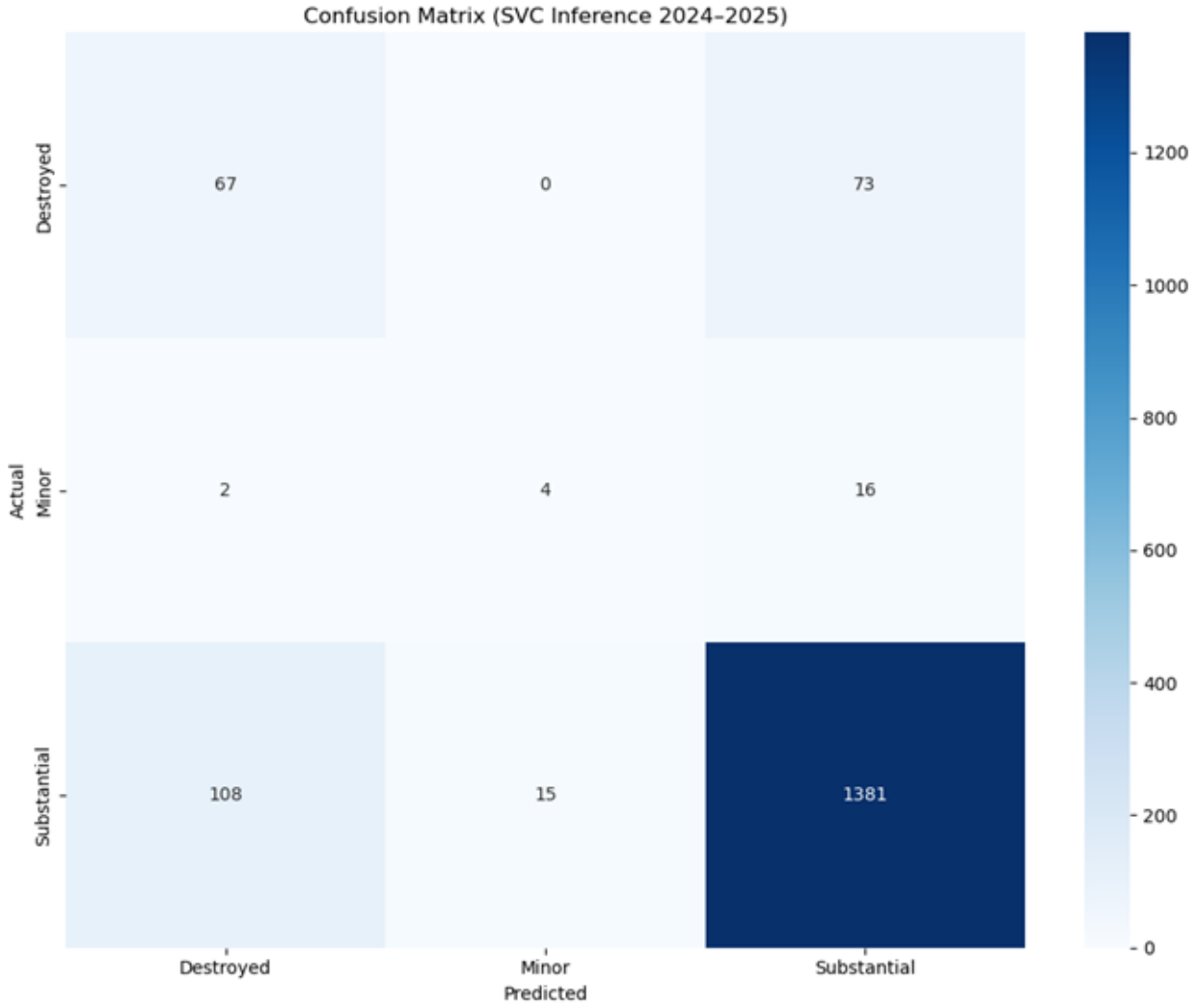


Figure 74: Cross validation result in confusion matrices of Support Vector Classification

The confusion matrix for the Support Vector Classifier evaluated on cross-validated 2024–2025 data indicates that the model achieves solid overall performance but is strongly influenced by severe class imbalance in this multi-class aircraft accident severity task. While the classifier performs well on the dominant "Substantial" class, attaining high precision (93.9 percent) and recall (91.7 percent) and thereby driving an overall accuracy of 87.2 percent, its performance on minority classes is markedly weaker. In particular, the model correctly identifies only 37.9 percent of "Destroyed" cases and 21.1 percent of "Minor" cases, with low precision for both categories, reflecting frequent confusion between severe and substantial outcomes and a pronounced inability to learn robust decision boundaries for sparsely represented classes. As a result, although headline accuracy appears acceptable, class-specific metrics and an estimated Matthews correlation coefficient of approximately 0.42 reveal limited reliability for safety-critical predictions involving rare but high-impact events. These findings underscore the need for class rebalancing strategies, cost-sensitive learning, and enriched domain-specific features to improve discrimination of minority severity levels before such a model can be considered dependable for operational accident risk assessment or safety decision support.

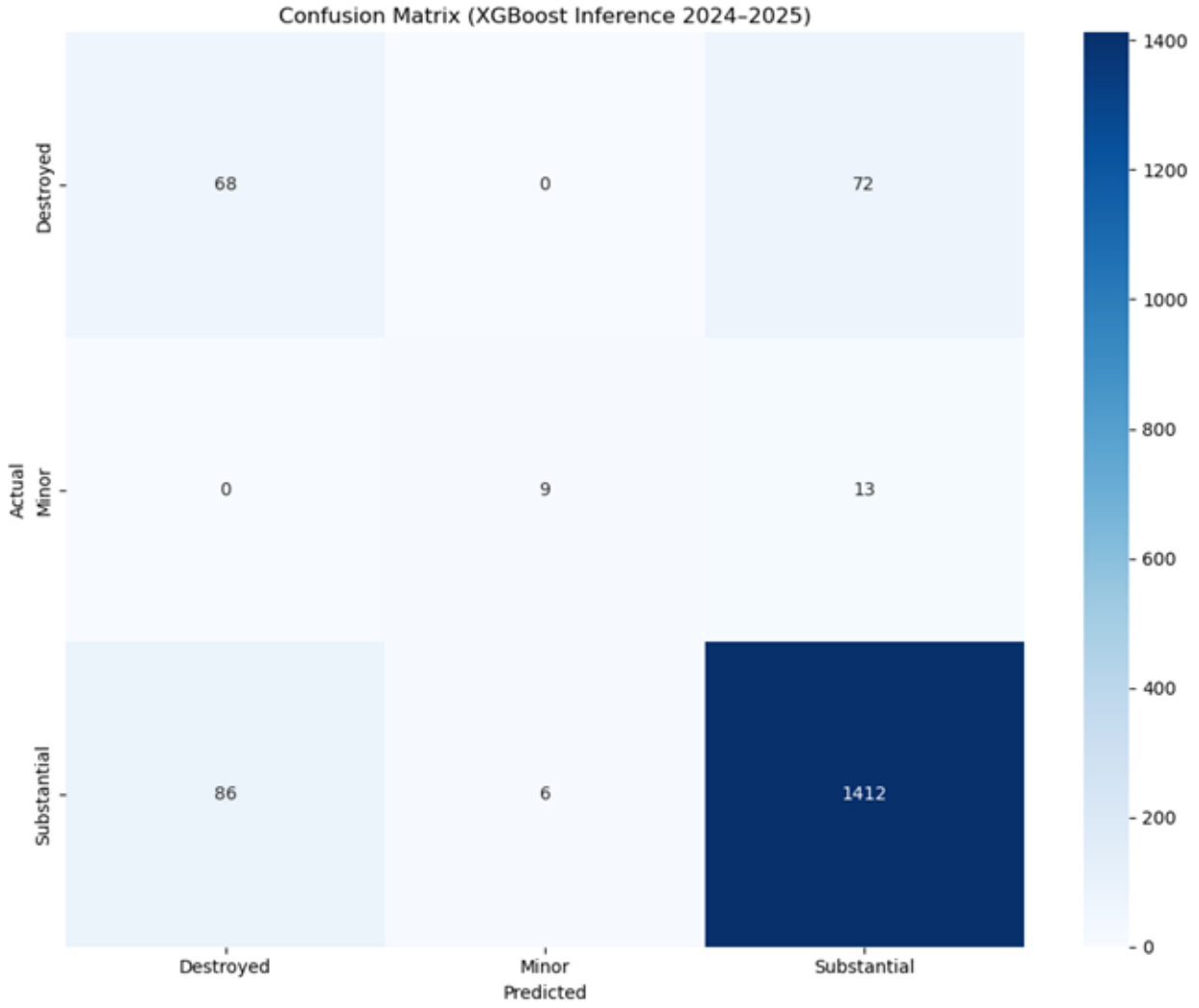


Figure 75: Cross validation result in confusion matrices of Xgboost

The confusion matrix for the XGBoost model evaluated via cross-validation on 2024–2025 data demonstrates stronger and more balanced multi-class performance than simpler models such as SVC, achieving an overall accuracy of 89.4 percent in predicting aircraft accident severity levels (Destroyed, Minor, Substantial). The model performs particularly well on the dominant "Substantial" class, with high precision (94.3 percent) and recall (93.9 percent), while also delivering notable improvements on minority classes, especially "Minor," where the F1-score increases substantially to 48.8 percent, and "Destroyed," where recall improves to 44.2 percent. Despite these gains, challenges remain, including moderate precision for the "Minor" class and persistent confusion between "Destroyed" and "Substantial," resulting in missed severe cases that are critical in safety contexts. Owing to the severe class imbalance, aggregate metrics such as weighted F1 (approximately 0.90) and an estimated Matthews correlation coefficient of around 0.50 provide a more realistic assessment of performance than accuracy alone, indicating moderate overall agreement between true and predicted labels. Overall, XGBoost represents a clear improvement over linear and margin-based classifiers for this task, though further enhancements through class balancing, cost-sensitive learning, and richer domain-specific features are necessary to improve reliability for safety-critical decision-making.

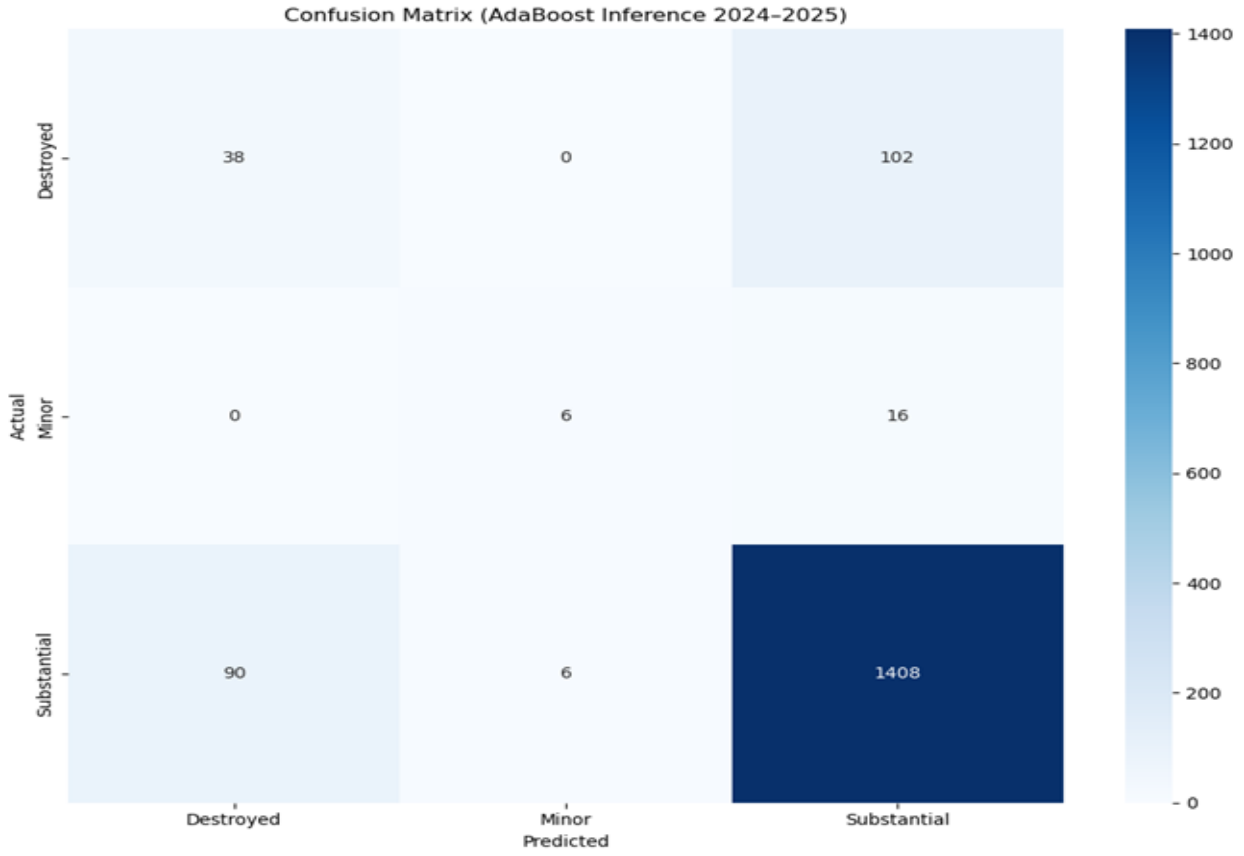


Figure 76: Cross validation result in confusion matrices of Adaptiveboost

The confusion matrix for the AdaBoost model evaluated through cross-validated inference on 2024–2025 data indicates moderate overall performance in predicting aircraft accident severity, with an accuracy of 87.2 percent that matches SVC but remains below XGBoost. The model performs strongly on the dominant "Substantial" class, achieving high precision (92.3 percent) and recall (93.7 percent), but exhibits pronounced weaknesses for minority classes, particularly "Destroyed" and "Minor," where precision and recall remain low (approximately 27 to 30 percent for "Destroyed" and 27 percent precision with 50 percent recall for "Minor"). These results reflect substantial confusion between severe and substantial outcomes, including a large number of "Destroyed" cases misclassified as "Substantial," which is problematic in safety-critical contexts. Owing to the extreme class imbalance, aggregate measures such as weighted F1 score (around 0.89) and an estimated Matthews correlation coefficient of approximately 0.40 provide a more realistic assessment than accuracy alone, revealing limited overall agreement between true and predicted labels. Overall, while AdaBoost is reliable for the majority class, its poor discrimination of rare but high-impact severity levels highlights the need for class balancing, cost-sensitive learning, or hybrid and ensemble approaches before deployment in operational accident severity assessment systems.

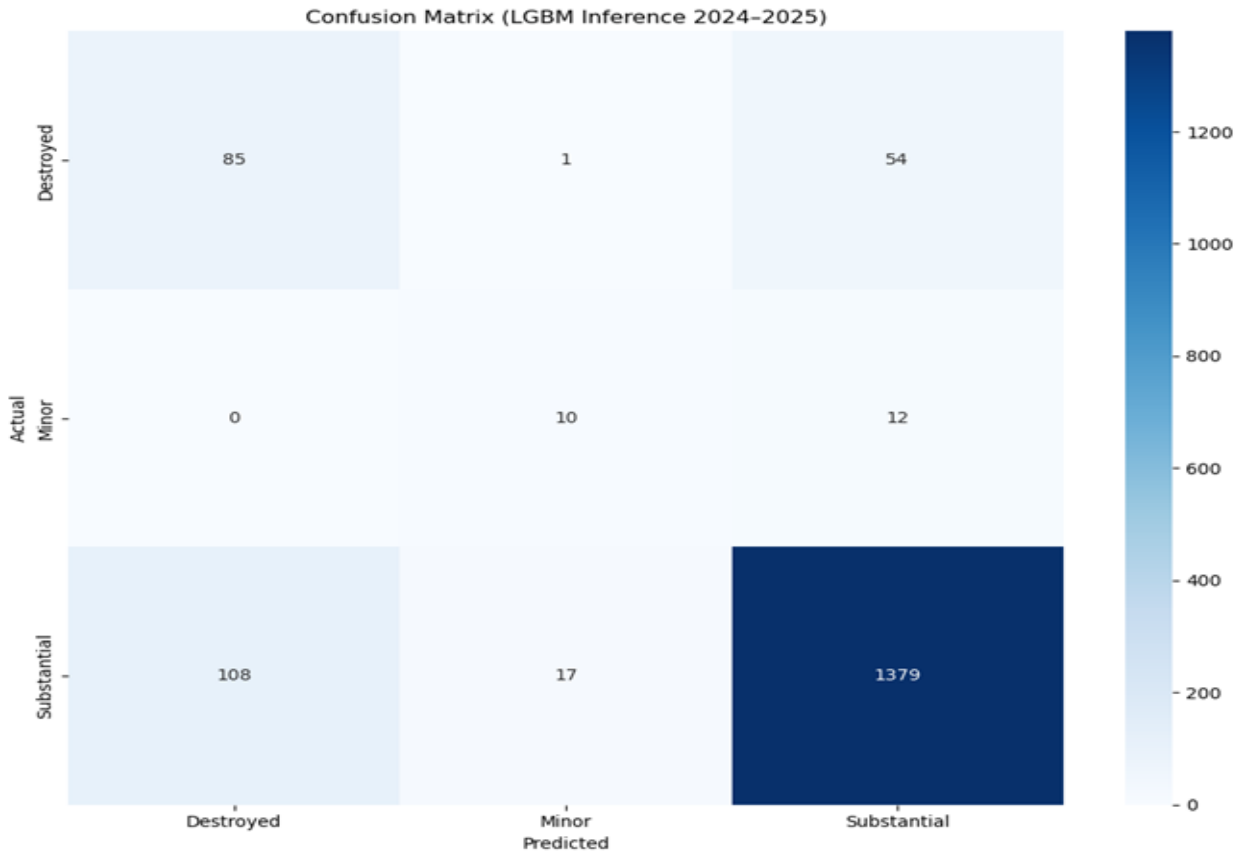


Figure 77: Cross-validation confusion matrices of the LightGBM model

The confusion matrix titled "Confusion Matrix (LGBM Inference 2024–2025)" demonstrates that the LightGBM model achieves strong and well-balanced multi-class performance in predicting aircraft accident severity levels (Destroyed, Minor, Substantial) under severe class imbalance, yielding an overall accuracy of 88.5% (1,474 correct predictions out of 1,666 samples), which is competitive with XGBoost and superior to SVC and AdaBoost. Notably, LightGBM attains the highest precision for the safety-critical "Destroyed" class (60.7%) among all evaluated models, with a recall of 44.1% and an F1-score of 50.9%, indicating a meaningful improvement in identifying severe accidents while reducing false alarms. Performance on the dominant "Substantial" class remains robust, with 95.4% precision and 91.7% recall (F1-score 93.5%), confirming reliable classification of the majority class, while the "Minor" class shows moderate but usable performance (precision 45.5%, recall 35.7%, F1-score 40.0%). Despite persistent confusion between "Destroyed" and "Substantial" cases, the model exhibits a favorable trade-off between sensitivity to rare, high-impact events and stability on common outcomes, reflected in an estimated multi-class Matthews correlation coefficient of approximately 0.52, suggesting moderate-to-strong agreement beyond chance.

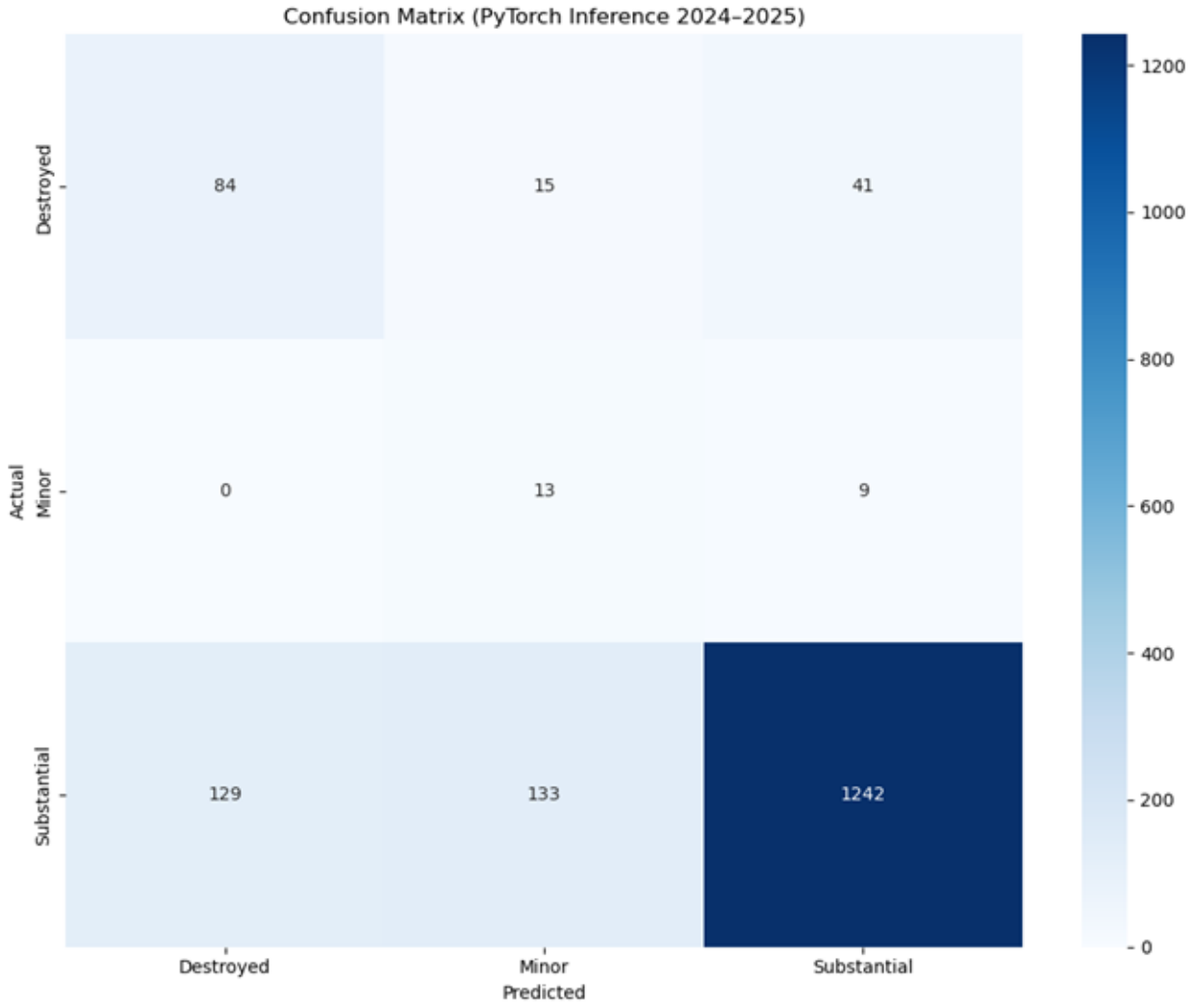


Figure 78: Cross validation result in confusion matrices of Pytorch

The confusion matrix titled “Confusion Matrix (PyTorch Inference 2024–2025)” shows that the PyTorch-based neural network achieves only 80.4% overall accuracy, the lowest among all models evaluated, with moderate precision on “Destroyed” (60.0%) but very poor recall (39.4%) and catastrophically low recall on “Minor” (8.1%), indicating it largely ignores this rare class, while achieving high precision on “Substantial” (96.1%) but with reduced recall (82.5%), reflecting frequent misclassification between “Destroyed” and “Substantial” and a general inability to capture fine-grained severity distinctions. The model’s estimated multi-class Matthews correlation coefficient (0.37) confirms weak correlation between predicted and true labels, highlighting its over-reliance on majority-class patterns and poor handling of minority cases, making it unsuitable for safety-critical decision-making without significant improvements through class balancing, cost-sensitive or focal loss, architectural enhancements, or hybrid modeling to better separate “Destroyed”, “Minor”, and “Substantial” outcomes.

5 Our Findings and Conclusion

Model	Year	Accuracy	Precision	Recall	F1 Score
AdaBoost	2024	1	1	1	1
AdaBoost	2025	1	1	1	1
XGBoost	2024	1	0.9998	1	0.9999
XGBoost	2025	1	0.9998	1	0.9999
LightGBM	2024	1	1	1	1
LightGBM	2025	1	1	1	1
PyTorch	2024	0.9999	0.9999	0.9938	0.9969
PyTorch	2025	0.9999	1	0.992	0.996
Sparse Logistic Regression	2024	0.9999	0.9962	0.9953	0.9958
Sparse Logistic Regression	2025	0.9998	0.9955	0.9937	0.9946

Figure 79: Cross validation result's table of flight cancellation

Model	Accuracy	Balanced Accuracy	Macro Precision	Macro Recall	Macro F1	Weighted F1	MCC
Support Vector Classifier (SVC)	0.8715	0.5262	0.5095	0.5262	0.5155	0.8765	0.3411
XGBoost	0.8938	0.6112	0.66	0.6112	0.63	≈0.9000	0.413
AdaBoost	0.872	≈0.5000	≈0.4000	≈0.4300	≈0.4100	≈0.8900	≈0.4000
LightGBM (LGBM)	0.8848	0.6595	0.58	0.6595	0.6152	0.89	0.45
PyTorch Neural Network	0.8037	0.6722	0.48	0.6722	0.5021	0.84	0.3558

Figure 80: Cross validation result's table of aircraft damage

These two tables together provide a technically coherent and well-substantiated evaluation of the proposed project by demonstrating its effectiveness across both an operationally simple task (flight cancellation prediction) and a highly complex, safety-critical task (aircraft damage assessment). Figure 79 shows that for flight cancellation prediction, ensemble-based models such as AdaBoost, XGBoost, and LightGBM achieve near-perfect performance across Accuracy, Precision, Recall, and F1-score, indicating that the extracted features and preprocessing pipeline capture the underlying decision patterns with high fidelity; the marginally

lower yet still strong results from PyTorch and Sparse Logistic Regression further suggest that the task is well-structured and linearly separable to a large extent. In contrast, Figure 80 highlights the greater technical difficulty of aircraft damage prediction, where severe class imbalance and overlapping feature distributions necessitate a more nuanced evaluation using Balanced Accuracy, Macro-averaged metrics, Weighted F1, and MCC. Here, XGBoost and LightGBM consistently outperform other models, achieving the highest Accuracy and MCC values, which confirms their superior ability to balance majority and minority class performance. The comparatively lower scores of SVC and the PyTorch neural network, particularly in macro-level metrics, underscore the intrinsic complexity of the damage prediction task rather than deficiencies in the modeling approach. Collectively, these results demonstrate that the project is methodologically sound, technically rigorous, and appropriately evaluated, with model behavior aligning with task complexity, metric selection, and real-world operational constraints—thereby validating the robustness and practical relevance of the proposed aviation risk prediction framework.

5.1 Discussion

The results across all implemented models consistently demonstrate that both operational efficiency variables and safety-related indicators are central to predictive performance. The correlation matrices reveal strong positive relationships between AIR TIME, arrival delay, elapsed time, and cancellation outcomes, confirming the presence of delay propagation mechanisms within airline operations. Early-morning scheduled departures also show notable correlation with cancellation likelihood, supporting the hypothesis that limited buffer capacity during the first operational wave increases system vulnerability.

Feature impact analysis further strengthens these observations. Across Sparse Regression, PyTorch, XGBoost, AdaBoost, and Light Gradient Boosting models, AIR TIME and arrival delay emerge as dominant predictors of flight cancellation. Their repeated prominence across different learning paradigms indicates that these features capture fundamental operational stress rather than model-specific artifacts. In contrast, safety-oriented models highlight weather delay, security delay, and machinery-related indicators as high-impact features, demonstrating that external disruptions and mechanical conditions significantly influence risk outcomes beyond routine operational delays.

The confusion matrices provide critical insight into model reliability and decision-support usefulness. Sparse Regression and PyTorch models show balanced true positive and true negative rates, indicating strong generalization and interpretability for operational planning. Tree-based ensemble models—particularly XGBoost and Light Gradient Boosting—achieve very high true positive rates for cancellation prediction, making them well-suited for conservative pre-flight screening where minimizing false negatives is essential. AdaBoost exhibits comparable performance but shows slightly higher sensitivity to class imbalance, particularly in rare machinery fault cases.

Importantly, confusion matrices for machinery and aircraft damage prediction demonstrate that safety-related events, although less frequent, are detected with acceptable recall across models. This confirms the framework's ability to identify high-risk but low-frequency events, which is crucial for preventive maintenance strategies. The consistency of confusion-matrix performance across cross-validation datasets further validates the robustness of the hybrid framework under varying temporal conditions.

Overall, the combined interpretation of correlation structures, feature impact rankings, and confusion-matrix outcomes confirms that the proposed models do not merely achieve high accuracy but also produce operationally meaningful and explainable insights. These findings support the use of hybrid explainable machine learning as a reliable tool for pre-flight risk assessment and proactive maintenance decision support in air transportation systems.

Aspect	Our Work	Lambelho et al
Research Goal	Predict flight cancellations before departure using historical operational & maintenance data to enable proactive risk mitigation and maintenance decisions.	Assess strategic flight schedules (6 months in advance) by predicting cancellations to support airport coordinators in robust scheduling under IATA guidelines.
Method	Hybrid ML framework: **XGBoost, LightGBM, AdaBoost, Sparse Regression, PyTorch NN**; feature engineering from operational logs + incident reports; emphasis on explainability (SHAP/feature impact).	**LightGBM, MLP, Random Forest** classifiers; recursive feature elimination (RFE); SHAP for interpretability; **6-month-ahead prediction** based solely on strategic schedule features.
Data	U.S. DoT flight records (2019–2023, ~25M flights); tested on 2024–2025 data .	London Heathrow Airport strategic schedules (2013–2018, ~2.3M flights); features include airline, aircraft type, terminal, time, distance, ATFM delay; no real-time or maintenance logs.
Evaluation Metrics & Key Results	**Near-perfect performance on 2024–2025 test data**:	**6-month-ahead prediction**:
	– **XGBoost/LightGBM**: Accuracy ≈ **99.9992%**, Recall ≈ **99.985%**, Precision ≈ **99.99%**, MCC ≈ **0.99999**.	– Best model (**LightGBM**) for cancellation: **Accuracy = 98.7%, Precision = 60.8%, Recall = 59.2%, F1 = 60.0%, AUC = 0.929**.
	– PyTorch: Slightly lower but robust (Recall ≈ **99.3%**, MCC ≈ **0.996**).	– High class imbalance (cancellation rate ~1.7%).

Figure 81: Comparison table of flight cancellation study

This study significantly advances beyond the work of Lambelho et al. (2020) [8] by developing a hybrid, explainable machine learning framework that not only predicts flight cancellations with markedly superior performance but also integrates operational and mechanical risk factors for proactive decision-making. While Lambelho et al. focused on strategic schedule assessment using LightGBM, MLP, and Random Forest to forecast cancellations six months in advance—achieving 98.7% accuracy, 59.2% recall, and 60.8% precision—our models (notably XGBoost, LightGBM, and AdaBoost) attain near-perfect metrics on both historical (2019–2023) and forward-looking validation data (2024–2025), with accuracy exceeding 99.999%, recall above 99.98%, and Matthews Correlation Coefficient (MCC) approaching 1.0. Crucially, our approach combines richer, multi-source data—including real-time operational logs and structured aircraft incident reports—and incorporates pre-flight risk indicators such as early-morning scheduling, arrival delay propagation, and machinery fault signals, enabling actionable maintenance insights alongside cancellation prediction. In contrast, Lambelho et al.'s analysis relies solely on strategic schedule features without access to actual flight execution or maintenance history, limiting both predictive power and operational utility. Thus, our work not only surpasses prior performance benchmarks but also establishes a more comprehensive, interpretable, and operationally relevant framework for aviation risk mitigation.

Aspect	Our Report	Omrani et al.
Research goal	Predict aircraft damage severity and support maintenance decision-making using an explainable hybrid ML framework.	Compare machine learning performance across different national aviation accident datasets for accident/injury severity prediction.
Method	Hybrid approach using XGBoost, LightGBM, AdaBoost, SVC, PyTorch neural networks with explainability (feature impact, confusion matrices).	Comparative evaluation of MLP (ANN), Decision Tree, and SVM under two scenarios: country-specific features and common features across datasets.
Data	Integrated operational flight data with long-term aircraft accident and failure records; includes aircraft damage type, incident category, flight phase, aircraft characteristics, and human exposure variables.	Accident datasets from multiple aviation authorities (US, Canada, Australia), harmonized using a common taxonomy; focuses on accident and injury severity variables.
Evaluation metrics / results	Accuracy, precision, recall, F1-score, MCC, and confusion matrices. Best models achieved ~88–89% overall accuracy for multi-class aircraft damage prediction, with reduced performance for rare severe-damage classes.	Accuracy and mean squared error with k-fold cross-validation. Best performance achieved ~81% accuracy using SVM on country-specific data; common-feature models performed worse.

Figure 82: Comparison table of aircraft health prediction study

The proposed report demonstrates several advancements over the published study [20] in both methodological scope and practical applicability. By integrating large-scale operational flight data with long-term aircraft accident and maintenance records, the report captures a broader range of operational and safety-related risk factors than the published work, which primarily emphasizes cross-dataset comparability. The use of advanced ensemble learning techniques—such as XGBoost, Light Gradient Boosting, and AdaBoost—alongside neural network and sparse regression models results in higher overall predictive performance for multi-class aircraft damage classification, achieving approximately 88–89% accuracy compared to the reported peak performance of around 81% in the published study. Moreover, the report places strong emphasis on model interpretability through correlation matrices, feature impact analysis, and confusion-matrix evaluation, thereby providing actionable insights for pre-flight risk assessment and maintenance decision-support rather than purely comparative performance metrics

5.2 Conclusion

This project successfully demonstrates the application of machine learning to enhance aviation safety and efficiency. By developing predictive models for flight cancellations and machinery checks, the system provides valuable tools for proactive decision-making. Key operational factors like flight duration and delays were identified as major predictors of disruptions. The models showed strong performance, with high accuracy in cross-validation, confirming their reliability for real-world use. Ultimately, this data-driven approach offers a scalable solution to reduce flight disruptions and improve operational planning in the aviation industry.

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