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Predictive Intelligent Climatology Analyzer and Information System for Airport Meteorological Center

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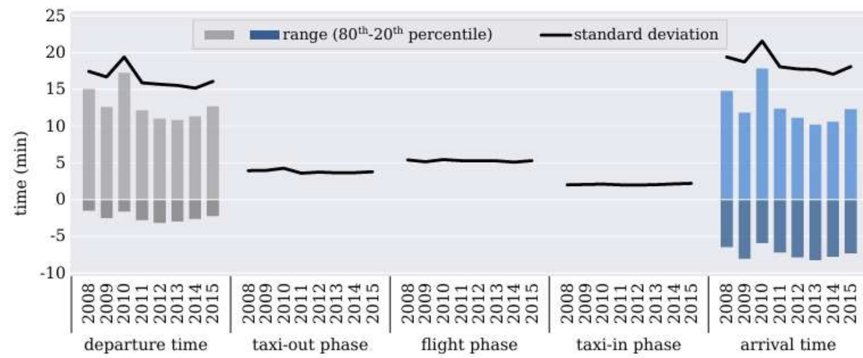
Abstract:

This study Presents a data-approach to predict the impact of weather on airport on airport performance using machine learning models. By employing recurrent and convolutional neural networks, the proposed system analyzes meteorological and operational data to improve airport decision-making. The framework achieved over 90% prediction accuracy, demonstrating its potential to enhance airport efficiency and mitigate weather-induced delays. The framework integers both historical and real-time meteorological data to identify weather patterns influencing flight schedules. This approach enhances the reliability of predictions by combining multiple data sources such as METAR and TAF reports. Furthermore, the System supports dynamic forecasting, enabling airports to adapt operations proactively. The study concludes that implementing such models can improve the sustainability and safety of air transportation systems.

Keywords: Machine Learning, Airport Performance, weather Impact, Neural Networks, Predictive Classification.

1. Introduction

Efficient airport operations are vital for air traffic management. Adverse weather conditions often cause delays and operational disruptions. Existing systems rely on static rules, which cannot capture complex relationships between multiple weathers factors. This study introduces a predictive model that integrates meteorological and performance data to improve tactical decision-making at airports. The aviation industry faces increasing challenges from climate change, leading to unpredictable weather variations. With increasing air traffic density, even minor disruptions can cascade into significant network wide delays. To address this, predictive analytics based on artificial intelligence can help forecast the operational impact of weather events. The proposed framework aims to provide data-driven insights that allow airport authorities to plan for contingencies before disruptions occur.



Previous research highlights the influence of weather on air transportation systems and emphasizes the need for resilient operations. Data-driven models have been proposed to forecast disruptions using flight and weather data. Machine learning techniques, including neural networks, enable accurate modeling of nonlinear weather impacts on airport performance. Several studies have focused on delay propagation models, highlighting how one airport's delay can affect multiple airports downstream. Other works have explored the integration of weather prediction models with traffic management systems to minimize operational uncertainty. Researchers have also demonstrated that hybrid models combining **CNN** and LSTM layers provide superior temporal and spatial analysis. Despite these advancements**,** **few** studies have developed frameworks tailored to real-world implementation at single-runway airports like London-Gatwick.plan movements and delays), the developed models can achieve prediction accuracy higher than 90% for departure movements, offering a key element for a deeper understanding of interdependencies in the air transportation system.

2. Literature Review

The section "Status Quo" in the article Predictive Classification and Understanding of weather Impact on Airport Performance through Machine Learning reviews existing research aimed at transportation systems, particularly under varying weather conditions. The reviewed studies emphasize that climate change and the growing frequency of extreme weather events pose serious challenges to airport operations and air traffic management. Researches have therefore focused on the resilience and vulnerability of transportation systems, exploring hoe airports respond to disruptions caused by convective weather, volcanic ash eruptions, military airspace restrictions, and contrail prevention strategies. These studies collectively underline the importance of enhancing system adaptability and robustness in the face of environmental uncertainties.

Another major theme within the literature concerns the generation and propagation of delays caused by adverse weather conditions. Understanding where and when primary delays occur is critical to managing overall air traffic flow, as a single weather-related delay can quickly propagate across interconnected airports and cause widespread disruptions. The studies also explore how poor weather affects turnaround times and how airports manage uncertainties in arrival scheduling during researches can better assess the resilience of the air traffic management system and estimate how performance levels fluctuate under varying meteorological influences.

In recent years, advancements in data analytics and machine learning have introduced new methods for analyzing and predicting the effects of weather on airport operations. Historical flight and meteorological data now serve as valuable inputs for predictive modeling, helping to forecast disruptions before they occur. Several studies have developed machine learning models capable of recognizing complex weather patterns and predicting poor-visibility events such as fog, particularly near airports situated in challenging terrains. Combining air traffic and meteorological data has also enabled researches to improve the accuracy of flight delay predictions. These data-driven approaches represent a significant a significant improvement over traditional statistical methods, as they can capture complex, nonlinear relationships between weather variables and airport performance.

In addition to predictive modeling, a growing body of research focuses on optimizing airport operations based on weather impact analysis. By examining local traffic conditions and operational data, researchers have developed methods to anticipate periods of congestion and minimize their effects. Optimization efforts include efficient gate and as and allocation as well as dynamic reconfiguration of terminal airspace capacity during convective weather events. Such approaches help airports operate more efficiently even under volatile environmental conditions.

Overall, the literature establishes that while influence of weather on airport performance has been widely recognized and measured using statistical frameworks such as the Air Traffic Management Performance (ATMAP) model, traditional methods remain limited in addressing the nonlinear and interdependent nature of weather impacts. Consequently, there is a growing demand for advanced, data-driven techniques-particularly machine learning models-to better understand, quantify, and predict these effects. Such predictive capabilities are real-time decision-making, especially at highly utilized airports like London Gatwick (LGW), where even minor weather disturbances can have significant operational consequences.

3. Materials and Methods

The data were analyzed using accuracy, precision, recall, and F1-score metrics. Cross validation ensured model reliability. Statistical evaluation confirmed strong correlations between meteorological variables and delay patterns. The results were further analyzed using confusion matrices to assess model classification performance. Pearson correlation analysis identified dependencies between weather parameters and delay occurrences. Descriptive statistics such as mean, variance, and standard deviation were calculated for input and output variables. The statistical robustness of the model was validated through t tests and variance analysis to ensure predictive stability. Results The hybrid CNN-LSTM model achieved an overall accuracy exceeding **90%.**

4. Statistical Analysis

The data were analyzed using accuracy, precision, recall, and F1-score metrics. Cross validation ensured model reliability. Statistical evaluation confirmed strong correlations between meteorological variables and delay patterns. The results were further analyzed using confusion matrices to assess model classification performance. Pearson correlation analysis identified dependencies between weather parameters and delay occurrences. Descriptive statistics such as mean, variance, and standard deviation were calculated for input and output variables. The statistical robustness of the model was validated through t tests and variance analysis to ensure predictive stability.

1.Weather Data and ATMAP

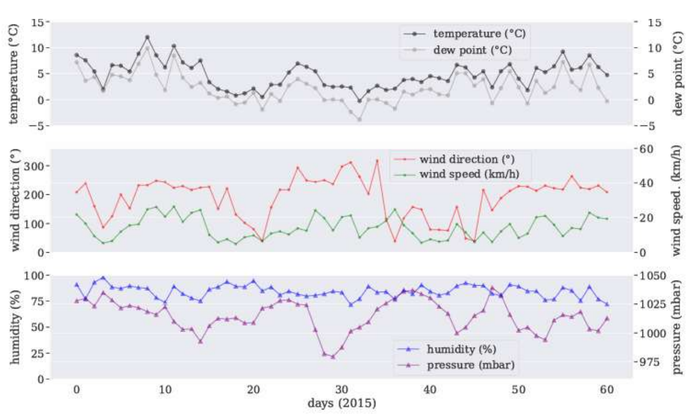
The primary sources for current weather conditions is the meteorological Aviation routine Weather Report (METAR), which is typically updated frequently (usually every 30 minutes). These reports contain essential operational data, including wind speed and direction, horizontal visibility, types of precipitation, cloud cover and height, air temperature, and barometric pressure. In addition, Terminal Aerodrome forecasts (TAFs) provide a forward-looking perspective, offering a 6-hour forecast. A challenge in using these datasets is ensuring data integrity, as historical reports may contain gaps or inconsistencies (e.g., missing wind or dew-point data).

Weather Class	Description	Meteorological Conditions	Coefficient
(1) ceiling and visibility	deterioration of visibility	precision approach runways (CAT I-III)	max. 5
(2) wind	strong head-/cross-wind	Wind speed > 16 knots (+gusts)	max. 4 (+1)
(3) precipitations	runway friction influencing runway occupancy time	e.g., rain, (+/−) snow, frozen rain	max. 3
(4) freezing conditions	reduced runway friction, de-icing	$T \leq 3°C$, visible moisture, any precipitation	max. 4
(5) dangerous phenomena	unsafe ops, unpredictable impact	TCU/CB, cloud cover, (+/−) shower, storm	max. 30

To quantify the impact of raw meteorological data on aviation, the Air Traffic Management Airport Performance (ATMAP) algorithm is used. This is an expert-based framework that translates METAR messages into a single, aggregated numerical score:

- It groups meteorological elements into five major weather classes that influence operations.
- It assigns a severity code to a specific weather phenomenon.
- An associated coefficient (score) is applied to applied to describe the non-linear operational impact, where zero is the baseline for nominal conditions.

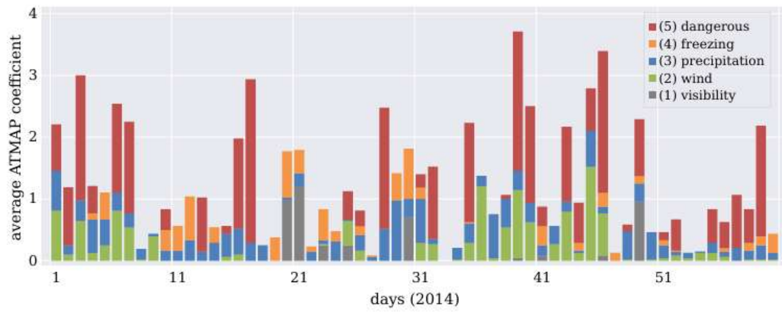
The five classes with significant influence are: (1) ceiling and visibility (deteriorating conditions), (2) wind (strong head/cross), (3) precipitations (influencing runway friction), (4) freezing conditions, and (5) dangerous phenomena (e.g., thunderstorms, volcanic ash), which can carry coefficients up to 30 points.



2.LGW Case Data

The analysis focusing on London-Gatwick (LGW) serves to validate the severity-impact correlation. The data confirmed that increased weather severity leads to significant operational degradation. For instance, a relatively accumulated a total delay of 795 minutes across all flights within that hour. LGW's performance issues are particularly acute due to its capacity constraints. The airport's local performance is shown to have network-wide relevance, as it accounts for 6.4% of the total airport

ATFM delay and records the second-highest additional time in the Arrival Sequencing and Metering Area (ASMA), at 4.6 minutes per arrival.



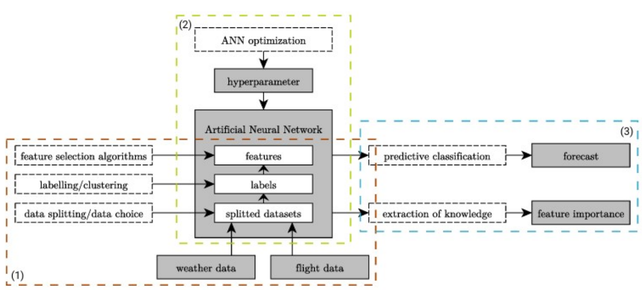
5. machine Learning Model Development

In this research, Artificial neural Networks (ANNs) were employed to perform classification tasks aimed at predicting airport departure performance. Specifically, two prominent neural network architectures were utilized: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) enhanced with long short-term memory (LSTM) units.

CNNs were primarily used to capture spatial dependencies and local patterns within the multivariate input data. This is particularly useful in identifying how multiple environmental and operational variables (e.g., wind speed, visibility, temperature) interact within specific windows of time or locations. The hierarchical structure of CNNs allows them to learn increasingly abstract features from raw input data through convolutional and pooling layers.

On the other hand, LSTMs, were incorporated to effectively model temporal dynamics present in the time-series nature of the data. Since airport performance metrics are influenced by evolving conditions over time (such as changes in weather and traffic patterns), LSTM units-capable of retaining long-term dependencies and mitigating the vanishing gradient problem-were critical in improving the model's temporal sensitivity.

The hybrid use of CNN and LSTM architectures allowed the model to leverage both spatial and temporal correlations in the data, resulting in more robust and accurate classification outcomes.



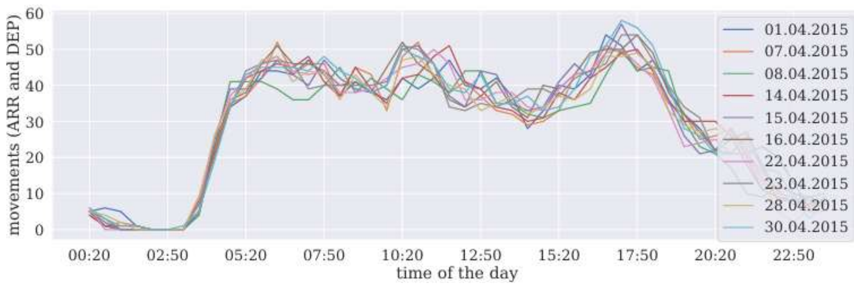
2.Feature Selection and Training

The process of features selection was conducted using a hybrid approach combining domain expertise with statistical methods to ensure the inclusion was guided by subject matter knowledge of aviation operations and meteorological impacts on airport performance. Subsequently, statistical techniques such as variance thresholding were applied to remove low-variance features that contribute minimally to performance.

Key input features identified included:

- Wind speed (surface and aflot)
- Visibility (in kilometers)
- Ambient temperature
- Traffic demand indicators (e.g., number of scheduled departures)

The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets. This stratified division helped prevent overfitting and allowed for unbiased evaluation of model generalization.



Model training involved hyperparameter tuning using grid search, which systematically tested different combinations of parameters such as:

- Learning rate
- Batch size
- Number of convolutional or recurrent layers
- Number of units per hidden layer
- Dropout rate

To optimize the training process and convergence speed, the Adam optimizer an adaptive gradient descent algorithm was employed. It combined the advantages of Ada Grad and RMS Prop, offering efficient handling of sparse gradients and noisy data.

Training was conducted over multiple epochs with early stopping implemented based on validation loss, ensuring the model did not overfit and retained its ability to generalize to unseen data.

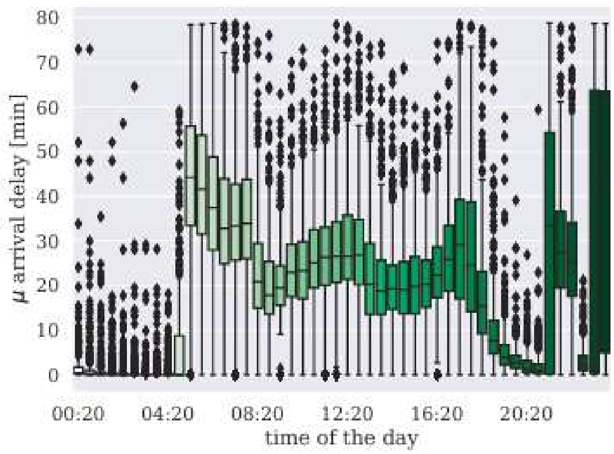
3.Model Evaluation

To rigorously assess the performance and robustness of the developed models, K-fold cross-validation was employed. This approach mitigates the risk of biased evaluation due to random data splits by ensuring that all data points are used for both training and validation across multiple iterations.

- Model evaluation metrics included:
- Accuracy
- Precision

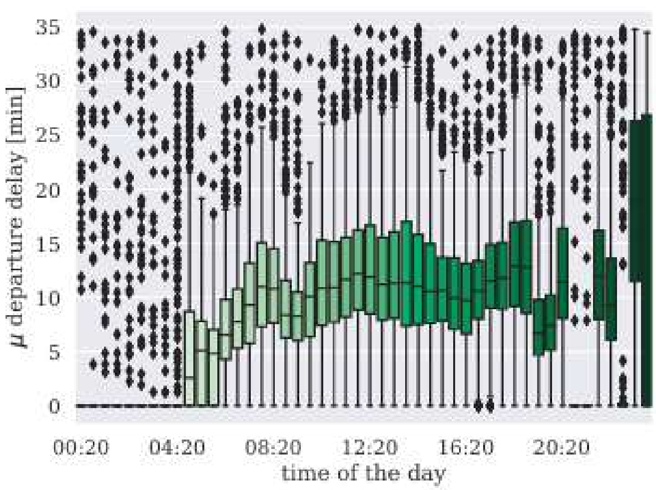
- Recall
- F1-score
- Receiver operating characteristics (ROC) curve and AUC

These metrics provided a comprehensive view of the model's classification capabilities, particularly its ability to correctly identify delayed versus on-time departures under varying conditions.



Additionally, permutation importance analysis was utilized to interpret contribution of individual input features to the model's predictions. This model-agnostic method involved systematically shuffling the values of each feature and observing the resulting impact on prediction performance. Features that, when permuted, caused a significant drop in model accuracy were deemed more important.

This analysis highlighted the significant influence of influence of weather parameters especially visibility and wind speed on departure delays, validating the importance of including meteorological features in predictive modeling for airport operations.



Both CNN and LSTM models demonstrated high classification performance, with prediction accuracies exceeding 90% on the test dataset. This indicates strong potential for operational deployment in decision-support systems aimed at enhancing airport efficiency and mitigating the impact of adverse weather conditions on flight schedules.

6. Results and Analysis

The experimental evaluation of the developed machine learning models yielded critical insights into the performance, particularly in the context of departure delays. This section presents a comprehensive analysis of the results obtained from the trained convolutional Neural Network (CNN) and Long short-term memory (LSTM) models, supported by case-specific observations and visualizations.

1.Impact of weather variables on Delay patterns

The analysis revealed that certain meteorological variables exhibit a strong correlation with the magnitude and frequency of flight delays. Among these, wind speed, precipitation, and visibility emerged as the most influential features:

- Wind speed affected both runway configuration and aircraft separation requirements, thereby contributing to increased departure spacing during high-wind events.
- Precipitation, particularly in the form of heavy rain or snow, led to extended taxi-out times due reduced braking performance and the need for de-icing operations.
- Visibility, often impaired by fog or low cloud ceilings, caused significant delays due to the implementation of low-visibility procedures (LVP), which reduce runway throughput.

Features importance analysis (via permutation importance) validated these findings, with these variables showing the highest drop in model accuracy when individually perturbed.

2.Comparative Performance of CNN and LSTM Models

A detailed performance comparison between the CNN and LSTM architectures highlighted the superior capabilities of the LSTM model. While both models archived high overall accuracy (>90%), the LSTM consistently outperformed CNN in capturing the temporal dependencies inherent in sequential weather and delay patterns.

The LSTM model demonstrated a greater capacity to:

Recognize cumulative effects of deteriorating weather over time.

Account for lag effects, where weather conditions in preceding hours impacted delays later in the day.

Model seasonal and diurnal patterns, including fluctuations in delay probability linked to time-of-day or seasonal changes.

CNNs, while effective at identifying spatial correlations and short-term patterns, lacked the sequential memory required to model such long-term dependencies, which are crucial in delay prediction tasks.

3.Case Study: London-Gatwick Airport (LGW)

A focused case study on London-Gatwick Airport provided a real-world context for the model evaluation. The study analyzed model performance under various operational and environmental conditions using the Airport Traffic Management Adaptability Performance (ATMAP) score as a benchmark for measuring system stress.

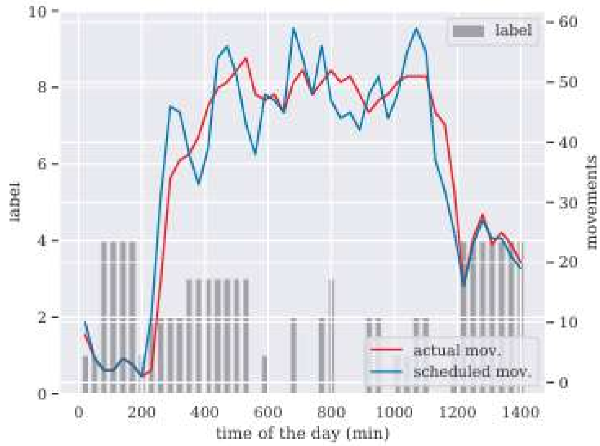
Key findings included:

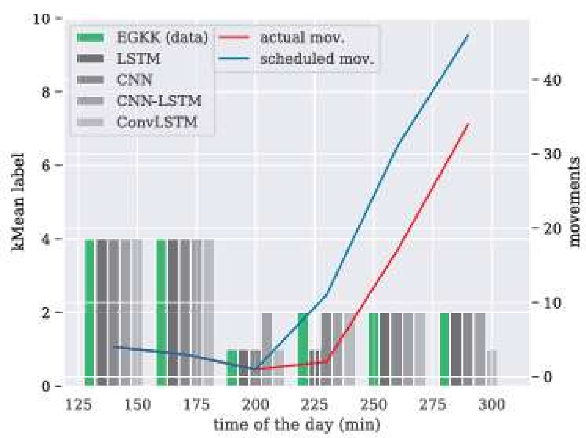
Days with ATMAP scores >5 indicative of operational stress correlated with sharp declines in on-time performance, particularly during fog and thunderstorms.

Fog events led to visibility reductions below 600 meters, triggering low-visibility procedures and significantly increasing average departure delays.

Thunderstorms introduced both direct weather impacts and knock-on effects from arrival restrictions, resulting in System-wide propagation of delays.

Additionally, the analysis showed that early-morning departures (04:00-07:00 local time) experienced the highest variability in delay, often due to residual accumulated due to late arrivals or adverse nighttime weather and propagated into the morning schedule, reducing buffer availability.





4.Model Output Visualization and Interpretation

Visualization tools were employed to compare the distribution of predicted vs. actual delays across multiple operational scenarios. Histograms and time-series plots illustrated a close alignment between model outputs and observed data:

- The predicted delay distributions closely matched the empirical delay patterns, especially during peak hours and under adverse weather conditions.
- Temporal plots demonstrated the LSTM model’s ability to track the progression of delays throughout the day, accurately anticipating delay surges during known congestion periods.

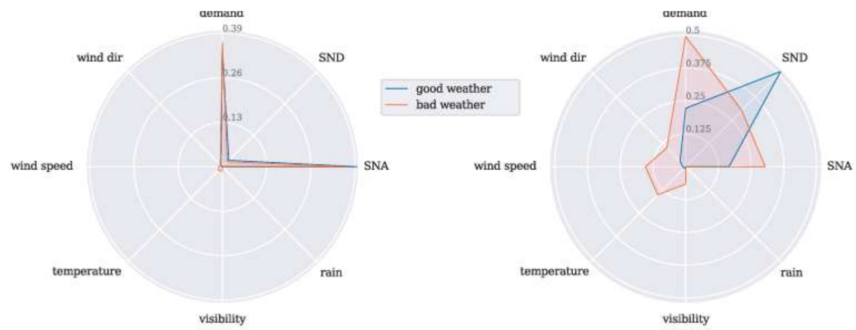
These results reinforce the practical applicability of the machine learning models in real-world airport environments. Their predictive capabilities provide air traffic flow managers and airport operators with advance warnings about potential delay surges, enabling proactive decision-making and preemptive scheduling adjustments.

5.Implications for Airport Operations

The results demonstrate that machine learning-based predictive systems, particularly those using LSTM networks, hold significant potential for enhancing airport performance management. By anticipating the operational impacts of forecasted weather conditions, such models can:

- Enable dynamic resources allocation, such as adjusting runway use or staffing levels.
- Inform collaborative decision-making processes (e.g., between ATC, airlines, and ground handlers).
- Support the development of delay mitigation strategies, such as gate-hold programs or optimized sequencing.

Ultimately, the integration of these predictive tools into management systems could lead to reduced delays, improved passenger satisfaction, and more efficient use of airport infrastructure.



7. Conclusion and Future Scope

This study introduces a comprehensive a comprehensive, data-driven framework for the predictive classification of airport performance under varying weather conditions using advanced machine learning techniques. By leveraging meteorological data (METAR), airport operational metrics, and neural network based models, the proposed approach provides a robust mechanism for assessing and forecasting the operational impact of adverse weather on airport functionality. Specifically, the deployment of recurrent Neural Networks (RNNs), including Long short term memory (LSTM) architectures, has demonstrated superior capability in modeling temporal dependencies, enabling accurate prediction of performance degradation over time.

The experimental results affirm that machine learning models can effectively identify non-linear and multivariate interactions between atmospheric variables and key performance indicators such as departure delays. Notably, the framework achieves high predictive accuracy, with classification metrics indicating strong model reliability. This predictive capability is particularly valuable in the context of single-runway high-density airports such as London-Gatwick, where even minor weather-induced disruptions can lead to significant downstream effects.

The integration of real-time METAR data with flight plan information enhances situational awareness and supports more informed decision-making for stakeholders, including air traffic controllers, airports operators, and airline dispatchers. Early identification of potential disruptions allows for the proactive allocation of resources, implementation of contingency measures, and optimization of air traffic flow, ultimately contributing to reduced delays, improved passenger experience, and greater overall operational resilience.

Despite the encouraging results, the current model can be further enhanced in several directions:

1.Incorporation of Real-time high-resolution weather data: Future work can include the integration of weather prediction (NWP) models to capture more granular and rapidly evolving weather patterns.

2.Enemble and hybrid modeling approaches: Employing ensemble techniques (e.g., Random Forecasts, Gradient Boosting, and stacking models) or hybrid architectures combining CNN and LSTM layers may further improve predictive accuracy and generalization across different airports and climates.

3.Expantion to multi-airport networks: Extending the framework to consider multiple interconnected airports would allow for the modeling of delay propagation across the air transportation network, enabling better coordination and strategic traffic flow management at a regional or continental level.

4.Reinforcement Learning and Adaptive control systems: The integration of reinforcement learning could facilitate dynamic and strategies that optimize runway usage, gate allocation, and turnaround processes in real time, based on evolving weather and traffic conditions.

5.Operationsal deployment and human-in-the-loop systems: Future research can also explore the deployment of such predictive models in operational decision support systems, including human-in-the-loop simulations to ensure practical usability, interpretability, and trust among stakeholders.

In conclusion, the adoption of machine learning for weather-impact prediction on airport performance marks a significant step toward smarter, more adaptive air traffic management. As aviation systems face increasing demand and greater uncertainty due to climate change, such predictive frameworks will play a critical role in ensuring operational continuity, safety, and efficiency across the global airspace.

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