TELKOMNIKA Telecommunication, Computing, Electronics and Control
Vol. 24, No. 2, April 2026, pp. 527∼535
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i2.27240

Hybrid classical–quantum ensemble learning for real-time flight delay prediction at Tribhuvan International Airport

Pavan Khanal[1], Nanda Bikram Adhikari[2]
[1]Civil Aviation Authority of Nepal, Kathmandu, Nepal
[2]Department of Electronics and Computer Engineering, IOE Pulchowk Campus, Tribhuvan University, Lalitpur, Nepal

Article Info

Article history:

Received Jun 16, 2025
Revised Dec 4, 2025
Accepted Jan 30, 2026

Keywords:

Categorical boosting
Extreme gradient boosting
Machine learning
Quantum boosting
Quantum boosting plus
Quantum machine learning
Voting classifier

ABSTRACT

This study investigates ensemble learning using classical and quantum-inspired models to predict flight delays at Tribhuvan International Airport (TIA), Nepal. It combines traditional machine learning algorithms with quantum-based approaches, quantum boosting (QBoost) and the hybrid QBoostPlus, leveraging quantum properties for faster computation. The dataset includes flight records from 2020 to 2024 and Meteorological Aerodrome Reports (METAR), analyzed across four sea- sons to capture delay patterns in domestic and international flights. A combined seasonal dataset assesses model generalization. Six models; VotingClassifier, adaptive boosting (AdaBoost), xtreme gradient boosting (XGBoost), categorical boosting (CatBoost), QBoost, and QBoostPlus are evaluated based on accuracy, precision, recall, F1 score, area under the curve(AUC), and execution time. CatBoost achieved high accuracy (up to 0.97) but slower execution (up to 10,570.63 ms). QBoostPlus provides competitive AUC scores (0.83–0.95) with faster execution, improving speed by up to 99.94% and generating predictions in as little as 6.46 ms. Although quantum-inspired models have slightly lower accuracy, their computational efficiency and stability show strong potential for real-time flight delay prediction. This is the first study applying quantum-inspired ensemble learning to Nepalese aviation data, showing promise for regional airports with limited infrastructure.

Corresponding Author:

Nanda Bikram Adhikari
Department of Electronics and Computer Engineering, IOE, Pulchowk Campus, Tribhuvan University
Lalitpur 44600, Nepal
Email: adhikari@ioe.edu.np

1. INTRODUCTION

Tribhuvan International Airport (TIA) in Kathmandu, Nepal, serves as the nation's primary international gateway, connecting to over 40 global destinations. Despite its strategic role, TIA faces operational challenges due to a single sloped runway, absence of an instrument landing system (ILS), and increasing traffic demand. According to official TIA data, international passenger traffic grew by 9.29% in 2024, averaging 13,598 passengers per day [1]. This surge has intensified congestion, delays, and resource limitations, emphasizing the need for intelligent flight delay prediction systems to support efficient airport operations.

Flight delay prediction has been extensively studied using various machine learning (ML) techniques. Deep learning approaches, such as convolutional neural network–long short-term memory (CNN-LSTM) frameworks, have shown promising results in forecasting delays based on historical data [2], [3]. Hybrid ML models combining different algorithms further improve prediction accuracy [4], [5], while ensemble learning methods like gradient boosting and incremental learning effectively capture complex delay patterns [6], [7]. Additionally, studies leveraging aviation big data have enhanced delay prediction models [8], and investigations into the impact of short-term features have refined model performance [9], [10]. Flight trajectory prediction has also benefited from hybrid deep learning techniques, improving four-dimensional (4D) trajectory forecasts [11], and spatiotemporal propagation learning has been proposed for network-wide delay prediction [12]. Recent advancements include transformer architectures for temporal modeling in airport delay prediction [13], [14]. In parallel, quantum machine learning (QML) techniques are emerging as novel approaches for aerodynamic classification and time series forecasting in aviation. Quantum support vector machines (QSVM) and data re-uploading quantum methods have demonstrated potential in handling large-scale spatiotemporal data and traffic forecasting [15], [16], opening new avenues for flight delay modeling.

Compared to hybrid models like stacking and bagging [17], [18], quantum boosting plus (QBoostPlus) integrates quantum-inspired optimization with ensemble fusion, using area under the curve (AUC)-based weighting to improve speed and accuracy without iterative retraining [19]. Transformer-based ensembles [13], [20] have shown high accuracy in flight delay prediction but with heavy computational costs, limiting real-time use in constrained environments. Recent QML developments [16] in transportation and time-series forecasting, such as quantum data re-uploading, offer competitive accuracy and faster convergence over classical models. Hybrid quantum models like quantum kernel long short-term memory (QK-LSTM) have improved predictive efficiency and reduced computational costs in climate time-series tasks [21]. Quantum long short-term memory (QLSTM) shows faster convergence and lower test loss than classical LSTM on solar forecasting [22], while quantum sequential recurrent neural network (QSegRNN) achieves comparable or better accuracy with fewer parameters [23]. These results highlight QML's potential to overcome latency and scalability issues in transportation and aviation forecasting.

This study presents the first application of quantum-inspired ensemble learning for flight delay prediction in Nepal, focusing on TIA. Existing ML models often lack the speed and scalability needed for real-time use in resource-constrained settings. To address this, we propose QBoostPlus a hybrid framework combining classical ensembles with quantum-inspired optimization to reduce complexity. Using a multi-season flight and meteorological aerodrome reports (METAR) weather datasets, the model improves both accuracy and efficiency in delay forecasting. It supports real-time decision-making and is adaptable to other regional airports, advancing smart airport initiatives.

The key contributions of this study include: (i) integrating classical ensemble models with quantum-inspired optimization for delay prediction; (ii) proposing QBoostPlus for fast and accurate delay prediction suitable for real-time use; (iii) evaluating seasonal and aggregate datasets to assess model generalization; and (iv) demonstrating trade-offs between accuracy and execution time to inform hybrid deployment strategies.

2. METHOD

2.1. Dataset and preprocessing

This study utilized two primary datasets: the AviBit Traffic Solutions Dataset, which includes 12 flight-related features such as flight number, date, scheduled departure and arrival times, travel time, origin and destination, distance and actual arrival time in the training set, and a test set with the same features except actual arrival time. The second is the METAR dataset, containing 13 meteorological features from the TIA METAR station, including visibility, sky conditions, temperature, wind, pressure, humidity, and precipitation. Both datasets were clean, with no missing values or duplicates. Data preprocessing involved merging the datasets into a single data frame (DataFrame), synchronizing weather data to coordinated universal time (UTC) and rounding timestamps to the nearest hour. More than 200,000 communication records were collected from 2020 to 2024. Key subsets that significantly contribute to the model's performance include: seasonal data with 9,522 training and 3,742 test samples, and a combined approach with 3,978 training and 1,610 test samples.

Feature engineering included encoding sky conditions, imputing zero values, removing redundant features, and aligning weather stations with origin and destination airports. Feature scaling was performed using the standard scaler (StandardScaler) to normalize input variables. For feature selection, columns with excessive missing data were removed, and the top 14 features were selected based on mutual information (MI) scores. MI measures the degree of dependency between each feature and the target variable, allowing us to prioritize inputs that contribute most to predicting delays. This approach improves model interpretability by identifying features with the strongest predictive relationships, offering insights into which flight and weather variables most influence delays. The final selected features comprised one flight characteristic distance; three origin weather features dew point temperature, precipitation, and few clouds at level 1; and ten destination weather features dry bulb temperature, dew point temperature, wind speed, wind direction, wind gust, pressure, visibility, precipitation, relative humidity, and scattered clouds at level 1.

We acknowledge that seasonal imbalance in the dataset (e.g., higher flight volumes in spring and summer compared to winter and autumn) may influence MI scoring, as features dominant in peak seasons could be overemphasized. To mitigate this, feature selection was performed on both seasonal subsets and the combined dataset to ensure generalization across varying traffic conditions.

Figure 1 illustrates the architecture of the QBoostPlus framework, which integrates quantum-inspired optimization within a lightweight ensemble model to enhance convergence, generalization, and operational efficiency.

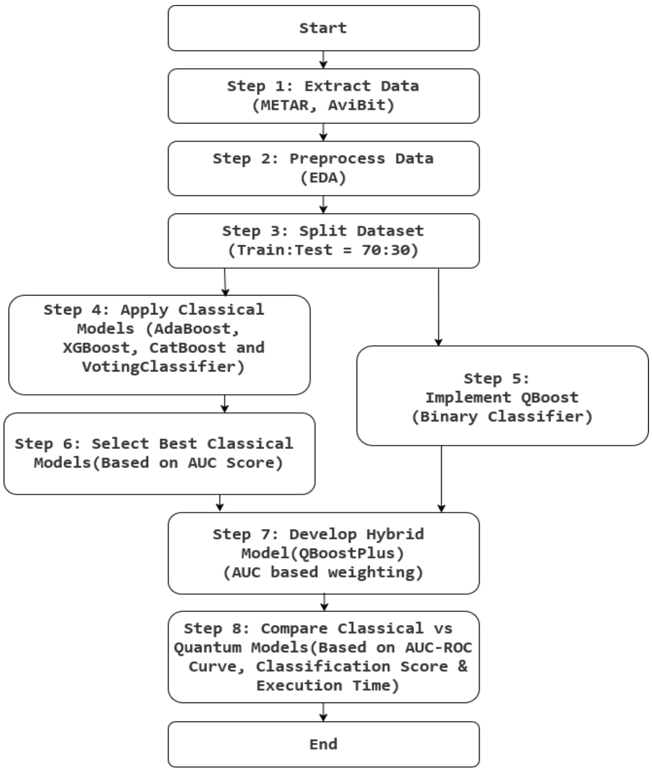

Figure 1. System flow diagram

2.2. Model building and implementation

To comprehensively evaluate predictive performance, we implemented three types of models: classical ML models, the QBoost model, and hybrid approaches.

2.2.1. Classical models

In our study, we utilized classical ensemble models including adaptive boosting (AdaBoost), extreme gradient boosting (XGBoost), categorical boosting (CatBoost), and voting classifier (VotingClassifier) for classification. AdaBoost sequentially improved performance by focusing on misclassified instances [24], [25]. XGBoost offered high accuracy and efficiency through gradient boosting with regularization [24], [26]. CatBoost effectively handled categorical features using ordered boosting [26]. The VotingClassifier combined predictions from multiple models using hard or soft voting, enhancing overall stability and accuracy [24], [25].

2.2.2. QBoost model

QBoost is a quantum-inspired classification algorithm that reformulates problems into quadratic unconstrained binary optimization (QUBO) format for quantum annealing on quantum processing units (QPUs).

Due to limited access to D-Wave hardware, we used the simulated annealing sampler (SimulatedAnnealingSampler) from the dimod library, which emulates quantum annealing on classical hardware while preserving the QUBO framework [27]. Although it mimics quantum concepts like superposition and entanglement, it lacks true quantum features such as tunneling and large-scale parallelism, limiting scalability. Nevertheless, this approach allows effective testing of quantum-inspired models for classification and optimization.

2.2.3. Hybrid model – QBoostPlus

QBoostPlus is a hybrid ensemble classification model that combines multiple weak classifiers using AUC-based weighting. Instead of relying on a single best model, it evaluates each classifier's AUC on a validation set and assigns weights through exponential scaling, giving more influence to stronger classifiers. This weighting strategy aligns with ensemble fusion theory, where model contributions are often scaled by performance metrics to maximize overall predictive power [28], [29]. Predictions are generated by aggregating the weighted outputs, enhancing both diversity and accuracy. Unlike traditional boosting, QBoostPlus avoids iterative training and instead focuses on performance-driven fusion of pre-trained models. The implementation involves selecting the best classifier based on AUC, optionally adding another, and evaluating the model's performance and execution time. Formal equation of QBoostPlus:

$$\hat{y}(x) = \text{sign}\left(\sum_{i=1}^{N} w_i \cdot h_i(x)\right) \tag{1}$$

where,
N = number of weak classifiers, $h_i(x)$ = prediction (or decision function output) of the i^{th} classifier on input x, w_i = weight assigned to the i^{th} classifier based on its AUC score (normalized so $\sum_i w_i = 1$), and $\hat{y}(x)$ = final predicted label (e.g., $+1$ or -1).

Probability estimation (using a sigmoid function with temperature scaling):

$$P(y = 1 \mid x) = \frac{1}{1 + \exp\left(-\frac{1}{T}\sum_{i=1}^{N} w_i \cdot h_i(x)\right)} \tag{2}$$

where, T = temperature parameter controlling the softness of probabilities.

2.2.4. Evaluation metrics

All models were evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and AUC-receiver operating characteristic (ROC), to assess their predictive performance comprehensively. In addition to these evaluation metrics, execution time was recorded to compare the computational efficiency of classical, quantum, and hybrid models, providing insights into both effectiveness and practicality for real-world applications.

2.3. Toolset and system configuration

The environment used Visual Studio Code (v1.95.3), Python 3.x, and libraries such as NumPy, pandas, scikit-learn, and Simulated Annealing from the dimod library. Experiments were run on a system with an Intel Core i5-1035G1 central processing unit (CPU) (1.00 GHz, up to 1.19 GHz), 8 GB random access memory (RAM), and Windows 11, which supported both ML and quantum-inspired simulations efficiently.

3. RESULT AND DISCUSSION

3.1. Analysis of combined approach for all seasons

The combined approach integrates flight data from all seasons into a single training and testing framework, enabling a holistic assessment of delay patterns. By aggregating seasonal variations, this approach captures recurring operational characteristics such as airport congestion and systemic inefficiencies while benefiting from a larger and more diverse dataset. As a result, the models exhibit improved stability and reduced susceptibility to overfitting. In addition, employing a single unified model simplifies deployment and lowers computational overhead, which is essential for real-time operational use.

Figure 2 illustrates the AUC–ROC performance of the evaluated models under the combined setting. XGBoost, CatBoost, the VotingClassifier, and QBoostPlus demonstrate the strongest discriminative capability, indicating reliable separation between delayed and on-time flights. In contrast, AdaBoost and QBoost show comparatively weaker performance, suggesting limited robustness under aggregated seasonal conditions.

Figure 3 presents the relationship between predictive performance and execution time. QBoostPlus achieves the fastest inference time, substantially outperforming other ensemble models. Although CatBoost and the VotingClassifier attain comparable predictive accuracy, their significantly higher execution times limit their suitability for latency-sensitive environments. These results indicate that QBoostPlus provides an effective balance between predictive capability and computational efficiency, making it a strong candidate for real-time flight delay prediction.

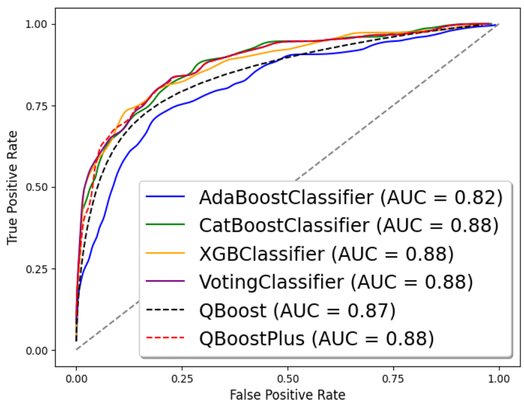

Figure 2. AUC ROC curve of combined approach

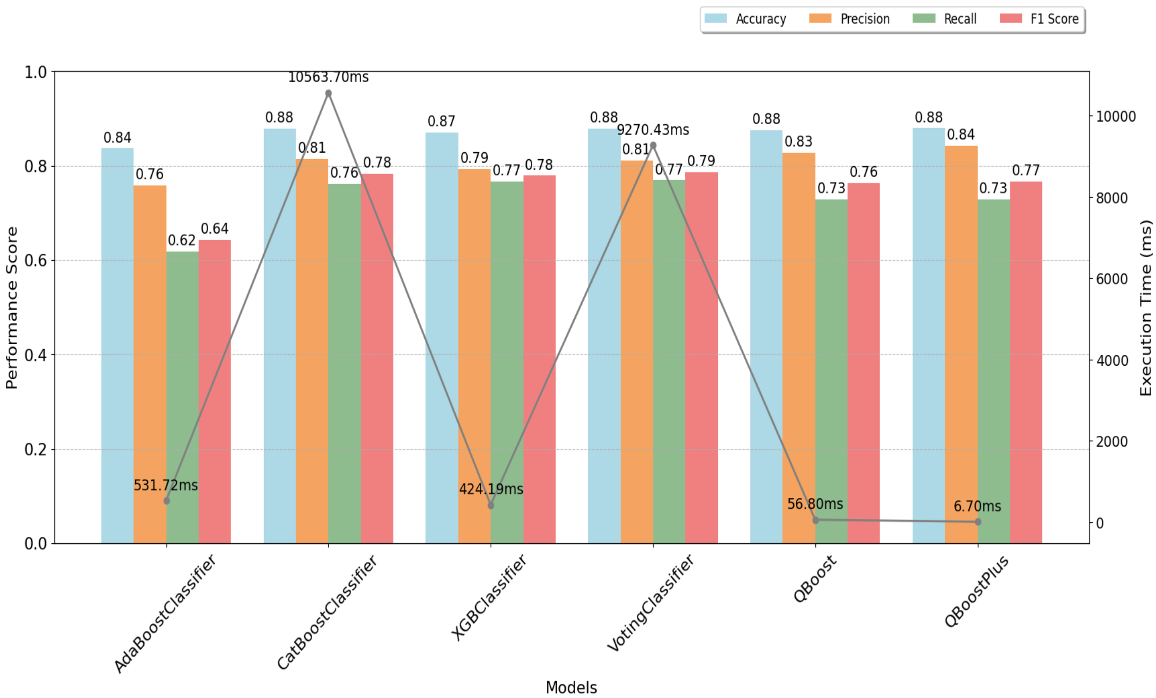

Figure 3. Classification performance vs. execution time of combined approach

3.2. Enhancing statistical robustness of model evaluation

To ensure reliable performance estimation, cross-validation and statistical significance testing were employed. Table 1, summarizes the average accuracy and standard deviation obtained from 5-fold and 10-fold cross-validation, along with paired t-test results.

The models demonstrate consistent generalization, with mean cross-validation accuracies ranging from approximately 85% to 93%. QBoostPlus achieves the highest average accuracy across both validation settings, while low standard deviations indicate stable performance. Paired t-test results show no significant differences between 5-fold and 10-fold validation (all p-values > 0.05), confirming the reliability of the reported estimates. These results highlight that QBoostPlus delivers strong predictive performance with efficient computational cost, supporting its suitability for practical deployment.

Table 1. Model performance with cross-validation and significance testing

Model	5-fold average	5-fold standard deviation	10-fold average	10-fold standard deviation	t-Test value	Significance level (p)
AdaBoost	0.8283	0.0045	0.8313	0.0110	-0.7045	0.4936
CatBoost	0.8585	0.0085	0.8610	0.0121	-0.4274	0.6776
XGBoost	0.8522	0.0120	0.8532	0.0146	-0.1292	0.9000
VotingClassifier	0.8595	0.0113	0.8612	0.0131	-0.2448	0.8123
QBoost	0.8512	0.0129	0.8668	0.0103	-2.1343	0.0741
QBoostPlus	0.9168	0.0197	0.9301	0.0242	-1.0472	0.3215

3.3. Seperate analysis of each season

Flight delays at TIA are strongly influenced by seasonal factors. Winter fog, spring storms, summer congestion and heat, and autumnal weather transitions introduce distinct operational challenges. To account for these effects, a season-wise evaluation was conducted to assess context-specific model behavior.

As shown in Table 2, reports the classification performance and execution time of each model across the four seasons. QBoostPlus consistently demonstrates strong predictive performance, achieving its highest accuracy during the summer season while maintaining competitive results in winter, spring, and autumn. Importantly, it preserves exceptionally low execution times across all seasonal datasets, highlighting its robustness under varying operational conditions.

Table 2. Classification performance and execution time of models across different seasons

Season	Model	AUC	Accuracy	F1-score	Precision	Recall	Execution time (ms)
Winter	AdaBoost	0.88	0.89	0.76	0.81	0.73	495.72
	CatBoost	0.90	0.91	0.81	0.88	0.88	4660.70
	XGBoost	0.89	0.92	0.84	0.88	0.81	219.86
	VotingClassifier	0.90	0.92	0.83	0.89	0.79	4636.98
	QBoost	0.89	0.90	0.81	0.83	0.79	55.75
	QBoostPlus	0.90	0.91	0.82	0.87	0.79	11.20
Spring	AdaBoost	0.82	0.90	0.63	0.66	0.62	360.62
	CatBoost	0.89	0.92	0.68	0.74	0.65	4184.21
	XGBoost	0.88	0.92	0.69	0.73	0.67	208.22
	VotingClassifier	0.89	0.92	0.69	0.75	0.65	4783.87
	QBoost	0.88	0.90	0.62	0.66	0.60	53.28
	QBoostPlus	0.89	0.91	0.63	0.68	0.61	10.59
Summer	AdaBoost	0.94	0.96	0.81	0.88	0.77	570.90
	CatBoost	0.93	0.97	0.85	0.98	0.78	4091.32
	XGBoost	0.95	0.96	0.82	0.86	0.79	125.19
	VotingClassifier	0.95	0.97	0.83	0.94	0.77	4466.01
	QBoost	0.95	0.95	0.82	0.81	0.84	58.26
	QBoostPlus	0.95	0.97	0.86	0.88	0.84	8.45
Autumn	AdaBoost	0.76	0.87	0.64	0.69	0.62	274.94
	CatBoost	0.83	0.89	0.70	0.77	0.66	3537.77
	XGBoost	0.82	0.89	0.70	0.74	0.68	162.01
	VotingClassifier	0.83	0.89	0.71	0.76	0.68	4010.41
	QBoost	0.82	0.87	0.68	0.70	0.68	55.21
	QBoostPlus	0.83	0.88	0.69	0.71	0.68	9.09

While CatBoost and the voting classifier occasionally achieve comparable accuracy, their substantially higher inference times reduce their practicality in environments with limited computational resources and strict real-time constraints [13]. Classical ensemble methods such as AdaBoost show higher precision in certain seasons but suffer from reduced recall, particularly during autumn, indicating sensitivity to class imbalance and temporal variability [6], [24]. QBoostPlus maintains a balanced trade-off between precision and recall, resulting in stable F1-scores even in challenging seasonal conditions. This behavior aligns with prior studies reporting the difficulty of delay prediction under imbalanced and temporally heterogeneous data distributions [6], [24]. Compared with recently proposed transformer-based approaches [13], which offer strong predictive performance at the expense of high computational complexity, QBoostPlus delivers comparable accuracy with significantly lower latency.

Overall, the seasonal analysis confirms that QBoostPlus effectively adapts to diverse operational contexts while preserving computational efficiency. Its application to flight delay prediction at TIA represents, to the best of our knowledge, the first use of a quantum-inspired ensemble learning approach in the Nepalese aviation domain. These results suggest strong potential for broader adoption in infrastructure-constrained airports where scalability and real-time responsiveness are critical [30].

4. CONCLUSION

This study explored classical and quantum-inspired ML models for flight delay prediction at TIA, introducing a hybrid framework that balances computational efficiency with predictive accuracy. The findings highlight the potential of quantum-inspired approaches for time-sensitive aviation tasks, particularly in airports with limited resources. This work contributes to advancing intelligent, adaptive delay prediction systems tailored to complex airport operations. Future research should focus on implementing this framework using actual quantum hardware and extending it to other regional airports to enhance scalability and practical utility.

ACKNOWLEDGMENTS

The authors thank Tribhuvan International Airport (TIA) and the Department of Hydrology and Meteorology (DHM), Nepal, for providing communication and meteorological aerodrome report (METAR) data for this study.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Pavan Khanal	✓	✓	✓	✓	✓	✓		✓	✓	✓				
Nanda Bikram Adhikari	✓	✓		✓	✓				✓			✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data used in this study were obtained from Tribhuvan International Airport (TIA). Due to policy restrictions, the dataset is not publicly available but may be provided upon reasonable request to the corresponding author, subject to institutional or regulatory approval.

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BIOGRAPHIES OF AUTHORS

Pavan Khanal received his Bachelor's degree in Computer Engineering from Tribhuvan University, Nepal, in 2009, and his Master's degree in Computer Systems and Knowledge Engineering from the Institute of Engineering, Pulchowk Campus, Tribhuvan University, in 2025. He is currently serving as a senior IT officer at the Civil Aviation Authority of Nepal. His current research interests include computer networking, cybersecurity, machine learning, and quantum computing. He can be contacted at email: pkhanal2008@gmail.com.

Nanda Bikram Adhikari received an M.Sc. in Engineering degree from the State Engineering University of Armenia in 1994 and a Ph.D. from Nagoya University, Japan, in 2004. From 2004 to 2007, he worked as a research fellow at the National Institute of Information and Communications Technology, Tokyo, Japan, developing a rainfall rate retrieval algorithm for the global precipitation measurement satellite mission. Since 2007, he has been an Associate Professor in the Department of Electronics and Computer Engineering, Institute of Engineering, Pulchowk Campus, Tribhuvan University. He has published over 40 articles in high-impact SJR-ranked ISI and Scopus journals and IEEE conferences, including Radio Science, IEEE Transactions on Geoscience and Remote Sensing, AGU, and MDPI Electronics. He also serves as a reviewer for more than 20 prestigious journals, including IEEE, Elsevier, and Springer. He has authored four books: Outlook of Remote Sensing, Fundamentals of Microwave Engineering, Performance Analysis of Cognitive Radio Networks for Resource Sharing, and Design and Implementation of Multi-channel Active Electrode EEG Device. His research interests include 5G and beyond networks, microwave wireless communications, software-defined networks, IoT applications, quantum computing, and AI-based signal processing. He can be contacted at email: adhikari@ioe.edu.np.