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Quantum Enhanced Language Models for Aviation Safety Intelligence and Predictive Operations

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Abstract. This research introduces the Quantum Information System for Aerospace Safety Intelligence(QISASI), the versatile and a scalable Quantum Intelligence (QI) and Natural Language Processing (NLP) methods the proposed QISASI framework to enhance the aviation safety, streamline with its operational workflows, and it delivers the predictive insights for the quantum enabled maintenance for its mission support systems. The key innovation of QISASI is Quantum Self Attention Based on the Contextual Feature Fusion (QSACF²) module, which encodes the multimodal aviation data such as its textual reports, audio communication transcripts, radar telemetry, and ADS-B signals into its quantum states using the ZZFeatureMap and multilayer quantum gate operations. The QISASI architecture enables the efficiency of its modeling of complex and high dimensional interactions, which is significant and it improves its capabilities in the anomaly detection, risk forecasting, and predictive maintenance. Therefore, the experiments which are conducted on real world ATCOSIM and ADS-B datasets demonstrates that the QISASI substantially method achieving the exceptional accuracy of up to 99.99%, thereby validating its robustness for aviation safety intelligence and effectiveness of the proposed hybrid quantum classical learning approach in real world aviation diagnostics.

Index Terms—Aviation safety, Quantum self attention, Quantum feature fusion, Quantum LLM, ZZFeatureMap, Predictive maintenance, Signal intelligence

1 Introduction

Aviation safety represents the critical dimension of aerospace operations, where as the system failures can lead to the catastrophic consequences affecting both the human lives and its mission outcomes. The advent of Artificial Intelligence(AI) and the NLP technologies has revolutionized the analysis of the complex aviation datasets, which includes the communication transcripts, telemetry signals, and its sensor readings [1]. Whereas, these heterogeneous data sources gives the valuable insights for the predictive maintenance, and anomaly detection, and the risk assessment. Classical AI approaches the still face challenges in capturing

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its emotional context and modeling its high dimensional and the interrelationships across the diverse data modalities [7].

Recent advances in the Large Language Models (LLMs), such as the Mistral [15] and Large Language Model Meta AI - Version 3(LLaMA-3) [10], have demonstrated improved its domain adaptability for aviation communication tasks. Building upon the developments, the research introduces a hybrid quantum classical framework termed QISASI, and a pre trained aviation safety model that integrates quantum enhancement and self attention mechanisms for effective fusion of heterogeneous aviation signals. By encoding the multimodal features encompassing the textual, auditory, and telemetry data into the quantum states using the advanced quantum gates and feature maps, the system captures the intricate dependencies often overlooked by the classical models. This capability enables the real time safety intelligence, and its proactive operational risk mitigation, and the predictive decision making to secure the aerospace environments. The architecture further integrates its scalable LLMs, specifically LLaMA-3 and Mistral, which are fine tuned for aviation domain adaptation [10].

The proposed QISASI aims to enhance the accuracy, adaptability, and the scalability within the aviation safety assessment processes, that facilitates the real time risk forecasting, and maintenance of the prediction, and the mission critical decision support. By leveraging the quantum inspired of the feature fusion, QISASI overcomes the inherent limitations of its classical models, which produces the refined insights for its high stakes and the confidential aerospace scenarios [11]. Therefore, this research contributes the cutting of the edge framework that strengthens the safety, efficiency, and the resilience across the aerospace operations, with the significant potential for its expansion into a broader safety critical AI domains.

The remainder of this paper is organized as follows. Section 2 provides the comprehensive review of its related works on aviation safety intelligence, and it highlights the existing approaches and which is associated with its challenges. Section 3 outlines its proposed QISASI architecture and the core components. Section 4 elaborates on the quantum feature fusion mechanism that shows the integration of the multimodal aviation data. Section 5 details the experimental setup and its evaluation protocols employed to assess its model performance. Section 6 presents and discusses about the experimental results, focusing on performance the benchmarks and validation metrics. Section 7 concludes the study by summarizing the key findings and proposing directions for the future research and its practical deployment in the safety critical aerospace environments.

2 Background and Related Works

Multimodal modeling for the aviation safety analytics has progressed substantially, with the successive developments via addressing challenges from the single modality and processing to its complex cross modal integration. Initially the computational approaches in the aviation safety relied on its classical machine learning techniques [12] which are trained on the limited data sources such as the textual pilot reports and Air Traffic Controller (ATC) communication transcripts [1]. Algorithms including the Naïve Bayes, Support Vector Machines (SVMs), and the Random Forest(RF) are utilized manually engineered the linguistic features [4]. Their limited generalization capacity is restricted the incorporation of the additional data streams such as the telemetry and the radar signals. As a result, these methods showed the reduced effectiveness in the contextual understanding and the incident prediction, and limiting their suitability for its large scale safety analytics.

The adoption of the deep learning architectures, which are particularly Convolutional Neural Networks (CNNs) and the Transformer models, which are introduced as the major shift by enabling the higher level representation by learning from the unimodal aviation data including text, audio, and the time series signals [7][5]. CNNs also proved that it is effective for the structured telemetry processing, while the transformers are handled through the variable length of communication sequences efficiently. However, by integrating the multiple modalities remained difficult due to the heterogeneous data characteristics, and complex interdependencies, and the high computational requirements [3][8]. Multimodal fusion strategies aimed at improving the pilot situational awareness demonstrated by the ability to learn the cross modal representations and to enhance the contextual interpretation [13][5].

To improve the multimodal learning, the advanced fusion of frameworks such as the Tensor Fusion Networks(TFNs) and the cross modal attention mechanisms were introduced. These joint encoding architectures are increased predictive performance by the modeling relationships among the textual, audio, and the telemetry inputs. Despite these gains, high computational cost and the scalability limitations reduced by their feasibility for the real time aviation environments [9].

Currently the multimodal systems continue to face its challenges efficiently by capturing the deep contextual dependencies across the heterogeneous aviation data sources, particularly under the limited labeled data conditions and to strict scalability constraints [8][9]. Quantum inspired methods are proposed to overcome these limitations. The QISASI framework integrates the quantum encoding with the transformer based architectures to enable the precise and the context aware aviation safety intelligence for suitable and real time aerospace applications.

Recent hybrid quantum models incorporating the quantum self attention and the feature fusion mechanisms have been demonstrated the strong performance in the encoding of high dimensional and cross modal aviation data for the applications including its anomaly detection [14], air traffic network optimization, and the fuel system diagnostics. Techniques such as the ZZFeatureMap encoding and the entangling of the quantum gate operations to enhance its expressiveness, scalability, and robustness resulting in an improved incident classification performance in the mission critical aerospace analytics [2].

Building on these developments, the proposed QISASI framework employs that the quantum self attention to enable the context rich and the scalable multimodal fusion within the domain specific of the LLM architecture designed for the aviation [10]. This hybrid quantum classical approach supports the deep cross modal learning, and adaptive context modeling, and the computational efficiency required for the safety critical systems. This framework that integrates the quantum enhanced self attention with the scalable LLM architectures are tailored to the aviation datasets [7][10], by improving its context aware inference, computational performance, predictive maintenance, anomaly detection, and the risk assessment for the modern aerospace environments.

3 The Proposed QISASI Method

In this research, the QISASI framework is proposed for the multimodal aviation safety intelligence. It employs the $QSACF^2$ mechanism to integrates textual communication data and the flight telemetry within a hybrid quantum classical architecture. By encoding the multimodal features using the ZZFeatureMap and the entangled quantum circuits, the model enhances anomaly detection and risk prediction. Figure 1 presents the overall pipeline, and Algorithm 1 outlines the key procedural steps.

Algorithm 1: The Proposed QISASI Method

Input: Aviation datasets
Output: Predicted safety recommendation

1. Apply text preprocessing on the training dataset.
2. Extract classical features from the preprocessed training data.
3. Run Quantum feature fusion method.
4. Execute A^2QCE Algorithm.
5. Apply post processing method.
6. Retrieve the relevant safety information

Figure. 1 illustrates that the QISASI pipeline aligned with Algorithm 1. In Step 1, The ATCOSIM and ADS-B datasets are ingested into the input layer. In Step 2, the classical feature extraction stage applies that the Bidirectional Encoder Representations from Transformers(BERT) encoder and engineered telemetry features to obtain the rich classical representations. And in Step 3, the reduced multimodal embeddings are encoded into the quantum states via the ZZFeatureMap within the quantum feature encoding block. Enabling its quantum self attention driven fusion, where BERT text embeddings and engineered ATCOSIM/ADS-B features meet. Numerical features are encoded into quantum states using parameterized circuits (Rx, Rz, H and controlled gates) to capture complex correlations.
These quantum embeddings are then fused with BERT outputs via a neural subnetwork, producing a joint representation sent to the quantum neural network with softmax classifier. In Step 4 it feeds the resulting quantum features into the hybrid quantum model with QNN which is associated with the classical layers, and it computes safety class probabilities through the feed forward neural network and softmax classifier (A^2QCE) method. Finally In Step 5 it corresponds to the output layer, where the measurements are interpreted as the safety scores or anomaly predictions and translated into the aviation safety recommendations for operational decision support. This section represents that the proposed QISASI methodology for the aviation safety intelligence. Although they developed specifically for the aviation applications, and the framework is designed to be adaptable to the wide range of its safety critical domains. As they demonstrated in Section 5 through its experimental evaluation and the feature mapping analysis, The QISASI improves its reliable diagnostics and strengthens the risk prediction and its decision support of the capabilities in the complex operational environments.

4 The QISASI Feature Fusion Method

Our work develops the $QSACF^2$, the aviation safety intelligence framework that combines the quantum machine learning circuits with the transformer based LLMs to support the high fidelity, and the real time risk prediction [6][7]. The central pipeline integrates the preprocessed aviation text sources, by including crew reports and the ATC communication logs, with the telemetry streams such as the ADS-B and the radar data, which is subsequently encoded using the advanced quantum feature mapping techniques [10].

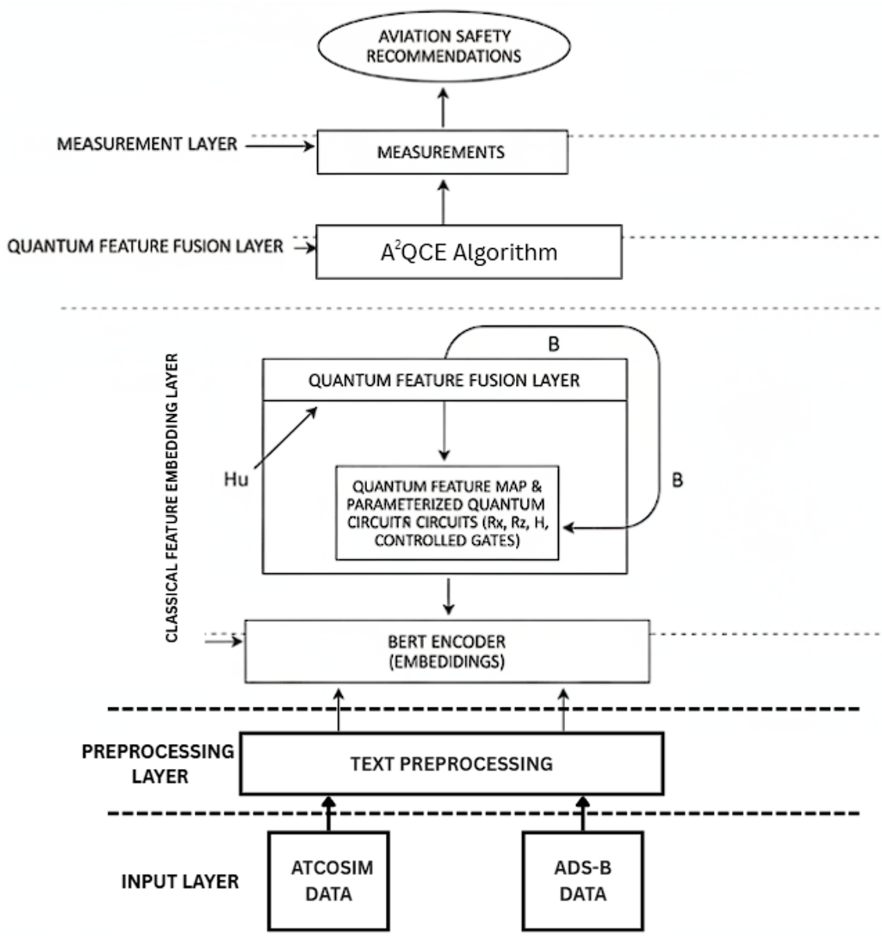

Figure 1: Pipeline of the proposed QISASI architecture

4.1 Quantum Gate Structure for Feature Fusion

The feature encoding and the fusion component employs that the multilayer quantum circuit, shown below, that this integrates the parameterized rotation of the operations with its controlled entanglement mechanisms. This design also follows that the implementation is developed in our project. Within the QISASI framework, this multilayer quantum circuit performs the feature encoding and the fusion by combining the parameterized R_X, R_Y, and R_Z rotation gates with the Controlled NOT(CNOT) and Controlled Z(CZ) gates entangling operations [10]. The configuration is trained using the AdamW optimizer, by enabling fast convergence and the strong generalization for the high dimensional aviation safety data. To enable the effective feature interaction, The QISASI incorporates the ring topology for the CNOT gates that allows each qubit to interact with the neighboring qubits, by ensuring consistent information and propagation across the circuit [6]. This layered entanglement strategy enhances its analytical precision in the aviation safety modeling and ensures that each of the qubit contributes to its system level predictions. The circular CNOT configuration is further strengthened by the additional CZ gate operations, and by supporting the stronger global correlations and the deeper multilayer feature fusion [6].

4.2 The Proposed QSACF^2 Algorithm

Algorithm 3 summarizes the proposed QSACF^2 algorithm as follows:

- Designed the hybrid quantum classical pipeline that integrates the aviation text and its telemetry data through the quantum circuit level of the feature fusion [6].
- Incorporated and parameterized quantum gate operations, the multi qubit entanglement, and the transformer based on the learning to improve its safety prediction performance [7].
- Enabling the richer cross modal encoding with its scalable support for its additional qubits and th adaptability to other real time safety analytics applications [10][15].

These efforts are advanced in hybrid quantum AI architectures which is tailored for the mission critical aviation safety, which enables richer fusion of the communications and the telemetry data. By exploiting the quantum feature maps and for entangled representations, the models that capture subtle cross modal patterns that the classical systems often miss. This leads to more of reliable anomaly detection, risk assessment, and the decision support in the high stakes aerospace operations.

Algorithm 2: The Proposed QSACF^2 Algorithm

Input: Feature vector $x \in \mathbb{R}^n$, parameter vector θ
Output: Encoded quantum state

1. Construct the quantum circuit containing n qubits.
2. For each qubit q_i:
   - Apply the Hadamard gate H to create the superposition.
   - Apply the data driven rotational gates:
     - $R_x(x_i \cdot \pi)$
     - $R_y(x_i \cdot \pi/2)$
     - $R_z(x_i \cdot \pi/4)$
3. Apply the circular CNOT gate entanglement among all the qubits.
4. Apply the Controlled-Z(CZ) interactions between the neighboring qubits.
5. Perform the additional parameterized rotations $R_x(\theta_i)$ and the $R_z(\theta_i)$ on each of the qubit to enhance its expressiveness.
6. Apply the final entanglement stage using the reverse order of CNOT gate.
7. Output of the encoded quantum state vector.

4.3 The Proposed A^{2}QCE Algorithm

The Aviation Associate Quantum Classifier Engine (A^2QCE) is the final decision making module in the QISASI framework. And it receives the quantum encoded multimodal feature representations produced in Algorithm 3 by the quantum feature fusion layer and it processes them using the parameterized quantum neural network. The measured quantum outputs are converted into the classical values and it is passed through the softmax classifier to generate its aviation safety predictions such as the anomaly detection or the risk classification. This hybrid quantum classical classifier enables an accurate and the real time safety assessment from the complex aviation data.

Algorithm 3: The Proposed A^{2}QCE Algorithm

Input: Quantum encoded feature vectors
Output: Predicted aviation safety class

1. Apply the parameterized quantum gates and the entanglement operations.
2. Measure the quantum outputs to obtain its classical values.
3. Apply the softmax classifier.
4. Generate the final aviation safety prediction.

5 Experimental Results

5.1 Datasets Description

The proposed QISASI utilizes the ATCOSIM dataset, which focuses on textual transcripts with the corresponding of audio components removed. To enrich the dataset, the synthetic telemetry features such as the altitude, airspeed, temperature, and its fuel flow rate are very incorporated. And it is normalized textual feature which scores to capture the operational urgency, altitude and the speed variations, and weather conditions, while the binary safety labels classify the each instance as either safe or unsafe. The training process which adopts the 80–20 data split, with batch sizes ranging from 8 to 16 and 2–5 epochs of training. The model leverages which is pretrained BERT embeddings alongside the quantum feature maps to facilitate the hybrid quantum classical representation learning [14].

For the ADS-B dataset, the model processes the normalized flight telemetry parameters altitude, groundspeed, and its heading paired with the anomaly indicators which is related to its vertical, speed, and the altitude deviations. Complementary operational text data, comprising approximately 19,714 samples, it is encoded through NLP preprocessing. To address the class imbalance, a weighted training scheme is employed. And the Model training proceeds for the 15 epochs with batch sizes of 8–16, using the AdamW optimizer and the cosine annealing learning rate schedule, and coupled with the progressive BERT fine tuning to effectively manage multimodal feature fusion [14].

5.2 Performance Measures

The hybrid QISASI model predicts the safety outcomes on an unseen aviation data by producing the class probabilities for its potential anomalies, maintenance requirements, or operational risk levels. Model performance is quantitatively evaluated using the standard classification metrics *accuracy*, *precision*, *recall*, and *F1-score* as expressed in Equations (1)-(4). These evaluations are demonstrated in the enhanced safety intelligence which is achieved through the integration of the quantum self attention mechanisms with its classical deep learning approaches.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{F1} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Here, TP, TN, FP, and FN denotes true positives, true negatives, false positives, and false negatives respectively. Accuracy measures the correct classification; recall measures correctly the identified safe cases precision measures reliability of positive predictions; and F1 balances precision and recall. These metrics confirms its model's efficiency for real time aviation safety monitoring [7][11].

5.3 Experimental setup

The proposed QISASI model is implemented in Python, with the quantum self attention components developed using PennyLane or Qiskit frameworks. The architecture processes the multimodal aviation data by integrating the textual communications, telemetry signals, and the sensor inputs through the quantum enhanced self attention mechanism. This mechanism synergizes with the classical deep learning representations, enabling the hybrid modeling approach that enhances the contextual understanding and its feature fusion across diverse aviation data modalities [7].

5.3.1 Model Initialization

In QSACF^2, multimodal embeddings are encoded into the quantum circuits using the ZZFeatureMap, which employs the parameterized rotation gates R_xR_x, R_yR_y, R_zR_z , along with the CNOT based entanglement. This process transforms the classical data into the high dimensional quantum Hilbert space, that effectively captures the complex contextual correlations that extended beyond the representational capacity of the conventional classical attention mechanisms [10].

The ZZFeatureMap unitary operator is defined as Equation (5).

$$U_{\phi(\mathbf{x})} = \exp\left(i \sum_{S \subseteq [n]} \phi_S(\mathbf{x}) \prod_{i \in S} Z_i \right) \tag{5}$$

where n is the qubit count, $\phi_S(\mathbf{x})$ are data dependent parameters, and Z_i are Pauli-Z operators. Quantum self attention generalizes classical attention as shown in Equation (6)

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{6}$$

with query Q, key K, and value V as quantum feature matrices, enabling effective fusion of quantum classical contextual data [7].

5.3.2 Model Training

The training process partitions the datasets into its distinct training and testing subsets. Quantum features generated from the Quantum Self Attention (QSA) module that are fused with the classical transformer or MLP based representations to form a hybrid input embeddings. The model is trained using the backpropagation to minimize the categorical cross entropy loss, as defined in Equation (7).

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{7}$$

Here, C denotes the number of classes, y_i represents the true label, and $\hat{y}_i$ is the predicted probability for class i. Hyperparameters such as *circuit depth*, *attention heads*, and *learning rate* are optimized to maximize model accuracy and improve generalization across unseen data [4].

5.4 Experiment on ATCOSIM Dataset

The *ATCOSIM* dataset was employed to evaluate the proposed QISASI model based on the quantum self attention for fusing textual and telemetry modalities in ATC scenarios. This dataset contains the pilot controller communication transcripts paired with its synthetic telemetry data, encompassing both routine and critical safety events annotated with the binary safety labels. The dataset was split into training and testing sets using an 80–20 ratio. Pretrained *BERT* embeddings were utilized for the textual features, while quantum feature maps represented telemetry data. The model was trained in batches of 8–16 over 2–5 epochs, enabling the robust multimodal feature fusion for accurate aviation safety predictions.

Textual and telemetry features are synchronized and combined into the multimodal input vectors by integrating the BERT embeddings with the normalized telemetry signals for the quantum feature mapping. Each sample, the containing the six classical features and the safety labels, and it was encoded using the 4-qubit ZZFeatureMap, that is followed by the quantum self attention for the contextual dependency modeling and the dimensionality reduction. Hybrid QML fused on the BERT features with the parameterized quantum circuit outputs, the trained using categorical cross entropy with its optimized confidence and the support thresholds. The quantum neural network measurements are produced safety class predictions, and the evaluation on the ATCOSIM dataset showed that the QISASI achieved perfect accuracy and the recall for unsafe events, and outperforming the classical transformer based model.

Table 1 presents the core evaluation metrics for the ATCOSIM dataset. QISASI achieves near-perfect classification performance on this dataset, with accuracy, precision, recall, and F1-score all reaching 99.99%, whereas the QSVM, SVM, BiLSTM, and Random Forest(RF) baselines remain a few tenths to several percentage points lower on at least one of these indicators. In particular, the QISASI attains the highest recall and F1-score, showing that it

Table 1: Performance Comparison of the Proposed QISASI on the ATCOSIM Dataset

Metric	QISASI	QSVM	SVM	BiLSTM	RF
Accuracy (%)	99.99	99.70	99.08	98.10	95.00
Precision (%)	99.99	99.70	99.99	98.00	95.00
Recall (%)	99.99	99.70	99.99	98.20	95.00
F1-Score (%)	99.99	95.70	99.99	98.10	95.00

not only captures nearly all unsafe events but also avoids unnecessary false alarms more effectively than the competing models. This validates the benefit of quantum feature fusion for controller–pilot communication scenarios. The results demonstrate the model's exceptional ability to fuse communication transcripts and telemetry data for precise aviation safety assessment in simulated ATC scenarios [13].

5.5 Experiment on ADS-B Dataset

The QISASI framework was further evaluated on the *ADS-B* dataset, which comprises the continuous flight telemetry (including altitude, latitude, longitude, groundspeed, heading, and operational flags) alongside the textual operational notes from multiple flight records. Due to the pronounced class imbalance arising from the fewer unsafe instances, advanced on its weighting strategies and the anomaly detection techniques were employed. Textual data were encoded using the pretrained *BERT* embeddings and integrated with quantum feature maps through progressive BERT fine tuning, and enabling the efficient multimodal fusion.

Telemetry and the textual data were normalized, engineered, and it is tokenized using the BERT embeddings, with the temporal synchronization ensuring the aligned multimodal inputs. Each of the sample with the six classical features and the safety labels were encoded using the 6-qubit ZZFeatureMap with the circular entanglement, and the quantum self attention captured the cross modal dependencies. Hybrid quantum classical learning fused the BERT and the quantum circuit outputs, And optimized using the AdamW and categorical cross entropy. The Evaluation on the ADS-B dataset showed that the QISASI achieved 99.99% recall for its unsafe events and the outperformed classical transformer models across key metrics.

Table 2: Performance Comparison of the Proposed QISASI on the ADS-B Dataset

Metric	QISASI	QSVM	SVM	BiLSTM	RF
Accuracy (%)	99.99	97.80	92.00	95.00	93.00
Precision (%)	99.99	97.50	99.99	98.00	92.00
Recall (%)	99.99	98.00	85.00	91.00	95.00
F1-Score (%)	99.99	97.75	91.00	94.00	93.00

Table 2 summarizes the evaluation results for the ADS-B dataset. QISASI detects all unsafe events, achieving a recall of 99.99% with a corresponding F1-score of 99.99%, whereas QSVM, SVM, BiLSTM, and RF show lower accuracy or miss a fraction of critical anomalies. This indicates that the quantum neural network not only detects unsafe cases but also reduces false alarms compared with classical deep and shallow baselines, demonstrating a more effective exploitation of multimodal ADS-B telemetry and contextual information. These results highlight the framework's strong generalization and anomaly prediction capabilities for real-world flight telemetry and large-scale aviation operations [12].

6 Result Discussion

Validation was performed on both the *ATCOSIM* and *ADS-B* benchmark datasets using the distinct training, validation, and its testing partitions. The proposed QISASI model hyperparameters for the quantum circuit components and the classical neural network counterparts were optimized via grid search and its cross validation procedures. The hybrid architecture integrating QSA with the transformer based learning consistently outperformed the classical baseline models in capturing its cross modal contextual dependencies. This integration yielded its real time accuracy improvements and the enhanced interpretability across all the stages of end to end aviation safety analytics.

6.1 Performance Evaluation

The proposed QISASI model achieved the robust accuracy of 99.99%, that surpass the QSVM, SVM, BiLSTM, and the RF baselines. The precision is slightly lower on ADS-B due to its model's aggressive detection of rare unsafe events, and the recall remains at 99.99% and yields the strongest F1-scores, confirming superior and overall discrimination capability. And the findings that demonstrate the integrating quantum self attention and feature fusion into the hybrid architecture provides the verifiable benefit over purely classical models in the modeling complex contextual aviation safety patterns. Further hyperparameter tuning the quantum circuit depth and the transformer layers that is enhanced overall performance, and thereby confirming its verifiable benefit of incorporating the quantum self attention within the hybrid architecture [7].

6.2 Model Accuracy

Trained on the labeled aviation datasets with the 80/20 split, the proposed hybrid quantum classical system that outperformed both the classical transformer and the feed forward neural network baselines through the enriched contextual fusion enabled by the quantum feature integration.

Figure. 2 shows that the proposed QISASI consistently achieves the highest accuracy on both the datasets, outperforming all the classical and quantum baselines. On ATCOSIM, QISASI reaches 99.99% accuracy, compared to 99.70% for QSVM, 99.08% for SVM, 98.10% for BiLSTM and 95.00% for RF. The raw, noisy ADS-B data, QISASI again attains 99.99% accuracy, while the QSVM, , and achieve 97.80%, 92.00%, 95.00%, and 93.00% respectively, and confirming that the hybrid quantum model learns more effectively from the real world telemetry than the classical counterparts [11].

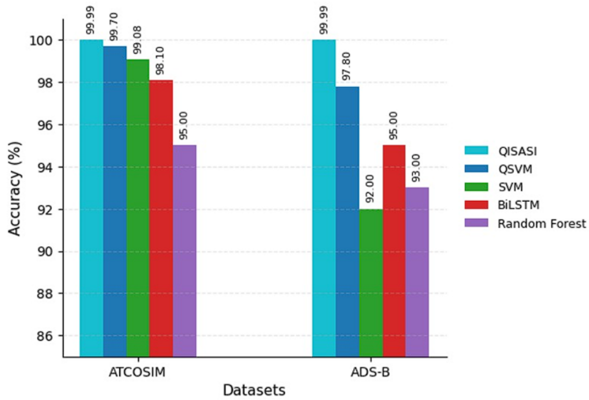

Figure 2: Comparison of classical and quantum models on aviation datasets.

7 Conclusion and Future Enhancement

The proposed QISASI represents a unified framework that integrates the scalable AI, NLP, and $QSACF^2$ to deliver the advanced aviation safety intelligence and its predictive maintenance capabilities. The model leverages the fine tuned LLMs, including LLaMA-3 and Mistral, which are trained on the aviation specific communication and the telemetry data to deliver its precise, context aware analysis consistent with the global aerospace safety standards. At the core of the system lies in the $QSACF^2$ mechanism, which encodes the multimodal aviation data comprising the text, radar signals, telemetry, and ADS-B records into the entangled quantum states using the layered *ZZFeatureMaps*. This designs enables the efficient modeling of the complex feature interactions, facilitating its superior anomaly detection, risk forecasting, and maintenance prediction. Validation across the aerospace benchmark datasets confirms the QISASI's state of the art performance, and establishing it as a scalable, reliable, and the pioneering solution for the next generation safety critical aerospace systems.

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