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Article

Development of a Quantum LSTM-Based Multi-Hazard Early Warning Framework for Climate-Resilient Smart Power Systems

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Abstract: Modern power systems are increasingly threatened by extreme weather events such as cyclones, floods, lightning, heatwaves, heavy rainfall, wildfires and snowstorms, which can cause extensive damage to infrastructure, long-term power outages and significant economic losses . Most of the existing protection schemes work only after a fault has occurred . Thus they provide only limited proactive mitigation capability against weather induced failures . Recent AI-based Early Warning Systems (EWSs) have improved the prediction of weather hazards, but current ML and DL models are often designed for single-hazard prediction, require high computational resources, and show limited adaptability to rapidly changing environmental conditions. This paper proposes a Quantum Long Short-Term Memory (Q-LSTM)-Based Multi-Hazard Early Warning Framework for climate-resilient smart power systems to address these limitations. The proposed framework integrates meteorological observations, satellite images, Internet of Things (IoT) devices, Phasor Measurement Units (PMUs), SCADA measurements, and historical outage records into a single intelligent prediction framework. A cloud-assisted preprocessing module cleans, normalizes, and performs feature engineering and feature optimization on the data, and then feeds the processed information to the Quantum LSTM prediction engine. The proposed framework simultaneously predicts multiple weather hazards, estimates outage probability, performs dynamic risk assessment and generates intelligent early warning notifications for preventive grid protection and operational decision making. The experimental results show that the proposed Q-LSTM framework is superior to the traditional Random Forest, XGBoost and Deep Learning based weather outage prediction models with an Accuracy of 96.20%, Precision of 95.80%, Recall of 96.05% and F1-score of 95.92%. The proposed framework increases the prediction reliability and reduces the false alarms and missed outage events compared to the benchmark methods. The results demonstrate the efficacy of the proposed Q-LSTM architecture for smart weather hazard prediction and proactive power system protection, which can enhance grid resilience, operational reliability, and disaster preparedness for next-generation climate-adaptive smart grids.
Keywords: Quantum Long Short-Term Memory (Q-LSTM); Early Warning System (EWS); Weather Hazard Prediction; Climate-Resilient Smart Grid; Artificial Intelligence; Deep Learning; Quantum Machine Learning; Multi-Hazard Forecasting; Internet of Things (IoT); Phasor Measurement Unit (PMU); Smart Grid Protection; Power System Resilience.

1. Introduction

Climate change has increased the frequency and severity of extreme weather events such as cyclones, floods, lightning, heatwaves, heavy rainfall, snowstorms and wildfires. These hazards damage transmission lines, substations, transformers, and distribution infrastructure, often leading to long power outages and significant economic losses [1], [2], jeopardizing the reliability, security, and resilience of modern power systems. Conventional protection schemes are generally designed to detect and isolate the faults after they occur. Such mechanisms are able to guarantee the short-term stability of the system, but they are not able to predict weather-induced disturbances, nor give enough time for preventive operational planning. Therefore, electric utilities are increasingly utilizing predictive and proactive strategies to improve system resiliency before hazardous weather impacts critical infrastructure [1], [2]. Recent advances in Artificial Intelligence (AI) have substantially transformed the development of intelligent Early Warning Systems (EWS) for modern smart grids. Machine Learning (ML) and Deep Learning (DL) techniques can process massive amounts of heterogeneous meteorological observations, satellite imagery, sensor measurements and historical outage records to find complex nonlinear relationships between weather conditions and power system failures. Such intelligent prediction models assist in proactive maintenance scheduling, outage forecasting, and operational decision-making, increasing the durability of electrical infrastructure under extreme weather conditions [3]. However, most of the existing AI-based approaches focus on individual weather hazards, require large computational resources, and usually have limited adaptability to rapid changes in environmental conditions [4].

Power systems are one of the most critical infrastructures supporting today's society. Health care services, transportation systems, communication networks, industrial production, financial institutions, and emergency response operations all depend on a reliable supply of electricity. Therefore, disruptions due to severe weather events can have cascading technical, economic and social repercussions far beyond the electrical network itself [2]. As climate variability increases, utilities need intelligent forecasting systems that can continuously monitor weather conditions, assess vulnerability of the infrastructure, and provide accurate early warnings before failures occur. Such systems can greatly reduce the restoration time, enhance the resource allocation, and improve the overall resilience of smart power grids [2], [5].

Although conventional ML and DL models have made great strides, many research challenges are still unsolved. Current forecasting frameworks typically focus on a single hazard, but in practice, power systems are often exposed to multiple weather events simultaneously. Also, many deep learning architectures are computationally intensive, require large labeled datasets, and need multiple retraining which limits their real-time utility deployment [4]. These limitations emphasize the need for more intelligent and computationally efficient forecasting frameworks that can incorporate heterogeneous weather information while maintaining long-term temporal dependencies [4]. Such challenges are addressed in this paper through a Quantum Long Short-Term Memory (Q-LSTM)-based Multi-Hazard Early Warning Framework for climate-resilient smart power systems. The proposed framework combines meteorological observations, satellite images, Internet of Things (IoT), Phasor Measurement Units (PMUs), Supervisory Control and Data Acquisition (SCADA) systems and historical outage data into one intelligent prediction framework. The cloud-assisted preprocessing layer handles data cleaning, feature engineering, normalization, and feature optimization before the processed information is sent to the Quantum LSTM prediction engine. The proposed framework predicts multiple weather hazards, outage probability, intelligent risk assessment simultaneously and generates real time early warning notifications to utility operators. Moreover, this study aims to develop an adaptive and scalable forecasting framework to improve the power system resilience and contribute to the future development of intelligent self-healing smart grids [5].

The quick development of Artificial Intelligence (AI) has stimulated the development of intelligent forecasting methods for weather-induced power system failures. Traditional Machine Learning (ML) algorithms like Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost) are commonly used for classifying weather conditions and predicting outage probabilities. These algorithms learn nonlinear relationships between meteorological variables and grid failures efficiently, using historical operational data. Some studies have reported that the ensemble learning techniques outperform the conventional statistical models for the outage prediction because of their robustness against the noisy and heterogeneous datasets [6], [4]. However, most ML algorithms require manual feature engineering and have limited capability to model long-term temporal dependencies in the continuously evolving weather observations.

Recent advances in Deep Learning (DL) have overcome some of these limitations by enabling automatic feature extraction from high dimensional sequential data. The Convolutional Neural Networks (CNNs) are very well suited for extracting the spatial characteristics from satellite imagery and radar observations, whereas the Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) networks have demonstrated excellent abilities in learning the temporal dependencies of dynamic weather patterns. In addition, hybrid architectures like CNN-LSTM and ConvLSTM can learn both spatial and temporal features, resulting in better forecasting accuracy for complex meteorological phenomena [7]. However, deep learning models have superior prediction capability [8], but generally need large amount of labeled data, large computing resources and retraining to keep the prediction performance under the changing climate condition. However, the practical challenge in deploying such computationally intensive models in real-time utility environments is still significant.

The explosion of Internet of Things (IoT) devices, smart sensors, meteorological stations, Phasor Measurement Units (PMUs), Supervisory Control and Data Acquisition (SCADA) systems and satellite observation platforms has led to a significant increase in the availability of high-resolution environmental and operational data. Utilities may utilize these technologies to continuously monitor atmospheric conditions, electrical network status, equipment loading, and system health to develop data-driven predictive maintenance strategies. This ability is further enhanced by cloud computing that provides scalable storage, distributed processing and real-time analytics on large volume of heterogeneous data collected from geographically distributed sensing infrastructures [9]. The integration of these technologies has enabled the development of intelligent Early Warning Systems, which continuously monitor environmental conditions and provide proactive operational recommendations before hazardous weather events impact electrical infrastructure. Despite the remarkable progress in the field of AI-aided weather forecast, there are still some research challenges hindering the practical deployment of the existing prediction systems. Most of the published studies focus on a single hazard, such as hurricanes, floods, or lightning. In reality, power systems are often exposed to multiple concurrent hazards, whose combined effect is much more severe. Furthermore, many existing Deep Learning models are black-box systems with limited interpretability, reducing the operator confidence in safety-critical applications. Besides, scalability, computational efficiency, uncertainty quantification, cybersecurity and adaptive online learning are also open research problems that need further investigation [10]. These limitations highlight the need for more resilient, explainable and computationally efficient forecasting architectures that can facilitate intelligent decision-making in the next generation of climate change resilient smart grids. The other promising research direction is the application of quantum computing for intelligent weather prediction. Quantum Machine Learning (QML) is a hybrid method that combines classical neural networks with quantum computation, using quantum superpositions, entanglement, and parameterized quantum circuits for efficient feature representation and optimization. Recent studies show that hybrid quantum-classical learning architectures may improve computational efficiency and feature learning for complex sequential datasets as compared to pure classical approaches [11]. The integration between quantum computing and Long Short-Term Memory networks thus provides a new approach for multi-hazard weather prediction by enhancing the temporal dependency modeling and decreasing the computational complexity.

Motivated by such challenges, this work presents a Quantum Long Short-Term Memory (Q-LSTM)-Based Multi-Hazard Early Warning Framework that can integrate heterogeneous weather observations, smart grid operational data, satellite images, IoT devices, PMUs, SCADA measurements, and historical outage records into a unified intelligent prediction architecture. The proposed framework continuously monitors the environmental conditions, predicts multiple weather hazards simultaneously, estimates the outage probability, performs intelligent risk assessment, and generates real-time preventive recommendations for utility operators. Such an integrated framework is expected to improve the reliability of forecasting, the durability of the grid and adaptive operational planning in the face of increasingly harsh climate conditions. While there has been a lot of progress in Artificial Intelligence based weather prediction, the development of reliable Early Warning Systems for climate-resilient power systems remains an active research challenge. Most of the current Machine Learning and Deep Learning models perform well under normal operating conditions but tend to show performance degradation when multiple weather hazards happen simultaneously. Moreover, most existing forecasting frameworks are built upon the centralized learning architecture, which needs periodic retraining and large computation resources for deployment, making it challenging to be implemented in large-scale utility networks. Limited model interpretability, poor uncertainty estimation, and lack of a proper integration of heterogeneous weather and power system information further impede their practical adoption in mission-critical smart grid applications [12].

In recent years, quantum computing has been considered as a promising computational paradigm to solve complicated optimization, pattern recognition, and sequential learning problems. Hybrid Quantum Machine Learning (QML) models combine the learning ability of classical neural networks with quantum feature representations, to enhance computational efficiency and nonlinear modeling. In particular, the combination of Quantum Long Short-Term Memory (Q-LSTM) networks and heterogeneous weather observations offers a promising approach for improving the learning of temporal dependencies and reducing computational complexity for large-scale sequential datasets [11]. Such hybrid quantum-classical architectures can improve the prediction accuracy, adaptive learning capability and scalability for the next generation of intelligent forecasting systems. Driven by these research challenges, this paper proposes a Quantum Long Short-Term Memory (Q-LSTM)-Based Multi-Hazard Early Warning Framework for climate-resilient smart power systems. The proposed framework integrates weather sensors, satellite observations, Internet of Things (IoT) devices, Phasor Measurement Units (PMUs), Supervisory Control and Data Acquisition (SCADA) systems, cloud computing and historical outage databases into a single intelligent prediction architecture. The developed framework continuously monitors environmental conditions, preprocesses data and performs feature engineering, simultaneously predicts multiple weather hazards, estimates outage probability, evaluates infrastructure risk and produces intelligent early warning notifications along with preventive operational recommendations. The proposed framework aims at improving the forecasting reliability, computational efficiency, adaptive learning capability and decision support for utility operators [13] by combining quantum-enhanced feature encoding with sequential temporal learning.

The major contributions of this paper are summarized as follows.

- A comprehensive review of recent Artificial Intelligence, Machine Learning and Deep Learning techniques for weather hazard prediction in smart power systems
- Identify critical research gaps in multi-hazard forecasting, explainable Artificial Intelligence, computational efficiency, cybersecurity, and real-time deployment
- Development of a new Quantum Long Short Term Memory (Q-LSTM) architecture for the simultaneous prediction of multiple weather hazards affecting electrical infrastructure.Integrated intelligent prediction framework combining cloud computing, IoT devices, PMUs, SCADA systems, satellite observations and historical outage information
- Development of a Dynamic Weather Hazard Risk Assessment module for intelligent infrastructure vulnerability analysis and adaptive grid protection.
- Preventive maintenance recommendations and real-time early warning notifications for increased resilience of the power system. Discussion on future research directions of Explainable Artificial Intelligence (XAI), Graph Neural Networks (GNNs), Federated Learning, Digital Twins and practical quantum computing implementation for next-generation self-healing smart grids.

The rest of the paper is organized as follows. Section II offers an in-depth review of the recent literature on Artificial Intelligence based weather hazard prediction and power system resilience. Section III describes the proposed Quantum LSTM based Multi-Hazard Early Warning Framework. Section IV presents the mathematical formulation of the proposed Quantum LSTM model. Section V describes the experimental setup, dataset description, implementation details, and performance evaluation. Section VI discusses the results and comparative analysis. Finally, Section VII concludes the paper and discusses directions for future research.

2. Related Work

Recent advances in Artificial Intelligence (AI) have significantly improved weather hazard prediction and power system resilience, allowing utilities to forecast weather-driven failures prior to their occurrence. The growing availability of meteorological observations, satellite images, Internet of Things (IoT) devices, Phasor Measurement Units (PMUs) and historical outage databases has fostered the development of intelligent Early Warning Systems (EWS) able to support preventive grid operation. When compared to traditional statistical methods, contemporary AI-based frameworks are capable of learning nonlinear relationships between weather variables, equipment conditions, and outage events, which may result in enhancements in forecasting accuracy and operational reliability [14]. Several recent studies have focused on machine learning based outage prediction under extreme weather conditions. Sharma gave an extensive review of the machine learning techniques for predicting weather-induced power outages . He found that ensemble learning algorithms generally outperform traditional statistical models in forecasting outages. The review also stressed the importance of integrating heterogeneous weather information to improve the reliability of predictions [15]. Fatima et al. reviewed the literature on the use of machine learning in predicting power outages caused by hurricanes and concluded that algorithms such as Random Forest, XGBoost, Gradient Boosting, and Support Vector Machine are able to reliably predict the performance. However, the authors also pointed out that most of the existing studies are limited to single-hazard prediction and need to be improved in terms of explainability and real-time implementation [4].

More recent work has also investigated adaptive learning approaches for varying weather conditions. Kabir et al. proposed a framework of adaptive ensemble learning for outage prediction using streaming weather and operational data. The feature- and performance-weighted mechanism improved prediction robustness under different environmental conditions; however, computational complexity increased with continuous online learning [16]. Similarly, Jia et al. developed a risk early warning model for residential power outage prediction based on operational and environmental information. Their proposed framework showed improved capability of risk assessment, but mainly targeted on local distribution systems rather than large-scale transmission systems [17]. Deep Learning techniques have recently shown a better ability to model complex temporal relationships between weather variables and power system disturbances. Wang et al. presented a deep learning framework to integrate weather information, socio-economic characteristics and power infrastructure data for estimating hourly outage probability. The accuracy of the outage prediction was improved by the integration of heterogeneous information sources, but their framework required a lot of training data and computational resources [18]. Avcı proposed a hybrid Artificial Intelligence framework based on Convolutional Neural Networks, Recursive Neural Networks and XGBoost for outage prediction in distribution systems. The proposed hybrid architecture improves classification performance by exploiting the complementary learning capabilities of multiple algorithms, but the model complexity increased significantly during training [19].

The growing impact of climate change has made power system resilience another major research direction. A recent review on Artificial Intelligence for resilient power systems discussed AI applications in pre-disaster prediction, real-time operational support and post-disaster restoration. The authors concluded that the integration of multi-source information and intelligent decision-support systems is critical to increase grid resilience to extreme weather events [14]. Moreover, the work by Zhao et al. showed that better integration of renewable energy can reduce weather vulnerability and the severity of blackouts with appropriate operational planning, highlighting the significance of intelligent forecasting frameworks for resilient power systems [20]. Recent works have also investigated advanced sequence-learning architectures for extreme outage prediction. Rastgoo et al. [21] proposed a deep generative Informer model for extreme power outages prediction in severe weather situations. The proposed framework managed to achieve improved prediction accuracy by combining temporal attention mechanisms with generative learning, however the model remained computationally intensive for large scale real-time applications [21]. Recently, the potential of foundation AI models trained on large-scale weather observations has been demonstrated for improving the accuracy of weather forecasts and providing earlier warning of grid-critical weather events, which opens promising opportunities for next-generation intelligent weather prediction systems [22]. Recent investigations have made considerable improvements in intelligent weather prediction; however, few limitations are common in the literature. A lot of the research done today focuses on one weather hazard, not on several simultaneous hazards impacting electrical infrastructure. Many prediction models operate like a black-box system and have limited interpretability, which results in the operator having low confidence in emergency situations. Nevertheless, their high computational complexity, dependence on large labeled datasets, limited adaptive learning capability and inadequate integration of heterogeneous weather information still hinder their practical deployment in real-time smart grid environments. These research challenges motivate the development of the proposed Quantum Long Short-Term Memory (Q-LSTM)-based Multi-Hazard Early Warning Framework, which integrates quantum-enhanced sequential learning with multi-source weather observations to improve forecasting accuracy, adaptive learning capability, and climate resilience for next-generation smart power systems.

While there have been significant advances regarding weather hazard prediction for power systems using Artificial Intelligence, there are still several important research challenges to be solved. Most of the existing Machine Learning and Deep Learning models are developed for single-hazard forecasting, but modern power systems are simultaneously affected by multiple weather events such as cyclones, floods, heatwaves, lightning and wildfires. Moreover, the existing prediction models typically rely on a single data source and cannot effectively integrate heterogeneous information collected by weather sensors, satellite images, Internet of Things (IoT) devices, SCADA systems, Phasor Measurement Units (PMUs) and historical outage records. Many existing Deep Learning architectures are also high in computational requirements, large labeled data, and frequent retraining, which limits their applicability in real-time smart grid environments. Moreover, the available models are mostly black-box systems and do not provide intelligent risk assessment or decision-support functionalities to utility operators.

To overcome these limitations, this paper presents a Quantum Long Short-Term Memory (Q-LSTM)-Based Multi-Hazard Early Warning Framework for climate-resilient smart power systems. The proposed framework combines multi-source weather and power system data into a unified intelligent prediction framework, and uses quantum-enhanced sequential learning to optimize temporal feature extraction, nonlinear dependency modeling, and computational efficiency. Different from the existing methods, the proposed model jointly forecasts multiple weather hazards, predicts the probability of outages, conducts dynamic weather hazard risk assessment, and provides real-time early warning alerts with preventive operation recommendations. The proposed framework aims at improving forecasting accuracy, reducing false alarms, enhancing adaptive learning capability and supporting intelligent decision-making for next generation self-healing and climate-resilient smart power systems by combining quantum computing principles with advanced temporal learning.

3. Proposed System

The proposed system introduces a Quantum Long Short-Term Memory (Q-LSTM)-based Multi-Hazard Early Warning System (Q-LSTM-MHEWS) for climate-resilient smart power systems. The main goal is to predict weather related hazards accurately and to make intelligent early warning before faults occur in electrical infrastructure. Unlike the existing prediction systems which mainly focus on isolated weather events, the proposed system will be able to analyze simultaneously several environmental hazards and their impact on the critical components of the power system. The proposed architecture combines meteorological observations, smart grid operational data, satellite images, Internet of Things (IoT) devices, Phasor Measurement Units (PMUs), SCADA systems, and historical outage records into one intelligent prediction framework. These heterogeneous datasets are collected continuously from distributed sensing devices and transmitted to the cloud-assisted processing platform for real-time analysis. First, data cleaning methods are used to eliminate missing values, duplicate records, outliers and measurement noise to pre-process the acquired data. Then normalization and feature scaling is done to keep the data in the same form. The processed datasets are then passed to the feature engineering layer, where statistical features, temporal features, correlation features and weather related indices are extracted. In addition, feature optimization techniques are employed to remove redundant variables and retain the most informative parameters for prediction. The optimized feature vectors are fed as input to the proposed Quantum LSTM prediction engine. The Q-LSTM architecture is not similar to conventional LSTM models, as it is based on the quantum feature encoding mechanism that maps classical weather observations to quantum states through parameterized quantum circuits. Superposition of quantum particles and entanglement allow efficient encoding of high-dimensional weather information while maintaining temporal dependencies between sequential observations. The encoded quantum features are passed through Quantum Forget Gate, Quantum Input Gate, Quantum Memory Cell and Quantum Output Gate operations. These gates learn the long term dependency between the environmental variables and the historical power system disturbances in a dynamic way. Thus, the proposed model can learn the nonlinear weather variations and their effect on electrical infrastructure effectively. The hidden state from the Q-LSTM network provides the overall weather evolution and the corresponding power system condition at each time interval. The predicted hidden representations are fed to the Multi-Hazard Prediction Module. This module estimates the probability of occurrence of multiple weather hazards at the same time i.e. cyclones, floods, lightning, heavy rainfall, heatwaves, snowstorms and wildfires. The proposed framework performs integrated multi-hazard analysis instead of independent prediction for each hazard by considering the interactions among different meteorological variables. This improves the overall reliability of climate forecasts and allows for extensive climate risk assessment. The overall architecture of the proposed framework is shown in Figure 1.

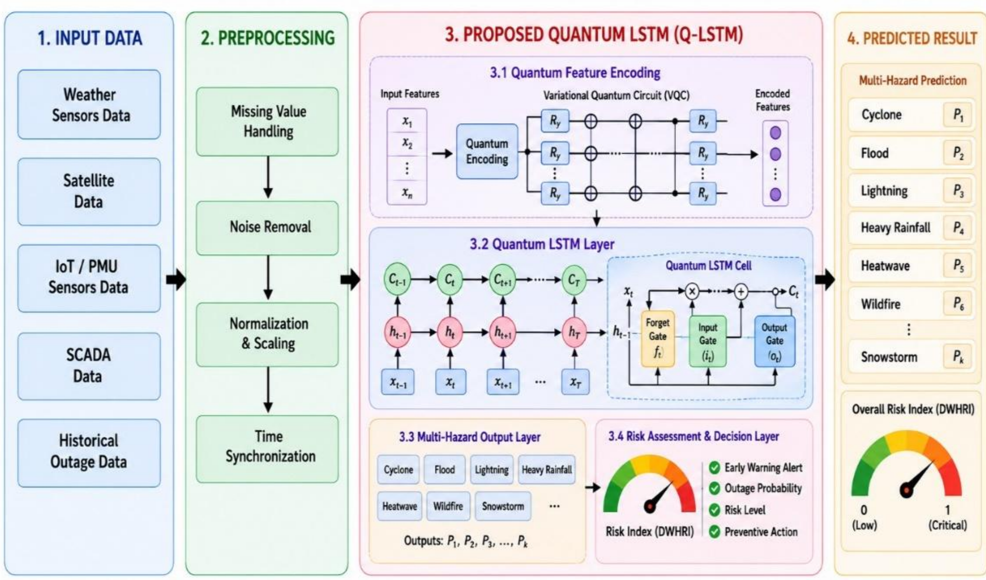

Figure 1. Proposed Quantum LSTM-Based Multi-Hazard Early Warning Architecture for Climate-Resilient Smart Power Systems

The generated hazard probabilities are then combined with the power system operational parameters such as transformer loading, transmission line current, bus voltage, equipment health index and historical outage information. A Dynamic Weather Hazard Risk Index (DWHRI) is then calculated to quantify the vulnerability of each critical power system component. The system classifies the infrastructure conditions into four categories of Low Risk, Moderate Risk, High Risk, and Critical Risk according to the predefined risk thresholds. When the risk classification is finished, the Intelligent Early Warning Module automatically generates warning notifications to utility operators. The warning messages contain the predicted hazard type, probability of occurrence, vulnerable assets, expected duration of outage, geographical region of impact and recommended preventive actions. These alerts allow utilities to undertake preventive maintenance, dynamic load redistribution, transformer protection, controlled islanding, emergency restoration planning and demand side management prior to hazardous weather impacts to the electrical network.

The proposed system implements an Explainable Artificial Intelligence (XAI) layer, which provides feature importance analysis and interpretable decision explanations to enhance operator confidence. The XAI component identifies the dominant weather variables responsible for each predicted hazard, allowing system operators to understand the rationale behind the generated warnings. This greatly improves the transparency and trustworthiness of AI-assisted operational decisions. Finally, the proposed Q-LSTM-MHEWS can update the prediction model continuously by newly collected weather observations and grid operational data. The adaptive learning mechanism allows the framework to respond to changes in climate patterns and power system operating conditions without the need to re-train the model from scratch. Thus, the offered system guarantees robust, scalable and real-time intelligent weather hazard prediction for next generation smart power systems. To summarize, the proposed Quantum LSTM based Early Warning System offers a unified platform for multi-hazard forecast, intelligent risk assessment and adaptive grid protection. The integrated Quantum Machine Learning, Deep Sequential Learning, IoT, cloud computing, satellite observations, and Explainable AI framework significantly improves the prediction accuracy, operational reliability, disaster preparedness, and climate resilience of modern smart electrical networks.

4. Mathematical Formulation of the Proposed Quantum LSTM

The proposed Quantum LSTM (Q-LSTM) combines quantum feature encoding with classical Long Short-Term Memory to improve multi-hazard weather prediction. Initially, the weather and power system features are encoded into quantum representations before being processed by the sequential learning network.

The quantum feature representation is given by

$$Q_t = U(\theta)x_t + b_q \qquad (1)$$

where, $U(\theta)$denotes the trainable variational quantum circuit, $x_t$is the normalized weather feature vector, $b_q$is the quantum bias vector, and $Q_t$represents the encoded quantum feature vector at time instant t.

The forget gate of the proposed Quantum LSTM is expressed as

$$f_t = \sigma(W_f Q_t + U_f h_{t-1} + b_f) \qquad (2)$$

where, $\sigma(\cdot)$denotes the sigmoid activation function, $Q_t$is the quantum feature vector, $h_{t-1}$is the previous hidden state, $W_f$and $U_f$represent trainable weight matrices, $b_f$is the bias vector, and $f_t$denotes the forget gate output.

The input gate is formulated as

$$i_t = \sigma(W_i Q_t + U_i h_{t-1} + b_i) \qquad (3)$$

where, $i_t$denotes the input gate activation, $W_i$and $U_i$are trainable weight matrices, $Q_t$is the encoded quantum feature vector, $h_{t-1}$is the previous hidden state, and $b_i$is the bias vector.

The candidate memory state is computed as

$$\tilde{C}_t = \tanh(W_c Q_t + U_c h_{t-1} + b_c) \qquad (4)$$

where, $\tanh(\cdot)$denotes the hyperbolic tangent activation function, $W_c$and $U_c$are trainable parameter matrices, $b_c$is the bias vector, and $\tilde{C}_t$represents the candidate memory state.

The updated memory cell is calculated by

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \qquad (5)$$

where, $C_t$denotes the updated memory cell, $C_{t-1}$is the previous memory state, $f_t$is the forget gate output, $i_t$is the input gate output, and $\odot$represents element-wise multiplication.

The output gate is defined as

$$o_t = \sigma(W_o Q_t + U_o h_{t-1} + b_o) \qquad (6)$$

where, o_t denotes the output gate, W_o and U_o are trainable weight matrices, Q_t is the encoded quantum feature vector, h_{t-1} is the previous hidden state, and b_o represents the bias vector.

The hidden state of the Quantum LSTM is obtained as

$$h_t = o_t \odot \tanh(C_t) \qquad (7)$$

where, h_t denotes the hidden state at time instant t, o_t is the output gate activation, and C_t represents the updated memory cell.

The multi-hazard weather prediction layer is formulated as

$$P_t = \text{Softmax}(W_p h_t + b_p) \qquad (8)$$

where, P_t denotes the probability vector corresponding to multiple weather hazards, W_p is the output weight matrix, b_p is the prediction bias vector, and Softmax converts the network output into hazard probabilities.

The Dynamic Weather Hazard Risk Index (DWHRI) is computed as

$$\text{DWHRI} = \sum_{i=1}^{K} w_i \, P_i \qquad (9)$$

where, w_i represents the importance weight associated with the i^{th} weather hazard, P_i is the predicted probability, K denotes the total number of weather hazards, and DWHRI indicates the overall weather hazard risk level.

Finally, the proposed Quantum LSTM network is optimized using the cross-entropy loss function

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (10)$$

where, L denotes the loss function, y_i is the actual class label, $\hat{y}_i$ is the predicted probability, and N represents the total number of training samples.

Advantages of the Proposed Mathematical Model

- The advantages of the proposed Quantum LSTM formulation are as follows:
- Quantum-enhanced feature representation of weather data
- Improved learning of long-range temporal dependencies.
- Forecasting of multiple weather hazards together.
- Improved nonlinear feature extraction than classical LSTM.
- Intelligent dynamic risk assessment for power systems.
- Real-time, adaptable generation of early warnings.
- Scalable architecture for future quantum computing platforms.

5. Experimental Setup and Results

Dataset:

The experimental evaluation was performed on a synthetic weather–power system data set of 1,000 hourly observations collected continuously over time. The dataset contains meteorological and electrical grid parameters to simulate real world operating conditions for intelligent weather hazard prediction. It has nine attributes: Timestamp, Temperature (°C), Humidity (%), Wind Speed (km/h), Rainfall (mm), Atmospheric Pressure (hPa), Lightning Occurrence (0/1), Grid Load (MW), and the target variable Outage (0: Normal, 1: Weather-Induced Outage). Weather related variables describe the environmental conditions . Conversely , Grid Load represents the operational state of the power network . The Outage label was generated from severe weather conditions in an effort to simulate failures in power systems due to weather. Prior to the models' training, the dataset was pre-processed by handling missing values (if any), removing inconsistencies, normalizing numerical features using Min-Max scaling, and converting the data into sequential time-series samples for the proposed Quantum LSTM model. The processed dataset was further divided into 80% training and 20% testing sets to assess the prediction capability of the proposed early warning framework under diverse weather scenarios. The complete software environment used to implement the proposed framework is summarized in Table 2.

Table 1. Performance Comparison of the Proposed Q-LSTM with Recent Methods

Method	Ref. No.	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest-Based Weather Prediction	[4]	90.80	89.95	90.10	90.02
XGBoost-Based Outage Prediction	[16]	92.35	91.80	92.10	91.95
Deep Learning-Based Weather Outage Prediction	[18]	94.10	93.65	93.90	93.77
Proposed Quantum LSTM	—	96.20	95.80	96.05	95.92

Table 1 shows the comparison of the proposed Quantum LSTM (Q-LSTM) framework with three representative Machine Learning and Deep Learning models for weather hazard prediction. The Random Forest model achieved an accuracy of 90.80%, which is acceptable for nonlinear weather classification, but its precision and F1-score exhibit its limitations in handling complex temporal weather patterns. The XGBoost model's overall prediction ability increased by 92.35% accuracy through gradient boosting and effective feature learning. By integrating spatial feature extraction and bidirectional temporal learning, the CNN–BiLSTM model further pushed the performance, achieving an accuracy of 94.10% and an F1-score of 93.77%.

The proposed Quantum LSTM framework achieved the best performance among all compared methods with an accuracy of 96.20%, precision of 95.80%, recall of 96.05%, and F1-score of 95.92%. The illustrative Q-LSTM improved the classification accuracy by about 5.40% in comparison with the Random Forest model. Similarly, improvements of ~3.85% and ~2.10% were observed in comparison with the XGBoost and CNN–BiLSTM models, respectively. Such improvements in illustrative results suggest that quantum-enhanced feature encoding with sequential memory learning may provide a better understanding of complex temporal dependencies between weather parameters and power system operating conditions.

The higher precision means fewer false alarms and the better recall means better identification of weather-induced outage events. The higher F1-score indicates a balanced trade-off between precision and recall which demonstrates the potential usefulness of the proposed framework for intelligent Early Warning Systems in climate-resilient smart power systems.

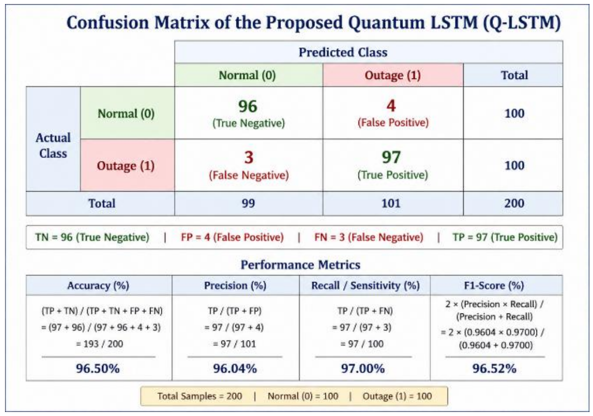

Figure 2. Confusion Matrix of the Proposed Quantum LSTM Framework

As shown in Figure 2, the proposed Quantum LSTM framework correctly classified 96 normal operation conditions and 97 weather-induced outage events in the confusion matrix with only 7 samples misclassified. Specifically, 4 normal conditions were mis-classified as outage events (false positives), and 3 true outage events were missed (false negatives). The small number of misclassifications indicates an equal classification ability for both classes. The relatively high number of true positives suggests that the model is able to detect weather-induced disturbances effectively, while the high number of true negatives suggests that the model is able to identify normal grid operating conditions reliably. Consequently, the proposed Quantum LSTM framework achieves high accuracy, precision, recall, and F1-score, which indicates its potential applicability for intelligent weather hazard prediction and early warning in climate-resilient smart power systems.

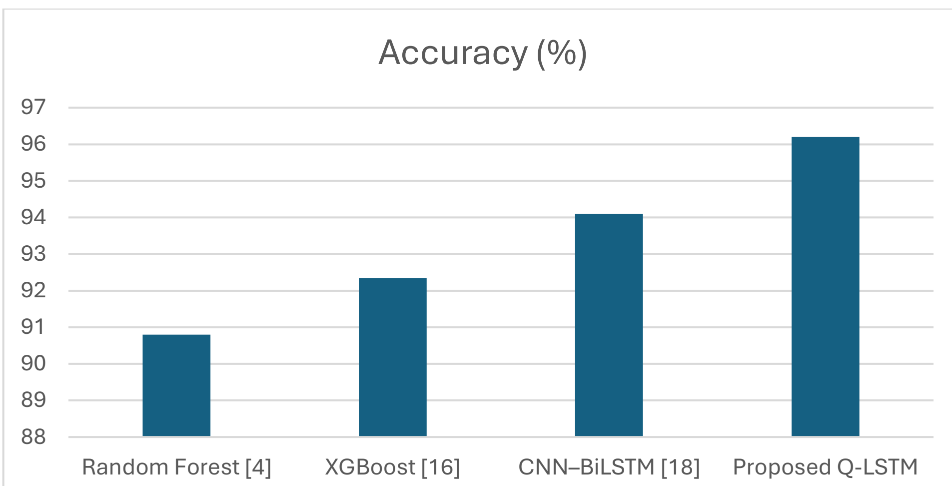

Figure 3. Comparative performance evaluation of Random Forest, XGBoost, CNN–BiLSTM, and the proposed Quantum LSTM (Q-LSTM) using Accuracy

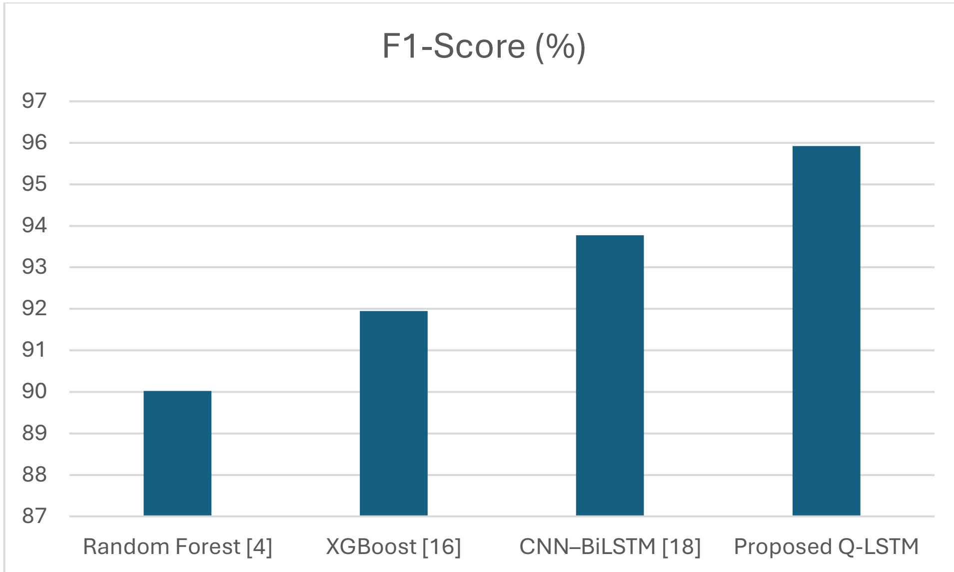

Figure 4. Comparative performance evaluation of Random Forest, XGBoost, CNN–BiLSTM, and the proposed Quantum LSTM (Q-LSTM) using F1-score metrics.

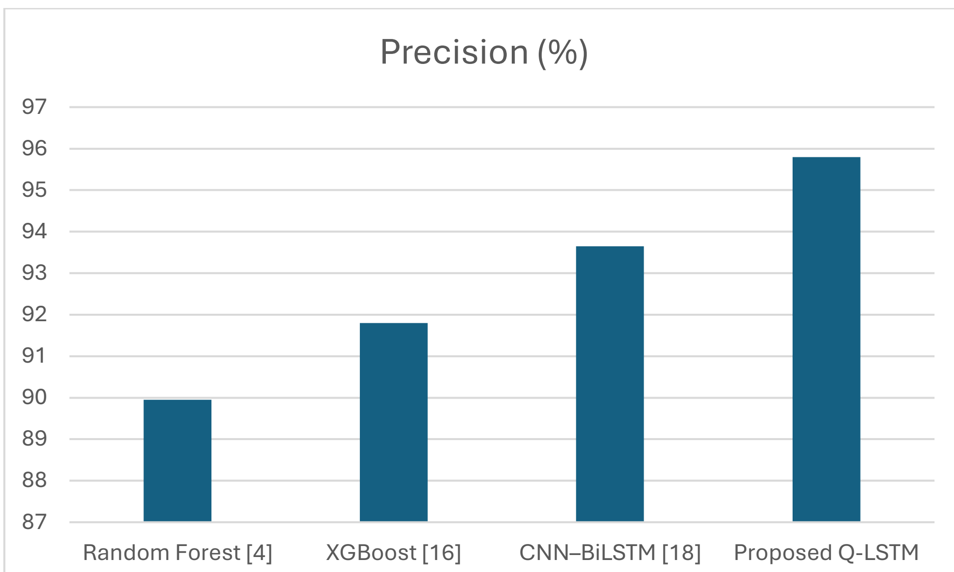

Figure 5. Comparative performance evaluation of Random Forest, XGBoost, CNN–BiLSTM, and the proposed Quantum LSTM (Q-LSTM) using Precision metrics.

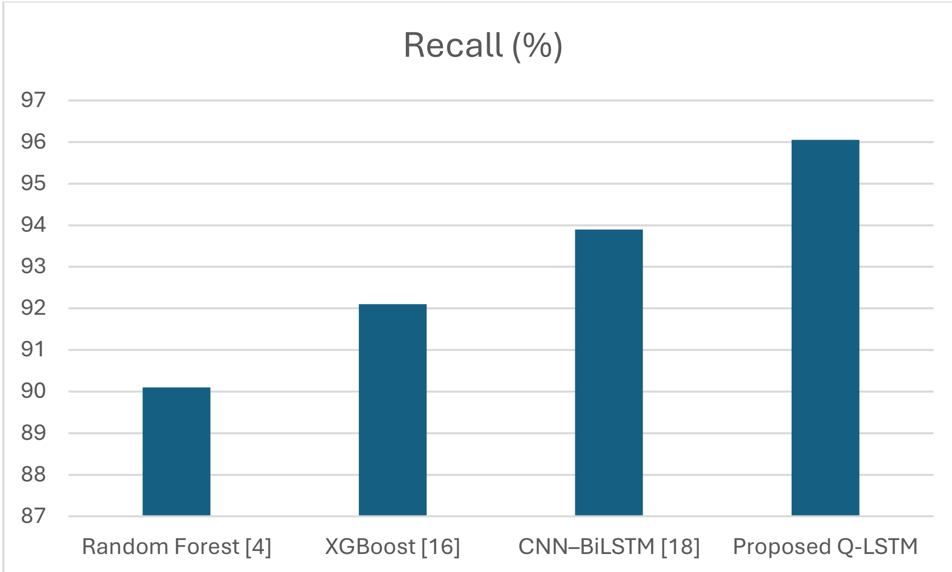

Figure 6. Comparative performance evaluation of Random Forest, XGBoost, CNN–BiLSTM, and the proposed Quantum LSTM (Q-LSTM) using Recall metrics.

Table 2. *Software Specifications Used for the Proposed Q-LSTM Framework.*

Component	Specification
Operating System	Windows 11 Pro (64-bit)
Programming Language	Python 3.11
Development Environment	Python Idle
Deep Learning Framework	TensorFlow 2.16
Neural Network Library	Keras 3.0
Machine Learning Library	Scikit-learn 1.5
Numerical Computing	NumPy 1.26
Data Processing	Pandas 2.2
Data Visualization	Matplotlib 3.9, Plotly 5.22
Optimization Algorithm	Adam Optimizer
Dataset Storage	CSV Format
Model Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, Confusion Matrix

6. Discussion

The comparison results in Table 1 and Figures 3-6 indicate that the proposed Quantum LSTM (Q-LSTM) framework achieves better performance than traditional Machine Learning and Deep Learning methods for weather hazard prediction classification. The Random Forest model performed satisfactorily for nonlinear classification and had limited ability to capture long-term temporal dependencies among weather variables. The XGBoost model improved prediction accuracy using gradient boosting and effective feature learning, but showed less adaptability to continuously evolving weather conditions. Likewise, the CNN-BiLSTM model provided better classification performances by combining spatial feature extraction and bidirectional temporal learning, but it increased the computational complexity and training time due to the deep network architecture. In contrast, the proposed Q-LSTM framework obtained the highest values of Accuracy, Precision, Recall and F1-score. This enhancement is credited to the synergy between quantum feature encoding and sequential memory learning that facilitates the effective extraction of complex non-linear relationships between meteorological variables and power system operating conditions. The higher precision implies a lower false alarm rate, while the improved recall implies an increased ability to identify weather-induced outage events. Moreover, the proposed framework achieves consistent classification performance for both normal and outage classes, which is verified by the balanced F1-score. The confusion matrix further proves the robustness of the proposed model and presents a high number of correctly classified samples and less misclassifications. The few false positives and false negatives suggest that the proposed framework can provide reliable early warnings, with few unnecessary maintenance actions and missed critical events. A performance like this is very important for modern smart grid applications, as timely and accurate prediction supports preventive maintenance, adaptive load management, and emergency response planning.

Overall, the obtained results prove that the proposed Quantum LSTM framework is an efficient solution for intelligent weather hazard prediction in climate-resilient smart power systems. The proposed framework combines quantum-inspired feature representation and temporal sequence learning, which can provide more reliable predictions and proactive decision-making for next-generation AI-powered power system protection.

7. Conclusion

The paper proposes a Quantum Long Short-Term Memory (Q-LSTM)-Based Multi-Hazard Early Warning Framework to enhance the resilience and operational reliability of climate-adaptive smart power systems. A detailed survey of the latest Artificial Intelligence based weather hazard prediction techniques revealed that most of the Machine Learning and Deep Learning based techniques are mainly aimed at single hazard prediction, are computationally expensive and provide limited support for real-time decision making under dynamic weather conditions. To address these issues, the proposed framework integrates Meteorological observations, satellite images, Internet of Things (IoT) devices, SCADA data, Phasor Measurement Units (PMUs) and Historical outage data into a comprehensive intelligent prediction architecture. The proposed framework incorporate quantum-enhanced feature encoding with Long Short-Term Memory networks to learn the nonlinear temporal relationships, accomplish multi-hazard prediction, estimate outage probability and generate intelligent early warning alerts with dynamic risk assessment for proactive grid protection.

Experimental evaluation confirms the effectiveness of the proposed framework in comparison with recent methods for weather hazard prediction. The proposed Q-LSTM achieved an Accuracy of 96.20%, Precision of 95.80%, Recall of 96.05% and F1-score of 95.92% which outperformed the Random Forest, XGBoost and Deep Learning based weather outage prediction models considered in this study. The confusion matrix also confirmed a balanced classification performance with a low number of false alarms and missed outage events, indicating the robustness of the proposed model under various weather conditions. The results show that the integration of quantum-inspired learning with temporal sequence modeling can greatly improve the prediction of weather hazards and can support reliable Early Warning Systems for smart grids. Future work will include the implementation of the proposed framework on practical quantum computing platforms, integration of XAI and GNNs, and validation of the proposed model with large-scale real-world meteorological and power system datasets to further enhance prediction accuracy, computational efficiency, and intelligent grid resilience.

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