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ORIGINAL RESEARCH

Enhanced power system fault detection using quantum-AI and herd immunity quantum-AI fault detection with herd immunity optimisation in power systems

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Abstract

Quantum computing and deep learning have recently gained popularity across various industries, promising revolutionary advancements. The authors introduce QC-PCSANN-CHIO-FD, a novel approach that enhances fault detection in electrical power systems by combining quantum computing, deep learning, and optimisation algorithms. The network, based on a Pyramidal Convolution Shuffle Attention Neural Network (PCSANN) optimised with the Coronavirus Herd Immunity Optimiser, shows promising results. Initially, historical datasets are used for fault detection. Preprocessing, which includes handling missing data and outliers using Adaptive Variational Bayesian Filtering is followed by Dual-Domain Feature Extraction to extract grayscale statistical features. These features are processed by PCSANN to detect faults. The Coronavirus Herd Immunity Optimisation Algorithm is proposed to optimise PCSANN for precise fault detection. Performance of the proposed QC-PCSANN-CHIO-FD approach attains 24.11%, 28.56% and 22.73% high specificity, 21.89%, 23.04% and 9.51% lower computation Time, 25.289%, 15.35% and 19.91% higher ROC and 8.65%, 13.8%, and 7.15% higher Accuracy compared with existing methods, such as combining deep learning based on quantum computing for electrical power system malfunction diagnosis (QC-ANN-FD), electrical power system fault diagnostics using hybrid quantum-classical deep learning (QC-CRBM-FD), applications of machine learning to the identification of power system faults: Recent developments and future directions (QC-RF-FD).

KEYWORDS
quantum computing, quantum computing techniques

1 | INTRODUCTION

An important component of electrical power systems is fault analysis and diagnosis, which is crucial in managing serious failures brought on by the cascade effects of defects. Critical issues such as blackouts and unwelcome voltage and current fluctuations can be prevented by implementing prompt preventative measures, which needs for quick and precise fault identification techniques. This requirement drives the growth of novel error identification and analysis techniques that identify and locate potential irregularities in electrical power systems to prevent performance deprivation [1]. For the purpose of diagnosing power system faults, a number of expert systems, such as rule-based techniques, have previously been presented [2]. Due to their incapacity to learn from mistakes and their difficulties consistently obtaining knowledge from experts, these approaches do have some limits. Process history-based defect diagnosis approaches do not require a description of the underlying processes when creating a mapping from inputs to appropriate outputs. When diagnosing power system faults, these pattern recognition techniques are credited with increased effectiveness and robustness to modelling flaws [3]. Quantum computing (QC) is ushering in new emerging computational technology and has the ability to affect issues on global scale. QC is subject to employ quantum mechanics theories to resolve complicated issues in variety of areas, including computer optimisation, machine learning. QC has received considerable attention from the scientific community in recent years [4]. Therefore, a viable approach for defect analysis and diagnosis involves utilising complementary characteristics of quantum and classical computers to create hybrid pattern recognition techniques and get over constraints. However, it has the major problems associated to the following factors difficult to understand, complex operations, time consuming, and error results. Subsequently, in this work QC-PCSANN-CHIO-FD is incorporated for getting better results in fault detection [5]. These motivate us to carry out this research work.

The major contributions of this research work are summarised below:

- In this research, QC-PCSANN-CHIO-FD is proposed.
- Develop an Adaptive variational Bayesian filtering based preprocessing method for handling missing data, outliers, and errors in the dataset.
- Propose a new variant of Coronavirus Herd Immunity Optimisation algorithm (CHIO) to optimise the pyramidal convolution shuffle attention neural network (PCSANN).
- QC-PCSANN-CHIO-FD model is implemented at MATLAB and effectiveness examined with several performance metrics.
- The proposed QC-PCSANN-CHIO-FD is implemented using MATLAB. To detect electrical power system fault, performance metrics like precision, accuracy, F1-score, Recall (Sensitivity), Specificity, Error rate, Computation time and RoC are considered.
- The efficiency of the proposed model is analysed with the existing methods, such as QC-ANN-FD, QC-CRBM-FD, QC-RF-FD respectively.

Rest of these manuscripts is organised as follows: Section 2 reviews the literature survey, Section 3 is research gap analysis, Section 4 describes the proposed methodology, Section 5 proves the results, and Section 6 concludes the manuscript.

2 | LITERATURE SURVEY

Several works were suggested in the literature related to deep learning and quantum computing-based fault identification, few recent works are divulged here. In 2021, Ajagekar and You [6] have presented combining deep learning based on quantum computing for electrical power system malfunction diagnosis. The research presents a hybrid conditional restricted Boltzmann machine-based deep learning structure for fault identification of electrical power systems that combines feature extraction capabilities of that machine with an effective deep network categorisation. Quantum Computation (QC)-based training approaches harness the complementary strengths of quantum assisted learning and conventional training methods to solve computational hurdles resulting from complexity of deep learning techniques. It provides high accuracy and has higher error rate.

In 2021, Ajagekar et al. [7] have presented electrical power system fault diagnostics using hybrid quantum-classical deep learning. Here, we develop a hybrid conditional restricted Boltzmann machine (CRBM)-based deep learning methods for fault identification of electrical power systems that extract the right features from time-series data. Using traditional learning techniques, the CRBM network training was computationally demanding. As a result, we use learning technique that was supported by quantum computer to train CRBM network, which results in better-quality ideal model parameters. It provides high precision and has high computation time.

In 2021, Vaish et al. [8] have presented applications of machine learning to the identification of power system faults: Recent developments and future directions. Here, the beginning, attempts were made to enumerate the problems with traditional fault detection, which made ML approaches popular. Also, given is a basic architecture and procedure for ML-based problem diagnostics. The several unsupervised and supervised learning strategies that have been applied by numerous researchers for defect diagnosis have then been examined individually. The presentation is reinforced throughout with tabulated information for how fault localisation, classification, and approaches function with various simulation tools and application systems. It provides high recall and has low accuracy.

In 2022, Ullah et al. [9] have presented applications for quantum computing in smart grid. This report describes the current research being done on smart grids already employed QC methodologies, as well as providing recommendations for employing QC in power and energy system applications in the future. The presented method covers the theoretical underpinnings of quantum computation, comparative descriptions of several quantum techniques and state of current research in quantum hardware and software tools. The presented method provides high specificity and has low precision.

In 2022, Zhou and Zhang [10] have presented quantum machine learning that is noise-resistant for evaluating the stability of power systems. The presented paper combines machine learning, data science, and quantum computing to possibly handle the power system TSA problem. Three contributions are as follows: for accurate and noise-resistant TSA, high expressibility, low-depth quantum circuit (HELD) was created, quantum natural gradient descent algorithm is devised, and a systematic examination of QTSA's performance under various quantum variables performed. QTSA supports analytics for power grid stability enabled by quantum machine learning. It provides high F1 score and has low recall.

3 | RESEARCH GAP AND NOVELTY

3.1 | Quantum computing

3.1.1 | Novelty

Large-scale parallel data processing and unmatched computational capability are two features of quantum computing.

3.1.2 | Integration

Fault detection algorithms can handle the complex and high-dimensional data present in electrical power systems by utilising quantum computing, which makes analysis and decision-making more effective.

3.2 | Pyramidal Convolution Shuffle Attention Neural Network

3.2.1 | Novelty

This neural network architecture improves feature extraction and pattern recognition by combining shuffle attention methods with pyramidal convolutional layers.

3.2.2 | Integration

Fault detection systems can improve accuracy and reliability by capturing complex data patterns and anomalies that indicate problems, thanks to the advanced neural network design.

3.3 | Coronavirus herd immunity optimiser

3.3.1 | Novelty

This optimiser attempts to improve defect detection algorithms by imitating the collective immunity notion, which is based on epidemiological concepts.

3.3.2 | Integration

Introducing a novel method to enhance system resilience and adaptability is the integration of herd immunity principles into fault detection algorithms. The system can better withstand and recover from errors by optimising fault detection based on collective immunity concepts, which lowers the likelihood of extensive disruptions.

The integration of these components addresses existing challenges in fault detection by

- Quantum computing will improve scalability and computational efficiency.
- Improving accuracy and robustness in pattern recognition and anomaly detection through advanced neural network architectures.
- Incorporating principles from epidemiology to optimise fault detection strategies, thereby enhancing system resilience and adaptability.

4 | PROPOSED METHODOLOGY

In this paper, an innovative approach that leverages the capabilities of quantum computing, deep learning, and advanced optimisation algorithms to significantly enhance the accuracy of fault detection in electrical power systems is proposed. The proposed network, termed QC-PCSANN-CHIO-FD, integrates several cutting-edge technologies to achieve this goal.

- Quantum computing is utilised to perform complex computations at unprecedented speeds, which is crucial for processing the vast amounts of data generated by modern power systems. By using quantum algorithms, optimisation problems is solved more efficiently than classical methods.
- Deep learning component of the system is based on a pyramidal convolution shuffle attention neural network (PCSANN). This architecture enhances the model's ability to focus on the most relevant features of the data, improving its ability to detect and classify faults accurately. The pyramidal structure allows the network to capture hierarchical features, while the shuffle attention mechanism helps in prioritising important information.
- The optimisation algorithm employed is the coronavirus herd immunity optimiser. Inspired by the concept of herd immunity, this optimiser mimics the way populations develop immunity to viruses, enhancing the network's performance through adaptive learning strategies. CHIO adjusts the parameters of the neural network to find the optimal configuration for fault detection.

Thus, the detailed description about QC-PCSANN-CHIO-FD is shown in Figure 1.

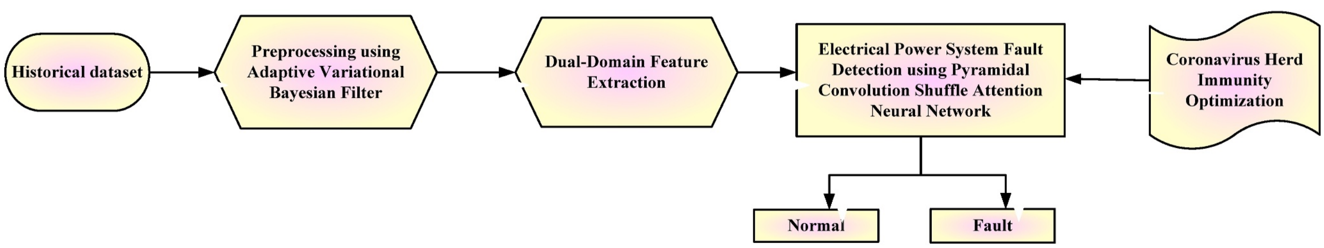

FIGURE 1 Block diagram of the proposed QC-PCSANN-CHIO-FD fault Detection system.

4.1 | Data acquisition

Input data's are received from historical dataset [11]. Simulated measurement data that includes normal and fault operations is normalised using the values of smallest and greatest observations collected during normal operation. This dataset is processed to provide observed and historical sets in order to train the network.

4.2 | Pre-processing using Adaptive Variational Bayesian Filtering

In this step, Adaptive Variational Bayesian Filtering (AVBF) performs the data pre-processing [12] which is utilised for handling missing data, outliers, and errors in the dataset. The data pre-processing converts nominal types of data into consistent data types and it is given in Equation (1)

$$\left(R_{i-1|i-1}\right)^{-1} = V_{i-1}V_{i-1}^{T} \tag{1}$$

where i denotes the discrete time index, V denotes the informative matrix, R denotes the inverse of informative matrix, $R_{i-1\,|\,i-1}$ denotes the assessed information matrix at time $i-1$, denotes the inverse of $V_{i-1}V_{i-1}^{T}$. A_j denotes the sampling point, and the state prediction is expressed in the below Equation (2)

$$\overline{A}_{j,i-1} = g\left(A_{j,i-1}\right) \tag{2}$$

In Equation (2), g denotes the state transition function. Then, the forecasted information is expressed in Equation (3)

$$R_{i|i-1} = \hat{Q}_{i|i-1}^{-1} \tag{3}$$

In time updating stage variational Bayesian point sampling and the measurement equation propagation are same. The associated information matrix $J(e+1)i$ and information state $j(e+1)i$ contributions are given in Equation (4)

$$J_i^{e-1} = B_i^T\left(\tilde{S}_{i|i}^{(E-1)}\right)_{B_i}^{-1} \tag{4}$$

where J denotes the associated information matrix, j denotes the information matrix, B is the measurement function, S and D are the covariance matrixes. Hence, the estimated information matrix $R(e+1)i\,|\,i$ and information vector $r(e+1)i\,|\,i$ in the eth iteration expressed in Equations (5), (6)

$$R_{i|i}^{(e+1)} = R_{i|i-1} + J_i^{(e+1)} \tag{5}$$

$$r_{i|i}^{(e+1)} = r_{i|i-1} + j_i^{(e+1)} \tag{6}$$

Here, $R(e+1)i|i$ denotes the estimated information matrix and $r(e+1)i|i$ denotes the information vector. AVBF handling the missing data, outliers and errors in dataset. Then, the preprocessed data is given to feature extraction phase.

4.3 | Feature extraction using Dual-Domain Feature Extraction

Following preprocessing, a method called feature extraction is used to extract a number of Grayscale statistic features. After preprocessing, the different types of features are extracted from the preprocessed output through Dual-Domain Feature Extraction (DDFE) [13]. It helps to extract Grayscale statistic features like standard deviation, mean, kurtosis, skewness. A quaternion formula, which is a development of the idea of complex numbers, is designated as the hyper complex input. It is expressed in Equation (7)

$$t(x,y) = z + ue + vf + ws \tag{7}$$

where e,f,s signifies the imaginary points, x,y signifies the quaternion variables, and t signifies the hyper complex input. This feature calculates the inner region's average and means absolute difference and compares them to the same dimensions in nearby background area. This is expressed in Equation (8),

$$PJ_{e,f} = \frac{P_{\text{in}}(e,f)}{x_{\text{in}}} - \frac{P_{\text{out}}(e,f)}{x_{\text{out}}} \tag{8}$$

where $PJ_{(e,f)}$ represents the grey level value, $P_{in}(e,f)$ signifies the input neighbourhood e,f, and $P_{out}(e,f)$ represents the output neighbourhood e,f. Hyper complex IR representation is used to relate features. It is expressed in Equation (9),

$$t(x,y) = h_1t_1 + h_2t_2e + h_3t_3f + h_4t_4s \tag{9}$$

where h_1,h_2,h_3,h_4 denotes the weight matrices and t_1,t_2,t_3,t_4 denotes the motion features. By this, the Grayscale statistic features are extracted using DDFE. The grayscale features, such as standard deviation, mean, kurtosis, and skewness. They are discussed below.

Equation (10) is used to calculate the mean of Grayscale statistic features.

$$\chi = \frac{\sqrt{\sum_{k=1}^{m} p}}{M} \tag{10}$$

where χ is the mean.

The standard deviation of the dermoscopic image feature can be expressed in Equation (11)

$$\text{SD} = \sqrt{\frac{1}{A}\sum_{a=1}^{A}\left(B(a)-\chi\right)^2} \tag{11}$$

The Kurtosis of dermoscopic image feature may be expressed by using Equation (12)

$$\mathrm{Kur} = \frac{C(B(a) - \chi)^4}{\delta^4} \tag{12}$$

where $C()$ represents the expected values of the signal samples.

Equation (13) used to calculate skewness of Grayscale statistic features.

$$S(i,a) = \frac{1}{A_s}\sum_{m}\sum_{n\in q}[u(m-1, n-r) - M(n,q)] \tag{13}$$

where u represents the Inverse Difference Normalised image, m represents the Informative Measure of Correlations and q indicates the spatial relationship of pixels. Then, these extracted features are given into Quantum computing-based PCSANN to effectively detect fault in the Electrical Power Systems.

4.4 | Fault detection in electrical power system using quantum computing based Pyramidal Convolution Shuffle Attention Neural Network

In this section, the Fault Detection in Electrical Power System using Quantum Computing-based PCSANN [14] is discussed. To capture more complex features without raising the computing cost, a pyramidal convolution incorporates a series of convolution kernels at different scales with varied spatial resolution and depth. Furthermore, pyramidal convolution recognises spatial feature correlations in multiple levels, allowing the convolution layer to classify detailed information. The features are split into groups expressed in Equation (14)

$$A = [A_1, A_2......A_N] \tag{14}$$

where A represents the feature map and N represents the number of groups. Then, the function efficiency is enhanced by the use of the linear function. Finally, the extracted features are introduced through embedding with the original assets, after its activation sigmoid function to obtain a class representation, and it is given in Equation (15)

$$A_{a1} = \alpha(h_w(q)).A_{a1} = \alpha(s_1 q_1 + k_1).A_{a1} \tag{15}$$

where h_w denotes the function linear, α denotes the activation sigmoid function, q_1 denotes the average pooled function, and s_1,k_1 is obtained from network training. Spatial perception can be preserved attention improvement. Finally, global information is embedded through multiplying the asset's value utilising sigmoid function and spatial attention function is given in Equation (16)

$$A_{a2} = \alpha(s_2.\mathrm{HR}(A_{a2}) + k_2) - A_{a2} \tag{16}$$

Here, HR indicates the groupnorm normalisation function and q_2 denotes the normalised feature. Return to the original dimension by merging the grouped blocks again. Following completion of attention learning and feature recalibration, the 2 branches are spliced in Equation (17)

$$A_{a2} = [A_{a1}, A_{a2}] \times S \times T \tag{17}$$

Here, S,T denotes the sub features. Then, every sub functions are grouped. Finally, channel grouping procedure is carried out. PCSANN is made up of a fully connected layer, an average pooling layer, and a total of four residual blocks. The completely connected layer's output vector moves forward through a sigmoid layer, and this is expressed in Equation (18),

$$\tilde{l}(w|J) = 1/(1 + \exp(-lh(w|J))) \tag{18}$$

Here, J denotes the input image, $\tilde{l}(w|J)$ denotes the probability score, and the global branching is given in Equation (19)

$$S(C) = \frac{-1}{W}\sum_{w=1}^{W} s_w \log\left(\tilde{l}(w|J)\right) + (1 - s_c)\log\left(1 - \tilde{l}(w|J)\right) \tag{19}$$

where s_w represents the true label, w and W represents the number of faults categorised as normal and fault. Finally, PCSANN detects the power system fault as normal and fault. Because of its convenience, pertinence, and inclusive belvedere, the artificial intelligence-based optimisation strategy is taken into account in PCSANN classifier. In this research study, the Coronavirus Herd Immunity Optimisation Algorithm (CHIOA) is exploited for optimising the optimum parameter α of PCSANN. Here, CHIOA is employed for tuning the weight and bias parameter of PCSANN.

4.5 | Optimisation using Coronavirus Herd Immunity Optimisation Algorithm

The weights parameter α of the proposed PCSANN is optimised using the proposed Coronavirus Herd Immunity Optimisation Algorithm (CHIOA) [15]. In this section, the nature-inspired optimisation algorithm approach, CHIOA using human-based behaviours is expressed.

4.5.1 | Stepwise procedure of CHIOA

Here, step-by-step procedure is defined to get ideal value of PCSANN based on CHIOA. Initially, CHIOA makes the equally distributing populace to optimise the optimum parameter α of PCSANN.

Step 1: Initialisation
At first populace to create herd immunity, CHIO produces a set of examples equal to population size at random. The generated cases are stored in the herd immunity population as a two-dimensional matrix of size n as calculated in Equation (20)

$$C = \begin{bmatrix} C_1^1 & C_2^1 & \dots & C_n^1 \\ C_1^2 & C_2^2 & \dots & C_n^2 \\ \dots & \dots & \dots & \dots \\ C_1^N & C_2^N & \dots & C_n^N \end{bmatrix} \tag{20}$$

where C signifies the population of immunity, n signifies the population members, and N signifies the problem variables.

Step 2: Random generation
Input parameters generated at random after initialisation. Best fitness value selection is depending upon their explicit hyper parameter condition.

Step 3: Fitness function estimation
The initialised evaluations are used to generate a random solution. Fitness function is assessed with parameter optimisation value for optimising weight parameter α of the classifier. This is calculated in Equation (21),

$$\text{fitness function} = \text{optimizing } (\alpha) \tag{21}$$

Step 4: Exploration phase
Evolution of herd immunity to coronavirus the primary CHIO loop for improvement is this one. According to three rules based on the gene, either stays the same or is impacted by social distance is computed in Equation (22)

$$y_e^d(f+1) \leftarrow \begin{cases} y_e^d(f) & q \geq L_q \\ M\left(y_e^d(f)\right) & q < \frac{1}{3} \times L_q \\ Z\left(y_e^d(f)\right) & q < \frac{2}{3} \times L_q \\ B\left(y_e^d(f)\right) & q < L_q \end{cases} \tag{22}$$

where L implies the random number, $y_e^d(f)$ signifies the gene and M signifies the initial random.

Step 5: Exploitation phase for optimising α
Based on the herd immune threshold, which applies the following equation, the status vector is updated for each case. It is given in Equation (23)

$$y_e^d(f+1) = L\left(y_e^d(f)\right) \tag{23}$$

where L is the random number, $y_e^d(f)$ is the gene, and M is the initial random.

Step 6: Termination condition
The weight parameter values of generator α from PCSANN are optimised using CHIO, which will iteratively repeat step 3 until fulfil halting criteria $C = C + 1$. Then, QC-PCSANN-CHIO-FD detects fault with higher accuracy by lessening computational time with error.

Principles from epidemiology, particularly herd immunity, are applied to improve fault detection in electrical power systems by drawing parallels between the expansion of fault and the propagation of faults. This integration involves adapting concepts, such as immunity and contagion to the context of power systems. Engineers leverage these principles to design more resilient and reliable power infrastructure. The rationale behind this integration lies in the similarities between the expansion of faults and the propagation of faults in power systems. In both cases, there is a risk of cascading effects leading to widespread disruptions. By understanding how fault expansion is carried out, the proposed system can develop strategies to detect, isolate, and mitigate faults in power systems. This approach offers a fresh perspective on enhancing the resilience and dependability of power infrastructure, ultimately leading to more robust systems capable of withstanding various challenges.

The fault detection system may efficiently identify, isolate, and mitigate faults in electrical power systems by combining several technologies, so enhancing efficiency, resilience, and dependability. This ambitious integration has the potential to transform the field and guarantee the ongoing stability of the power infrastructure. It marks a revolutionary improvement in fault detection approaches.

5 | RESULT WITH DISCUSSION

The experimental outcomes of the suggested method are discussed in this section. The simulations are run on a PC with an Intel Core i5 processor running at 2.50 GHz, 8 GB of RAM, and Windows 7. The suggested method is then simulated in MATLAB using the mentioned performance indicators. The proposed QC-PCSANN-CHIO-FD approach is implemented in MATLAB using historical dataset. The obtained outcome of the proposed QC-PCSANN-CHIO-FD approach is analysed with existing systems like (QC-ANN-FD) [6], (QC-CRBM-FD) [7], (QC-RF-FD) [8] respectively.

5.1 | Performance measures

This is a crucial step for choosing the optimal classifier. Performance measures are assessed to assess performance, including accuracy, ROC.

5.1.1 | Accuracy

Accuracy measures the proportion of samples (positives and negatives) besides total samples and it is given by Equation (24),

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \tag{24}$$

5.1.2 | ROC

It is the ratio of false negative to the true positive area and it is given by Equation (25)

$$ROC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right) \tag{25}$$

5.2 | Performance analysis

Figures 2 and 3 depicts the simulation results of the proposed QC-PCSANN-CHIO-FD method. Then, the proposed QC-PCSANN-CHIO-FD method is likened with existing QC-ANN-FD, QC-CRBM-FD and QC-RF-FD methods respectively.

Figure 2 displays the accuracy analysis. Here,QC-PCSANN-CHIO-FDattains 29.82%, 21.32%, and 27.85% better accuracy for normal; 26.01%, 25.15%, and 24.31% better accuracy for fault estimated with existing QC-ANN-FD, QC-CRBM-FD and QC-RF-FDmethods.

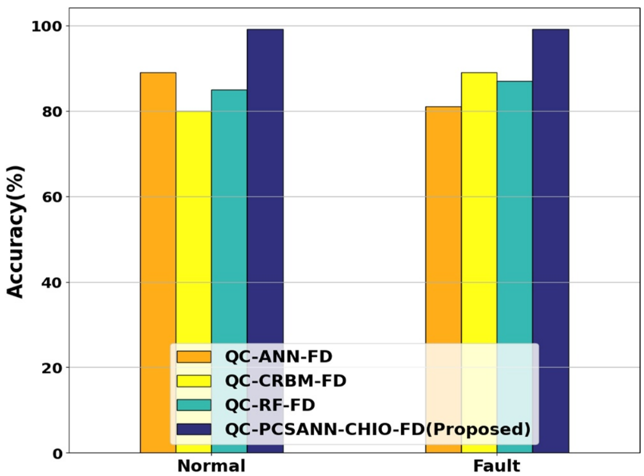

FIGURE 2 Performance analysis of accuracy.

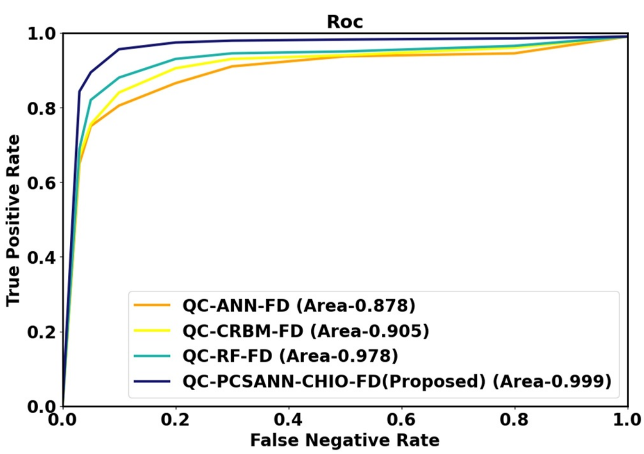

FIGURE 3 Performance analysis of ROC.

Figure 3 depicts the analysis of RoC. The proposed QC-PCSANN-CHIO-FD technique then provides a higher ROC in 13.49%, 6.95% and 9.78% than the existing QC-ANN-FD, QC-CRBM-FD, QC-RF-FD methods.

The proposed algorithm can be integrated with existing power monitoring systems to provide real time detection and response to faults. By using historical data and sensors and SCADA system, the proposed system will be able to monitor the power system fault.

To determine faults, the proposed method can make power systems more dependable. Instantaneous and accurate detection of failure points reduces the downtime and prevents large-scale blackouts. Detecting the fault before its occurring will also help systems work at their best by saving energy and using all available resources.

Developing accurate and reliable models that effectively mimic the dynamics of herd immunity within power systems may pose technical challenges. Incorporating real-time data and adapting to dynamic changes in the power grid's topology and operating conditions could be complex. Ensuring the scalability and applicability of the model across different types of power systems and network configurations may require careful validation and testing.

6 | CLARIFICATION AND CONTEXTUALISATION OF PROPOSED SYSTEM

Quantum computing:

- Clarification: Quantum computing offers unparallelled computational power and can potentially transform fault detection algorithms by processing huge data set and performing complex calculations simultaneously.
- Contextualisation: The application of quantum algorithms and computing presents a novel opportunity to overcome the computational challenges associated with fault detection in large-scale electrical power networks. By using parallel processing, complexity management capabilities, and advanced data analysis techniques, quantum-based fault detection systems can significantly increase the efficiency and accuracy of fault detection operations. In the end, this will increase the electricity infrastructure's resilience and dependability.

Pyramidal convolution shuffle attention neural network:

- Clarification: The architecture that combines pyramidal convolutional layers with shuffle attention mechanisms for feature extraction and pattern recognition.
- Contextualisation: Neural networks and other deep learning approaches are advantageous because of their versatility, scalability, generalisation ability, end-to-end

learning approach, and non-linearity. Because of these features, neural networks are better able to detect tiny anomalies that may be signs of a malfunction and interpret complicated data patterns seen in electrical power systems, which ultimately increases the resilience and dependability of the power infrastructure.

Coronavirus herd immunity optimiser:

- Clarification: This optimiser uses the concepts of herd immunity found in epidemiology to improve defect detection methods. It seeks to improve the fault detection strategies' resilience by imitating the idea of collective immunity.
- Contextualisation: Power systems become more flexible and resilient when herd immunity concepts are incorporated into fault detection algorithms, as this lowers the likelihood of cascading failures. When fault detection systems learn from naturally occurring systems that exhibit collective immunity, they can withstand external threats more successfully and dynamically adapt to changing fault settings. In the end, this makes the electrical infrastructure more stable and dependable.

Espoused fault detection in electrical power systems:

- Clarification: This indicates the primary focus of the research, which is on fault detection within electrical power systems.
- Contextualisation: For electrical power systems to be dependable, stable, and resilient, fault detection is essential. Operators can contribute to the effective and dependable operation of electrical infrastructure by preventing interruptions, safeguarding assets, maintaining grid resilience, and improving customer satisfaction by quickly identifying and resolving defects.

Utilising technology such as advanced analytics and machine learning, advanced fault detection approaches are essential for improving electrical power system speed, accuracy, and dependability. These techniques reduce risks, avert interruptions, and guarantee the continuous dependability and resilience of the electrical system by quickly and accurately identifying issues.

7 | CONCLUSION

Quantum Computing-based PCSANN optimised with the Coronavirus Herd Immunity Optimiser (QC-PCSANN-CHIO-FD) has been successfully implemented for fault detection in electrical power systems. This innovative approach, QC-PCSANN-CHIO-FD, has been applied using MATLAB, leveraging a historical dataset to evaluate its performance.

The performance of the proposed QC-PCSANN-CHIO-FD approach was compared against three existing methods: QC-ANN-FD, QC-CRBM-FD, and QC-RF-FD. The evaluation metrics included precision, F1 score, error rate, and recall. The results demonstrated significant improvements in fault detection accuracy and reliability:

- **Precision**: QC-PCSANN-CHIO-FD achieved high precision rates of 25.9%, 14.64%, and 23.6% compared to the existing methods. This indicates a substantial increase in the correctness of the fault detections made by the proposed approach.
- **F1 Score**: The F1 scores, which balance precision and recall, were also higher with QC-PCSANN-CHIO-FD, showing improvements of 28.14%, 20.78%, and 12.7%. This reflects the model's enhanced ability to accurately identify faults while minimising both false positives and false negatives.
- **Error Rate**: The proposed approach showed a significantly lower error rate of 14.223%, 15.85%, and 16.29% compared to the existing methods. A lower error rate indicates more reliable fault detection with fewer misclassifications.
- **Recall**: QC-PCSANN-CHIO-FD demonstrated high recall rates of 9.98%, 10.98%, and 5.65%. High recall signifies the model's effectiveness in identifying the majority of actual faults, ensuring comprehensive fault coverage.

QC-PCSANN-CHIO-FD approach has proven to be a significant advancement in fault detection for electrical power systems. By integrating quantum computing, deep learning, and an innovative optimisation algorithm, this method achieves higher precision, better F1 scores, lower error rates, and improved recall compared to existing methods. This improvement underscores the potential of QC-PCSANN-CHIO-FD in enhancing the reliability and efficiency of power system fault detection, which is crucial for maintaining the integrity of vital infrastructure.

AUTHOR CONTRIBUTIONS

M. L. Sworna Kokila: Data curation; formal analysis; investigations; methodology; resources; validation; visualisation; writing original draft; writing, review & editing. **V. Bibin Christopher:** Conceptualisation; formal analysis; methodology; project administration; resources; supervision; validation; writing original draft; writing, review & editing. **G. Ramya:** Conceptualisation; formal analysis; investigation; methodology; validation; writing – original draft; writing, review & editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER

None.

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REFERENCES

1. Elmasry, W., Wadi, M.: EDLA-EFDS: a novel ensemble deep learning approach for electrical fault detection systems. Elec. Power Syst. Res. 207, 107834 (2022). https://doi.org/10.1016/j.epsr.2022.107834
2. Deng, Z., Wang, X., Dong, B.: Quantum computing for future real-time building HVAC controls. Appl. Energy 334, 120621 (2023). https://doi.org/10.1016/j.apenergy.2022.120621
3. Ajagekar, A., You, F.: Quantum computing and quantum artificial intelligence for renewable and sustainable energy: a emerging prospect towards climate neutrality. Renew. Sustain. Energy Rev. 165, 112493 (2022). https://doi.org/10.1016/j.rser.2022.112493
4. Atik, J., Jeutner, V.: Quantum computing and computational law. Law, Innovation Tech. 13(2), 302–324 (2021)
5. Alrifaey, M., Lim, W.H., Ang, C.K.: A novel deep learning framework based RNN-SAE for fault detection of electrical gas generator. IEEE Access 9, 21433–21442 (2021)
6. Ajagekar, A., You, F.: Quantum computing based hybrid deep learning for fault diagnosis in electrical power systems. Appl. Energy 303, 117628 (2021). https://doi.org/10.1016/j.apenergy.2021.117628
7. Ajagekar, A., You, F.: Fault diagnosis of electrical power systems with hybrid quantum-classical deep learning. In: Computer Aided Chemical Engineering, vol. 50, pp. 1173–1179. Elsevier (2021). https://doi.org/10.1016/b978-0-323-88506-5.50181-9
8. Ullah, M.H., et al.: Quantum computing for smart grid applications. IET Generation, Transm. & Distribution 16(21), 4239–4257 (2022). https://doi.org/10.1049/gtd2.12602
9. Vaish, R., et al.: Machine learning applications in power system fault diagnosis: research advancements and perspectives. Eng. Appl. Artif. Intell. 106, 104504 (2021). https://doi.org/10.1016/j.engappai.2021.104504
10. Zhou, Y., Zhang, P.: Noise-resilient quantum machine learning for stability assessment of power systems. IEEE Trans. Power Syst. 38(1), 475–487 (2022). https://doi.org/10.1109/tpwrs.2022.3160384
11. . https://www.kaggle.com/datasets/esathyaprakash/electrical-fault-detection-and-classification
12. Dong, X., Chisci, L., Cai, Y.: An adaptive variational Bayesian filter for nonlinear multi-sensor systems with unknown noise statistics. Signal Process. 179, 107837 (2021). https://doi.org/10.1016/j.sigpro.2020.107837
13. Zhang, R., et al.: Deep-IRTarget: an automatic target detector in infrared imagery using dual-domain feature extraction and allocation. IEEE Trans. Multimed. 24, 1735–1749 (2021). https://doi.org/10.1109/tmm.2021.3070138
14. Chen, K., Wang, X., Zhang, S.: Thorax disease classification based on pyramidal convolution shuffle attention neural network. IEEE Access 10, 85571–85581 (2022). https://doi.org/10.1109/access.2022.3198958
15. Al-Betar, M.A., et al.: Coronavirus herd immunity optimizer (CHIO). Neural Comput. Appl. 33(10), 5011–5042 (2021). https://doi.org/10.1007/s00521-020-05296-6

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