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RESEARCH PAPER

Quantum Computing Enhanced Deep Representation Learning for Multi-Class Industrial Fault Detection Approach

C. Santhosh[1] · **R. Sivaraj**[2] · **M. Vijayakumar**[3]

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Abstract
Fault Detection and Diagnosis (FDD) has gained significant interest in recent days among advanced industrial automation. Sustaining operational consistency and avoiding downtime in industrial systems necessitate sophisticated FDD. Conventionally, industrial fault diagnosis used model-driven method based on specialist knowledge and manual features. The common application of machine learning (ML) technique has completed it probable to substitute these conventional methods with more effective solutions able to timely fault detection by employing huge number of sensory information. Over the latest years, deep learning (DL) approach have been leveraged to fault diagnosis because of their effective feature representation capabilities, bringing novel opportunities to the advancement of fault detection. This study proposes a Quantum Computing Enhanced Deep Representation Learning for Multi-Label Industrial Fault Detection and Classification (QCEDRL-MIFDC) methodology. The purpose of the proposed model is to detect and classify faults in industrial systems using quantum computing approaches. In this initial stage, data preprocessing is performed through encoding, outlier removal and data normalization to ensure high-quality data for efficient learning. Moreover, the model employs a hybrid feature selection strategy combining LASSO, Elastic Net, Adaptive LASSO, and Group LASSO to identify the most relevant and informative features. For fault detection, a quantum variational autoencoder-transformer (QVAET) model is utilized to classify four types of faults: no fault, overheating, leakage, and power fluctuation faults. Finally, model training is carried out using the Nadam optimizer to efficiently update parameters and accelerate convergence. The experimental analysis of the QCEDRL-MIFDC model is performed using benchmark Industrial Fault Detection Dataset. Extensive comparative results report the promising performance of the QCEDRL-MIFDC model over recent state of art techniques.

Keywords Fault detection and diagnosis · Industrial automation · Electrical machine · Deep learning · LASSO · Nadam optimizer

1 Introduction

The growth of Industry 4.0 is driving major variations in manufacturing, where Artificial Intelligence (AI) plays a critical part in improving operational outcomes. AI expands previous fundamental automation by delivering useful analytics and insights that allow industries to advance efficiency, decrease downtime, and rises effectiveness (Hsu et al. 2026). In manufacturing, AI applications are considerably enhanced efficiency, flexibility, and quality in industrial condition. It shows an alteration in how manufacturing procedure are handled and performed. Fault Detection and Diagnosis (FDD) is a major subfield within industrial automation and regulator systems. It includes classifying deviations or anomalies from standard system behavior (Sahu et al. 2024). However, fault attention on defining and dividing

✉ C. Santhosh
santhosh@psgitech.ac.in

R. Sivaraj
sivarajr@nandhaengg.org

M. Vijayakumar
tovijayakumar@gmail.com

[1] Department of Artificial Intelligence and Data Science, PSG Institute of Technology and Applied Research, Coimbatore, Tamil Nadu, India

[2] Department of Computer Science and Engineering, Nandha Engineering College, Erode, Tamil Nadu, India

[3] Department of Information Technology, Erode Sengunthar Engineering College, Thudupathi Post, Perundurai, Erode, Tamil Nadu, India638 057

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the primary concern of anomaly. These processes allow early involvements that support to minimize unexpected downtime and maintenance expense (Liu et al. 2025). Data-driven models (DDMs) frequently named as multi-variate statistical procedure observation approach have reflected important attention and is broadly used for monitoring the industrial process. A certain approach based on previous process information and rarely requires complete information of the basic methods of the batch or continuous processes, thereby creating them simpler to apply in process operations and control (Dewangan et al. 2026).

The challenges of FDD are mostly solved through various methods: knowledge-based, model-based, and signal-based methods. In this instance, model-based model is a DDM or statistical models. Within these deep learning (DL) and machine learning (ML) systems provide an effective approach for developing the both prognostic and diagnostic methods (Ali and Kamal 2025). The general ML techniques such as k-nearest neighbors (k-NN), random forest (RF), and support vector machines (SVM) models, and they are often utilized for diagnostics challenge in a type of situations (Zaidi et al. 2026). Quantum computing (QC)-driven applications is obtained attention newly because of the single abilities with a important portion in the optimizer field with applications in molecular design, logistics optimization, operational planning, process operations and scheduling as well as energy systems (Kocatekin et al. 2026). The inherent randomness and ambiguity related to QC operations, arising from the internal magnetic fields, thermal variations, and other noise resources, can be a interference for application of optimization. Nevertheless, this non-ideal action could be used to expand effective statistical ML models (Alobaidy et al. 2025). QC-improved ML methods are presented for pattern recognition, generative ML, handwriting recognition, data fitting, and quantum recommendation models (Ayana and İnan 2024). These QC-driven DDMs could be utilized in monitoring and process control for industrial production. The benefits of Quantum provided by QC within method and speed of function can advantage of fault observation in intricate process method with swift and accurate fault diagnosis is anticipated (Leite et al. 2024). On the other hand, the application of QC-driven models is restricted because of the commercially accessible quantum computers challenging various restriction such as lower amount of quantum bits, restricted connectivity, and reduces quantum memory. Thus, combining QC-improved learning models with traditional ML methods to address some restrictions becomes necessary and is a effective strategy for monitoring processes (Shen et al. 2024).

Although great progress has been made in the field of industrial fault diagnosis, these methods are mostly single-stage feature selection mechanisms or traditional deep learning models that may not fully reflect feature dependence and context features. This study presents a Quantum Computing Enhanced Deep Representation Learning for Multi-Label Industrial Fault Detection and Classification (QCEDRL-MIFDC) model. The major goal is to classify faults in industrial systems using quantum computing approaches. To accomplish that, the QCEDRL-MIFDC system follows a data preprocessing, hybrid feature selection, quantum-based classification and parameter optimization to achieve precise and efficient fault detection and classification. The performance of the QCEDRL-MIFDC approach is validated utilizing a benchmark Industrial Fault Detection dataset, and the results are evaluated across multiple performance metrics.

- Employ a hybrid feature selection strategy that integrates LASSO, Elastic Net (EN), Adaptive LASSO (AL), and Group LASSO (GL) to recognize discriminative and relevant features, which helps to reduce redundant information.
- Design a quantum variational autoencoder-transformer (QVAET) approach for classifying four types of faults: 0-no fault, 1-overheating, 2-leakage and 3-power fluctuation, identifying complex patterns and capture both sequential and contextual relationships in the input data.
- Integrate the Nadam optimizer to adaptively modify learning rates, ensuring faster convergence, and improved fault classification performance.
- Conduct the performance of the proposed model on benchmark Industrial Fault Detection Dataset and calculate the results under various aspects.

2 Prior Studies on Industrial Fault Detection

This section presents key prior work in the field of industrial fault detection. Yüksek (2026) introduced an innovative hybrid method that integrates GRU and CNN for the precise and real-world detection. This model identifies 5 various from of faults includes change in rotor field current, phase opening and disconnection of the exciting voltage and rotor speed. In Panigrahi et al. (2024), the application of DL models is proposed. These models create utilization of NNs to comprehend intricate anomalies and patterns that are information gathering from machinery. There are numerous methods that are becoming studied to see whether or not they are efficient in defect detection at timely phases, restricting downtime, and removing expensive interruptions. Zhu and Zhang (2026) presented an innovative attention ensemble algorithm and DMSAM-OAdB. Initially, the multi-scale sparse attention mechanism (MSAM) obtains and fuses feature data from diverse scales to create the

correlation between characteristics and adaptively regulates the feature weighted by soft thresholding function to highlight the important features were filtering the redundant data. Afterward, a deep network method (DMSAM) made by MSAMs and stacking multiple convolutional layers is iteratively trained as the base classification for the optimization AdaBoost model (OAdB).

In Kiran et al. (2025), the hybrid DL technique is suggested employing GRU and CNN models for textile defect recognition in the textile industry. The objective is to rise the critical procedure's accuracy, efficiency, and reliability. Because fabric defect detection is an important part in quality control, among the physical functions that is progressively automatic employing the above-mentioned models. Kuo et al. (2025) explored a combined structure that synergistically integrates fault identification, LCA, and DES for resolving both operation efficacy and stability in photolithography. ML method is extended for defect identification. DES has utilized by integrating an examination control model learned by the defect detection outcomes, to minimize redundant process and enhance production effectiveness, where LCA enumerates the cause and to allow sustainability validation associated with industrial process. In Wei et al. (2026), a lightweight multi-scale defect detection network (MSDD-Net) is presented for automated analysis. This model uses a DDHFNet for discriminative multi-scale texture feature extraction. The proposed model integrates gated sampled with multi-dilation convolution by increasing both longer-range and shorter-range representations.

The authors Siddique et al. (2025) suggested a hybrid fault-detection structure for milling cutting tools intended to solve 3 constant tasks in industrial monitoring such as restricted fault classes, noisy vibration signals, and variability through operating states. Logarithmic constant wavelet scalograms are built to offer accurate time–frequency localizes and show fault-associated harmonics. Feature extraction is attained across a two-branch encoding, while unique pathway takes localization patterns where the other maintains longer-range dependency, leading to discriminative and compact fault description. In Cai et al. (2024), an incremental vectorized data descriptor system employing Gaussian kernel function is introduced for industrial process fault detection in a combined structure. An adaptive threshold and a reconstruction radius are presented to promote precise in the fault diagnosis. The proposed method a combined incremental structure for fault detection that depends on support vector data descriptor, which is capable of achieving the fault identification and recognition synchronously. The comparative study of industrial fault detection system is depicted in Table 1.

Recently, hybrid systems combining deep learning and optimization-based approaches for complex industrial monitoring problems have also been shown to be effective, with intelligent faults diagnosis and deep representation learning playing a key role. Some advanced representation learning techniques that combine context-based feature analysis, optimization methods and intelligent monitoring devices have demonstrated better robustness and classification performance in noisy industrial environments. Likewise,

Table 1 Literature review of industrial fault detection models

Authors	Years	Goals	Methodologies	Results	Research gap
Yüksek (2026)	2026	Enable predictive maintenance through accurate real-time fault detection	CNN and GRU models	Accuracy of 100%	Most existing methods are unsuitable for real-time industrial fault detection
Panigrahi et al. (2024)	2024	Limit costly interruptions through accurate predictive maintenance	CNN and RNN methods	Precision of 0.85	Most prior studies do not provide comparative evaluations across multiple methodologies
Zhu and Zhang (2026)	2026	Iteratively train deep networks to enhance classification accuracy on industrial data	Deep network model	Boosts fault recognition	Minority class faults are often misclassified due to weak discrimination capability
Kiran et al. (2025)	2025	Capture both spatial and temporal relationships in fabric defect data	CNN, ANN, GRU and LSTM methods	Accuracy of 0.9841	Existing models may not achieve high enough classification accuracy for reliable industrial application
Kuo et al. (2025)	2025	Remove defective wafers efficiently to reduce unnecessary processing	ML, DES and LCA approaches	Optimizes fault diagnosis	Environmental impacts are typically not quantified in semiconductor manufacturing studies
Wei et al. (2026)	2026	Ensure the network meets industrial deployment constraints while maintaining high detection accuracy	MSDD and GSMD methods	mAP of 86.8%	Prior methods often fail to generalize across different industrial materials or datasets
Siddique et al. (2025)	2025	Capture both local and long-range feature dependencies via a dual-branch encoder	DL approach	Accuracy of 99.78%	Single-model decision mechanisms lack robustness against noise and variability
Cai et al. (2024)	2024	Update decision boundaries incrementally based on original support vectors and new samples	ML and DL methods	Strengthens anomaly detection	Incremental learning capabilities are largely missing in industrial fault diagnosis frameworks

the efficient extraction of features from data and adaptive learning models are crucial for effective and dependable industrial automation and fault diagnosis (Umer et al. 2025; Khandelwal et al. 2025). Inspired by these developments, the proposed framework combines hybrid feature optimization and quantum-inspired contextual representation learning, to facilitate the improvement of the industrial fault diagnosis in Industry 4.0 environments.

The interpretable and intelligent industrial fault diagnosis framework, combining deep learning, contextual analysis and explainable predictive mechanisms, for industrial monitoring environments have been the subject of recent research. In Industry 4.0 applications, the advanced industrial monitoring models based on hybrid representation learning, explainable fault analysis and intelligent sensor-driven prediction have been proven to be more reliable and stable in operation. All of these developments further inspire the hybrid feature optimization and contextual deep representation learning in the proposed industrial fault diagnosis framework.

The industrial fault detection can be seen as a progression from knowledge-driven and classical machine learning methods to deep representation learning and hybrid intelligent models up until the recent emergence of quantum-inspired learning. While manually selected features or manually engineered features can be used to achieve effective classification using conventional machine learning methods like k-NN, Random Forest and SVM, they may be hampered by the case where fault information is spread out over multiple correlated sensor variables. Automatic representation learning was then further enhanced with deep learning methods, which were able to identify nonlinear patterns directly from the sensor observations. The capacity of capturing spatial, temporal and contextual dependencies have been further enhanced by the hybrid CNN–GRU, attention-based and Transformer-based architectures. But traditional deep models could potentially contain redundant attributes from the sensors and can be heavier in computational representation. The hybrid intelligent approaches thus integrate feature-selection or optimization mechanisms with deep networks to enhance the efficient representation and classification performance. Quantum-inspired learning is another research direction where quantum-state based representation can be introduced into the classical learning pipeline. However, the current methods usually treat feature selection, latent representation learning and contextual analysis separately.

3 System Architecture and Methodology

This section introduces the comprehensive workflow of the QCEDRL-MIFDC approach, developed to enable precise fault detection analysis. The proposed model follows a multi-stage pipeline consisting of data preprocessing, hybrid feature selection and quantum-based classification and parameter optimization. The systematic architecture of the QCEDRL-MIFDC framework is depicted in Fig. 1 and is defined through the following steps.

- **Data Preprocessing:** Initially, data preprocessing is performed to transform raw data into a suitable format for analysis. This comprises encoding raw data, removing outliers, and normalizing features to ensure high-quality input for efficient learning and accurate fault detection.
- **Hybrid Feature Selection via LASSO Techniques:** Following that preprocessing, a hybrid feature selection strategy integrating LASSO, EN, AL, and GL is employed. This method captures both individual and grouped feature relationships, ensuring important patterns are retained. It effectively reduces irrelevant or redundant features, enhancing the efficiency of fault detection and classification.
- **Quantum-based Classification:** The QVAET model is employed to classify multiple types of faults by extracting latent features and analyzing their sequential and contextual dependencies. By capturing intricate relationships in the data, the model enhances fault detection performance and robustness.
- **Parameter Optimization:** In this final stage, the Nadam optimizer integrates adaptive learning rates with nesterov momentum to efficiently update model parameters, while its lookahead mechanism stabilizes training and reduces oscillations, resulting in faster convergence and improved overall model performance.

3.1 Data Preprocessing

Data preprocessing involves converting raw data into a structured format, eliminating outliers, and normalizing features. This process enhances data quality and supports effective model training for reliable fault classification.

Data encoding: In industrial fault detection, databases often involve both numerical sensor readings and categorical features such as equipment type, operational modes or fault codes (Mowla et al. 2026). By utilizing the database in ML techniques, each feature will be signified numerically. Correct data encoded converts symbolic and categorical data into numerical types that maintain their fundamental relations. This process assures that the methods could interpret the data efficiently and take useful patterns.

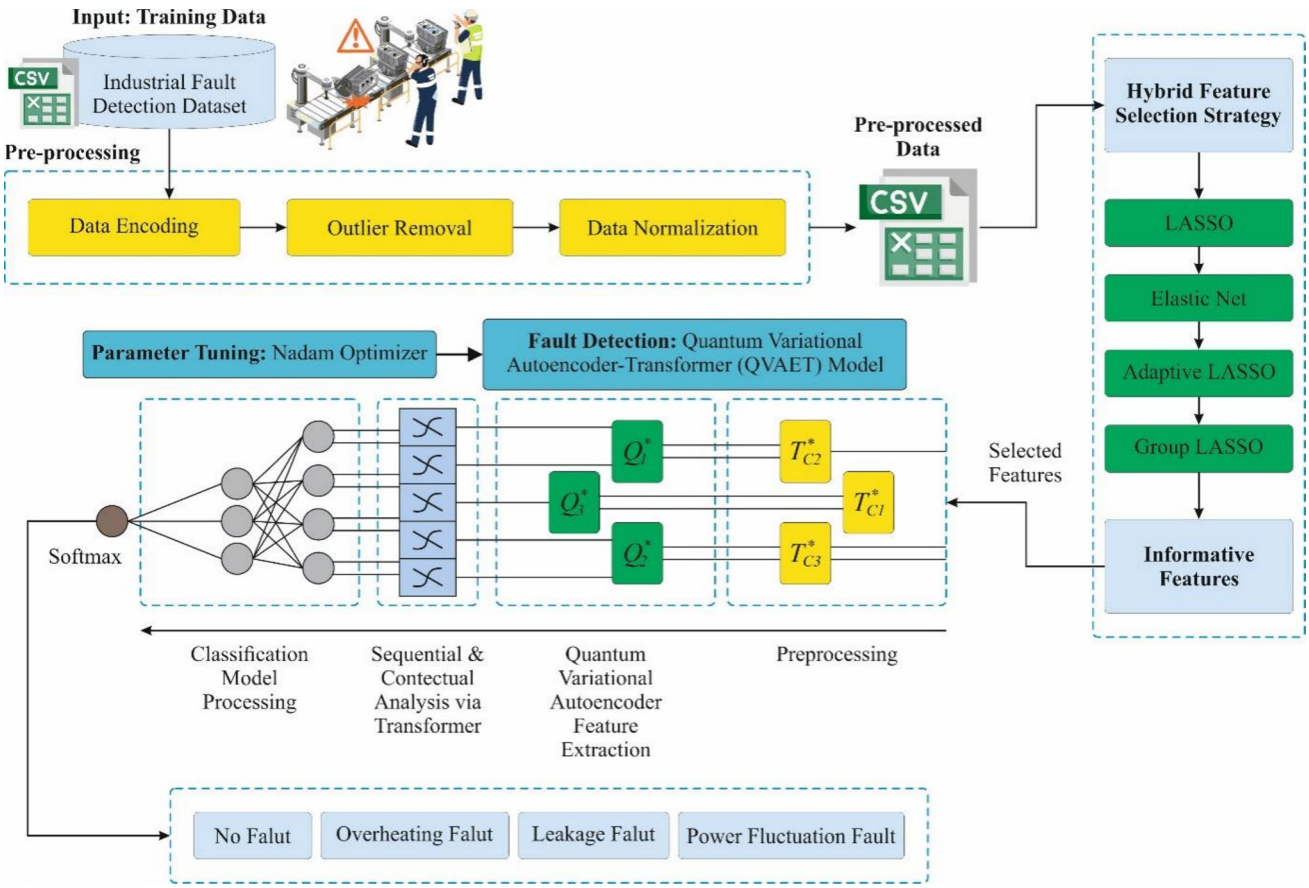


Fig. 1 Systematic architecture of the QCEDRL-MIFDC framework

Outlier removal: Outliers removal is a negative effect on transformer-driven method performance. Outliers are the data points that differ significantly from the rest of the database. The purpose for the existence of outliers is because of feature data points. Several methods are accomplished by researchers in the previous for detecting thr outliers. Z-score is utilized for detecting and removing the outliers.

Data normalization: Min-Max normalization approach is used for scaling numerical characteristics into an evenness range. This model converts all features value to subtract the minimal value and divided by the range. Min-Max normalizes is vital for ensuring that each feature donate similarly in model training, particularly for methods sensitive to the scale of input data like NNs. For normalization, it became simpler for the method to converge in training and evade biased towards variable with high numerical ranging. The preprocessing stage is especially significant in industry fault analysis, with balanced feature depictions could considerably effect classifier outcomes. The Min–Max normalization calculation is given in Eq. (1).

$$p = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where X means the original value of the feature, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the feature, respectively, and p is the normalized value of the feature. Normalization is a process that transforms each numerical feature into the range.

3.2 Hybrid Feature Selection using LASSO

Most industrial sensor datasets include redundant, correlated and grouped variables that can negatively impact model performance for fault diagnosis. Using a single regularization-based feature selection method may not be sufficient to solve all these problems. In this paper, a hybrid feature selection method based on LASSO, Elastic Net (EN), Adaptive LASSO (AL) and Group LASSO (GL) is used (Farhadi et al. 2024). LASSO first shrinks the coefficients of these irrelevant and sparse features to zero. Finally, Elastic Net can deal with highly correlated sensor variables by using L1 and L2 regularization. The adaptive LASSO is an enhanced feature selection algorithm that further improves consistency of feature selection by assigning adaptive weights to regression coefficients. Last but not least, Group LASSO maintains meaningful grouped relationships between industrial

sensor features and allows for group-wise feature selection. The sequential combination of these complementary techniques enables the extraction of a compact but informative feature subset, which would lead to higher classification accuracy and less computational complexity.

LASSO: Lasso regression model is a common approach for FS. It is valuable in conditions with a higher amount of prediction. This model intends to reduce both the Residual Sum of Squares (RSS) and predictor mistake. It attains a l_1 -norm penalty on the absolute amount of the coefficient of regression, leading to automatic lessening in some co-efficient to zero in the process of FS. Nevertheless, same to any other model, it has detailed merits and demerits. Among the demerits is that the maximal number of chosen features is restricted by the count of instances, and another is its incapability of FS as a group.

In LASSO estimator, the l_1-norm used in the penalization worse squares, described as follows:

$$\widehat{\beta}=\underset{\beta\epsilon R^p}{argmin}\left\{\frac{1}{2}\|Y-X\beta\|_2^2+\lambda\|\beta\|_1\right\} \tag{2}$$

where $X\in\mathbb{R}^{nxp}$ denotes the input feature matrix, $y\in\mathbb{R}^n$ denotes the target vector, $\beta\in\mathbb{R}^p$ denotes the regression coefficient vector, n denotes the number of observation, p denotes the number of features, and $\lambda\geq 0$ denotes the LASSO regularization parameter controlling the degree of coefficient shrinkage. The L_1- norm penalty promotes spare solutions by forcing some coefficients to zero.

EN: This technique is a FS model utilized to address the restrictions of ridge and lasso approaches. It integrates the benefits of both lasso and ridge models by using a linear integration of l_1-and l_2-norm penalty to reduce the loss function. Automate FS and constant shrinkage were offered by EN with the capability of group selection for correlated features. The goal is to reduce co-efficient and evaluate a technique depend upon non-zero co-efficient.

The EN penalty has been created by integrating dual penalties such as l_1-and l_2-norm that object function could be described.

$$\hat{\beta}^{elastic}=\underset{\beta}{\text{argmin}}\left\{\frac{1}{2}\parallel y-X\beta\parallel^2+\lambda\left[\frac{1}{2}(1-\alpha)\parallel\beta\parallel_2^2+\alpha\parallel\beta\parallel_1\right]\right\} \tag{3}$$

The relative contribution of the L_1 and L_2 norm penalties is determined by the value of α which is in the interval [0,1]. The formulation is LASSO when α = 1, and ridge regularization when α = 0.

AL: This method is a new version of the Lasso approach with its particular benefits, able to minimize certain co-efficients to 0. It makes FS and shrinkage to weight operation. The weighted vector is described as $\widehat{W}=\frac{1}{|\widehat{\beta}_{ols}|^{\gamma}}$, here, $\widehat{\beta}$ represented the ordinary least squares (OLS) estimation of the i_{th} co-efficient of regression. The parameter γ regulates the level of shrinkage. The unique benefits of AL have its capability of performing the FS even in instances where the amount of prediction is considerably bigger than the instance size. Since the AL could minimize certain co-efficient to zero precisely efficiently eliminating the correspond to predictive from the method. If the amount of prediction (p) is higher than observers (n), ($p>n$), the ridge estimation $\widehat{\beta}_{ridge}$ could be utilized rather than the OLS estimation $\widehat{\beta}(ols)$. The AL estimation computes as Eq. (4):

$$\hat{\beta}^{Alasso}=\arg\underset{\beta}{min}\left\{\|y-X\beta\|^2+\lambda\sum_{j=1}^{p}w_j|\beta_j|\right\} \tag{4}$$

$w_j>0$ is the adaptive weight of the j-th coefficient. The adaptive weights regulate the amount of shrinkage for the feature coefficients, which is the ability to shrink less informative coefficients towards zero.

GL: The GL estimation is a one of the shrinkage models, which expands the Lasso approach to make FS at the level of group. This is utilized for selecting the groups of related features in higher-dimension data and for classifying groups of features. In this study, GL choose trees as a group and uses shrinkage to them. It implies that each the co-efficient inside a group became either non-zero or zero together. By achieving the group, the vector of parameter β is separated into groups $G_1,G_2,\ldots,G_q$ let $\bigcup_{j=1}^{q}G_j=\{1,2,\ldots,p\}$. The vector β is changed the group.

$$\beta=(\beta_{G_1},\beta_{G_2},\ \ldots,\beta_{G_q})'\quad \beta_{G_j}=\{\beta_r;r\in G_j\} \tag{5}$$

The GL penalty is computed as below:

$$\hat{\beta}^{Alasso}=\underset{\beta}{\text{argmin}}\left\{\frac{1}{2}\|y-\beta^TX\|^2+\lambda\sum_{j=1}^{q}m_j|\beta_{G_j}|\right\} \tag{6}$$

In this equation, m_j balances among groups of diverse sizes. It is the groups have distinct number of features and so the penalty term must have more robust impact on the groups with lesser features. To solve this problem, the co-efficient m_j is described as follows:

$$m_j=\sqrt{T_j} \tag{7}$$

Let, T_j signifies the count of features in the j_{th} group.

The hybrid feature selection process is carried out sequentially in the proposed framework to promote informative

sensor attributes from the industrial dataset. LASSO first removes irrelevant and sparse features and Elastic Net later handles the correlation between features via combined regularization. Moreover, Adaptive LASSO enhances the weighted coefficient selection and Group LASSO maintains the grouped feature relationship between correlated industrial sensor parameters.

3.3 Quantum-Driven Classification Module

The work introduces a hybrid quantum-inspired latent representation framework called. QVAET integrates a quantum variational autoencoder and transformer architecture to analyze complex data patterns, with an overview of fundamental quantum computing concepts for clarity (Chen and Fang 2025).

Qubits and Quantum States: A qubit is the basic unit of quantum data, analogous to a bit in traditional computation. In contract, different a conventional bit is 1 or 0, a qubit could be in a state known as superposition, while the concurrently maintains both 1 and 0 states. The quantum qubit state is computed as Eq. (8):

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{8}$$

Here, $|0\rangle$ and $|1\rangle$ represent the fundamental steps, and α and β denotes intricate coefficient.

where, $|0\rangle$ and $|1\rangle$ denote the computational basis states of a qubit, while α and β denote their corresponding complex probability amplitudes. The amplitudes satisfy the normalization constraint $|\alpha|^2 + |\beta|^2 = 1$, ensuring that the total measurement probability is equal to one. The probability of measuring the state $|0\rangle$ is $|\alpha|^2$, whereas the probability of measuring $|1\rangle$ is $|\beta|^2$.

$$|\alpha| 2+ |\beta| 2 = 1 \tag{9}$$

Quantum Gates and Quantum Circuits: Quantum gates change the qubits state were signified by particular matrices. It involves fundamental operators such as the Pauli and Hadamard gates, and more adaptable single-qubit rotation gate that uses a rotation to a qubit state about an axis of the Bloch sphere. Quantum circuits were sequences of these gates organized to make quantum model by using state of qubits.

Measurement and Observables: In quantum mechanism, observables were represented by operation with respect to physical quantities such as energy or position. The procedure of measures impacts the qubit state, collapse from a superposition to among the foundation states that depends on the possibility described by the coefficient of states. Figure 2 depicts the structure of quantum variational autoencoder.

QVAET: This method offers advanced input measures T_C^* that act as the method input to QVAET (Barma et al. 2025). Over the quantum QVAE function, the element classifies intricate multi-dimension hidden patterns embeds in the input measures, allowing the method to best comprehend fundamental data structures. Leveraging a transformer-driven structure, the method examines characteristics for capturing the series dependency and contextual relations among measures, improving the ability for precise predictive.

$$G = QVAET\left(T_C^*\right) \tag{10}$$

The QVAE obtains hidden characteristics G from the input T_C^*. These higher-dimension attribute take complex patterns and relations inside the information. This method then passes the hidden characteristics G into the transformer-driven structures that measures them for contextual associations and sequence connections. Self-attention module is utilized for determining the significance of all measures related to others, supporting the method comprehend their collection influence on the predictive challenge. By integrating sequential data processing with contextual examination, the transformer elements allow the method for detecting the latent patterns, which are complex for classifying utilizing traditional approaches.

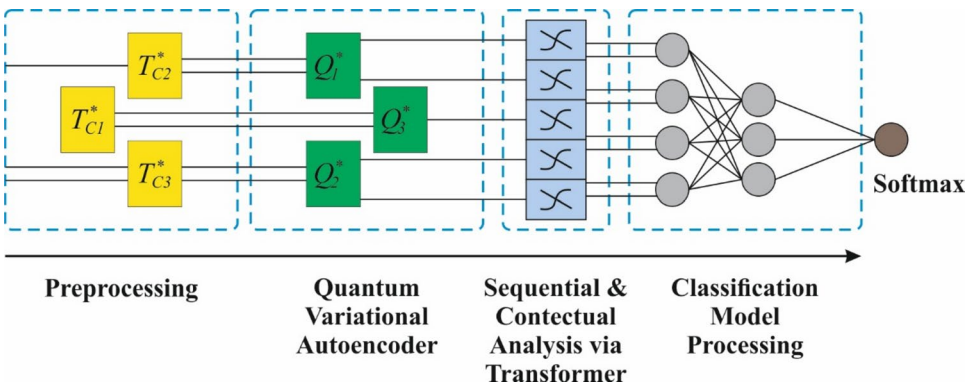


Fig. 2 Structure of quantum variational autoencoder

$$Q = Transformer\,(G) \tag{11}$$

The transformer process outcome Q to process the hidden characteristics G and classifying major sequences and contextual interactions. These produced characteristics Q are furthered to the predictive layer that assesses the learnt patterns for determining the possibility of a target performance. The final predictive $\hat{z}$ reproduces the inference depends on the feature extraction and relations, enabling the method to create informed decisions and enhance overall predictive precision.

$$\hat{z} = prediction\,(Q) \tag{12}$$

The method's final outcome $\hat{z}$ implies the predicted value rely on the produced characteristics and learnt relations. Figure 3 indicates the architecture of transformer module.

The suggested QVAET approach utilizes a quantum-inspired representation learning strategy and a transformer-based contextual analysis for industrial fault diagnosis in a hybrid fashion. This study mainly aims at the improvement of latent feature representation capability using variational quantum state mapping and extracting contextual dependency. The proposed framework is not of the kind that claims to be "theoretically superior to classical computing" nor to achieve "exponential speedup" in computation. Rather, the contribution of this work is the combination of the quantum inspired latent feature learning with deep contextual analysis to enhance the performance for fault discrimination in industrial use cases within a hybrid classical–quantum simulation environment.

The industrial sensor features are first encoded to a compact latent representation with the variational quantum encoding process. By using quantum-state representation, several feature states can be represented in a probabilistic latent space, with the coefficients corresponding to the different quantum states being the contribution of the different latent states. This representation then goes to the Transformer module for contextual analysis. The variational part of the model is therefore not as straightforward as in a standard deterministic VAE. The VAE learns a continuous latent distribution using typical neural transformations while the quantum-inspired variational stage encodes the latent state with a parameterized quantum state and quantum circuits. The goal of the resulting representation is to offer a more comprehensive representation of the underlying features to discriminate complex and partially overlapping fault patterns that occur in industrial applications. The Transformer then adds to this representation by learning the relations and contexts between the latent features using self-attention.

3.4 Optimization Strategy

The Nadam optimization also called a Nesterov Adam, is a modified version of Adam optimize that integrates Nesterov momentum, integrating adaptive learning rates in a lookahead gradient upgrade for quick convergence (Ayyed and Al-Sinjary 2025). This calculates bias-corrected 1 st and 2nd moment estimation of gradients whereas regulating the momentum term to expect upcoming gradient directions. It allows the optimization to enhance steadiness and

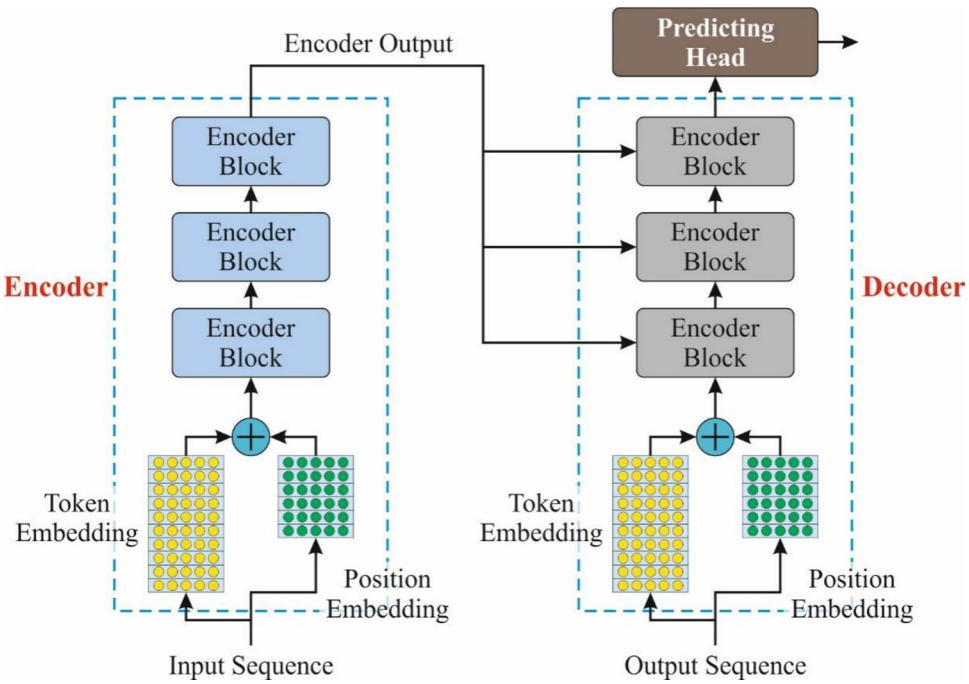


Fig. 3 Architecture of transformer module

training efficacy. Nadam is broadly utilized in DL model for enhanced convergence and strong outcomes.

$$g_t^{\wedge} \leftarrow \frac{g_t}{1 - \prod_i^t = 1\beta_{1i}} \tag{13}$$

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{14}$$

$$m_t^{\wedge} = \frac{m_t}{1 - \prod_{i=1}^{t+1} \beta_{1i}} \tag{15}$$

$$u_t = \beta_2 u_{t-1} + (1 - \beta_2) g_t^2 \tag{16}$$

$$u_t^{\wedge} = \frac{u_t}{1 - \beta_2^t} \tag{17}$$

Moreover, the upgrade of the momentum vector for the further timestep β_{t+1}, the vector m also involves the gradient upgrade for the recent timesteps gbt.

$$m_{t-1}^{\wedge} \leftarrow (1 - \beta_1) \cdot g_t^{\wedge} + \beta_{t+1} \cdot m_t^{\wedge} \tag{18}$$

Next, alter Nadam's parameter as follows:

$$\theta_t = \theta_{t-1} - \frac{\alpha}{\sqrt{u_t^{\wedge}} + \varepsilon} m_{\bar{t}-1} \tag{19}$$

4 Performance Evaluation

The proposed framework is experimentally validated to check the stability and consistency of the framework, and the experimental evaluation is performed for two different train–test partition configurations, 80:20 and 70:30. This performance consistency under different data distributions across the two evaluation settings shows the efficiency and generalization ability of the proposed industrial fault detection framework.

The performance evaluation of the QCEDRL-MIFDC method can be examined using the Industrial Fault Detection Dataset (Barma et al. 2025). This database is intended for automated fault diagnosis in application of Industry 4.0 employing IoT-driven smart sensors. It includes information of industrial sensor data gathered from several resources such as Flow Rate Sensors (L/min), Temperature Sensors (°C), Pressure Sensors (kPa), Vibration Sensors (m/s^2), Voltage Sensors (V), and Current Sensors (A). The dataset includes 36 features, of which 24 are selected. Table 2 presents the dataset consists of four fault types: no fault, overheating fault, leakage fault, and power fluctuation fault, with a total of 1000 samples.

Table 2 Details of dataset

Fault type	No. of records
No fault (normal operation) (0)	725
Overheating fault (1)	91
Leakage fault (2)	95
Power fluctuation fault (3)	89
Total records	**1000**

The Industrial Fault Detection dataset is moderately imbalanced with much more normal operating condition data but much less data per individual fault category. Oversampling or undersampling was not used in the experiments to manipulate the data distribution and to eliminate artificial sampling bias. Instead, class-wise precision, recall, F-score, G-measure and confusion matrix analysis was reported to give a clear picture of the performance of the model. Experimental results show that the proposed framework retains good classification performance under a minority fault class, despite the fact that the dataset is inherently imbalanced.

4.1 Experimental Setup

The proposed QCEDRL-MIFDC framework is implemented in python with TensorFlow and Keras library. The experiments were performed on a workstation with the following specifications: Intel Core i7, NVIDIA RTX-series GPU, 16 GB of RAM, and running Windows. The model was trained for 300 epochs, with an adaptive learning rate (Nadam). All benchmark methods were tested with consistent hardware resources, train-test partitions, preprocessing methods and performance evaluation criteria, to ensure that they are being tested in the same conditions.

Figure 4 presents correlation heatmaps of features grouped into three sets (0–8, 8–16, and 16–25), illustrating the relationships among variables. Most features show low correlation, indicating independence and minimal redundancy in the dataset. Some moderate to high correlations is observed among similar FFT-based features, reflecting shared frequency characteristics. Additionally, the fault type exhibits weak correlation with individual features, suggesting that fault classification depends on a combination of multiple attributes.

Table 3 and Fig. 5 show the fault detection result of the QCEDRL-MIFDC method with 80:20 of TRAP/TESP. On confusion matrices, the QCEDRL-MIFDC approach has effective detection of four class exactly. Moreover, the classification results with 80% TRAP, the QCEDRL-MIFDC models achieve average value with $accur_y$ of 96.13%, $preci_n$ of 88.81%, $recal_l$ of 79.50%, F_{score} of 83.52% and $G_{measure}$ of 83.83%, respectively. In the meantime, with 20% TESP, the QCEDRL-MIFDC approach reach average value with $accur_y$ of 93.00%, $preci_n$ of 80.49%, $recal_l$ of 72.21%, F_{score} of 75.59% and $G_{measure}$ of 75.97%, respectively.

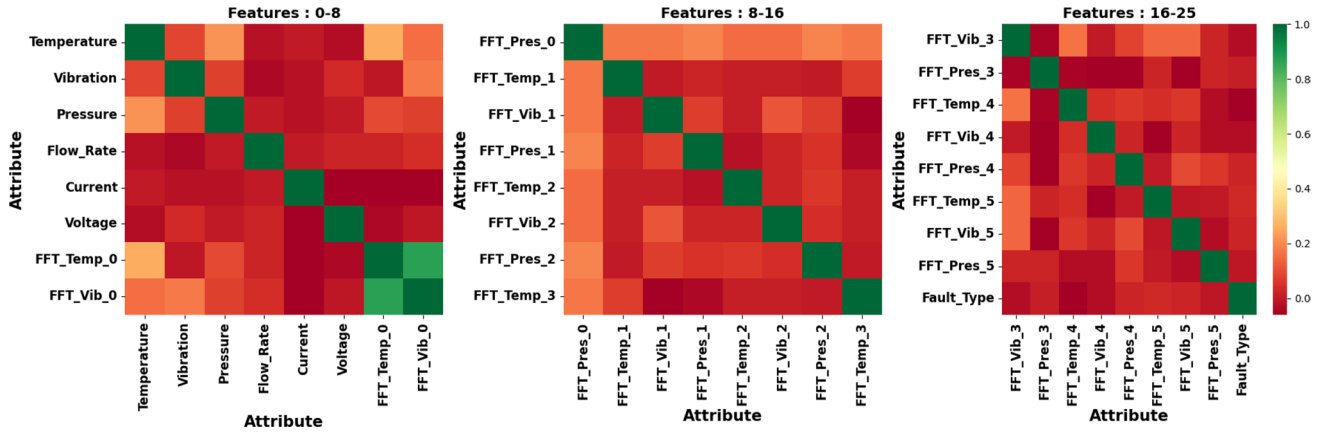


Fig. 4 Feature correlation heatmap representations

The proposed QCEDRL-MIFDC framework was designed and optimized with python in deep learning environment with TensorFlow and Keras library. All experiments were performed on a workstation running on Windows operating system, which has Intel Core i7 processor, NVIDIA RTX-series GPU, and 16 GB RAM. All the competing approaches were compared under the same implementation settings, such as FLOPs, GPU utilization, inference time and execution time.

The industrial fault detection benchmark data set used in this paper is structured sensor observations (not overlapping windows of time). Hence, there is no dependency leakage for overlapping window generation in the experiment setup.

Figure 6 depicts the training (TRAING) and validation (VALIDN) $accur_y$ curves of the QCEDRL-MIFDC system with 80:20. The TRAING $accur_y$ consistently increasing, depicting effective learning and proper convergence of model. The VALIDN $accur_y$ observes closely the training curve with a minimum gap, depicting lesser over-fitting and better generalizes solutions.

Figure 7 indicates the TRAING and VALIDN loss curves of the QCEDRL-MIFDC technique with 80:20. Both losses decrease significantly in the initial epochs and then gradually constant, suggesting efficient convergence and learning. The lesser gap between TRAING and VALIDN loss validates improved generalizes and lower over-fitting.

The training and validation curves show that the curves converge steadily during the learning process. There is a moderate difference between the performance on training and validation sets, but the gap is controlled without significant instability, suggesting that the model has good generalization ability and controlled overfitting behavior.

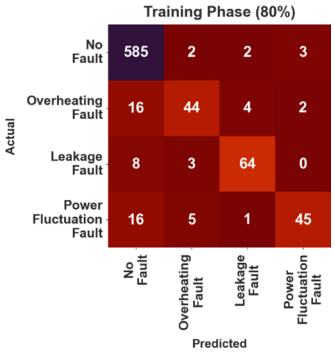
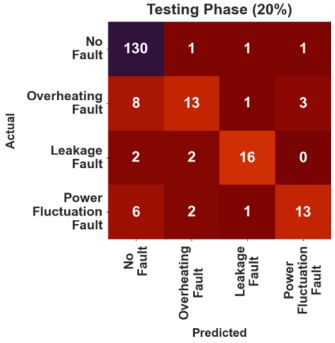
Table 4 and Fig. 8 show the fault detection result of the QCEDRL-MIFDC method with 70:30 of TRAP/TESP. On confusion matrices, the QCEDRL-MIFDC approach has effective recognition of four class exactly. Moreover, the classification results with 70% TRAP, the QCEDRL-MIFDC approaches attain average outcomes with $accur_y$ of 96.07%, $preci_n$ of 85.47%, $recal_l$ of 80.30%, F_{score} of 82.37% and $G_{measure}$ of 82.62%, respectively. In the meantime, with 30% TESP, the QCEDRL-MIFDC approach obtain average outcomes with $accur_y$ of 94.67%, $preci_n$ of 82.50%, $recal_l$ of 72.38%, F_{score} of 76.36% and $G_{measure}$ of 76.89%, respectively.

Figure 9 denotes the TRAING and VALIDN $accur_y$ curves of the QCEDRL-MIFDC model with 70:30. The TRAING $accur_y$ consistently increasing, depicting effective learning and proper convergence of the model. The VALIDN accuracy observes approximately the training curve with a lower gap, depicting reduced over-fitting and better generalizes outcomes.

Figure 10 portrays the TRAING and VALIDN loss curves of the QCEDRL-MIFDC approach with 70:30. Both losses decrease significantly in the initial epochs and then gradually stable, representing efficient convergence and learning. The lesser gap between TRAING and VALIDN loss validates better generalizes and minimal overfitting.

The test-set recall values for the no-fault, overheating, leakage and power-fluctuation conditions are 97.74%, 52.00%, 80.00% and 59.09%, respectively, under the 80:20 configuration. The lower recall of overheating and power fluctuation faults suggest that the fault patterns are more challenging to distinguish from other operating conditions based on the available sensor observations. This may be due to a weak direct correlation between the individual sensor characteristics and the fault label. The correlation analysis indicates that the individual features have relatively low correlation with the fault type and some FFT derived features have moderate to high correlation. It means fault identification is based on the combination of attributes of the sensors and not on one dominant attribute. The hybrid LASSO, Elastic Net, Adaptive LASSO and Group LASSO stage is then used to remove irrelevant information while maintaining correlated feature relationships. The selected

Table 3 Fault detection result of the QCEDRL-MIFDC approach with 80:20

Confusion matrix	Class labels	$Accur_y$	$Preci_n$	$Recal_l$	F_{score}	$G_{measure}$
	No fault	94.13	93.60	98.82	96.14	96.17
	Overheating fault	96.00	81.48	66.67	73.33	73.70
	Leakage fault	97.75	90.14	85.33	87.67	87.70
	Power fluctuation fault	96.63	90.00	67.16	76.92	77.75
	Average	**96.13**	**88.81**	**79.50**	**83.52**	**83.83**
	No fault	90.50	89.04	97.74	93.19	93.29
	Overheating fault	91.50	72.22	52.00	60.47	61.28
	Leakage fault	96.50	84.21	80.00	82.05	82.08
	Power fluctuation fault	93.50	76.47	59.09	66.67	67.22
	Average	**93.00**	**80.49**	**72.21**	**75.59**	**75.97**

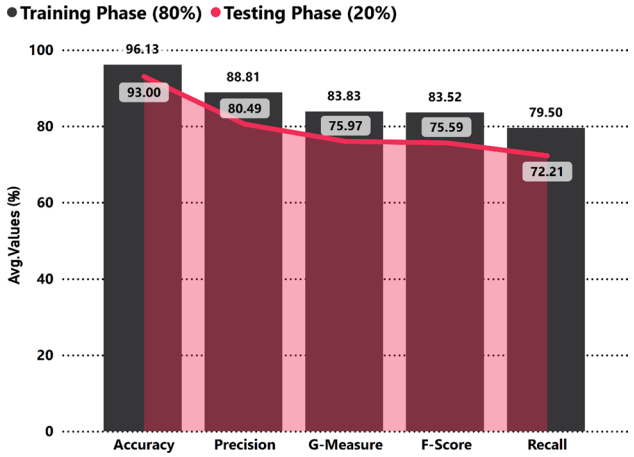


Fig. 5 Average of the QCEDRL-MIFDC method with 80:20

features then go through the QVAET stage where they will be converted into latent representations before finally being processed with contextual self-attention to discover relationships between the learned representations. In particular, this is important for classes of faults for which the sensor properties could overlap. Therefore, the classification performance observed is viewed as an effect of the iterative process of feature screening and contextual representation learning, not just a single feature. The switch from 80:20 configuration to 70:30 configuration also shows the dependence of the recognition of minority faults on the training information. The % recall for the test-set reduces to 72.38% for the 70:30 configuration relative to 72.21% at 80:20 and the F-score reduces from 75.59% to 76.36%, respectively.

Fig. 6 Training and validation accuracy curves of the QCEDRL-MIFDC approach with 80:20 split

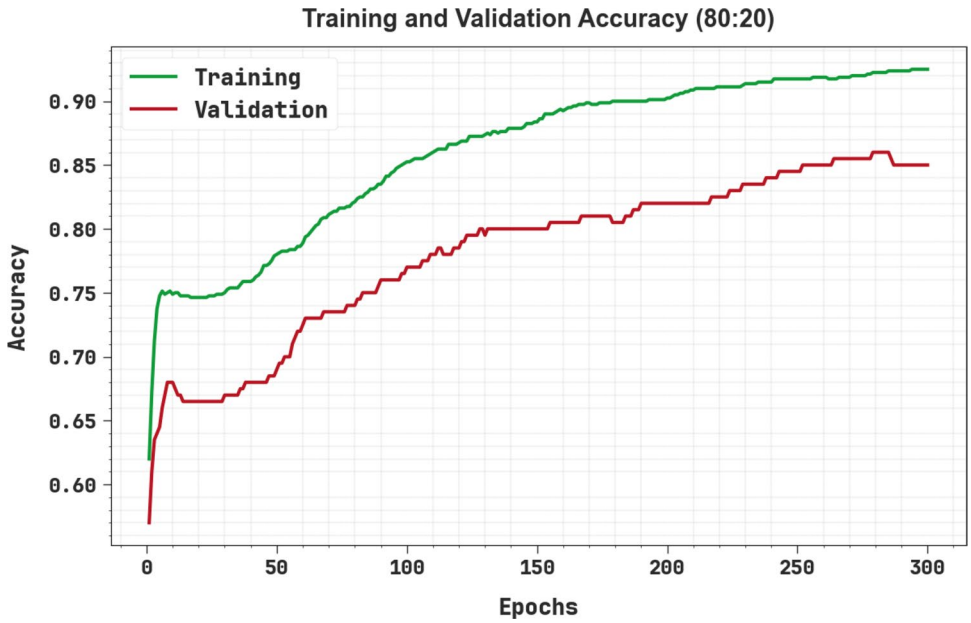


Fig. 7 Training and validation loss curves of the QCEDRL-MIFDC approach with 80:20 split

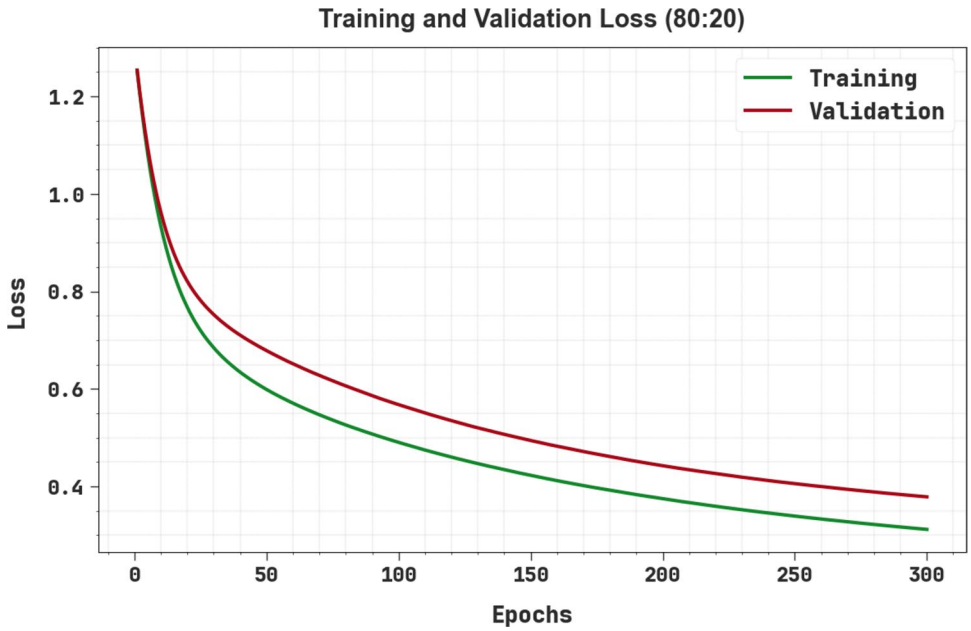
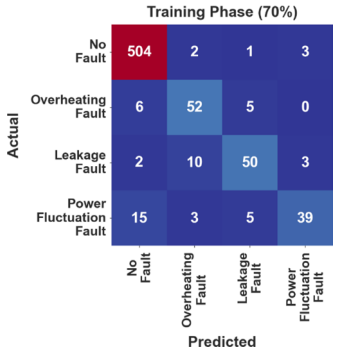
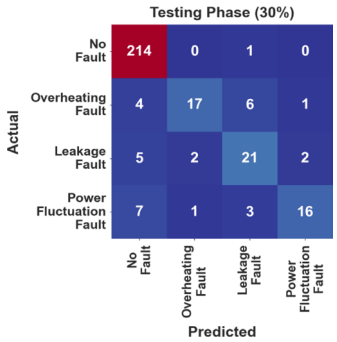


Table 4 Fault detection result of the QCEDRL-MIFDC approach with 70:30

Confusion matrix	Class labels	$Accur_y$	$Preci_n$	$Recal_l$	F_{score}	$G_{measure}$
	No fault	95.86	95.64	98.82	97.20	97.22
	Overheating fault	96.29	77.61	82.54	80.00	80.04
	Leakage fault	96.29	81.97	76.92	79.37	79.41
	Power fluctuation fault	95.86	86.67	62.90	72.90	73.84
	Average	**96.07**	**85.47**	**80.30**	**82.37**	**82.62**
	No fault	94.33	93.04	99.53	96.18	96.23
	Overheating fault	95.33	85.00	60.71	70.83	71.84
	Leakage fault	93.67	67.74	70.00	68.85	68.86
	Power fluctuation fault	95.33	84.21	59.26	69.57	70.64
	Average	**94.67**	**82.50**	**72.38**	**76.36**	**76.89**

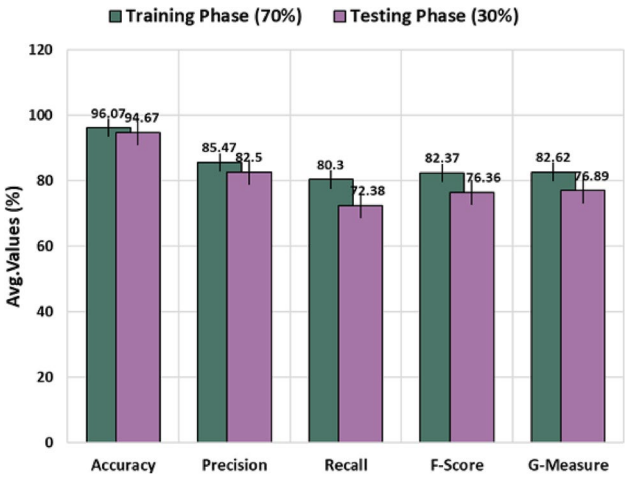


Fig. 8 Average of the QCEDRL-MIFDC method with 70:30

The relatively small differences suggest that the framework has relatively similar recognition performance for the two partition settings, but that recognition performance for minority classes is more difficult than the recognition performance for the normal classes.

Table 5 represent the comparative results of the QCEDRL-MIFDC method with other models under various evaluation metrics (Moshrefi et al. 2024; Elmazi et al. 2024). The resulted that the GNB method has obtained the worst performance with $accur_y$ of 94.67%, $preci_n$ of 82.50%, $recal_l$ of 72.38%, and F_{score} of 76.36%, while the KNN, Digital Twin, and SVM-LINEAR approaches have got slightly higher outcomes. In addition, the DP-GAN, HOS-Bayes and ResNeXt-22 methodologies have attained reasonable and closer result. Finally, the QCEDRL-MIFDC technique has achieved maximal performance with $accur_y$ of 96.13%, $preci_n$ of 88.81%, $recal_l$ of 79.50%, and F_{score} of 83.52%.

Figure 11 exhibit the computational time of the QCEDRL-MIFDC method with other models. Based on CT, the QCEDRL-MIFDC technique has got lower value with CT of 1.58s, while the GNB, KNN, DP-GAN, Digital Twin, HOS-Bayes, ResNeXt-22, and SVM-LINEAR have obtained higher value with CT of 4.92s, 7.86s, 6.21s, 4.34s, 6.85s, 7.13s, and 7.81s, respectively.

Table 6 represent the computation efficiency of the QCEDRL-MIFDC approach using FLOPs(M), GPU(M), and Inference time (ms). Based on inference time, the outcome indicated that the QCEDRL-MIFDC method has reaches minimal value of 1.38 ms, FLOPs of 2.76M and GPU of 934M, whereas the ResNet-31, ResNeXt-22, DenseNet-37, VggNet-18, Inception-ResNet-59, and FCNet-5 methodologies have attains maximal value of 2.77 ms, 6.85 ms, 3.38 ms, 7.10 ms, 3.23 ms and 6.77 ms, respectively.

Compared to the deep learning architectures, QCEDRL-MIFDC needs 2.76M FLOPs, 934M GPU usage, and 1.38 ms of inference time, while the deep learning architectures need higher inference time ranging from 2.77 to 7.10 ms. The lesser number of computations can be associated with two architectural features of the proposed framework. The hybrid feature-selection stage, which is the first stage, minimizes the original sensor representation by selecting 24 features from 36 features. This minimises the amount of redundant information fed through the next learning stages. Second, QVAET first learns a latent representation of the data before doing any contextual analysis, which enables the Transformer to work with a representation that is much smaller than the original feature space. Before that, the measured computational efficiency is coupled with the

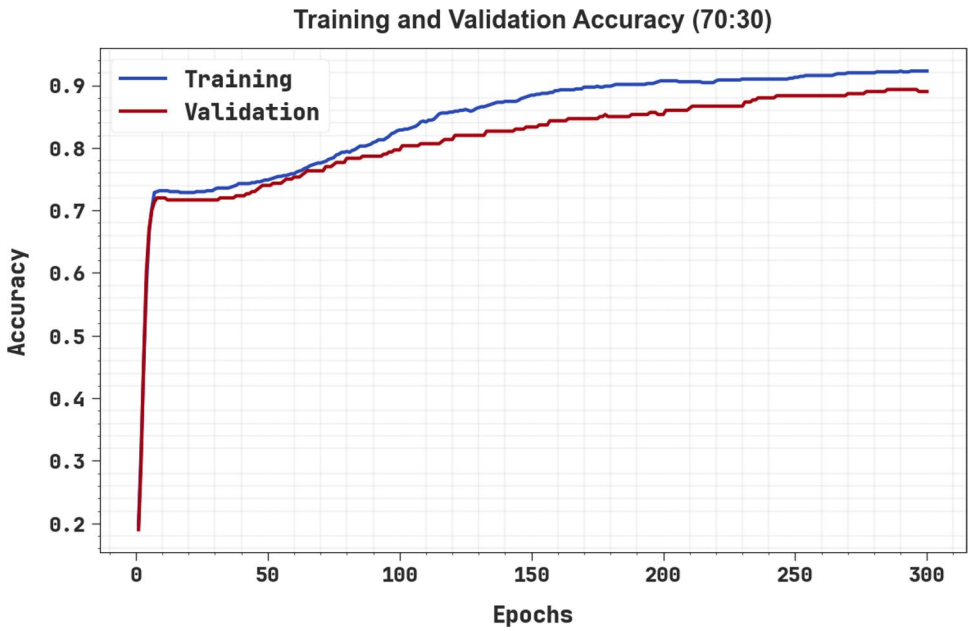


Fig. 9 Training and validation accuracy curves of the QCEDRL-MIFDC approach with 70:30 split

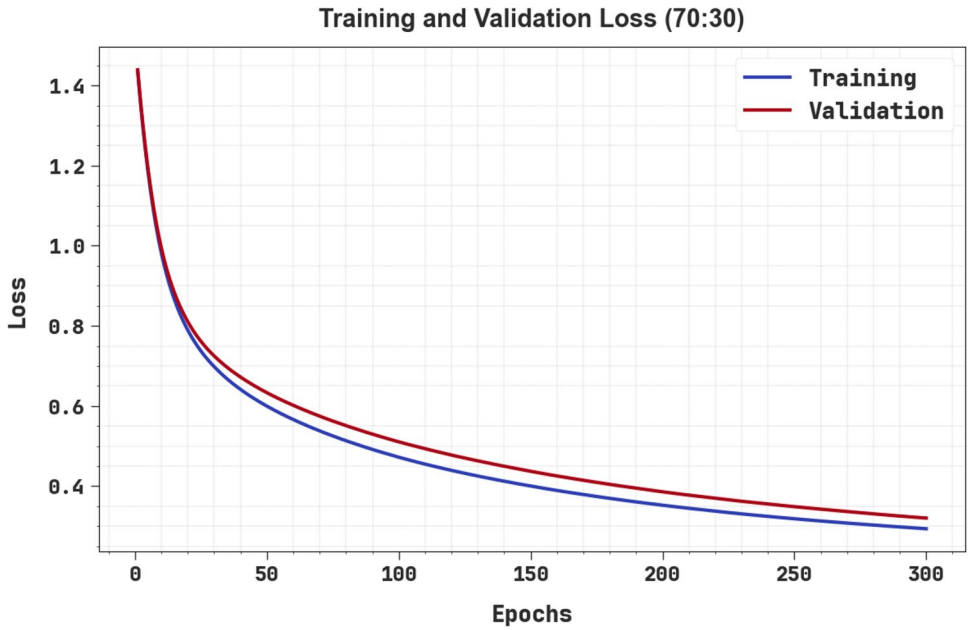


Fig. 10 Training and validation loss curves of the QCEDRL-MIFDC approach with 70:30 split

Table 5 Comparative result of the QCEDRL-MIFDC approach with existing methodologies

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)	Computational time (sec)
GNB	73.10	82.51	69.54	75.43	4.92
KNN	79.80	65.75	69.00	67.34	7.86
DP-GAN	95.30	74.39	74.19	74.29	6.21
Digital twin	80.00	65.92	70.24	68.01	4.34
HOS-Bayes	91.76	79.66	77.04	78.33	6.85
ResNeXt-22	94.30	81.80	71.04	76.04	7.13
SVM-LINEAR	90.79	78.39	75.44	76.89	7.81
QCEDRL-MIFDC	96.13	88.81	79.50	83.90	1.58

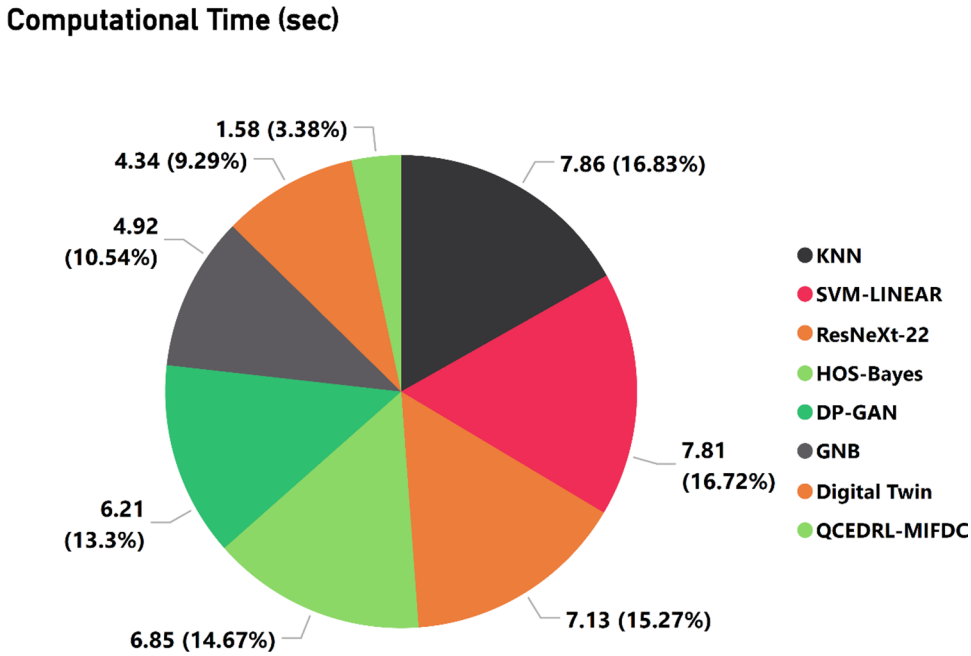


Fig. 11 Computational time comparison of the QCEDRL-MIFDC approach with existing models

Table 6 Computation efficiency of the QCEDRL-MIFDC method with other techniques

Models	FLOPs (M)	GPU (M)	Inference time (ms)
ResNet-31	5.89	4018	2.77
ResNeXt-22	58.50	3659	6.85
DenseNet-37	624.06	2363	3.38
VggNet-18	8.53	4361	7.10
Inception-ResNet-59	9.89	4963	3.23
FCNet-5	209.92	2020	6.77
QCEDRL-MIFDC	2.76	934	1.38

combination of feature reduction and compact latent representation learning.

The comparison of the two settings: 80:20 and 70:30 reveals that the overall performance of the proposed framework remains unaffected when the proportion of training data is changed. In the training part, the average accuracy goes up from 96.13% to 96.07% and the average precision goes up from 88.81% to 85.47%. The average accuracy ranges from 93.00% to 94.67% for the same test portions, and the average recall ranges from 72.21% to 72.38% for the same test portions. The relatively stable accuracy and recall scores suggest that the framework is not reliant on any specific partition setting. The precision and F-score changes, however, show that the reduced training set can have an impact on the representation of minority fault classes. This is in line with the class imbalance of the data set and suggests that broader cross-domain generalization needs to be validated with larger data sets.

The proposed QCEDRL-MIFDC framework has synergic integration of hybrid feature optimization and contextual representation learning, which accounts for the superior performance. The hybrid feature selection stage proved to be efficient in eliminating redundant attributes in the sensors and retaining meaningful relationships between correlated variables. Then the QVAET architecture learns discriminative latent representations and captures contextual dependencies between the sensor observations, which allows for more accurate separation of similar fault categories. The proposed framework can be beneficial for the Industry 4.0 manufacturing scenario from an industrial perspective as it can enable early fault detection, lower the risk of unexpected equipment downtime, ensure more industrial operational reliability, and enhance decision-making in the manufacturing environments.

5 Conclusion

This study has proposed a QCEDRL-MIFDC approach. The aim of the proposed model is to classify faults in industrial systems utilizing quantum computing models. Initially, data preprocessing is performed through encoding, outlier removal and data normalization to assure high-quality data. Besides, the model utilizes a hybrid feature selection approach integrating LASSO, EN, AL, and GL to recognize the most relevant and informative features. For fault detection, a QVAET system is leveraged to categorize four types of faults: 0-no fault, 1-overheating, 2-leakage and 3-power fluctuation. Eventually, model training is carried out utilizing the Nadam optimizer to effectively update parameters and accelerate convergence. The experimental outcomes of the QCEDRL-MIFDC system is performed utilizing benchmark Industrial Fault Detection Dataset. Although, the classification of industrial faults reached encouraging results, there are some drawbacks in this study. The benchmark dataset is moderately imbalanced with samples, affecting the performance of the minority fault class (recall). To validate the proposed framework with larger industry standard datasets like CWRU and real-time industrial monitoring environment can be done in future. The proposed framework could also be improved by incorporating additional explainable AI mechanisms, statistical significance analysis methods, and enhanced minority fault learning strategies, which would further enhance its robustness and interpretability. Extensive comparative results report the promising performance of the QCEDRL-MIFDC model over recent state of art approaches. The QCEDRL-MIFDC framework shows competitive fault classification performance, there are still some limitations. First, the number of normal samples in the Industrial Fault Detection Dataset is 725, while there are only 91 samples of overheating, 95 of leakage and 89 of power fluctuation. The class imbalance is moderate and may negatively affect the representation of minority fault patterns during model training and is seen especially in the recall of some of the fault categories. Hence, future studies are carried out on learning strategies aware of the minorities, such as class-weighted objectives and precise oversampling, while maintaining the original-distribution evaluation as a benchmark. Secondly, the present study is based on one publicly available industrial fault dataset. Two train–test configurations (80:20 and 70:30) were employed to look at performance consistency, but cross-dataset generalization has yet to be established. The framework will then be addressed with larger, independently gathered industrial datasets, such as the CWRU and other machinery-fault benchmarks, to test its robustness in both equipment type and operating condition and in the distribution of faults. Third, the experiments in the present research were carried out based on the structured sensor observations and simulation-based learning environment. Thus, the performance of the framework in response to real-time sensor streams, measurement noise, communication issues, environmental changes and varying operating conditions needs to be further explored. Future work will include real-time industrial

data and controlled interference conditions to evaluate any robustness and deployment feasibility. Last, the ablation of the components of the integrated framework of hybrid feature selection, QVAET representation learning and Nadam optimization is not contained in the current experimental design. Future studies will focus on the contribution of the hybrid LASSO strategy, QVAET module and Nadam optimizer separately and will also explore explainable AI and statistical significance analysis. These extensions can give more evidence on the level of contribution, interpretability, and statistical robustness of the components.

Authors' Contributions C. Santhosh— Concept creation, methodology, software, drafting the first copy of the paper R. Sivaraj—Literature review, methodology, supervision, reviewing the original draft M. Vijayakumar—Concept, simulation, validation.

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Data Availability The data that support the findings of this study are openly available in Kaggle repository at https://www.kaggle.com/datasets/programmer3/industrial-fault-detection-dataset/data, reference number (Barma et al. 2025).

Declarations

Competing Interests The authors declare no competing interests.

Consent for Publication Not Applicable.

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