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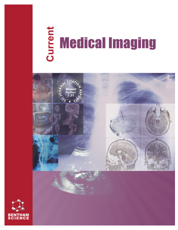

RESEARCH ARTICLE

Classification of Pneumonia *via* a Hybrid ZFNet-Quantum Neural Network Using a Chest X-ray Dataset

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Abstract:

Introduction:

Deep neural networks (DNNs) have made significant contributions to diagnosing pneumonia from chest X-ray imaging. However, certain aspects of diagnosis and planning can be further enhanced through the implementation of a quantum deep neural network (QDNN). Therefore, we introduced a technique that integrates neural networks with quantum algorithms named the ZFNet-quantum neural network for detecting pneumonia using 5863 X-ray scans with binary cases.

Methods:

The hybrid model efficiently pre-processes complex and high-dimensional data by extracting significant features from the ZFNet model. These significant features are given to the quantum circuit algorithm and further embedded into a quantum device. The parameterized quantum circuit algorithm using qubits, superposition theorem, and entanglement phenomena generates 4 features from 4098 features extracted from images *via* a deep transfer learning model. Moreover, to validate the outcome measures of the proposed technique, we used various PennyLane quantum devices to detect pneumonia and normal control images. By using the Adam optimizer, which exploits an adaptive learning rate that is fixed to 10^{-6} and six layers of a quantum circuit composed of quantum gates, the proposed model achieves an accuracy of 96.5%, corresponding to 25 epochs.

Results:

The integrated ZFNet-quantum learning network outperforms the deep transfer learning network in terms of testing accuracy, as the accuracy gained by the convolutional neural network (CNN) is 94%. Therefore, we use a hybrid classical-quantum model to detect pneumonia in which a variational quantum algorithm enhances the outcomes of a ZFNet transfer learning method.

Conclusion:

This approach is an efficient and automated method for detecting pneumonia and could significantly enhance outcome measures related to the speed and accuracy of the network in the clinical and healthcare sectors.

Keywords: Machine learning, Deep learning, Transfer learning, Convolutional neural network, Pre-trained model, Quantum computing, Quantum variational circuit, Quantum neural network, Hybrid model, Pneumonia detection, Chest X-rays.

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1. INTRODUCTION

Pneumonia is a rapidly developing lung infection. It can be caused by bacteria or viruses. This condition leads to air sac inflammation and accumulation of fluid in the lining of the lungs, known as pleural effusion. It is a leading cause of death in children under the age of five and is responsible for more than 15% of deaths [1]. The disease is particularly widespread in underdeveloped and developing nations. Overcrowding, pollution, poor hygiene standards, and limited medical

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resources contribute to its prevalence. Hence, prompt diagnosis and treatment play a critical role in preventing the disease from becoming fatal. Diagnostic tools such as computed tomography (CT), magnetic resonance imaging (MRI), or radiography (X-rays) are usually employed for radiological examinations of the lungs. Among these techniques, X-ray is a cost-effective and noninvasive diagnostic technique for assessing lung conditions.

Although chest X-ray examinations are a common tool for detecting pneumonia, they are prone to interpretability and unpredictability [2 - 4]. Hence, a computerized system is needed to improve the accuracy of these methods. This study addresses this need by developing a computer-aided diagnosis (CAD) system. It employs a hybrid combination of CNN models and quantum circuits for precise binary detection of imaging modalities.

Deep neural networks (DNNs) are essential tools in artificial intelligence (AI). Neural networks are used to solve intricate problems related to computer vision tasks [5, 6]. CNN models are algorithms for deep neural network techniques. They are extensively used for detection, classification, and segmentation tasks. However, the optimal performance of these models requires a substantially large dataset. Unfortunately, obtaining a vast dataset for image detection and classification tasks is challenging and time-consuming. Specialists are required to classify every input sample. In this paper, we used the transfer learning technique. This approach provides a useful solution to minimize this challenge. This technique involves utilizing a trained model on a large imaging dataset. Furthermore, this model can be further fine-tuned to solve a specific task involving a smaller dataset. CNN models have been trained on datasets such as ImageNet [7]. It occupies approximately 12 million images. It is frequently used in computer vision applications such as detection and classification tasks.

By leveraging quantum mechanical phenomena, we explore the potential of quantum circuits in various machine learning applications. In this study, we incorporate the use of quantum circuits in our deep learning model to improve its interpretability. Of particular interest is the variational circuit algorithm. It utilizes quantum bits to execute operations on various quantum gates or circuits.

Recent studies have highlighted the potential of hybrid classical-quantum models for diagnosing diseases through medical imaging [8]. Such models offer advantages in processing complex and high-dimensional data efficiently. Moreover, the successful application of deep learning in detecting diseases such as COVID-19 showcases the ability of these models to analyze chest X-ray images accurately [9].

In our study, we devised a novel algorithm. It integrates the ZFNet architecture with the variational circuit algorithm for pneumonia detection. The ZFNet model is used to extract 4098 significant features. These meaningful features are applied to the quantum algorithm. This quantum variational algorithm employs quantum mechanical phenomena. For instance, superposition, entanglement, and interference can enhance the accuracy while utilizing quantum circuit depths. Quantum bits are manipulated using various quantum gates. We tested the efficacy of this hybrid algorithm using X-ray imaging. The quantum-based hybrid neural network model provides a precise pneumonia diagnosis.

The key contributions of our article are as follows:

• To detect pneumonia, we implemented a hybrid ZFNet-quantum neural network model against an X-ray imaging dataset. The network is built using a pre-trained ZFNet neural network amalgamated with a quantum circuit algorithm to achieve an accurate diagnosis.

• To validate the model's effectiveness, we utilized various quantum devices, namely, the PennyLane default simulator, pennyLane qiskit.aer simulator, and pennyLane qiskit.basicaer simulator.

• To compare the performance of the proposed network, we also trained the imaging data on classical neural networks such as ZFNet, AlexNet, ResNet18, and ResNet34.

The article is organized as follows: Section 2 presents the literature review. We introduce the hybrid ZFNet-quantum neural network algorithm for detecting pneumonia in section 3. The results and analysis using a chest X-ray imaging dataset are analyzed in section 4 and we also compare the performance of pre-trained neural networks with that of the hybrid ZFNet-quantum neural network method. Furthermore, the conclusions of the paper are presented in section 5.

2. LITERATURE REVIEW

2.1. Current Research

Detecting pneumonia from chest X-rays has long been a challenge [10, 11]. The limited availability of public data complicates this issue. Extensive machine learning (ML) techniques have been explored to address this challenge. For instance, the authors [12] used an X-ray dataset to extract features for classification. They extracted 8 significant feature vectors by segmenting regions to classify them. They exploited a multilayer perceptron (MLP) classifier and achieved 95.39% accuracy. Moreover, the authors [13] employed 11 insightful features for pneumonia detection using a schizophrenia patient dataset. They tested several machine learning algorithms, such as regression models based on logistic regression and classification models based on support vector machines and decision trees. However, these methods lack generalizability. They were trained on trivial datasets.

Compared to ML modeling, which requires the extraction and selection of handcrafted features for solving particular tasks such as classification, detection, recognition, and segmentation [14, 15], DNN models enable end-to-end classification and detection tasks without manually extracting handcrafted features [16, 17]. Various fields utilize deep learning-based models [18 - 22], and multiple researchers have proposed biomedical image detection techniques. The limitations and future directions of image processing techniques utilized in the medical sector were explored [23]. CNN architectures are mostly compatible with solving image-related detection and classification problems, as they extract significant features by convolving input images with filters. Because of their translation invariance and superior performance in image classification tasks, CNNs are preferred over traditional image processing methods and machine learning algorithms, making them a popular choice among researchers.

In their studies [24, 25], the authors developed a simple CNN model using an X-ray imaging dataset for the classification of healthy controls from pneumonia patients. Both studies utilized a data-augmented approach to address the limited availability of data. The CNN model [24] achieved a classification accuracy of 90.68%, while another study [25] obtained a higher accuracy of 93.73%. However, it should be noted that data augmentation can only help improve the size of the dataset. The outcome measures of CNNs can or cannot be improved. The DenseNet-121 architecture was employed [26], and the authors obtained 76.8% accuracy in detecting pneumonia. They further analyzed the poor performance of their model by suggesting that they lacked a patient history dataset.

The authors [25, 27 - 31] utilized CNN models for classifying pneumonia and reported promising results. The latter study aimed to clarify the effectiveness of customized CNNs in distinguishing healthy controls from pneumonia patients and distinguishing between contagious and virus-related types of pneumonia in pediatric X-rays. The authors [32] segmented lung images and further utilized various augmentation methods to identify pneumonia using a CNN model based on segmented regions. Similarly, the authors [33] also used augmented techniques based on the AlexNet and GoogLeNet architectures and achieved an accuracy of 95%. The authors [34, 35] used convolutional neural networks to classify pneumonia. In a study [36], the authors employed a CNN structure and introduced a different objective function, sinloss, to detect pneumonia. Some aouthors used Mask-RCNN for pulmonary image segmentation and pneumonia identification, incorporating both global and local features while also applying dropout and L2 regularization [37].

Furthermore, transfer learning has emerged as an advanced technique for solving the issue of data insufficiency in computer vision applications. This approach involves utilizing information carried out using large datasets to train a network on existing smaller datasets for solving specific tasks. Recent studies [38 - 41] have exploited transfer learning methods by leveraging various CNN architectures already trained on the ImageNet dataset [26] for pneumonia classification.

Recent explorations into hybrid classical-quantum networks offer promising directions for enhancing computational performance in medical diagnostics. In Alzheimer's disease detection, a novel approach showed significant improvements in processing efficiency and diagnostic accuracy, demonstrating the potential of quantum computing in healthcare [8]. Brain tumor classification has also benefited from hybrid deep-learning models, yielding high accuracy in identifying tumor types [42]. These advancements highlight the growing interest in integrating quantum computing with traditional machine learning for medical applications. Moreover, the application of deep learning to detect COVID-19 from chest X-rays achieved remarkable accuracy, emphasizing the power of CNNs in medical image analysis [43]. The evolving field of medical image fusion, through techniques such as anisotropic diffusion and cross bilateral filtering, further illustrates the potential for advanced algorithms to improve diagnostic accuracy and support clinical decision-making [44].

Transformer-based models and context-aware networks have recently gained traction in medical image analysis, offering improved performance in complex tasks. For example, the Context-aware Network Fusing Transformer and V-Net have been applied for semisupervised segmentation of the 3D left atrium, showing promising results in improving segmentation accuracy in challenging medical images [45]. Additionally, an actor-critic-based detection and semi-supervised segmentation approach for the 3D left atrium from LGE-MRI has demonstrated the effectiveness of integrating reinforcement learning techniques with deep learning models for precise medical image analysis [46]. These advancements suggest that transformer-based models could offer new avenues for enhancing pneumonia detection.

This literature demonstrates the CNN model's robustness in classifying pneumonia disease using a pretrained neural network [47]. Nevertheless, this model has certain drawbacks and restrictions, such as training speed, which decreases according to the complexity of the dataset and model, high-dimensional datasets, and graphics processing unit (GPU)/tensor processing unit (TPU) requirements, which can affect the model's performance and effectiveness. Therefore, this study implements the hybrid ZFNet-quantum neural network approach to enhance the model's classification accuracy and speed. This approach employs quantum parameterized circuits to optimally process quantum data [48]. This study focuses on hybrid models that extract informative feature vectors using neural networks and merge them with variational circuits to perform detection tasks [49 - 51]. Additionally, hybrid models utilize transfer learning amalgamated with quantum algorithms [8, 52 - 54] to maximize performance outcomes and speed up computer vision tasks.

2.2. Research Gap

Previous studies have made significant strides in detecting pneumonia using machine learning and deep learning models. Researchers have employed CNN models extensively. These methods have demonstrated success in classifying pneumonia from chest X-rays. Despite these advancements, challenges remain. The availability of large, annotated datasets is a hurdle. This limits the performance of deep learning models. Transfer learning has offered a pathway to mitigate this challenge. It leverages pretrained models to enhance classification tasks with smaller datasets. However, the potential for further enhancing accuracy and efficiency in pneumonia detection exists.

Hybrid classical-quantum neural network models present a promising solution. They have shown remarkable results in medical diagnostics. The detection of Alzheimer’s disease using these models has proven more efficient. It has demonstrated higher accuracy than classical approaches. Similar improvements have been noted in brain tumor classification. These successes underscore the potential of quantum computing to revolutionize medical imaging analysis.

The current research has not fully explored the integration of quantum computing with deep learning in pneumonia detection. This gap indicates an opportunity. A hybrid ZFNet-quantum neural network model could significantly improve diagnostic processes. It can offer better accuracy and efficiency. This approach would be particularly beneficial in clinical settings. Therefore, rapid and accurate diagnosis is critical.

Moreover, advancements in medical image fusion techniques suggest additional pathways for innovation. These methods have shown potential in enhancing image analysis. They do so by improving the clarity and detail of medical images. Integrating these techniques with hybrid quantum models could further advance pneumonia detection capabilities.

In summary, the research gap lies in the unexplored integration of quantum computing with deep learning for pneumonia diagnosis. The potential for hybrid models to enhance diagnostic accuracy and efficiency is significant. This study aims to address this gap. This study seeks to contribute to the field by demonstrating the efficacy of a ZFNet-quantum neural network model in detecting pneumonia from chest X-rays.

3. METHOD

3.1. Pretrained CNN Model

A conventional DNN is capable of receiving raw data as input and automatically identifying the necessary relationships to carry out classification. These networks are called deep neural networks and are composed of multiple layers of nodes that can find hidden pattern representations and compute mappings *via* nonlinear activation independently. The entire classical network is formed by concatenating multiple layers together. The DNN model is represented in the form of an equation and is given as [49]:

$$\mathcal{L}i = \sum_{k=1}^{n} x_k \rightarrow y_k = \phi(\mathrm{W}x_k + b) \quad (1)$$

where x_k represents the classical input vector, y_k denotes the classical output vector, W and b are the weights and biases of the network, Ø is the nonlinearity introduced in the network and *Li* represents the layers of the network.

ZFNet is a type of CNN architecture that consists of an 8-layer CONVNet model. The architecture of the ZFNet model is illustrated in Fig. (**1**), which describes the model's input and processing steps. We use 224x224x3 images as our input. The 1st layer consists of 96 filters of size 7x7 and nonlinear activation functions such as ReLU are applied. Then, it is followed by a max pooling layer with a stride of 2. The next layer consists of 256 filters, each utilizing a 3x3 size. These filters are once again subjected to local contrast normalization. The 3rd and 4th layers of the architecture produce 384 3x3 filters with a stride of 1. The 5th layer includes 256 3x3 filters, followed by the max pooling layer, which has a 3x3 filter size. This layer also utilized local contrast normalization. The 6th and 7th layers are composed of 4096 units. In the end, the output layer is connected and consists of 1000 neurons, which represents the number of classes. In our case, there were two classes, pneumonia patients and normal controls, so we used a binary classifier to distinguish between them using X-ray data.

ZFNet is an improved variant of AlexNet that achieves higher accuracy. A key difference between the two approaches is that ZFNet uses 7x7 filters, whereas AlexNet uses 11x11 filters. This is because larger filters tend to discard a significant amount of pixel information, which can be preserved by using smaller filter sizes in earlier convolutional layers. The number of filters increases as the network depth increases, and ReLU activation functions are used. As a result of these modifications, our new architecture of ZFNet was able to retain more information in the convolutional layer features.

3.2. Quantum Circuit Algorithm

Quantum computers leverage quantum mechanical properties to achieve complex computational tasks. Unlike

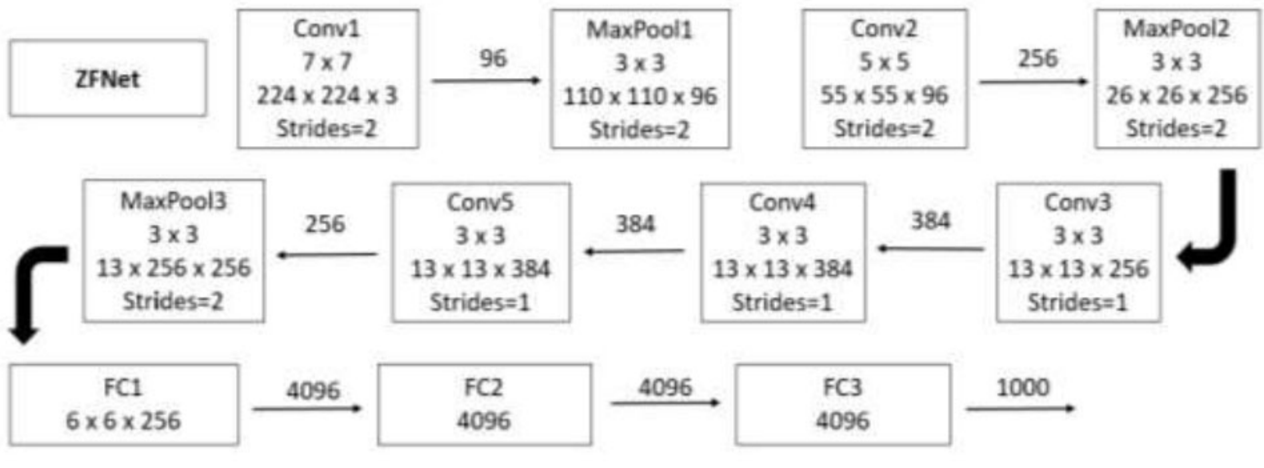

Fig. (1). Schematic of a classical convolutional neural network.

classical computers, which utilize binary bits that can only exist as 0 or 1, quantum computers employ qubits that can instantaneously occur in numerous states, enabling vastly more intricate computations to be carried out. Qubits serve as the fundamental building blocks of quantum computers and can be embodied by particles such as atoms, ions, or photons. The state of a qubit is characterized by a quantum state vector, which can be composed of complex combinations of multiple states simultaneously. This property enables quantum computers to perform significantly more complex computations faster and more efficiently than classical computers.

Superposition is a key concept in quantum computing that refers to a qubit's capacity to exist in numerous states simultaneously. This attribute enables a single qubit to perform multiple computations concurrently, resulting in highly efficient computations. Specifically, a qubit can represent both 0 and 1 at the same time, which allows for faster and more efficient computation compared to classical computers.

$$A|\phi\rangle = \binom{\vartheta}{\delta} = \vartheta|\mathbf{0}\rangle + \delta\,|\mathbf{1}\rangle \qquad (2)$$

where v and δ represent complex numbers and satisfy the given equation $|\vartheta^2| + |\delta^2| = 1$.

Entanglement is another fundamental concept in quantum computing that describes the correlation between two or more qubits. If we change the state of one qubit, it automatically affects the state of the other qubit. This capability facilitates the development of potent algorithms that can address intricate problems that are beyond the capacity of classical computers.

In quantum computing, interference occurs when two or more quantum states combine to produce a new state. This phenomenon enables quantum systems to execute specific types of computations considerably faster than conventional computers.

A quantum circuit is a model used to describe the behavior of quantum systems, particularly in quantum computers. It is similar to classical circuits in that it involves a sequence of operations that act on input qubits to produce output qubits. Each qubit in the QVC is represented by a line, and the operation performed on each qubit is denoted by a gate that transforms the state of the qubit. Commonly used symbols to represent gates include the Hadamard gate, CNOT gate, and Toffoli gate. The output of the circuit is determined by measuring the state of the qubit. Quantum circuits have various applications, including quantum simulation, quantum cryptography, and quantum error correction. They are also used to implement quantum algorithms that can resolve several tasks more proficiently than conventional algorithms.

Quantum gates are operations that manipulate the state of a quantum system by acting on qubits (quantum bits), and in quantum computing, they are characterized by unitary matrices. The basic unitary gates include the Pauli gates (X, Y, and Z) and the Hadamard gate (H), among others. Each gate is associated with a unitary matrix that describes how it transforms the state of a single qubit. By combining these gates, more complex quantum circuits can be created, and the resulting unitary matrix for the circuit can be utilized to simulate its behavior on a quantum computer. Unitary matrices are crucial in quantum computing because they preserve the norm of a vector, which ensures the conservation of probabilities during quantum operations.

$$\acute{U}\,\acute{U}^{\dagger} = \acute{U}^{\dagger}\acute{U} = \boldsymbol{I} \qquad (3)$$

where $\boldsymbol{I}$ is the identity matrix, U is the unitary matrix and U† represents the unitary transpose matrix.

This study utilized the chest X-ray dataset and applied the hybrid ZfNet quantum circuit model for training. The learning process was carried out using quantum variational circuits, which have shown promising results in image classification and detection and offer advantages over classical learning techniques. A QVC is a type of quantum circuit in which the circuit parameters are used to prepare a quantum state. The QVC typically consists of layers of gates that act on a set of

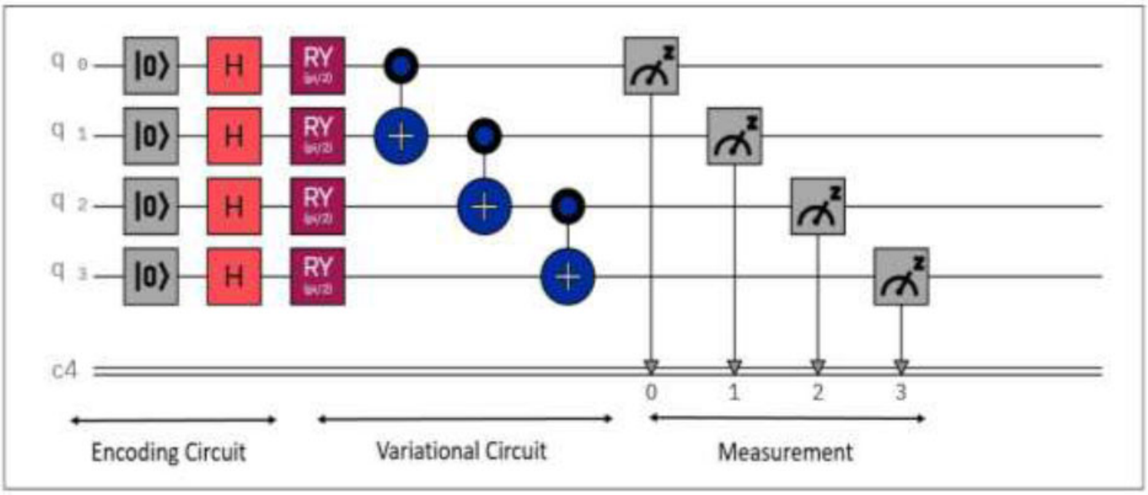

Fig. (2). Schematic of the quantum variational circuit.

qubits. The gates in each layer are chosen from quantum gates, such as single-qubit rotations and two-qubit entangling gates. The parameters of the circuit are associated with the angles of the single-qubit rotations and the entangling gates. The main steps involved in a variational quantum circuit are encoding state, variational circuit design, and quantum measurement state, as shown in Fig. (**2**).

3.2.1. Encoding Circuit

The initial step is encoding the classical vector into a quantum vector. Quantum encoding serves as a framework that connects the classical input data A with its corresponding quantum state |Ai. It generates a quantum embedding state from the classical input vector, essentially mapping classical data to quantum states.

$$\boldsymbol{Y}: \mathrm{A} \rightarrow |\mathrm{A}\rangle = (\mathrm{A})|\mathbf{0}\rangle \quad (4)$$

3.2.2. Variational Circuit Design

The QVC circuit is designed by choosing a set of quantum gates to act on a set of qubits. These gates typically include single-qubit rotations and two-qubit entangling gates.

$$\acute{\mathrm{U}}(\vartheta)|\Phi\rangle = \left(\prod_{i=1}^{j} \acute{\mathrm{U}}_i\right)|\Phi\rangle \quad (5)$$

3.2.3. Quantum Measurement

In the quantum measurement state, the quantum vector is converted into a classical vector.

$$\mathrm{S}: |\mathbf{X}\rangle \rightarrow \mathbf{Y} = \langle \mathbf{X}|\mathbf{Y}|\mathrm{X}\rangle \quad (6)$$

The quantum variational circuit can be represented in the form of an equation and is given as

$$\boldsymbol{qvc} = \mathrm{S} \cdot \mathcal{L} \cdot \boldsymbol{Y} \quad (7)$$

where ***Y*** denotes the encoding circuit, S represents the decoding circuit at the measurement layer and *qvc* is called the quantum variational circuit.

The circuit parameters are adjusted using a classical optimization algorithm to optimize a specific objective function. This optimization can be performed using a variety of classical optimization techniques, such as the Adam optimizer. Overall, the main idea of a parameterized quantum circuit is to use circuit parameters to prepare different quantum states and optimize a specific objective function using classical optimization algorithms.

The hybrid ZFNet-quantum neural network algorithm is given below. First, the dataset is organized and preprocessed before being fed into the Hybrid ZFNet-quantum neural network. ZFNet generates meaningful features. The significant feature vector is applied to QVC, which encodes the classical vector into the quantum vector by creating superposition and entanglement states utilizing various quantum gates. Finally, a measurement state is used to decode the quantum vector into a classical vector, which is then fed into the last layer of the CNN for classifying the chest X-ray imaging dataset.

Hybrid ZFNet-quantum neural network Algorithm

Input: Chest X-ray imaging data has been applied as input to detect pneumonia

Output: To classify pneumonia from healthy controls using a hybrid ZFNet-quantum neural network model

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Steps:

- First, download the dataset from the Kaggle database and labeled it.
- Then, preprocess and normalized the images database.
- Extract significant features from the dataset by using convolutional neural network architecture such as ZFNet and give to QVC. The variational circuit algorithm is given as follows:

Quantum Circuit algorithm	
$\mathcal{D} = (\mathbf{X}n, \mathbf{Y}n)$	Classical dataset
$\frac{1}{\sqrt{j}}\sum_{i=1}^{j}\lvert i\rangle X_i$	Converting classical dataset into a quantum dataset
$\frac{1}{\sqrt{j}}\sum_{i=1}^{j}\lvert i\rangle\lvert M(X \cdot X_i)\rangle$	To create a superposition state by using an inner product
$\lvert \boldsymbol{M}^*\rangle = \frac{1}{\sqrt{f}}\sum_{i=1}^{j}\lvert i\rangle M(X \cdot X_i)$	To decode the quantum data into classical data
$\boldsymbol{M}^*$	Returning value $\boldsymbol{M}$

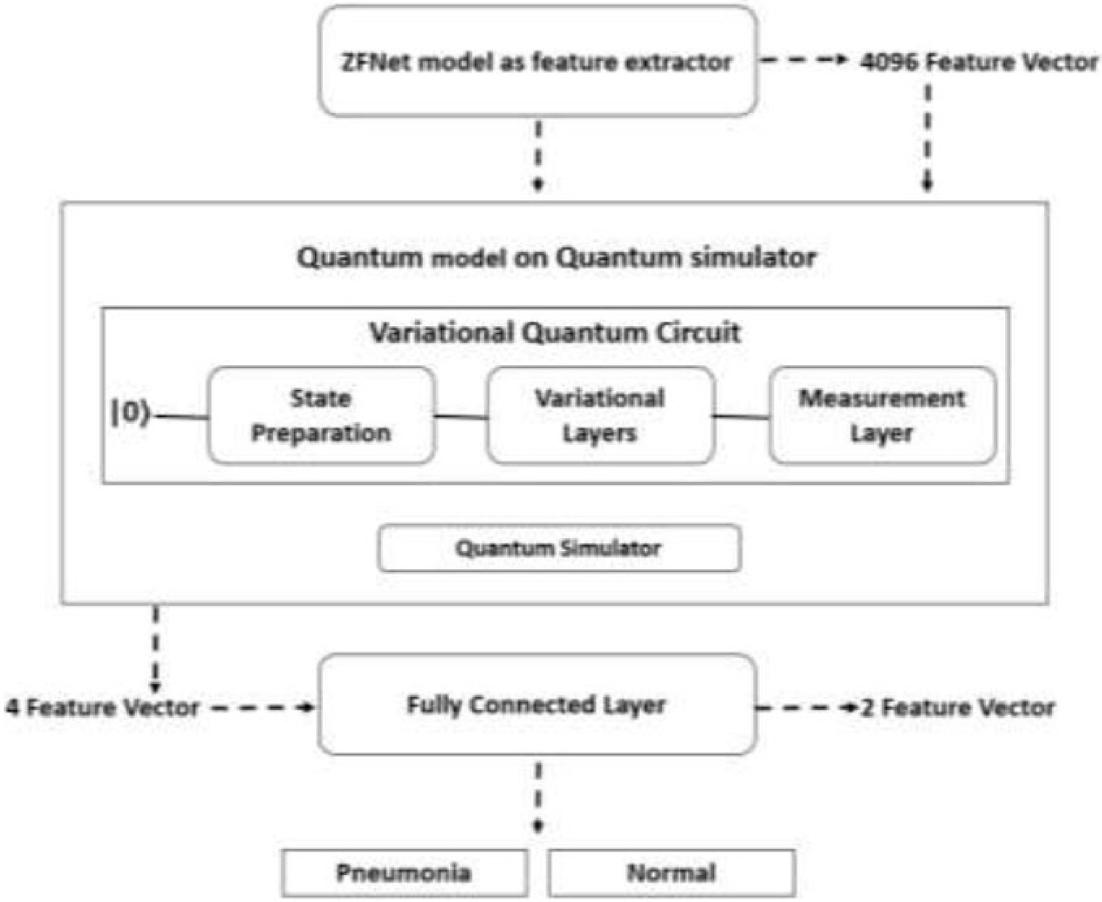

Fig. (3). Hybrid ZFNet-quantum neural network.

3.3. Hybrid ZFNet-Quantum Neural Network

In our research paper, we present an innovative approach for detecting pneumonia using a transfer learning approach based on ZFNet and a quantum circuit algorithm applied to a chest X-ray dataset. Our model incorporates a CNN architecture to extract significant features, which are then fed as input to a quantum circuit for pneumonia classification from healthy controls. Specifically, we constructed a hybrid model that combines the ZFNet architecture with the variational circuit algorithm on the chest X-ray dataset.

A schematic of the hybrid ZFNet-Quantum neural network for pneumonia detection is presented in Fig. (**3**). A hybrid classical-to-quantum transfer learning algorithm involves using classical CNNs as feature extractors and then utilizing quantum algorithms and devices for postprocessing these features. The ZFNet model extracts 4096 significant features that are fed to the quantum model. The quantum circuit model maps the input data into quantum bits by using the Hadamard gate and CNOT gate. The Hadamard gate is used for the state preparation of qubits, and to transform the state of qubits to another state, the CNOT gate and the rotational gate are used and the measured outputs correspond to the classification labels of the task. The quantum circuit outputs 4 feature vectors and is connected to a nontrainable matrix that feeds into a binary classification layer to distinguish pneumonia patients from healthy controls. The hybrid classical to quantum transfer learning approach is presented as follows:

$$\mathcal{L}_{4\rightarrow 2} \cdot \mathrm{QVC} \cdot \mathcal{L}_{4096\rightarrow 4} \tag{8}$$

where $\mathcal{L}_{4096\rightarrow 4}$ is the classical feature extractor vector that gives 4096 vectors to the QVC, $\mathcal{L}_{4\rightarrow 2}$ is the output given by the QVC circuit, and fit is given to the last fully connected layer for classification between pneumonia patients and normal controls.

3.4. Transfer Learning

In deep learning, it is considered better to start with a pre-trained model rather than training an entire network from scratch and then manipulating the final layer according to the given requirements, as demonstrated in Fig. (**4**). When dealing with small datasets, pretrained methods can successfully perform specific tasks and provide beneficial results. In deep learning, there are two types of transfer learning. One is fine-tuning, in which pretrained models are used for training, and the other is feature extraction, in which we freeze the first layers and adjust the last layer to further train the network and perform the specific task [51].

The transfer learning technique involves utilizing the knowledge and information gained from a previous task to improve performance on a new, related task. Rather than starting from scratch with a new dataset to train the model, transfer learning permits us to leverage what was learned in the prior task as a starting point for the new one, reducing the need for data and computation. Numerous studies suggest that, in many cases, it is more advantageous to use a preexisting deep neural network rather than training an entirely new model from scratch. Fine-tuning the last layer to cater to a precise task serves as an effective technique for addressing small dataset challenges using the DNN model. The pretrained model has already resolved a particular problem, and it can be repurposed to address different yet similar issues. These pretrained models are usually trained on large datasets such as ImageNet or COCO for image-related tasks.

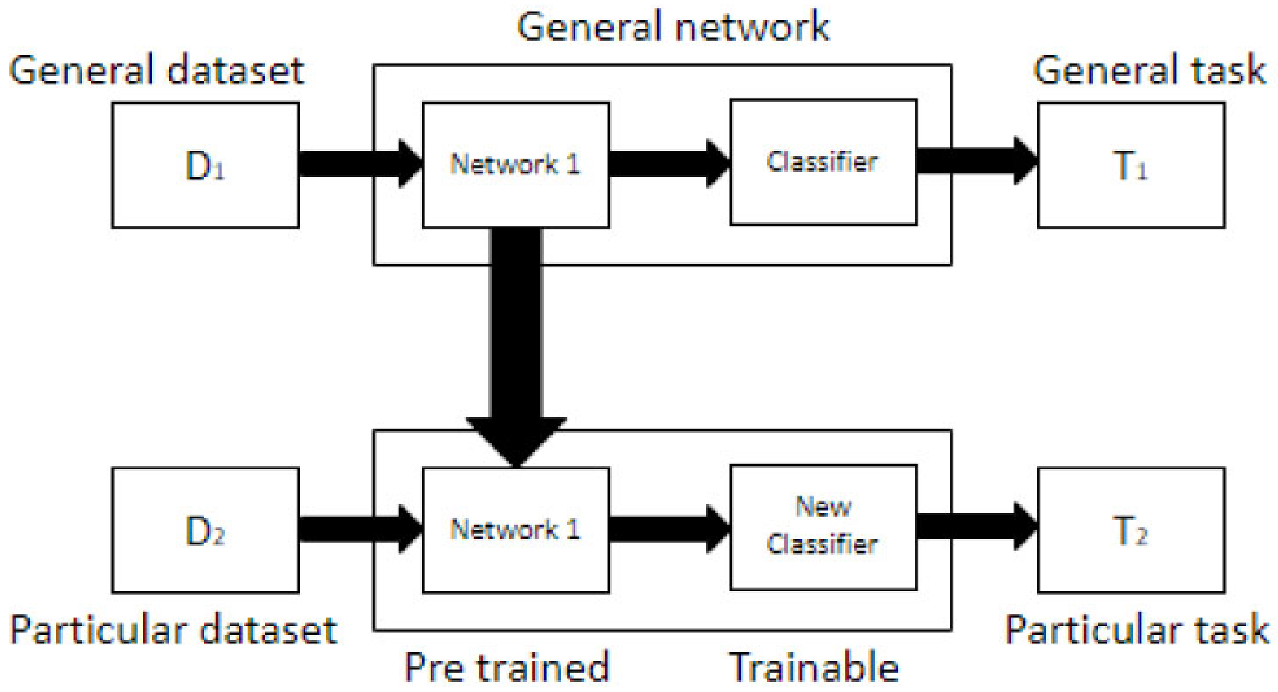

Fig. (4). Demonstration of the transfer learning method.

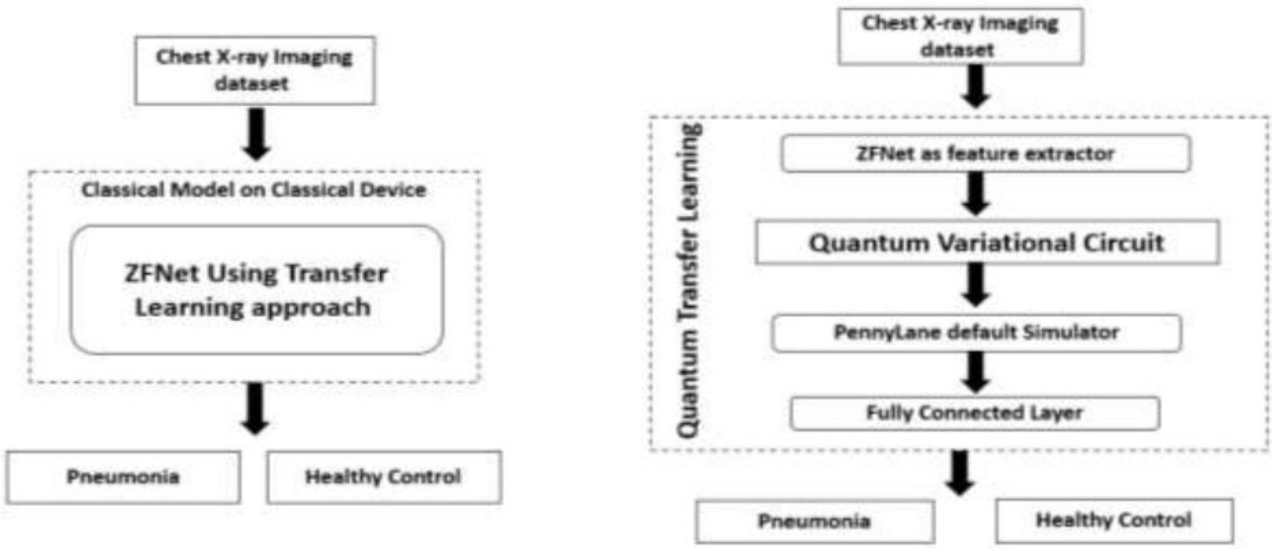

Fig. (5). Transfer learning using the ZFNet model and a transfer learning approach using a hybrid ZFNet quantum neural network.

In deep learning, two common approaches to transfer learning are used. The first is fine-tuning, and the second is feature extraction.

1. Fine-tuning involves using a pretrained model as a starting point for training on a new task. The parameters of the pretrained model are adjusted, and new layers are added on top of it to suit the new task. This approach helps in eliminating the random initialization of the network. To fine-tune a model, the pretrained model is trained on smaller amounts of data specific to the new task, and a lower learning rate is used to prevent overfitting.

2. Feature extraction involves using a pretrained model to extract relevant information from the input. In this approach, the weights of all layers in the pretrained model are frozen, except for the last layer, which is then trained for the new task.

In this work, two stages were utilized to solve the binary classification task. The first is the classical transfer learning approach. In this method, we utilized a ZFNet pretrained neural network model as a feature extractor. In the end, a new classifier layer is added to the network so that it can be trained on a new dataset. The second is the quantum transfer learning approach, in which the classical model is used to extract significant features from the dataset. A significant feature is given to the QVC circuit, in which various quantum simulators are used. Finally, the QVC circuit with the new classifier layer is trained on a new dataset, as shown in Fig. (**5**). Our study focused on employing the transfer learning approach using a hybrid ZFNet-quantum neural network to detect pneumonia utilizing different quantum simulators.

4. RESULTS AND DISCUSSION

4.1. Dataset Description and Preprocessing

The Kaggle platform was used to download the dataset. The dataset contained two binary classes, pneumonia and normal control cases, comprising a total of 5863 images. The dataset was organized into three main folders (train, test, and val) with subfolders for each image category (pneumonia/normal). The dataset was split such that 80% was allocated for training the network and 20% of the dataset was used for testing the network.

Before network training, preprocessing techniques must be applied to the imaging dataset. Preprocessing of the X-ray images was performed in three steps. First, we used data-augmented techniques such as resizing, cropping, rotating, and flipping the training examples to avoid overfitting and enhance efficiency and robustness. Next, the dataset was converted into PyTorch tensors. Finally, in the normalization step, the input samples were normalized to a range of 0 to 1.

4.2. Pneumonia Detection Using a ZFNet Pretrained Network

This experiment aimed to use a DNN architecture to distinguish pneumonia patients from healthy controls. A transfer learning method was employed, utilizing pretrained models such as ZFNet to classify healthy and pneumonia patients. The ZFNet architecture, which is based on the transfer learning approach, has been trained on X-ray imaging. The last layer of ZFNet is used as a classifier and is responsible for classifying the output vector against the imaging dataset. Common hyperparameters utilized in deep learning to train the classical ZFNet model on chest X-ray datasets are as follows:

4.2.1. Optimizer

The optimizer is used to update the network parameters, such as weight and biases during the training of the model. In this method, we used the Adam optimizer to update the learning parameters for the ZFNet model on the X-ray dataset. It is particularly suitable when dealing with large datasets, which makes it computationally efficient.

4.2.2. Learning Rate

The Adam optimizer uses a step size of 10−6 to update the model parameters during training.

4.2.3. Batch Size

The batch size is defined as the number of training examples passed through the network during training, and in this method, we set the batch size equal to 16.

4.2.4. Epochs

The complete dataset that passes multiple times through the network during model training is called the epoch, and it is set to 25.

4.2.5. Activation Function

ReLu is used as an activation function to introduce nonlinearity in the network.

4.2.6. Cost Function

This computes the difference between the actual output and the predicted output. To improve the accuracy of the DNN, the objective function must be minimized during backpropagation. In this approach, we used cross entropy to minimize the error during the training of the network.

Table **1**. The hyperparameter values for the ZFNet pretrained approach.

The common methods for evaluating model performance are the accuracy, recall, precision, F1-score, and confusion matrix, which are defined as follows:

4.2.7. Accuracy

Accuracy is a metric used to evaluate the performance of a model, particularly for binary and multiclassification problems. It is used to determine the correct predictions classified by the model.

$$Accuracy = \frac{\mathcal{T}p + \mathcal{T}n}{\mathcal{T}p + \mathcal{T}n + \mathcal{F}p + \mathcal{F}n} \quad \textbf{(9)}$$

4.2.8. Precision and Recall

These are useful performance measures for balanced and imbalanced classification problems where the distribution of classes is even or odd. The precision evaluates the performance of the model by determining true positive predictions from all positive predictions. Recall measures the performance of the model by evaluating the true positives from all real positive labels in the dataset.

$$Recall = \frac{\mathcal{T}p}{\mathcal{T}p + \mathcal{F}n} \quad \textbf{(10)}$$

$$Precision = \frac{\mathcal{T}p}{\mathcal{T}p + \mathcal{F}p} \quad \textbf{(11)}$$

4.2.9. F1-score

F1-score is a metric that is used in DNNs for binary classification tasks, and it integrates recall and precision to evaluate the complete outcome measure of the model.

$$F1 - Score = \frac{Recall \times Precision}{Recall + Precision} \times 100 \quad \textbf{(12)}$$

The model performance on the X-ray imaging modality using a pretrained ZFNet model is presented in Table **2**.

The confusion matrix is represented in the form of a matrix that shows true positive and negative labels and false positive and negative predicted labels. The ZFNet model is implemented on an imaging set, and the following confusion matrix illustration is presented in Fig. (**6**) for the ZF pretrained network.

A graphical representation of the training accuracy and training loss for pneumonia classification on the ZFNet pretrained approach is presented in Fig. (**7**).

4.3. Pneumonia Detection Using a Hybrid ZFNet-Quantum Neural Network

We proposed a CNN architecture based on a quantum circuit algorithm termed "Hybrid ZFNet-quantum neural network" for X-ray classification tasks. The proposed model is implemented by integrating a classical neural network with a quantum circuit for detecting pneumonia in healthy controls in an imaging dataset. In a hybrid model, the 4098 feature vector is taken from the ZFNet architecture and applied to an algorithm based on a quantum circuit. It is composed of qubits, rotations, and CNOT gates. Moreover, we train the hybrid model using various quantum simulators by integration with the PyTorch library to validate the speed of the model.

Table 1. Hyperparameter values of the ZFNet pretrained model.

Name of Hyperparameters	**Loss Function**	**Learning Rate**	**Epochs**	**Optimizer**	**Decay**	**Batch Size**
Standards	Cross Entropy	10^{-6}	25	Adam	1×10^{-4}	16

Table 2. Performance of the ZFNet pretrained model using an X-ray imaging modality.

Model	**Imaging Modality**	**Precision (%)**	**Test Accuracy (%)**	**F1- score (%)**	**Recall (%)**
ZFNet pretrained neural network	X-ray	92	94	93	91

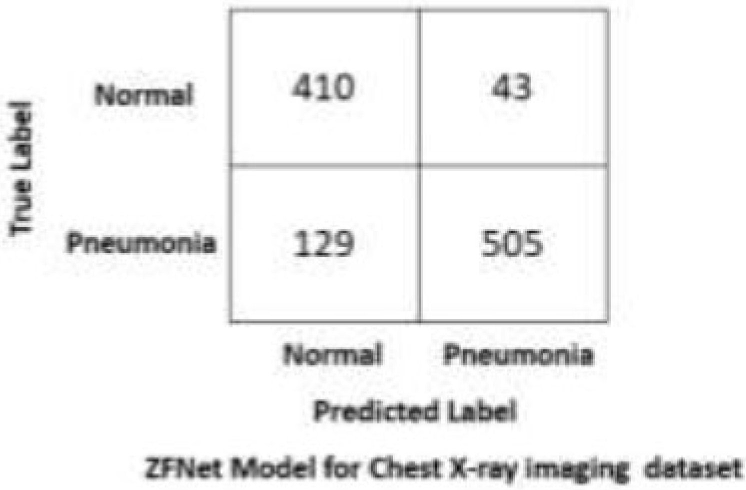

Fig. (6). Confusion matrix using the pretrained ZFNet model for the chest X-ray imaging dataset.

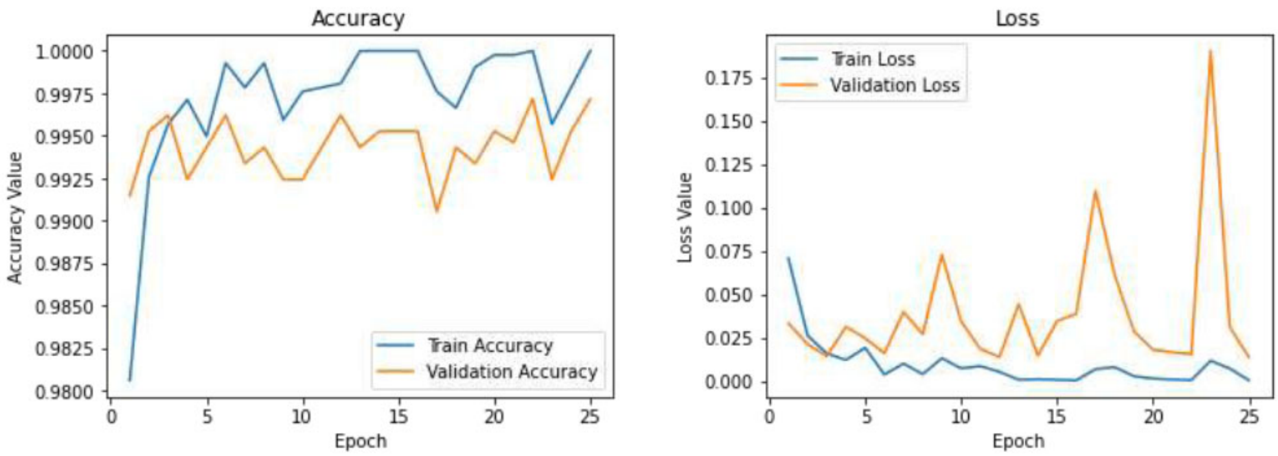

Fig. (7). Accuracy and loss plot for the ZFNet pretrained model with respect to the number of epochs.

Several hyperparameters need to be set during training to achieve the optimal outcomes of the implemented technique. Various hyperparameters were utilized for training the proposed hybrid approach on the imaging dataset. A learning rate of 10^{-6} was chosen to determine the loss function at the minimum point. The number of data images applied to the model for training is called the batch size, and it is equal to 16. The complete dataset passed through the network multiple times is called the epoch, and it is set to 20. The loss function used during backpropagation was cross-entropy. To update the learning parameters of the implemented hybrid technique, the

Table 3. Hyperparameter standards for the hybrid ZFNet-quantum neural network.

Names of Hyperparameters	Batch Size	Circuit Depth	Learning Rate	No. of Qubits	Loss Function	Epochs
Standards	16	6	10^{-6}	4	Cross Entropy	25

Table 4. Performance of the hybrid ZFNet-quantum neural network using chest X-ray imaging.

Proposed Hybrid Model on various Devices	Database	F1-Score(%)	Recall(%)	Precision(%)	Test Accuracy (%)
PennyLane simulator	X-ray	94	93.5	89	97.5
PennyLane qiskit.aer simulator	X-ray	91	91.5	92	95.5
PennyLane qiskit.basic.aer simulator	X-ray	90.5	91	92	95

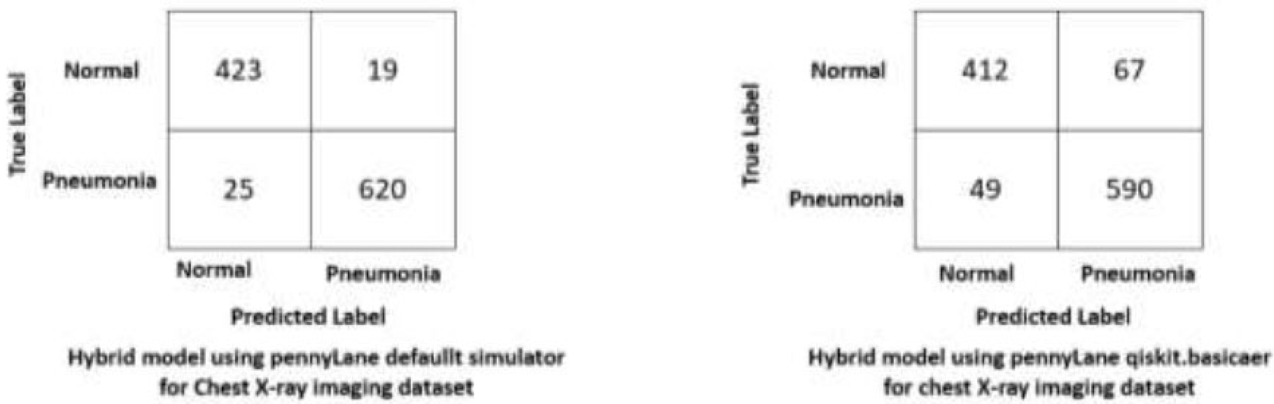

Fig. (8). Confusion matrix using the hybrid ZFNet-quantum neural network for the X-ray dataset.

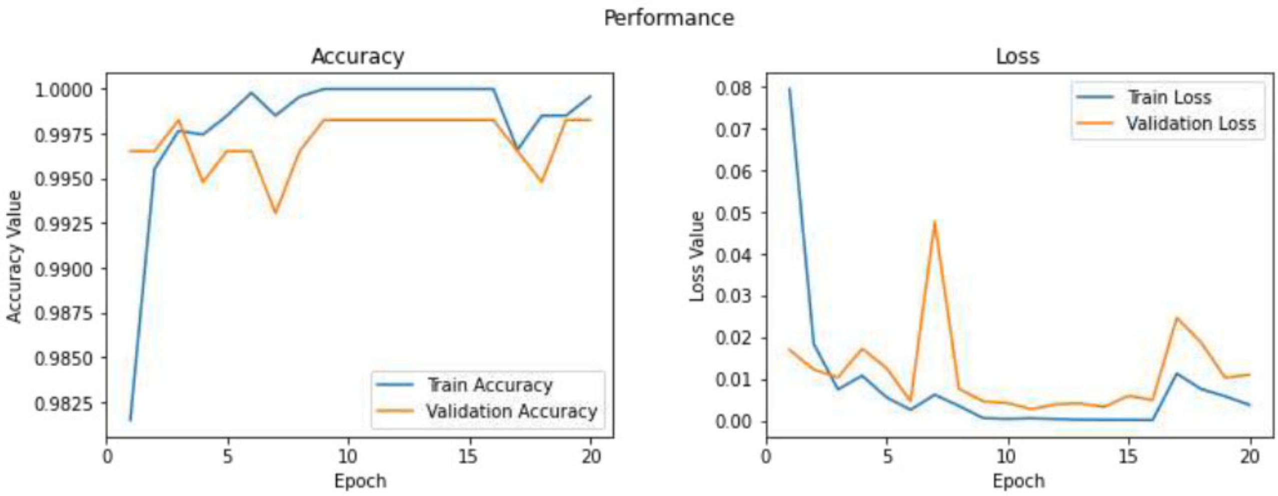

Fig. (9). Accuracy and loss plot for the Hybrid ZFNet-quantum neural network with respect to the number of epochs.

Adam optimizer algorithm was utilized. The number of quantum bits used for converting the data and preparing the state was 4, and the circuit depth layer corresponded to 6. The hyperparameters and their corresponding values are presented in Table **3**.

Table **4** shows the performance metrics against the implemented technique in detecting pneumonia using X-ray data. We utilized the PennyLane library to implement the hybrid model and chose the PennyLane default simulator and qiskit.basicaer to run the network. The hybrid model was further integrated with the PyTorch library for binary classification. The results obtained from various simulators leveraging the X-ray database are presented in Table **4**.

Fig. (**8**) depicts the confusion matrix for the implemented hybrid ZFNet-quantum neural network against the chest X-ray dataset. Moreover, Fig. (**9**) presents a graphical representation of the accuracy and loss across several epochs for pneumonia detection with the proposed model.

The X-ray imaging data were also utilized to implement classical CNNs, namely, AlexNet, ResNet18, and ResNet34, to compare their performance with that of the implemented approach for pneumonia detection. The proposed model outcomes are compared with those of classical convolutional networks, and the results are presented in Table **5**. This table demonstrates that the implemented model, which incorporates a hybrid ZFNet-quantum neural network, achieves enhanced performance outcomes when it leverages the X-ray database.

The results of the ablation study are summarized in Table **6** below.

The testing accuracy and F1-score of the CNNs based on classical methods and the proposed method against chest X-ray imaging are presented in the form of a graph and are shown in Figs. (**10** and **11**).

Table 5. The performance outcomes on an imaging database using a classical convolutional neural network.

Model	Imaging Modality	Precision(%)	Recall(%)	F1- score(%)	Test Accuracy(%)
AlexNet	X-ray	91	93	89	90
ResNet18	X-ray	89	90	87	91.5
ResNet34	X-ray	88.5	89.9	93	90.5
ZFNet	X-ray	92	91.5	93	94
Proposed model	X-ray	89	93.5	94	97.5

Table 6. Performance metrics for the ablation study on the Hybrid ZFNet-quantum neural network.

Model	Precision(%)	Recall(%)	F1- Score(%)	Test Accuracy(%)
ZFNet	92	91.5	93	94
Proposed model usingPennyLane simulator	89	93.5	94	97.5
PennyLane qiskit.aer simulator	92	91.5	91	95.5
PennyLane qiskit.basic.aer simulator	92	91	90.5	95

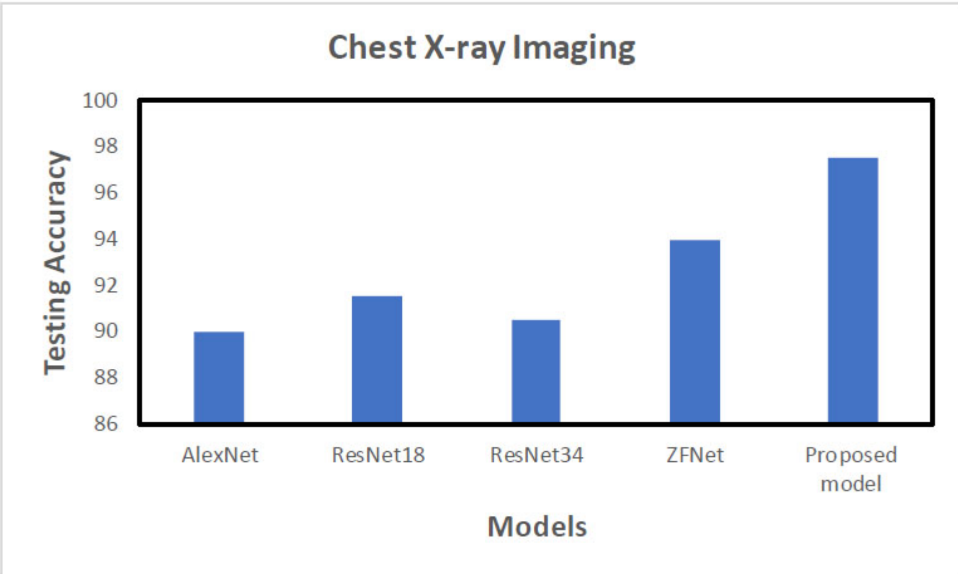

Fig. (10). Comparison between the classical model and a hybrid model concerning testing accuracy.

Furthermore, the hybrid ZFNet-quantum neural network implemented in this study was compared with other state-of-the-art CNN models using the chest X-ray dataset. The results of this comparison are presented in Table **7**. The table demonstrates that the approach employed, which integrates convolutional networks with quantum circuits, achieved superior performance in terms of testing accuracy compared to existing classical methods. Additionally, a graphical representation of the comparison with a state-of-the-art model can be observed in Fig. (**12**).

Table 7. Comparison of the proposed hybrid with existing classical networks.

Reference	Imaging Modality	Method	Testing Accuracy (%)
[27]	X-ray	CNN	92.4
[25]	X-ray	2D-CNN	93.73
[28]	X-ray	DenseNet-121	97
[29]	X-ray	CNN	96.2
[30]	X-ray	CNN	96
[31]	X-ray	CNN	94
[34]	X-ray	Xception model	87

(Table 7) contd.....

Reference	Imaging Modality	Method	Testing Accuracy (%)
[38]	X-ray	ensemble model	94
[39]	X-ray	Residual network	95
[40]	Chest X-ray (CXR) scan images	AlexNet	94
[41]	chest X-ray images	VGG16	96
[26]	ChestX-ray14	CheXNet	80
[45]	X-ray	Context-aware Network	90.09
[46]	X-ray	Actor-Critic based detection and segmentation	92.76
[47]	X-ray	ResNet50	93.06
[55]	X-ray	Vision Transformer	96.45
[56]	X-ray	Vision Mamba	96.6
Proposed Hybrid Method	X-ray	Hybrid ZFNet-quantum neural network	97.5

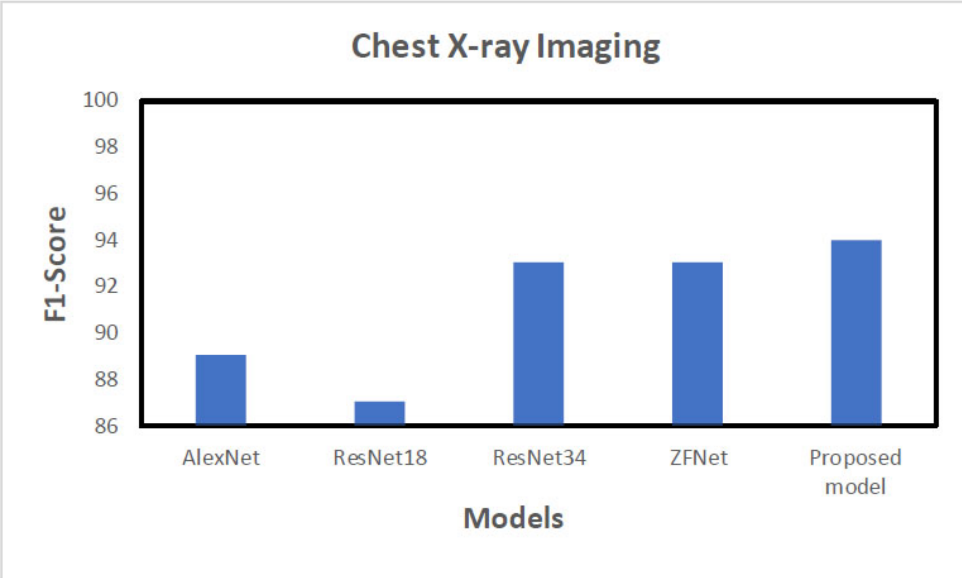

Fig. (11). Comparison between the classical model and a hybrid model concerning the F1 score.

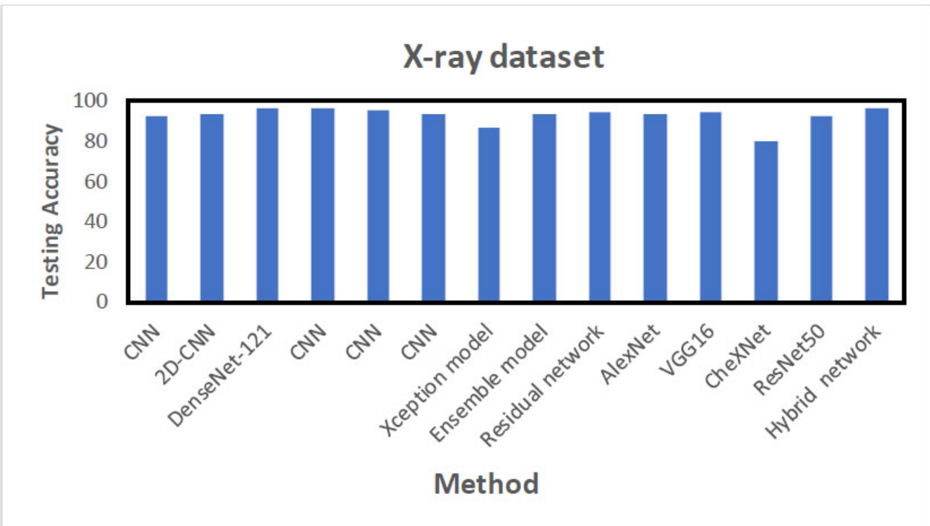

Fig. (12). Comparison between the CNN architecture and the hybrid network.

In this study, we implemented the hybrid ZFNet-quantum neural network against chest X-ray imaging data. For comparison purposes, we also implemented classical CNN architectures such as ZFNet, AlexNet, ResNet18, and ResNet34 for binary classification of pneumonia patients from healthy controls. The proposed model achieved 97.5% accuracy, and the classical model achieved 94% accuracy. This shows that when a classical neural network is integrated with a quantum variational circuit, it reduces the number of circuit learning parameters that minimize the computational intricacy of the model, which helps improve the performance of the model.

Quantum learning algorithms leverage quantum mechanics phenomena, and these quantum properties help in developing variational and parameterized quantum circuits. We further used these quantum properties in the field of ML and deep neural networks to solve image-related tasks such as object detection, classification, and segmentation in CAD systems.

Furthermore, various quantum devices, such as the pennyLane default simulator, qiskit.aer simulator, and qiskit.basicaer simulator, were used to train the hybrid model. These quantum devices are used for improving the speed and accuracy of the network because the circuit parameters are learned from the unitary matrix. Compared with classical methods, quantum computing has more computational power for high-dimensional datasets.

The healthcare sector utilizes practical applications of quantum computing to provide better health-related services, optimize prices, advance e-health systems, and speed up diagnostic procedures. The biomedical data are presented in complex and raw form. The application of quantum computing in computer vision and image-related tasks helps in finding meaningful information and patterns from complex data in clinical settings. In the future, real quantum hardware devices can be used to implement the hybrid classical-quantum neural network and can also be used to solve multiclassification tasks.

CONCLUSION

In this paper, we implemented a hybrid technique to classify pneumonia using X-ray imaging data. The hybrid model integrates two fields—classical deep learning and quantum computing—and is employed against a chest X-ray imaging dataset. Informative features from high-dimensional data were extracted using the ZFNet model and quantum circuit algorithm to classify the imaging dataset. Moreover, we also utilized the classical transfer learning method to train a ZfNet model on the same imaging dataset. Then, a comparison between the performance outcomes of the proposed hybrid approach and the classical CNN architecture is presented. We conclude that the hybrid ZFNet-quantum neural network improves the testing accuracy and other outcome measures, as this technique helps in extracting significant feature vectors by leveraging quantum circuit algorithms and quantum simulators, which increases the training speed of the model. This advanced computational algorithm will help provide feasible and viable solutions in the healthcare and clinical sectors.

AUTHORS' CONTRIBUTION

It is hereby acknowledged that all authors have accepted responsibility for the manuscript's content and consented to its submission. They have meticulously reviewed all results and unanimously approved the final version of the manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

Not applicable.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The datasets used in this study are publicly available at https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia?resource=download

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None.

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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