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Quantum-Classical Framework for Tamil Handwritten Character Classification using SQCNN and Bayesian-Optimized VQC

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Abstract. Handwritten character recognition for Tamil characters is challenging because of the characters displaying high level of similarity between them and also due to the variations in different handwriting styles. Quantum CNN models have been explored recently in character recognition tasks especially when the amount of training data is limited. Quantum models have the ability to encode and process the information in higher dimensional spaces using quantum properties like superposition and entanglement. In this paper, a hybrid quantum-classical framework has been proposed which is used for classification of ten handwritten Tamil characters. This hybrid framework consists of a Scalable Quantum Convolutional Neural Network which does patch wise local feature extraction and a Bayesian-optimized Variational Quantum Circuit which is used as a global feature extractor and then final classification is done using a classical fully connected layer. This hybrid model achieves better classification accuracy for Tamil handwritten characters while reducing the total number of trainable parameters required to train the model.

1 Introduction

Handwritten character recognition plays a major role in the field of pattern recognition and is majorly used in applications such as analyzing handwritten documents. Analyzing handwritten characters from regional languages like Tamil are complex because of the natural structure of the characters which have loops and curves and also because of the high similarity between the characters. CNN models have been majorly used for handwritten recognition tasks and they have achieved accurate results in classifying the characters but they are also limited as they need huge amount of datasets for producing accurate results. To address these limitations, quantum CNN models have been introduced which makes use of quantum properties like superposition and entanglement which helps in mapping the classical input data to a richer and high dimensional space which allows for more expressive feature representations compared to classical neural networks while minimizing the total number of trainable parameters. Quantum CNN's [1] were introduced as a quantum counterpart to classical CNN's. They were built upon the convolution and pooling operations of CNN but along with that, they utilized quantum properties to capture the features and correlations in data more effectively. QCNNs

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were very effective in domains such as image classification, pattern recognition where they demonstrated the potential to provide rich expressiveness of data compared to classical models.

Despite these advantages, traditional QCNNs were limited by their scalability issue, primarily due to the constraints in the availability of qubits and circuit depth as they process the entire image at a single time. To overcome these limitations, Scalable Quantum Convolutional Neural Networks [2] were proposed which employed patch-wise processing of the entire image for feature extraction. The entire image is divided into patches and then passed through the SQCNN circuit which reduces the qubit requirements and complexity of the circuit while allowing parameter sharing. SQCNN thus addressed one of the major bottlenecks from QCNN models and is feasible to be applied onto large scale pattern recognition tasks.

To perform classification from the extracted quantum features, Variational Quantum Circuit [3] has been employed. VQCs are parameterized circuits which consist of rotation gates and entanglement gates whose parameters are optimized by classical optimization algorithms. The design of the VQC circuit is very crucial for better training of the model and to achieve better accuracy. The performance of the quantum circuits is highly influenced by the choice of rotation gates and entanglement layers and the circuit depth. Manual selection of these hyperparameters is time-consuming and it reduces the efficiency and scalability of the quantum model. To overcome the limitation of manual selection of the hyperparameters, Bayesian Optimization algorithm [4] has been used to search through the architecture space and selecting the optimal hyperparameters without manual tuning.

In this paper, a hybrid quantum-classical model has been proposed that combines a SQCNN for patch-wise feature extraction and a Bayesian-optimized VQC used for classification. This paper aims to achieve the following primary objectives:

- To develop a hybrid quantum-classical framework that utilizes the expressiveness of quantum models while maintaining computational efficiency
- To implement a Bayesian-optimized VQC to identify the optimal configuration of VQC circuit architecture.
- To reduce the high-dimensional input features into quantum feature representations using scalable QCNN techniques.

2 Related Work

Handwritten character recognition is an important problem in pattern recognition, playing a crucial role in many applications including document digitization and human–computer interaction. Traditional deep learning techniques, particularly CNNs have achieved notable success in this domain. Recently, quantum machine learning models such as Quantum Neural Networks and Quantum Convolutional Neural Networks [1] have been used for image classification tasks due to their computational advantages.

Data Pre-processing is a fundamental step in image classification tasks, as it transforms raw data into a suitable form for encoding into quantum circuits. Wang et al. [5] developed Variational Quantum Deep Neural Networks (VQDNN) incorporating PCA dimensionality reduction method to overcome qubit constraints, demonstrating feasibility on MNIST [6] and UCI [7] datasets in simulation. PCA reduces the number of features in an image which helps in enabling the data to be represented within the limited qubit resources available on current quantum simulators. This preprocessing step is crucial because current quantum devices can only encode data between 10 to 30 qubits.

Data encoding is an essential component of quantum models, as it is used to convert the classical features into quantum state amplitudes that are further processed by quantum circuits. Various data encoding techniques are present where Rath and Date [8] performed a comparative analysis of classical to quantum mapping techniques including basis, angle and amplitude encoding, finding angle encoding to be the most effective in preserving classification accuracy and F1 scores across multiple classical machine learning classifiers. Magallanes et al. [9] introduced a learnable angle encoding technique that reduces qubit usage and circuit depth where the encoding angle parameters are trained during the learning process. Gong et al. [1] proposed a hybrid QCNN architecture using a tree-structured hybrid amplitude encoding combining angle and amplitude encoding to embed classical features into quantum states.

Sun et al. [2] introduced a Scalable Quantum Convolutional Neural Network (SQCNN) that combines quantum properties with convolutional neural networks to efficiently extract spatial features from image patches. This method achieves better accuracy for image classification tasks when compared to the previous quantum models mainly because of their scalability. The feature extraction is done patch wise where the full image is split into smaller patches and these smaller patches are then processed by separate quantum circuits. This method thus reduces the total number of qubits required to represent the entire image. However, limitations such as the dependence on a fixed quantum circuit architecture is a constraint.

Mangini et al. [10] designed a hybrid pipeline combining classical autoencoders with quantum neural classifiers for industrial data, which improves learning efficiency. Classical autoencoders compress high-dimensional data into compact representations while capturing non-linear feature representations effectively. The compressed data is passed onto the quantum classifiers which process these features to make predictions, combining the strengths of both.

Shi et al. [11] proposed hybrid quantum-classical CNN models for remote sensing image classification, achieving superior performance compared to classical CNNs. This hybrid approach uses classical convolutional layers to obtain initial features from the images, they are then fed into quantum circuits for final classification, reducing the quantum resource requirements. Xiao et al. [12] introduced complex-encoded quantum convolutional neural networks that leverages complex-valued quantum states. Complex encoding uses both the amplitude and phase of quantum states to encode more information per qubit. Mordacci et al. [13] developed multi-class quantum convolutional neural networks designed to handle classification tasks with multiple output classes, extending quantum classifiers beyond binary classification to recognize many classes.

Salehin et al. [14] surveyed automated machine learning techniques focusing on neural architecture search (NAS). Neural architecture search is done to automate the process of designing neural network architectures by evaluating multiple combinations of hyperparameters to identify the optimal model configuration without manual means of trial and error. Various NAS methods have been compared including RL based NAS, evolutionary algorithms and gradient based techniques on benchmark datasets. Tibaldi et al. [4] proposed the Bayesian optimization method for selecting the parameters in Quantum Approximate Optimization Algorithms (QAOA), which demonstrates quicker convergence and a better parameter search when compared to other global optimizers. Bayesian optimization method is useful when designing quantum circuits as it is used to explore the hyperparameter space to find the optimal set of parameters without manual trial and error. Tamiya and Yamasaki [15] introduced Stochastic Gradient Line Bayesian Optimization (SGLBO), which combines stochastic gradient descent with Bayesian optimization for the training of variational quantum circuits. This hybrid approach is used to optimize the circuit which makes training more reliable for various other tasks or datasets. Chen [3] designed an image classification framework using variational quantum algorithms that replaces conventional pooling with quantum feature processing, reducing model parameters and improving performance. Quantum pooling is done to compress information from multiple qubits into fewer qubits, analogous to classical pooling layers that is done to reduce the dimensions of the feature maps while keeping only the important features.

The reviewed literature shows that the existing quantum machine learning models can achieve competitive performance when compared to classical models like CNN's on benchmark datasets, but they are also presented with ongoing challenges like limited qubit availability. Newer approaches like the scalable quantum processes the images patch wise which helps in reducing the qubit count thereby reducing the complexity. Optimization techniques like Bayesian Optimization are helpful as they are used to find out the optimal set of hyperparameters needed to design the quantum circuits faster. These existing methodologies thus provide a foundation for developing classification systems using hybrid quantum-classical models for tasks such as handwritten character recognition.

3 System Design

The proposed hybrid quantum-classical framework is represented in Figure 1 which has been designed for the classification of Tamil handwritten characters. The system includes multiple modules which are: Data pre-processing, Quantum data encoding, Quantum Feature Extraction using SQCNN, Bayesian Optimization of VQC and then the VQC module which is used for final classification. This hybrid framework uses a classical image pre-processing layer and quantum models which are built upon quantum properties and then a fully connected layer used for predictions.

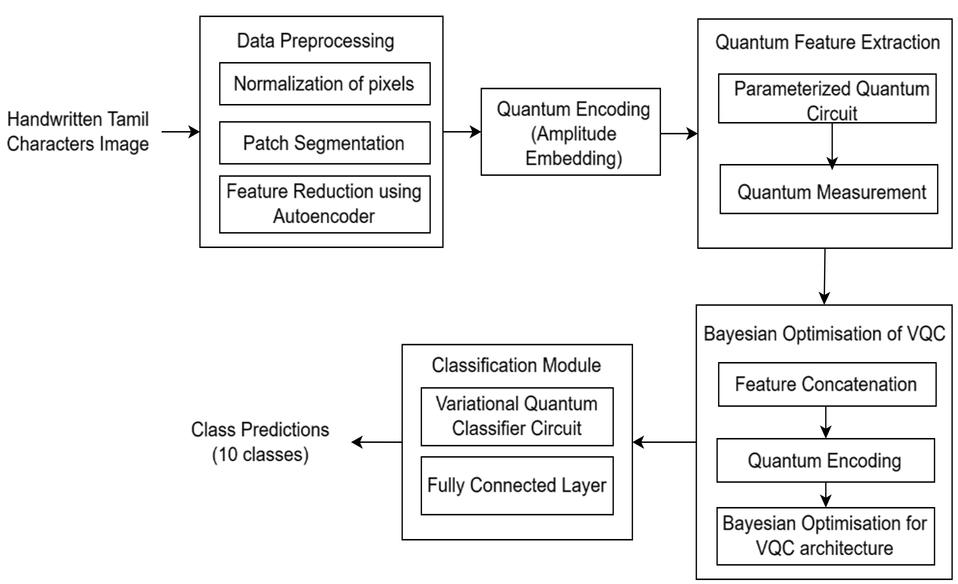

Fig. 1. Hybrid Quantum-Classical Model for Tamil Handwritten Image Classification

4 Module Description

4.1 Dataset Description

The dataset that has been used in this paper is the Unconstrained Tamil Handwritten Character Database (UTHCD) [16]. This dataset contains hundreds of samples of handwritten Tamil characters collected from different individuals across varying writing styles. Each character sample exhibits variations in stroke, shape, curvature, and writing speed. The dataset includes multiple classes representing both the Tamil vowel and consonant set. The images from the dataset are in .bmp format and ten Tamil characters from அ to ஔ were taken for classification in this paper.

4.2 Data Pre-processing

This module takes raw handwritten images from the Tamil characters dataset and prepares them for quantum modules. It includes normalization of the pixel values to a consistent scale. Then patch segmentation has been done for the entire image where the image is divided into four smaller patches and for each patch, feature reduction is done using autoencoders to extract the essential features while reducing the dimensionality of the images and to match the qubit requirements.

4.3 Quantum Encoding

The Data Encoding module is used to transform the classical features obtained through autoencoder into quantum state amplitudes that are further processed by quantum circuits. This module makes use of the Amplitude Embedding [3] technique which encodes the classical feature vector into the amplitudes of a quantum state. Given a normalized classical feature vector $\boldsymbol{x} = [x_0, x_1, \dots, x_{N-1}]$, the corresponding quantum state is expressed as:

$$|\psi(x)\rangle = \sum_{i=0}^{N-1} x_i |i\rangle \qquad (1)$$

where $|\psi(x)\rangle$ is the encoded state and $|i\rangle$ is the i-th basis state. The feature vector is normalized and it must satisfy the condition: $\sum_{i=0}^{N-1} |x_i|^2 = 1$. The square of the amplitude gives the measurement probability for that quantum state. Using amplitude embedding, feature vector from the patches with N features can be represented using only $\log_2(N)$ qubits. This encoding allows the quantum system to represent an exponentially large amount of information with fewer qubits, making it suitable for handling high dimensional datasets.

4.4 Quantum Feature Extraction

The Quantum feature extraction module uses a Scalable Quantum Convolutional Neural Network [2] to obtain the local and spatial features. The SQCNN process the encoded quantum states of each patch through parameterized quantum circuits consisting of rotation gates and entanglement layer which efficiently capture the local features. Rotation gates are applied to every qubit to learn the local features by transforming the qubits and then entanglement layer is implemented using CNOT gate which allows the circuit to capture the correlations between different qubits. This sequence of rotation and entanglement operations are repeated across multiple layers. After obtaining the features, measurement is done using Pauli-Z operator to produce the classical feature vector that retain the essential information from all patches which is passed onto subsequent classification modu les. The gate parameters are then trained so that the resulting quantum circuit learns only the most important features.

4.5 Variational Quantum Classifier

A Variational Quantum Classifier [17] is used for classification tasks where a variational quantum circuit learns to distinguish between different classes of data. The VQC is a parameterized quantum circuit which consists of single qubit rotation gates with trainable parameters and entanglement gates. The VQC module is employed as the classification module which aggregates the local patch wise features from the SQCNN and it applies additional quantum transformations using the rotation and entanglement gates to obtain the global features of the all the patches combined, that is for the entire image. The output of the VQC is measured through Pauli-Z gate which provides the global features which are then passed onto the fully connected network to produce the final class predictions.

4.6 Bayesian Optimization of VQC

The features extracted and measured from the SQCNN module are first aggregated and then re-encoded to serve as inputs for the Variational Quantum Circuit. In order to optimize the performance of the VQC, Bayesian Optimization [4] is used to search through the search space of hyperparameters which then extracts the optimal set of hyperparameters which can be used to design the VQC circuit. This optimization helps in improving the classification accuracy of the model as it selects the hyperparameters like the circuit depth, the choice of quantum gates and the type of entanglement to be introduced, without manual trial and error.

In Bayesian Optimization, the model starts by picking out different VQC architectures and measuring their accuracy. After every trial, the optimizer then builds a probabilistic model known as the Gaussian model which is used to predict the set of hyperpara meters for the next trial. Instead of testing every combination manually, the optimizer uses these predictions to choose the next best configuration to try based on the surrogate model. This makes the search efficient and also avoids unnecessary evaluation s. During each iteration, the VQC performs a forward pass using the current set of hyperparameters defined in the circuit and then the loss is calculated to measure the performance of the model. Based on this feedback, the optimizer decides whether to do exploration or exploitation. Through this iterative loop, the Bayesian optimization algorithm narrows down to the best possible circuit and updates the VQC architecture. The best set of hyperparameters obtained for the VQC circuit is displayed in Table 1 with validation accuracy of 0.5200.

Table 1. Bayesian Optimization Results for VQC Architecture.

Parameter	Value
Number of Iterations	15
Best Validation Accuracy	0.5200
VQC Depth (Layers)	3

Entanglement Topology	Circular
Rotation Gates (Single qubit rotation)	RX, RY, RZ
Best Structure	3L, Circular, RX-RY-RZ

4.7 Model Training

After obtaining the best set of hyperparameters for the VQC circuit, the entire hybrid model including both the SQCNN feature extractor and the VQC classifier is then trained end to end. During training, the feature vectors from the SQCNN are measured and then passed onto the VQC circuit where the encoded input features are processed using trainable quantum gates which after measurement outputs expectation values which represent the important features learnt by the quantum circuit. These quantum derived features are then passed on to a classical fully connected network which combines these features and maps them to class logits. Then, softmax function is applied to the logits to obtain class probabilities for classification.

The hybrid model is then trained end to end by minimizing the cross-entropy loss. Gradients with respect to the quantum circuit are obtained using the parameter shift rule. The Adam optimizer is used to update the parameters iteratively, enabling efficient convergence during training and then parameters of the fully connected neural network layer are updated using the gradients which are obtained through backpropagation and joint optimization of both quantum and classical parameters is done using Adam optimizer.

5 Results and Discussions

The hybrid quantum-classical model was implemented using PennyLane [18], which is an open source Python library which is used for quantum computing and quantum machine learning. PennyLane platform was chosen in this paper because it simplifies the development of quantum models and it also offers a better interface between the quantum circuits and deep learning libraries like PyTorch and TensorFlow which helps well while training hybrid quantum classical models. PennyLane also does automatic differentiation which helps in optimizing the quantum circuit parameters using classical gradient based methods. These capabilities make PennyLane advantageous for building quantum neural networks.

Table 2. Evaluation Results.

Number of Qubits	Evaluation Metrics
6	Accuracy: 0.6678 Precision: 0.7057 Recall: 0.6678 F1-Score: 0.6560
7	Accuracy: 0.6689 Precision: 0.6621 Recall: 0.6689 F1-Score: 0.6619

Previous quantum classification models have shown good results on benchmark datasets like MNIST and Fashion-MNIST but they have not been tested much on complex handwritten datasets like Tamil characters dataset. Thereby in this paper, a hybrid quantum-classical model has been used for classification of Tamil handwritten characters. The hybrid model's performance which is mentioned in Table 2 was evaluated using standard metrics, including accuracy, recall, precision, F1 score and number of qubits. The model was trained for 100 epochs with batch size as 32 and was evaluated on the validation dataset. The model was split into Training data: 6815 samples, Validation Data: 1203 samples and Test data: 1800 samples. The model was compared by encoding the data with both 6 and 7 qubits.

Figure 2 shows the confusion matrix that was obtained during the hybrid model's training phase for the 10 Tamil characters from அ (class 0) to ஓ (class 9). Majority of the values are concentrated along the diagonal which indicates that the model has learned to identify majority of the Tamil characters correctly during training.

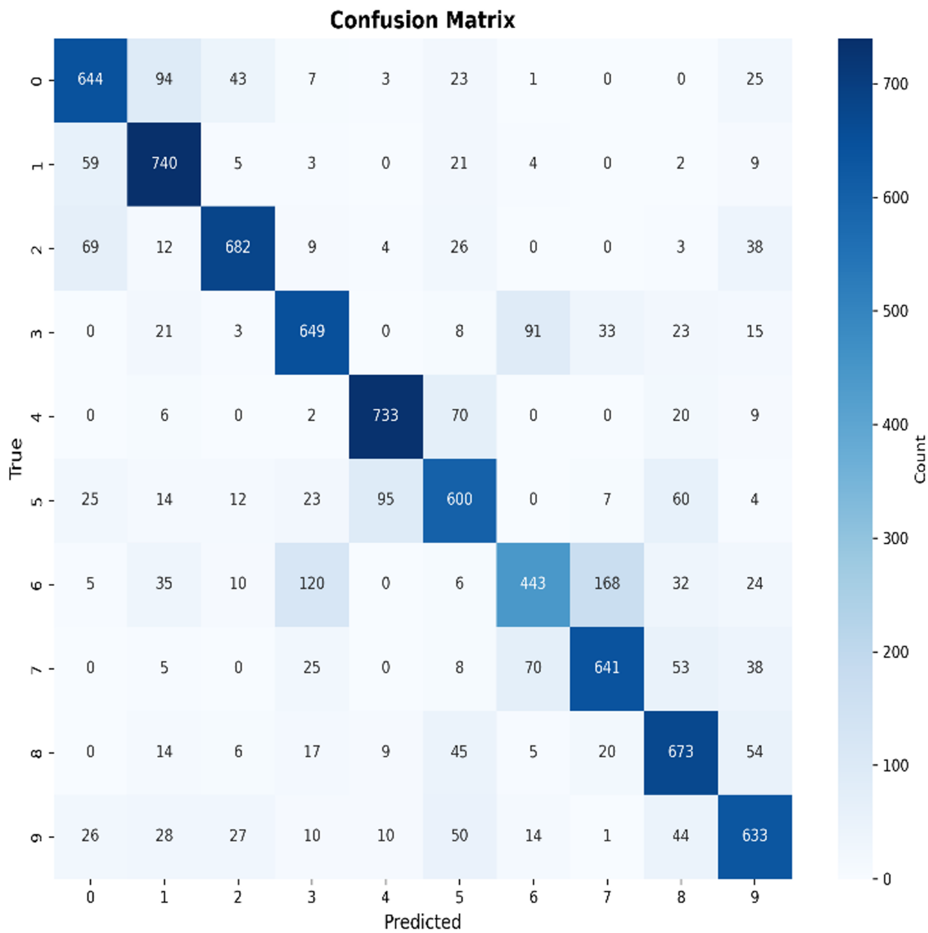

Fig. 2. Confusion Matrix for Training data

Figure 3 illustrates the confusion matrix obtained for the 10 Tamil characters with the test dataset using the hybrid model. The model is able to identify majority of the classes correctly with a high value, particularly for Classes 0, 1, 3, 4, 5, and 9, where the diagonal values representing the count of true prediction is higher when compared to the false predictions.

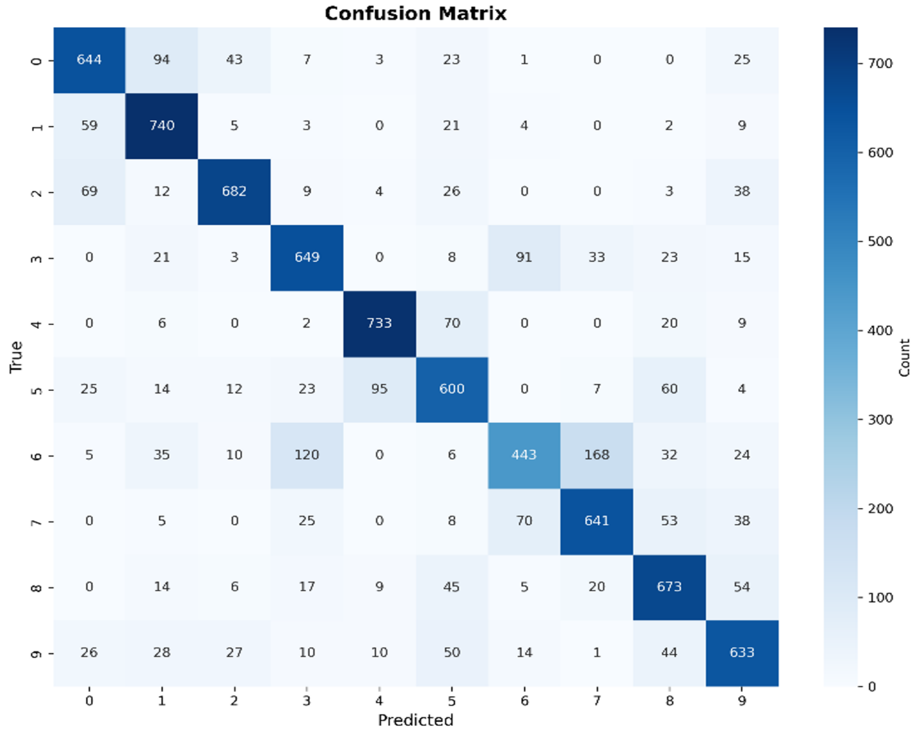

Fig. 3. Confusion Matrix for Test data

Figure 4 illustrates how the accuracy of the hybrid model increases during the training phase. The training accuracy increases along with the number of epochs which means that the model is learning to make better predictions. The validation accuracy also improves over time but with slight changes in the curve which is because of the differences in handwriting styles. The convergence of both the curves indicates that the model is performing well on both the training and validation dataset. This stable accuracy confirms that the hybrid quantum–classical model is learning well from the dataset.

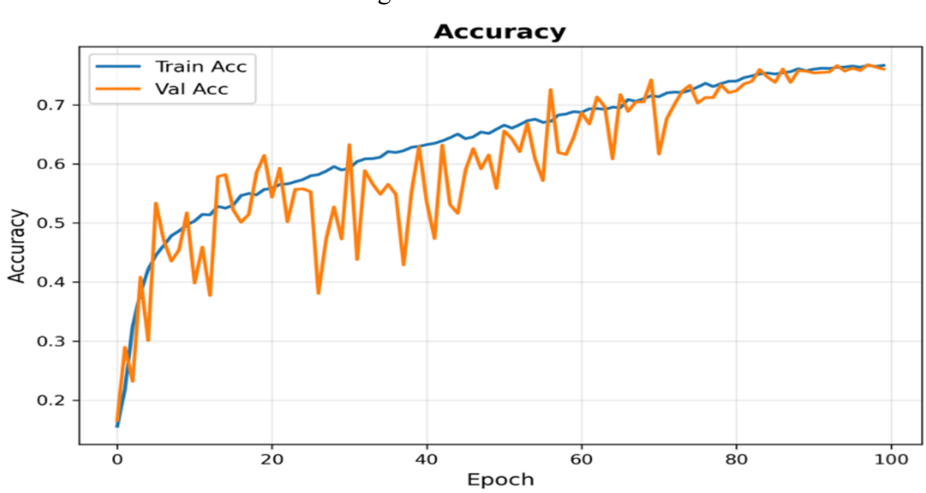

Fig. 4. Accuracy curve

Figure 5 illustrates the hybrid model's training and validation loss curve. The loss decreases as the number of epoch increases, which shows that the model is learning well. The initial loss values start at 2.2 and slowly reduce to around 0.85 by the final epoch. This decrease in the loss value indicates that the hybrid quantum-classical model contributes well in reducing the classification errors. Overall, the decreasing loss curve shows that the model is learning effectively.

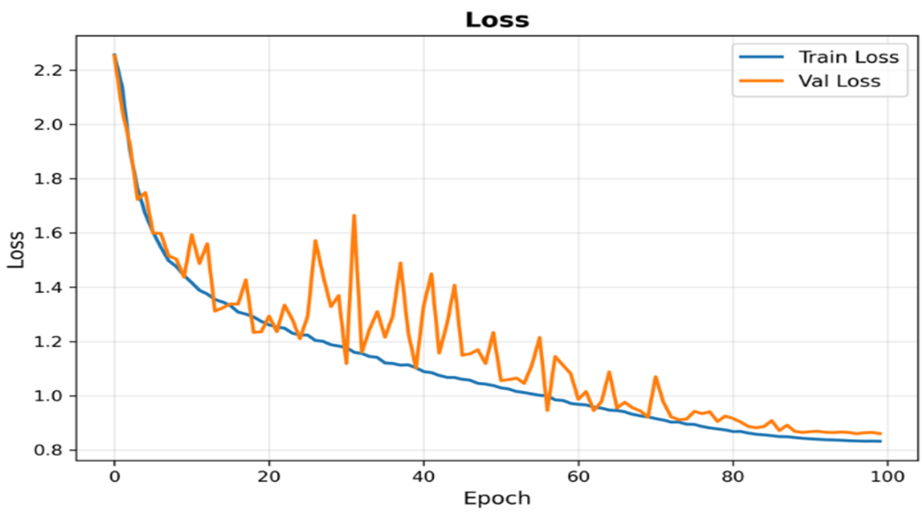

Fig. 5. Loss Curve

6 Conclusion and Future Scope

The proposed hybrid quantum-classical model for Tamil Handwritten Characters Classification using a Scalable Quantum Convolutional Neural Network (SQCNN) combined with a Bayesian Optimized Variational Quantum Classifier (VQC) has demonstrated great potential in the field of handwritten character recognition. The primary goal of this hybrid model was to accurately classify the Tamil handwritten characters using the hybrid model while also reducing the computational complexity by using fewer parameters.

The SQCNN extracts the local features from the image patches hierarchically through which the model learns the unique curves and loops of Tamil characters. Classical convolutional neural networks consist of multiple convolutional and pooling layers with many layers in order to learn the features and classify with better accuracy, while the SQCNN model processes the image patches using small quantum circuits which performs better feature representation while maintaining the circuit complexity. The Bayesian Optimized VQC module enhances the hybrid model as it is used to automatically select the optimal hyperparameters, thereby reducing the need for manual selection of hyperparameters. As this module explores different circuit architectures and selects only the optimal hyperparameters, this optimization algorithm can be adapted for various other tasks or datasets. The hybrid quantum–classical model can achieve better accuracy even when working with smaller datasets. Quantum models learn meaningful features from images using properties like superposition and entanglement, which helps the model to learn efficiently without requiring huge amount of data. Thus the proposed model performs moderately well in classifying Tamil handwritten characters, effectively capturing important features with fewer number of parameters and qubits.

The future work of this paper would be to explore different optimization algorithms for designing the quantum model. The Bayesian optimization module can also be modified where the search space is extended to include a wider range of parameters in order to explore more combinations. The quantum circuits can also be redesigned to make them much more expressive which helps in improving the model's accuracy. Quantum simulators other than Pennylane, like TensorFlow Quantum and Qiskit can also be used to implement the proposed model. The hybrid model can also be extended to classify more handwritten characters.

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