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Classical and Quantum SVM for Electromyography-Based Myopathy Detection: A Comparative Exploration

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Abstract

Introduction: Electromyography (EMG) analysis is one of the most fundamental approaches for diagnosing neuromuscular diseases. Current advancements in technology have the potential to improve diagnosis accuracy using artificial intelligence (AI). Quantum machine learning (QML), while still in its early stages, offers promising potential for various medical applications, but its effectiveness in real-world diagnostic tasks needs further exploration. Thus, the aim of this study is to employ both quantum and classical support vector machines (SVMs) to classify EMG signals into two classes, healthy and myopathy, and compare their performance.
Methods: Various approaches were tested; classical SVM and quantum-kernel-based SVM, both with manually extracted features, and convolutional neural network (CNN)-based deep features extraction techniques. This allows for an evaluation of the strengths and limitations of this new technology, acknowledging the potential of both classical and quantum methods.
Results: The obtained results showed that the proposed quantum methods yielded promising outcomes and comparable to classical methods. Particularly, the competitive results of the quantum SVM (QSVM) with the CNN-based deep feature extraction approach, which delivered a high training and testing accuracies of up to 96.7% and 85.1%, respectively.
Conclusion: These findings encourages the necessity for more advanced QML research, particularly in medical applications as quantum technology progresses.

Keywords: *Electromyography (EMG); diagnosis; myopathy; quantum machine learning (QML); support vector machine (SVM).*

Introduction

Disease diagnosis is the process of determining which disease causes a person's symptoms. However, the complexities of symptomatology frequently provide limitations to accurate medical diagnosis, which is crucial for optimal treatment and avoiding serious consequences. Thus, analyzing data from many sources with expert systems can assist reducing human error and improve outcomes.[1,2] Recently, artificial intelligence (AI) and machine learning (ML) algorithms have received considerable amounts of interest in the healthcare area. To efficiently diagnose a variety of disorders, in addition to various ML methods, many scientists have developed deep learning (DL) approaches, which uses more layers than a standard ML model, to extract deeper information from data.[1] These approaches can aid in disease assessment in its early stages, risk estimation and suggest treatments, by evaluating many data and identifying patterns, allowing machines to learn without the need for explicit programming. Hence, scientists are interested in new predictive model technologies for disease prediction that use ML algorithms.[1,3]

Neuromuscular disorder (NMD) is one of the complex and widespread diseases in the world, which leads in muscle weakness and fatigue. Electromyography (EMG) signals are the fundamental tool for assessing and diagnosing these diseases, as they are an important source of information on the health and performance of the musculoskeletal system.[5] With the introduction and advancement of ML, it is now possible to

Authors' contribution: A – Research concept and design, B – Collection and/or assembly of data, C – Data analysis and interpretation, D – Writing the article, E – Critical revision of the article, F – Final approval of the article.

better predict neuromuscular issues and distinguish between patients with NMDs and healthy people, using EMG signals with various classification methods used in ML.[5,6]

AI technologies such as image recognition, data mining, and DL efficiently address huge data processing challenges. However, these algorithms are often complex and time-consuming.[7] Recently, quantum machine learning (QML) has used the engaged parallelism of quantum computing and the advantages of acceleration and parameter reduction to better optimize classical ML and address its issues.[8] Because traditional computers' capacity to operate high-dimensional data is limited, researchers have examined many quantum computing models to handle multidimensional objects. Nowadays, QML is widely employed in practically every discipline of study, including chemistry, industry, healthcare, physics, and biomedicine.[7,8] As quantum computing and technologies expand at a rapid rate in the early 2020s, industries are racing to attract and develop quantum skills, map real-world challenges to quantum algorithms, and prepare for quantum technology's benefits.[9] Quantum computers (QC), which use quantum mechanical features such as superposition, entanglement, and tunneling, can solve problems much faster than traditional devices. Hence, they represent the next major advances in computing, with some already in use and perhaps even more significant advances in the near future. A diagram representing a global architecture of a quantum computer is shown in **Figure 1**.[8,10]

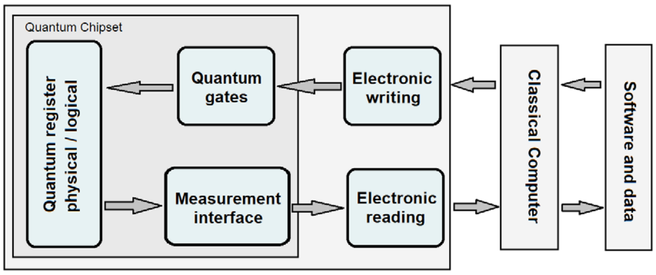

Figure 1. Global architecture of a quantum computer.

In the healthcare domain, and more precisely for the neuromuscular disease diagnosis, researchers have employed different AI and ML algorithms. Including the support vector machine (SVM)[11-13], random forest (RF)[14,15], deep learning[16] and many other models. Given the potential of quantum computing, exploring its application in NMD detection is timely and necessary, as it may provide a complementary perspective to classical approaches with regard to computational capacity and performance. However, up to the time of writing this article, to our knowledge no research works have been published dealing with employing QML algorithms to identify various NMDs using EMG data. Therefore, in this work, we present an exploratory study investigating the applicability of quantum methods, particularly quantum SVM, for myopathy detection using EMG signals, and carefully comparing their performance with classical SVM. A quantum SVM with deep features extraction model showed excellent and promising performance, where it gave a high training and testing accuracies of up to 96.7% and 85.1%, respectively. The features in the proposed model were extracted using pre-trained classical CNN, and then the deep features' vector was passed to an SVM classifier with quantum kernel, characterized by a 5-qubits quantum circuit.

Some of the research papers dealing with NMDs and myopathy classification, and others with QML in medical diagnosis, are presented in section 2. Details of the methods used and the results obtained are discussed in sections 3 and 4. Whereas section 5 presents the conclusion.

Literature Review

Significant advancement has been made in the classification of EMG signals for the diagnosis of neuromuscular diseases. Researchers attempted to use various signal processing and ML approaches to circumvent the constraints and limitations of manual reading and interpretation of EMG data, such as subjectivity and potential errors.

Kefalas et al.[14] presented an end-to-end automated ML method for differentiating the EMG recordings into healthy and unhealthy categories. Their research employed a data set of EMG time series from patients with amyotrophic lateral sclerosis (ALS) or inclusion body myositis (IBM), and healthy individuals. Their fully automated pipeline included feature extraction, selection, and random forest classification, resulting in promising performance at the muscle and patient levels, with areas under the curves (AUCs) of 81.7% and 81.5%, respectively. However, constraints were the short dataset size and the possibility of variable outcomes due to random segment selection. Similarly, Tannemaat et al.[17] created an automated classifier capable of distinguishing between EMG signals from healthy, ALS, and IBM patients. They achieved high diagnosis accuracy with their method for distinguishing ALS from normal participants, but not between normal and IBM patients. Future enhancements include additional testing in larger datasets were suggested as option to improve the model's accuracy. Tuncer and Doğru Bolat[16] on the other hand, developed a ML system which employs a DL architecture (Long Short Term-Memory) to identify EMG data from EMGLab database, as normal or symptomatic of myopathy. Their solution achieved better classification results as compared to existing methods with 100% accuracy. However, the authors suggested the need for more research to expand the number of classes and datasets. Tengshe et al.[12] developed an automated system for identifying several neuromuscular diseases based on EMG signals, using the frequency decomposition method (FDM) and various ML classifiers to achieve high diagnostic accuracy. Future directions included developing methods that are not subject-dependent, as well as using data collected from various muscles of control individuals to improve the algorithm's efficiency. Another automated method for identifying neuromuscular diseases is proposed by Cherifi et al.[13]. Their methodology included preprocessing, decomposition, and classification processes for EMG signals. They compared between various classifiers and feature extraction methods. Impressive performance was observed in successfully classifying the EMG signals (100%) on training data, and testing accuracy of 78.35% when using discrete wavelet decomposition with the linear SVM. Abdel-maboud and Alfonse[15] made a successful classification of EMG signals with the accuracy of 99%, which can enhance the early detection of the concerning disorders. While, Afzal et al.[18] proposed a method that involves preprocessing of the EMG signals and identifying *cepstral* features using K-Nearest Neighbors (KNN) for classification. The technique reached 98.7% accuracy, beating other classifiers. Future work involves the extension of the current dataset to have a balanced class distribution and clinical investigation.

These research works show the progress that has been achieved in the use of automated EMG signals classification for diagnosing NMDs using ML and DL techniques. Still, quantum machine learning has also been studied extensively over the past few years, as a potential game-changer in healthcare.[9] Using quantum computing's computational power, the main issues like early disease identification, diagnosis, and classification, are being addressed.

One exciting area of investigation is the cardiovascular disease, which is a major concern in healthcare. Maheshwari et al.[19] improved the classification accuracy by using optimal quantum support vector machine (OQSVM) and hybrid quantum multi-layer perceptron (HQMLP) methods. Their findings are promising, but obstacles such as noisy intermediate scale quantum (NISQ) devices show that there is still potential for improvement. Similarly, Ozpolat and Karabatak[20] investigated the use of quantum-based ML algorithms for categorizing heart rhythms based on electrocardiogram (ECG) readings and found interesting results, despite resource and data usage limitations. Kumar et al.[21] also suggested a strategy for detecting heart failure. The authors compared QML methods such as quantum random forest (QRF) and quantum K-nearest neighbor (QKNN) to traditional ML algorithms, and found that QML algorithms performed better in the diagnosis of heart failure. QML had impressive accuracy metrics, highlighting the promise of revolutionizing cardiac treatment. Similarly, the application of the hybrid classical-quantum models in identifying cardiomegaly in chest X-ray achieved promising outcomes when it comes to the accuracy, as estimated by Decoodt et al.[22].

Then there was the pressing need to discover COVID-19 quickly, which spurred scientists to investigate quantum transfer learning methods. Some of the paramount works executed by Umer et al.[23] include the development of a quantum circuit-based training model that integrates deep features from pre-trained models in the classification of COVID-19 using chest radiographs. Another field in which QML can serve successfully is skin cancer diagnosis. Das[24] designed a computer-aided diagnostic (CAD) system with QSVM as the classifier for skin cancer detection and the outcomes were also promising. Breast cancer detection using both traditional ML and QML algorithms demonstrated the potential of QML to improve diagnostic accuracy, as shown by Premanand et al.[25]. Khan et al.[26] applied quantum convolutional neural networks (QCNNs) for the classification of brain cancers, and demonstrated remarkable classification accuracy. Furthermore, Gupta et al.[27] focused on developing the diabetes prognosis tool using the DL and QML methods. Although the study showed that the DL model gave better results than the quantum model, the work has showed that the QML method will increase the diagnoses' accuracy in future. In addition, Rao et al.[28] presented a technique for identifying respiratory diseases that was a combination of CNN and quantum classifiers. Their remarkable accuracy in diagnosing respiratory disorders demonstrates quantum transfer learning's ability to reduce computational costs while improving model performance.

These works present a picture of promising potential. While quantum hardware and software challenges and limitations persist in all the presented works, researchers are still working to develop more accurate, efficient, and scalable diagnostic technologies using QML, ultimately improving patient outcomes and healthcare delivery.

Materials and Methodology

Theoretical Background on Quantum Computing

Quantum computing uses principles found in quantum physics such as superposition of states or entanglement in offering new computational solutions. In contrast to other forms of computations, quantum computing provides significantly better problem solving capacities.[29] The investigation of how to develop usable quantum algorithms is still being conducted, although most of the current studies are focusing on investigating the capabilities of existing imperfect quantum devices with a limited number of qubits, and which are mainly restricted to laboratory settings. Quantum algorithms have the potential to outperform conventional algorithms for certain computer tasks with exponential information within the quantum registers, by using the two basic principles of quantum computing, namely superposition and entanglement.[29,30] For instance, Shor's algorithm, which is capable of factoring great numbers, something that is a challenge to traditional computing processes, because such a procedure has a sub-exponential temporal complexity.[30] Also the Rivest-Shamir-Adleman (RSA) algorithm, which would take billions of years to solve using classical methods may theoretically be completed in a matter of hours by a quantum computer.[29]

Quantum systems, which are characterized in general by d-dimensional quantum systems (where $d = 2$ for qubit system), allow d^n classical values to be represented simultaneously in quantum registers (a set of n quantum states) via superposition. Quantum computations are based on reversible computation principles, in which the initial state can theoretically be recovered from the result state. Entanglement in quantum circuit computations creates interconnected quantum system states. However, measurements on quantum registers are used to obtain classical numerical values, which aids in subsequent calculations.[29]

A single qubit, denoted as $|x_i\rangle$, is a quantum two-level system that can store a superposition of both $x_i = 0$ and $x_i = 1$. **Figure 2** illustrates a general representation of a qubit compared to a classical binary bit.[10] A set of n qubits can be given by a quantum state $|\psi\rangle$ that stores an arbitrary entangled superposition of all n-bit binary numbers as;

$$|\psi\rangle = \sum_{k=0}^{2^n-1} \alpha_k\,|k\rangle = \sum_{x_i\in\{0,1\}} \alpha_{x_{n-1}x_{n-2}\ldots x_0}\,|x_{n-1}\rangle\,|x_{n-2}\rangle\ldots|x_0\rangle, \quad (1)$$

where the 2^n weights or amplitudes of each basis state $|k\rangle$ are represented by the complex numbers α_k , whose index k is a string of bit values $x_{n-1}x_{n-2}\ldots x_0$.[31]

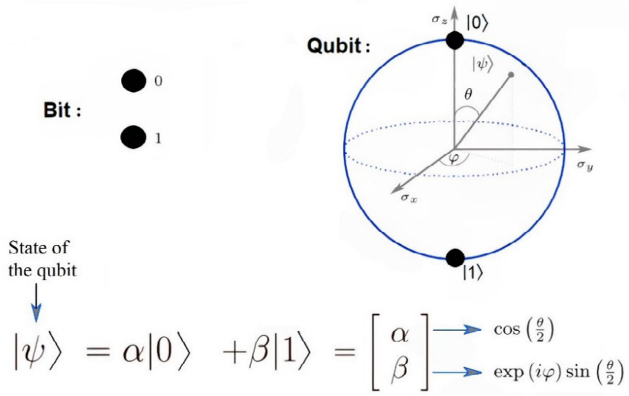

Figure 2. Bit states vs. qubit states: Bloch sphere representation and mathematical formalism.

As with any form of computer system, quantum computers are known to consist of a number of basic components. Quantum adders act as basic building blocks in quantum CPUs which use quantum bus to increase communication level between fundamental components. Quantum registers are composed of quantum memories, which consist of stationary quantum states and help in storage and manipulation of information. Quantum gates, which serve as crucial components of quantum computers, perform unitary operations on quantum states. At the physical layer, quantum gates are implemented by different physical instantiations including ion traps, superconductors, and quantum dots, that will enhance the quantum computing technology.[29] Some elementary quantum gates are represented in **Figure 3**.

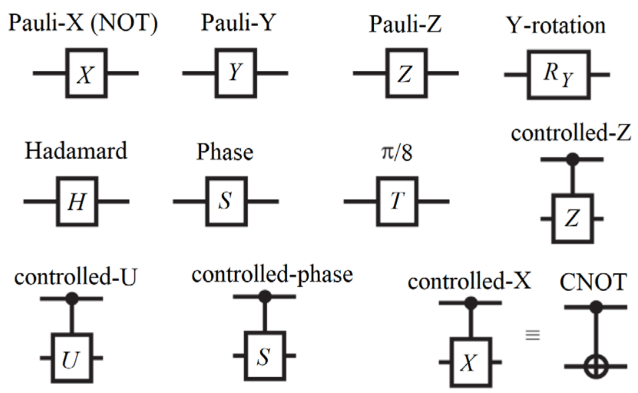

Figure 3. Circuit representations of some elementary quantum gates.

The combination of using both quantum computing and machine learning can be referred to as quantum enhanced machine learning, the aim of which is to leverage their capabilities to overcome problems facing each of them. The growth in the amount of information presents classical machine learning to challenges that quantum computing might help address because of the greater computational power.[24] By converting the classical states into quantum states for storing the descriptors, quantum machine learning eliminates the problem of performance reduction in classical models and opens up the possibilities for revolutionary improvements in the approaches to data handling.[19,24]

Dataset Acquisition and Preprocessing

In this study, we used the publically available EMG signals dataset from EMGLAB.net website. The signals were acquired and analyzed in 2001, as part of the PhD thesis of Nikolic M. in the Faculty of Health Sciences, University of Copenhagen.[32] The thesis was entitled "Detailed Analysis of Clinical Electromyography Signals EMG Decomposition, Findings and Firing Pattern Analysis in Controls and Patients with Myopathy and Amytrophic Lateral Sclerosis".

The data included a healthy or normal control group, a group of patients with myopathy, and a group of patients with Amyotrophic Lateral Sclerosis (ALS). The healthy group consisted of ten normal subjects aged between 21 and 37 years, four females and six males. The myopathy group consisted of seven patients, two females and five males, aged between 19 and 63. All seven patients presented with myopathic features both clinically and by electrodiagnostic studies. The ALS group consisted of eight patients, four females and four males with the age ranging from 35 to 67 years. The *brachial biceps* and *medial vastus* muscles were used for the collection of data. EMG signals were obtained from five points in the muscle at three insertion levels (deep, medium, low), with sampling frequency of 23437.5 Hz.[32]

For our work, the EMG signals selected are all obtained from the *Brachii Biceps* muscle. We created two groups of data, training and testing datasets. The training data consisted of EMG samples derived from seven healthy subjects and four with myopathy. While the testing data EMG samples were selected from two healthy and two with myopathy of the remaining subjects. Dividing the subjects between training and testing data was a technique to ensure the generalizability and the efficiency of the proposed models. More details about our selected dataset's components are shown in **Table 1**.

The dataset consists of 12-seconds EMG signals recorded for each subject. To improve the models' efficiency, a segmentation technique is performed for data augmentation. Four separate samples of 1-second EMG signals were derived from each 12-second signal. For the myopathy subjects in the testing data, eight 1-second samples were taken from each EMG signal. This was done to ensure that there was a roughly equal number of data points from both healthy and myopathy people, resulting in a more balanced and realistic data set for use. Removing the samples containing NaN values, results in 554

Table 1. Subject demographics, clinical details, and samples distribution in training and testing datasets.

		Subjects	Age/sex	Diagnosis	No. of samples per subject	Total No. of samples	
Training data	Healthy	H2	26/F	–	40	280	556
		H3	37/M		40		
		H5	23/M		40		
		H6	21/F		40		
		H7	27/M		40		
		H8	23/F		40		
		H9	29/M		40		
	Myopathy	M2	44/M	Plexus scapulohumeral dystrophy.	100	276	
		M3	41/F	Polymyositis.	64		
		M4	26/M	Myopathy unclassified.	48		
		M5	63/F	Polymyositis.	64		
Testing data	Healthy	H1	29/M	–	120	240	544
		H4	27/F		120		
	Myopathy	M6	33/M	Myopathy unclassified.	128	304	
		M7	19/M	Myopathy unclassified.	176		

samples in the training dataset and 544 samples in the testing set. After the acquisition of the data, notch filter at 50 Hz frequency is applied first to remove any possible power line interference from the EMG signals. The signals are then cleaned up further by using a Butterworth band-pass filter with a lower cut-off frequency of 2 Hz and an upper cut-off frequency of 10 KHz. This range is commonly used to capture the relevant EMG signal frequencies while reducing noise and artifact frequencies, making our data ready for further processing.[12,15] **Figure 4** illustrates samples of 0.25 seconds extracted from healthy and myopathy EMG signals, before and after applying the filters.

Features Extraction

After filtering the signals to reduce the noise, we proceed to the feature extraction phase. Feature extraction is a crucial step in signal processing mainly in applications such as EMG signal classification and analysis. These features are supposed to capture information from the signals that may be employed to describe some aspects of muscle work or neuromuscular disorders.

The first used features extraction technique includes the time-domain and frequency-domain features commonly referenced from the literature. Time-domain features describe the signal's behavior across time. In our work, seven time-domain features were computed for each EMG sample; the mean value of each EMG signal, the standard deviation, the zero-crossing rate, the root mean square (RMS), the variance, the mean absolute value (MAV), and the wavelength.[33] The frequency-domain features evaluate the frequency composition of sig-

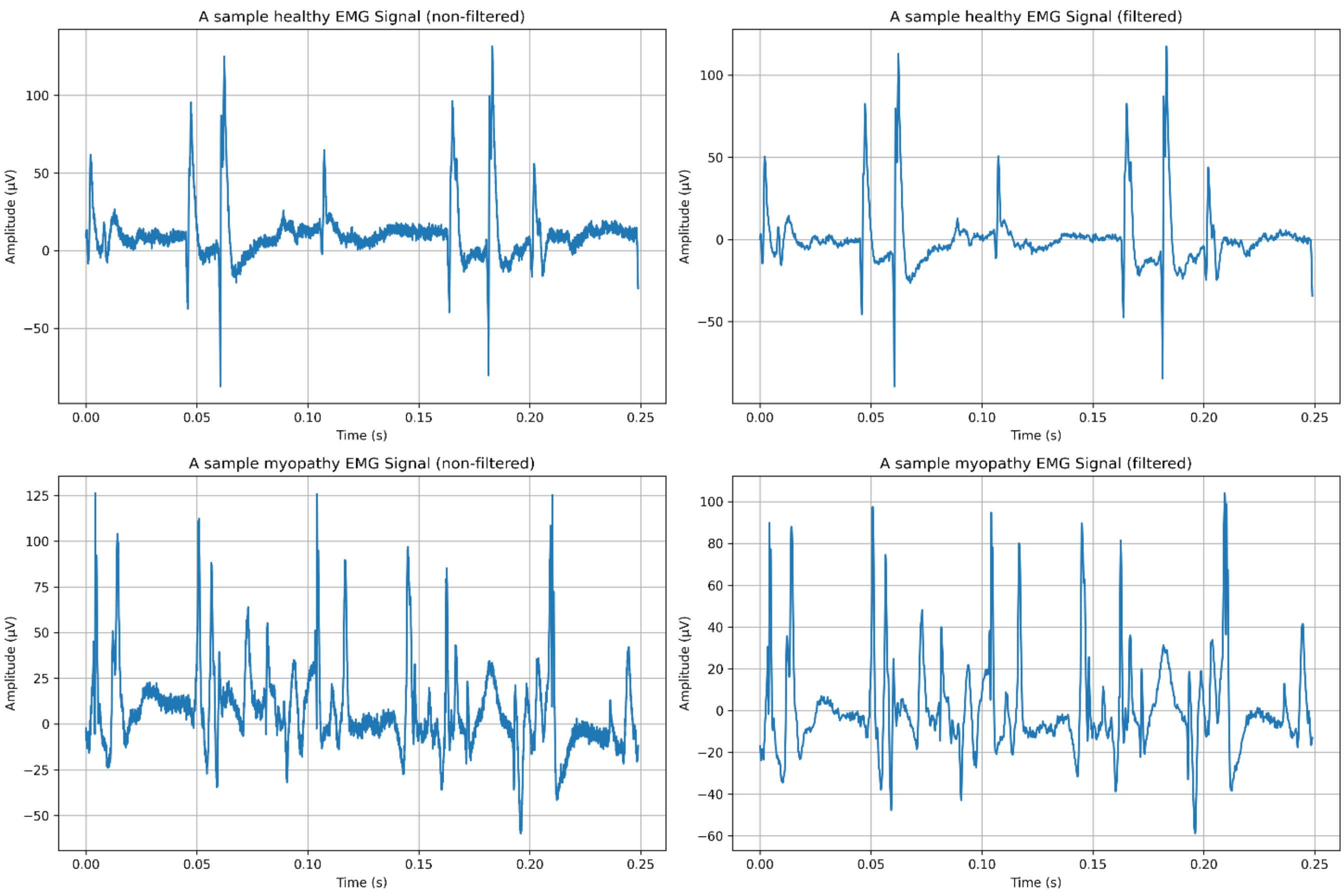

Figure 4. Examples of healthy and myopathy EMG signals before and after filtering.

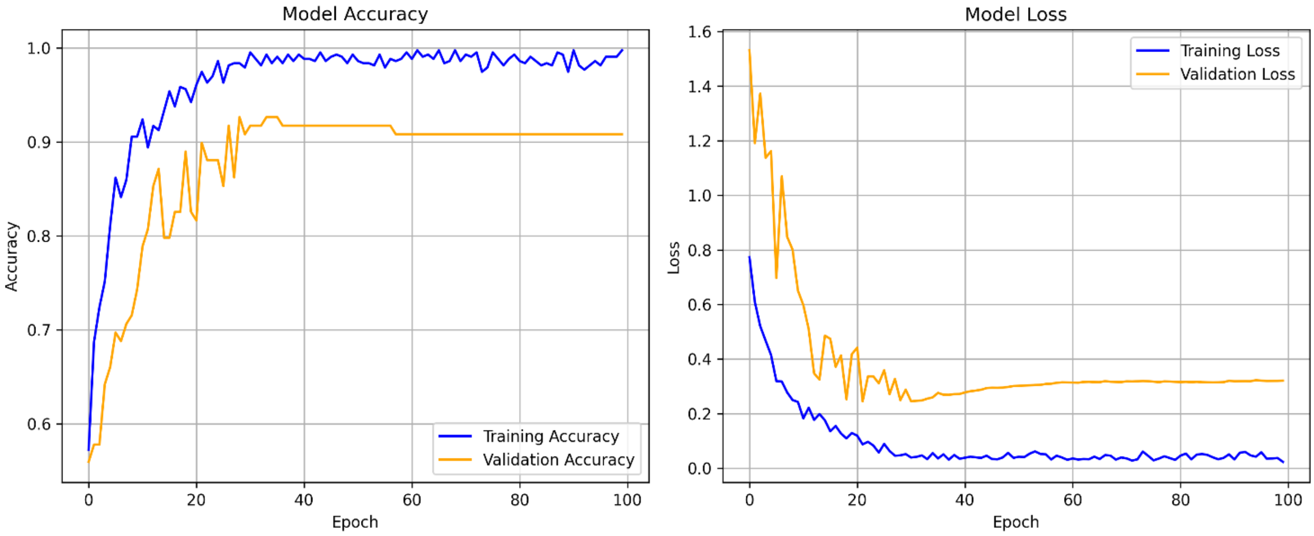

Figure 5. Training vs. validation accuracy and loss plots for the CNN model during training epochs.

nals. We applied Welch's technique on all the EMG signals to calculate their power spectral density (PSD). It shows an estimate of the spread of signal power in form of power density on different frequencies. Observing the PSD can sometimes help to identify muscle activity or abnormalities. Then PSD is used to determine such frequency-domain features that are peak frequency, mean frequency and spectral entropy, as well as median frequency.[33]

The second method includes using a CNN on EMG signals to automatically extract deep features. First, the data from the training set was loaded and reshaped to fit the input requirements of the CNN, which was designed with numerous layers to automatically learn and extract characteristics from EMG signals. **Table 2** displays the CNN model's architecture, which includes convolutional layers, pooling layers, batch normalization, dropout layers, flattening, and fully connected (dense) layers with rectified linear unit (ReLU) activation. The last layer employs a sigmoid activation function for binary classification. The CNN was designed to extract 35 deep features, the maximum number of features our designed quantum circuit can handle.

Table 2. The CNN layers' architecture.

Layers	Filters	Size/Rate	Activation
1D-Convolusion_1	128	9	ReLU
1D-MaxPooling_1	-	8	-
Batch Normalization	-	-	-
Dropout	-	0.3	-
1D-Convolusion_2	64	9	ReLU
1D-MaxPooling_2	-	8	-
Batch Normalization	-	-	-
Dropout	-	0.3	-
1D-Convolusion_3	32	9	ReLU
1D-MaxPooling_3	-	8	-
Batch Normalization	-	-	-
Dropout	-	0.3	-
Flatten Layer	-	-	-
Dropout	-	0.3	-
Dense_1	100	-	ReLU
Dense_2	35	-	ReLU
Dense_3	1	-	Sigmoid

The model was built and compiled with *Adam* optimizer, and the *binary cross-entropy* loss function. The learning rate scheduler *ReduceLROnPlateau* was employed to dynamically adjust the learning rate depending on the validation loss in order to prevent over-learning. Throughout the training process, the CNN gradually learn hierarchical features from the input time series EMG data. First convolutional layer catches local patterns like spikes and waveforms, whereas deeper layers combine these simple features to form the advanced ones. The technique is further improved with the batch normalization and the dropout layers that reduce overfitting and improve model's generalizability.[34,35] A small portion from the initial training data (specifically 20%) was reserved as validation dataset that is exclusively used during the training of the CNN model to monitor its performance. The learning rate was also dynamically adjusted to improve the model›s training accuracy over epochs, as shown in **Figure 5**, which suggests that the CNN was able to extract significant features for the classification task.

The two different features extraction techniques were used to explore the potential benefits of CNN's ability to extract deeper features, aiming to determine whether this could enhance the performance of the suggested quantum and classical classification models, over the use of manually extracted features. This method automated the feature extraction process, instead of manual selection of time-domain and frequency-domain features.

Classification

Classical approach

For the classification of the EMG data, we adopted the classical support vector machine (SVM). This method involves a number of crucial sub-procedures such as data preparation, hyperparameter tuning, and model building and training.

The initial step includes loading the training and testing datasets. Since SVMs are sensitive to the magnitudes of inputs, the features of both training and testing datasets need

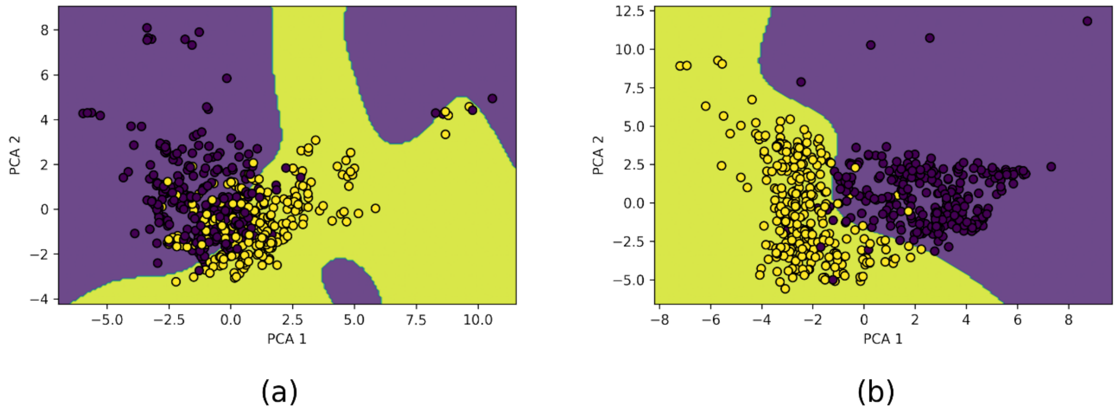

Figure 6. SVM decision boundary plots with RBF kernel with (a) manually extracted features and (b) CNN-based deep features.

to be scaled. To do this, we apply the *StandardScaler* from the *Sklearn* library in which the data is standardized having a mean equal to zero and a standard deviation equal to one. This step ensures that the input features contribute equally to the SVM model (each of them exists with equal factor).

The SVM's performance generally depends much on the hyperparameters used, such as the penalty '*C*' and the kernel coefficient '*gamma*'. In this approach we used *Grid Search* with cross-validation for defining the best values of the used SVM parameters. This technique uses a process of entering different values for hyperparameters, cross validating each one and selecting the best out of them considering the accuracy it was provided with. The best settings using the manually extracted features were $C = 40$ and *gamma* = '*scale*', with the radial basis function (RBF) kernel, while $C = 10$ and *gamma* = '*scale*' are chosen for the deep features classification. Using these optimal parameters, we train the SVM model on the training dataset and the model now is ready to be used for myopathy detection using the unseen testing dataset.

Figure 6 represents the decision boundary plots for the two classical approaches, which show how the models separate and distinguish between the two classes. The plots are obtained after reducing the dimensions of the features into two dimensions for the visualization purposes, using the principal component analysis (PCA) reduction technique.

Quantum approach

In order to employ quantum properties for the EMG signals classification, in this section we use an SVM model with quantum kernel approach to distinguish between our myopathy and healthy data. Both features extraction with CNN and the manual techniques are used to extract features from the same previous used training and testing datasets. After getting the features ready, both the 11 scaled manually extracted features, and the 35 CNN extracted deep features are fed into the quantum model for training. The used quantum approach is based on the work of Hubregtsen et al.[36]. The methodology involves loading the features, designing then optimizing a quantum kernel and finally incorporating it in an SVM. A block diagram representing the training and testing process for the QSVM with deep features approach is shown in **Figure 7**.

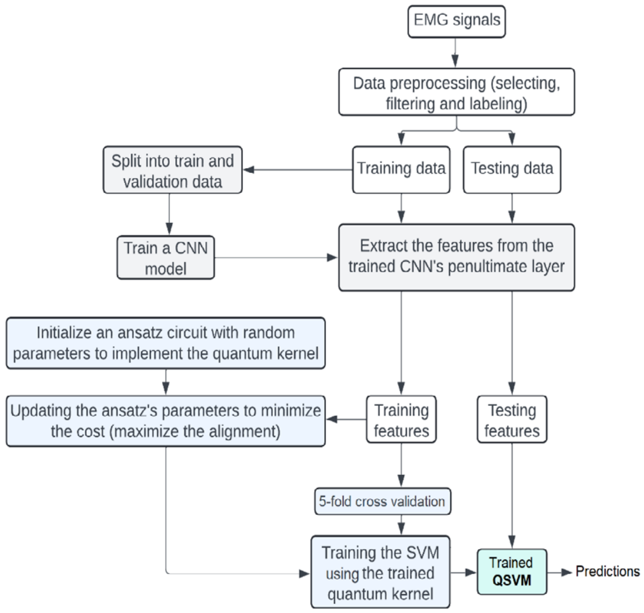

Figure 7. The quantum SVM with CNN-based deep features approach workflow.

The quantum machine learning library '*pennylane*' is used in this approach. As a first step, the features are embedded into the space of quantum states using a parameterized quantum circuit called ansatz circuit ($U(x)$). This is known as feature map, and it is achieved using the following equation:

$$|\psi(x)\rangle = U(x)|0\rangle, \quad (2)$$

where $U(x)$ is a unitary operation dependent on the specific datapoint x, and $|\psi(x)\rangle$ is the corresponding quantum state.

The ansatz circuit ($U(x)$) is constructed using building blocks called 'Layers', which consist of quantum gates that entangle and manipulate the input features, with certain variational parameters. Our proposed ansatz circuit is illustrated in **Figure 8**. It is built of 5 wires (5 output qubits) and 7 layers of basic quantum gates. Hadamard gates applied at the beginning of each layer to each qubit, which creates a superposition of states. Rotational gates; RZ guided by the datapoint features (35 RZ gates for 35 features), and RY directed by the variational parameters optimized during training. Finally, the controlled rotational gates (Controlled RZ or CRZ), which are two-input gates, applied between qubits in a structured pattern

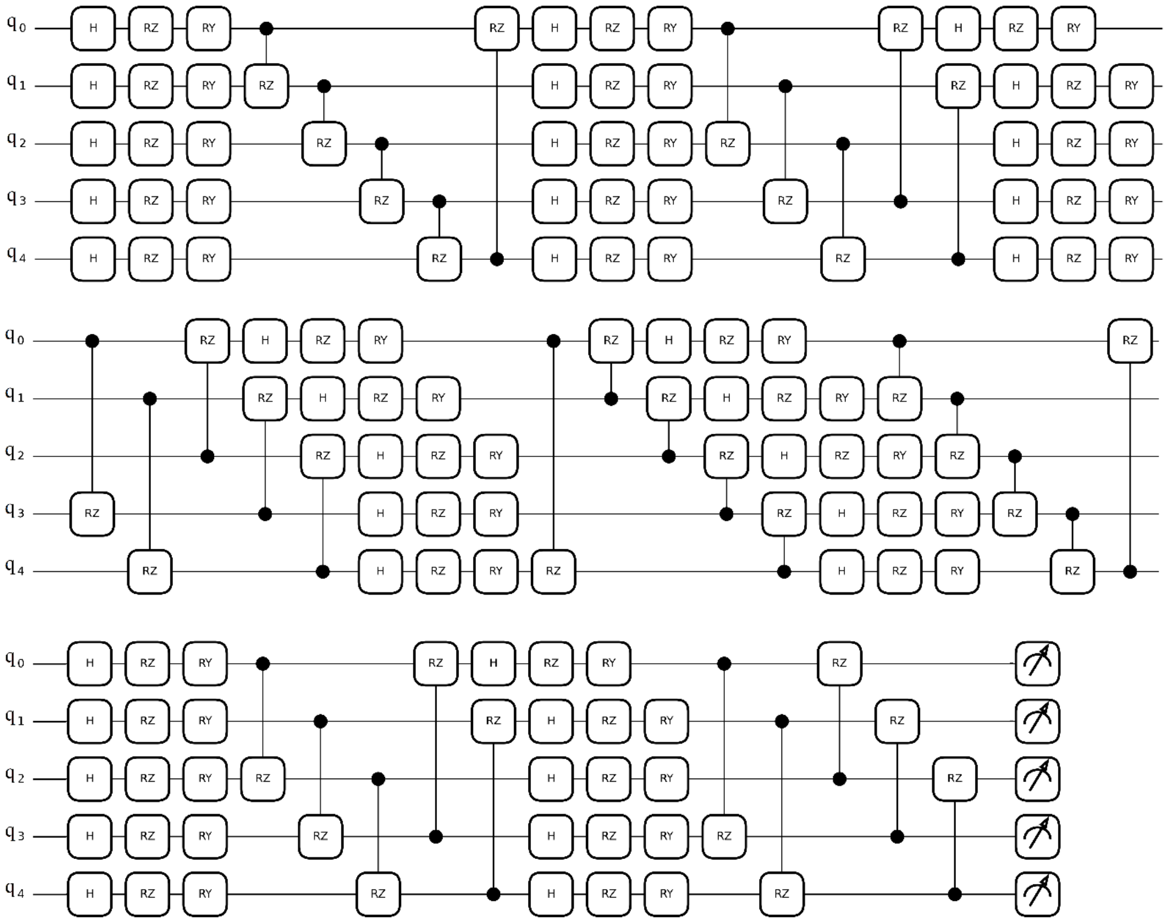

Figure 8. The proposed ansatz circuit of the quantum kernel.

that changes with each layer. This introduces entanglement between qubits to capture feature correlations in ways that classical models cannot.[29]

The quantum embedding kernel value is then simply calculated as the inner product between quantum states as follows:

$$k\left(x_1,x_2\right)=\left|\langle\psi\left(x_1\right)|\psi\left(x_2\right)\rangle\right|^2=\left|\langle 0\left|U^{\star}\left(x_1\right)U\left(x_2\right)\right|0\rangle\right|^2, \quad (3)$$

where $U^*(x)$ is the adjoint of $U^*(x)$.[36]

After selecting the quantum kernel, the second step consists of optimizing the kernel by enhancing and fixing the variational parameters, which were randomly initialized, using kernel target alignment (KTA), to ensure a good classification performance on our target data. This involves computing the kernel matrix 'K' for the training data, by using **equation (3)** for each pair of data points, which represents the similarities between them. Then in order to calculate the cost function, we need to define an ideal kernel that we use to compare with the current kernel values. It can be obtained from the training labels 'y', where the entries are calculated as:

$$K'_{ij}=y_i y_j. \quad (4)$$

The obtained kernel 'k'' acts as a predictor that outputs the correct similarity for two data points:

$$k'(x_1,x_2)=\begin{cases} 1 & if\ x_1\ and\ x_2\ are\ in\ the\ same\ class. \\ -1 & if\ x_1\ and\ x_2\ are\ in\ different\ classes. \end{cases} \quad (5)$$

To compare the kernel matrix with the ideal one, we use KTA. The alignment between two vectors ranges between -1 (if the vectors are in opposite directions) and +1 (if the vectors are in the same direction). Treating the matrix as column vectors, KTA is the alignment between the two matrices 'K' and 'K'', which is calculated as:

$$TA\left(K\right)=A\left(K,K'\right)=\frac{\langle K',K\rangle}{\sqrt{\langle K,K\rangle\langle K',K'\rangle}}, \quad (6)$$

where $\langle K', K\rangle$ is the Frobenius inner product between the two matrices, and defined as:

$$\langle K',K\rangle=\sum_{ij}K'_{ij}K_{ij}=\sum_{ij}y_i y_j k(x_i,x_j). \quad (7)$$

Hence, **equation (6)** can be rewritten in terms of the kernel function and training dataset as:

$$TA\left(K\right)=\frac{\sum_{ij}y_i y_j k\left(x_i,x_j\right)}{\sqrt{\left(\sum_{ij}k\left(x_i,x_j\right)^2\right)\left(\sum_{ij}y_i^2 y_j^2\right)}}=\frac{\sum_{ij}y_i y_j k\left(x_i,x_j\right)}{n\sqrt{\sum_{ij}k\left(x_i,x_j\right)^2}}, \quad (8)$$

where $y_i^2=1$ for all labels, and n is the number of data points in the training dataset.[36]

Each term $(y_i y_j k(x_i, x_j))$ of the sum in the numerator, is the product of two points' kernel functions and their labels. If both points are in the same class ($y_i y_j = +1$), the kernel value improves the kernel target alignment, however if the classes are different ($y_i y_j = -1$), the term reduces it. Thus, the kernel target alignment measures how good the kernel is aligning with the labels. Hence, with gradient descent, we can use the KTA as a measure in the cost function to adjust the kernel parameters to maximize the alignment, and improve the kernel's ability to separate the classes. The cost in the present study is defined as the negative of the target alignment hence maximizing the KTA will help in minimizing the cost. We do this optimization as follows: in each step, a different subset of the training data is used for the calculation of the KTA, the quantum kernel parameters being adjusted accordingly.[36]

Lastly, using the obtained optimized parameters, we define the trained kernel matrix function. To perform classification using the quantum enhanced feature space, our custom kernel is inserted in the SVM classifier from 'scikit-learn' by means of the 'kernel' parameter within the 'svc' class. The classifier is trained using 5-fold cross-validation to prevent overfitting and ensure the model generalizability across different subsets of the training data. In this technique, the training database is split into five folds; four folds are used for training the classifier while the fifth one is used for evaluation. The process is repeated five times, each time with a different subset as the evaluation set, to ensure robust evaluation. After training the classifier, its performance may then be evaluated on the testing dataset in order to compare it with the classical approach.

Results and Discussion

This section presents the classification performance of the SVM models considered in this study, with both the quantum-enhanced kernel and the classical RBF kernel. We use several metrics, including accuracy, precision, recall, F1-score, and the confusion matrix to evaluate the performance for each method. These metrics provide the complete picture on each model's ability to differentiate between different EMG signals classes. **Table 3** displays the performance metrics obtained for both training and testing datasets. The metrics obtained for all approaches are also visually represented in **Figures 9** as bar graphs. These graphical representations allow for a clearer comparison of the performance across different approaches. Additionally, **Figure 10** shows the ROC (Receiver Operating Characteristic) curve and the AUC (Area Under the Curve) for all models. The ROC curve demonstrates the trade-off between the true positive rate (sensitivity) and false positive rate (specificity) at different thresholds. The AUC value measures the model's overall ability to distinguish between positive and negative classes, with 1 representing perfect classification and 0.5 meaning random guessing.

The classical SVM approach, which included 11 manually extracted features from both the time and frequency domains, produced promising results on the training set, with an accuracy of 93.6%, precision of 94.2%, recall of 93.2% and an

Table 3. The resulted performance metrics of all models for training and testing data.

Approaches	Performance metrics	Results: Training data	Results: Testing data
Classical SVM with manual feature extraction	Accuracy	0.936	0.816
	Precision	0.942	0.769
	Recall	0.932	0.833
	F1-score	0.937	0.800
Quantum SVM with manual feature extraction	Accuracy	0.923	0.800
	Precision	0.925	0.784
	Recall	0.925	0.754
	F1-score	0.925	0.769
Classical SVM with CNN-based deep feature extraction	Accuracy	0.982	0.862
	Precision	0.975	0.845
	Recall	0.989	0.842
	F1-score	0.982	0.843
Quantum SVM with CNN-based deep feature extraction	Accuracy	0.967	0.851
	Precision	0.965	0.809
	Recall	0.971	0.867
	F1-score	0.968	0.837

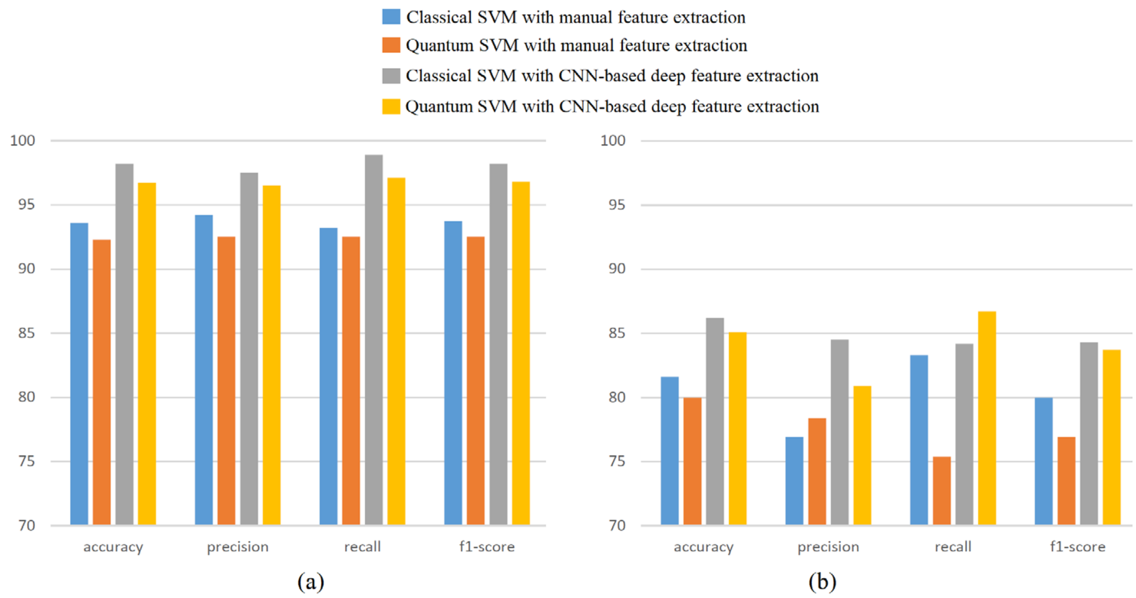

Figure 9. The obtained performance metrics from the proposed approaches evaluation on (a) training and (b) testing datasets.

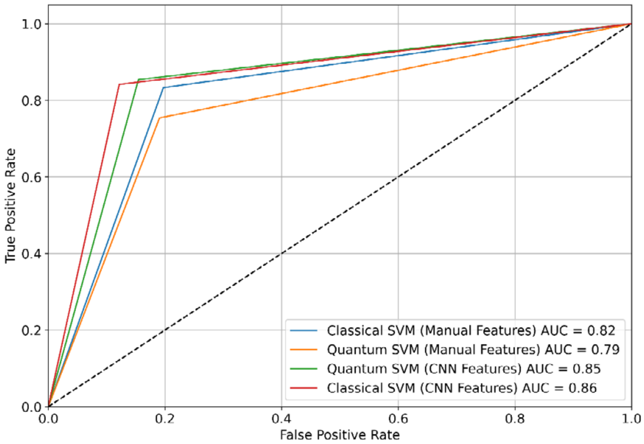

Figure 10. The ROC Curve and AUC for the proposed classification models.

f1-score of 93.7%. However, it shows a slight decrease when the same pipeline is applied to the testing dataset, where an accuracy of 81.6%, precision of 76.9%, recall of 83.3% and an f1-score of 80% are observed. If the performance on unseen data decreases, it means that while the classical SVM model is good at learning the underlying patterns in our training set, it does not generalize perfectly to new unseen data. This could be a case of overfitting, which occurs when the model performs according to the patterns observed in the training dataset, and the model's ability to perform on a test set could be severely affected.

With the same 11 features extracted manually, the quantum SVM performed similarly to classical SVM, with a training accuracy of 92.3%, and precision, recall and f1-score all reached 92.5%. Performance decreased slightly on the testing dataset as well where the obtained accuracy is 80%, precision 78.4%, recall 75.4% and f1-score of 76.9%. These results show potential for quantum methods especially in medical diagnosis. Because the performance of classical and quantum SVMs appears to be so close, it is possible that the advantages were not fully realized due to limitations in current quantum simulation and a lack of quantum hardware in the experimentation process.

The third method, which combines quantum SVM with CNN-based deep feature extraction, outperformed the previous approaches, which are based on manual feature extraction technique, on the training dataset with an accuracy of 96.7%, precision of 96.5%, recall of 97.1% and f1-score of 96.8%. This approach also outperformed the previous pipelines on the testing dataset, with an accuracy, precision, recall and f1-score of 85.1%, 80.9%, 86.7% and 83.7%, respectively. The use of CNN-based features extraction appears to have paid off, as the model improved in generalization performance with respect to new data samples, due to the ability for deep features to learn hierarchical representations capturing complex aspects present within datasets. However, the classical SVM with the deep features performed the best overall, with training accuracy, precision, recall and f1-score achieved 98.2%, 97.5%, 98.9% and 98.2%, respectively. On the testing dataset, the evaluation metrics also produced excellent results where an accuracy of 86.2%, precision of 84.5%, recall of 84.2% and f1-score of 84.3% are obtained. **Figure 11** illustrates the confusion matrices for both training and testing datasets for the four classical and quantum methods. This matrices represent a complete report of the prediction results like the true positive, true negative, false positive and false negative predictions made by the models.

The comparison between classical and quantum SVMs demonstrates that, while quantum SVMs have potential, they are currently comparable to classical methods in all aspects, with no significant improvement in performance. Due to the constraints of simulating quantum algorithms on classical computers and the current state of quantum computing, the expectations of quantum supremacy, in which quantum algorithms solve certain problems faster than their classical counterparts, may not be fully achieved in this case.

However, there is still much value in research on the construction of quantum SVMs. With the advancement of quantum technologies and computers, particularly the development of quantum processors, quantum methods will probably surpass classical ones, especially when working with large datasets. It has been proved that QSVM has theoretical potential for computational speedups, where there are some mathematical operations, for instance matrix inversion; which is vital in optimization process of SVMs; that can be processed faster due to the quantum parallelism of quantum computing. In addition, quantum algorithms such as HHL (Harrow, Hassidim, and Lloyd), have an exponentially faster solutions to linear equations systems that are the basis of the decision boundaries in SVMs.[37] This speedup could prove immensely helpful particularly when working with high-dimensional data, where classical SVM can turn out to be computationally and time-intensive. In the case of medical data, which usually includes large and interdependent features, this would result in shorter diagnostic time and increased efficiency.

Furthermore, quantum feature maps in QSVMs that maps the data into higher dimensional space states, helps enhancing and increasing the separability of the data in the complex high-dimensional feature spaces.[38] This is especially applicable in medical applications, as with EMG signals, where the interactions between features are complex. Therefore, in theory, QSVMs are able to detect deeper patterns in the data than classical SVMs, due to the quantum feature maps.

Finally yet importantly, QSVM is considered as a technology of tomorrow. Despite the fact current quantum processors are embryonic, they are anticipated to evolve rapidly. When these improvements occur, QSVMs shall be more scalable, to fit large scale medical datasets that the classical algorithms cannot handle as much as quantum algorithms would do.[39] The current findings are not revolutionary; however, they emphasize the importance of additional research to better understand the various aspects and potential of quantum algorithms, particularly for future applications that contribute to faster and more accurate diagnostics in the sphere of medicine.

Despite its promise, like all existing quantum algorithms, QSVM is not immune to the limitations of current quantum hardware. The fact that quantum computers are noisy and

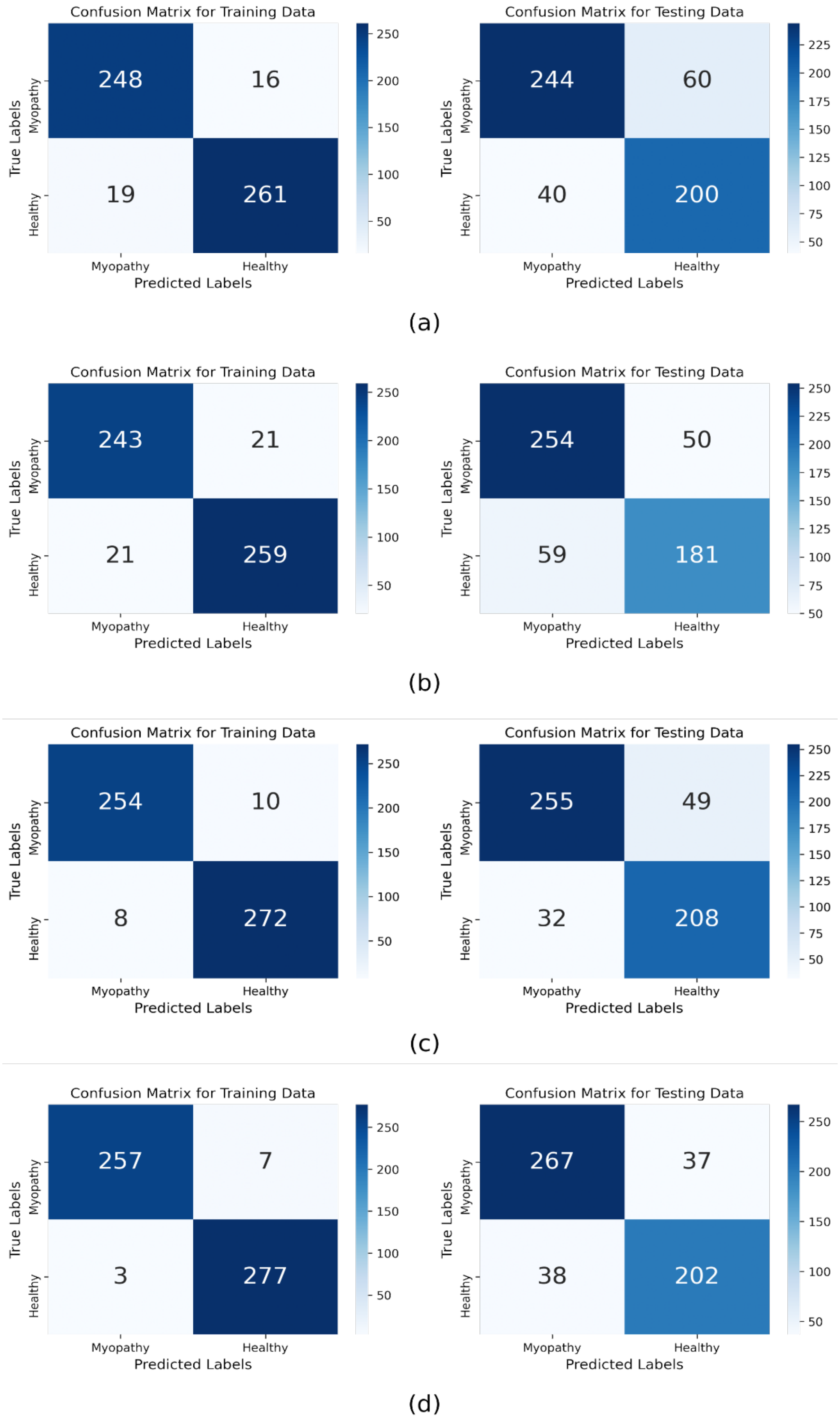

Figure 11. Confusion matrices for the training and testing data of: (a) Classical SVM with manual feature extraction. (b) Quantum SVM with manual feature extraction. (c) Quantum SVM with CNN-based deep feature extraction. (d) Classical SVM with CNN-based deep feature extraction.

the short coherence time of qubits, result in computational errors.[40] Another challenge is the complexity involved in implementing and evaluating quantum SVM approaches, which still require expertise in both quantum computing and ML. Quantum algorithms, that needed to be simulated on classical hardware, were time-consuming. The amount of computation required, and issues such as RAM limitations, prevented from conducting more complex quantum experiments by increasing the number of qubits and quantum circuit complexity. Additionally, QSVM's performance difference from the classical approaches has been a significant challenge towards its implementation in the healthcare area. In this work, the accuracy was higher for the classical SVM with CNN features (86.2%) compared with that of QSVM (85.1%). Even though the difference is small, it may indicate that QML has not arrived at the level it can outperform DL algorithm applications in medical domain.

These limitations highlighted the need for better quantum simulators and, eventually, quantum computers. Furthermore, the generalization ability in all approaches is quite low, as indicated by the small difference in performance metrics between the training and testing sets. To reduce this risk, 5-fold cross-validation was used, however, comparing the accuracies of the models on the training data to those obtained when testing, increases the chance that overfitting is still present in a certain degree. For this reason, the future work could consider the use of regularization techniques or any better form of validation for the approaches.

When comparing our obtained results to previous works, there is no doubt that our approaches, particularly the hybrid classical-quantum approach, have achieved some level of success. For example, Kefalas et al. [14] used a random forest classifier with an AUC of 81%. It improved from 3% on the muscle level to 7% on the fine-grained classification, which is equivalent to the testing accuracy of the technique we introduced. Likewise, Tuncer and Doğru Bolat's deep learning-based approach[16] demonstrated 100% accuracy on training data, comparable to our quantum SVM with CNN deep features training outcomes, but they also pointed out that testing on unseen data is a critical aspect to know the true score. In QML context, Das[24] and Premanand et al.[25], found positive outcomes when utilizing QSVMs for cancer detection. Similarly to our hybrid approach, the work done by Umer et al. [23] combined deep feature sets from pre-trained COVID-19 models with quantum circuits to achieve excellent detection accuracy. Their success extends the utility of hybrid classical-quantum models to medical diagnostics, particularly when classical feature extraction approaches prove to be inadequate. The QML study detailed by Maheshwari et al.[19] demonstrate that while quantum enhancing could provide solid results, other compared quantum-based methods have not overcome the capabilities of the classical approach. Additionally, the issues that arise with Ozpolat and Karabatak's method[20], such as limited available resources, are consistent with the findings of this study, especially given the time-consuming process of quantum simulation.

In conclusion, the current work represents a major leap forward, laying the groundwork for future research in quantum machine learning for myopathy detection using EMG signals, and medical diagnosis in general. The performance of quantum devices is gradually improving; they are becoming more effective than classical methods; in a short time, the gap will be closed, resulting in the introduction of new diagnostic and therapeutic procedures for neuromuscular diseases. Further research could focus on incorporating quantum hardware into the experiments, or utilizing more complex circuits or exploring other novel quantum methods particular to healthcare setting.

Conclusion

Quantum machine learning algorithms are one of the newest trends in the field of medical diagnosis and disease classification. As quantum computing progresses, its potential to contribute to medical diagnosis, including neuromuscular disease detection, warrants careful consideration and further exploration. In this study, the quantum SVM with CNN-based deep feature extraction showed promising accuracy in classifying the EMG signals into healthy and myopathy classes, with a training and testing accuracies of 96.7% and 85.1% respectively. The obtained results indicate the potential value of quantum methods, and imply that future integration of quantum computing into diagnostic procedures can improve diagnostic effectiveness. Nonetheless, the challenges found in this work, such as computational complexity and simulation limits on classical hardware, emphasizes the importance of further research and explorations as quantum technology continues to advance.

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