A Fusion of Supervised Contrastive Learning and Variational Quantum Classifiers

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***Abstract*—In medical applications, machine learning often grapples with limited training data. Classical self-supervised deep learning techniques have been helpful in this domain, but these algorithms have yet to achieve the required accuracy for medical use. Recently quantum algorithms show promise in handling complex patterns with small datasets. To address this challenge, this study presents a novel solution that combines self-supervised learning with Variational Quantum Classifiers (VQC) and utilizes Principal Component Analysis (PCA) as the dimensionality reduction technique. This unique approach ensures generalization even with a small training dataset while preserving data privacy, a vital consideration in medical applications. PCA is effectively utilized for dimensionality reduction, enabling VQC to operate with just 2 Q-bits, overcoming current quantum hardware limitations, and gaining an advantage over classical methods. The proposed model was benchmarked against linear classification models using diverse public image datasets to validate its effectiveness. The results demonstrate remarkable accuracy, with achievements of 90% on PneumoniaMNIST, 90% on BreastMNIST, 80% on PathMNIST, and 80% on ChestMNIST medical datasets. Additionally, for non-medical datasets, the model attained 85% on Hymenoptera Ants & Bees and 90% on the Kaggle Cats & Dogs dataset.**

***Index Terms*—Representation learning, self-supervised learning, supervised contrastive learning, variational quantum classifiers, quantum machine learning.**

I. INTRODUCTION

IN THE rapidly evolving field of medical image analysis, deep learning has emerged as a transformative force. Over the years, breakthrough inventions have revolutionized the way we interpret and extract valuable insights from medical images [1], [2]. The significance of medical image analysis cannot be overstated, as it plays a pivotal role in early disease detection, accurate diagnosis, and personalized treatment planning. However, despite its crucial importance, medical image analysis faces several challenges that impede its full potential.

One of the primary obstacles in medical image analysis is the scarcity of labeled image data. The process of manually annotating medical datasets is laborious and time-consuming, resulting in the limited availability of labeled data [3]. This paucity of labeled data can hinder the performance and generalization capabilities of deep learning models in medical image analysis [4].

The shortage of labeled data in deep learning leads to various challenges. Models trained on limited labeled data are prone to overfitting, where they memorize specific examples rather than learning meaningful representations [5]. Consequently, when confronted with new and unseen data, these models may fail to generalize effectively, impacting their real-world performance in medical image analysis.

The motivations driving this research, stem from various factors including the limitations of medical data availability, the shortcomings of existing self-supervised and quantum self-supervised learning approaches in terms of generalizability with limited data, and the inadequate accuracy achieved by quantum self-supervised learning methods even when applied to large datasets.

The existing self-supervised architectures, which include both classical and hybrid quantum-classical models [6], [7], [8], [9], employ Linear Classifiers, Neural Networks (NNs), or Quantum Neural Networks (QNNs) to classify extracted features. However, they have limitations, including:

- **Challenges of Low Accuracy:** The model's accuracy remains below on test data even when using extensive datasets.
- **Poor Generalization:** Inadequate generalizability when dealing with a limited amount of labeled training data.
- **Costly Quantum Hardware:** Excessive reliance on costly quantum hardware, where improved accuracy is directly tied to the number of Q-bits employed.

Researchers address limited labeled data challenges through representation learning methods, aiming to reveal meaningful patterns and features, providing informative representations [10]. Self-supervised learning holds promise for overcoming data scarcity by utilizing unlabeled data and auxiliary tasks to learn valuable representations without explicit annotations [11]. Supervised Contrastive learning (SCL) is another potent technique that encourages differentiation between similar and dissimilar instances within the learned representation space, resulting in discriminative representations useful for classification and other tasks [12].

Quantum computing has introduced a new approach to tackling generalization issues with limited labeled data. A

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group of quantum theorists at Los Alamos National Laboratory demonstrated that their theoretical research establishes that machine learning on quantum computers necessitates significantly simpler data than previously believed [13]. Variational quantum classifiers (VQC) have shown promise in diverse applications like medical image analysis [14]. By utilizing quantum superposition and entanglement, VQCs excel at generalizing with limited labeled data [15]. This makes them attractive for medical image tasks. VQCs' strength lies in efficiently exploring the vast quantum state space, allowing them to capture intricate patterns in data [16], [17].

VQCs, coupled with Principal Component Analysis (PCA), offer a promising remedy for the quantum hardware constraints faced by conventional quantum computing methods. The streamlined nature of VQCs, when combined with PCA's dimensionality reduction, allows them to function with fewer quantum bits (Q-bits) [9]. This advantage is especially significant in medical image analysis, where existing quantum hardware is constrained by Q-bit count and circuit noise.

This study introduces a model that combines supervised contrastive learning with VQCs and PCA for dimension reduction, effectively addressing generalization challenges due to limited labeled data and quantum hardware constraints. The model demonstrates its superior performance over traditional deep learning methods in medical image analysis tasks. Significant contributions to the field of medical image analysis and quantum machine learning are made in this work:

- **Efficient medical image classification with limited labeled data:** A novel generalized model is proposed for classifying medical image data with a minimal number of labeled images. The model's efficiency is empirically validated, demonstrating its potential to handle data scarcity.
- **Enhancing model accuracy with data pre-processing techniques:** A series of data pre-processing techniques are developed to improve the model's accuracy.
- **Enhancing quantum model efficiency:** To overcome the limitations posed by constrained quantum hardware resources, a combination of principal component analysis and variational quantum classifier is introduced. This integration enhances the practicality and flexibility of the proposed model.

In the upcoming Related Work section, the authors explore representation learning, contrastive learning, data privacy with contrastive loss, quantum self-supervised learning, and VQC, with an emphasis on their performance and advantages. In the Design section, the authors provide a thorough exposition of the proposed methodology, dataset selection, and experimental setup. Experimental results and comparisons are included to demonstrate the superiority of the authors' proposed model over traditional linear classification methods and Hybrid Quantum-Classical models. The section also discusses the current limitations of the model and its potential for advancing medical image analysis through quantum computing.

II. Related Works

This section delves into the realm of related research encompassing supervised contrastive learning (SCL), variational quantum classifiers, and the landscape of existing quantum self-supervised learning approaches.

A. Representation Learning With Supervised Contrastive Learning

SCL is a powerful method for acquiring meaningful representations, especially in scenarios with limited labeled data. It has shown promise in various domains, including computer vision and natural language processing [12], [11]. By incorporating a contrastive loss within supervised settings, the network learns to distinguish positive and negative pairs, improving its ability to generalize to new, unseen data [7]. Researchers have explored two variations of the supervised contrastive (SupCon) loss [7] to identify the most effective formulation.

In the study [7], ResNet variants were employed as encoders, trained with the SGD optimizer using supervised contrastive loss. The training utilized 128 projection units and produced a 2048-sized encoded feature vector, which underwent linear classification. Achieving a top-1 accuracy of **81.4%** on the ImageNet dataset using ResNet-200, the study [7] surpassed the best-reported result for this architecture by 0.8%. These researches consistently demonstrated superiority over cross-entropy loss [18] when applied to various datasets and different ResNet [19] variants. Despite its advantages, such as resilience against natural corruptions and stability across different hyperparameter settings, including optimizers and data augmentation methods, SCL has limitations. Notably, it is sensitive to hyperparameters, complicating the search for optimal configurations across diverse tasks [10]. Furthermore, the effectiveness of SCL relies heavily on access to a sufficiently large labeled dataset, limiting its practicality in scenarios with severely limited labeled data [20].

B. Model Generalization for Fewer Data Using Variational Quantum Algorithms

With the potential to outperform classical counterparts in certain tasks, variational quantum algorithms have gained significant attention as a promising approach in quantum machine learning. These algorithms offer advantages such as efficiently handling complex computational problems by leveraging quantum parallelism, quantum entanglement, and superposition [21]. Their successful applications span various domains, including quantum chemistry, optimization, and supervised learning tasks [8], [22].

Utilizing quantum circuits for iterative model parameter optimization, variational quantum algorithms learn features in supervised learning. This procedure results in the identification of optimal quantum states that represent the target data distribution [23]. Their adaptability to the underlying data distribution renders them suitable for tackling challenges in supervised learning, particularly when labeled data is limited [24]. These algorithms prove particularly advantageous in tasks involving high-dimensional data representation due to their ability to encode classical data into quantum states and execute quantum operations [16]. However, the effectiveness of variational quantum algorithms hinges on the presence of noise-resilient quantum devices and efficient error mitigation strategies, especially in scenarios involving a higher number of Q-bits [25].

C. Quantum Self-Supervised Learning Using Quantum Neural Networks

Jaderberg and colleagues' research [6] introduces a contrastive learning framework that combines classical and quantum neural networks. By employing random image augmentation, this hybrid network learns visual representations by aligning different perspectives of the same image in both classical and Hilbert spaces. Despite limitations related to quantum simulation size and training duration, the hybrid encoder achieves an average test accuracy of $\mathbf{(46.51 \pm 1.37)\%}$ on the **IBMQ Paris** device [26]. In contrast, replacing the quantum neural network with an equivalent classical counterpart results in a test accuracy of $\mathbf{(43.49 \pm 1.31)\%}$.

Furthermore, study [27] introduces a novel Quantum-Inspired Self-Supervised Network (QIS-Net) designed for the fully automatic segmentation of brain MR images, addressing challenges faced by deeply supervised Convolutional Neural Network (CNN) architectures. The QIS-Net comprises three layers of quantum neurons, represented as Q-bits, with bi-directional propagation of quantum states between the intermediate and output layers. Testing yields promising accuracy and reasonable dice similarity scores compared to other methods.

D. Advancing Data Privacy: Supervised Contrastive Learning Outperforms Traditional Models

SCL has shown remarkable potential for data privacy preservation compared to traditional supervised classification models. Several recent studies provide substantial evidence to support this assertion.

In study [28], the experimental findings indicate that contrastive models trained on image datasets are notably less susceptible to membership inference attacks. This heightened privacy protection arises from the inherent advantage of contrastive models in resisting overfitting, ensuring that sensitive data remains better safeguarded. And the study [29] proposes an effective approach to further enhance data privacy with SCL. By introducing an obfuscator module [30] that perturbs encoded features and minimizes the correlation between private representations and original data, this method reinforces privacy while retaining model utility for classification tasks. Furthermore, study [31] offers additional strategies to bolster data privacy in the context of SCL. It recommends adapting the contrastive learning scheme for robustness against adversarial attacks and extending self-supervised contrastive methods to the supervised setting, enhancing the model's discriminative abilities. Collectively, these studies provide compelling evidence that SCL offers improved data privacy preservation, supported by innovative techniques and robustness enhancements.

In this review, four research domains were explored: Supervised Contrastive Learning (SCL), Variational Quantum Algorithms, Quantum Self-Supervised Learning, and Data Privacy-preserving with SCL. Each area holds unique promise and challenges in the evolving landscape of machine learning and quantum computing. SCL emphasizes feature separability and generalization, while Variational Quantum Algorithms tackle high-dimensional and limited labeled data tasks. Quantum Self-Supervised Learning shows real-world potential despite quantum hardware limitations. Notably, SCL demonstrates a particular strength in addressing data privacy concerns and adversarial attacks.

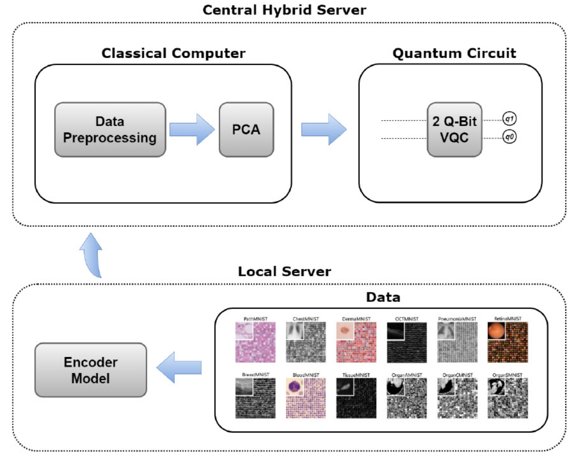

Fig. 1. Proposed Architecture Overview. This novel model implementation establishes a localized encoder model, engaging with patient image data. The 2048 feature vector is sent to the central hybrid server. Transmitted data undergoes preprocessing and PCA for dimensionality reduction. The features enter the real quantum device for classification.

III. The Design

Within this section, the authors provide an overview of the proposed model architecture, dataset selection (both medical and non-medical), implementation of the representation learning framework, and utilization of dimensionality reduction techniques. It also covers variational quantum algorithms, training, and experimental configuration.

A. Architecture Overview

In this study, our proposed innovative hybrid model merges SCL and VQC with PCA-based dimensionality reduction. This integration combines quantum and classical components, as depicted in Figure 1. This novel architecture is composed of 3 main modules, each contributing to the overall system's efficiency:

- **Representation Learning Framework (Encoder Model):** This initial module focuses on acquiring meaningful data representations.
- **Principal Component Analysis (PCA):** After a mandatory data pre-processing step, PCA refines and reduces the acquired representations from the Encoder Model further
- **Variational Quantum Classifier (VQC):** The third module VQC, executed on a quantum circuit, brings the quantum advantage to the architecture. Leveraging the capabilities of quantum computing, this module performs classification tasks based on the refined data representations by the PCA.

B. Dataset Selection

In this study, 6 distinct public datasets were employed, with each serving specific purposes in the analysis:

- **PneumoniaMNIST:** A Pneumonia Chest X-Ray dataset for medical image analysis [32].
- **BreastMNIST:** A Breast Ultrasound dataset for medical image analysis [32].
- **PathMNIST:** A Colon Pathology dataset, expanding the applicability to diverse medical image analysis tasks [32].
- **ChestMNIST:** An additional Chest X-ray dataset, demonstrating adaptability in chest imaging analysis [32].
- **Hymenoptera Ant & Bees:** Showcasing the versatility and robustness of our methodology across various datasets [33].
- **Kaggle Cats and Dogs Dataset:** An additional public binary classification dataset to demonstrate the robustness [34]

To address the limitation of limited labeled data, per [15], [7], [12], the dataset sizes were constrained to a maximum of 120 samples. Each dataset was composed of 120 samples and divided into training, validation, and test subsets, each containing 80, 20, and 20 samples, respectively. Random sampling techniques were employed when selecting the dataset samples to ensure the integrity of the analyses and to avoid biases. This approach guarantees that the results remain unbiased and applicable across different dataset sizes.

C. Representation Learning Framework (Encoder Model)

The initial module encompasses the representation learning framework [7], [12], known as the Encoder network, comprising three integral components:

- *Data Augmentation Model:* This module incorporates data-augmenting layers to improve the model's ability to predict new features. It utilizes various augmentation techniques such as normalization, horizontal flip, rotation, affine transformations, and color adjustments, customized for each dataset. Specific values are computed based on dataset characteristics.
- *Encoder Model:* The encoder model, based on ResNet50 [19], serves as both a feature learning mechanism and a foundation for feature prediction [7]. The last layer is substituted with an identity layer, effectively functioning as a 2048 feature vector prediction module. The data augmentation sub-module, integrated at the encoder's head, processes image data and feeds its output to the encoder.
- *Projection Head Model:* The final component is the Projection Head model, which consists of a single hidden layer that transforms the 2048 features into 128 new features. These newly generated features undergo evaluation using a specialized loss function known as the Supervised Contrastive Loss (SupCon) [7].

The encoder network, including data augmentation layers and the projection head, is trained using Supervised Contrastive Loss and Stochastic Gradient Descent [7].

D. Pre-Process Feature Vectors

A crucial step is Data Pre-processing, positioned between the Representation Learning Framework and the PCA module. Before delving into PCA details, let's examine the carefully designed data pre-processing for this system. Utilizing the 2048 feature vectors from the encoder network, a new dataset is formed with these features and their corresponding labels.

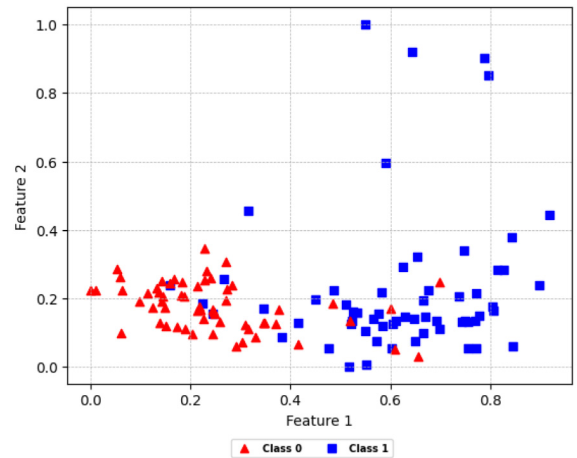

Fig. 2. Effectiveness of Data Pre-Processing & PCA. The correlation between 2 features in the PneumoniaMNIST encoded data.

The data pre-processing facet within this system encompasses three pivotal steps:

- **Outlier Removal:** Automated outlier removal employs a one-class classification algorithm [35] to enhance data integrity by identifying and eliminating anomalies.
- **Scaling the Dataset:** The dataset is scaled using mean and standard deviation, standardizing the data for compatibility with subsequent stages.
- **Normalization:** Scaled data then undergoes normalization, refining distribution, and establishing uniformity for quantum classification tasks.

Undoubtedly, the data pre-processing phase is crucial in this system, significantly improving the accuracy of quantum classification results. Additionally, a future avenue of exploration in this study involves incorporating more data pre-processing techniques and conducting evaluations to gauge their impact.

E. Dimensionality Reduction Using PCA

The subsequent component in this architecture is the Principal Component Analysis (PCA) module, introduced to tackle the curse of dimensionality issue [36]. With a 2048 feature vector and limited labeled data, dimensionality becomes a concern. To build an effective classification system, overcoming this challenge is vital through efficient dimensionality reduction. This is especially important to utilize quantum hardware effectively and leverage the inherent generalizability of quantum algorithms.

PCA reduces the 2048 feature dimensions by balancing the number of components with the explained variance. In Figure 2 and the Appendix, the correlation between the 2 features is illustrated. The encoded PneumoniaMNIST dataset displays a notable correlation value of 0.88, indicating increased effectiveness in subsequent processing.

F. Variational Quantum Classifier

The third module in our architecture encompasses the Variational Quantum Classifier (VQC), a pivotal component responsible for classification. To prepare the data for the VQC, the feature vectors generated by PCA undergo a conversion into a one-hot encoder format [8], followed by the construction of the VQC.

1) VQC Architecture Overview: VQC begins with encoding classical data into quantum states using quantum gates. A parameterized quantum circuit (variational ansatz) adapts the quantum operations for various datasets. During training, it optimizes the circuit parameters to minimize a cost function. VQC consists of two essential components:

- *Data Encoding Circuit:* The first step in VQC involves converting data into quantum states using IBM Qiskit's **ZZFeatureMap** [26]. This feature map utilizes a second-order Pauli-Z evolution circuit allowing data interactions to be encoded. The Pauli-Z operator is a 2×2 matrix that acts on the quantum state. It changes the sign (or phase) of the 0—⟩ state while leaving the —1⟩ state unchanged.
- *Variational Circuit:* Referred to as TwoLocal in IBM Qiskit [26], this structure consists of alternating rotation and entanglement layers [8]. TwoLocal employs layered structures in the circuit design with localized interactions among nearby qubits. These layers consist of sequences of quantum gates, and the name "TwoLocal" implies limited-range interactions within each layer.

2) VQC Mathematical Overview for Binary Classification: In this classifier, the result is considered as the measured expectation value. For binary classification with input data vectors $\vec{x}_i$ and binary output labels $y_i = 0, 1$, a parameterized quantum circuit is constructed for each input vector. This circuit generates the quantum state:

$$\left|\psi\left(\vec{x}_i;\vec{\theta}\right)\right\rangle = U_{W\left(\vec{\theta}\right)} U_{\phi(\vec{x}_i)}|0\rangle \tag{1}$$

Here, $U_{W(\vec{\theta})}$ represents the unitary transformation related to the variational circuit, while $U_{\phi(\vec{x}_i)}$ corresponds to the unitary transformation associated with the data encoding circuit. After constructing and measuring the n-qubit circuit, an n-length bit-string is generated. This bit-string is then utilized to determine the binary output, which governs the classification result. The classification determination employs a Boolean function $f : 0, 1^n \rightarrow 0, 1$, often utilizing the parity function.

3) Variational Training: Notably, binary classification tasks are the specialization of the VQC algorithm. In variational training, a crucial phase, two optimization techniques are offered: the Gradient-based method and the gradient-free method [8]. The Gradient-based approach was chosen, as the gradient-free method heavily relies on extensive quantum hardware, which hinders usability and adaptability. Nonetheless, the challenge of the Barren plateau problem [37], which can hinder optimization, is encountered. To address this challenge, the Initial Guess Method was employed [37].

In this study, the cross-entropy loss function was employed, and the optimizer chosen was the Simultaneous Perturbation Stochastic Approximation (SPSA) optimizer [38]. Based on experimental results, this combination ensures effective training and optimization of the VQC, resulting in accurate classification outcomes.

G. Experimental Configuration

In our experimental setup, both classical and quantum simulators were used. A GPU was employed for machine learning inference and graphics-intensive tasks, supported by 4 vCPUs and 16 GiB of memory. The system utilized 2nd Generation Intel Xeon Scalable Processors and a **NVIDIA T4 Tensor Core GPU**. Performance assessment included the use of the **IBM QASM Simulator** to evaluate the VQC. Furthermore, practical quantum device testing was conducted on the **IBM Canberra** system. The IBM Canberra system features 27 Q-bits and an impressive Quantum Volume (QV) of 32, denoting its computational capability. It delivered a substantial processing capacity of 2.2K CLOPS (Circuit Layer Operations Per Second), facilitated by the Falcon r6 processor type, emphasizing its prowess in quantum computing experimentation.

Furthermore, in this study, the assumption has been made that the parameters described in Section II-D for supervised contrastive learning settings represent the optimal configuration. The subsequent section delves deeper into the experimental design and presents the results achieved through the proposed approach, combining supervised contrastive learning with VQC and PCA.

IV. Experiments & Results

This section offers a comprehensive overview of the experiments conducted to validate the effectiveness of the proposed model. It elaborates on empirical assessments that encompass the accuracy, robustness, generalizability, usability, and adaptability of the model.

A. Evaluating Proposed Model Generalizability With Limited Image Data

A comprehensive assessment of the performance and accuracy of our proposed model, which combines SCL and VQC with PCA-based dimensionality reduction, was conducted. A range of machine learning metrics, including classification accuracy, precision, recall, and F1-score, were applied across the MedMNIST2D medical datasets.

Figure 3 confirms the convergence of our proposed model's VQC module for all medical and non-medical datasets. Notably, remarkable test accuracy was achieved by our proposed model: **90%** on PneumoniaMNIST, **90%** on BreastMNIST, **80%** on PathMNIST, and **80%** on ChestMNIST medical datasets.

B. Comparative Benchmark Test Against Self-Supervised Models

Given the limitations of neural network classifiers on classical computers [6] and the optimal accuracy achieved by linear classifier models [7], this study aimed to evaluate our proposed model against a set of linear classification models (SupCon) suggested by [7]. These models include Ridge Classifier (RC) [39], Logistic Regression (LR) [40], Perceptron (PERC) [41], Passive Aggressive Classifier (PAC) [42],Linear SVC (L-SVC) [43], and SGD

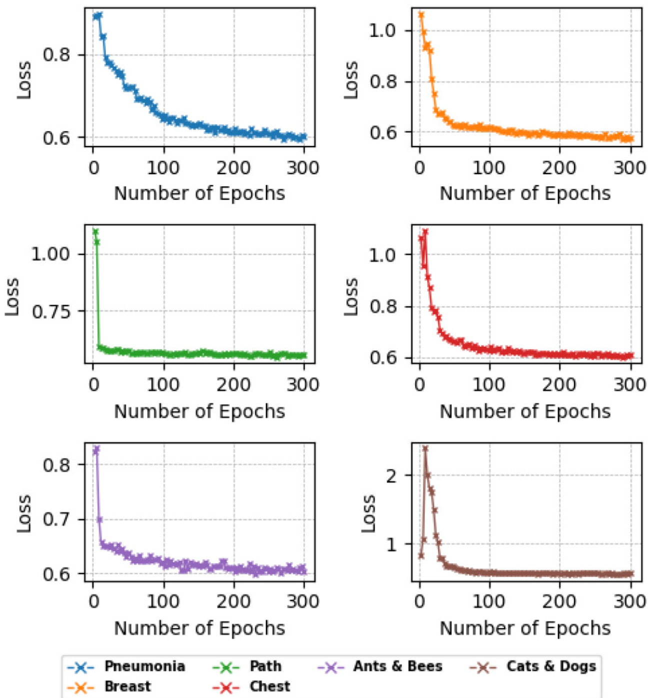

Fig. 3. According to the loss graph of our proposed model's VQC classifier, it is evident that the classifier has achieved convergence.

TABLE I
COMPARISON OF OUR PROPOSED MODEL AND LINEAR CLASSIFICATION MODELS AND HYBRID QUANTUM SELF-SUPERVISED MODEL IN TERMS OF TEST ACCURACY

Classifier	Pneumonia-MNIST	Breast-MNIST	Path-MNIST	Chest-MNIST	Ants & Bees	Cats & Dogs
Classical Supervised Contrastive Learning						
RC	0.65	0.60	0.65	0.60	0.50	0.50
LR	0.65	0.65	0.65	0.70	0.65	0.70
PERC	0.65	0.60	0.65	0.60	0.55	0.55
PAC	0.60	0.60	0.60	0.60	0.50	0.50
L-SVC	0.65	0.65	0.65	0.65	0.50	0.50
SGD	0.65	0.60	0.60	0.60	0.50	0.50
Hybrid Quantum Supervised Contrastive Learning						
QNN	0.75	0.70	0.70	0.70	0.85	0.80
VQC-SIM	**0.90**	**0.90**	**0.80**	**0.80**	**0.85**	**0.90**
VQC-IBM	**0.90**	**0.90**	**0.80**	**0.80**	**0.85**	**0.90**

Classifier (SGD) [44]. Additionally, our evaluation involved benchmarking our proposed method (SupCon-VQC) against the Hybrid Quantum Self-Supervised model (SupCon-QNN), which combines SCL with Quantum Neural Networks (QNN). All benchmarking experiments were conducted using datasets with 120 samples. Both our proposed model and the SupCon-QNN model were tested on the **IBM QASM local simulator (VQC-SIM)** and **IBM Canberra (VQC-IBM)** throughout these experiments.

As demonstrated in Table I, none of the linear classifiers attained an accuracy exceeding the **65%** threshold across the medical datasets. However, this disparity is mitigated by the notably shorter training time of the linear classification models compared to the variational quantum classifier (VQC) in our model.

C. Assessing Proposed Model Robustness and Generalizability Using Non-Medical Datasets

To comprehensively assess our proposed model's robustness, an evaluation using classification accuracy, precision, recall, and f1-score machine learning metrics over the Hymenoptera Ant & Bees and Kaggle Cats & Dogs datasets, which fall outside the medical domain was employed. The Hymenoptera Ant & Bees dataset, and Kaggle Cats & Dogs dataset, pose numerous challenges for machine learning classification, such as class imbalance, visual similarity between species, background and pose variability, intra-class variation, fine-grained categories, noise, limited data, and generalization difficulties. These datasets serve as a vital benchmark for assessing machine learning algorithms' performance in classification tasks, particularly in the context of biological images [45]. Impressively, our proposed model exhibited an accuracy rate of **85%** for the Hymenoptera Ant & Bees and **90%** for the Kaggle Cats & Dogs dataset. Despite achieving a relatively high accuracy, there remains room for improvement in addressing the unique challenges posed by these datasets.

D. Impact of Reduced Sample Size on Model Performance

In this study, the performance of our model was systematically evaluated by gradually decreasing the number of samples per class, ranging from 150 down to as low as 25 samples, with intermediate sample sizes of 125, 100, 75, and 50. This extensive evaluation was conducted across those sample sizes and encompassed all the datasets under consideration. Remarkably, even with a minimal dataset of just 25 images per class, remarkable results were achieved by our proposed model, with an 80% test accuracy observed across all medical datasets, including PneumoniaMNIST, BreastMNIST, PathMNIST, and ChestMNIST. Moreover, on the non-medical datasets, Ants & Bees and Cats & Dogs, an impressive 75% test accuracy was attained by our model. Figure 4 visually demonstrates a strong positive correlation between the model's accuracy and the reduction in the number of training samples, in line with the expectations.

E. Determining the Minimum Q-Bit Requirement for Quantum Hardware Execution

Optimizing the number of Q-bits in quantum circuits is crucial, as it aligns with the feature dimension. This optimization can be achieved through principle component analysis (PCA) to select the most informative feature set. This approach captures the dataset's essence while minimizing the quantum resources needed for accurate representation. To methodically reduce feature dimensionality while maintaining consistent effectiveness, 2 experiments were conducted:

1) Based on Explained Variance: In this experiment, dimensions ranging from 2 to the maximum of 2048 features to achieve **80%-90% explained variance** [46] per dataset were explored. The relationship between components and explained variance is depicted in Figure 5. Remarkably, all medical datasets consistently reached over **90%** explained variance using only **2** principal components.

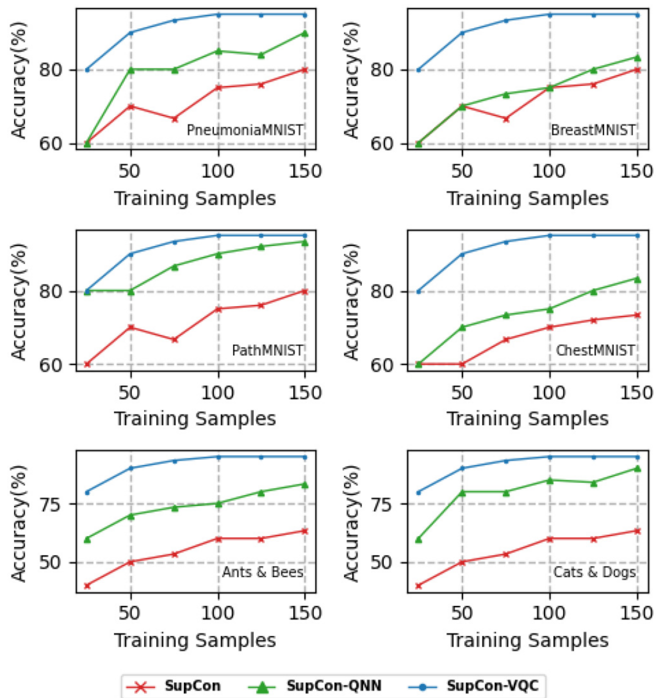

Fig. 4. The figure illustrates that even when the training data is significantly reduced, our proposed VQC-based SCL model maintains a respectable level of accuracy.

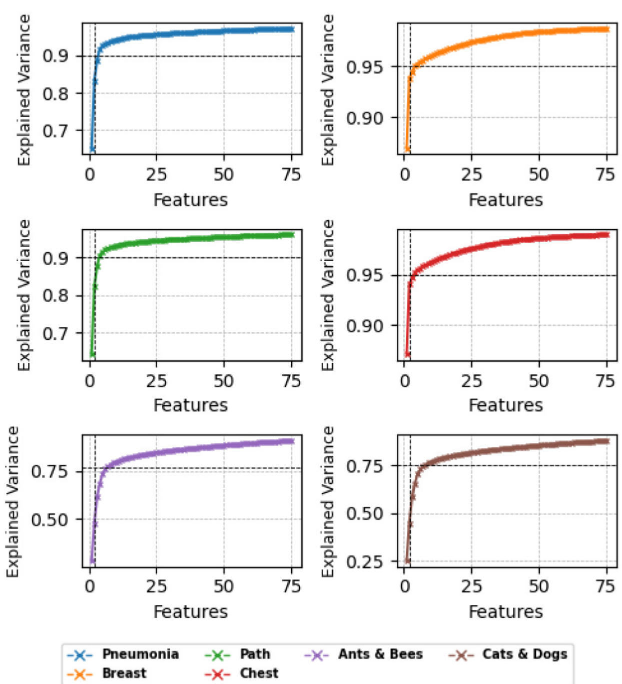

Fig. 5. Principle Component Analysis. To retain **90% (0.9)** of the original variance, the number of components needed to achieve that threshold on the explained variance graph can be identified. Based on the diagram, transformed MedMNIST2D datasets meet the criteria with approximately **2** principal feature components.

2) Based on Test Accuracy: In a subsequent experiment, a plot to visualize our proposed model's test accuracy as we gradually increased the number of feature components identified by PCA was created. This investigation was conducted with up to 10 feature components due to quantum hardware constraints. As a potential direction for future research, this exploration could be extended to cover a larger number of feature components. Notably, Figure 6 illustrates that the accuracy of our proposed model was subject to minimal variations and, as the number of feature components increased, it began to decline due to overfitting with a large feature space.

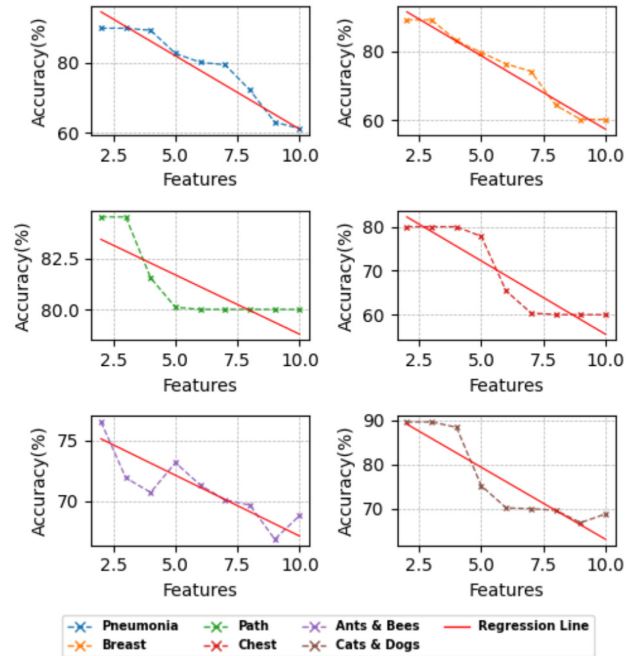

Fig. 6. Testing accuracy as the number of feature components increases. As the number of feature components increases, there is no substantial improvement in test accuracy initially. However, as the number of features continues to increase, accuracy significantly decreases due to higher dimensionality and model over-fitting.

The outcomes of these two experiments indicate that reducing the feature dimensions to just 2 principal components from the original 2048 features is adequate for accurate class identification in medical datasets. For Hymenoptera Ant & Bees and Kaggle Cats & Dogs datasets, more features are required due to image complexity compared to MedMNIST2D datasets. Nevertheless, high accuracy is still maintained by our model, with 85% achieved on Hymenoptera Ant & Bees and 90% on Kaggle Cats & Dogs, all with just 2 principal components.

F. Real Quantum Device Testing and Validation

Upon identifying the minimum required number of Q-bits for the classifier VQC in our proposed model, the findings from Experiment A and Experiment C were validated on the **IBM Canberra** quantum device [26]. As demonstrated in Table I, despite the inherent noise introduced by real quantum hardware limitations, the results remained consistent. This robustness is due to our strategic use of a minimal number of Q-bits, which helps mitigate the impact of noise on quantum computations [47]. This approach ensures the reliability and consistency of our model's performance across quantum platforms.

In this study, the performance of the proposed model was assessed with limited image data, and comparative benchmark

TABLE II
COMPARATIVE ANALYSIS OF SELF-SUPERVISED MODELS WITH OUR PROPOSED MODEL

Ref. No.	Dataset	Encoder Model	Classifier	Findings	Limitations
[7]	ImageNet	ResNet200, ResNet100, ResNet50	Linear	• Achieve 81.4% top-1 accuracy on ImageNet. • Outperform cross-entropy on different datasets and ResNet variations.	• Hyperparameter sensitivity. • Requires large labeled datasets.
[6]	ImageNet	ResNet50	QNN	• Effective without large labeled datasets. • Rapid convergence.	• Low accuracy. • High accuracy needs more Q-bits.
Our Proposed Model	**MedMNIST 2D Datasets, Ants & Bees, Cats & Dogs**	**ResNet50**	**PCA & VQC**	**• Boost accuracy with minimal Q-bits using PCA & Data preprocessing. • Generalizes with fewer data. • Robust against complex datasets.**	**• Complex datasets reduce accuracy. • VQC Q-bits equal to feature dimension.**

tests were conducted against linear classification models. The model's generalizability was examined using non-medical datasets, and the impact of reduced sample size on model performance was investigated. Furthermore, the minimum q-bit requirement for quantum hardware execution was determined. Additionally, data privacy and the model's robustness against adversarial attacks were explored in the context of classical SCL models. The studies [28], [29] explores privacy concerns related to contrastive models trained on image datasets, focusing on membership and attribute inference attacks. Contrary to supervised models, contrastive models demonstrate greater resistance to membership inference attacks, attributed to their reduced overfitting. However, they are more susceptible to attribute inference attacks, potentially due to their capacity to generate informative data representations. These findings shed light on the nuanced privacy implications of contrastive models, with implications for data protection strategies. As part of future work, authors intend to test the complete model against adversarial attacks. And, while the datasets used were binary-class, future work could extend our model for multi-class classification by incorporating multiple feature maps, classical optimizers, and varying repetitions of parametrized circuits [48], [49], [50] within the VQC framework.

V. CONCLUSION AND DISCUSSION

Our innovative solution blends supervised contrastive learning (SCL) with Variational Quantum Classifiers (VQC) and leverages Principal Component Analysis (PCA) for dimensionality reduction, enabling effective generalization in medical machine learning despite limited training data. The fusion of supervised contrastive learning and VQC improves performance, especially with constrained training data. Additionally, inherent defense against adversarial attacks through supervised contrastive loss calculation enhances the model's adaptability in the medical domain. Utilizing PCA for dimensionality reduction, the VQC operates efficiently with just 2 Q-bits, effectively tackling quantum hardware limitations. Our approach is validated through comparisons with linear models, and hybrid quantum models on public medical image datasets, achieving notable accuracy of 90% on PneumoniaMNIST, 90% on BreastMNIST, 80% on PathMNIST, and 80% on ChestMNIST medical datasets. And, for non-medical datasets, the model attained 85% on Hymenoptera Ants & Bees and 90% on the Kaggle Cats & Dogs dataset. Our architecture emerges as a robust solution, merging SCL and VQC with PCA-based dimensionality reduction, achieving accuracy and data privacy in medical image analysis while using 2 Q-bits on quantum hardware, signifying progress in this field.

This study focused on developing a generalized model to overcome challenges posed by limited labeled data while considering quantum hardware constraints, to outperform existing quantum self-supervised models [6], [27]. Further enhancements can be explored by optimizing data pre-processing techniques and experimenting with different configurations of the Data Encoding Circuit and Variational Circuit for an optimal VQC architecture. Additionally, alternative quantum classification algorithms might offer improved outcomes. A comparative analysis of self-supervised models, including our proposed model, is presented in Table II.

Looking ahead, extending our model's capability to handle multi-class classification scenarios is a priority. Additionally, the current inbuilt data privacy mechanism of SCL preserves patient image data privacy to a certain extent from membership inference attacks, but further advancements are required to ensure comprehensive data protection. Lastly, the challenge of long quantum model convergence times during training on real quantum devices and simulators should be addressed to improve the model's efficiency and practicality. Reference code is released at.[1]

APPENDIX

A. Datasets Analysis

In this research, 4 public medical datasets, namely PneumoniaMNIST, BreastMNIST, PathMNIST, and ChestMNIST, along with 2 public non-medical datasets Hymenoptera Ant and Bees and Kaggle Cats and Dogs Dataset

[1]GitHub Repository: https://github.com/AsithaIndrajith/dr-hqcl.

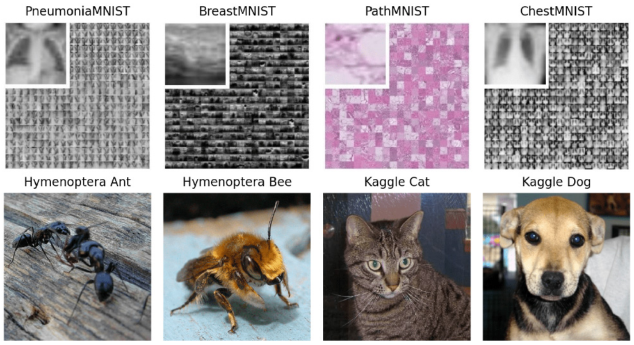

Fig. 7. Experimented Datasets. The first row of images encompasses various medical datasets, while the second row showcases non-medical datasets

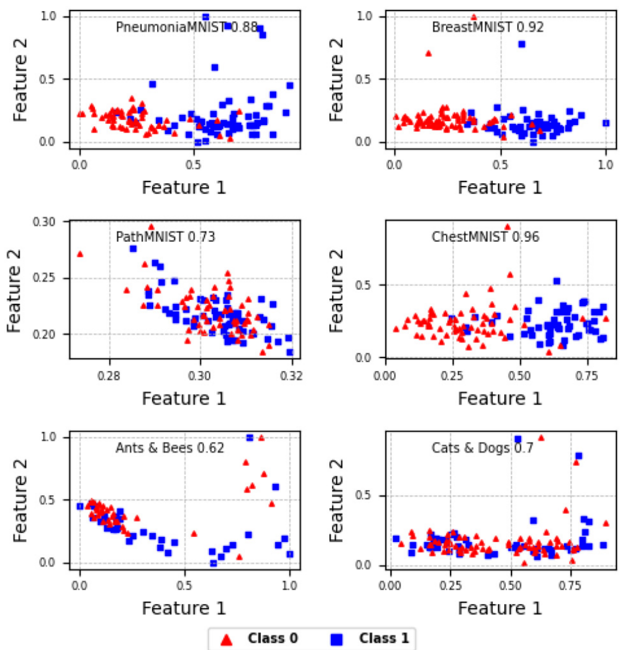

Fig. 8. PCA Datasets Analysis. The correlation between 2 features, where an increase in feature correlation value corresponds to improved visual feature classifiability.

utilized (Figure 7). Each dataset comprises 120 random data samples, featuring only 2 classes as the focus of this study centers on binary classification tasks. The sources and details of all 6 public datasets are elaborated in Section III-B.

1) SCL Transformed Datasets: Subsequently, each dataset underwent a transformation process to generate a 2048-feature dataset (SCL Datasets) along with corresponding data labels, employing the Supervised Contrastive Learning (SCL) method elucidated in Section III-C.

2) PCA Transformed Datasets: Following the data transformation through SCL, the transformed data of each dataset underwent preprocessing, as outlined in Section III-D. Finally, the dimensionality of the 2048-feature datasets was reduced to 2 features, resulting in PCA Datasets, leveraging Principal Component Analysis (PCA).

The datasets transformed through Supervised Contrastive Learning (SCL Datasets) and dimensionality-reduced datasets (PCA Datasets) are accessible on the IEEE Data Port [51].

Figure 8 depicts the feature correlation scatter plots of the PCA Datasets, encompassing PneumoniaMNIST, BreastMNIST, PathMNIST, and ChestMNIST from MedMNIST2D, as well as the non-medical datasets Hymenoptera Ant and Bees and Kaggle Cats and Dogs Dataset, each consisting of 120 samples. The visualization distinctly highlights the relationship between visual feature classifiability and the correlation values mentioned in each plot.

Subsequently, PCA Datasets generated for each dataset were directly evaluated using a Variational Quantum Classifier (VQC). Within the variational quantum classifier, a Data Encoding circuit (ZZFeatureMap) transformed classical PCA Datasets into quantum states, which were then processed further by the variational circuit. This intricate process is thoroughly detailed in Section III-F.

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