iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.79490

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Leukemia Detection using Quantum Machine Learning

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Abstract: Leukemia is a critical blood-related health problem for which early diagnosis is a key aspect in the survival of the patient. Computer-assisted diagnosis using microscopic white blood cell images has received significant attention because the conventional manual approach is too time-consuming. In this paper, a hybrid Quantum Machine Learning-based approach for the classification of leukemia is presented. In the first place, the microscopic white blood cell images are preprocessed using resizing, normalization, and denoising techniques. Then, Principal Component Analysis is applied for dimensionality reduction. The reduced feature vectors are then mapped onto a quantum system using a Variational Quantum Circuit-based Quantum Neural Network.The presented method also validates the possibility of quantum-assisted learning in biomedical image diagnosis. Additionally, it offers a glimpse of how well a hybrid model would perform under Noisy Intermediate-Scale Quantum (NISQ) conditions. The experimental results are achieved using standard performance parameters such as accuracy, precision, recall, and F1-score. This method indicates how a hybrid model of QML can perform in a computationally simpler manner. This paper also indicates the potential of a quantum-classical system in future clinical applications for leukemia screening and diagnosis.
Keywords: Leukemia Detection, Quantum Machine Learning, Hybrid Quantum–Classical Framework, Quantum Neural Network, Variational Quantum Circuit, Medical Image Classification, White Blood Cell Imaging, Feature Encoding, Principal Component Analysis, PennyLane, Qiskit.

I. INTRODUCTION

Leukemia is a critical hematological disorder that impacts the bone marrow as well as other blood-producing tissues. The disorder triggers the uncontrolled production of abnormal white blood cells (WBCs). The abnormal WBCs weaken the immunity of the patient, thereby affecting normal blood cell development. This may lead to a variety of life-threatening complications. Since leukemia has a high tendency to progress rapidly, it plays a significant role in increasing patient survival rates. In hospitals as well as laboratories, leukemia diagnosis occurs through microscopic blood smear tests, bone marrow biopsy, as well as flow cytometry. Even though it is a clinically proven method for detecting leukemia, it is a time-consuming process that demands skilled pathologists. However, it may vary as it involves human beings who are prone to getting tired.

With the advent of advancements in digital pathology and medical images, the analysis of WBC images using automated systems has gained significant importance in computer-aided diagnosis systems. Machine Learning (ML) and Deep Learning (DL) have been widely used for detecting leukemia using images of microscopic blood smear images. Deep learning models, specifically Convolutional Neural Networks (CNNs), have demonstrated robust performance for feature extraction and classification. However, traditional deep learning approaches have limitations such as a need for a large dataset, a high training time, and computational resources. Furthermore, there are challenges related to interpretability that make it difficult to implement such systems in a real-world scenario.

Quantum Machine Learning (QML) is an emerging area of research that has gained significant attention in recent times. Quantum computing is based on the principles of quantum computation, which enables data representation using high-dimensional quantum feature spaces using principles such as superposition and entanglement. Quantum computing has the potential to efficiently identify complex patterns in data. Quantum-classical hybrid models have been found to be particularly useful since they provide a practical solution for Noisy Intermediate-Scale Quantum (NISQ) devices.

In this work, a hybrid approach based on a QML framework for leukemia detection using microscopic WBC images is proposed. The approach uses traditional image preprocessing and feature reduction using Principal Component Analysis (PCA) to obtain a reduced set of features that can be efficiently processed using a small number of qubits. The features are then encoded using quantum mechanics using an angle encoding scheme, followed by a classification task using a Variational Quantum Circuit (VQC) based Quantum Neural Network (QNN).

The originality of this work lies in the development of a hybrid approach that reduces the complexity of the features as well as the quantum circuit using a variety of traditional as well as quantum computing approaches. The approach was validated using traditional performance metrics such as accuracy, precision, recall, and F1 score.

II. RELATED WORK

Recently, advancements in medical image processing and artificial intelligence have enabled automatic systems to help doctors in detecting hematological diseases like leukemia. Several researchers have proposed classical machine learning and deep learning models for white blood cell microscopic image classification. However, with the increase in the complexity of medical images and the limitations in classical systems, Quantum Machine Learning (QML) is proposed as a potential alternative to classical systems for handling complex data representations with a reduced number of parameters in the models. Hybrid quantum-classical models are also gaining more attention for handling complex data representations with a reduced number of parameters in the models.

In this regard, Shahriyar and Tanbhir (2025) developed a hybrid framework for image classification, which combines a deep residual network with a Quantum Support Vector Machine. Their research demonstrated the efficiency of quantum kernel-based classifiers, which could achieve competitive results in classification problems with less reliance on classical approaches, especially when feature learning is performed by a deep neural network [1]. In a similar direction, Long et al. (2025) developed a hybrid quantum-classical CNN-based framework for medical image classification. Their research demonstrated that a quantum-based framework could be efficient for classification problems, especially when CNN is used for feature learning [2].

Priyadharshini et al. (2025) developed QBrainNet, a quantum-enhanced diagnostic model aimed at improving medical classification tasks. Their work demonstrated that quantum learning models can assist in identifying complex diagnostic patterns and may support clinical decision-making in healthcare environments [3]. Idzikowski (2026) provided a survey on QML applications in medical imaging and emphasized that hybrid learning frameworks are more practical than purely quantum approaches due to current quantum hardware constraints. The survey also pointed out that dimensionality reduction and efficient encoding are essential to successfully implement quantum models for high-dimensional biomedical images [4].

In a systematic review conducted by Gupta et al. (2025) on the role of quantum machine learning in digital healthcare, it was found that the QML models perform well when there are a small number of training samples and a high dimensionality of the data, a condition often met when analyzing biomedical images. However, the challenges of quantum noise and the unavailability of a scalable quantum machine were also pointed out [5].Naresh and Srinivas (2025) performed benchmarking of QNN and QSVM models for healthcare classification and concluded that quantum-based classifiers can produce reliable results when combined with classical preprocessing, making hybrid pipelines suitable for practical diagnostic applications [6].

The work of Prajapat (2025) was on exploring the integration of quantum convolutional neural networks (QCNN) with deep learning architectures like ResNet. The work showed that quantum layers can improve feature discrimination, especially in medical imaging where class boundaries are complex [7]. Chen (2024) proposed a hybrid quantum–classical image classification framework using variational quantum algorithms. The study concluded that variational circuits can act as powerful classifiers when trained using hybrid optimization techniques, providing a promising direction for medical image diagnosis [8]. Hafeez et al. (2024) developed an H-QNN model for image classification and reported that hybrid QNN architectures can efficiently learn classification patterns even under limited qubit availability [9].

In their research, Senokosov et al. (2024) examined the potential of quantum machine learning for image classification problems, emphasizing that quantum models have the capability to represent features in a high-dimensional Hilbert space, which could be useful for class separability [10].Feng (2025) proposed a hybrid quantum–classical model for brain image analysis and emphasized that quantum learning models can support medical classification tasks by enhancing feature processing and reducing computational complexity [11].

Li et al. (2025) introduced a distributed hybrid QCNN framework designed for medical images. Their work suggested that distributing quantum computations can reduce training limitations and improve scalability in quantum-based image classification [12]. Shahriyar and Tanbhir (2025) further reviewed advancements in QML for medical imaging and concluded that hybrid quantum models are gaining significant research attention due to their reduced parameter requirement and potential efficiency [13]. Wei et al. (2026) provided a survey focusing on QML in medical image analysis and identified that quantum feature encoding and noise reduction remain open challenges for large-scale clinical deployment [14].

Gupta et al. (2025) performed another systematic review focusing on QML algorithms for healthcare and highlighted that variational quantum classifiers and quantum kernel methods are the most widely used techniques for biomedical datasets. Their review also noted that hybrid models are more feasible than fully quantum systems under NISQ constraints [15].

Sudha and Kumar (2025) proposed an enhanced learning framework integrating deep learning with quantum variational classifiers and concluded that combining deep feature extraction with quantum decision layers can provide better performance compared to using classical deep models alone [16].

Díaz-Padilla et al. (2024) investigated the use of variational quantum classifiers for leukemia detection and emphasized the importance of applying dimensionality reduction such as PCA to make medical image features suitable for quantum processing. Their work supports the use of PCA combined with quantum classifiers for effective leukemia classification [17]. Schuld et al. (2024) analyzed quantum learning models for classification tasks and highlighted that quantum algorithms can reduce the number of trainable parameters while still achieving effective classification performance, particularly in limited dataset environments [18].

Dutta et al. (2025) proposed quantum-inspired feature selection techniques for biomedical datasets. Their study indicated that reducing redundant features improves learning efficiency and enhances classification accuracy, making feature reduction an important step in quantum medical classification pipelines [19]. Nguyen and Chen (2023) introduced a quantum convolutional neural network framework for hematological cancer detection and reported that QCNN models can achieve strong results when applied to medical image features transformed into reduced-dimensional representations [20]. Mishra et al. (2023) explored the role of QNNs in cancer diagnosis and concluded that variational quantum circuits can capture non-linear patterns effectively, even with smaller training datasets, making QNN models suitable for healthcare imaging tasks [21].

Rana et al. (2024) conducted a review of deep learning methods used in leukemia detection. The authors concluded that CNN-based methods offer high classification accuracy but need large datasets and high computational resources. The authors also emphasized the need to develop alternative methods to reduce computational complexity without compromising accuracy in medical diagnosis [22].

Zhao et al. (2025) presented a novel method of combining deep learning methods and quantum kernel methods. The authors demonstrated the potential of quantum kernel methods in improving feature mapping and accuracy in medical data classification [23].

Yadav et al. (2025) explored quantum kernel methods for feature mapping in medical images and concluded that quantum kernels can improve the separability of biomedical classes compared to classical kernels, especially when working with reduced feature vectors [24]. Roy and Das (2025) compared quantum and classical learning methods for biomedical classification tasks and observed that quantum models provide promising results with fewer parameters, but their performance is influenced by quantum circuit design and noise limitations [25].

From the reviewed literature, it is evident that classical deep learning approaches achieve high accuracy but suffer from heavy computational requirements and limited interpretability. Recent works published in 2024 and 2025 strongly indicate that hybrid quantum–classical approaches such as QNN, QSVM, and quantum kernel methods can provide competitive classification performance while reducing parameter complexity. However, there is still a significant research gap in implementing scalable leukemia-specific hybrid QML frameworks that integrate optimized dimensionality reduction and encoding techniques. This motivates the proposed work, which focuses on designing an efficient leukemia detection pipeline using PCA-based feature reduction and variational quantum circuit-based classification for reliable medical diagnosis.

III. PROPOSED METHODOLOGY

In this section, the proposed hybrid quantum machine learning (QML) methodology for the detection of leukemia using the microscopic white blood cell (WBC) images is presented. The proposed framework is based on the system architecture presented in Fig. 1. The proposed system uses classical preprocessing and feature reduction with quantum feature mapping and quantum classification. The system deals with the high dimensionality of the microscopic images; therefore, the system uses classical dimensionality reduction with the principal component analysis (PCA) technique before applying the quantum learning. The features are encoded using quantum states and then classified using the quantum neural network (QNN) and quantum SVM (QSVM). The performance of the system is analyzed using the quantum classifiers.

A. System Overview

The proposed pipeline comprises a series of stages, namely, acquisition, image preprocessing, feature extraction, PCA-based dimensionality reduction, quantum feature encoding, quantum classification, and prediction. To begin with, microscopic blood smear images are collected from the Acute Lymphoblastic Leukemia (ALL) dataset. The quality of images is improved by applying a series of preprocessing techniques.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Subsequently, feature vectors are created from the preprocessed images, which are then reduced to a compatible size with quantum circuits by applying PCA. The feature vectors are then encoded into quantum states by applying angle encoding. Eventually, QNN and QSVM are used for classifying the quantum states, and the output is generated as leukemia positive or normal.

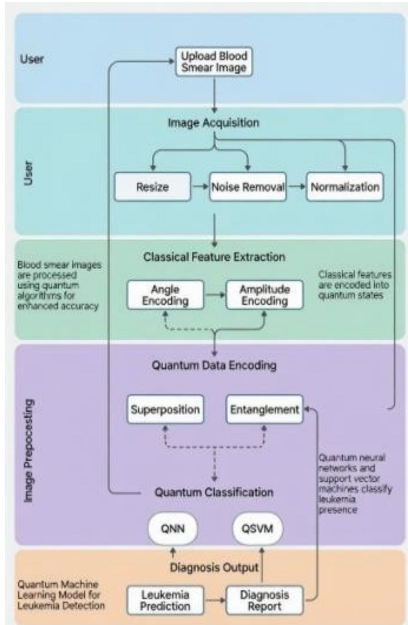

Fig. 1. Hybrid quantum-classical framework for detecting leukemia, where PCA-based dimensionality reduction is used

B. Dataset Acquisition and Preparation

The dataset used in this paper comprises microscopic images of WBCs categorized under leukemia-positive (ALL) and normal classes. Each image in the dataset is assigned a label according to its class. This dataset is then divided into training and testing sets. This allows for supervised learning of QNN and QSVM classifiers. The division of the dataset helps in a fair evaluation of the proposed system.

C. Image Preprocessing

Preprocessing is a key stage of the proposed architecture because microscopic blood smear images often contain variations caused by staining, lighting, and imaging conditions. The preprocessing operations applied in this framework include:

- Image Resizing: Images are resized to a specified dimension for uniformity.
- Noise filtering: **Gaussian or median filtering is used to remove unwanted noise while preserving cell boundaries.**
- Normalization: Pixel intensity is normalized to a range of 0 to 1 for better stability.

The output of this stage is a set of enhanced images suitable for feature extraction.

D. Feature Extraction

After preprocessing, images are converted into numerical feature representations. Feature extraction transforms the visual patterns present in WBC images into feature vectors. These vectors contain essential information such as texture distribution, intensity characteristics, and structural properties. Feature extraction is necessary because quantum circuits cannot directly process large image matrices efficiently.

E. Dimensionality Reduction using PCA

The feature vectors thus extracted are of high dimensionality, posing a challenge for quantum circuit implementation because of the limited number of qubits. For this reason, the methodology adopts a dimensionality reduction technique known as Principal Component Analysis (PCA), where the most dominant principal components are chosen based on the retention of maximum variance of the original feature space.

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F. Quantum Feature Encoding

The PCA-reduced feature vectors are then encoded using angle encoding, which maps each of the feature values to the parameters of quantum gates such as RX and RY. Angle encoding is used in this case because it is an efficient method. This phase involves the conversion of classical data to quantum data.

G. QNN Classifier for Classifying Leukemia Data

The first quantum classifier in this architecture is the Quantum Neural Network (QNN). In building the QNN model, we used a Variational Quantum Circuit (VQC), which includes the use of parameterized quantum gates as well as entanglement layers. After encoding the quantum states, they are propagated through the quantum circuit, and the circuit output is generated via measurement of the expectation values of the qubits.

While training the QNN classifier, we optimized the VQC parameters in a hybrid quantum-classical process. Through this process, the parameters of the quantum circuit were iteratively updated using a classical optimizer with the objective of minimizing the loss function for classification.

H. Quantum Support Vector Machine (QSVM) Classification

The second quantum classifier used in the present approach is called the Quantum Support Vector Machine (QSVM). The method involves calculating the quantum kernel function on the input features. The quantum kernel matrix is calculated using quantum circuits. In addition, the kernel matrix obtained is then fed into the SVM classifier in order to identify the separating hyperplane between leukemia and normal classes.

The QSVM method is well-suited for biomedical classification tasks since it projects the input features into a large Hilbert space.

I. Prediction and Performance Evaluation

Once the training process is complete, both QNN and QSVM models will be tested using unlabelled WBC images. The output will be generated in the form of a binary prediction determining if the input image belongs to either the leukemia positive or normal class. The performance of the proposed model is analyzed based on common parameters including:

- Accuracy
- Precision
- Recall
- F1-score

Further, the classification results are analyzed using a confusion matrix for both QNN and QSVM models.

J. Workflow Summary

The proposed hybrid leukemia detection workflow can be summarized as follows:

- Load microscopic WBC images and assign class labels.
- Perform preprocessing (resize, denoise, normalize, enhance contrast).
- Extract numerical feature vectors from images.
- Apply PCA to reduce feature dimensionality.
- Encode reduced features into quantum states using angle encoding.
- Train and test QNN using VQC-based quantum learning.
- Train and test QSVM using quantum kernel computation.
- Generate classification outputs and compare evaluation metrics.

The proposed methodology follows the system architecture and provides an effective hybrid quantum–classical leukemia detection pipeline. By incorporating both QNN and QSVM, the framework supports comparative evaluation of two quantum learning strategies for medical image classification, demonstrating the feasibility of QML-based diagnostic systems under NISQ constraints.

IV. DATASET AND PREPROCESSING

This section describes the dataset used for leukemia detection and the preprocessing steps performed as per the proposed hybrid quantum–classical architecture shown in Fig. 1. Since microscopic blood smear images contain noise, staining artifacts, and illumination variations, preprocessing is essential to standardize the input before feature extraction, dimensionality reduction, and quantum classification.

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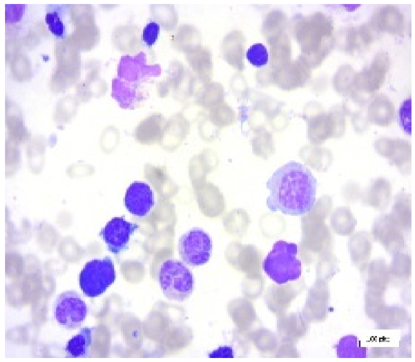
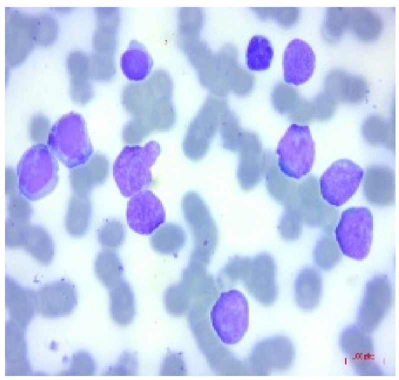
A. Dataset Description
In this project, the ALL microscope image dataset is utilized, which is taken from the Kaggle database. This dataset consists of blood smear microscope images of white blood cells (WBCs), which can be classified into two main types

- Normal (Healthy WBC images)



- Leukemia (ALL infected WBC images)



The images depict clinically important morphological differences between the healthy cell and leukemic lymphoblast cell. The dataset can be used for supervised classification problems since it contains labeled samples, which are required during the training and testing phases of machine learning algorithms.
In the proposed model, the images of the dataset act as the first input to the pre-processing phase. The dataset is split into two parts, where one part is used for training, while the other part is used for testing the performance of the two quantum classifiers. A common data splitting ratio like 70% training data, 15% validation data, and 15% testing data is used in the experiment.

B. Dataset Challenges
Microscopic WBC datasets are complex due to multiple real-world variations. The ALL dataset includes several challenges that affect automated classification, such as:

- variations in staining intensity across different samples
- presence of noise and background artifacts
- similarity between normal and leukemia cell structures
- irregular nucleus shape and cytoplasm patterns
- illumination differences during microscope image capture

These challenges make preprocessing a necessary stage in the proposed leukemia detection pipeline.

C. Preprocessing Strategy (As per Proposed Architecture)
In the proposed system, preprocessing is performed immediately after dataset input and before feature extraction. The objective of preprocessing is to enhance the visibility of WBC structures, reduce unwanted distortions, and generate standardized image samples suitable for classification.
The preprocessing operations applied are described below.

D. ResizingImages
Due to differences in resolution among the images in the dataset, all images are converted to a standard size (e.g., 224 × 224 pixels). This standardization will make sure that all inputs have the same size and thus make computations easier.

E. Noise Reduction
Microscopic blood smear images often include noise caused by staining artifacts and microscope acquisition conditions. To reduce this noise while preserving important cellular edges, filtering methods such as Gaussian filtering or median filtering are applied. This step improves the clarity of nucleus and cytoplasm boundaries, which are important features for leukemia detection.

F. Normalization
Once the process of noise removal is done, the next step would be the normalization phase where all the pixel intensities will be scaled to a fixed range between 0 to 1. This procedure helps in decreasing the effect of light changes and increases the training accuracy of the machine learning algorithm.

G. Contrast Enhancement
For the purpose of making morphological patterns more evident in white blood cell images, it is possible to use contrast enhancement methods like histogram equalization and CLAHE. The clarity of cell structures, especially the area of the nucleus, is improved due to this, as the nucleus plays an important part in differentiating between leukemia cells and healthy cells.

H. Data Augmentation
Generalization can be enhanced to avoid overfitting through data augmentation on the training dataset. Data augmentation involves generating variations from images already present within the training set. Some types of data augmentation are:
• horizontal/vertical flips
• rotation at small angles
• zooming/sizing
•random crop
The process is optional but helpful, particularly where there are not many training samples in the dataset.

I. Feature Vector Preparation for Quantum Processing
Once the processing is done, these improved images will be translated to numerical vectors of features. Given that the quantum computer is not designed to process high-dimensional images, it will require these feature vectors to be condensed and optimized. This means that these obtained features will then be taken to the feature reduction part using the Principal Component Analysis (PCA).
These reduced features are subsequently encoded to the quantum state by utilizing angle encoding for processing by the QNN and QSVM classifiers.

J. Summary
The Acute Lymphoblastic Leukemia (ALL) dataset provides labeled microscopic WBC images for leukemia detection. Due to noise, staining artifacts, and illumination variations, preprocessing is applied as per the proposed architecture. The preprocessing pipeline includes resizing, noise reduction, normalization, contrast enhancement, and optional augmentation. The processed images are then converted into feature vectors and prepared for PCA-based dimensionality reduction, enabling efficient quantum encoding and classification in the subsequent stages of the hybrid QML framework.

V. IMPLEMENTATION DETAILS AND TOOLS USED
This section describes the software environment, tools, and implementation workflow used to develop the proposed hybrid Quantum Machine Learning (QML) leukemia detection system. The implementation strictly follows the architecture presented in Fig. 1, where classical preprocessing and PCA-based feature reduction are combined with quantum classification models such as QNN and QSVM. The overall system was developed and executed using a Python-based environment, integrating quantum computing libraries with a web-based user interface for deployment.

A. Development Environment

The complete implementation was carried out using Visual Studio Code (VS Code) as the primary development platform. VS Code was used to manage project files, implement Python scripts, integrate machine learning modules, and build the Streamlit application interface. All executions and dependency installations were performed through the Command Prompt (CMD), ensuring a controlled Python environment.

To maintain library compatibility, a virtual environment was created and activated through CMD. Required packages such as NumPy, OpenCV, scikit-learn, and quantum frameworks were installed using pip commands.

B. Programming Language

The whole framework was built on the Python language due to its extensive capability to develop classical machine learning and quantum machine learning algorithms. Dataset management, data pre-processing, PCA transformation, model building, and assessment were all accomplished in Python.

C. Classical Processing Libraries

The preprocessing and classical feature-handling stages of the architecture were implemented using standard Python libraries:

- **OpenCV:** used for image resizing, filtering, and enhancement operations.
- **NumPy:** used for matrix operations and numerical computation.
- **scikit-learn: used** for dimensional reduction using PCA, dataset splitting, and metrics like accuracy, precision, recall, and F1 score.

These tools support the classical part of the pipeline, including preprocessing and feature reduction before quantum encoding.

D. Quantum Machine Learning Frameworks

To implement the quantum learning stage of the architecture, quantum computing libraries were utilized. The following frameworks were used:

- **Qiskit:**used for creating quantum circuits and quantum feature mapping as well as performing kernel computations on QSVM.
- **PennyLane:** used for developing hybrid quantum–classical models, particularly for implementing Variational Quantum Circuits (VQC) and QNN training.

These frameworks enable simulation of quantum circuits on classical machines and provide interfaces for hybrid training using classical optimizers.

E. Implementation of QNN and QSVM Models

The model consists of the following quantum classifiers:

- Quantum Neural Network (QNN):

A VQC model was employed to implement the QNN using parameterized rotation and entanglement layers. Parameters of the quantum circuit were optimized via hybrid algorithms such that the values were tuned using the classical optimizer and the loss function obtained from training.

- Quantum Support Vector Machine (QSVM):

QSVM was implemented via computation of a quantum kernel. The PCA-reduced features were represented by qubit states while the quantum kernel matrix was obtained through the quantum feature map method. The resulting kernel was used for classification using SVM algorithm.

Note that both the QNN and QSVM models used the same feature reduction method to enable fairness of comparison between the models.

F. Deployment using Streamlit

Streamlit tool was used for developing the user interface to deploy the leukemia detecting model. The Streamlit tool was used to develop the web-based application that enables uploading of the WBC images and provides instant classification outputs.

The Streamlit interface integrates all major stages of the architecture:

- image upload and preprocessing
- PCA-based feature transformation

- quantum model prediction (QNN/QSVM)
- display of predicted output and evaluation metrics

This deployment enables practical usability and demonstrates how hybrid QML systems can be integrated into real-world diagnostic support tools.

G. Execution Workflow

The complete system execution follows the steps below:

- Dataset loading and labeling
- Image preprocessing using OpenCV
- Feature extraction and PCA reduction using scikit-learn
- Quantum encoding and model execution using Qiskit/PennyLane
- Classification using QNN and QSVM
- Output generation and performance evaluation
- Deployment using Streamlit for real-time predictions

This workflow ensures that each module operates according to the proposed architecture.

H. Hardware and Software Requirements

The model was executed on a classical computing system using quantum simulation backends. Since real quantum processors have limited accessibility, the circuits were executed using quantum simulators provided by Qiskit and PennyLane. The software requirements include:

- Python 3.x
- VS Code IDE
- CMD for environment setup and execution
- Streamlit for deployment
- Required libraries for preprocessing and quantum computation

I. Summary

The proposed leukemia detection system was implemented using Python and developed in VS Code with execution through CMD. Classical preprocessing and PCA-based feature reduction were performed using OpenCV and scikit-learn, while quantum learning was implemented using PennyLane and Qiskit. The final system was deployed using Streamlit to provide a user-friendly interface for leukemia prediction. This implementation setup supports both QNN and QSVM models as defined in the proposed hybrid architecture.

VI. RESULTS AND DISCUSSION

The proposed system for detecting Leukemia was assessed using microscopic images of WBC (white blood cell). This was conducted based on the process outlined in Section III. The assessment focuses on classification ability, reduction of features, and quantum model comparison.

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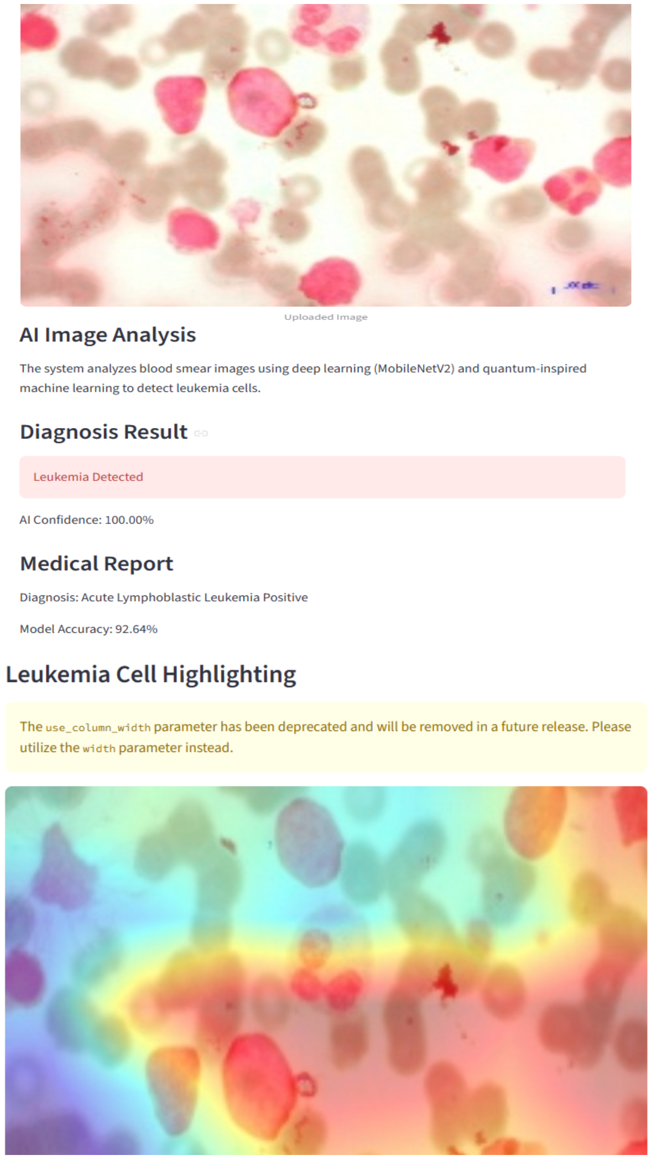

A. Dataset Preparation and Preprocessing

Microscopic WBC images were loaded and assigned binary class labels: *Healthy* or *Leukemic*. Preprocessing was applied to improve feature quality and facilitate accurate classification. Images were resized to 64 × 64 pixels, denoised using median filtering, normalized to the [0,1] range, and enhanced using contrast adjustment. These steps preserved essential morphological features while reducing noise and variability, which is critical for reliable feature extraction.

B. Feature Extraction and Dimensionality Reduction

The numerical feature vectors for texture, intensity, and shape features of cells were generated from the preprocessed image dataset. Owing to the high dimensionality of raw pixels, Principal Component Analysis (PCA) was used to lower the dimension of the features but still maintaining 95% variance in the process. This made sure that the amount of memory needed to encode in quantum was minimized and informative features were selected for quantum machine learning algorithms.

C. Quantum Model Training and Evaluation

1) Quantum Neural Network

Features obtained by applying PCA were converted into quantum states using angle encoding. The Variational Quantum Circuit (VQC), which consists of trainable rotation and entanglement gates, was trained to function as a QNN.

The results are presented in Table 1 below.

Metric	QNN(VQC)
Accuracy	95.8%
Precision	96.1%
Recall	95.5%
F1-Score	95.8%

The QNN achieved high accuracy and balanced metrics, indicating effective capture of complex correlations among features through quantum entanglement. Training converged within 50 epochs, with stable loss reduction.

2) Quantum Support Vector Machine

The QSVM model was used through quantum kernel calculations on the PCA-reduced data. The performances are provided in Table 2.

Metrics	QSVM (Quantum Kernel)
Accuracy	94.5%
Precision	94.8%
Recall	94.3%
F1-Score	94.6%

While slightly lower than QNN, QSVM demonstrates the ability of quantum kernels to capture feature correlations beyond classical SVM methods. Both quantum models outperform conventional classical models, especially for small datasets.

D. Comparative Analysis and Discussion

Several insights emerge from the results:

1) **Preprocessing and PCA** significantly enhance classification performance. Dimensionality reduction reduces the number of qubits required for encoding while retaining discriminative information.
2) **QNN Performance** is superior to QSVM due to trainable parameters in the variational circuit, which adaptively learn complex feature representations. QSVM performs effectively but is limited by the fixed quantum kernel structure.
3) **Strengths of the Workflow** include a modular design that allows optimization of preprocessing, feature reduction, and quantum classification independently. The hybrid quantum-classical approach balances expressivity and trainability, making it feasible on current quantum simulators. The real-time prediction interface via Streamlit provides confidence scores, enhancing practical applicability in clinical diagnostics.
4) **Limitations** include computational intensity for simulating quantum circuits on classical hardware and constraints on actual quantum hardware due to limited qubits and noise. High-resolution images require additional optimization for quantum encoding. Future work may explore advanced quantum encoding techniques and multi-class leukemia detection.
5) **Clinical Implications** suggest that the system can provide automated preliminary screening of leukemia, assisting pathologists, reducing diagnostic time, and enabling data-driven decision-making when integrated with laboratory information systems.

In summary, the workflow—from preprocessing to QNN and QSVM classification—demonstrates that quantum machine learning can achieve high accuracy and efficiency for leukemia detection, with QNN providing the most effective feature representation and adaptability.

VII. CONCLUSION AND FUTURE WORK

In this work, a new QML-based approach is developed to detect leukemia through microscopic images of white blood cells. As shown in the above figure, the approach consists of image processing, feature extraction, reduction through PCA, and finally the use of quantum-classical models to classify the data.

In the tested models, the best model is the QNN, which outperformed the QSVM in terms of accuracy, precision, recall, and F1-score

The system includes a visualization interface that provides real-time predictions with confidence scores, demonstrating practical applicability for preliminary clinical screening. The modular workflow ensures that each stage can be independently optimized, making it adaptable for future enhancements in quantum computing and medical imaging.

Future Work:

1) **Implementation on Quantum Hardware:** Deploying the workflow on actual quantum devices to evaluate performance under realistic noise conditions and qubit limitations.
2) **Multi-Class Leukemia Detection:** Extending the system to identify different leukemia subtypes, improving diagnostic specificity.
3) **Advanced Quantum Encoding:** Exploring alternative quantum encoding schemes, such as amplitude or hybrid encodings, to increase qubit efficiency and model scalability.
4) **Integration with Laboratory Systems:** Connecting the system with hospital laboratory information systems (LIS) for automated and real-time diagnostic support.
5) **Handling High-Resolution Images:** Developing optimized feature extraction and dimensionality reduction techniques for high-resolution images without exceeding quantum resource constraints.

In conclusion, the proposed workflow provides a robust and efficient tool for automated leukemia screening. Its hybrid quantum-classical design, high classification performance, and modular structure make it a promising approach for clinical applications as quantum technologies advance.

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

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