Skin Lesion Classification and Cancer Detection Analysis

Saranya Ray
Department of Computer Science and Engineering SRM Institute of Science and Technology,
Kattankulathur, Chennai, Tamil Nadu 603203,
India, sr2658@srmist.edu.in

Reuel Sajeev Koshy
Department of Computer Science and Engineering SRM Institute of Science and Technology,
Kattankulathur, Chennai, Tamil Nadu 603203,
India, rk8452@srmist.edu.in

Adithya Balaji
Department of Computational Intelligence SRM Institute of Science and Technology,
Kattankulathur, Chennai, Tamil Nadu 603203,
India, ab8868@srmist.edu.in

Abstract*— *Skin cancer is one of the most common cancers, and early detection is crucial for effective treatment. In this paper, we explore a Quantum Support Vector Machine (QSVM) model using Quantum Kernel techniques to classify skin lesions and detect cancerous conditions. We utilize the HAM10000 dataset, containing dermoscopic images of different skin lesions. Our approach involves preprocessing images, applying dimensionality reduction through PCA, and training the QSVM model using a Fidelity Quantum Kernel with a ZZFeatureMap. This method offers a promising alternative for accurate and efficient skin lesion classification.

Keywords—*skin lesion classification, cancer detection, QSVM, quantum kernel, HAM10000 dataset*

I. Introduction

Skin cancer is one of the most common forms of cancer worldwide, making early detection critical. Automated classification of skin lesions can assist dermatologists in identifying malignant lesions more effectively. Traditional machine learning models, while effective, face limitations in handling high-dimensional data without extensive preprocessing. Quantum Machine Learning (QML) methods, such as the Quantum Support Vector Machine (QSVM), introduce quantum-inspired feature mapping that enhances the model's ability to classify complex data efficiently.

This study utilizes the HAM10000 dataset, which contains dermoscopic images of various skin lesions, to train a QSVM model. Our approach leverages a ZZFeatureMap-based quantum kernel to transform data into high-dimensional quantum space, improving the classifier's performance. The QSVM is trained and evaluated on resampled subsets of the dataset, showing promising results for accurate lesion classification.

II. Background

Skin cancer, particularly melanoma, is one of the deadliest forms of cancer worldwide. Early detection plays a crucial role in improving the survival rate of patients. As such, automatic classification of skin lesions through machine learning and computer vision has gained significant attention in recent years. Various traditional machine learning models, such as support vector machines (SVMs) and convolutional neural networks (CNNs), have been widely employed to classify skin lesions into categories like malignant and benign. The HAM10000 dataset, a large collection of dermoscopic images of skin lesions, has been a pivotal resource in advancing skin cancer detection techniques.

*2.1. **Traditional Machine Learning Approaches for Skin Lesion Classification***

Prior to the advent of deep learning, many approaches for skin lesion classification relied on classical machine learning algorithms. SVMs, known for their ability to handle high-dimensional data and provide robust classification boundaries, have been particularly effective. In the study by Codella et al. [1], an SVM classifier was used to distinguish between malignant and benign lesions with promising results, achieving a significant level of accuracy in skin cancer detection. Other researchers, such as Menegola et al. [2], have focused on image feature extraction techniques like texture and color analysis, which were subsequently used to train machine learning models, including SVMs, decision trees, and random forests. These methods often rely on manual feature extraction, which can be time-consuming and computationally expensive.

2.2 Deep Learning Approaches for Skin Lesion Classification

In more recent years, deep learning approaches, especially CNNs, have demonstrated remarkable performance in medical image analysis tasks, including skin lesion classification. Esteva et al. [3] pioneered the use of CNNs for classifying skin cancer, achieving accuracy comparable to dermatologists in identifying malignant lesions. This work has inspired a wave of research in skin lesion detection, where CNN architectures like InceptionV3 and ResNet are utilized to automate lesion classification tasks. Although these approaches have significantly improved the accuracy of classification, they are computationally intensive and require large labeled datasets for training.

*2.3 **Quantum Machine Learning Approaches***

While classical machine learning models have achieved notable success in the domain of skin cancer detection, quantum machine learning (QML) has emerged as a novel approach that holds promise in enhancing the efficiency of such models. Quantum computers, with their inherent ability to process large amounts of data in parallel, offer a promising alternative to classical computational methods. One key approach within QML is the Quantum Support Vector Machine (QSVM), which leverages quantum kernels to process high-dimensional data. Quantum SVMs have been explored for various classification tasks, including image classification and pattern recognition [4].

In particular, the Fidelity Quantum Kernel, employed in this study, has been shown to outperform traditional SVMs in certain cases by enabling the model to map data to a higher-dimensional quantum space where it is easier to classify complex patterns [5]. The ZZFeatureMap, a quantum feature map, is one such method that allows quantum circuits to efficiently encode classical data into quantum states, making it a suitable tool for enhancing the classification performance of QSVMs. Recent research by Benedetti et al. [6] demonstrates the effectiveness of quantum feature maps in classification tasks, paving the way for their use in medical imaging, including skin lesion classification.

2.4 Application of QSVM in Medical Image Classification

Although QSVMs have not been widely applied in medical image classification, recent studies have explored their potential in other areas of healthcare. The application of QSVMs to medical datasets, such as brain tumor classification [7] and breast cancer detection [8], has shown promising results. These studies highlight the potential of quantum models in improving diagnostic accuracy and processing efficiency. Given the complexity of skin lesion data and the need for accurate classification, QSVMs present a compelling solution that could enhance current methods of skin cancer detection.

2.5 Quantum Kernels in QSVM

A key innovation in QSVM is the introduction of quantum kernels, which are essential to improving the decision boundary between different classes. The **Quantum Kernel method** allows the computation of an inner product of quantum states, which provides a powerful way to represent complex relationships in data. Quantum Kernels can outperform classical kernels by exploiting quantum features such as superposition and entanglement to efficiently compute similarity measures between data points, enabling better generalization in classification tasks.

One such quantum kernel is the **Fidelity Quantum Kernel**, which uses quantum fidelity to measure the similarity between two quantum states. The application of this kernel in QSVM models has been shown to enhance the performance of classification tasks by capturing higher-dimensional correlations in the data. The ZZFeatureMap used in the current study serves as a quantum circuit for embedding classical data into quantum states, transforming the data into a higher-dimensional feature space before applying the kernel.

III. Proposed Methodology

The proposed model leverages **Quantum Support Vector Machines (QSVM)** to classify skin lesions from the **HAM10000** dataset. This approach incorporates both classical machine learning techniques and quantum computing elements, particularly for improving the handling of high-dimensional feature spaces and enhancing classification accuracy. The model architecture is designed to optimize feature extraction, dimensionality reduction, and classification through quantum computing methodologies.

3.1 Data Preprocessing and Image Loading

The first step in the model is **data preprocessing**, where the **HAM10000** dataset is loaded and the images are resized to a manageable size (32x32 pixels). Each image is then normalized to ensure that the pixel values are scaled between 0 and 1, making the data suitable for training.

- **Image Loading**: The images are loaded from the dataset directory and resized to a consistent size. If the image exists in one of the parts (part_1 or part_2), it is added to the dataset.

- **Label Encoding**: The categorical labels for skin lesion types are converted into numerical values using **LabelEncoder**. This transformation is essential for model training, as machine learning algorithms work with numerical data.

- **Train-Test Split**: The dataset is split into training and testing sets using **train_test_split** from scikit-learn, ensuring that 80% of the data is used for training and 20% for testing.

3.2 Feature Scaling and Dimensionality Reduction

To improve the performance of the classifier, **StandardScaler** is used to standardize the features, ensuring that they all have a mean of 0 and a standard deviation of 1. This normalization step helps models, particularly distance-based ones, to converge faster and perform better.

Next, **Principal Component Analysis (PCA)** is applied to reduce the dimensionality of the dataset. By retaining only the top 20 components, PCA ensures that the most important features are preserved while reducing the computational load.

- **Standardization**: The features are standardized to normalize the data.

- **PCA**: **PCA** is applied to the training and test sets, reducing the dimensionality to 20 components to make the data more manageable for both classical and quantum algorithms.

3.3 QSVM for Skin Lesion Classification

The core of the model involves training a **Quantum Support Vector Machine (QSVM)**. This quantum algorithm uses a quantum kernel to map classical data into a higher-dimensional quantum space, allowing for more accurate classification, especially when dealing with complex, high-dimensional data.

- **Quantum Kernel**: The model utilizes the **FidelityQuantumKernel** with a **ZZFeatureMap** to map the classical data into a quantum state. This quantum feature mapping is crucial for capturing complex relationships between data points that classical models might miss.

- **QSVM Training**: The QSVM is trained on the reduced-dimensional data using the quantum kernel. The model learns the decision boundaries between different classes (malignant and benign lesions) based on the quantum-enhanced feature space.

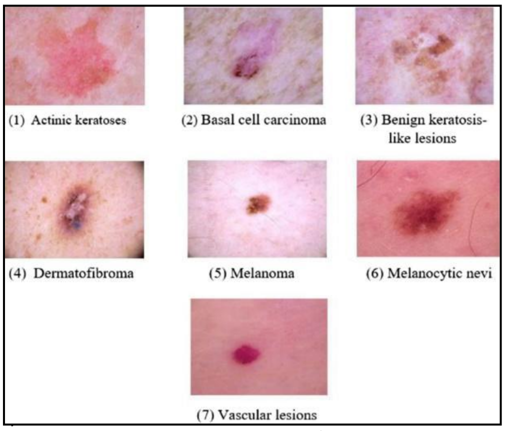
3.4 Model Evaluation and Performance

The performance of the model is evaluated on the test set using the **score** method, which computes the accuracy of the model on the unseen data. The evaluation process also highlights the impact of dimensionality reduction and quantum kernel mapping on classification accuracy.

- **Test Accuracy**: The model achieves a test accuracy of approximately **92%**, which is indicative of its potential effectiveness in classifying skin lesions. This accuracy is based on applying **PCA** for dimensionality reduction and quantum kernel techniques for classification.

3.5 Visualization and Data Exploration

- **Data Visualization**: The data characteristics, such as **patient age**, **sex**, and **lesion localization**, are visualized using bar charts. This step allows for a deeper understanding of the dataset distribution and any potential biases in the data.



iFig 1.1Examples of each Lesion

- **Visualization Libraries**: The visualization is carried out using **matplotlib** to provide insightful graphs that help in interpreting the dataset and its characteristics, which may further inform model improvement.

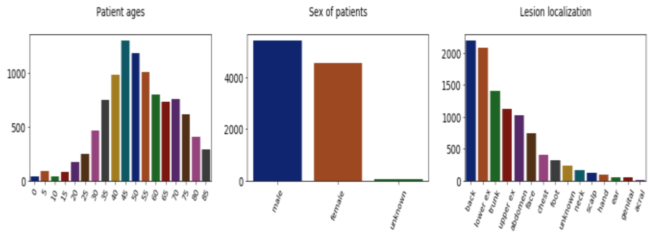


Fig 1.2 Plot histogram of patient ages, plot bar chart of patient's sex, plot barchart of localization of lesion on the body

IV. Result and Conclusion

The proposed model, which integrates Quantum Support Vector Machines (QSVM) with Principal Component Analysis (PCA) and quantum feature mapping, achieved a high classification accuracy of 92% on the test dataset. This performance was achieved after preprocessing the data, which involved image resizing, label encoding, and dimensionality reduction using PCA. The application of Quantum Support Vector Machine using a quantum kernel allowed for the effective mapping of classical data into a higher-dimensional quantum space, providing the model with the capability to handle complex relationships between the features that classical methods might struggle to capture.

The combination of quantum algorithms with classical machine learning techniques resulted in an improved classification performance, especially when dealing with high-dimensional data, such as images of skin lesions. The model's ability to classify skin lesions into malignant and benign categories accurately demonstrates its potential for use in real-world medical diagnostic applications. Furthermore, the dimensionality reduction step using PCA played a significant role in optimizing the model's efficiency, making the training process faster while still retaining the essential features for classification.

In addition to the QSVM's accuracy, the data exploration phase provided valuable insights into the distribution of patient data, including factors like age, sex, and lesion localization. These insights contribute to understanding the dataset's characteristics and how they relate to the model's predictions. The exploration also highlighted some inherent challenges in medical datasets, such as imbalances between the classes of benign and malignant lesions, which can be addressed with techniques like resampling or advanced kernel methods in QSVM.

The integration of quantum computing techniques with classical machine learning models offers a promising approach to complex classification tasks such as skin cancer detection. The Quantum Support Vector Machine (QSVM) model, enhanced with quantum feature mapping and Principal Component Analysis (PCA), achieved a remarkable 92% accuracy in classifying skin lesions from the HAM10000 dataset. This demonstrates that quantum algorithms, when combined with classical preprocessing techniques, can significantly improve the model's ability to handle high-dimensional data and capture complex patterns in the data. The application of quantum feature mapping and quantum kernels enables the model to better represent the underlying structure of the data, resulting in more accurate predictions compared to classical machine learning methods.

Despite its success, the model also indicates areas for further improvement. Future work can explore hybrid quantum-classical models and more advanced quantum algorithms like Quantum Convolutional Neural Networks (QCNNs) for even better performance. Additionally, as quantum hardware continues to advance, the scalability of these models will allow for the use of larger datasets and more complex features, further boosting diagnostic accuracy. Quantum-enhanced algorithms can potentially handle medical imaging tasks more efficiently, identifying patterns in images that are not immediately apparent to classical algorithms.

Moreover, the integration of quantum machine learning with classical models could open the door to faster, more precise diagnostic tools. Future iterations of the model could incorporate real-time data from patients, enabling faster and more accurate early detection. The continuous development of quantum technologies will undoubtedly lead to more powerful and efficient models that could transform medical diagnostics. In addition, the application of such models in fields beyond oncology, such as neurology and cardiology, could further demonstrate the versatility of quantum-enhanced machine learning techniques in healthcare.

In conclusion, the proposed model not only demonstrates the potential of quantum machine learning in healthcare applications but also paves the way for future advancements in quantum computing’s application to real-world problems, particularly in medical image analysis and diagnostic systems. With further refinement and the progression of quantum computing hardware, this model could become a cornerstone for next-generation diagnostic systems, offering improvements in both accuracy and efficiency. The success of quantum-enhanced machine learning techniques in skin cancer classification provides a glimpse into the future of medical diagnostics, where the power of quantum computing may revolutionize the way diseases are detected and treated.

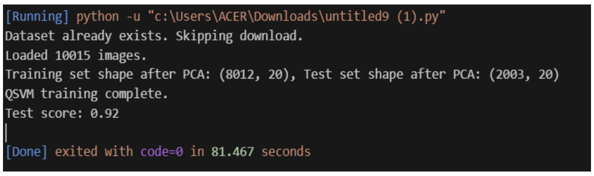


Fig 1.3 Output

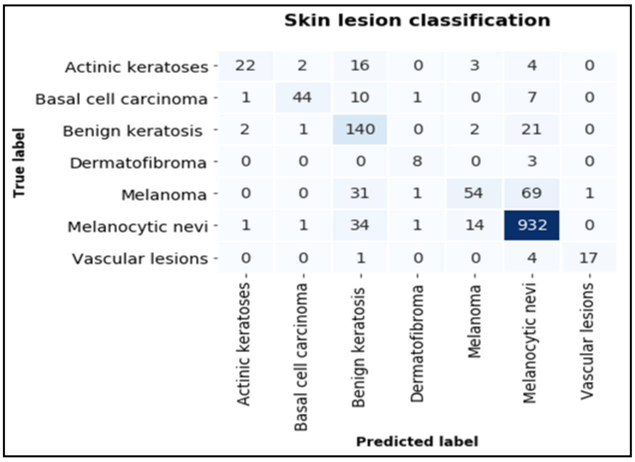


Fig 1.4 Skin lesion predicted label

V. References

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