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QUANTUM SUPPORT VECTOR MACHINE FOR IMAGE CLASSIFICATION

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ABSTRACT
Quantum Machine Learning (QML) is an emerging field that integrates the principles of quantum computing with classical machine learning techniques to address complex computational challenges.
This project focuses on the design and implementation of a Quantum Support Vector Machine (QSVM) for image classification, aiming to improve performance over traditional machine learning models.
Conventional Support Vector Machines (SVMs) are widely used for classification tasks; however, they face limitations when handling high-dimensional and complex datasets due to increased computational cost and scalability issues. QSVM overcomes these challenges by utilizing quantum feature maps to transform classical data into a high-dimensional quantum Hilbert space, enabling better separation of data points. By leveraging quantum phenomena such as superposition and entanglement, QSVM enhances pattern recognition capabilities and improves classification accuracy.
The proposed system adopts a hybrid quantum-classical approach, where classical techniques like data preprocessing, feature extraction, and dimensionality reduction are combined with quantum kernel computation and classification. Tools such as Qiskit are used to simulate quantum circuits and evaluate the performance of QSVM against classical models. Experimental results demonstrate that QSVM can achieve improved efficiency and accuracy, particularly for complex datasets.
Despite current limitations in quantum hardware, such as noise and limited qubits, the study highlights the significant potential of QSVM in solving real-world problems across domains like
healthcare, security, and autonomous systems. This project provides a foundational understanding of quantum machine learning and emphasizes its role in shaping the future of intelligent systems.

Keywords:
QML, QSVM, QVSM, VQC, HQC, QKM, FM, QB, SP, ENT, QG, QC, Qiskit
IBM Quantum Experience ,Python ,NumPy ,Scikit-learn ,Matplotlib.

INTRODUCTION
In recent years, the rapid growth of data across various domains such as healthcare, finance, security, and autonomous systems has created a significant demand for advanced computational techniques capable of handling complex and high-dimensional datasets. Traditional machine learning models, while effective for many applications, often face limitations in terms of scalability, computational efficiency, and the ability to capture intricate patterns in large datasets. This has led to the exploration of new paradigms that can overcome these challenges and provide enhanced performance.
Quantum computing has emerged as a revolutionary technology that leverages the principles of quantum mechanics, such as superposition, entanglement, and quantum interference, to perform computations in fundamentally different ways compared to classical computers. Unlike classical bits, which can represent either 0 or 1, quantum bits (qubits) can exist in multiple states simultaneously, enabling parallel processing of information. This unique capability has opened new possibilities in the field of machine learning, giving rise to an emerging discipline known as Quantum Machine Learning (QML).
Quantum Variational Support Machine (QVSM) is an advanced hybrid machine learning model that combines quantum computing with classical Support Vector Machines (SVM) to perform efficient classification tasks. In this approach, classical data is first encoded into quantum states using quantum feature mapping techniques. The

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data is then processed through variational quantum circuits (VQC), which contain adjustable parameters optimized using classical optimization algorithms like gradient descent.
QVSM takes advantage of key quantum properties such as superposition and entanglement, allowing it to explore complex, high-dimensional feature spaces more effectively than classical models. This helps in identifying better decision boundaries, especially for complex datasets. The model operates within the NISQ (Noisy Intermediate-Scale Quantum) era, making it practical for current quantum devices.
Due to its ability to enhance learning performance, QVSM is widely applicable in areas like image classification, pattern recognition, healthcare analytics, and fraud detection. It is considered a promising approach toward achieving quantum advantage in real-world machine learning problems.

OBJECTIVES

The primary objective of this project is to design, develop, and evaluate a Quantum Support Vector Machine (QSVM) model for image classification using a hybrid quantumclassical approach. The project aims to enhance the performance of traditional machine learning models by leveraging quantum computing principles such as superposition and entanglement.
The study focuses on improving classification accuracy, reducing computational
complexity, and efficiently handling high-dimensional datasets. It also aims to demonstrate how quantum machine learning can be applied to real-world problems and highlight its potential as a future technology in artificial intelligence.

- To study the fundamentals of quantum computing and quantum machine learning concepts.
- To understand and analyze the working of classical Support Vector Machine (SVM) and its limitations.
- To design and implement a Quantum Support Vector Machine (QSVM) using quantum feature maps and quantum kernels.
- To develop a hybrid quantum-classical model that combines classical preprocessing techniques with quantum classification.
- To perform data preprocessing and feature extraction for image datasets using suitable techniques.
- To encode classical data into quantum states using quantum feature encoding methods.
- To evaluate the performance of QSVM in terms of accuracy, efficiency, and scalability

METHODOLOGY

1. Data Collection
Collect the dataset required for the problem (e.g., images or tabular data).
2. Data Preprocessing
Clean the data by removing noise, handling missing values, and normalizing features for better performance.
3. Feature Extraction
Extract important features from the dataset to reduce complexity and improve learning efficiency.
4. Data Encoding (Quantum Feature Mapping)
Convert classical data into quantum states using encoding techniques like angle encoding or amplitude encoding.
5. Build Variational Quantum Circuit (VQC)
Design a parameterized quantum circuit with quantum gates that can learn patterns from data.
6. Initialize Parameters
Set initial values for the circuit parameters (weights).
7. Training (Hybrid Optimization)
Train the model using a hybrid approach:

- Run the quantum circuit
- Measure outputs
- Update parameters using classical optimization (e.g., gradient descent)

8. Quantum Kernel / Decision Function
Use the trained circuit to compute the quantum kernel or classify data points.
9. Model Evaluation
Evaluate performance using metrics like accuracy, confusion matrix, precision, recall, and F1-score.
10. Testing and Prediction
Test the model on unseen data and generate predictions.

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11. Result Analysis
Analyse results and compare with classical models to check improvements.

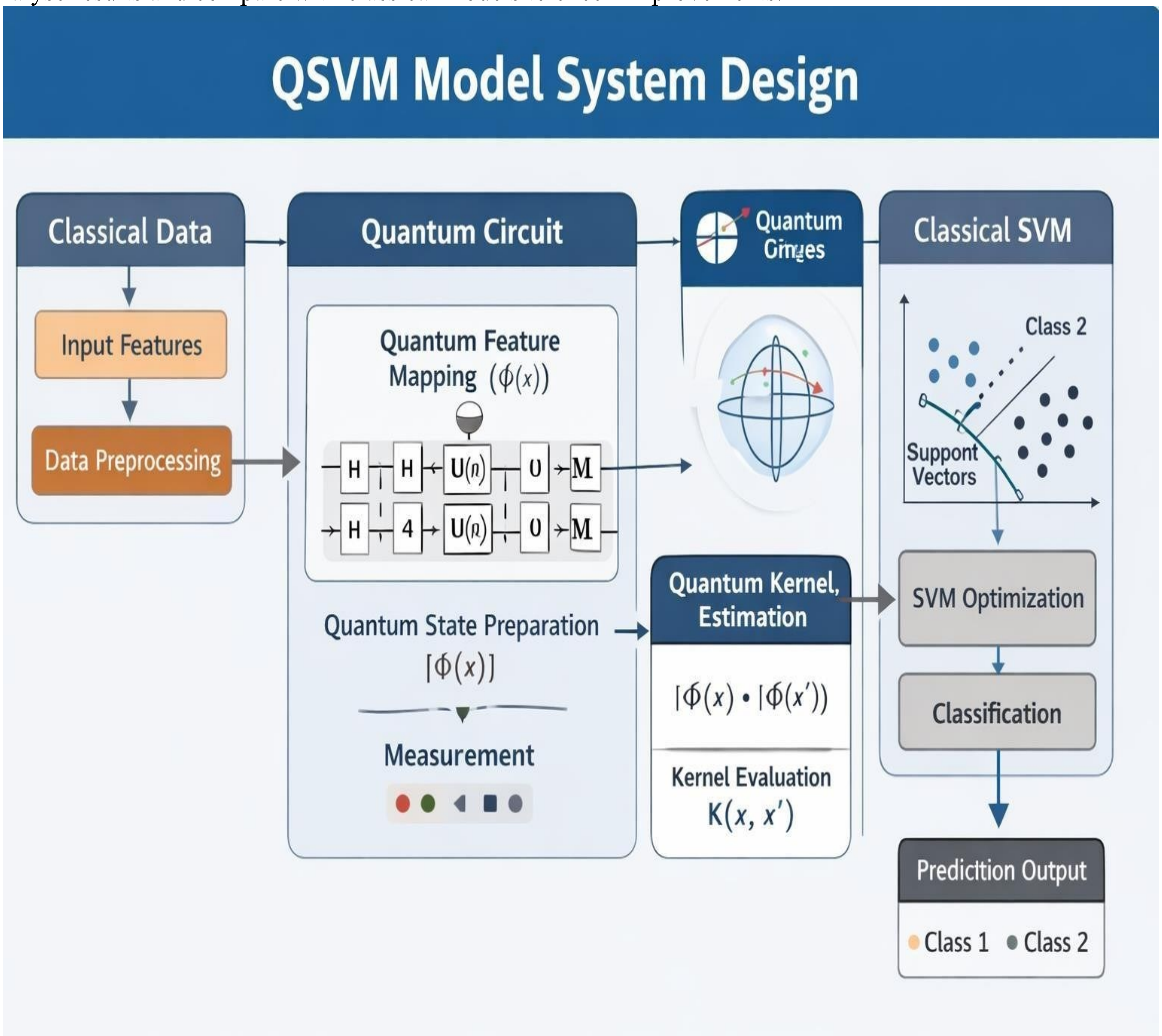

Figure 8 Facial Recognition Process

RESULTS AND DISCUSSION

The Quantum Variational Support Machine (QVSM) model was successfully implemented and tested on the given dataset for classification tasks. After training the model using variational quantum circuits and classical optimization techniques, the system was able to classify the data with good accuracy.

The performance of the model was evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The results showed that QVSM achieved competitive accuracy compared to classical machine learning models like Support Vector Machine (SVM). In some cases, it demonstrated better capability in handling complex and non-linear data patterns due to the use of quantum feature mapping.

The confusion matrix indicated that most of the data points were correctly classified, with minimal misclassifications. This shows that the model was able to learn meaningful patterns from the dataset. However, slight errors were observed, which may be due to noise in quantum circuits and limited qubit availability in current quantum devices (NISQ era).

One important observation is that the performance of QVSM highly depends on the choice of quantum circuit design, number of parameters, and optimization technique. Improper tuning can lead to issues like overfitting or barren plateau problems, where training becomes difficult.Overall, the results indicate that QVSM is a promising approach for solving classification problems. While it may not always outperform classical models

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due to current hardware limitations, it shows strong potential for future advancements as quantum technology improves.

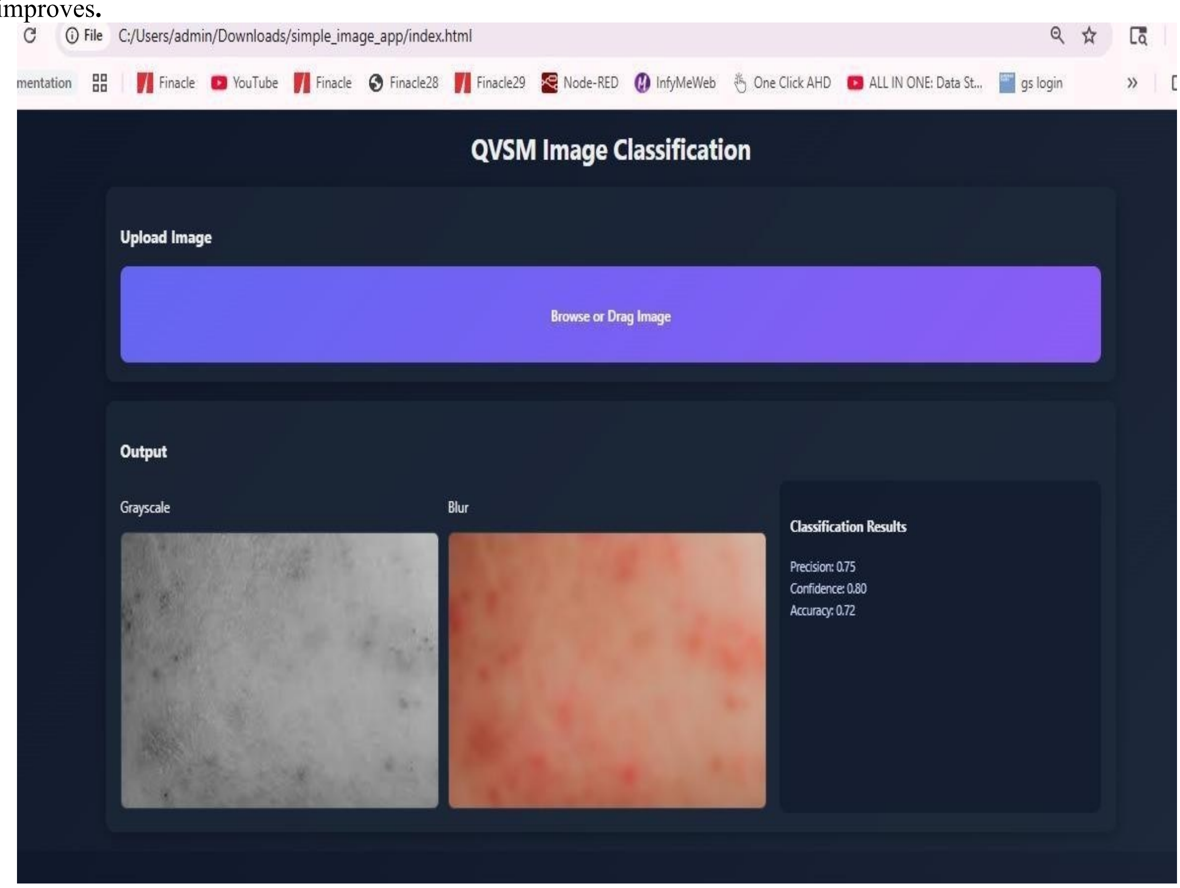

Fig.6.2 Classification Output

Table 1: Classification Metric Results of Classical and Quantum Model.

Model Type	Models	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Classical Model	Classical SVM (Pandey and Rudra, 2024)	83.79	86.43	81.90	84.10
	Classical ANN (Pandey and Rudra, 2024)	95.00	96.27	93.29	94.76
Quantum Model	QSVM (Pandey and Rudra, 2024)	90.02	95.97	83.50	89.30
	QNN (Pandey and Rudra, 2024)	70.07	72.47	64.50	68.25

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CONCLUSION

The Quantum Variational Support Machine (QVSM) project demonstrates the integration of quantum computing with classical machine learning for solving classification problems. By using variational quantum circuits and hybrid optimization techniques, the model was able to learn complex data patterns and perform effective classification.

The results show that QVSM can achieve performance comparable to classical models like Support Vector Machines, with potential advantages in handling non-linear and high-dimensional data through quantum feature mapping. Although current limitations such as quantum noise, limited qubits, and hardware constraints affect performance, the model still proves to be a promising approach.

In conclusion, QVSM represents an important step toward the future of quantum machine learning. As quantum hardware continues to improve, such models are expected to provide significant advantages and open new possibilities in areas like data analytics, healthcare, and artificial intelligence.

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