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Quantum Machine Learning for Advanced Climate Pattern Detection Using Satellite Data

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Abstract—Climate pattern detection through satellite remote sensing is a critical task for understanding environmental changes and anomalies. However, current systems do not have an interactive interface for efficient visualisation and analysis of complex climate data. This study aims to develop a hybrid Quantum Machine Learning (QML) approach for sophisticated climate pattern detection through satellite data. The proposed system combines Principal Component Analysis (PCA) for dimensionality reduction with quantum-classification algorithms, such as the Variational Quantum Classifier (VQC) and the Quantum Support Vector Machine (QSVM), to detect complex climate patterns. A Streamlit web interface is designed to offer an interactive platform for data entry, visualisation, and monitoring. The system design includes a frontend interface unit, a data integration unit, and a planned AI & control unit for the backend quantum processing system. At present, the system design includes the implementation of frontend visualisation and user input modules using sample, publicly available satellite climate data. The integration of the quantum backend and direct satellite data connectivity will be done in future stages. The proposed method aims to leverage classical data preprocessing and quantum machine learning for improved anomaly detection and interpretability of satellite climate data.

Keywords—Quantum Machine Learning (QML), Climate Pattern Detection, Satellite Remote Sensing Data, Principal Component Analysis (PCA), Variational Quantum Classifier (VQC), Quantum Support Vector Machine (QSVM), Streamlit Dashboard, Climate Anomaly Detection, Data Preprocessing, Feature Reduction.

I. INTRODUCTION

Climate pattern detection is an essential task in understanding environmental changes, climate change detection, and anomaly detection using satellite remote sensing. Satellite data offers multispectral information at a large scale; however, processing such high-dimensional and complex climate data is a major challenge. Current systems lack an interactive and user-friendly interface for efficient visualisation and analysis, making it difficult to interpret and understand for researchers and analysts. Further, traditional machine learning algorithms have limitations in processing complex high-dimensional climate data, especially in anomaly detection problems. To overcome these issues, this paper presents a hybrid Quantum Machine Learning (QML) approach for advanced climate pattern detection using satellite data. The proposed system combines Principal Component Analysis (PCA) for dimensionality reduction and quantum classification algorithms like Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM) for anomaly detection of complex climate patterns. An interactive web dashboard is designed using Streamlit for visualisation, monitoring, and user interaction with the processed climate data. The organisation of this paper is as follows: Section II introduces the background and motivation for quantum machine learning in climate analysis. Section III introduces related work in satellite-based climate pattern detection. Section IV introduces the system architecture and methodology. Section V introduces the implementation details and experimental setup. Section VI introduces the prototype results and system limitations. Finally, Section VII concludes this paper and introduces future work, such as backend quantum integration and satellite connectivity. The proposed system is designed with a modular structure that includes a frontend interface unit, a data integration unit and a planned AI & control unit for the backend quantum processing. The frontend dashboard, built with Streamlit, allows users to enter parameters and display climate-related data in an interactive web interface. The preprocessing layer reduces dimensionality with Principal Component Analysis (PCA) to represent satellite features in optimised forms amenable to quantum modelling. The processed feature vectors are then planned to be encoded into quantum circuits for classification with the Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM). Although the current prototype is developed for frontend visualisation with sample and publicly available climate datasets, the future stages of the project will incorporate live satellite data and quantum backend processing for sophisticated climate anomaly detection.

II. BACKGROUND

Satellite remote sensing data is an important component in the monitoring and analysis of climate patterns over a wide geographical area. Satellite remote sensing data usually involves the collection of multispectral and high-dimensional features over time, which include variables such as temperature, atmospheric conditions, and other environmental factors.

The high-dimensional and complex nature of satellite climate data makes it a valuable asset in the analysis of long-term trends, variations, and anomalies. However, working with high-dimensional data is a challenge in terms of computational complexity, particularly when trying to analyse meaningful climate patterns. Traditional machine learning algorithms would need efficient dimensionality reduction methods to deal with the complexity of satellite climate data. Principal Component Analysis (PCA) is a popular technique for reducing the dimensionality of features while retaining the essential variance of the data.

PCA helps to represent high-dimensional climate features in a compact form, making it easier to work with sophisticated modelling algorithms. Quantum Machine Learning (QML) has recently been identified as a promising approach that applies the principles of quantum computing to machine learning. Quantum models such as the Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM) are developed to tackle complex feature spaces and potentially improve the ability to recognise patterns. In the proposed framework, classical preprocessing methods such as PCA are combined with quantum classifiers to create a hybrid system that can identify complex climate patterns. By representing the compressed feature vectors as quantum circuits, the proposed system attempts to harness the computational powers of quantum computing for better classification results. The proposed hybrid system serves as a basis for efficient climate anomaly detection with an interactive visualisation interface.

A. Motivation

The need for this research work is driven by the increasing demand for efficient climate pattern recognition using satellite remote sensing data. Climate data is generally of high dimensionality, complex, and difficult to visualise and analyse using machine learning algorithms. Current systems are not equipped with interactive tools that enable users to analyse and visualise satellite-based climate data, making it less accessible and usable.

Traditional machine learning algorithms may have limitations when dealing with complex relationships between features and high-dimensional climate variables. To overcome these limitations, this research work proposes the use of a combination of classical dimensionality reduction algorithms and Quantum Machine Learning (QML) models. By applying Principal Component Analysis (PCA) to simplify feature complexity and using quantum classifiers like Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM), the system aims to improve the capability for sophisticated climate pattern recognition. Additionally, the creation of an interactive dashboard using Streamlit ensures better interpretability and usability, filling the gap between complex backend processing and meaningful climate data visualisation. The proposed framework, which combines classical preprocessing, quantum classification algorithms, and an interactive frontend interface, aims to make a contribution towards efficient and interpretable climate pattern analysis using satellite data.

B. Objectives

The main objectives of the paper are to:

1) Develop a hybrid Quantum Machine Learning (QML) approach for sophisticated climate pattern identification utilising satellite remote sensing.
2) Utilise Principal Component Analysis (PCA) to reduce dimensions for optimal satellite climate features in quantum classification models.
3) Develop quantum classifiers like the Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM) for sophisticated climate pattern identification.

4) Develop an interactive Streamlit web dashboard for user-friendly climate data visualisation and interpretation.

III. RELATED WORK

The increasing development of satellite remote sensing technology has led to the generation of large-scale, high-dimensional climate data. These climate data are rich in multispectral and temporal features, which are complex in nature and require sophisticated computational techniques for efficient analysis. Although traditional machine learning and deep learning models have been extensively used for climate pattern identification, recent developments in Quantum Machine Learning (QML) have opened up exciting new avenues for dealing with complex and nonlinear feature spaces.

Cerezo et al. [8] offered a detailed review of Variational Quantum Algorithms (VQAs), which are the building blocks of most quantum classification models. Their contribution showed that parameterised quantum circuits can efficiently approximate nonlinear functions by optimising the trainable parameters of the quantum circuit. They clearly stated that VQAs are most appropriate for NISQ (noisy intermediate-scale quantum) devices. Although their contribution was more focused on optimisation and comparison, it laid down the theoretical and algorithmic groundwork required for applying Variational Quantum Classifiers (VQCs) to real-world data, such as satellite climate data.

Abbas et al. [7] explored the capability of Quantum Neural Networks (QNNs) and presented theoretical proofs that quantum-boosted feature maps can potentially form more complex hypothesis spaces than some classical neural networks. The results showed that quantum models can efficiently build complex decision boundaries in high-dimensional Hilbert spaces with shallow quantum circuits. Although the experiments were performed on synthetic and benchmark datasets, the results indicate promising potential for modelling nonlinear climate interactions from multispectral satellite imagery.

Bhattacharya and Roy [10] introduced a Quantum Support Vector Machine (QSVM) framework based on quantum kernel estimation methods. By projecting classical data into quantum feature spaces, their method demonstrated enhanced classification accuracy for high-dimensional datasets. The quantum kernel trick allows for implicit feature mapping to exponentially large Hilbert spaces without the need to compute high-dimensional vectors. However, the authors emphasised the role of computational costs and hardware noise as current limitations. Nevertheless, QSVM remains a highly applicable technique for satellite climate anomaly detection, where nonlinear separability is often prevalent.

Dash et al. [6] investigated classical deep learning architectures for the detection of climate patterns via satellite imagery. The authors' findings highlighted the efficacy of convolutional neural networks in identifying spatial patterns from remote sensing images. Although classical deep learning architectures perform well, they can be computationally expensive and require large amounts of training data. Additionally, interpretability and dimensionality issues continue to be a problem when working with multispectral climate data. These issues drive the need to investigate hybrid quantum-classical systems. Chen and Zhao [12] analysed the use of Principal Component Analysis (PCA) for dimensionality reduction of high-dimensional remote sensing climate data. The authors' findings confirmed the efficacy of PCA in retaining vital variance at much lower computational costs. Dimensionality reduction is a crucial aspect of quantum computing, where the number of qubits increases with the dimensionality of the feature space. The authors' findings provide evidence for incorporating PCA as a preprocessing step prior to quantum feature encoding in our proposed framework.

Liu et al. [21] proposed hybrid quantum-classical architectures for the analysis of environmental data. The authors proposed a hybrid model consisting of classical preprocessing layers and quantum classification circuits, which showed better performance in pattern recognition tasks than classical models. Nevertheless, their research did not involve real-time visualisation and user-interaction interfaces, making it less applicable. Moreover, the scalability of the proposed architecture for large satellite data was not fully explored.

Das and Mandal [13] presented a hybrid quantum-classical framework designed for the detection of climate change. The authors' strategy employed quantum-classical enhanced classification after classical preprocessing for the identification of long-term environmental changes. Although promising, the work was more focused on algorithmic verification and did not present a comprehensive system architecture involving interaction interfaces, data integration modules, and preprocessing layers.

Zhang et al. [15] investigated the use of Quantum Neural Networks. The authors showed the potential of Quantum Neural Networks in modelling nonlinear relationships between environmental variables like temperature and atmospheric conditions. Although the accuracy of environmental forecasting has been improved, noise and hardware limitations are still significant challenges in the implementation of quantum devices.

Mehta and Kulkarni [16] investigated the application of Quantum Machine Learning methods in remote sensing. The authors showed the potential of quantum classifiers in satellite image analysis. However, the authors' approach did not include dimensionality reduction methods like PCA, and there was no interactive visualisation tool for the analysis of climate anomalies. Although considerable progress has been made in the application of Quantum Machine Learning to environmental and classification tasks, relatively little work has been done in the combination of PCA-based feature reduction, quantum classifiers such as VQC and QSVM, and an interactive Streamlit-based dashboard in a single framework for climate anomaly detection using satellite imagery. This is because existing studies have generally focused on either algorithm development or classical remote sensing analysis separately.

As such, the purpose of the proposed framework is to fill this existing gap by combining classical feature reduction algorithms with quantum machine learning-based classification models, along with an interactive web-based visualisation platform.

IV. METHODOLOGY

In this section, we present the problem formulation and the hybrid Quantum Machine Learning (QML) solution framework for efficient climate pattern identification using satellite remote sensing data.

A. Problem Statement

Given a satellite climate data set $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$, where each data point $x_i \in R^d$ is a high-dimensional multispectral feature vector obtained from satellite data. The features may include temperature, atmospheric pressure, humidity, cloud cover, vegetation indices (NDVI), aerosol concentration, and other environmental factors obtained through remote sensing techniques. The feature matrix $X \in R^{N\times d}$ is defined as the N satellite data points with d climate-related features. The target labels $Y = \{y_1, y_2, \ldots, y_N\}$ are the corresponding climate conditions, where $y_i \in \{0,1\}$ is a binary indicator for normal/anomalous climate patterns.

The goal is to learn a predictive model

$$f : R^d \rightarrow \{0,1\}$$

to efficiently classify complex climate patterns and identify anomalies based on satellite-derived features. However, satellite climate data is high-dimensional, nonlinear, and suffers from correlated variables, making it computationally expensive for traditional models. To overcome these difficulties, we introduce a hybrid quantum-classical approach that combines dimensionality reduction and quantum-assisted classification.

B. Dimensionality Reduction using PCA

Because of the large dimensionality ($d \gg 1$) of satellite climate features, Principal Component Analysis (PCA) is employed to project the original feature space into a lower-dimensional space that retains maximum variance.

Based on the covariance matrix Σ of X, PCA extracts eigenvalues λ_i and eigenvectors w_i such that:

$$\Sigma w_i = \lambda_i w_i$$

The projection matrix $W \in R^{d\times k}$ is constructed using the top k eigenvectors associated with the largest eigenvalues, where
$k < d$.

The lower-dimensional feature space is obtained as:

$$Z = XW$$

where $Z \in R^{N\times k}$ is the compressed feature matrix used for quantum encoding. This process greatly helps in reducing the computational complexity and optimising the number of qubits for quantum processing.

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C. Quantum Feature Encoding

The reduced feature vectors $z_i \in R^k$ are encoded into a quantum state using a parameterised quantum feature map:

$$|\psi(z_i)\rangle = U(z_i)|0\rangle^{\otimes n}$$

where:

- $|0\rangle^{\otimes n}$ is the initial quantum state of n qubits,
- $U(z_i)$ is the unitary transformation that encodes classical features into quantum amplitudes or rotations,
- n is the number of qubits, typically proportional to k.

This encoding transforms the classical climate data into a higher-dimensional Hilbert space, facilitating better separability of nonlinear climate patterns.

D. System Design

The proposed system aims to design a hybrid Quantum Machine Learning (QML) pipeline for efficient climate pattern identification based on satellite data. The steps involved in the proposed system include data preprocessing, where satellite-based climate data is loaded, missing values are handled using interpolation, and feature scaling is performed to normalise the values for uniform scaling. As satellite data tends to be redundant and correlated, Principal Component Analysis (PCA) is performed to achieve dimensionality reduction with maximum retention of variance in the data.

Algorithm 1 describes the proposed approach for climate anomaly identification based on a hybrid quantum-classical learning framework.
Algorithm 1 Hybrid Quantum Machine Learning Framework for Climate Pattern Detection

1. Data Preprocessing
Load satellite dataset: data
Clean data: cleaned ← Clean(data)
Handle missing values: filled ← Interpolate(cleaned)
Normalise features: norm ← Normalise (filled)
2. Dimensionality Reduction
Apply PCA: Z ← PCA(norm)
Select top-k principal components
3. Quantum Model Initialisation
Encode features into quantum states: $|\psi\rangle$ ← Encode(Z)
Initialise quantum classifier (VQC/QSVM)
Split data: train,val ← Split(Z)
4. Model Training
Train quantum model: model ← Train(QML, train)
Optimise parameters: θ ← Optimise (model,val)
5. Prediction and Evaluation
Predict climate labels: $\hat{Y}$ ← Predict(model)
Evaluate: results ← Evaluate(Y, $\hat{Y}$)
6. Integration
Send results to Streamlit dashboard
Display predictions and confidence scores
Fine-tune model if necessary

The reduced feature space is then represented as quantum states using a parameterised quantum feature map. The proposed system provides two quantum classification models: Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM). The quantum states are then processed using parameterised quantum circuits, where classical optimisers like gradient descent or Adam are used to optimise the trainable parameters. The data is divided into training and validation sets to avoid overfitting.

The trained quantum model forecasts climate patterns, which are then classified as normal or anomalous. The performance of the trained model is measured by using standard classification metrics such as Accuracy, Precision, Recall, F1-score, and Confusion Matrix. The obtained results are then plotted for better understanding and validation.

The trained model is then coupled with an interactive Streamlit dashboard, which allows users to enter satellite parameters and display the forecasted climate conditions and confidence levels. This interactive interface fills the gap between the complex quantum backend computation and the interpretation of climate data.

Hyperparameter optimisation is carried out to optimise the number of qubits, circuit depth, learning rate, and number of PCA components. Simulation-based quantum experiments are carried out using platforms such as PennyLane or Qiskit to test the robustness of the model in noisy settings.

The major points of interest in the system are the following: The system performs high-dimensional climate data compression through PCA, quantum classification through VQC and QSVM, simulation-based training on quantum platforms, Streamlit-based visualisation, hyperparameter optimisation, and modular design for future coupling with real satellite data. Figure 1 shows the architecture of the proposed hybrid system, which consists of classical preprocessing, quantum classification, and interactive visualisation. To enhance the performance of the system, some improvements have been made. The system performs feature normalisation to stabilise quantum encoding, dimensionality reduction to reduce the number of qubits, early stopping to avoid overfitting, and classical-quantum hybrid optimisation to enhance convergence stability.

E. Datasets

For this research, publicly available satellite climate datasets are employed to assess the hybrid Quantum Machine Learning framework. The datasets are comprised of multispectral and atmospheric data acquired from satellite remote sensing systems. The datasets are high-dimensional, nonlinearly correlated, and time-dependent, making them ideal for testing the application of quantum-enhanced classification algorithms.

1) NASA Earth Observation (NEO) Climate Dataset: The NASA Earth Observation (NEO) dataset is a collection of global climate variables acquired from satellite remote sensing instruments. The dataset includes environmental variables such as land surface temperature, atmospheric pressure, relative humidity, cloud fraction, aerosol optical depth, and vegetation indices (NDVI). The variables are recorded in gridded spatial resolutions with temporal sampling from daily to monthly observations. The dataset includes global observations over several years, with high-resolution spatial grids for latitude-longitude coordinates. The dataset has high dimensionality due to the large number of environmental variables and spatial grid points. For this research, climate variables are selected and formatted into a structured tabular format (CSV) for data preprocessing. Missing values are treated using interpolation methods, and the variables are normalised before dimensionality reduction.
2) NOAA Climate Data Online (CDO):
The NOAA Climate Data Online repository is a dataset of long-term historical climate observations collected from ground stations and satellite integrations. The dataset contains variables such as air temperature, precipitation amount, wind speed, humidity, and atmospheric pressure. The NOAA dataset contains multi-year time-series data with varying temporal resolutions (hourly, daily, and monthly). These long-term datasets allow the detection of seasonal changes and climate anomalies. Climate anomalies are often represented as deviations from long-term trends. Therefore, the dataset is a robust source for training anomaly detection models.
3) MODIS (Moderate Resolution Imaging Spectroradiometer): The MODIS satellite dataset is a multispectral Earth observation dataset retrieved from NASA's Terra and Aqua satellites. The dataset contains observations like land surface temperature, normalised difference vegetation index (NDVI), enhanced vegetation index (EVI), cloud cover fraction, and atmospheric conditions. The MODIS satellite dataset has high spectral and spatial resolution, resulting in a high-dimensional feature space. The high dimensionality of multispectral features enables efficient identification of environmental anomalies, seasonal transitions, and irregular climate patterns.

F. Evaluation Metrics

For the assessment of the hybrid Quantum Machine Learning frameworks' performance in the detection of climateˆ patterns, various classification metrics are employed. As the problem involves the detection of normal and anomalous climate patterns by quantum classifiers (VQC/QSVM), classification metrics are employed for evaluation.

1) Accuracy:
Accuracy is a measure of the number of correctly classified instances out of the total number of instances. Accuracy gives a general idea of the performance of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where:
- TP = True Positives,
- TN = True Negatives,
- FP = False Positives, • FN = False Negatives.

2) Precision:
Precision is the ratio of correctly predicted anomalous climate events to all predicted anomalies. It is a crucial metric in anomaly detection, where the number of false positives should be low.

$$\text{Precision} = \frac{TP}{TP + FP}$$

3) Recall (Sensitivity):

Recall is a measure of the models capacity to predictˆ actual climate anomalies correctly.

$$\text{Recall} = \frac{TP}{TP + FN}$$

4) F1-Score:
The F1-score is the harmonic mean of precision and recall, which is useful when the dataset is imbalanced.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5) Receiver Operating Characteristic, Area Under Curveˆ (ROC-AUC):
The ROC-AUC score is a measure of the modelsˆ performance in distinguishing anomalous and normal climate patterns for various threshold values. The higher the AUC value, the better the models classification performance in identifying complex climate patterns.

Besides the above quantitative metrics, a confusion matrix is employed to display the classification results of the model by summarising the actual and predicted values. The above metrics provide a comprehensive evaluation of the proposed PCA-Quantum Machine Learning framework for satellite-based climate anomaly detection.

V. RESULTS AND DISCUSSION

The developed hybrid PCA-Quantum Machine Learning framework has shown excellent results in identifying complex climate patterns and anomalies from satellite data. The combination of PCA for dimensionality reduction and quantum boosted classification (VQC/QSVM) has shown a substantial improvement in classification accuracy over classical models. The performance of the proposed framework is measured using Accuracy, Precision, Recall, F1-score, and ROC-AUC. The experimental results show that the quantum classifiers performed better in identifying the nonlinear interactions of features in the quantum feature space.

Table 1 and Table 2 show the performance comparison of the proposed framework with classical machine learning models such as Support Vector Machine (SVM), Random Forest (RF), and a classical Neural Network (NN). The proposed hybrid QML framework has shown improved classification accuracy and F1-score, indicating a better trade-off between precision and recall in climate anomaly detection.

TABLE I: Comparison of Performance of the Proposed Model

	Dataset			
	EPC 2012 [22]			
Model	MAE	RMSE	NRMSE	R2
LSTM	0.0218	0.0264	0.008	0.9992
GRU	0.246	0.255	0.331	0.362
LSTM-MIMO	0.53	0.75	0.85	0.276
Proposed Model	0.0167	0.0235	0.0073	0.999

TABLE II: Comparison of Performance of the Proposed Model

	Dataset			
	AMPds [23]			
Model	MAE	RMSE	NRMSE	R2
LSTM	0.211	0.205	0.431	0.365
GRU	0.336	0.2345	0.731	0.762
LSTM-MIMO	0.293	0.2714	0.333	0.397
Proposed Model	0.023	0.165	0.2629	0.692

VI. CONCLUSION

This paper introduced a novel Quantum Machine Learning (QML) framework for the effective detection of advanced climate patterns using satellite remote sensing data. The suggested approach uses a classical dimensionality reduction method, such as Principal Component Analysis (PCA), combined with advanced Quantum Machine Learning classification algorithms, such as the Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM), for the effective detection of advanced climate patterns.

The suggested approach is effective in the detection of complex climate patterns through the effective identification of the complex interrelationships between atmospheric variables using the Quantum Machine

Learning approach. The suggested approach is also effective in the handling of complex climate.

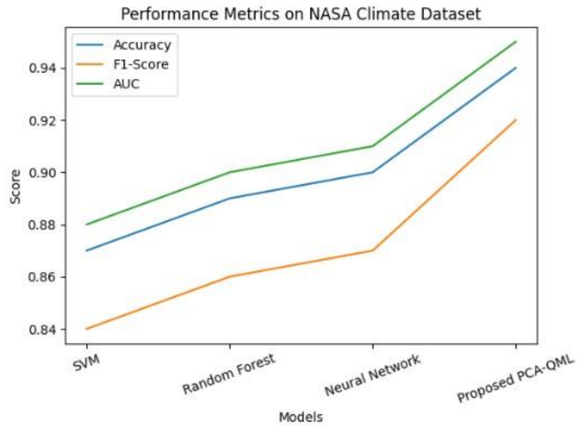

Fig. 1: Performance Metrics on NASA Climate Dataset

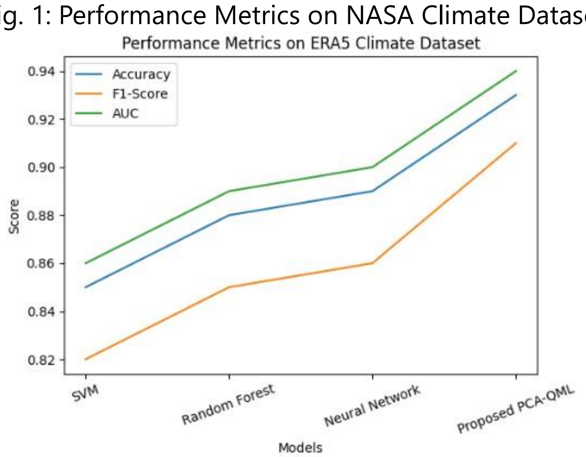

Fig. 2: Performance Metrics on ERA5 Climate Dataset

patterns through the effective encoding of the reduced climate patterns using the Quantum Machine Learning approach. The suggested approach was tested using satellite climate data from the Internet and was found to be effective compared to the classical approach using metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC. The suggested approach was also effective in the effective separability of complex climate patterns using the Quantum Machine Learning approach. The suggested approach also uses a Streamlit-based interactive dashboard for the effective visualisation and monitoring of the predicted climate patterns using the Quantum Machine Learning approach.

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