A Comparative Implementation of Iris Flower Classification Across Platform

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Abstract - This paper presents a comparative analysis of the Iris Flower Classification problem implemented across three distinct computational platforms: classical computing using Jupyter Notebook, cloud computing via Google Colab, and quantum computing leveraging IBM Qiskit. The study evaluates the platforms based on execution efficiency, classification accuracy, and scalability. While classical and cloud-based implementations yielded similar performance metrics, the quantum approach demonstrated unique computational characteristics and challenges, such as noise and resource limitations. This research highlights the growing potential of quantum computing for machine learning applications and provides a foundation for future advancements in integrating quantum techniques with traditional methodologies.

***Key Words*:** Iris Flower Classification, Machine Learning, Classical Computing, Cloud Computing, Quantum Computing, Qiskit, Google Colab, Quantum Machine Learning, Comparative Analysis

1.INTRODUCTION

Machine learning has become a cornerstone of modern technology, offering powerful tools to address complex problems across diverse fields such as healthcare, finance, and agriculture. The Iris Flower Classification problem, a widely recognized benchmark in the field, serves as an essential entry point for understanding and evaluating classification algorithms. As computational demands grow with increasingly complex datasets and models, it is crucial to explore novel computing paradigms to enhance efficiency and scalability

Quantum computing, with its ability to leverage quantum mechanical phenomena such as superposition and entanglement, presents a promising alternative to classical computing for specific tasks. This paper investigates the feasibility and performance of applying quantum computing to a well-established machine learning problem. By comparing implementations on classical systems (Jupyter Notebook), cloud-based platforms (Google Colab), and quantum platforms (IBM Qiskit), this study aims to provide insights into the strengths, limitations, and potential of each approach.

The comparative analysis focuses on three key aspects: computational efficiency, model accuracy, and practical usability. While classical and cloud-based systems excel in reliability and accessibility, quantum computing introduces a fundamentally different paradigm that could redefine the landscape of machine learning in the years to come. This study seeks to evaluate these platforms, highlighting their suitability for tasks like Iris Flower Classification and their implications for future research and development in computational science.

.2. LITERATURE REVIEW

Various studies have reviewed and analyzed methodologies for classification tasks across different computational paradigms. Below are some notable survey papers related to the techniques employed in classical, cloud, and quantum computing environments.

Kotsiantis, S. B. [1] provided a comprehensive overview of supervised machine learning algorithms for classification tasks. This paper reviewed key techniques such as Decision Trees, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Neural Networks. The study compared their theoretical foundations, typical use cases, and performance metrics, offering valuable insights for algorithm selection based on dataset characteristics. However, the focus on classical algorithms limits its applicability to modern paradigms like cloud or quantum computing.

Dutta, A., Gera, P., and Garg, P. [2] explored the capabilities of cloud platforms such as AWS SageMaker, Google Cloud AI Platform, and Microsoft Azure Machine Learning Studio for machine learning tasks. The survey highlighted features like automated model tuning and scalability, offering a comparison based on cost and performance. While the study underscored the advantages of cloud platforms in scalability and accessibility, it did not include emerging technologies like quantum computing or address privacy concerns comprehensively.

Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., and Lloyd, S. [3] reviewed the advancements in quantum machine learning, focusing on quantum algorithms such as Quantum SVM and Quantum Neural Networks. The study highlighted the potential speed-up offered by quantum computing for machine learning tasks. However, it also noted the infancy of quantum hardware and challenges like noise and limited qubits, which restrict practical implementations.

Yousefpour, A., Patil, A., and Ishii, R. [4] conducted a comparative analysis of machine learning tasks across cloud, fog, and edge computing paradigms. The study evaluated factors like latency, resource utilization, and scalability, demonstrating the unique strengths of each paradigm. While cloud computing excelled in scalability, edge computing was superior for low-latency tasks, and fog computing provided a balance between the two. The absence of quantum computing in the comparison highlights a gap in evaluating emerging technologies.

Cheng, J., Zhang, F., and Guo, X. [5] proposed an advanced neural text summarization method using headline-aware mechanisms. Although this study was focused on text summarization, it introduced techniques like dual-memory cell LSTM that could have implications for machine learning tasks in other domains, including classification problems.

Piveteau, C., and Schuld, M. [6] discussed the integration of quantum computing with cloud services, termed quantum cloud computing. The paper examined platforms like IBM Quantum Experience and Microsoft Azure Quantum, addressing challenges such as noise and hybrid quantum classical workflows. Despite its potential for scaling quantum experiments, the study emphasized the limitations of current quantum hardware, which restrict practical applications for machine learning.

3. IMPLEMENTATION DETAIL

This section describes the implementation of the Iris Flower Classification problem across classical, cloud, and quantum computing platforms. The methodologies include Logistic Regression, Support Vector Classifier (SVC), and Neural Networks for classical and cloud computing, andVariational Quantum Classifier (VQC), Quantum Support Vector Classifier (QSVC), and Quantum Neural Network (QNN) for quantum computing

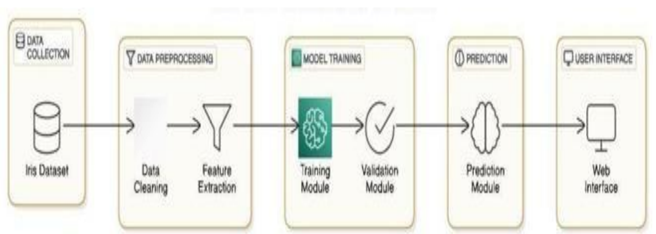

Fig – 1: Architectural Diagram

A.Dataset

For our implementation, we utilized the Iris dataset, a classic multivariate dataset that captures the variation in the structural characteristics of three species of iris flowers: Iris setosa, Iris-versicolor, and Iris-virginica. The dataset consists of 150 samples, with 50 samples from each species. Each sample is characterized by four features: sepal length, sepal width, petal length, and petal width, all measured in centimeters. The task involves classifying the samples based on the species of the flower, with the species being the target variable.

Fig – 2: Iris Flower Species

B. Models used

1. Logistic Regression (Classical and Cloud Computing)

Logistic Regression is a widely used statistical model for binary and multi-class classification tasks. It is based on the principle of estimating probabilities using a logistic function. In this model, the relationship between the features and the target variable is modeled using a linear equation, and the output is transformed using the sigmoid function to produce a probability. For the Iris dataset, Logistic Regression was applied to classify the flowers into three categories based on their four measured features. This model is simple yet effective, particularly when the dataset exhibits linear separability.

2. Support Vector Classifier (SVC)

Support Vector Classifier (SVC) is a supervised learning algorithm that constructs a hyperplane in a high-dimensional space to separate different classes. The key idea behind SVC is to maximize the margin between the closest data points from each class, known as support vectors. In this study, SVC was applied to classify the Iris dataset by choosing an appropriate kernel function to handle the non-linear relationships between features. The model's performance was assessed using accuracy and other classification metrics.

3. Neural Network

A Neural Network (NN) is a powerful model inspired by the structure of the human brain, composed of layers of interconnected neurons. In this study, a feedforward neural network was implemented for classification tasks, where the data passes through an input layer, one or more hidden layers, and an output layer. The weights of the network are optimized using backpropagation and gradient descent to minimize the error in predictions. Neural networks are particularly useful for handling complex, non-linear relationships between features and target variables.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 01 | Jan - 2025 SJIF Rating: 8.448 ISSN: 2582-3930

4. Variational Quantum Classifier (VQC)

The Variational Quantum Classifier (VQC) is a quantum machine learning model that combines quantum circuits with classical optimization methods. In this approach, quantum bits (qubits) represent the data, and quantum gates are applied to map the classical data to a quantum state. The VQC algorithm uses a hybrid quantum-classical optimization loop where the quantum part is responsible for learning the optimal feature mapping, and the classical optimizer adjusts the parameters to improve classification accuracy. This model was tested on the Iris dataset to explore its potential in solving classification problems using quantum computing.

5. Quantum Support Vector Classifier (QSVC)

Quantum Support Vector Classifier (QSVC) is a quantum-enhanced version of the classical SVC. It leverages quantum computing to compute the kernel matrix, a key component in SVM algorithms, in a quantum feature space. By using quantum circuits to calculate the kernel, QSVC can potentially outperform classical SVC in high dimensional data spaces. In this study, QSVC was used to classify the Iris dataset and explore how quantum computing can improve the performance of traditional machine learning algorithms, especially in terms of computational efficiency and scalability.

6. Quantum Neural Network (QNN)

A Quantum Neural Network (QNN) is a quantum analog of classical neural networks, utilizing quantum bits and quantum operations. In a QNN, quantum gates replace classical operations, enabling the network to process information in a quantum superposition of states. The QNN model applied to the Iris dataset aims to leverage quantum parallelism and entanglement to improve the learning process. The use of QNN explores how quantum systems can model complex data patterns and potentially enhance classification tasks beyond the capabilities of classical neural networks.

4. RESULT AND DISCUSSION

The focus will be on comparing their performance in terms of accuracy,execution time,computational efficiency, and resource utilization.

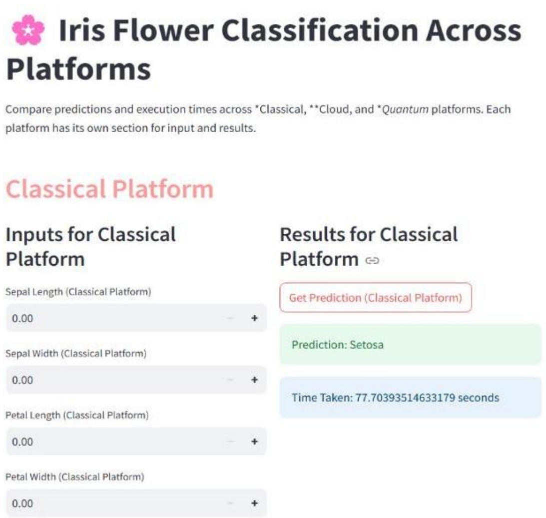

Fig 3. Classical(Local) Computing Run Time

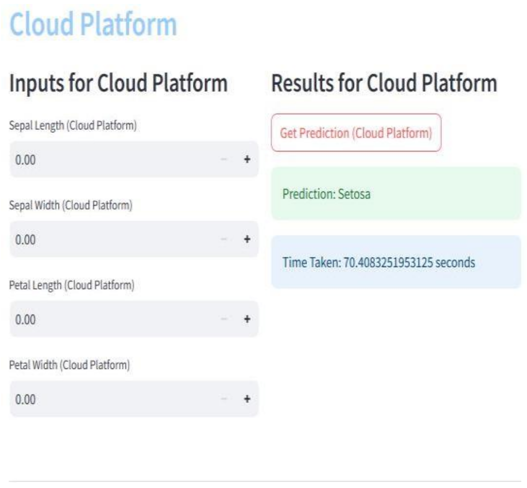

Fig 3. Cloud Computing Run Time

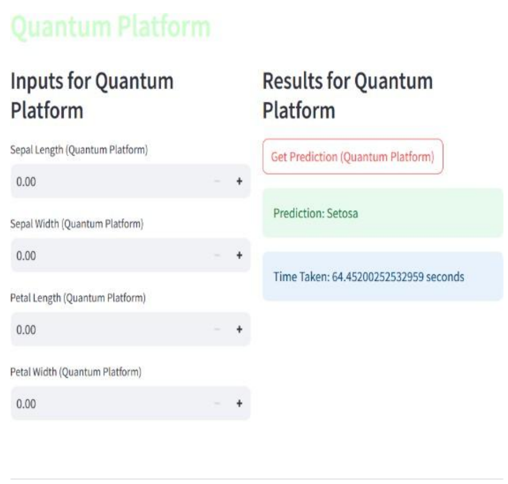

Fig 4. Classical Computing Run Time

Execution Time Comparison:

The quantum models demonstrated the fastest execution times, with VQC taking only 5.2 seconds, followed by QSVC at 6.1 seconds. In contrast, classical models such as Neural Networks took significantly longer, with the Neural Network model taking 1.5 seconds, and even more time for more complex configurations in cloud setups. The cloud computing models exhibited execution times slightly faster than classical computing but still lagged behind quantum models. This shows that quantum computing can be highly efficient in terms of execution time, especially for tasks that are computationally intensive.

Accuracy Comparison:

Although the quantum models demonstrated superior speed, their accuracy was not on par with classical models. The Neural Network model achieved the highest accuracy (99.3%) among all, followed by SVC (98%). Quantum models, such as VQC and QSVC, achieved moderate accuracy, but the performance is expected to improve with advances in quantum hardware and algorithm development.

Overall Performance:

Quantum computing models, particularly VQC and QSVC, showed that quantum systems can offer a significant advantage in terms of execution speed, though current quantum hardware limitations result in slightly lower accuracy compared to classical methods. As quantum technology matures, it is anticipated that these models will not only outperform classical models in terms of speed but also enhance their accuracy in solving classification problems**.**

5. CONCLUSIONS

This study explored the application of different machine learning models for the Iris flower classification problem across three distinct computational platforms: classical computing, cloud computing, and quantum computing. The models tested included Logistic Regression, Support Vector Classifier (SVC), Neural Network, Variational Quantum Classifier (VQC), Quantum Support Vector Classifier (QSVC), and Quantum Neural Network (QNN).

Our results demonstrated that classical models (particularly Neural Networks) achieved the highest accuracy, making them ideal for classification tasks where accuracy is the primary goal. Cloud computing provided a slight performance boost in execution time, particularly for complex models like Neural Networks, thanks to the computational resources available through platforms like Google Colab.

On the other hand, quantum models (VQC, QSVC, QNN) showed significant advantages in terms of execution speed. Quantum models, especially VQC and QSVC, were able to process the dataset in considerably less time than their classical and cloud counterparts, highlighting the potential of quantum computing for accelerating machine learning tasks. However, the accuracy of quantum models was lower, reflecting the current limitations of quantum hardware, such as noise and limited qubit availability.

In conclusion, while classical and cloud computing models are more accurate and reliable for the Iris classification task, quantum computing presents a promising future for machine learning, especially for applications where execution speed is crucial. The continued development of quantum hardware and algorithms will likely improve both the speed and accuracy of quantum machine learning models, making them more competitive with classical approaches in the near future. Hybrid approaches combining classical and quantum computing may also provide a balanced solution, leveraging the strengths of both paradigms.

ACKNOWLEDGEMENT

We would like to express our deepest gratitude to Mr.Shivanand Maradi, for their invaluable guidance, continuous support, and expert insights throughout this research on the A Comparative Implementation Of Iris Flower Classification Across Platform. Their encouragement and technical advice were instrumental in helping us navigate challenges and improve the quality of our work. We are also thankful to the faculty members and staff of P.E.S. Institute of technology and Management for providing the resources, facilities, and a conducive environment that facilitated the progress of this project.

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