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AI-Based Disease Prediction Using Quantum Inspired Optimization Techniques

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Abstract- Early and accurate disease prediction is a major challenge in modern healthcare systems. Delayed diagnosis often leads to higher treatment costs and lower patient survival rates. Artificial Intelligence (AI) and Machine Learning (ML) techniques are widely used to help with medical decision-making by analyzing complex healthcare datasets. However, traditional machine learning models often face issues with inefficient feature selection, poor hyperparameter tuning, and slow convergence during optimization. This is especially true when working with high-dimensional medical data. To tackle these challenges, this paper presents an AI-based disease prediction framework that uses quantum-inspired optimization techniques. This approach combines classical machine learning classifiers with optimization strategies based on quantum computing principles, such as probabilistic state representation and superposition-based search. These quantum-inspired methods allow for efficient exploration of the solution space, which leads to better feature selection and optimized model parameters. We evaluate the proposed framework using a publicly available healthcare dataset from Kaggle. We compare the performance of traditional machine learning models and quantum-inspired optimized models using accuracy, precision, recall, and F1-score metrics. The experimental results show that the quantum-inspired optimized model consistently performs better than conventional approaches. This study demonstrates that quantum-inspired optimization provides a practical and scalable solution for improving AI-driven disease prediction systems without the need for actual quantum computing hardware.

Keywords – Quantum-Inspired Computing, Artificial Intelligence, Disease Prediction, Healthcare Analytics, Machine Learning.

I. INTRODUCTION

The healthcare sector is going through a major digital change because of the widespread use of electronic health records (EHRs), medical imaging systems, wearable health-monitoring devices, and IoT-enabled medical sensors. These technologies produce large amounts of diverse data, such as clinical records, lab reports, and physiological measurements. Extracting useful information from this data is crucial for early disease detection, personalized treatment, and better healthcare delivery.

Artificial Intelligence (AI) has become an important tool for analyzing healthcare data by allowing automated learning, pattern recognition, and predictive modeling. Machine Learning (ML), a part of AI, has been effectively used in various healthcare tasks including disease diagnosis, prognosis, medical image analysis, and patient risk assessment. Traditional ML models, like Logistic Regression, Support Vector Machines (SVM), Decision Trees, and Random Forest, have shown reliable performance in predicting diseases.Despite these achievements, classical machine learning approaches encounter several challenges. Healthcare datasets often include redundant, irrelevant, or noisy features that harm prediction accuracy. Moreover, traditional optimization techniques for adjusting parameters and selecting features depend on gradient-based or heuristic methods, which may take time to converge or get stuck in local optima. These issues diminish the reliability and generalizability of ML models.

Quantum computing has gained interest for its potential to solve complex optimization problems more efficiently than classical computing. However, practical quantum computers are still in the early stages of development and are not yet available for large-scale use. Consequently, quantum-inspired computing has come up as an alternative that mimics quantum principles within classical computational frameworks.

This paper presents a quantum-inspired optimization-based AI framework aimed at improving disease prediction accuracy. By integrating quantum-inspired optimization strategies into traditional ML models, the proposed system enhances feature selection and parameter optimization while ensuring that it remains computationally feasible.

This paper suggests a quantum-inspired machine learning method for early disease detection.

II. RELATED WORK

Many studies have looked into the use of machine learning techniques in healthcare analytics. Traditional machine learning models have been widely employed to predict diseases like diabetes, cardiovascular issues, and cancer. These models depend heavily on good feature selection and tuning of parameters to perform well.

Recent progress in deep learning has improved prediction accuracy in healthcare, especially in medical imaging. However, deep learning models usually need large datasets and significant computing power, making them less practical for small or medium-sized healthcare datasets.

Researchers have also examined quantum computing in healthcare, focusing on areas like molecular modeling, genomics, and drug discovery. They have shown that quantum algorithms can potentially speed up optimization and data processing tasks. However, because of the limited availability of quantum hardware, researchers have proposed quantum-inspired algorithms to mimic quantum behaviors using classical systems.

Several studies have pointed out the possibilities of quantum-inspired optimization for solving complex combinatorial problems. Still, there are only a few practical applications of these techniques for disease prediction. This research adds to the existing body of work by presenting a workable quantum-inspired AI framework aimed specifically at predicting diseases in healthcare.

Problem Definition
Disease prediction using healthcare data is a complex problem that involves many features, parameters, and constraints. Traditional machine learning models use standard optimization methods that may not effectively search the entire space. As a result, these models often face issues like poor feature selection, lower prediction accuracy, and higher costs in computation.

This research focuses on creating an efficient optimization strategy. The goal is to improve the predictive performance of AI-based systems for disease prediction while keeping it practical for real-world healthcare scenarios.

III. PROPOSED METHODOLOGY

A. System Architecture
The proposed framework follows a modular architecture that includes several stages:

- Data Collection: Gathering healthcare data from a publicly available dataset.
- Data Preprocessing: Eliminating missing values, normalizing, and transforming data.
- Feature Selection: Identifying the relevant medical attributes.
- Quantum-Inspired Optimization: Optimizing feature subsets and model parameters.
- Classification: Predicting diseases using machine learning classifiers.
- Evaluation: Assessing performance using standard metrics.
- This structured pipeline ensures better prediction accuracy and efficient computation.

IV. QUANTUM-INSPIRED OPTIMIZATION TECHNIQUES

Quantum-inspired optimization techniques draw from principles of quantum mechanics, such as superposition and probabilistic state changes. Unlike classical optimization methods, which evaluate one solution at a time, quantum-inspired approaches examine several potential solutions at once using probability distributions.

In the proposed framework, quantum-inspired optimization is used to:

- Select optimal feature subsets
- Tune machine learning hyperparameters
- Improve convergence speed

This method allows for better exploration of the solution space and lowers the chances of getting stuck in local optima.

Dataset Description
The experimental evaluation uses a publicly available healthcare dataset from Kaggle, specifically the Diabetes Prediction Dataset. This dataset includes medical records of patients along with different physiological attributes.

- Number of Instances: Approximately 750
- Attributes: Age, BMI, Glucose Level, Blood Pressure, Insulin, Skin Thickness, etc.
- Target Variable: A binary outcome indicating disease presence.

The dataset is cleaned to eliminate inconsistencies and ensure reliable model training.

Implementation Details
The proposed system is implemented using Python because it has strong support for data science and machine learning. Libraries like NumPy, Pandas, and Scikit-learn are used for data processing, model training, and evaluation.

The machine learning classifiers used in this study include Logistic Regression, Support Vector Machine, and Random Forest. We apply quantum-inspired optimization techniques during feature selection and hyperparameter tuning to improve model performance.

V. RESULTS AND DISCUSSION

The experimental results show that quantum-inspired optimized models perform better than traditional machine learning models. We evaluate performance using accuracy, precision, recall, and F1-score metrics.

The improved performance comes from effective feature selection and better parameter optimization made possible by quantum-inspired techniques. These results confirm that combining quantum-inspired optimization with classical AI models works well for healthcare applications.

Advantages and Limitations

The proposed framework provides better prediction accuracy, efficient optimization, and scalability for healthcare datasets. However, it simulates quantum-inspired techniques using classical systems, and it does not use real quantum hardware. Furthermore, the size of the dataset limits generalization.

VI. CONCLUSION

This study introduced an AI framework for disease prediction that is inspired by quantum optimization. By combining quantum-inspired techniques with traditional machine learning models, this approach improves prediction accuracy and computational efficiency. The experimental results show that quantum-inspired optimization can be a practical solution for AI-driven healthcare analytics.

Future Work

Future research may focus on applying the proposed framework to actual quantum computing platforms. It might also look at increasing the dataset size and connecting the system with real-time healthcare monitoring systems.

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