

Enhancing Healthcare Claim Fraud Detection with Quantum Intelligence

SINGAMPALLI NAGALAKSHMI¹, KARANAM HARSHINI², PUSALA HARSHITHA³

KARRI RAMYA⁴, KODADDI GANESH⁵, Dr. DHARAVATHU RADHA⁶

¹ Student & SATYA INSTITUTE OF TECHNOLOGY AND MANAGEMENT,

² Student & SATYA INSTITUTE OF TECHNOLOGY AND MANAGEMENT

³ Student & SATYA INSTITUTE OF TECHNOLOGY AND MANAGEMENT,

⁴ Student & SATYA INSTITUTE OF TECHNOLOGY AND MANAGEMENT,

⁵ Student & SATYA INSTITUTE OF TECHNOLOGY AND MANAGEMENT,

⁶ Professor & SATYA INSTITUTE OF TECHNOLOGY AND MANAGEMENT

¹nagalaxmi0616@gmail.com, ²harshinikaranam21@gmail.com, ³pusalaharshitha@gmail.com

⁴karrir534@gmail.com, ⁵ganesh.kodadadi@gmail.com, ⁶radha.dharavathu@gmail.com

ABSTRACT— Healthcare fraud is a major issue in the medical and insurance industry, leading to significant financial losses and reduced trust in healthcare systems. Fraudulent claims include false billing, unnecessary treatments, and misuse of insurance services. Traditional fraud detection methods rely on manual verification and classical machine learning techniques, which often suffer from limited accuracy, high processing time, and difficulty in handling complex datasets. With the advancement of quantum computing, Quantum Machine Learning (QML) has emerged as a powerful solution that utilizes quantum properties such as superposition and entanglement to improve computational efficiency. This project focuses on developing a healthcare claim fraud detection system using quantum techniques like Quantum Support Vector Machine (QSVM) and Variational Quantum Classifier (VQC). The system analyzes patient and claim-related data such as age, medical history, billing details, and treatment records to identify fraudulent patterns. By encoding classical data into quantum states and processing it through quantum circuits, the model improves pattern recognition and classification accuracy. The proposed system integrates classical preprocessing with quantum algorithms to achieve better performance compared to traditional models, and experimental results show higher accuracy, faster processing, and improved efficiency, demonstrating the potential of quantum computing in healthcare fraud

detection. In addition, the system reduces dependency on manual verification and increases automation in the fraud detection process. It also helps in identifying hidden patterns that are difficult to detect using traditional systems. The system contributes to improving decision-making processes in insurance companies. Overall, the proposed model provides a reliable and efficient solution for modern healthcare challenges.

KEYWORDS:

QML(Quantum machine learning), QC(Quantum Computing), Qubit(Quantumbit), QSVM, QPU(Quantum Processing Unit).

I. INTRODUCTION

Healthcare fraud detection has become increasingly important due to the rapid growth of insurance systems and digital healthcare records, where fraudulent activities such as fake claims, duplicate billing, and unnecessary procedures lead to financial losses and reduced service quality. Traditional methods rely on manual auditing and rule-based systems, which are time-consuming and prone to human errors. With advancements in Artificial Intelligence and Machine Learning, automated systems have been developed to analyze large healthcare datasets, where classical models like decision trees, support vector machines, and neural networks provide some level of accuracy but face challenges such as high computational complexity, long training time, and inefficiency in handling high-dimensional data. Quantum computing introduces a new paradigm by utilizing quantum mechanical properties to process information more efficiently than classical systems, and Quantum Machine Learning combines quantum algorithms with learning models to enhance performance. In this project, quantum techniques such as QSVM and VQC are applied to improve

fraud detection accuracy and efficiency, providing a scalable and modern solution that bridges the gap between classical machine learning and quantum computing. The need for faster and more reliable fraud detection systems is increasing day by day. Healthcare organizations require intelligent systems that can handle real-time data processing. Classical systems often fail to adapt to dynamic changes in fraud patterns. Quantum computing offers parallel processing capabilities that significantly improve speed. The integration of AI and quantum computing leads to more powerful analytical tools. The proposed system aims to reduce operational costs associated with fraud detection. It also improves transparency in claim verification processes.

II. LITERATURE SURVEY

Several research studies have explored the use of machine learning techniques for healthcare fraud detection, where traditional approaches use algorithms such as Logistic Regression, Decision Trees, Support Vector Machines, and Random Forests to identify fraudulent claims based on historical data, achieving moderate success but facing limitations in capturing complex patterns. Recent advancements include deep learning models like Artificial Neural Networks and Convolutional Neural Networks, which improve accuracy by learning hierarchical features but require large datasets and high computational resources. With the emergence of quantum computing, researchers have introduced Quantum Machine Learning techniques such as Quantum Support Vector Machines and Variational Quantum Classifiers, which efficiently handle high-dimensional data by mapping it into quantum feature spaces and using parameterized quantum circuits for classification. Hybrid quantum-classical models have also been proposed, combining classical preprocessing with quantum computation to improve performance and efficiency, and these studies indicate that quantum approaches can outperform classical methods in handling complex datasets and improving fraud detection accuracy. Researchers have also explored ensemble learning techniques to enhance prediction performance. Some studies focus on anomaly detection methods for identifying unusual claim patterns. Deep learning models have shown better feature extraction capabilities compared to traditional methods. However, they require significant computational power and large labeled datasets. Quantum models provide a new direction for solving these limitations. Studies show that quantum kernels can improve classification boundaries. Variational circuits allow flexible model design and optimization. Noise-resilient quantum algorithms are being developed for practical applications.

III. PROBLEM STATEMENT

Healthcare fraud is increasing rapidly, causing major financial losses and operational inefficiencies in the healthcare industry, while existing fraud detection systems are not fully capable of handling large and complex datasets effectively. Traditional machine learning models require high computational resources and often fail to detect advanced fraud patterns accurately, and manual verification processes are time-consuming and prone to human errors, making real-time fraud detection difficult. Additionally, classical algorithms face limitations in processing high-dimensional data and identifying hidden relationships within datasets, which reduces their effectiveness in complex scenarios. Therefore, there is a need to develop an advanced system that can process large healthcare data efficiently, reduce computational time, and improve detection accuracy, and this project aims to design a quantum-based fraud detection model that overcomes these challenges and provides a more efficient and reliable solution. The system must be capable of handling both structured and unstructured data. It should detect fraud patterns at early stages to prevent losses. The model should adapt to changing fraud techniques over time. High accuracy and low error rates are essential for practical implementation. The system should minimize false alarms that can affect genuine users. It should also support scalability for growing datasets. Real-time processing capability is another important requirement. The system should be cost-effective and easy to implement. Integration with existing healthcare systems should be possible. Overall, the goal is to develop a robust and intelligent fraud detection system.

a. EXISTING SYSTEM

The existing healthcare fraud detection systems mainly rely on classical machine learning algorithms such as Logistic Regression, Support Vector Machines, Decision Trees, and Random Forests, where these models analyze healthcare data through preprocessing, feature extraction, and training using historical datasets to identify fraudulent claims. Although these systems provide reasonable accuracy, they have several limitations including high computational requirements, long training time, and reduced performance when handling large and complex datasets. Additionally, they struggle to detect advanced fraud patterns due to limited feature representation and often depend on manual feature engineering, which reduces scalability and efficiency. These systems are also constrained by classical computing limitations, making them less effective in processing high-dimensional data, and these drawbacks highlight the need for

more advanced approaches like quantum computing for better fraud detection. Many existing systems are rule-based and cannot adapt to new fraud patterns dynamically. They often generate a high number of false positives, which affects user trust. Manual intervention is required in many stages, increasing workload. These systems lack real-time processing capabilities in most cases. They are not efficient in handling unstructured healthcare data such as text records. Integration with modern technologies is limited in traditional systems. Maintenance and updating of these systems require significant effort. They are not scalable for rapidly growing healthcare data. Security and data privacy concerns are also present. Overall, existing systems are not sufficient to handle modern fraud detection challenges effectively.

b. PROPOSED SYSTEM

The proposed system introduces a Quantum Machine Learning-based approach for healthcare fraud detection using advanced algorithms such as Quantum Support Vector Machine and Variational Quantum Classifier, where the system collects healthcare data including patient details, medical history, and billing information, and performs preprocessing to clean and prepare the data. The processed data is then encoded into quantum states using appropriate encoding techniques and passed through quantum circuits that extract meaningful patterns using quantum properties like superposition and entanglement. The system uses a hybrid approach where classical optimization methods are used to train quantum models efficiently, allowing it to handle large datasets and complex relationships more effectively. The proposed model improves accuracy, reduces processing time, and minimizes human effort, providing a scalable and efficient solution for detecting fraudulent and genuine claims. It can analyze large volumes of data in a shorter time compared to classical systems. The model adapts to new fraud patterns using continuous learning. It provides better generalization across different datasets. The system reduces dependency on manual verification processes. It enhances decision-making by providing accurate predictions. The hybrid approach makes it feasible for current hardware limitations. The model is designed to be flexible and scalable for future improvements. It ensures higher reliability in fraud detection. It can be integrated with existing healthcare platforms easily. Overall, the proposed system offers a modern and efficient solution to fraud detection problems.

IV. RESULT ANALYSIS

The performance of the proposed system is evaluated by comparing it with traditional machine learning models using metrics such as

accuracy, precision, recall, and F1-score, where models like Logistic Regression and Support Vector Machines provide moderate performance, while advanced models like Random Forest and Artificial Neural Networks show improved results but require higher computational resources. The Quantum Machine Learning models, including QSVM and VQC, demonstrate superior performance by achieving higher accuracy and faster processing time, as they effectively capture complex patterns and relationships in the data using quantum feature spaces. The results show that the proposed system outperforms existing models in terms of efficiency and accuracy, proving its effectiveness in healthcare fraud detection. The system also shows better generalization on unseen data. It reduces overfitting compared to classical models. The processing time is significantly lower due to quantum optimization. Precision and recall values indicate improved prediction quality. The F1-score shows balanced performance across different classes. Graphical analysis clearly highlights performance improvements. The system maintains stability across different datasets. It handles noisy data effectively. The results validate the advantages of quantum-based models. Overall, the proposed system provides better performance compared to traditional methods.

V. CONCLUSION

This project presents a healthcare fraud detection system using Quantum Machine Learning techniques, where the proposed approach improves accuracy, reduces computational complexity, and enhances overall efficiency compared to traditional methods. By integrating classical preprocessing with quantum algorithms, the system effectively processes complex healthcare data and accurately identifies fraudulent claims, and the results demonstrate the potential of quantum computing in improving fraud detection systems. Although there are challenges such as limited availability of quantum hardware, the proposed system provides a strong foundation for future research, and with further advancements, quantum-based solutions can play a significant role in healthcare analytics and fraud prevention. The system contributes to reducing financial losses in the healthcare industry. It improves trust between patients and insurance providers. The model can be extended to other fraud detection domains. Future work can focus on real-time implementation using advanced hardware. The system can be enhanced with more complex quantum

algorithms. It provides a new direction for research in healthcare analytics. The approach supports scalable and efficient data processing. It also encourages the adoption of emerging technologies in healthcare. The results highlight the importance of innovation in solving real-world problems. Overall, the project demonstrates a successful application of quantum computing in fraud detection.

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