<TITLE>

1. INTRODUCTION
2. NEED OF THE PRODUCT
   1. Explain in detail why the product is needed?
   2. If an extension of existing, then explain drawbacks of the existing
   3. Applications of the product

*(where will it be used, how is it useful to the society)*

1. SURVEY
2. **Document 1: Integrating Machine Learning Algorithms with Quantum Annealing**

**Solvers for Online Fraud Detection**

* **Objective**: This research explores the use of a Quantum Machine Learning (QML) framework to improve the detection of fraudulent transactions in online systems. The approach integrates classical machine learning algorithms, like Support Vector Machines (SVM), with quantum annealing solvers.
* **Challenges Addressed**: The paper identifies key issues in fraud detection, such as the need for real-time analysis and dealing with highly imbalanced datasets where fraudulent transactions are much rarer than normal ones.
* **Methodology**: The study compares a quantum-enhanced SVM model with 12 other machine learning algorithms across two datasets—one moderately imbalanced (Israel credit card transactions) and one highly imbalanced (bank loan data). Quantum-enhanced methods showed better performance in terms of speed and accuracy on time-series, highly imbalanced data.
* **Results**: The quantum-enhanced SVM demonstrated superior speed and accuracy in some scenarios, especially for time-series data. Feature selection significantly improved speed but had a marginal effect on detection accuracy.

**Document 2: Implementation of Quantum Machine Learning Technique for Insurance Claim Fraud Detection**

* **Purpose**: This research applies Quantum Machine Learning (QML), specifically Quantum Support Vector Machines (QSVM), to detect fraud in insurance claims. The quantum approach is advantageous for complex datasets that can benefit from parallel processing capabilities.
* **Techniques**: The study outlines key concepts of quantum computing, like superposition and entanglement, which enable more efficient data processing. It also emphasizes the importance of feature engineering, data normalization, and using quantum kernels to optimize SVM classifiers.
* **Implementation**: The QSVM algorithm is implemented on IBM Quantum Experience, demonstrating how quantum circuits are structured for machine learning. Steps include data preprocessing, kernel generation, and execution on quantum computers.
* **Comparison**: The research compares QSVM with classical SVM, noting the potential speed and accuracy improvements offered by quantum approaches. However, the quantum advantage is limited by current hardware constraints, such as the number of qubits and error rates​.

**Document 3: Mixed Quantum-Classical Method for Fraud Detection with Quantum Feature Selection**

* **Objective**: This study applies Quantum Support Vector Machine (QSVM) algorithms to detect payment fraud, comparing it with traditional AI/ML methods, like Random Forest and XGBoost, using a real-world payment transaction dataset.
* **Innovation**: It introduces a hybrid model that combines quantum and classical techniques, leveraging QSVM’s quantum feature mapping to enhance detection accuracy. The research emphasizes how quantum feature selection can improve the performance of mixed quantum-classical fraud detection models.
* **Data**: The study uses IBM's Safer Payments platform and a dataset with 2.4 million payment transactions, enriched with engineered features. Feature selection was crucial for performance, and a drastically reduced dataset was needed to fit quantum hardware limitations.
* **Outcomes**: The QSVM and hybrid models provided better accuracy and efficiency, but their success highly depended on the chosen features and algorithms. The mixed approach highlighted the potential of quantum computing to complement classical methods, improving key performance indicators like hit rate and false alarm ratio

**Document 4: Financial Fraud Detection using Quantum Graph Neural Networks:**

1. Quantum Graph Neural Networks (QGNNs): QGNNs combine the principles of Quantum Computing (QC) with Graph Neural Networks (GNNs) to process graph-structured data more efficiently. The authors employ Variational Quantum Circuits (VQC) to enhance the performance of QGNNs.
2. Methodology: The paper details the architecture of QGNNs and compares their performance against classical GNNs using a real-world financial fraud detection dataset. The authors conducted experiments that demonstrated QGNNs achieved an Area Under the Curve (AUC) of 0.85, outperforming classical GNNs.
3. Advantages of QGNNs: The authors highlight the potential of QGNNs to improve the accuracy and efficiency of fraud detection by effectively capturing complex relationships and patterns in financial transactions through quantum properties like superposition and entanglement.
4. Challenges: Despite their advantages, the paper acknowledges challenges such as the interpretability of quantum computations and concerns regarding the security of quantum systems.
5. Conclusion and Future Research: The findings suggest that QGNNs represent a promising new approach for enhancing financial fraud detection systems. The paper concludes by proposing directions for future research to further explore the capabilities of QGNNs in combating financial fraud.

**Overall Insights from the Research**

1. **Quantum-Enhanced Algorithms**: Across the studies, quantum methods, especially Quantum Support Vector Machines (QSVMs), are explored as enhancements to classical fraud detection algorithms, providing improvements in accuracy and speed.
2. **Hybrid Approaches**: Combining classical and quantum techniques shows promise, especially in handling complex feature spaces and imbalanced datasets. These methods can complement traditional machine learning, especially when using quantum feature selection.
3. **Challenges and Limitations**: Current quantum hardware limitations, like the number of qubits and data dimensionality constraints, necessitate data reduction techniques, which could affect model performance. Practical integration with real-world systems also requires addressing latency and data handling issues.
4. **Future Directions**: Further advancements in quantum computing could make these techniques more accessible and effective for fraud detection in financial and insurance sectors.
5. PROBLEM FORMULATION
   1. Problem Formulation

We are addressing the challenge of fraud detection in insurance, where traditional ML methods struggle with complex, high-dimensional data. Our goal is to use Quantum Machine Learning (QML), specifically Quantum Support Vector Machines (QSVM), to improve detection accuracy and efficiency.

* 1. Product objectives
* Detect fraud by identifying complex patterns in claims data.
* Improve accuracy while minimizing false positives.
* Leverage quantum computing for faster analysis.
* Build a scalable framework adaptable to other financial sectors.
  1. Novelty

The novelty lies in applying QML to insurance fraud detection. Unlike classical ML, QML offers enhanced data representation, parallel processing, and potentially simpler models that maintain high accuracy.

* 1. Scope of the project
* The insurance domain.
* Simulating quantum models using tools like Qiskit.
* Developing a prototype as proof-of-concept, recognizing that further testing will be needed for real-world deployment.

1. PROPOSED DESIGN
   1. Proposed model (or Architectural design with components or functionalities to be explained here)
   2. Database design

*(DFDs, CFDs, ER diagrams)*

* 1. Use cases

1. IMPLEMENTATION
   1. GUI design (Screenshots of GUI with explanation)
   2. Modules implementation (Pseudocode / algorithm of the model)
2. EXPERIMENTATION & RESULTS
   1. Datasets / Tables (Description of fields of dataset)
   2. Test cases (or Hypothesis)
   3. Parameter tuning experiments (if any)
   4. Results
3. CONCLUSION
4. REFERENCES / BIBLIOGRAPHY

*(Any research papers, websites, products referred should be listed here)*

1. APPENDIX

*Technical paper*

*Patent filing (if any)*