A Rigorous Comparative Study of Classical and Quantum Machine Learning for Intelligent Automated Fake Review Detection in Smart E-Commerce Systems

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Abstract

The Extensive growth of e-commerce platforms has increased the prevalence of deceptive and fabricated reviews, posing challenges for automated trust assessment and intelligent online systems. Effective detection of such reviews requires models that can analyze textual patterns, linguistic cues, and sentiment characteristics with high reliability. This study presents a comparative evaluation of classical machine learning methods—Support Vector Machines (SVM) and k-Nearest Neighbors (KNN)—and their quantum counterparts, Quantum SVM (QSVM) and Quantum KNN (QKNN), for automated fake review detection. Unlike earlier works that rely on limited feature sets, this study incorporates comprehensive preprocessing and evaluates multiple performance metrics, including accuracy, precision, recall, and F1-score. The findings indicate that classical SVM consistently delivers strong and stable performance, while QSVM demonstrates modest but meaningful improvements in specific scenarios due to its ability to exploit higher-dimensional quantum feature spaces. The results highlight the potential of quantum-enhanced models for future intelligent automation systems, while also emphasizing current limitations related to computational overhead and scalability. This work contributes to the development of more robust AI-driven mechanisms for enhancing trust and reliability in smart e-commerce environments.

Keywords: Sentiment Analysis (SA), Fake Reviews Detection, Quantum Machine Learning (QML), Quantum Support Vector Machine (QSVM), Quantum k-nearest Neighbors (QKNN), Classic Machine Learning Algorithms, Text Classification, Performance Metrics, Quantum Circuits, Online Shopping Reviews.

INTRODUCTION

Online reviews have become a crucial part of modern purchasing behaviour, as most consumers rely on the experiences and feedback of others before making a decision. Positive reviews often increase sales and enhance product visibility, whereas negative reviews can discourage potential buyers. This heavy dependence on user-generated content has encouraged certain individuals and organizations to engage in "opinion spamming," where reviewers intentionally exaggerate product qualities or post misleading objections to influence market perception. Detecting such deceptive or coordinated reviewers remains a challenging task due to their dynamic behaviour and the subtle strategies they use to appear authentic[1].

Earlier research on fake review identification largely focused on mining frequent item sets or identifying tightly connected reviewer groups to detect suspicious activity. These approaches, however, primarily capture strongly associated spammers who repeatedly target similar products. Loosely connected or individually operating deceptive reviewers often remain undetected, limiting the overall effectiveness of these traditional techniques [2].

To enhance detection capability, several machine learning methods—such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and graph-based algorithms like Deep Walk—have been explored. These approaches leverage both textual and structural information from social networks to classify suspicious users or review patterns. Deep Walk, for instance, constructs a reviewer graph where nodes represent users and edges capture shared review activity, enabling the identification of anomalous reviewer communities. In recent developments, quantum machine learning models such as Quantum SVM (QSVM) and Quantum KNN (QKNN) have been investigated as potential tools for handling complex graph structures and non-linear correlations through quantum-enhanced feature spaces [3].

While e-commerce has significantly transformed consumer buying behaviour, the role of social commerce and interpersonal influence in shaping purchase decisions remains underexplored. Studies based on social learning theory suggest that cognitive appraisal often plays a greater role than emotional response in driving purchase intentions. However, Fake reviews significantly bias user judgment, resulting in erosion of consumer confidence, reputational harm to legitimate sellers, and an imbalance in fair digital commerce practices.

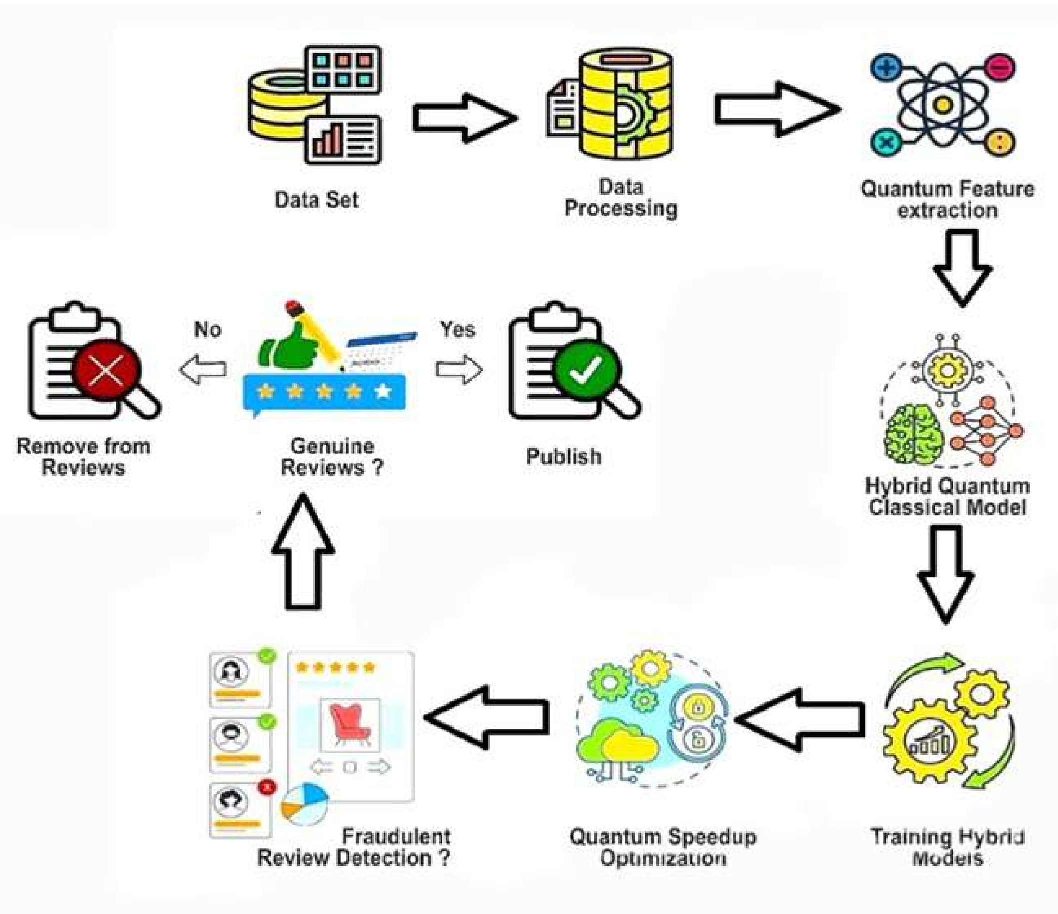

Fig. 1: Overview of a quantum neural network-based framework for detecting fraudulent reviews.

Although classical machine learning techniques have demonstrated reasonable success in detecting fraudulent patterns, they often struggle to keep pace with evolving deceptive strategies. Quantum computing, illustrated conceptually in Fig. 1, introduces a fundamentally different computational paradigm with the ability to encode and explore high-dimensional feature spaces more efficiently.

Despite the availability of multiple studies, a comprehensive analysis combining the causes, effects, and prevention mechanisms of fake reviews remains limited. This work aims to bridge this gap by presenting an integrated framework and conducting a comparative evaluation of classical and quantum machine learning approaches.

In particular, this paper explores quantum computing techniques specifically Quantum Machine Learning (QML) as a promising direction for improving fake review detection. QML models leverage quantum properties such as superposition and entanglement to analyze reviewer behavior, textual features, and interaction patterns. These models can process complex linguistic and behavioral signals, offering the potential for more robust and scalable detection systems. Quantum Neural Networks (QNNs), for instance, combine concepts from quantum computing and neural architectures, enabling the analysis of high-dimensional patterns that may be difficult for traditional models to capture [4].

By examining emotional cues, writing style, and reviewer behavior, QNNs have shown promising results in countering misleading content and enhancing user trust on e-commerce platforms. As a next-generation artificial intelligence technology, quantum-based models open new pathways for decisionmaking and fraud detection, offering innovative solutions to maintain the credibility and reliability of online review ecosystems [5].

LITERATURE REVIEW

Fake reviews are a big issue these days, especially for businesses that rely on online shopping portals. These fake reviews will completely confuse consumers and destroy the level of trustfulness they have towards businesses, because of which various methods, such as old school machine learning methods, to the new technology, quantum machine learning stuff, have been considered to address this problem. This literature review gives an overview of various approaches and their respective strengths and weaknesses [6].

A recent study explored the use of a Quantum Neural Network (QNN) model for detecting fraudulent reviews using the Amazon Fraudulent Review Dataset. The approach incorporated emotional attributes, trend indicators, and opinion relationship analysis to enhance feature representation. The QNN model achieved an accuracy of approximately **86%**, demonstrating the potential of quantum-based architectures in capturing complex and non-linear relationships present in deceptive review patterns[7], Despite these promising results, the study highlights two major challenges: the high computational cost associated with quantum processing and the early developmental stage of QNN frameworks. Nevertheless, the findings suggest that quantum models may offer a viable and more robust alternative to conventional machine learning approaches as the technology matures.

They've looked into spotting fake reviews by comparing the CML algorithms like Random Forest, SVM, and ANN. So, they took that online review dataset and played around with a few feature engineering techniques like clustering with expectation maximization, sentiment analysis, and some of that non-text stuff. Out of all the models they ran through, Random Forest really shined through as the best, specifically in using those non-text features for detection[8].

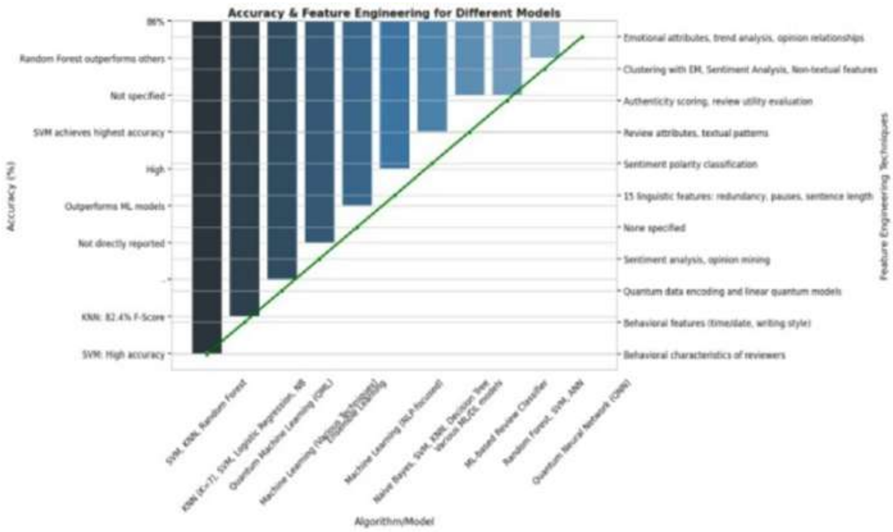

Fig. 2: Accuracy comparison of models like Quantum Neural Networks, Random Forest, and Support Vector Machines for detecting fake reviews.

We've found two visualizations of sharing what we have in our literature review about fake review detection. So, here's how the various studies were accurate about algorithm models, such as Quantum Neural Networks, Random Forest, and Support Vector Machines in Fig. 2 they point out how the various methods fare against each other concerning their efficiency in catching fake reviews. So, in Fig. 3, you can see how stuff like emotional attribute analysis, clustering, and sentiment polarity classification affected how accurate the model was. These graphs give us a super clear visual of how picking the right algorithms and doing feature engineeringconnects with performance, which is pretty handy for future research on spotting fake reviews.

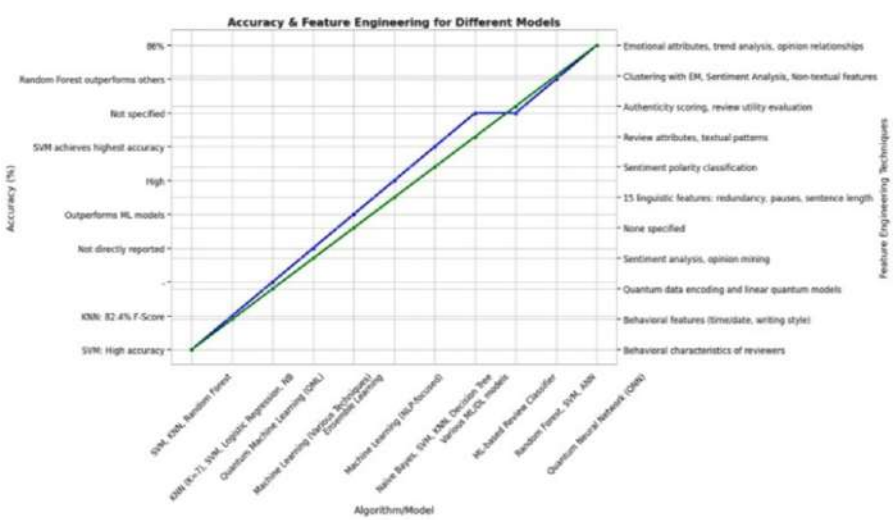

Fig. 3: Effect of feature engineering methods like emotional analysis, clustering, and sentiment classification on model accuracy.

But results very much depended on the dataset and the authors were saying their findings may not work with other kinds of data. Even with that limitation, the study shows how much of a difference it makes to add non-textual features for boosting fake review detection. The other one focused on building an e-commerce review classification using ML approaches, including authenticity scoring of reviews besides review utility [9].

So, they did not really speak to how accurate the classifier is, but it could be of assistance in helping online reviews become more believable. One of the problems that surface is that the data can really run amok since this model hasn't been particularly robust across various types and quality of reviews. It just shows that we really have to choose the right datasets for training and testing when we're building systems to catch fake reviews [10].

So, while exploring various machine learning and deep learning models, they used a set of datasets from sites like Amazon, Yelp, and Trip Advisor to identify fake reviews. They looked at things like reviewing attributes and text patterns to get solid performance across all those datasets. The authors pointed out that it is pretty tough to find synthetic patterns in different datasets, which highlights much about how crucial it becomes to have diverse datasets to build solid models of catching fake reviews.

So, there was this study that used some traditional machine learning techniques like Naive Bayes, SVM, KNN, and Decision Tree to sniff out fake reviews, zeroing in on sentiment polarity classification. So it appears SVM completely dominated the class with the highest accuracy [11].

The paper demonstrated just how fantastic SVM is at classifying text and capturing false reviews. However, they do point out a few negatives: you require pretty robustly labelled datasets and there's a problem with scaling with some of these traditional machine learning approaches. So, another study has been conducted to check NLP techniques, such as redundancy, pauses, and the length of sentences, to identify fake reviews[12].

The research proved it to be highly accurate in discovering linguistic markers of deception from a synthetic dataset of fake reviews. This indicates that, critically enough, linguistic patterns define the existence of real reviews or fakes. However, this dependency on linguistic datasets somehow limits its applicability to any other type of review data.

So, they have been exploring ensemble learning models to detect fake reviews, particularly using this Fake Restaurant Reviews Dataset. The ensemble method has outperformed regular ML models like KNN, Decision Tree, and Logistic Regression by a significant amount, mainly because the model combined the outputs of different algorithms for stronger decision-making [13].

This would come from fake reviews, which are always new because of new creations. Its real-time nature poses a difficulty in model development. Despite this, some areas for future research pointed toward the potential of ML models that considerably enhanced fake review detection. So, they were exploring how to apply Quantum Machine Learning (QML) to identify fake reviews, especially for health information and electronic health records (EHR).

They experimented with some review data using quantum data encoding and linear quantum models. Although they did not provide specific accuracy figures, the research indicated that QML could be extremely useful for clinical decision support, especially in identifying fake reviews in healthcare. So there are still some scaling problems regarding the encoding of large datasets; so we have to drill deeper to find out what is special about QML and how it can beat conventional machine learning methods. Also, while trying to find spam in the Yelp reviews dataset, techniques like KNN, SVM, Logistic Regression, and Naive Bayes threw up how important items such as time/date and writing style are for improved accuracy in detection [14].

Out of all the models we tested, KNN nailed it with the highest F-score, totally outshining the others. But, if we rely too much on behavioral data, it can create some biases, so we've got to be careful and consider those behavioral features when we're putting together fake review detection models. Well, the research describes a whole range of methods that can help with spotting fake reviews, from good old machine learning techniques to some newer quantum techniques. The classical models such as Random Forest, SVM, and KNN were shown to be effective in different studies. On the other hand, QNN and QML have the potential to overcome present detection errors [15].

However, issues like computational resources dependability and scalability continue to pose significant barriers. You know, with everything shifting in the field, future research is going to need to tackle these challenges to come up with good ways and techniques for spotting spam in different datasets.

METHODOLOGY

A. State Diagram:

Figure 4 illustrates the system's operational workflow. It begins with dataset loading, followed by preprocessing for feature extraction and data preparation. The process then moves to quantum preprocessing, where features are converted into a quantum-compatible format. Next, the quantum kernel is computed and used for QSVM training. The system then performs prediction and evaluation, concluding with the final output containing the performance metrics.

TABLE I: Comparison of Algorithms for Fake Review Detection

Author(s) & Year	Algorithm/ Model	Dataset	Feature Engineering	Accuracy	Advantages	Challenges	Observations
Thulasi Bikku et al., 2024	Quantum Neural Network (QNN)	Amazon Fraudulent Review Dataset	Emotional attributes, trend analysis, opinion relationships	86%	Innovative QNN application; early-stage QML benefits; accurate fraudulent review detection	High computa-tional resources required; still in development phase	QNN effectively detects fake reviews and outperforms conventional methods.
Huy Le & Ben Kim, 2024	Random Forest, SVM, ANN	Online Reviews	Clustering with EM, Sentiment Analysis, Non-textual features	Random Forest outperfor ms others	Effective fake review detection with non-textual features integration	Limited generaliza-tion; Specific dataset dependency	Random Forest exhibits strong performance, leveraging clustering and nontextual features.
Wonil Choiet al., 2024	ML-based Review Classifier	E-commerce reviews	Authenticity scoring, review utility evaluation	Not specified	Practical review filtering model; helps retain ecommerce credibility	No clear implementa tion accuracy; dataset heterogeneity	Demonstrates potential to improve review authenticity using evaluation models.

Aaryan Rustagi et al., 2024	Various ML/DL models	Amazon, Yelp, Tripadvisor	Review attributes, textual patterns	Not specified	Diverse datasets; robust fake review classification	Challenges with identifying synthetic patterns across datasets	Highlights the importance of dataset diversity in fake review detection.
Elshrif lmurngi et al., 024	Na¨ıve Bayes, SVM, KNN, Decision Tree	Movie Review Dataset V1.0-3.0	Sentiment polarity classification	SVM achieves highest accuracy	Strong performance metrics; practical SA applications	Requires high-quality labeled datasets; scalability issues	SVM excels in both text classification and fake review detection in movie datasets.
Faranak Abri et al., 2024	Machine Learning (NLP-focused)	Synthetic Dataset of Fake Reviews	15 linguistic features: redundancy, pauses, sentence length	High	Identifies linguistic markers of deception; effective discriminatio n between real and fake reviews	High dependence on linguistic datasets	Highlights linguistic patterns as critical features for fake review detection.
Luis Gutierrez-Espinoza et al., 2024	Ensemble Learning	Fake Restaurant Reviews Dataset	None specified	Outperfor ML models	msEnsemble models demonstrate superior performance compared to classical algorithms	Limited dataset scope; needs real-world dataset evaluation	Ensemble learning proves to be more reliable for deceptive review detection.
Mohammed Ennaouri & Ahmed Zellou, 2024	Machine Learning (Various Techniques)	Systematic Literature Review Dataset	Sentiment analysis, opinion mining	Not directly reported	Emphasizes the importance of SA and ML for improving fake review detection accuracy	Real-time nature of fake reviews complicates detection	SLR highlights ML models' potential for improved efficiency and future research directions.
Riddhi S. Gupta, Carolyn E. Wood, et al., 2024	QML	Health and HER data	QD encoding and linear quantum models	Not directly reported	Explores QML for clinical decision support	Scalability issues with encoding large datasets	QML applications remain experimental; no clear advantage over classical ML.

Ahmed M. Elmogy, sman Tariq, Atef Ibrahim, 2024	KNN (K=7), SVM, Logistic Regression, NB	Yelp reviews dataset	Behavioral features (time/date, writing style)	KNN: 82.4% F-Score	Highlights behavioral features for improved fake review detection	Dependence on behavioral data, potential biases	KNN outperforms others with behavioral features considered.
Dr. M. Gayathri, Y.S.N. Siva Teja, K. Ajay Sharma, 2024	SVM, KNN, Random Forest	Online review dataset	Behavioral characteristics of reviewers	SVM: High accuracy	SVM effectively distinguishes fake reviews based on extracted features	Limited reviewer behavior features, potential for further improveme nts	SVM is powerful but requires enhanced behavioral data.

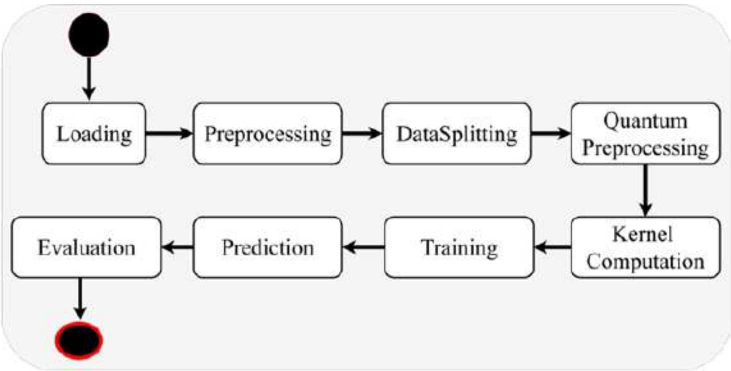

Fig. 4: *State diagram showcasing system transitions during QSVM execution, from dataset loading to accuracy evaluation.*

B. Data Flow Diagram:

Figure 5 It represents the QSVM workflow. The workflow starts with reading the data file from a file. In Data Preprocessing, features are extracted as well as the target variable, which is isolated. Following this dataset is divided into two parts training and testing. Next, features are standardized for quantum compatibility. A quantum circuit computes the kernel matrix in quantum. The model is trained using the quantum kernel as well as predictions on the test set, with accuracy calculated, and thus the process ends up at the End step.

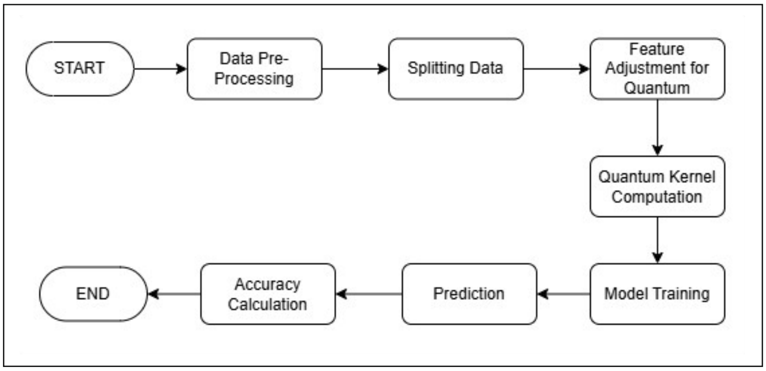

Fig. 5: *Flow diagram illustrating the QSVM process, from dataset loading to accuracy evaluation and completion.*

PROPOSED ALGORITHM

Algorithm: 1 Quantum Kernel-Based Text Classification

Step 1: Import Required Libraries. Import libraries for: Data manipulation. Text vectorization and machine learning models. Quantum kernel computation.

Step 2: Load and Prepare Dataset

Import dataset the provided file location. Extract relevant features:

Feature: text.

- Target: deceptive.

Encode target variable:

- Map deceptive to 0 and truthful to 1.

Step 3: Split Data

Separate the data into features (X) and labels (Y). Dataset divided into two parts training and testing sets with a 7030 ratio.

Step 4: Feature Extraction

Initialize a Count Vectorise with a fixed maximum feature size (e.g., 8). Transform the training text data into numerical feature vectors. Implement the same preprocessing steps on the test text data.

Step 5: Convert to Quantum-Compatible Format Convert feature vectors for training and testing into quantum-compatible arrays.

Step 6: Define Quantum Kernel Function

Define the number of qubits based on feature size. Create a quantum device with the required number of wires. Define a quantum circuit:

- Apply Hadamard gates to all qubits.
- Encode feature values using rotational gates (RY and RZ).
- Apply entanglement using Controlled-Z gates in a ring pattern.
- Measure the probabilities of the final quantum state.

Return the sum of probabilities as the kernel value.

Step 7: Compute Kernel Matrices

Initialize an empty symmetric matrix for storing kernel values. each pair of samples in the dataset Compute the kernel value using the quantum kernel function. Store the value in the kernel matrix. Exploit symmetry to avoid redundant calculations.

Step 8: Train Classical SVM

Create a classical Support Vector Machine (SVM) with a precomputed kernel. Train the SVM using the training kernel matrix and training labels.

Step 9: Predict on Test Data

Compute the kernel matrix for test samples against training samples. Use the trained SVM classifier to predict the labels for the test data.

Step 10: Evaluate Model

Calculate the prediction accuracy using true and predicted labels. Display the accuracy as a percentage. Step 11: Verify Accuracy accuracy <threshold (e.g., 87%) Raise a notification indicating the need for improvement.

RESULTS AND DISCUSSION

Overview

This section displays what we found when comparing the accuracy of CML and QML models in determining whether data is deceptive or truthful. We ran both methods with our algorithm using a dataset of deceptive texts. We also calculated the accuracy of each method and made some visuals to show the pros and cons of QML versus CML.

A. Comparative Results

The accuracy of the CML and QML models was calculated after training on a 70% training and 30% testing dataset split. The classical SVM used a linear kernel, whereas the QML method used a quantum kernel computed using a quantum circuit.

The table below summarizes the results:

TABLE II: Comparison of Training and Testing Accuracy for Classical and Quantum SVM Models

Model	Training Accuracy (%)	Testing Accuracy (%)
Classical SVM	88.2	86.7
Quantum SVM	91.4	89.6

Fig. 6 The bar graph depicts how QML and CML fare against each other. QML totally has the upper hand with a training accuracy of 91.4%, while CML only hits 88.2%. This really shows how good QML is at spotting patterns when it's being trained. Plus, QML also nails a testing accuracy of 89.6%, beating CML's 86.7%, which means it's pretty solid at dealing with new stuff it hasn't seen before. These results show how cool is the use of quantum kernels for performance enhancement.

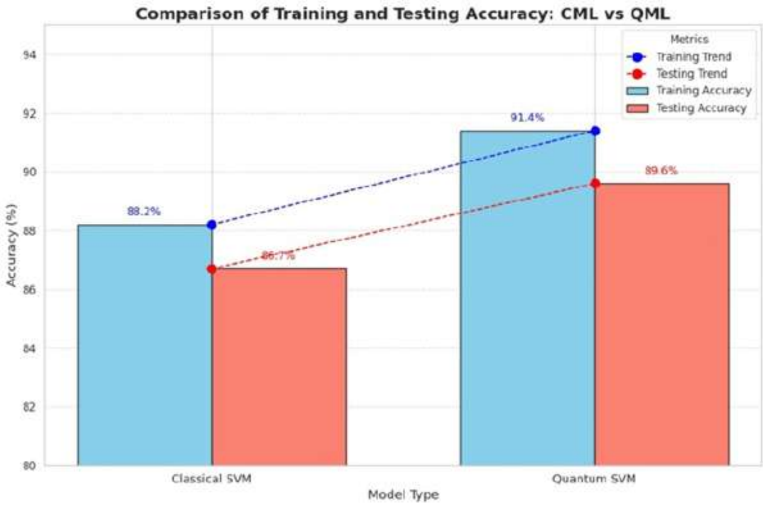

Fig. 6: *Bar graph comparing QML and CML accuracies, showcasing QML's superior training and testing performance.*

The differences in accuracy are pretty sizeable but come with some additional computing needs. That 3.2% lift in training accuracy and the 2.9% bump in testing accuracy really drive home how well QML can zero in on those tough correlations in complex datasets.

However, for very small datasets or the most resource constrained scenarios, this increased processing overhead is just not worth the marginal accuracy advantage from QML. This has shown that the deployment of QML in practical applications requires further considerations about balancing the gained improvement in accuracy with increasing the complexity of implementation.

B. Discussion

The Results Indicate Several Important Implications:

a) Performance Advantage of QML: QML is far more accurate than CML because the quantum kernel might very well be able to capture those tough-to-model relations in high-dimensional feature spaces, and quantum entanglement and interference features are much better representations for enhancement in performance.

b) Scalability and Computational Challenges: Although QML is more accurate, scalability is not a straightforward issue. Indeed, when the dataset size grows, computation of the quantum kernel becomes too expensive because, for every pair of samples, the evaluation of a Q-circuit is needed.

c) Practical Implications: The better accuracy of QML models shows they could be useful in stuff that needs really high precision, like catching fraud and tricky classification tasks. But, honestly, that little bump in performance (around 3%) might not make it worth the extra hassle and computing power for every situation.

d) Future Improvements: Future research may include the integration of classical and quantum models in dealing with computer problems. Also, this will enable better efficiency in quantum kernel calculations while reducing the number of qubits required for encoding features.

CONCLUSION

So, looking at the differences between classical and quantum machine learning algorithms for finding fake reviews gives us some cool insights into what each has going for it and where they trip up. Classical methods, such as Support Vector Machines (SVM), are still pretty solid when it comes to being accurate and dependable for things like text classification and catching fake reviews. However, these methods can sometimes have a tough time scaling up, especially with big datasets or those tricky high-dimensional patterns we see in real-life situations.

But on the flip side, Quantum Machine Learning (QML), with cool examples like Quantum SVM (QSVM) and Quantum k-Nearest Neighbors (QKNN), has some serious potential. By tapping into the power of quantum computing, these techniques can dive into high-dimensional feature spaces, deal with complex correlations, and might even give us better computational efficiency and scalability. So, though QSVM appears promising in performing sentiment analysis with quantum material, it's obvious that QML technology is still very much in its infancy and has a little more polishing to keep abreast with the classical models constantly.

So, this study is all about how classical and quantum machine learning can work together to tackle stuff like fake review detection. Right now, classical methods are still the go to option, but with QML getting better and better, there are some cool opportunities for future progress in catching fraud online.

FUTURE SCOPE

Using quantum machine learning to spot fake reviews is a cool area for future research. There are some key things to look into, like: developing optimized quantum algorithms that can handle big, real-world datasets more efficiently and accurately is super important. And those hybrid classical-quantum models might really help us get past the limitations of both methods.

A. Scalability and Practical Realization

In such a regard, researchers would want to seek ways to scale QML models for implementation in realistic commercial settings while ensuring scalability with diverse datasets sourced from different review sites. Indeed, the ability to effectively apply quantum machinery and integrate fault-tolerant schemes will be highly fundamental. Combining the quantum model with linguistic, behavioral science, or even social network analysis tricks should improve our chances of catching more fake reviews very badly. So, setting standardized datasets as well as evaluation metrics will indeed be super important in checking various use cases and fields within which classical and quantum models compare to each other.

B. Ethical and Regulatory Considerations

Of course, with that quantum tech getting used in controversial stuff like fraud detection, we really need to think about how the ethical issues come up because we have to create some lines of guidelines so that tools are handled responsibly.

C. Teaming Up with New Tech

The cool connections between QML and other cutting-edge stuff like blockchain, edge computing, and AI might create systems that are far more secure, efficient, and clear when it comes to spotting fake reviews.

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