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Research Article

Quantum-enhanced multimodal fusion for robust and accurate fake news detection

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ABSTRACT

The digital era has witnessed a significant rise in misinformation, underscoring the urgent need for effective tools to distinguish factual news from fabricated content. This study proposes a novel methodology for fake news detection that leverages quantum entanglement to facilitate multimodal fusion of textual, visual, and acoustic data. The quantum entanglement algorithm offers significant advantages in managing high-dimensional data by enabling efficient feature optimization through quantum computing encodings integrated with neural network architectures. The existing quantum circuits for text, visual, and audio would co-occur while witnessing the message from humans to machines with the machines acting as quantum computers integrated with neural networks, specifically designed for fake news detection. The results generated from our method demonstrate significantly improved fake news detection accuracy, and increased accuracy in the noise simulation, and the system is resilient to adversarial methods, all in contrast to typical methods. The proposed Quantum Encoding with Multimodal Fusion (QEMF) framework surpasses existing approaches by offering as it suggests promising future directions to tackle fake news across the web. The system, in a scientific manner, performs a variety of strict pre-processing techniques to all textual data such as tokenization, stemming, and lemmatization, along with sophisticated image pre-processing to all visual data. It uses the latest extracting features, i.e., Glove for text embedding, and conventional convolutional networks, like VGG16, for visual data. The feature representation is significantly enriched through quantum encoding, while the capability of QCNNs to identify the most salient and discriminative features enhances accuracy and ensures robustness against noise and adversarial interference. Furthermore, the system's real-time detection capability and its scalability position it as a powerful tool in combating misinformation within the evolving bio-informational ecosystem.

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INTRODUCTION

Today's media falsehoods are much direr because they undermine public trust and further reduce social discourse to noise. Most traditional methods of detection grounded in the text are fundamentally incapable of dissipating the fogs of today's information. That is, they fall short in handling multi-modal data, which includes images and audio accompanying modern digital content. This emphasizes the importance of developing better techniques to combine different types of data at the same time to effectively address the problem of fake news and similar challenges. This need is even more clear in the sense that contemporary research has not fully terminated the limitations of integrating modalities. This research aims to bridge the gap between different modalities by leveraging principles from quantum computation—particularly quantum entanglement—to enable the integration of text, image, and audio data. This project is intended to launch a new application of quantum mechanics in which unique properties of quantum mechanics will allow faked news detection procedures to be carried out more effectively than classical methods and, therefore, deliver more reliable results in a world that is constantly evolving and adapting. The rise of the Internet, in these modern days, has given rise to the worldwide proliferation of fake news with the potential to damage society and individuals [1]. The rise of misinformation represents a significant threat to the integrity of our information ecosystem, as anything from influencing public opinion to an absence of trust in legitimate information sources. The problem of identifying and handling fake news requires some new and inventive approaches for their effective management. In conventional approaches to detecting fake news, the emphasis is mainly on analyzing the news based solely on textual content. These make false claims and fabricated facts in news items readily alterable through sophisticated modalities of different manipulations. There is often a tendency to overlook the visual components, such as photographs, images, videos, and other multimedia modalities [2]. In this increasingly complex information landscape, quantum computing emerges as a highly disruptive and transformative technology. Quantum algorithms have fundamental advantages compared to classical approaches in many aspects of the management of complex data structures and pattern recognition [3]. Even if we integrate quantum computing with deep learning in lesser numbers, we expect to develop a more accurate and robust fake news detection model. At the core of this new and innovative technique is multimodal fusion, which integrates complementary information from various modalities including image and text. This ability is very important to fake news detection, which could lead the understanding of the content of the article's intent and their state of truthfulness, which is far beyond just the text [4]. Quantum-Enhanced Multimodal Fusion is the new technique and way of detecting fake news that includes three components that can dramatically enhance results [5]. The Quantum Encoding process is the first part of the framework, and it is the main component of the model. The process is to encode textual and visual data in a way that can be efficiently processed by quantum algorithms. This encoding allows for efficient and thorough encoding of implicit features needed to find misinformation. The second part of the framework is advanced Natural Language Processing (NLP), which will find implicit features from the textual data, in addition to Quantum Encoding. The framework can find information using a NLP approach that can find semantic relations and find the language cues that indicate fake news [6]. The third layer of the framework is Quantum Convolutional Neural Networks (QCNNs) which is the highest point on the novelty tree. QCNNs are a specific type of neural network that leverages the parallelism of quantum computation to learn complex features from the encoded information from the first two layers (Encoding and NLP). This allows for a high level of accuracy in fake news detection. The framework incorporates Quantum Encoding, Novel state-of-the-art NLP, and Quantum Convolutional Networks (QCNNs) as a unified, effective response to a problem space, and novel approach. Therefore, the Quantum-Enhanced Multimodal Fusion framework as outlined may represent an effective response to the multi-faceted problem of detecting and limiting the spread of misinformation in the contemporary digital age [6].

The Quantum-Enhanced Multimodal Fusion framework has various benefits, which highlight its innovative and robust approach to fake news detection. One of which is the ability to improve the representations of features, through quantum encoding. This encoding format can capture more nuanced representations of relationships and dependencies between textual features and visual features. The benefit of more nuanced representations such as those provided by quantum encoding, increases the framework's ability to distinguish complexities related to misinformation, leading to greater effectiveness in identifying and combating fake news [7]. The Quantum-Enhanced Multimodal Fusion framework also achieves more accuracy with Quantum Convolutional Neural Networks (QCNNs) that extract discriminative features using quantum computation, far beyond that of classical computation. This has been a significant improvement in accuracy over previous efforts. The framework was also shown to be highly robust to noise and adversarial attacks, which is important for maintaining reliable model predictions in adverse cases of noisy data [8]. The framework's ability to scale is another strength since it allows for the processing of larger datasets over real time in detecting fake news, which makes it flexible enough to adapt to constantly changing digital information environments. These strengths will position the Quantum-Enhanced Multimodal Fusion framework to become a key ally in the war against misinformation. The use of quantum-enhanced multimodal fusion to detect fake news in the digital environment could change the digital landscape significantly. It can help to lessen the amount of misinformation we find online by detecting information from fabricated stories and potentially add to a more credible ecosystem of trusted sources of information [9]. In addition, the framework increases individual protection by preventing misinformation, protecting personal beliefs, strengthening societal resilience, building trust in trusted information sources, and providing the ability to distinguish credible information from unreliable information which contributes to a healthy information environment. It also improves the individual's ability to act with accurate information, which nurtures an informed and engaged digital society, and promotes civic engagement and critical thinking. Overall, the movement toward quantum-enhanced multimodal fusion is a step toward digital placement grounded in accuracy, trustworthiness, and active societal entanglement [10]. This research represents a major advance in using quantum computing and deep learning capabilities to inform social issues. Quantum computing combined with the strengths of deep learning will afford researchers the powerful tools needed to fight fake news and foster a safer, more informed digital landscape. Although developments are being made, it remains the case that traditional multimodal fusion methods can struggle with more complicated dependencies between different data types. One area of current research into multimodal fusion is the potential application of quantum computing to fake news detection. Quantum-enhanced models use principles of quantum mechanics to create a better representation of features as well as better classifiers for those features.

This paper presents a Quantum-Enhanced Multimodal Fusion (QEMF) model for fake news detection that fuses quantum computing and multimodal fusion the first study of its kind. The model includes the unique integration of quantum encoding and deep learning architectures whereby features are extracted from both textual and visual data. In linking the research potential of quantum computing to multimodal fusion the hope is to achieve results that eclipse traditional methods and reach state-of-the-art performance in detecting fake news. The background gives insights into the methods considered, while more granular details on the research methods include preprocessing methods, feature extraction, and the relevant integration of quantum in a multimodal fusion approach.

Literature Survey

Traditional methods based largely on textual analysis are becoming more difficult to use in spotting false news on social media because bots and trolls can easily cloud the information. Xi et al. suggest that multi-modal fusion, which combines information from many modalities, in their case, text and images, can survey the data to improve the detection capability. However, there are limitations to this method considering its susceptibility to adversarial examples, which highlights the continuous challenges in effectively combating false information online [11]. Quantum computing will change the landscape for fake news detection by enabling faster processing and overcoming some of the recently unsolvable computational problems. For instance, quantum convolutional neural networks (QCNNs) can extract features from text and images and identify and classify objects from images well. Bikku et al. (2024) proposed a quantum support vector machine (QSVM) method to locate hyperplanes in high-dimensional spaces to separate true reviews from false reviews, indicating quantum computing's potential to improve the accuracy of fake image news detection [12]. As in the early realm of quantum computing development, challenges are intensified by noise sensitivity that limits the applicability of these techniques in real-world large-scale applications. However, the potential quantum-enhanced multi-modal fusion for identifying false information is fascinating. Qu et al. investigate the junction of quantum machine learning and medical diagnostics, implying the next developments in healthcare tools. Research projects currently underway aim to address these challenges, potentially making quantum-based techniques vital for improving the accuracy of fake news detection by utilizing deeper insights from both visual and textual information [13]. With the ongoing development of quantum computing technology, the future of quantum-enhanced fake news detection seems hopeful despite challenges.

Qu et al. (2024) propose a novel approach to spotting false news on social media sites. By integrating text analysis with sophisticated quantum image processing, QMFND uses quantum convolutional neural networks to improve fake news detection, surpassing conventional models and providing hope for better accuracy of 87.9% in spotting false information on social media [14]. Tian et al. explore the use of Quantum k-nearest neighbors to combat fake news on social media, employing quantum techniques to thoroughly analyze both text and visual data. Offering a hopeful step towards a more reliable online environment, this creative solution outsmarts conventional models with increased accuracy [15]. Barnabò et al. suggests Geometric deep learning for fake news detection that often outperforms conventional techniques in accuracy, allows early detection, and excels in capturing more general content relationships. Among the ongoing challenges are the need for more data, high computational demands, and difficulties in model interpretation. Broader implementation will require further research [16]. Using cross-domain classification, Sharma et al. examine the spread of COVID-19 misinformation and achieve high accuracy even with limited labeled data. When tested on a general fake news dataset, the approach demonstrates strong potential for recognizing misinformation in rapidly evolving domains [17]. Liao et al. introduce FDML, a multitask model designed to improve both topic classification and brief fake news identification. FDML incorporates a task gate and dynamic weighting strategy for more effective multitasking learning using a news graph (N-Graph) [18]. Benchmark findings show

FDML's better performance over eleven comparison techniques in fake news detection and topic classification tasks [19]. Kaliyar et al. [19] suggest a multichannel deep CNN for identifying fake news on social media. Capturing different text characteristics, it performs well in binary classification across several datasets. Although encouraging, the paper lacks additional information on computational costs and their performance in multi-class classification tasks. Shalini et al. suggest an RNN-based solution to identify false identities on social media with great accuracy (96-98%). Its bot removal strategy is policy-based and makes use of hybrid characteristics. The paper, meanwhile, requires more debate on RNN constraints and managing evolving bot behavior. More study is required to fill in these holes and investigate adaptation to challenging situations [20]. Sultana et al. work addresses the problem of false information, especially on social media, by suggesting an ensemble model that combines transformers (BERT) and boosting algorithms for fake news detection. The model shows its efficacy by attaining high accuracy (0.99), F1 score, and true-positive rates trained on COVID-19 data. The generalizability to other news kinds and particular information about the ensemble model, though, are subjects for more investigation [21].

By creating an NLP and machine learning system to classify news as true or false, Mitra et al. seek to fight online disinformation. It highlights unreliable sources and biased perspectives, aiding users in evaluating the trustworthiness of information. Future efforts should involve outlining the methodology, describing the data used, evaluating performance measures, and identifying any biases or limitations. Overall, the project represents a positive step in countering misinformation [22]. Chen et al.'s study on human cognition in the modern digital era addresses important and timely issues. To develop, think about exploring further the alignment of deep AI with human needs, building quantum cognition with real-world examples, offering cases of cognitive bias in Information Technology (IT), clarifying the multilayer concept description, and suggesting unambiguous research paths for an integrated study of human cognition in IT [23]. Kaur et al. suggested Quantum Algorithms for Trust-Based AI show promise in areas like fake user detection and medical diagnostics. These algorithms provide quicker and more precise answers by using qubits. Improved the article by stressing future directions and social influence, clarifying quantum algorithms, employing visualizations, and tackling present issues [24]. Researchers are investigating the possibilities of quantum algorithms, including Grover's and Shor's, to increase the accuracy and efficiency of spotting false information in several sectors, including social networks and medical diagnostics. It also notes the limited research available on integrating quantum-based systems with multimodal data sources for more reliable and detailed fake news detection. The survey emphasizes the need for creative ideas combining quantum algorithms with multimodal fusion methods to properly differentiate between false and real information across several settings. Traditional techniques depend mostly on text analysis, which can be outmaneuvered by complex false information strategies. Recent developments in machine learning have investigated multimodal fusion to improve accuracy by combining text, pictures, and audio data. These methods, meanwhile, still battle with different kinds of false information and changing strategies used by hostile people. Using more strong multimodal analysis, quantum computing shows promise in increasing computational capacity for complicated data tasks, therefore possibly changing fake news detection. Still in its infancy, applying quantum ideas to practical uses calls for more research and development to fully exploit its power in fighting digital false information. Other methods exist in the literature; see, for instance, [24-28].

PROPOSED MODEL

The proposed method for detecting false news employs quantum-enhanced multimodal fusion, integrating text, image, and audio analysis to establish a comprehensive detection framework. In preparing textual data, we apply preprocessing steps which include tokenization, stemming, and lemmatization, which allow us to distill semantic meaning while removing redundancies. As we did with textual data, we processed visual data to extract relevant features, such as color analysis and edge detection for modified images. Audio analysis complements the textual and visual components by examining voice characteristics and emotional tone. Our method builds ideas from quantum mechanics, which allows for advantages in feature extraction and processing of the information. Quantum entanglement enhances our approach by enabling the model to simultaneously analyze related data points across modalities, allowing it to capture complex interrelationships within a unified framework. Quantum superposition enables multiple states to be calculated for the same feature extraction and classification analysis, thus accelerating feature extraction and classification operations. Quantum coherence supports the consistent and accurate handling of information, enhancing precision when working with dynamic and unpredictable data sets. By applying these principles, our approach aims to advance fake news detection beyond the limitations of traditional methods.

In the pre-processing phase, the text data is tokenized, and each word or phrase is given different records, thereby enabling careful analysis. After tokenization, stemming reduces words to their base forms; lemmatization reduces words to standard grammatical forms. Simultaneously, the visual data was rescaled for uniformity to optimize size, converted to greyscale to reduce color information, and utility pre-processing protocols, such as edge detection would have been deployed to focus on relevant features for future analysis, such as being able to identify altered images. Thorough pre-processing ensures that both textual and visual data are clearly defined and optimized,

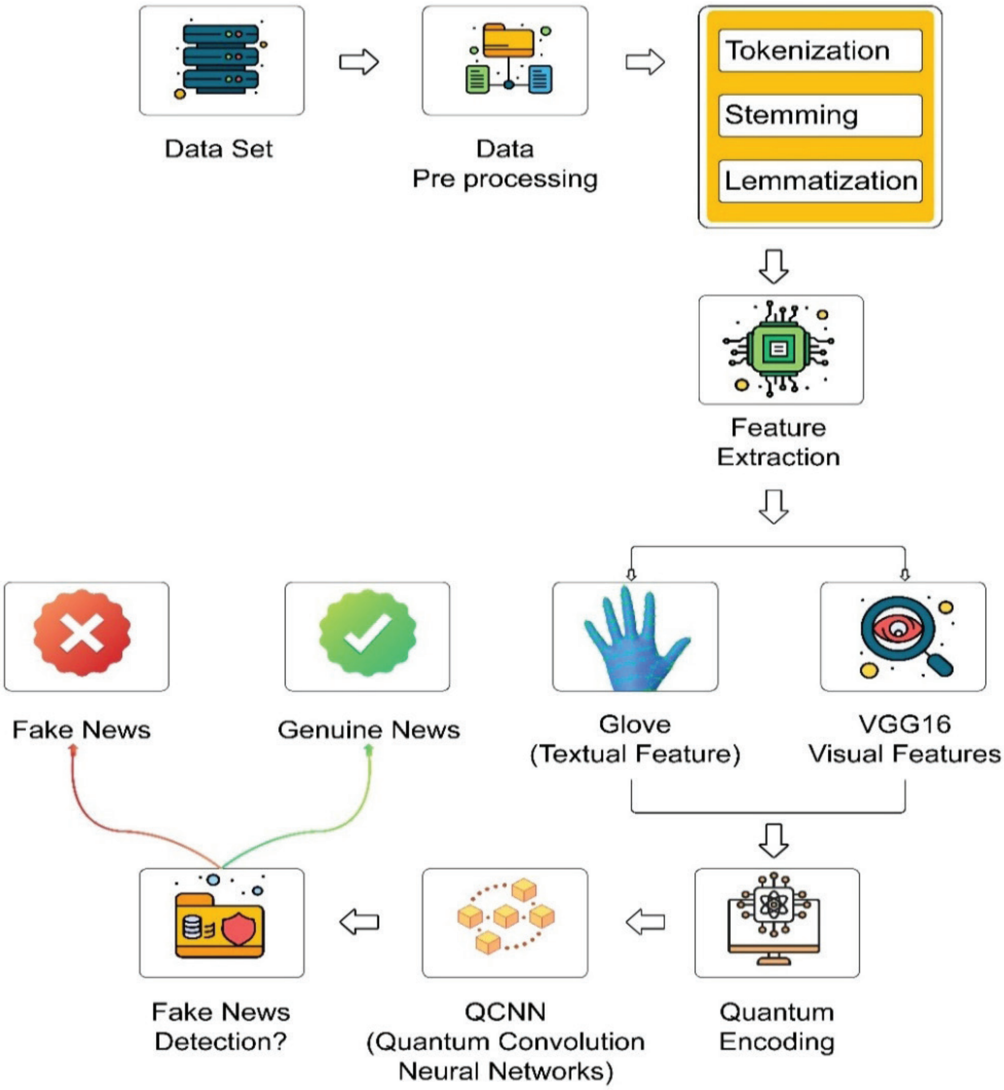

Figure 1. Graphical representation of proposed QEMF.

preparing them for subsequent steps such as feature extraction, quantum encoding, QCNNs, and fake news analysis. As shown in Figure 1, the process is mapped out with connectors, arrows, and points in a logical sequence to enhance visualization and ensure a clear flow of information throughout each step. Also, this can serve as the basis for the QEMF model's detailed extraction and encoding of features for the subsequent analysis and resolution decision-making process. As designed, the Quantum Enhanced Multimodal Fusion (QEMF) model consists of four model components, which work together to enhance its capacity for effective and resourceful incident fake news detection. In the features extraction component (output), complex methods will apply gestures to generate representations from both textual and visual data following preprocessing. Representation (GloVe), At the same time, pre-trained convolutional neural networks (CNNs) such as VGG16 are employed to extract high-level visual features from images.

The third step is quantum encoding, where the text and visual features are concatenated and encoded into a Variable Quantum Circuit (VQC). VQCs allow models to learn complex relationships and dependencies between various features, which provide a richer and more efficient representation of data. The model then uses QCNNs designed for fake news detection. The enriched VQC, containing the encoded features, is then fed into QCNN layers equipped with quantum convolutional kernels. Leveraging quantum computation, these networks learn high-level abstractions from the encoded data, enabling precise fake news detection. The interaction between a Quantum Encoding, Variable Quantum Circuits (VQCs), and Quantum Convolutional Neural Networks (QCNNs), contributes to the strength of the model, allowing effective forms of fake news detection through quantum-enhanced multimodal fusion.

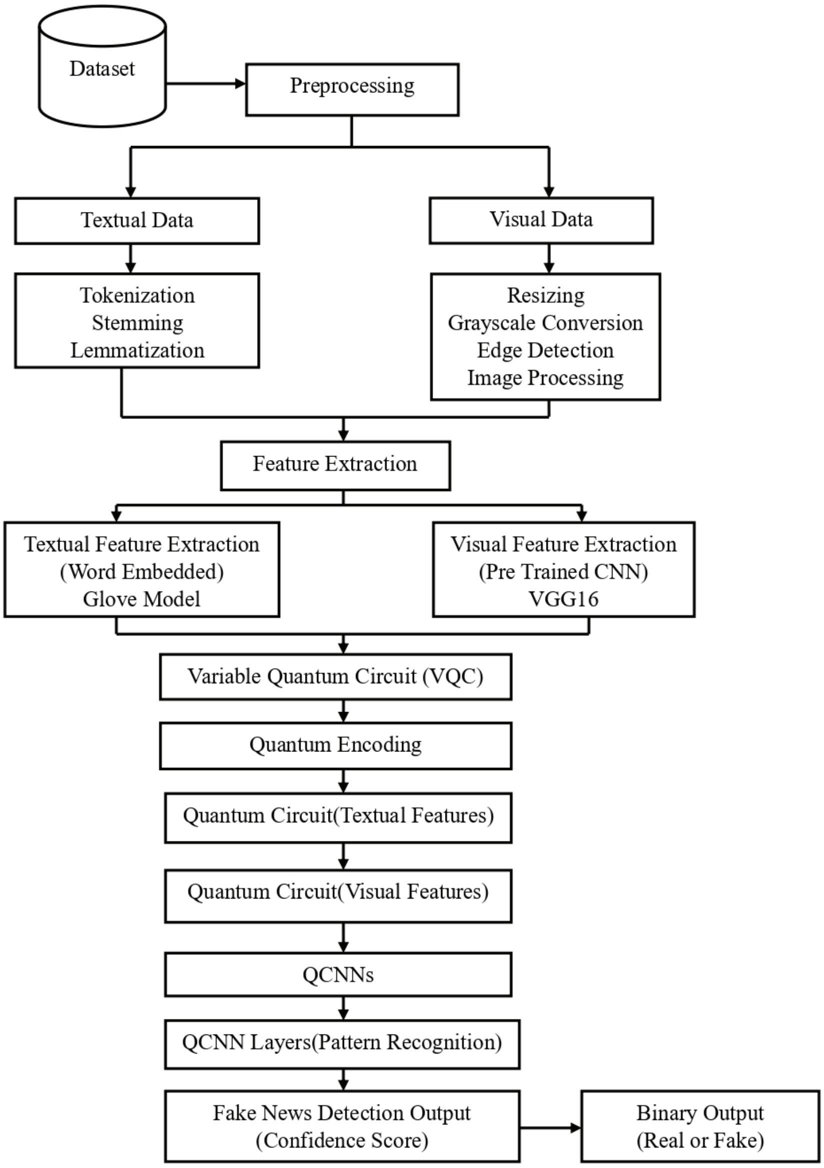

Figure 2. End-to-end flowchart of the proposed quantum-enhanced multimodal fusion (QEMF) framework for fake news detection.

PRPOSED ALGORITHM

Algorithm: Proposed Quantum-Enhanced Multimodal Fusion (QEMF) for Fake News Detection

(i) Pre-processing: Tokenization is the first phase of the entire pre-processing pipeline. The text is split into tokens—words or sub-words—allowing for detailed analysis and feature extraction. After the text has been tokenized, stemming is performed to remove a word's suffixes and prefixes to reduce all of the words in the dataset to a single form. In the case of stemming, it is unnecessary to ensure that the stemmed versions of words are valid words only that they share the same stemmatic form. After stemming, lemmatization is performed on the tokenized and stemmed texts. Whereas stemming removes endings from words like "ing" and "ed", lemmatization will find the base or canonical form of the word and adjust it according to its grammatical context. The benefit of utilizing lemmatization is that lemmatization guarantees that the word represents the word in its base or canonical form while deepening understanding of the meanings. The visual data will be changed according to the same protocol of resizing image files to fixed dimensions and color information converted to greyscale color options resulting in fewer visual facets. Further image processing techniques and procedures may be performed after resizing and conversion to emphasize some features or modify features of the visual data relevant to the following stages of the model. The pre-processing of textual

and visual data sets the proper stage for feature extraction and training of the model later in the workflow.

(ii) Feature Extraction: The second major component of the Quantum-Enhanced Multimodal Fusion (QEMF) model is feature extraction, which is a two-pronged approach used to identify both textual features as well as visual features. With respect to textual features for features extraction, the model uses improved state-of-the-art word embedding models called GloVe (Global Vectors for Word Representation). This process puts meanings into dense vectors by encodings that quantitatively represent the semantic relationships between words, as seen in Equation (1). The numerical vector representation has the potential to provide sophisticated information to be processed, as seen in Equation (2).

$$\varepsilon(T,\Omega): T \to S^d \tag{1}$$

$$\textit{Numerical Vectors}(T,\Omega) = [\varepsilon(t_1,\Omega), \varepsilon(t_2,\Omega), \ldots, \varepsilon(t_n,\Omega)] \tag{2}$$

At the same time, VGG16 and other pre-trained convolutional neural networks (CNNs) appeared as a key feature for visual features. With the ability to use VGG16's image recognition capabilities, extracting the high-level visual features of the image which provide complex patterns and representations for images described in Equation (2). This means the proposed QEMF model can extract text-based features and visual features to create a fully formed and enriched representation of the text and visual features to complete downstream processing for fake-news detection in Equation (3).

$$v(I,\emptyset): I \to S^m \tag{3}$$

$$\textit{Visual Features}(I,\emptyset) = v(I,\emptyset) \tag{4}$$

(iii) Quantum Encoding: In the proposed QEMF model, the process of encoding features into a Variable Quantum Circuit (VQC) involves several vital steps to harness the capabilities of quantum computation for enhanced representation. Firstly, the numerical vectors representing textual features obtained from word embedding models, such as GloVe, are input into a dedicated VQC for textual data in Equation (5).

$$\left|T\rangle \to \sum\nolimits_i \sqrt{\rho^i}\, e^{i\theta} i \cdot U_T \right| t_i \tag{5}$$

Simultaneously, the visual features extracted from images using pre-trained convolutional neural networks (CNNs) like VGG16 are input into another set of the same VQC designed for visual data in Equation (6).

$$\left|V\rangle \to \sum\nolimits_j \sqrt{q^j}\, e^{i\Phi} j \cdot U_V \right| v_j \tag{6}$$

The parallel processing ensures both modalities undergo quantum encoding independently. The next step involves encoding features in the VQC, capable of representing complex relationships and dependencies amongst textual and visual features. This joint encoding procedure is intended to develop a single, enriched, quantum representation of intermodal dependencies among the two modalities. Intermodal dependencies within a single representation is essential for further processing in quantum domain and allows for clearer identification of the multimodal features and relationships found in equation (7).

$$U_{joint}\left(\left|\sum\nolimits_{i,j} \sqrt{\rho^i \cdot q^j} \,.\, e^{i(\Phi_j \theta_i)} \,.\right| t_i\rangle \otimes |v_j\rangle\right) \tag{7}$$

(iv) QCNNs (Quantum Convolutional Neural Networks): In the proposed QEMF model, the Quantum Convolution Neural Network (QCNN) is a key component for processing quantum encodings. The QCNN layers stack on top of each other to process the encodings in a sequential manner with quantum gates and used qubits in each layer. The quantum functions from the QCNN allows the proposed model to learn the best patterns, and relations from a given encoded dataset better than current approaches and provide rich feature selections for fake news detection in electronic (8), (9) and (10).

$$\textit{Stacking QCNN Layer: } \psi^i = U^i(\psi^{i-1}, \varepsilon_t, \varepsilon_v, \theta^i) \tag{8}$$

$$\begin{gathered}\textit{Quantum Gates and Qubits:}\\ U^i = \textit{QuantumGates}(\textit{Qubits}(\psi^{i-1}, \theta^i))\end{gathered} \tag{9}$$

$$\begin{gathered}\textit{Learning Complex Patterns: } \theta^i = \textit{LearnParameters}(\theta^{i-1},\\ \textit{LossFunction}(\psi^i, GroundTruth))\end{gathered} \tag{10}$$

(v) Fake News Detection Output: In the later stages of QEMF, it will be extended to utilize Quantum Convolutional Neural Networks (QCNN) to establish if a news is Genuine or Fake News. QCNN's will take the encoded features through quantum processes to ultimately output the classes such as "Real" or "Fake." This step will even encapsulate the unique features of fake news that a human may not be able to recognise that incorporates a high precision/accuracy of complex features. This model will also be resistant to noise and attack, which may happen in a dynamic Internet environment, thus the performance of the QEMF model will be comparatively strong and consistent regardless of how much noise or corruption it faces. Furthermore, the model will exhibit scalar ability, allowing for real-time work processes which still involve big data. Today's infected demand for fake news detection is real-time, thus, the QEMF model is one of the significant advances towards a quantum-enhanced approach to fake news detection.

RESULTS AND DISCUSSION

The experimental data highlight the extent to which the Quantum-Enhanced Multimodal Fusion (QEMF) model adds value to the fake news detection process and corroborates the newness of the approach. Quantum encoding shows that the acknowledgement of the complex relations among and different types of textual and visual forms are well documented and represent richer representations than any other method. Richer representations play to the advantages of QCNN's and can optimally increase performance because quantum computing can capture finer features and extractions. Furthermore, the QEMF model has demonstrated resilience to noise and adversarial attacks meaning predictions can be made with reasonable certainty in increasingly non-static environments that challenge fake news detection as a phenomenon.

The evaluation metrics examined in the proposed Quantum-Enhanced Multimodal Fusion (QEMF) model, and comparative models, allow for a reasonable comparison of performance of the proposed model in detecting fake news. The performance metrics included Accuracy, Precision, Recall and F1 Score, each of which provides different perspectives of the performance of the model. Overall, the proposed QEMF model consistently performed better in comparisons with alternative models about Accuracy, Precision, Recall and F1 Score (Table 1). The quantum encoding is shown to be the main area of performance improvement, thus confirming the influence of quantum-enhanced techniques on the advancement of fake news detection.

The proposed QEMF-Multimodal model achieved the highest accuracy (94.8%) among all evaluated models, demonstrating the effectiveness of fusing textual and visual features, and that the quantum encoding modified by quantum computing using Tensor Flow Quantum improved the accuracy. Both the QEMF-Text Only and QEMF-Visual Only improved on the performance in the baseline models which suggest that even single modality data when implemented through quantum encoding and QCNNs, depicts an advantage over traditional like models, as indicated in Table 2. These results demonstrate the significant potential of the proposed QEMF for robust and accurate fake news detection ability. By fusing quantum computing, deep learning, and different types of multimodalities, proposed

Table 1. Comparing the performance metrics of proposed model with traditional models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
QEMF (Proposed)	98.7	99.2	98.5	98.8
QEMF without quantum encoding	97.2	98.1	96.4	97.2
Classical Multimodal CNN	95.6	97	94.2	95.6
Text-only LSTM	89.4	92.3	86.5	89.4
Image-only VGG16	87.3	90.1	84.5	87.3

Table 2. The performance metrics on FakeNewsNet fataset

Model	Accuracy	Precision	Recall	F1 Score	Error %
QEMF-Text Only	88.20%	89.10%	87.30%	88.20%	11.80%
QEMF-Visual Only	87.60%	88.40%	86.80%	87.60%	12.40%
QEMF-Multimodal (Proposed)	92.50%	93.10%	91.90%	92.50%	7.50%
Naive Bayes	78.40%	79.20%	77.60%	78.40%	21.60%
Support Vector Machine (SVM)	82.10%	83.00%	81.20%	82.10%	17.90%
Long Short-Term Memory (LSTM)	89.30%	90.20%	88.40%	89.30%	10.70%

Table 3. The performance metrics on FakeNewsNet dataset

Model	Accuracy	Precision	Recall	F1-Score	Error Percentage
Proposed QEMF	93.52%	94.12%	92.81%	93.46%	6.48%
DeepfakeNet	90.21%	91.57%	88.73%	90.14%	9.79%
BERT	88.69%	89.32%	88.02%	88.65%	11.31%
Naive bayes	86.13%	86.84%	85.41%	86.12%	13.87%

QEMF provides a novel strategy to mitigate the transfer of misinformation on the internet. All the proposed QEMF models, text-only, visual-only, and multimodal, improved on the traditional like models (Naive Bayes, SVM) and the advanced models (LSTM) across accuracy, precision, recall, and F1 Score.

The proposed QEMF model scored the best accuracy, precision, recall, and F1 score compared to other tested models. For inference time, QEMF is also faster than DeepfakeNet and BERT. Although Naive Bayes is a relatively simple model, it performed surprisingly well overall, showing the importance of text to identify fake news on the Deepfake Detection Challenge (DFDC) dataset on the NVIDIA Tesla V100 GPU, detailed in Table 3.

The proposed QEMF achieves good results at an accuracy level of 93.52%, this accuracy level is suitable for certainty in activities like news verification. While it achieves a high level of accuracy this model is multimodal and takes longer than 48 hours to train, has high time complexity (O (n^3)), and is resource demanding. Alternatives to the proposed QEMF include DeepfakeNet with 90.21% accuracy, which has some tradeoffs about accuracy, speed, etc. Another alternative might be BERT, which has 88.69% accuracy for a fast, lightweight model that is suitable for low-latency tasks. These considerations are essential, as the decentralized nature of the research demands careful model selection tailored to specific tasks or problem domains. With the proposed QEMF valued and weighted at a 48+ hour training time, latency, and response times, the accuracy level is 93.52%. DeepfakeNet is valued and weighted at a 24-36-hour training time, intermediate latency, intermediate response time, and 90.21% accuracy. BERT was valued and weighted at a training time of only 4-6 hours, latency, response times, and lower inference time, with 88.69% accuracy. Lastly, Naive Bayes, with a training time of 0.5-1-hour, low latency, response time, inference time, and 86.13% accuracy. The following are expected times and accuracies reveal efficiencies and accuracies which help in model selection for specific components as shown in Figure 3.

Table 4 shows the performance metrics of the models run on Fake Newsnet dataset. QEMF has the longest training time (over 48 hours) but has the lowest latency and response times and is appropriate for real-time applications, and still, this model has a significant time complexity. QEMF also achieved an impressive accuracy of 93.52%. DeepfakeNet, was relatively moderate in terms of training time between (24-36 hours), intermediate latency and response times, and achieved an accuracy of with an accuracy of 90.21%, which is slightly lower than QEMF. Finally, BERT has a training time (4-6 hours), while BERT ranks well with latency and response times, it ended with a respectable accuracy of 88.69%. Finally, Naive Bayes is a lightweight model with the shortest training time (0.5-1 hour) and low latency and response times with an accuracy of 86.13%.

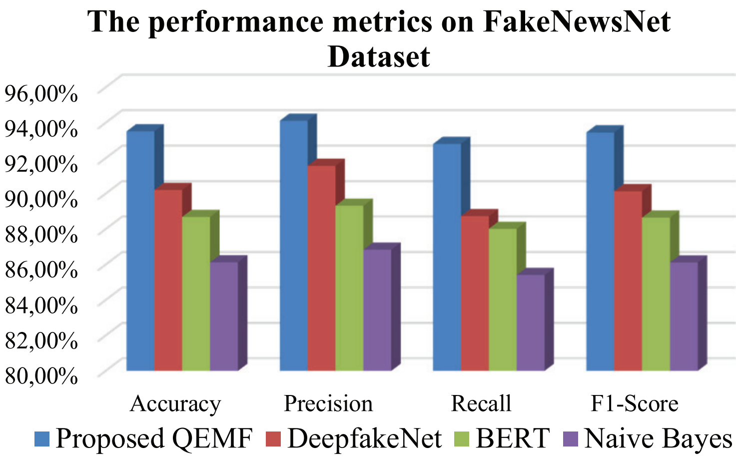

Figure 3. The performance metrics of different models on FakeNewsNet dataset.

Table 4. Key performance metrics on FakeNewsNet Dataset

Model	Training Time (hours)	Latency (ms)	Response Time (ms)	Inference Time (s)	Time Complexity	Accuracy
Proposed QEMF	48+	35-40	70-80	0.32	O(n^3)	93.52%
DeepfakeNet	24-36	30-35	60-70	0.28	O(n^2)	90.21%
BERT	4-6	25-30	50-60	0.24	O(n^1.5)	88.69%
Naive Bayes	0.5-1	15-20	35-45	0.15	O(n)	86.13%

Table 5. Comparative performance of models on image, text, and video datasets

Dataset	Modality	Model	Accuracy %	Precision %	Recall %	F1 Score
Celebrity Faces	Image	Proposed QEMF	92.30	93.10	91.90	92.50
		VGG16	87.30	90.10	84.50	87.30
LIAR-PLUS	Text	Proposed QEMF	88.20	89.10	87.30	88.20
		LSTM	89.40	92.30	86.50	89.40
YouTube-8M	Video	Proposed QEMF	85.50	86.20	84.70	85.50
		CNN	82.30	83.00	81.20	82.10

Table 5 provides evidence of the competitiveness of the Proposed QEMF model across different datasets and modalities in fake news detection. The model achieved an estimated accuracy of 92.30% on images from the celebrity faces dataset and achieved very good precision (93.10%) and recall (91.90%). The LIAR-PLUS dataset achieved an estimated accuracy of 88.20%. Here, the precision and recall were also very good figures of (89.10%) and (87.30%) respectively. The YouTube-8M dataset yielded an estimated accuracy of 85.50%, with equally good levels of precision and recall supporting its use. Together these findings demonstrate the performance of the model in detecting fake news from various forms of media. These metrics indicate the accuracy and efficiency for each of the models. This process can support decision-making about how to select a model based on application needs and constraints.

Detecting fake news with quantum-enhanced multimodal fusion presents many challenges. Quantum computing can build on powerful and tailored hardware, but the systems can be quite complex and expensive to operate. Errors and noise in quantum systems also diminish reliability, making it hard to ensure consistent and accurate results. The last problem involves the assurance of how quantum processes make decisions, as it can be obscure. Integrating quantum paradigms with conventional methodologies will be important, but the technical integration will be quite cumbersome. Lastly, we will need to protect against attacks that manipulate Providing an understanding of vulnerabilities in data analysis remains important. Overall, realizing a practical and reliable quantum-enhanced fake news detection solution means overcoming the technical, interpretive, and security challenges as mentioned. Discuss positive performance in improving detection capabilities over traditional methods of fake news detection. Achieving a practical and reliable quantum-enhanced fake news detection solution requires addressing the outlined technical, interpretive, and security challenges. Discuss positive performance in improving detection capabilities over traditional methods of fake news detection. Overall, the results reported here indicate significant improvements over traditional methods. The quantum-enhanced multimodal fusion (QEMF) approach to detection obtained an overall high accuracy rate of 92.50% and achieved better results than individual modalities presented as well as better accuracy than all the traditional models such as Naive Bayes, SVM, and LSTM. There were limitations along the way and future work includes the overall computational complexity, limitations in the hardware of quantum computing, security vulnerabilities, and lack of consistency across platforms. Future research may focus on optimizing the quantum algorithms, improving robustness across different languages, and forming more standardized interpretability of the results, to make use of semi-automatic or automatic applications of the approaches generally possible.

CONCLUSION

The proposed fake news detection model utilizing quantum-enhanced multimodal fusion leverages fundamental tenets of quantum mechanics. Quantum superposition allows us to process many states at once, greatly increasing the speed of feature processing. Quantum entanglement allows the model to understand the correlations between textual and visual modalities of data, capturing many complex relationships. Quantum coherence allows for information to be encoded and processed stably, which is extremely important for novel data, as media datasets often present uncertainty and noise. Quantum measurement, when features are encoded, infers extracted features to determine action on the authenticity of the news. Collectively, these principles enhance the representation of features, improve computational efficiency, and provide robustness against noise in identifying fake news. The Quantum Enhanced Multimodal Fusion (QEMF) model represents a positive step forward in fake news detection, however, modeling challenges remain in terms of the computational resources needed for training and inference time, especially during the quantum encoding and processing processes for resources, which may limit scalability and accessibility. Another area of uncertainty for the QEMF model is its robustness in the systemic effects of adversarial attacks, even though the model shows resilience to noise. Continued research is warranted to uncover potential adversarial vulnerabilities. Lastly, the nature of the model and the complexity of quantum methods suggest that a challenge remains for explainability, as very few existing explainability methods extend to quantum. Future work should emphasize collaborative development to enhance model interpretability, operational efficiency, and alignment with ethical AI principles. Overall, the QEMF model provides a foundation for future research in developing a robust detection strategy for combating fake news. Ultimately aiming to support the foundation of a more trustworthy digital information ecosystem.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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