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REVIEW

Current Trends in Quantum Technologies for Advancing Bioimaging Techniques

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Abstract: Abstract Quantum computing (QC) has emerged as a transformative technology with the potential to surpass classical computational limits, especially in complex domains like medical imaging. This study investigates the integration of QC and quantum machine learning (QML) into medical imaging, with a focus on MRI, EEG, and CT. A structured literature review was conducted to identify recent developments, focusing on studies using accessible open-source data and English-language peer-reviewed publications. By leveraging quantum principles such as superposition and entanglement, hybrid quantum-classical models have demonstrated enhanced accuracy, speed, and efficiency in diagnostic tasks. In MRI, QML has improved early detection and classification of neurological diseases like Alzheimer's and brain tumours. In EEG analysis, quantum algorithms such as Quantum EEGNet and Quantum Support Vector Machines have shown superior performance in detecting disorders, including schizophrenia and autism spectrum disorder. Additionally, quantum algorithms for CT image reconstruction and classification have achieved faster processing with fewer artifacts and greater fidelity. Despite current hardware constraints, results highlight the promise of QC in addressing existing limitations in medical diagnostics. The findings support continued development of QML models and quantum-enhanced workflows, with potential to revolutionise clinical practice by offering more accurate, efficient, and personalised care in neurological imaging and analysis.

Keywords: Quantum Machine Learning; Convolutional Neural Network; Quantum Neural Network; Deep Learning; MRI; EEG; CT

INTRODUCTION

Quantum computing (QC) represents an emerging field that applies quantum-mechanical principles to complex computational problems, with the potential to surpass classical computing capabilities. [1]. The concept of QC was postulated in the 1980s in an article written by Nobel Laureate Richard Feynman, who suggested that the study of simulating quantum systems requires the construction of a quantum computer [2]. Moving forward, Peter Shor developed an algorithm presented at the 35th Annual Symposium on Foundations of Computer Science, which demonstrated that quantum computers could factor large numbers faster than any classical computer, showing potential in important domains such as cryptography [3]. Therefore, despite its promising capabilities, quantum computing raised significant concerns—particularly regarding its potential to compromise sensitive information in areas like cybersecurity [4] and data privacy [5]. In the present, QC found its purpose in diverse domains such as drug discovery and molecular simulation [6], machine learning and artificial intelligence [7], financial modelling in trading and investment [8], or climate prediction, astrophysics, and particle physics [9]. Following the success of Variational Quantum Eigensolver simulations used in the process of molecular development [10], scientists expanded the use of quantum technology capabilities to other medical domains, such as imaging techniques. Medical imaging is facing increasing pressure to deliver faster, more accurate diagnoses amid rising scan volumes and clinician shortages, driving a clinical need for automation and efficiency. At the moment, machine learning (ML) and deep learning (DL) have become essential tools, offering superior performance in image classification, segmentation, and disease detection, comparable to human expertise [11]. However, the continuous need for a better signal processing technique, which would be capable of offering higher resolution results in the domain of Magnetic Resonance Imaging (MRI) [12] or Electroencephalogram (EEG) [13], led to the development of hybrid quantum

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algorithms in medical imaging. Although quantum imaging is not directly dependent on QC, ongoing research in the field offers considerable promise for improving diagnostics through more precise and non-invasive medical assessments.

This review investigates the emerging role of QC and quantum applications in advancing medical imaging technologies, particularly in MRI and EEG signal processing, by examining how developments in quantum algorithms and hybrid computation have the potential to overcome classical limitations in diagnostic resolution, speed, and accuracy. It also investigates the broader context in which QC evolved—from theoretical foundations and cryptographic challenges to its current applications in molecular simulation and biomedical innovation.

MATERIALS AND METHODS

A meticulous medical literature search was conducted using the Web of Science scientific database between July 8th and July 12th 2025, targeting articles published within the last 5 years. The search strategy utilised various keyword combinations, including: "quantum computing", "MRI", "EEG", "Quantum imaging", "quantum mechanics", "quantum phenomena", and "machine learning". The initial screening of all retrieved articles was conducted by reviewing their titles and abstracts to evaluate their relevance to the research topic. Studies were considered eligible for full-text analysis if they met specific inclusion criteria: written in English, full-text accessible, open access and categorised as narrative reviews or original articles related to current progress in the development of QC or quantum algorithms in medical imaging, the basics of quantum mechanics and quantum machine learning. Any articles falling outside these parameters were excluded from further evaluation. Each stage of the review was carried out independently by the researchers.

RESULTS AND DISCUSSION

Machine learning and the development of quantum hybrid systems

ML represents a subfield of AI that enables systems to learn from data and improve their performance on a specific task without being explicitly programmed for each decision. The techniques are classified into 3 categories: supervised learning, unsupervised learning, and reinforcement learning. ML algorithms are being increasingly adopted in medical imaging and pathology to enhance the speed and precision of disease diagnosis. Convolutional Neural Networks (CNNs), in particular, have become widely used for interpreting medical images from modalities such as X-rays, CT scans and MRIs [14]. These models are capable of autonomously identifying and categorising abnormalities such as tumours and lesions, supporting clinicians and radiologists in making faster and more accurate diagnostic decisions [15]. By learning from extensive collections of labelled medical images, ML systems can detect subtle patterns that may escape human observers, contributing to earlier diagnosis and potentially better patient outcomes.

The field of Quantum Machine Learning (QML) has emerged from the combination of AI and ML to improve algorithmic efficiency [16]. It builds upon the principles of quantum computing to enable inherent solution parallelism [17], facilitating optimal constraint solving in line with Moore's law [18]. Quantum algorithms rely on Boolean algebra operators (such as OR, AND, NOT gates) alongside principles of quantum physics. Data representation in these systems is based on quantum bits (qubits), which are grounded in the theoretical properties of electron spin [19]. Notably, quantum computing allows for the encoding of information beyond classical binary states, including complex and negative values. Furthermore, taking advantage of quantum phenomena such as superposition and entanglement offers the potential for substantial speedups in performing ML tasks compared to traditional approaches. Quantum algorithms can accelerate essential operations such as matrix manipulation, which supports many techniques, including clustering and principal component analysis [20]. Adaptation of classical algorithms such as support vector machines [21] and neural networks [22] into quantum frameworks has shown promise in improving computational efficiency, especially for high-dimensional datasets. In fields like healthcare, where data is often vast and intricate, QML may dramatically enhance processes such as medical image analysis, genomics, and drug discovery [23],[24].

Quantum algorithms in MRI

MRI is a critical diagnostic tool for neurological disease, offering detailed visualisation of brain structure and function. In Alzheimer's disease (AD), MRI helps detect early atrophy in key regions such as the hippocampus [25]. A model for the diagnosis and classification of different grades of severity (non-demented, mild demented, moderate demented, and very mild demented) of AD was conceived using a QML classifier and 5-qubit quantum hardware or simulator. The presented model surpassed the classical Support Vector Machine in both classification accuracy and training speed, especially when dealing with low-resolution MRI data, but further investigation is needed to assess its feasibility for integration into medical diagnostic systems [26]. The development of this technology would innovate the domain of diagnosis for AD, as the self-reported cognitive assessments commonly used are susceptible to response bias and misclassification [27],[28]. In order to detect mild early-stage cognitive impairment, Choi et al. used functional MRI technology and correlated it with a hybrid quantum-classical algorithm. In classical simulations, the hybrid model outperformed traditional CNNs in balanced accuracy and highlighted two brain regions (the right hippocampus and left parahippocampus) associated with cognitive decline [29]. For brain tumours, MRI provides precise localisation and tissue characterisation, essential for diagnosis and surgical planning [30]. Rajamohana et al. proposed a method that integrates classical and hybrid quantum-inspired graph neural networks for tumour classification. The hybrid Quantum Graph Neural Networks achieved performance metrics on par with advanced classical neural networks, with training accuracy rising from 41% to 64% and validation accuracy improving from 31% to 52%. These results highlight the model's effectiveness in differentiating between normal and tumour images [31]. In tuberous sclerosis complex (TSC), MRI reveals cortical tubers and subependymal nodules, aiding early diagnosis and monitoring [32]. Lin et al. created a quantum neural network called QR-Net, which integrated CNNs with a quantum neural network layer for TSC classification. The model utilised two layers, the first one converting classic input into a quantum state, and a second one that used entanglement and qubit interactions to process the states. Compared to traditional 3D-ResNet models, QR-Net demonstrated superior performance in classifying TSC-related epilepsy, achieving higher accuracy and AUC scores across the study cohort [33]. MRI also plays a key role in Parkinson's disease by identifying subtle changes in the basal ganglia and brainstem [34]. MRI's high-resolution structural and functional insights are indispensable in understanding, diagnosing, and managing these complex diseases.

Quantum algorithms in EEG

EEG is a widely utilised, non-invasive method for recording the brain's electrical activity, playing a key role in both clinical diagnostics and neuroscience research. It has been essential in exploring brain function, identifying neurological disorders, and advancing brain-computer interface technologies. While traditional analysis approaches, such as ML and DL models like EEGNet, have shown strong performance across various EEG applications, they may struggle to fully capture the intricate, high-dimensional patterns inherent in EEG signals [35].

Quantum-EEGNet (QEEGNet) is an innovative hybrid neural network that combines quantum computing with the classical EEGNet framework to enhance EEG signal representation and analysis. By embedding quantum layers into the architecture, the model aims to capture more complex patterns in the EEG data, offering potential computational benefits. Evaluated on the BCI Competition IV 2a dataset, QEEGNet outperformed the traditional EEGNet across most subjects and showed greater robustness to noise, underlining the promise of quantum-enhanced models in advancing EEG-based research and applications [35]. Furthermore, another hybrid quantum-classical neural network model that integrates a variational quantum circuit into a deep neural network for EEG, electromyogram, and electrocorticogram analysis showed state-of-the-art competence with a small number of parameters for the variational quantum circuit [36].

Even though EEG is not currently involved in the diagnosis of Schizophrenia or Autism Spectrum Disorder (ASD) as a standalone diagnostic tool, it plays an increasingly important role in research and adjunctive clinical assessment. Aksoy et al. evaluated the performance of QML models, particularly Quantum Support Vector Machines (QSVM), for the early diagnosis of schizophrenia using EEG data. EEG signals from four selected channels were decomposed into five frequency sub-bands via Discrete Wavelet Transform (DWT), and statistical features were extracted from each sub-band to construct the feature set. Principal Component Analysis (PCA) was applied for dimensionality reduction, and the resulting features were encoded into quantum states using various feature maps for input into QSVM. The results demonstrated that, despite the limitations of current quantum hardware, QSVM achieved state-of-the-art classification accuracy, even outperforming classical algorithms, while utilising a reduced number of qubits. The study also highlights the potential benefits of QML in handling noisy EEG data and suggests further investigation into feature map configurations, quantum-classical hybrid models, and implementation on real quantum devices [37]. Another study investigated the use of EEG-based biomarkers for ASD classification, emphasising the selection of optimal electrode pairs and the application of advanced ML techniques. EEG signals from electrode combinations C3-C4, C3-Cz, and C4-Cz were analysed, with C4-Cz demonstrating superior performance when paired with QSVM. Feature extraction included peak frequency, Stockwell transform coefficients, and peak-to-peak amplitude, enhancing the discriminative power of the input data. The QSVM model, using amplitude embedding, achieved a classification accuracy of 98.9%, outperforming classical support vector machine baselines. These results highlight the potential of QML in EEG-based ASD diagnostics and point to future directions involving MEG integration, neural structured learning, and large-scale population studies [37].

Quantum algorithms in CT

The use of quantum technology in CT doesn't involve novel discoveries in the diagnosis of neurological diseases but presents different improvements in the domain of image acquisition [38], accuracy [39], processing [40], and storage [41]. Jun et al. present a quantum image reconstruction algorithm aimed at enhancing the fidelity of CT scans by mitigating artifacts inherent in classical reconstruction methods such as filtered back projection. The algorithm encodes the unknown CT image into a quantum state represented by qubits and minimises the discrepancy between the experimentally acquired sinogram and the Radon transform of the quantum state using a global energy optimisation framework. Implemented on gate-based quantum computers or quantum annealers, the method leverages quantum parallelism to efficiently explore the solution space. It is applicable to various CT configurations, including cone-beam geometries, and operates independently of the light source, provided the projection data is well-defined. This approach enables high-accuracy reconstruction with reduced artifacts, representing a significant advancement in quantum-enhanced medical imaging [38]. For the improvement of CT processing speed, Sengupta et al. proposed a model for classifying COVID-19 from CT images, distinguishing it from non-COVID pneumonia cases. Leveraging the efficiency of quantum simulation, the quantum neural network (QNN) achieved faster convergence and superior performance on large-scale, biased image classification tasks. Compared to classical DL models, the QNN showed an accuracy improvement of over 2.92% and an average recall of 97.7%. Training runtime on quantumoptimised hardware was 52 minutes, significantly faster than the 1 hour and 30 minutes required on a K80 GPU. These results highlight the potential of QNNs in enhancing medical image classification, particularly in high-stakes diagnostic contexts like COVID-19 [40].

CONCLUSION

The integration of ML with quantum computing has opened new frontiers in the analysis and interpretation of complex medical data, especially in the field of neurological diagnostics. Traditional ML models, such as CNNs and SVMs, have already demonstrated significant success in tasks like medical imaging and EEG signal analysis. However, the emergence of QML offers the potential to further enhance computational efficiency, accuracy, and speed by leveraging quantum principles such as superposition, entanglement, and quantum parallelism.

Across multiple imaging modalities (MRI, EEG, and CT) hybrid quantum-classical models have consistently outperformed or matched their classical counterparts, often with fewer parameters and faster training times. From Alzheimer's and Parkinson's disease to epilepsy, brain tumours, and developmental disorders such as ASD, QML approaches have enabled more sensitive and specific classifications by uncovering patterns not easily discernible with conventional methods. Furthermore, advancements in quantum algorithms for CT image reconstruction and classification demonstrate the versatility of QML beyond diagnosis, extending into image enhancement and processing.

Despite current hardware limitations, these early successes underline the transformative potential of quantum-enhanced ML in medical diagnostics. Continued research into hybrid architectures, feature encoding strategies, and real-device implementation will be crucial for translating experimental results into clinical practice. As quantum hardware matures, the integration of QML into medical imaging and brain signal analysis promises to revolutionise diagnostic workflows, offering more accurate, timely, and individualised care.

Conflicts of interest and sources of funding

The authors declare no conflict of interest.

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Authors' contribution

Conceptualization, Carmen Adella Sîrbu; methodology, Carmen Adella Sîrbu; investigation, Vlad Buica; writing—original draft preparation, Vlad Buica; writing—review and editing, Carmen Adella Sîrbu;

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