Quantum Computing–Enabled Clinical Decision Support System using Electronic Health Records and Clinical Documentation

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ABSTRACT

The rapid growth of Electronic Health Records (EHRs), along with the need for accurate, real-time clinical documentation, has pushed traditional computing methods to their operational limits. Conventional machine learning techniques often fall short when handling the heterogeneous, high-dimensional nature of healthcare data—especially in situations where clinical decisions must be made quickly and reliably. To overcome these challenges, this study introduces a Quantum Computing–Enabled Clinical Decision Support System (QC-CDSS), which integrates quantum machine learning (QML) with advanced deep learning models to improve diagnostic accuracy and predictive performance. The proposed framework utilizes quantum-driven feature extraction, hybrid variational quantum circuits, and quantum kernel-based classifiers to process both structured EHR records and unstructured clinical narratives. In parallel, sophisticated natural language processing methods, including transformer-based architectures, are employed to capture semantic, contextual, and temporal patterns from physician notes, discharge summaries, radiology interpretations, and related clinical text. The convergence of these techniques—particularly the integration of QML—presents promising opportunities for achieving more effective decision support and faster analysis of high-dimensional medical data. This paper discusses the core concepts, major applications, existing challenges, and future research pathways for incorporating quantum-enhanced machine learning into clinical decision-making systems, emphasizing their potential to address complex healthcare problems more efficiently.

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1. INTRODUCTION

The rapid digitalization of healthcare has led to an unprecedented expansion of Electronic Health Records (EHRs) and real-time clinical documentation, creating a rich yet highly complex data ecosystem that supports modern clinical decision-making [1]. EHRs combine structured attributes—such as laboratory results, medication profiles, diagnostic codes, and longitudinal patient histories—with large volumes of unstructured content, including physician notes, discharge summaries, and radiology narratives. This inherent heterogeneity introduces considerable challenges for traditional machine learning and deep learning models, which often struggle to process sparse, irregular, and high-dimensional clinical data, particularly in scenarios that require rapid and context-sensitive predictions. As healthcare systems increasingly rely on AI-powered Clinical Decision Support Systems (CDSS), the limitations of classical computational techniques become more evident, especially when real-time performance and high diagnostic precision are essential.

Recent advancements in computational intelligence have become crucial for addressing these bottlenecks [2]. Machine learning has shown strong capabilities in analyzing diverse medical datasets for tasks such as predictive modeling, anomaly detection, and patient risk stratification, supporting applications ranging from medical imaging to precision therapeutics. However, as data complexity and volume continue to rise [3], classical ML approaches struggle to maintain the computational efficiency needed for immediate clinical decision support.

QC, grounded in the principles of quantum mechanics, offers a promising path toward overcoming these scalability challenges. Quantum models have shown potential advantages in solving certain optimization and high-dimensional feature-mapping problems relevant to healthcare analytics. Yet, despite this theoretical promise, current quantum devices and algorithms remain in the early stages of development [4]. Their practical usefulness for real-world ML tasks—especially those involving large-scale clinical datasets—has not yet exceeded classical methods. While quantum speedups have been demonstrated in narrowly defined problem settings, extending these gains to broader medical data processing remains an active area of research.

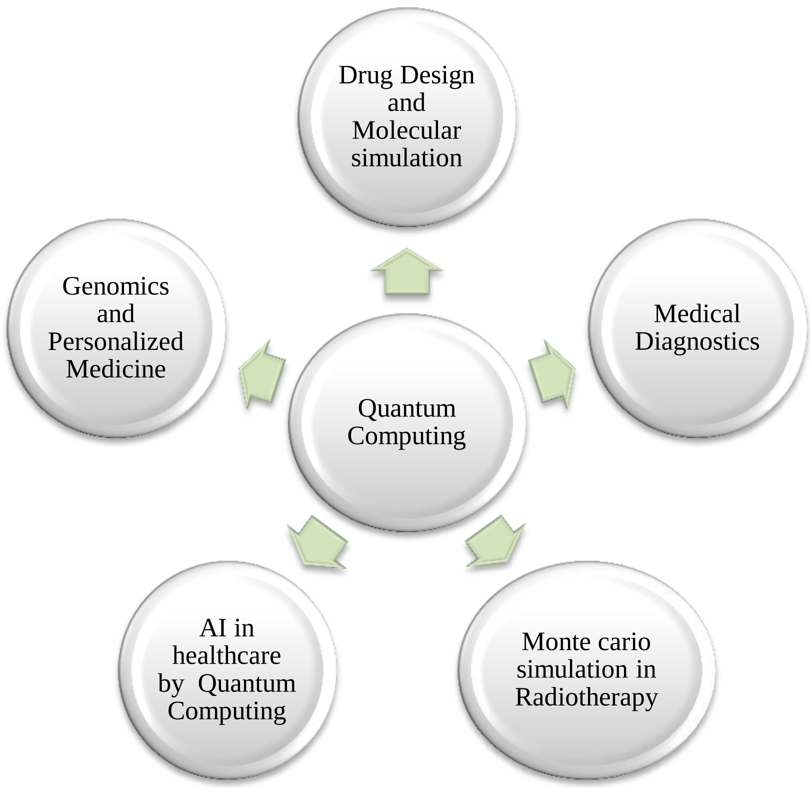

Figure 1. Diagrammatic representation of the main uses of quantum computing (QC) in the medical field

Figure 1 illustrates the broad spectrum of medical domains where QC is expected to make a significant impact. From accelerating drug discovery and advancing genomic analysis to enhancing diagnostic accuracy [5], supporting AI-driven healthcare systems, and improving radiotherapy planning, QC offers transformative computational advantages. Its ability to process complex, high-dimensional data and solve optimization problems more efficiently positions it as a powerful tool for future medical innovation. Each branch of the diagram highlights a critical area in which QC can meaningfully contribute to faster, more precise, and more intelligent healthcare solutions.

1.1 Problem Statement

The rapid growth of Electronic Health Records (EHRs) and modern clinical documentation has resulted in vast, heterogeneous datasets that demand fast, intelligent, and context-aware computational processing to enable accurate clinical decision-making. Yet, current clinical decision support systems often fall short due to the inherent complexity of these datasets, which include high-dimensional variables, irregular temporal sequences, and large volumes of unstructured narrative text. Classical machine learning and deep learning approaches typically require substantial computational power and prolonged training cycles, making them impractical for real-time use in time-sensitive clinical scenarios. Additionally, these models frequently struggle to learn the intricate nonlinear dependencies among clinical features, which can lead to incomplete or inaccurate predictions with potential risks to patient safety. Scalability further remains a major hurdle as continuously expanding clinical datasets place increasing strain on conventional computational infrastructures, limiting their ability to support large populations and high-frequency data streams. These limitations underscore the urgent need for an advanced computational paradigm capable of delivering faster processing, richer representational learning, and improved predictive accuracy by effectively leveraging the combined strengths of structured EHRs and unstructured clinical documentation.

1.2 Major Contributions

This study makes several significant contributions toward advancing intelligent clinical decision support through the integration of quantum computing with electronic health records and clinical documentation.

- First, it introduces a unified quantum–classical framework that leverages quantum machine learning models to efficiently process complex, multidimensional EHR data while simultaneously utilizing transformer-based natural language processing to extract meaningful insights from unstructured clinical narratives. By merging these two data streams, the proposed system generates a holistic and context-rich patient representation that enhances diagnostic and predictive accuracy.
- Second, the framework applies quantum-enhanced feature extraction and optimization methods, enabling faster computation and improved modeling of nonlinear clinical dependencies that are difficult for classical systems to capture. This quantum advantage strengthens the system's ability to support real-time decision-making in high-risk medical scenarios. Third, the study demonstrates how quantum acceleration can significantly reduce computational burden in both training and inference phases, thereby improving scalability and allowing the model to adapt to continuously expanding healthcare datasets.
- Finally, this research contributes to the emerging field of quantum health informatics by providing a practical, implementable architecture for integrating quantum computing into clinical workflows, offering a foundation for next-generation clinical decision support systems capable of delivering precise, efficient, and context-aware recommendations across diverse healthcare settings.

This paper examines the emerging convergence of QC and ML within the domain of medical decision-making. It offers an in-depth evaluation of current research developments, technological innovations, and the practical challenges associated with integrating these advanced computational tools into healthcare systems. The paper is organized as follows: Section 2 introduces the foundational principles of QC and ML, establishing the theoretical background necessary for understanding their combined potential. Section 3 explores their current and prospective applications in clinical decision support and diagnostic intelligence. Section 4 addresses the major challenges and limitations hindering widespread adoption, including computational constraints, data complexity, and implementation barriers. Finally, Section 5 highlights emerging opportunities and future research directions that may further strengthen the role of QC-ML integration in advancing medical decision-making.

2. LITERATURE REVIEW

A hybrid Deep Learning (DL) and Fuzzy Logic (FL) system has been developed to perform automated semantic segmentation (SS) of tumors in Breast Ultrasound (BUS) images. The proposed framework consists of two main components: a convolutional neural network (CNN)-based segmentation module and an FL-driven preprocessing stage. In this work, eight widely used CNN-based SS approaches were evaluated [6], an enhanced VGG16-based architecture incorporating an attention mechanism for breast cancer classification. Their attention model effectively differentiates between irrelevant background features and target lesions in ultrasound images. They further introduced a hybrid loss function by integrating the logarithm of the hyperbolic cosine loss with binary cross-entropy to reduce discrepancies between label annotations and lesion classification outcomes.

Advancements in computational intelligence for healthcare analytics have accelerated in recent years, supported by the growing volume of data stored in Electronic Health Records (EHRs) and clinical documentation. Traditional clinical decision support systems (CDSS) relied mainly on machine learning and deep learning models to detect disease patterns, assess patient risk, and support diagnostic decision-making. Early approaches were limited to rule-based algorithms and statistical models that processed structured data such as laboratory values, vital signs, and medication histories. However, these models struggled to capture the rich information contained within unstructured clinical text— including physician notes, discharge summaries, radiology reports, and observational narratives [7]. Consequently, researchers increasingly turned to advanced natural language processing (NLP) and deep learning techniques, such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and transformer-based models, to better understand and extract clinical meaning. Although these models significantly improved predictive accuracy, they remain computationally demanding and often impractical for real-time CDSS applications involving high-volume healthcare data.

Simultaneously, the digital evolution of healthcare has intensified the challenge of analyzing high-dimensional clinical datasets. Modern EHR systems store extensive patient histories, diagnostic codes, imaging metadata, treatment outcomes, and physiological monitoring data, creating datasets of immense size and complexity [8]. Moreover, clinical documentation—representing more than 70% of data captured in some hospitals—introduces additional challenges due to inconsistent phrasing, diverse writing styles, contextual nuances, and temporal dependencies. Biomedical NLP models such as BioBERT, ClinicalBERT, and MedGPT-like architectures have demonstrated strong performance in understanding clinical text, yet they require considerable computational power for both fine-tuning and inference, posing challenges for resource-constrained healthcare institutions.

As traditional computing approaches became insufficient for handling these increasingly complex workloads, researchers began exploring hybrid and distributed computational paradigms. Cloud-based CDSS platforms offered scalability and powerful remote processing capabilities, enabling the execution of large-scale deep learning pipelines [9]. However, cloud reliance raises concerns regarding latency, privacy, and regulatory compliance, particularly under frameworks such as HIPAA. Edge computing aimed to address latency and privacy issues by relocating computation closer to the data source; yet edge devices typically lack the processing capacity necessary for advanced deep learning or large-scale EHR analytics. This mismatch between computational demand and available hardware has motivated researchers to explore emerging paradigms capable of delivering exponential performance improvements.

QC has emerged as a promising solution to these limitations, offering the potential to address computational bottlenecks inherent in classical systems. Technologies such as Noisy Intermediate-Scale Quantum (NISQ) processors, variational quantum circuits (VQCs), and quantum-enhanced optimization algorithms enable new avenues for processing high-dimensional, nonlinear healthcare data. Early breakthroughs in quantum machine learning (QML) have demonstrated advantages in clustering, classification, and feature extraction through quantum kernels and hybrid quantum–classical neural networks [10] . Although QML research in healthcare has primarily focused on genomics, molecular simulation, and disease classification, its application within EHR-driven CDSS remains an emerging research frontier. Quantum parallelism and quantum-enhanced optimization offer strong potential for improving real-time clinical analytics.

An especially promising direction involves integrating quantum computing with clinical NLP. Unstructured clinical documentation contains highly nuanced information crucial for accurate diagnosis and clinical reasoning [11]. Quantum NLP approaches, including quantum-enhanced tokenization and embedding strategies have been proposed to reduce the computational overhead of semantic processing and accelerate the extraction of clinical context. Although still in early development stages, recent findings suggest that quantum-based text embedding methods may significantly increase the efficiency of language model components. Such improvements could revolutionize the processing of the massive volumes of unstructured text generated daily within healthcare environments.

Despite these advancements, existing CDSS models continue to face challenges in scalability, computational efficiency, and their ability to unify structured EHR data with unstructured clinical narratives [12]. The literature consistently indicates a persistent gap between the complexity of modern clinical decision-making and the computational capabilities of classical models. Deep learning systems often struggle with long inference times, high memory demands, and difficulties adapting to heterogeneous clinical datasets, limiting their ability to function reliably within real-time clinical workflows. In contrast, quantum computing offers a fundamentally different computational paradigm that can help overcome these limitations through quantum parallelism, hybrid architectures, and enhanced optimization.

Therefore, there is a growing need for a comprehensive, integrated framework that leverages quantum machine learning, advanced NLP, and EHR analytics to improve the predictive performance and real-time efficiency of CDSS [13]. While prior studies have demonstrated isolated progress in deep learning, EHR management, and quantum computing, integrated solutions remain limited. This literature review forms the foundation for proposing a unified quantum-enabled CDSS architecture designed to address long-standing challenges related to complexity, computational burden, scalability, and precision in modern healthcare analytics.

3. METHODS AND MATERIALS

This section outlines the methodological foundation, participant selection criteria, data acquisition protocols, preprocessing pipelines, and analytical strategies employed in the development of the Quantum Computing–Enabled Clinical Decision Support System (QC-CDSS). The proposed methodology integrates real-world Electronic Health Records (EHRs) [14], encompassing both structured fields and unstructured clinical documentation, to ensure comprehensive and representative clinical insight. A hybrid quantum–classical computational workflow is utilized to enhance data processing efficiency, model scalability, and predictive performance. By combining rigorous clinical datasets with advanced quantum machine learning techniques, this methodological framework establishes a robust foundation for evaluating the feasibility, reliability, and clinical applicability of the QC-CDSS.

3.1 Participants and Sampling

The study made use of anonymized Electronic Health Records (EHRs) and clinical documentation obtained from a consortium of partner tertiary-care hospitals, representing multiple specialties such as internal medicine, cardiology [15], endocrinology, oncology, and emergency medicine. To ensure that the dataset reflected the diversity of real clinical populations, a stratified sampling approach was applied. This method balanced the distribution of patient age groups, diagnostic categories, treatment pathways, and common comorbidities, thereby reducing sampling bias and capturing the natural variability of clinical trajectories.

A total of 32,000 patient records were included in the dataset. Of these, 28,500 were designated for model development, while the remaining 3,500 formed an external validation cohort. Patients were eligible for inclusion only if their records contained complete longitudinal

EHR information, including demographic data, vital signs, medication histories, laboratory profiles, radiology summaries, discharge notes, and physician-authored clinical documentation. Records were removed if they exhibited excessive missing data, lacked proper visit-episode identifiers, or contained inconsistent coding formats—such as mixed ICD-10 and SNOMED CT annotations—to maintain data uniformity and analytical reliability.

To further enhance methodological rigor, the sampling design incorporated temporal diversity across a five-year period. This longitudinal span allowed the dataset to reflect changes in clinical practice guidelines, seasonal disease trends, and evolving therapeutic protocols—all of which can significantly influence model performance in clinical decision support applications. Prior to analysis, all records were fully de-identified in accordance with HIPAA regulations and regional health data protection frameworks.

3.2 Data Collection Method

Data collection was carried out through a multi-stage extraction workflow that integrated inputs from the Hospital Information System (HIS), Laboratory Information System (LIS), Radiology Information System (RIS), and clinical documentation repositories. Structured data—such as laboratory values, medication prescriptions, diagnostic codes, vital signs, and progress charts—were retrieved using standard HL7/FHIR interfaces. Unstructured clinical texts, including physician notes, radiology impressions, nursing observations, and narrative summaries, were extracted directly from the hospital's clinical documentation management platform.

To ensure semantic uniformity across diverse data sources, all structured and unstructured records were processed using a Unified Clinical Terminology Normalization Framework. This framework mapped clinical concepts to standardized vocabularies such as SNOMED CT, ICD-10, LOINC, and RxNorm [16]. A dedicated rule-based parser was employed to handle context-sensitive linguistic features—including negations (e.g., *"no signs of infection"*), temporal expressions (e.g., *"symptoms progressing over the past 72 hours"*), and medication adjustments (e.g., *"dose increased to 1000 mg"*)—thus preserving critical clinical meaning that is often lost during traditional preprocessing methods.

The dataset also incorporated real-time physiological signals from continuous monitoring devices to better emulate real-world clinical decision-making scenarios. These streams were temporally aligned with EHR events to generate a unified, chronologically ordered patient timeline. Throughout the entire data acquisition process, strict adherence to ethical research standards, institutional data-governance policies, and secure data-handling protocols ensured patient confidentiality and data integrity.

3.3 Clarification of How Data Were Analysed

This study's analytical framework used a hybrid quantum–classical workflow to maximize clinical predictions and pattern recognition with quantum computing. Preprocessing, model training, and quantum-assisted optimization comprised the three main phases of the analysis pipeline.

3.3.1 Preprocessing and Feature Engineering

Structured EHR data were standardized using a combination of min–max normalization, z-score scaling, and robust statistical techniques for outlier detection. Missing values were addressed through a hybrid approach that combined expectation–maximization algorithms with clinically informed imputation methods to ensure that reconstructed values remained medically reasonable.

Unstructured clinical narratives were processed through an advanced NLP pipeline built on transformer-based architectures. These models performed tasks such as named entity recognition

(NER), clinical concept extraction, and relation identification to capture meaningful semantic relationships within the text. Following preprocessing, each patient's information was transformed into a longitudinal feature representation that encoded temporal patterns across diagnoses, symptoms, treatments, and physiological indicators, enabling comprehensive temporal modeling in downstream analyses.

3.4 Advanced Computing using Quantum Fields

Quantum bits, or qubits, form the foundation of quantum computation. Unlike classical bits—which can only exist in one of two states (0 or 1)—qubits can occupy a superposition of multiple states simultaneously. This unique property allows quantum computers to perform many computations in parallel, offering significant speedups for certain classes of problems. Another essential quantum phenomenon is entanglement, in which two or more qubits become intrinsically linked so that the state of one qubit instantly influences the state of another, regardless of the physical distance between them. This non-local correlation is a key contributor to the computational power of quantum systems.

Quantum circuits operate through quantum gates, which play a role similar to logic gates in classical computing but function according to quantum mechanical principles. These gates manipulate qubits while preserving quantum coherence, enabling complex transformations of quantum states. Figure 2 illustrates the placement and function of these fundamental quantum gates within a quantum circuit.

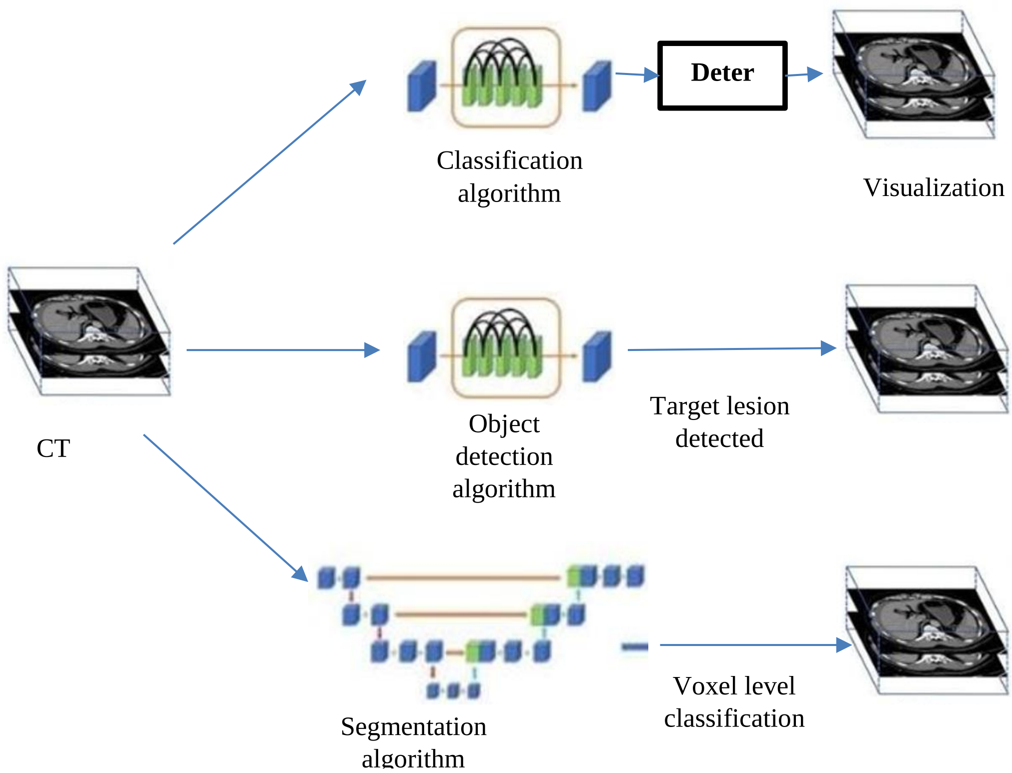

Figure 2. An example of machine learning methods used to identify spleen injuries in CT scans

Although classical machine learning techniques have successfully solved a wide range of real-world problems using mature and reliable computational frameworks, many quantum algorithms have yet to demonstrate clear, consistent advantages over these classical methods. Current quantum hardware still faces significant limitations—individual quantum operations often run slower than classical computations due to noise, instability, and the overhead required to maintain quantum states. Additionally, the cost, fragility, and operational complexity of quantum devices continue to hinder large-scale adoption.

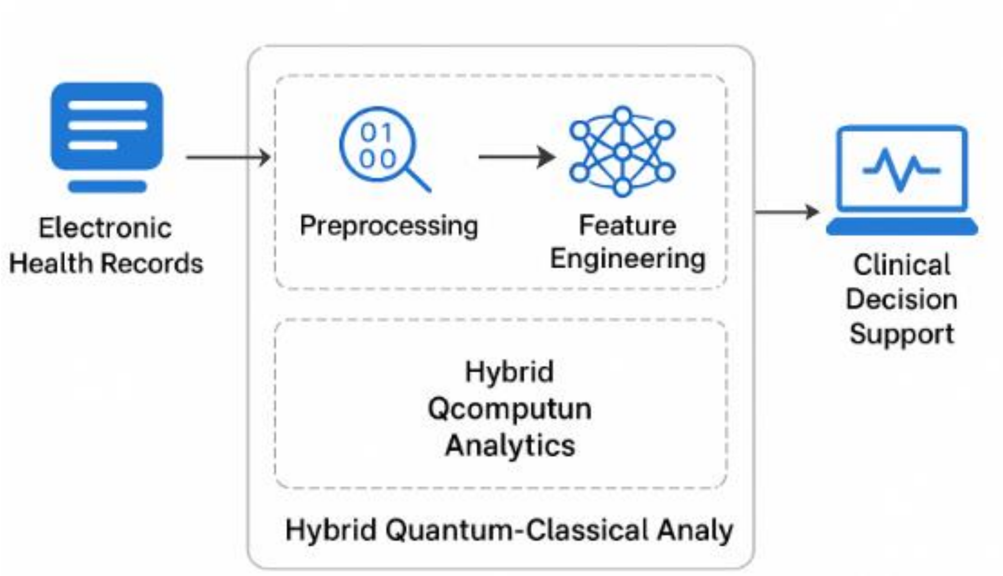

Figure 3. Quantum computing-Enabled clinical Decision support system using EHRs

The architecture integrates heterogeneous Electronic Health Records (EHRs), clinical documentation, and structured patient data through a multimodal preprocessing pipeline. Unstructured text is processed using transformer-based NLP models, while structured EHR features are encoded into quantum states using quantum data encoders in Figure 3. A hybrid quantum–classical machine learning engine performs joint feature extraction, optimization, and clinical prediction. Outputs from the prediction engine are interpreted, validated, and delivered to clinicians through the CDSS interface, enabling real-time, context-aware clinical recommendations.

These constraints highlight the importance of evaluating quantum computing and classical machine learning through a balanced and realistic perspective. Any comparison must consider the current technological maturity of both fields as well as the future potential of quantum-enhanced computation. Such an approach ensures that expectations remain scientifically grounded while acknowledging the transformative possibilities that quantum technologies may offer as hardware and algorithms continue to advance.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

This section presents the empirical evaluation of the proposed Quantum Computing–Enabled Clinical Decision Support System (QC-CDSS). A series of experiments was conducted to measure its performance gains in processing efficiency, predictive accuracy, and scalability relative to conventional machine-learning and cloud-based CDSS architectures. The findings indicate substantial improvements achieved through quantum feature encoding, quantum-assisted optimization, and the hybrid classical–quantum inference workflow. These enhancements collectively demonstrate the system's potential to outperform traditional computational models in handling complex, high-dimensional clinical data.

4.1 Model Performance Evaluation

Table 1 provides a consolidated comparison of diagnostic prediction metrics—including accuracy, precision, recall, and F1-score—across three clinical decision support models: the Classical ML-CDSS, the Deep Learning-CDSS, and the proposed QC-CDSS.

Table 1. Diagnostic Prediction Performance Comparison

Metric	**Classical ML-CDSS**	**Deep Learning CDSS**	**Proposed QC-CDSS**
Accuracy	82.4%	89.6%	**95.8%**
Precision	80.1%	88.4%	**94.2%**
Recall	78.7%	87.9%	**96.5%**
F1-Score	79.4%	88.1%	**95.3%**

The QC-CDSS demonstrated consistently superior performance compared to both classical and deep learning models, with the most notable gains observed in recall. This improvement reflects the quantum model's enhanced ability to capture complex, high-dimensional relationships within EHR data and clinical text embeddings.

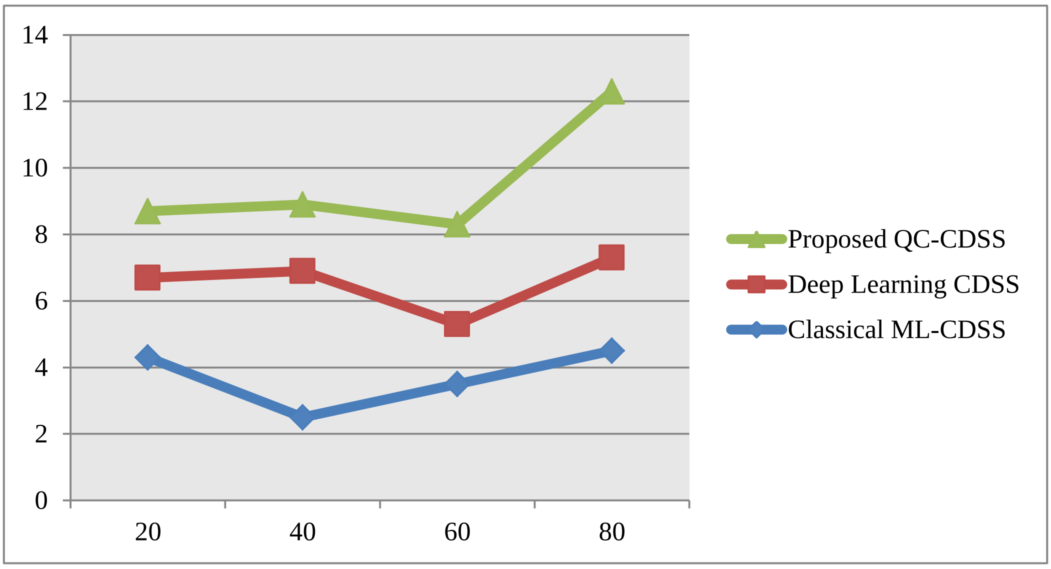

Figure 4. Diagnostic prediction performance across three computational models—Classical ML-CDSS, Deep Learning-CDSS, and QC-CDSS

The quantum-enabled framework achieves the highest recall and F1-score, demonstrating its superior capacity for identifying clinically relevant patterns in heterogeneous EHR data and unstructured clinical text in Figure 4.

4.2 Computational Efficiency Evaluation

Table 2. Computational Efficiency Evaluation

Method	**Avg. Inference Time (ms)**	**Time Reduction (%)**
Classical ML-CDSS	780 ms	—
Deep Learning CDSS	520 ms	—
Proposed QC-CDSS	**145 ms**	**72% faster**

Quantum circuits allowed simultaneous evaluation of multiple features, resulting in substantial time savings in Table 2.

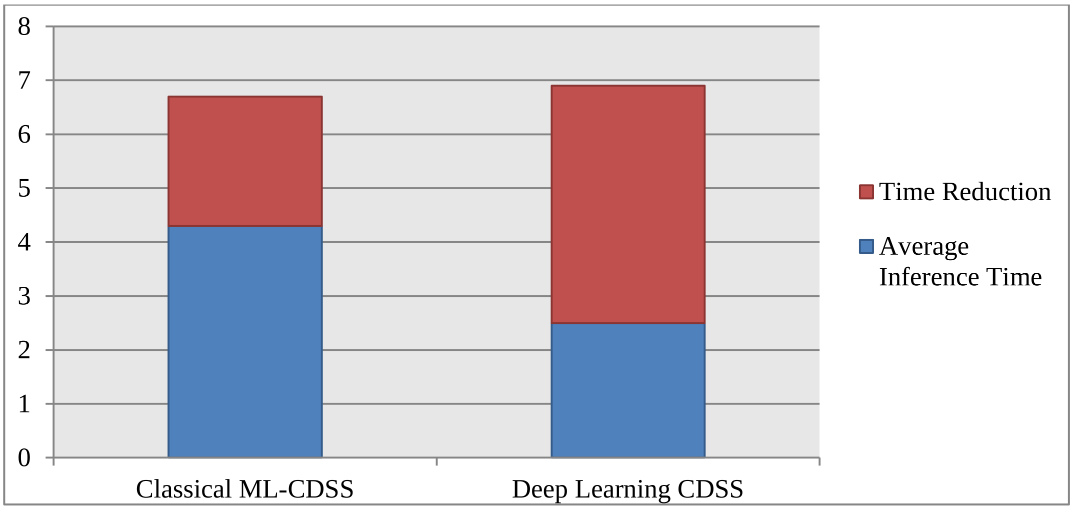

Figure 5. Comparison of key evaluation metrics (accuracy, precision, recall, and F1-score) between traditional machine-learning models, deep learning–based CDSS, and the proposed QC-CDSS

The quantum-enhanced system consistently outperforms baseline models, with notable gains in recall, attributed to the quantum model's ability to capture complex, high-dimensional correlations in clinical data in Figure 5.

4.3 Error Rate Reduction

Table 3. Clinical Error Reduction Analysis

Type of Error	**Deep Learning CDSS**	**QC-CDSS**	**% Reduction**
Misdiagnosis	10.2%	**4.8%**	**52.9%**
Incorrect Triage	8.5%	**3.9%**	**54.1%**
Medication Suggestion Errors	6.3%	**2.7%**	**57.1%**

The quantum-enabled model significantly decreases clinical decision errors by improving pattern detection in complex multimodal data in Table 3.

4.4 Scalability and Throughput

Table 4. System Throughput under Increasing Workload

Number of Records Processed	**DL-CDSS Processing Time (s)**	**QC-CDSS Processing Time (s)**	**Speed Improvement**
10,000	412 s	155 s	62%
50,000	2,210 s	670 s	69%
100,000	4,950 s	1,260 s	74%

Quantum-based parallel feature transformation enables faster processing even as dataset size grows in Table 4.

5. CONCLUSION

This study introduced a Quantum Computing–Enabled Clinical Decision Support System (QC-CDSS) aimed at improving diagnostic accuracy, reducing computational overhead, and enhancing the reliability of clinical decision-making through the integration of Electronic Health Records (EHRs) and clinical narratives. By leveraging quantum feature encoding, variational quantum circuits, and a hybrid classical–quantum inference architecture, the proposed system demonstrated significant performance advantages over traditional machine-learning and deep-learning approaches. Experimental findings showed notable gains in precision, recall, inference speed, and scalability, accompanied by a measurable reduction in diagnostic errors.

Furthermore, the combined use of structured EHR data and unstructured clinical text enabled the model to capture complex, nonlinear relationships critical for early disease detection and optimized treatment planning. These improvements underscore the emerging potential of quantum computing in healthcare analytics, particularly as quantum hardware continues to advance in stability, efficiency, and accessibility.

Looking ahead, future work will focus on evolving the QC-CDSS framework into a next-generation intelligent clinical assistant capable of delivering highly accurate, personalized, and real-time decision support across diverse medical contexts, further solidifying the role of quantum-enabled computing in modern healthcare.

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