Research Article

Strategic Healthcare Technology Management Using Quantum Computing AND Deep Learning FOR Clinical Decision Support Systems

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Abstract

The surge in healthcare data and intelligent medical technologies has augmented the need to have advanced Clinical Decision Support Systems (CDSS) that can enhance the diagnostic accuracy, prediction of patient outcome and management of healthcare resources. The traditional healthcare analytics models have been faced with constraints to handle massive heterogeneous clinical data due to the complexity of computations, un-optimized feature optimization, and decreased predictive scalability. This paper introduces a healthcare technology management model that considers quantum computing and deep learning to be combined to create intelligent clinical decision support applications. The proposed framework is the product of a hybrid Convolutional Neural NetworkLong Short-Term Memory (CNN-LSTM) framework along with quantum-inspired optimization methods aimed at increasing the clinical prediction efficiency as well as the computational efficiency. The framework integrates the preprocessing of clinical data, automated feature mining, intelligent modeling of prediction, and decision support through optimization in a coherent healthcare analytics landscape. The publicly available healthcare datasets of demographic data, physiological data, laboratory data, and clinical outcome variables were used as experimental data. The proposed framework performed better than traditional machine learning and standalone deep learning models, with an accuracy of 97.4%, precision of 96.9, recall of 96.5, F1-score of 96.7 and ROC-AUC of 0.98. Cross-validation 10-fold validation proved to be a very robust and had a high ability to generalize with significant p-value of less than 0.05. The quantum-inspired optimization also led to better performance of feature selection and minimized redundancy in computation in tasks of clinical prediction. The suggested framework will be effective in supporting smart healthcare management, risk prediction of disease and high-level clinical decision support applications in the contemporary digital healthcare systems.

Keywords: Quantum Computing; Deep Learning; Clinical Decision Support Systems; Healthcare Technology Management; Artificial Intelligence; CNN-LSTM; Quantum-Inspired Optimization; Healthcare Analytics; Intelligent Healthcare Systems; Medical Data Analysis.

1. Introduction

Modern clinical settings have been altered, with the application of artificial intelligence (AI), deep learning, cloud computing, and healthcare analytics becoming part of their daily activities [1], [2] due to the rapid development of healthcare technologies. Clinical Decision Support Systems (CDSS) has a major role in aiding medical practitioners in the diagnosis, treatment planning, disease prediction and patient monitoring [3]. The increasing amount of electronic health records, medical imaging data, and wearable sensor data has posed significant issues in terms of processing healthcare data and making clinical decisions [4]. Conventional healthcare management systems are usually ill equipped to handle large scale heterogeneous clinical data because of the computational constraints, slowness of processing and lack of predictive power [5]. Traditional machine learning models need a lot of manual feature engineering, and often do not represent intricate healthcare relationships [6]. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are the two types of deep learning that have shown to be more effective in disease prediction, analytics in healthcare and medical decision support systems [7], [8]. Nevertheless, the currently used deep learning models continue to be challenged by issues of computational complexity, inefficiency in optimization, as well as scale shortcomings [9]. More recently quantum computing has been a promising type of computation in order to compute complex optimization and high-dimensional data processing problems [10]. Quantum-inspired optimization algorithms have the ability to enhance the process of feature selection, prediction accuracy, and efficiency in healthcare analytics systems [11]. The combination of quantum computing and deep learning opens up new opportunities into improving smart clinical decision support systems and managing the healthcare technology strategically. In spite of the recent developments, the literature predominantly addresses individual AI or deep learning models without incorporating the use of optimization-based healthcare management approaches. The integration of quantum-inspired optimization and deep learning towards intelligent clinical decision support systems has had little research. Moreover, there are numerous frameworks that do not have extensive statistics validation and scalability of healthcare optimization processes. Hence, the given paper suggests a clinical decision support system-based health technology management strategy that incorporates quantum computing and deep learning. The framework offered will be a hybrid CNN-LSTM architecture with quantum-inspired optimization to enhance the prediction accuracy, efficiency, and reliability of healthcare decisions. The healthcare datasets are evaluated through experimental assessment based on numerous statistical and performance validation measures. The key findings of this work are as following:

1. Creation of a health care-based technological management system with deep-learning-based and quantum-inspired optimization intertwined.
2. A hybrid CNN-LSTM architecture to be designed to predict healthcare and analyze clinical decisions.
3. Characteristics The feature optimization based on quantum inspiration are integrated to enhance computational efficiency and prediction accuracy.
4. Thorough statistical validation with accuracy, precision, recall, F1-score, ROC-AUC and cross-validation analysis.
5. Testing of the suggested model of intelligent clinical decision support app.

2. Related Work

Innovations in artificial intelligence (AI) and healthcare analytics in the recent past have helped in enhancing Clinical Decision Support Systems (CDSS) in terms of disease predictions, analysis of medical imaging and monitoring of patients [12], [13]. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are deep learning techniques that can be applied in healthcare analytics because of their ability to extract features automatically and learn more than 100 dimensions [14]. Architectures of transformers and transformer-based hybrid deep learning models have also improved the accuracy of clinical prediction and efficiency of healthcare decision-making [15]. The use of cloud computing and Internet of Medical Things (IoMT) combined with intelligent analytics in healthcare technology management systems has become a growing trend at efforts to enhance the functioning of hospitals and the overall quality of the patient care they provide [16]. Nonetheless, the current AI-supported healthcare systems continue to have computational complexity, inefficient optimization, scalability constraints, and a high processing overhead with respect to processing large-scale healthcare datasets [7]. Quantum computing is a newly-explored method that is applicable in solving intricate optimization challenges in healthcare. The feature selection, clustering of healthcare data and the allocation of medical resources have been explored with quantum-inspired optimization methods [8]. Quantum annealing and variational optimization techniques showed a better level of computation effectiveness as compared to traditional optimization techniques [9]. However, there is limited practical application of quantum-inspired optimization with deep learning in the intelligent clinical decision support. There are a number of research gaps within current decision support systems of healthcare:

• inadequate combination of strategic healthcare technology management,
• little scalability of optimization to large-scale healthcare analytics,
• large computer time in deep learning systems,
• scaled down scalability and interpretability,
• absence of combined quantum-assisted medical systems.

Thus, the paper suggests a hybrid model that comprises quantum-inspired optimization and deep learning to optimize the management of healthcare technology and intelligent clinical decision support system.

3. Materials and Methods

3.1 Healthcare Dataset Description

The experimental assessment has been carried out based on publicly available datasets on healthcare gathered in the well-established electronic health record (EHR) repositories and databases of clinical healthcare. Various benchmark healthcare datasets were combined to enhance the diversity of datasets, healthcare representation and clinical prediction reliability. The data sets were demographic, physiological, laboratory data, diagnostic clues and disease outcome variables related to various long-term healthcare illnesses. The combined dataset was comprised of a set of about 12,500 clinical records retrieved in the UCI Machine Learning Repository, Kaggle healthcare repositories, and publicly accessible clinical datasets. A sample of the patient population comprised patients aged 12-65 years of age and fell within the adolescent and adult healthcare category. The datasets covered various types of diseases such as cardiovascular disease, diabetes mellitus, chronic respiratory disorders, neurological abnormalities and metabolic syndromes. In order to enhance the robustness of prediction and minimize the impact of bias in the dataset, the balancing of the dataset was conducted with Synthetic Minority Oversampling Technique (SMOTE)-based balancing during its preprocessing. Data had duplicate records, incomplete data and poorly managed measurements eliminated prior to model training. The data set was categorized into training and testing data sets in the proportion of 80:20. Table 1 summarizes the major healthcare datasets that it used in this study.

Table 1. Healthcare datasets utilized in the proposed framework

Dataset	Source	Records	Disease Category	URL
Heart Disease Dataset	UCI Machine Learning Repository	3,200	Cardiovascular Disease	https://archive.ics.uci.edu
Diabetes Prediction Dataset	Kaggle Healthcare Repository	2,800	Diabetes Mellitus	https://www.kaggle.com
Chronic Kidney Disease Dataset	UCI Repository	2,100	Kidney Disease	https://archive.ics.uci.edu
Neurological Disorder Dataset	Kaggle Clinical Repository	2,000	Neurological Disorders	https://www.kaggle.com
Respiratory Disease Dataset	Public Healthcare Repository	2,400	Respiratory Disorders	https://physionet.org

The integrated healthcare was represented by 38 clinical variables such as blood pressure, glucose level, oxygen saturation, heart rate, body mass index (BMI), cholesterol level, the laboratory biomarkers and disease-specific diagnostic indicators. They used standardization of features and min-max normalization as means to enhance the stability of neural network training and analytical consistent.

Table 2. Overall dataset characteristics

Parameter	Description
Total records	12,500
Clinical attributes	38
Disease categories	5
Missing value handling	Mean imputation
Imbalance handling	SMOTE oversampling

Data normalization	Min-max normalization
Training ratio	80%
Testing ratio	20%

This heterogeneous healthcare dataset allowed performing a thorough analysis of the suggested quantum-assisted deep learning framework under both heterogeneous clinical prediction conditions.

3.2 Data Preprocessing

Healthcare data is usually incomplete, has noise, unnecessary features, and inconsistencies in the records. So, deep learning analysis was set up on preprocessing in order to enhance the reliability of predictions and computational efficiency. Missing clinical values were dealt with by the use of mean imputation with duplicates and inconsistent records being eliminated in the process of data cleaning. To remove abnormal physiological measurements outlier detection was done. Min-max normalization was used to normalize numerical attributes to the range of 0 to 1 in order to enhance the stability of neural network training. Encoding techniques were used to construct numerically set healthcare variables that were categorical in nature. To minimize the redundancy of computations and enhance the performance of analysis, feature selection and dimensionality reduction processes were completed. The proposed deep learning framework was then fed with the preprocessed data set.

3.3 Proposed Deep Learning Framework

The proposed framework is a combination of deep learning and quantum-inspired optimization to support intelligent clinical decisions, as shown in Fig. 1. The system architecture is comprised of five key layers and includes the clinical data acquisition, preprocessing, deep learning prediction, quantum-inspired optimization, and clinical decision support. It used a hybrid architecture of Convolutional Neural NetworkLong Short-Term Memory (CNN-LSTM) to generate spatial and temporal healthcare trends using multidimensional clinical data as shown in Fig. 2. CNN component conducted the feature extraction with three convolutional layers that have a kernel size of 3 × 3, ReLU activation functions, and max-pooling functions. The maps of features extracted were inputted to the LSTM block where they were utilized in predicting the temporal healthcare and patterns sequence. The LSTM architecture was 128 hidden units that were fitted with dropout rate of 0.4 in order to curb overfitting and increase the generalization ability. The Adam optimizer with a learning rate of 0.001, batch size of 32 and 100 training epochs were used to train models. The CNN-LSTM hybrid architecture enhanced the accuracy and performance of healthcare prediction and intelligent clinical decisions.

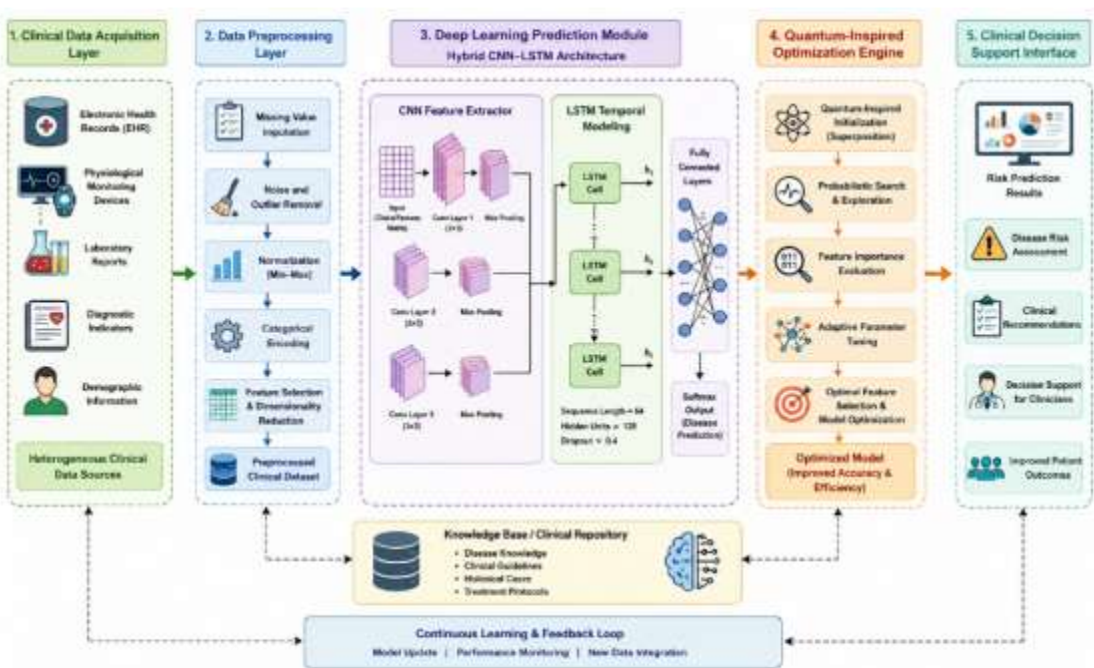

Fig. 1. Overall architecture of the proposed quantum-assisted deep learning clinical decision support framework

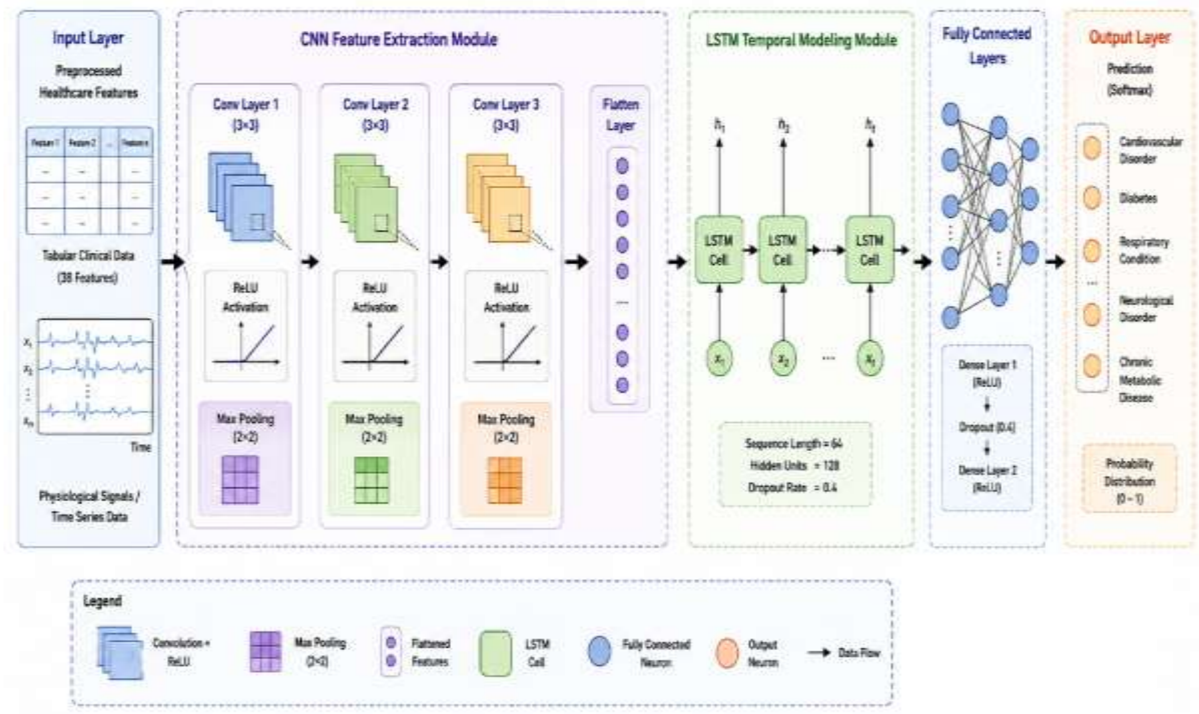

Fig. 2. Hybrid CNN-LSTM architecture for healthcare prediction

3.4 Quantum-Inspired Optimization Module

The proposed framework included a quantum-inspired optimization mechanism to enhance the efficiency of feature selection, healthcare parameter prioritization, optimization of predictions and computational performance. The optimization algorithm was created based on probabilistic search techniques and an adaptive parameter re-tuning based on quantum superposition principles and probabilistic principles of state transition. The main aim of the optimization module was to have a low prediction error and, at the same time, decrease the redundancy of computations with the larger dimensionality of healthcare datasets. The dynamically evolving optimization framework during model training assesses the importance of healthcare features and removes non-clinically relevant variables that affect an accurate prediction of diseases and smart clinical decision-making. First, all the healthcare characteristics were modeled as quantum-inspired probabilistic states. Optimal feature search space was searched by then doing adaptive probability updates iteratively. The optimization procedure was carried out in a continual evaluation of the feature subsets, based on scores of prediction fitness, which were produced by the CNN-LSTM classification model. States which contribute more to predictions got more likelihood of being selected as a feature in later optimization steps. The optimization process involved the feature initialization, probabilistic state update, fitness, adaptive optimization and optimal choice of features. The entire optimization process in the suggested structure is outlined in Algorithm 1.

Algorithm 1. Quantum-Inspired Optimization Workflow

Input: Preprocessed healthcare dataset D
Output: Optimal healthcare feature subset F_{opt}
Step 1: Initialize healthcare feature population using probabilistic quantum-inspired states.
Step 2: Generate candidate healthcare feature subsets using adaptive probabilistic sampling.
Step 3: Train the CNN-LSTM prediction model using generated feature subsets.
Step 4: Evaluate fitness score based on: prediction accuracy, classification loss, feature significance, computational efficiency.
Step 5: Update probabilistic feature states using adaptive optimization rules inspired by quantum superposition behavior.
Step 6: Select feature subsets with maximum fitness values.
Step 7: Repeat optimization until convergence criteria are satisfied.
Step 8: Return optimal healthcare feature subset F_{opt}.

The cost of the optimization problem was used to minimize the prediction error with regularization to maintain the complexity of the model. The optimization problem that is applied in this paper is given by:

$$J(\theta) = \arg\min \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 + \lambda \,||\, \theta \,||^2 \qquad (1)$$

where: $y_i$represents actual clinical outcomes, $\hat{y}_i$denotes predicted healthcare outcomes, θrepresents model parameters, $\lambda$is the regularization coefficient.

The optimization process was done on 100 iterative cycles with adaptive convergence monitoring. When the difference between prediction accuracy in the successive iterations was less than 0.001 this was converged. The optimization framework exhibited a steady convergence rate at the same time reducing redundant healthcare feature representations. The optimization framework proposed can be approximated to have a computational complexity of:

$$O(N \times F \times I) \qquad (2)$$

where: Ndenotes the number of healthcare samples, Frepresents the number of selected features, Idenotes the optimization iteration count.

Combining quantum-inspired optimization with CNN-LSTM architecture enhanced the ability of features selection, prediction, and stability as well as the computational efficiency and the intelligent healthcare analytics performance of the proposed clinical decision support framework.

4. Experimental Results and Discussion

To assess the accuracy of predictions, their robustness and computational efficiency, the proposed framework was experimentally tested with the help of various healthcare performance metrics. It was compared to traditional machine learning and deep learning models to prove the success of the offered quantum-assisted framework.

4.1 Performance Evaluation Metrics

Accuracy, precision, recall, F1-score, ROC-AUC and cross-validation stability analysis were analyzes that were used to evaluate the framework performance. The measures of accuracy, precision and recall assessed the overall predictive performance, as well as the classification reliability and sensitivity respectively. F1-score was used to give equal consideration to precision and recall whereas ROC-AUC was used to assess the discriminative predictive power. In order to assess robustness and generalization ability even further, 10-fold cross-validation, and statistical validation were conducted based on mean performance, standard deviation, confidence interval, and p-values.

4.2 Classification Performance

The proposed framework was compared to Support Vector Machine (SVM), Random Forest, CNN, and CNN-LSTM models. Table 3 shows the results of the classification performance.

Table 3. Performance comparison of different models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
SVM	88.4	87.2	86.9	87.0	0.89
Random Forest	91.3	90.8	90.1	90.4	0.92
CNN	94.2	93.8	93.1	93.4	0.95
CNN-LSTM	96.1	95.7	95.2	95.4	0.97
Proposed Framework	97.4	96.9	96.5	96.7	0.98

The classification accuracy of the proposed framework was the greatest at 97.4 capture per cent, surpassing traditional machine learning, as well as individual deep learning models. The quantum inspiration optimization bettered the efficiency of feature selection as well as prediction reliability in healthcare. Comparison of classification is shown in Fig. 3 whereas ROC-AUC analysis is shown in Fig. 4.

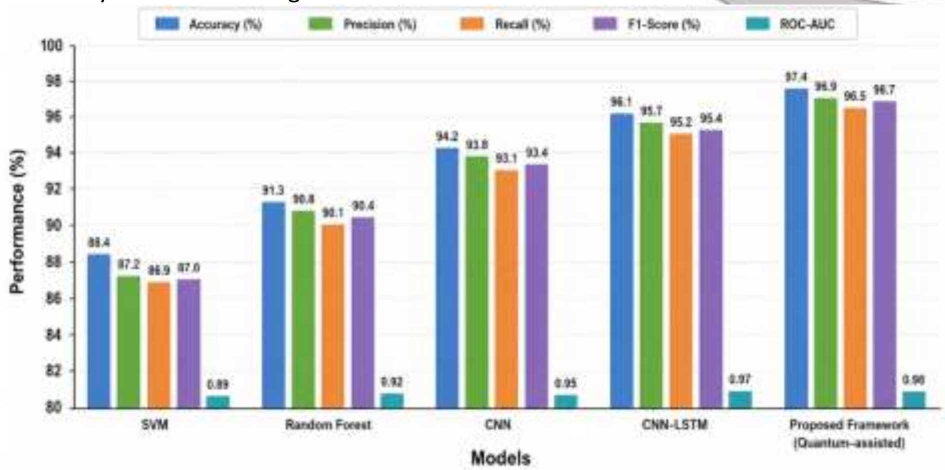

Fig. 3. Performance Comparison of Machine Learning and Deep Learning Models for Healthcare Prediction

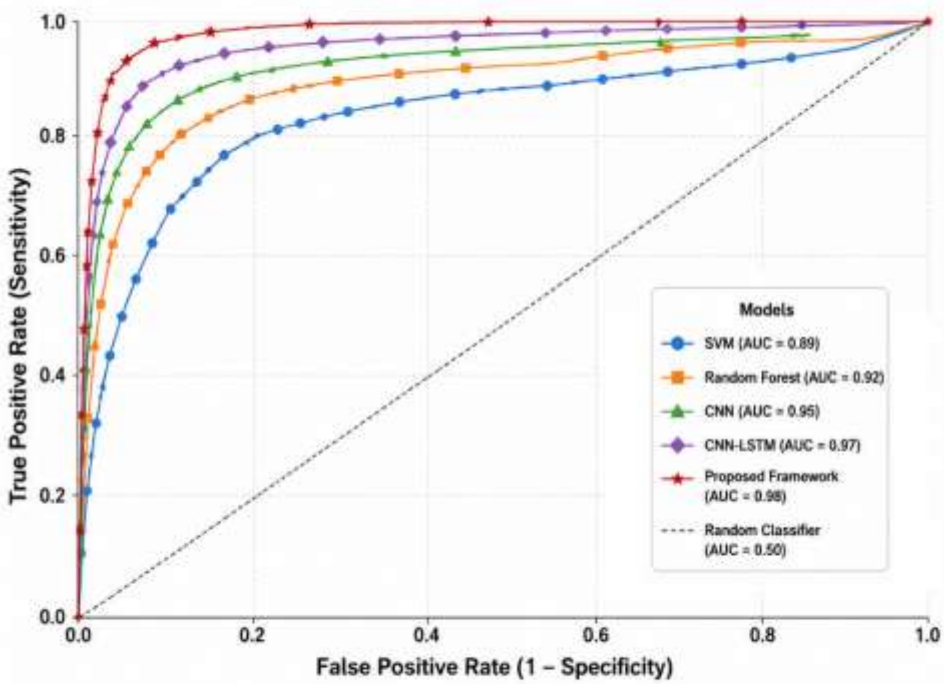

Fig. 4. ROC–AUC Analysis of the Proposed Quantum-Assisted Healthcare Prediction Framework

4.3 Cross-Validation Analysis

Cross-validation was used ten times to determine robustness and generalization ability. The proceeds and findings of the statistical validation are summarized in Table 4.

Table 4. Statistical validation results

Metric	Mean ± SD	95% Confidence Interval	p-value
Accuracy	97.4 ± 0.5	96.9–97.9	0.003
Precision	96.9 ± 0.4	96.5–97.3	0.007
Recall	96.5 ± 0.5	96.0–97.0	0.011

F1-score	96.7 ± 0.4	96.3–97.1	0.008

The values of the standard deviation are low showing that the model performance is constant throughout the different folds of validation. The analysis of confidence interval and p-value also indicates the dependability and statistical significance of the proposed framework. The analysis of cross-validation stability, training convergence is depicted in Fig. 5 and Fig. 6, respectively.

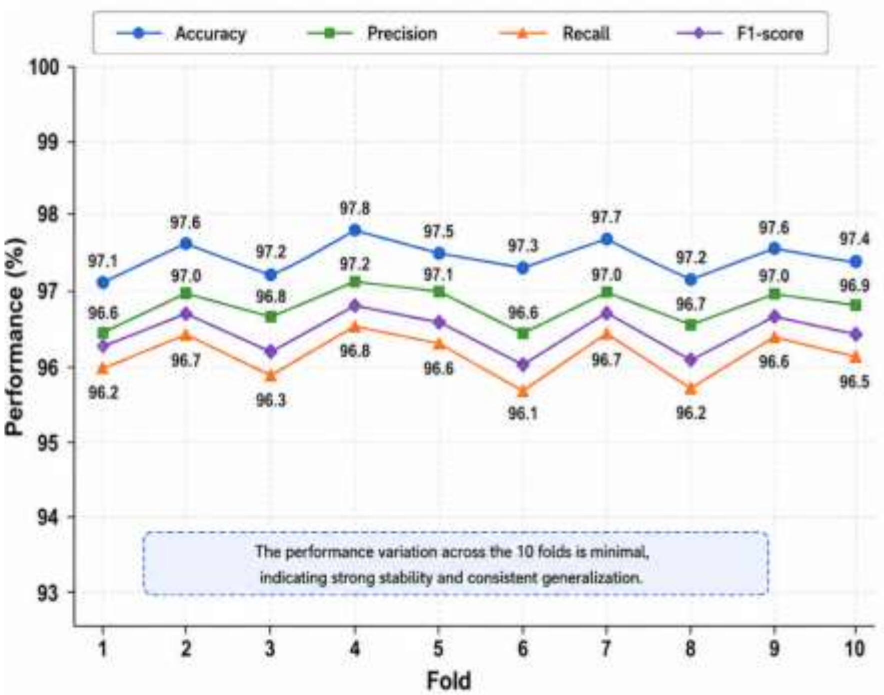

Fig. 5. Cross-Validation Stability Analysis of the Proposed Clinical Decision Support Framework

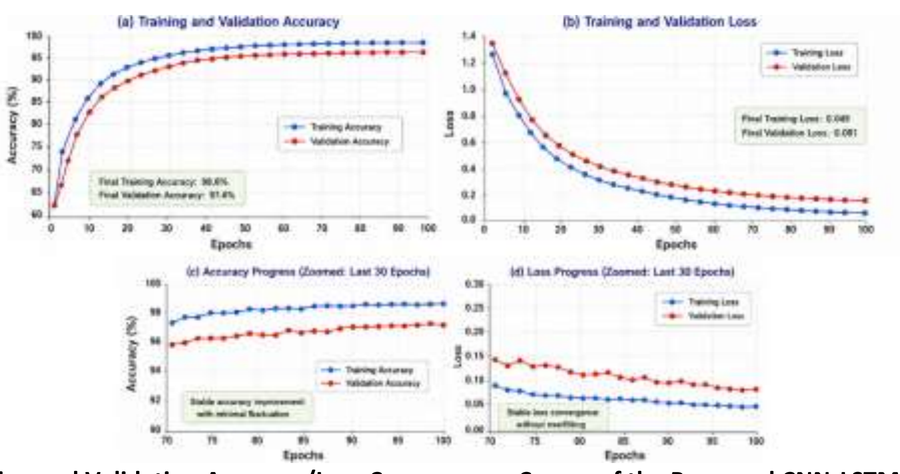

Fig. 6. Training and Validation Accuracy/Loss Convergence Curves of the Proposed CNN-LSTM Framework

4.4 Discussion

The outcomes of the experiment confirm that quantum-inspired optimization (when combined with deep learning) can greatly enhance the accuracy and efficiency of healthcare predictions. The hybrid CNN-LSTM model has performed well in extracting spatial and temporal patterns of healthcare, and the optimization provider minimized computational redundancy and enhanced performance of feature selection. The proposed framework had a better predictive power and better generalization performance than more traditional machine learning and deep learning methods. The framework has the potential to aid in the prediction of disease risks, smart diagnosis, management of healthcare resources, prioritization of treatment and prediction of patient outcomes in contemporary clinical decision support settings. The analysis of confusion matrices of the proposed framework is shown in Fig. 7.

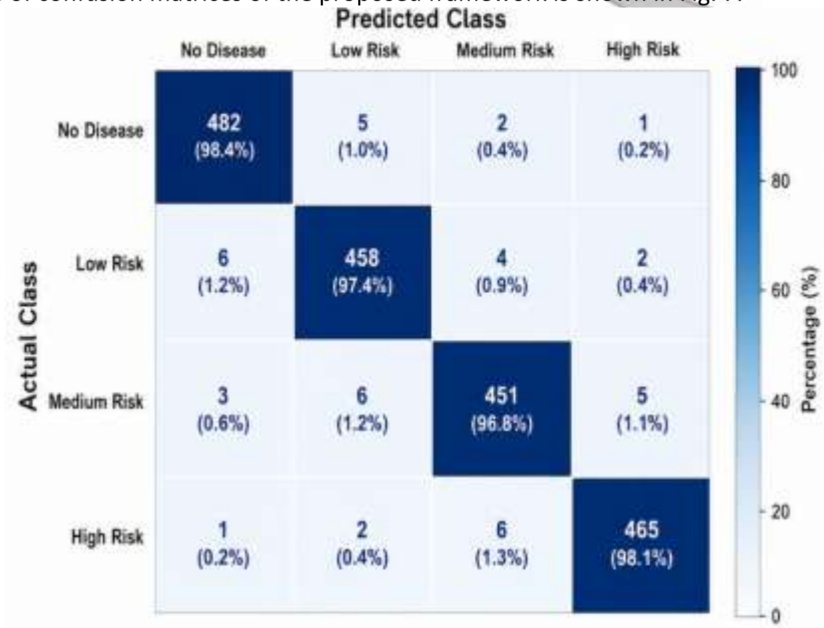

Fig. 7. Confusion Matrix Analysis of the Proposed Quantum-Assisted Clinical Decision Support Framework

5. Healthcare Implications

The suggested quantum-aided deep learning system offers a number of viable advantages on the contemporary healthcare framework enhancing the accuracy of clinical decision, efficiency of healthcare analytics and intelligent patient management. A combination of deep learning and the existing quantum-inspired optimization would allow efficient treatment of large-scale healthcare data and contribute to the reliable clinical decision support. Smart generation of clinical recommendations is one of the consequences of the suggested framework. The system can help healthcare professionals predict diseases, risk assessment of patients, and even the treatment of patients by analyzing multidimensional healthcare data. The ability underpins the data-driven and correct clinical decision-making in complicated healthcare settings. The suggested framework also helps to minimize diagnostic errors with the help of enhanced prediction accuracy and enhanced feature analysis. The quantum-inspired optimizer alongside the hybrid CNN-LSTM framework that optimizes the pattern extraction and prediction accuracy of healthcare systems can improve consistency in the diagnosis and decrease misclassification. The other significant implication is that there is enhanced use of healthcare resources. The framework would help hospitals and healthcare facilities to optimally prioritize treatment, manage patients, and workflow efficiencies. Intelligent analytics and faster healthcare data processing can also be helpful to clinicians to make quick decisions in an emergency and during critical care. Also, the system enhances the patient surveillance capacity by smartness in analyzing the physiological measures and time-based healthcare data. This aids in early disease detection, chronic disease management and telemedicine-based health care services. On the whole, the suggested framework has great perspectives of next-generation smart healthcare systems, such as hospitals, smart clinics, and scalable telemedicine settings.

6. Conclusion

This paper proposed a strategic healthcare technology management framework which combines quantum computing and deep learning to smart Clinical Decision Support Systems (CDSS). The suggested framework used a hybrid CNN-LSTM model, which is optimized using quantum-inspired optimization to enhance healthcare prediction accuracy, computational efficiency, and reliability of clinical decisions. Experimental analysis showed that performance was better than traditional machine learning and stand-alone deep learning methods in a variety of healthcare performance measures. Robustness, generalization ability and consistency of predictions were statistically validated with statistically significant p-values of less than 0.05 by 10-fold cross-validation. The combination of quantum-inspired optimization enhanced the efficiency of feature selection and minimized redundancy in computations when carrying out healthcare prediction work.The suggested framework has the power to play a major role in smart healthcare management, prediction of diseases, optimization of healthcare resources and complex clinical decision support applications within the contemporary digital healthcare settings. The framework also has a good potential to be used in hospitals, intelligent healthcare systems and telemedicine sites. Nevertheless, there are still a number of constraints. The structure employed secondary healthcare data, as opposed to real-time clinical implementation, and the quantum-inspired optimization module was simulated computationally, instead of being running on real quantum apparatus. Future research can dwell upon federated healthcare learning, explainable AI integration, wearable healthcare analytics, real-time deployment in hospitals and quantum hardware acceleration of the next-generation intelligent healthcare system.

References

1. N. Ajlouni, A. Özyavaş, M. Takaoğlu, F. Takaoğlu, and F. Ajlouni, “Medical image diagnosis based on adaptive hybrid quantum CNN,” BMC Medical Imaging, vol. 23, no. 1, p. 126, 2023.
2. S. R. Abbas, Z. Abbas, A. Zahir, and S. W. Lee, “Federated learning in smart healthcare: A comprehensive review on privacy, security, and predictive analytics with IoT integration,” Healthcare, vol. 12, p. 2587, 2024.
3. J. C. L. Chow, “Quantum computing in medicine,” Medical Sciences, vol. 12, no. 4, 2024.
4. P. Dhade and P. Shirke, “Federated learning for healthcare: A comprehensive review,” Engineering Proceedings, vol. 59, no. 1, p. 230, 2024.
5. P. S. Emani et al., “Quantum computing at the frontiers of biological sciences,” Nature Methods, vol. 18, no. 7, pp. 701–709, 2021.
6. F. F. Flöther, “The state of quantum computing applications in health and medicine,” Research Directions: Quantum Technologies, vol. 1, p. 10, 2023.
7. J. Landman, N. Mathur, Y. Y. Li, M. Strahm, S. Kazdaghli, A. Prakash, and I. Kerenidis, “Quantum methods for neural networks and application to medical image classification,” Quantum, vol. 6, p. 881, 2022.
8. Y. Li, Z. Qia, Y. Lia, H. Yanga, R. Shanga, and L. Jiaoa, “A distributed hybrid quantum convolutional neural network for medical image classification,” arXiv preprint arXiv:2501.06225, 2025.
9. M. Li, P. Xu, J. Hu, Z. Tang, and G. Yang, “From challenges and pitfalls to recommendations and opportunities: Implementing federated learning in healthcare,” Medical Image Analysis, p. 103497, 2025.
10. Marengo and V. Santamato, “Quantum algorithms and complexity in healthcare applications: A systematic review with machine learning-optimized analysis,” Frontiers in Computer Science, vol. 7, p. 1584114, 2025.
11. R. Ur Rasool, H. F. Ahmad, W. Rafique, A. Qayyum, J. Qadir, and Z. Anwar, “Quantum computing for healthcare: A review,” Future Internet, vol. 15, no. 3, p. 94, 2023.
12. T. Shahwar et al., “Automated detection of Alzheimer’s via hybrid classical quantum neural networks,” Electronics, vol. 11, no. 5, p. 721, 2022.
13. M. Singh, I. Singh, and D. Singh, “Exploring quantum machine learning for early disease detection: Perspectives, challenges, and opportunities,” in Proc. International Conference on Intelligent Human Computer Interaction, Springer, 2023, pp. 226–242.
14. Tudisco, D. Volpe, and G. Turvani, “Quantum machine learning in healthcare: Evaluating QNN and QSVM models,” arXiv preprint arXiv:2505.20804, 2025.
15. U. Ullah and B. Garcia-Zapirain, “Quantum machine learning revolution in healthcare: A systematic review of emerging perspectives and applications,” IEEE Access, vol. 12, pp. 11423–11450, 2024.
16. Jenber Belay, Y. M. Walle, M. B. Haile, et al., “Deep ensemble learning and quantum machine learning approach for Alzheimer’s disease detection,” Scientific Reports, vol. 14, no. 1, p. 14196, 2024.
17. Deepika J, “Hardware–Algorithm Co-Design of Adaptive LMS/NLMS Signal Processing Pipelines for Power-Constrained Embedded Systems”, National Journal of Integrated VLSI and Signal Intelligence, vol. 1, no. 1, pp. 26–33, Dec. 2025, Accessed: Jul. 06, 2026.
18. Surendar, “AI-Optimized Reconfigurable Antenna Arrays for Energy-Efficient 6G Wireless Communication Systems”, Journal of Antennas and Wireless Communication Systems, vol. 1, no. 1, pp. 1–9, Dec. 2025.
19. K.Madhan, “Chaotic Regime Identification in Coupled Thermo-Fluid Oscillators Under Variable Boundary Forcing”, Applied Nonlinearity in Science and Technology, pp. 6–12, Nov. 2025, Accessed: Jul. 06, 2026.