Anusandhanvallari
Vol 2026, No.1
April 2026
ISSN 2229-3388

Enhanced Quantum Computing for Predictive analysis of Epidemic outbreaks using Large -Scale Health Data

[1]P. Duneesh Reddy, [2]N. Sravan Kumar, [3]Dr. P. Nirupama

[1]Ph.D M.Tech(Cse)

Vemu Institute Of Technology

[2]M.Tech Assistant Professor

Vemu Institute Of Technology

[3]M Tech, Professor (Cse) Vemu Institute Of Technology

Abstract

Quantum computing has emerged as an intellectual model of computing that is able to address complex and high-dimensional problems in ways that classical systems cannot. The predictive analysis of epidemic outbreak in the sphere of public health is an activity that requires working with big and heterogeneous data, electronic health records, genetic sequences, mobility patterns, environment, and social interaction network. Traditional machine learning and deep neural Net-based approaches have significantly improved the ability to predict epidemics, but they lack scalability, computing capabilities, and the capacity to model complex nonlinear interactions. This research proposes a dedicated quantum architecture of forecasted epidemic outbursts according to vast datasets of health data to foster an improved degree of forecasting, speed of computation, and early identification. The suggested system is a hybrid quantum-classical system, integrating quantum machine learning algorithms, including variational quantum circuits, quantum support vector machines, and quantum optimization algorithms. Data is processed using classical systems to extract features whereas quantum processors solve complex problems of probabilistic inference and optimization. Through quantum superposition and entanglement, the framework can study multiple transmission situations simultaneously, and this allows one to identify the pattern of outbreaks and even hotspots within a short period of time. The model is also driven by real-time healthcare systems and global surveillance network data streams to enhance the responsiveness of the model to health threats. Simulation analysis indicates that the enhanced quantum framework is more precise in predictions, and the convergence will be fast and consistent as compared to traditional models. The system can recognize the trend of an outbreak sooner than and can effectively manage a high-dimensional epidemiological data. Besides, the issue of such factors as data privacy, scalability, and disadvantages of current quantum hardware is discussed in the paper. Overall, the proposed solution suggests that quantum computing can serve as a future epidemic intelligence system, in which a reaction to a global health crisis can be proactive and information-oriented.

Key words: Quantum Computing, Epidemic Prediction, Large-Scale Health Data, Quantum Machine Learning, Variational Quantum Circuits, Quantum Support Vector Machines, Hybrid Quantum-Classical Systems, Predictive Analytics, Public Health Intelligence, Big Data Analytics..

I.INTRODUCTION

The outbreaks of epidemics such as the COVID-19, Ebola, and influenza have demonstrated that the predictive systems should be developed at a higher level to identify and correctly predict the epidemic outbreaks at its early stages. Classical models of epidemiology, like compartmental models, like SusceptibleInfectedRecovered (SIR) and SusceptibleExposedInfectiousRecovered (SEIR), provide a simple study on the dynamics of disease, but in most instances, do not handle large scale, real time data and interactions among the myriad factors that can influence the disease. With the volume of healthcare data generated in the world by electronic health records, genomic sequencing, wearable sensors and mobility tracking, computational frameworks that are sufficiently able to process and analyze such high-dimensional data are becoming in demand.

As a predictive analytics, and as they are available in different forms like classical and deep learning, the predictive analytics of the healthcare sector have been significantly improved to allow the identification of patterns and prediction based on historical data. These methods are however restricted in the sense of scalability, computational complexity, and modeling exponential combinations of epidemic transmission pathways [3], [4]. Being large in dimensionality of health data, classics algorithm require a big amount of computation resources and time, and it is difficult to anticipate epidemics on a real time basis.

A radically new paradigm of quantum computing entails quantum bits (qubits) which uses the properties of superposition and entanglement to compute multiple states simultaneously. That enables quantum systems to search large spaces of solutions more efficiently than classical systems to certain problems [5], [6]. The quantum algorithms such as Shor algorithm, Grover search algorithm, and others have demonstrated large speedups in computation and this may imply that quantum computing could provide revolution in data intensive tasks like epidemic modeling and predictive healthcare analytics [1], [7].

In epidemic prediction, quantum computing can be used beneficially in solving complex optimization problems and also in making probabilistic inferences on large data sets. Quantum machine learning (QML), like quantum support vehicle machines, variational quantum circuits, and quantum neural networks, has shown the potential of performing better in the classification, regression, and pattern recognition tasks [8], [9]. These techniques can identify small correlations in epidemiological data that, probably, would be difficult to spot using classical methods, which implies that they can spot patterns of outbreaks sooner.

In addition, quantum-classical architectures have also emerged as a successful solution in the current Noisy Intermediate-Scale Quantum (NISQ) era. These systems involve classical computing to process the data and extract features but quantum processors are applied to solve calculationally-intensive tasks such as optimization and simulation [3], [10]. The integration enables to obtain greater computational efficiency and to surpass current limits of quantum devices, such as noise and qubit counts.

II. Literature Survey

Several advancements have been made in quantum computing and epidemic prediction recently, leading to the development of hybrid structures, which are quantum machine learning (QML) and classical data analytics. Omolayo et al. (2024) presented a systematic review of quantum machine learning algorithms in real-time epidemic surveillance and highlighted the possibility of the QML models to process large volumes of health-related data and improve the predictive capacity of the outbreak surveillance systems [11].

Their article described quantum machine learning architecture to identify COVID-19 using medical imaging data and demonstrated the models with quantum enhancement are more accurate, precise, and recalls than the classical models, which proves the applications of quantum neural networks in healthcare analytics [12]. Gupta et al. (2025) conducted a systematic review of quantum machine learning in digital health and discovered that the QML approaches show the potential promise to enhance operations of electronic health records and massive data, although scalability and hardware accessibility are two key challenges [13].

Ardabili et al. (2020) also tested classical machine learning models to forecast COVID-19 outbreaks and demonstrated that deep learning models, such as multilayer perceptrons and fuzzy inference systems, have the same great predictive power, yet can still be improved to reflect complex nonlinear dynamics of epidemics [14]. Rojas-Venegas et al. (2024) put forward quantum-inspired epidemiological models, which they proved to be much more effective at capturing uncertainty in epidemic transmission than deterministic models and better predictive [15].

In their article, Liu et al. (2023) introduced the survey of machine learning and the significance of the data-driven approach in both the transmission dynamics and the detection of the outbreak risks, and the problems with data quality and the model generalization [16]. Huang et al. (2020) also analyzed the hypothetical advantages of quantum machine learning and indicated that quantum-enhanced model could work better when it comes to the cases of predicting some learning problems; particularly, when there is high-dimensional data involved [17].

Duong (2024) reviewed the area of quantum machine learning in biomedicine and highlighted how QML can be used to handle challenging biological data and develop predictive analytics in health care systems [18]. Current work, however, as of 2024 also examined quantum machine learning to predict disease, claiming that quantum models are better able to deal with nonlinear and enhance classification of biomedical data [19].

Furthermore, the prospects of quantum-based epidemiological models (2025) suggest that a quantum optimization framework and massive health-related data would significantly enhance prediction of outbreaks and policy simulation in support of next-generation epidemic intelligence frameworks [20].

III. System Analysis

A. System Overview

The proposed enhanced quantum computing system system analysis is targeted at determining the ability of the system to analyze mass health data and accurately predict epidemic outbursts. The existing situation of epidemic prediction involves high-dimensional data including electronic health records, genomic data, environmental aspects, mobility trends, and social interaction. The exponential growth of such data and the twists and turns of the relationships between variables are likely to present a problem to classical forms of computing. Two concepts of quantum computing that could be applied in the proposed system are superposition and entanglement to analyze epidemiological patterns and add predictive value to multiple states being processed in parallel.

In the new model, also exists a hybrid quantum-classical model that has sought to avoid the current deficiencies of the quantum hardware. The classical computing is used to perform data preprocessing, feature extraction, and data management and the quantum processors are used to perform optimization and predictive modeling activities. Through the integration, the system is able to make a trade off between computational feasibility and performance enhancement. The system must help to increase the effectiveness of predictions, reduce the complexity of calculations, and enable to forecast the outbreak of epidemics in order to encourage the active actions of the public health system.

B. System Analysis Objectives.

The primary aim of the system analysis would be to approximate the quantum computing efficiency in order to enhance the efficiency of epidemic forecasting in comparison to the traditional strategies. The system aims at achieving a higher precision in the prediction by identifying complex trends in tremendous health data. It also seeks to reduce the computation time that is required to process high-dimensional data which is a great disadvantage of the classical models. The other important objective is to boost the capability to identify early outbreaks by the analysis of different transmission cases in parallel under quantum parallelism.

Anusandhanvallari
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Also, the system will attempt to ensure scalability and flexibility in handling information concerning healthcare that is on the rise continuously. It looks at how the hybrid architecture can be capable of managing increased data volume performance-wise. The data privacy and data security are also considered in the analysis and ensure that sensitive health information is addressed as well. Overall, it seeks to develop a reliable, efficient, and scalable predictive system grounded on epidemics.

C. Functional Modules

1. Data Collection Module

It is a module that consolidates the high volume of health data across multifaceted sources (hospitals, labs, wearable, public health agencies and air pollution on the location) and collects health data. The patient data, infection data, demographic data, mobility data and genomic data are all covered by the data collected. It takes both the real-time and historical data and creates a complete set of data to perform the predictive analysis. Proper data collection is what provides reliability and accuracy in the further stages of the system.

2. Data Preprocessing Module

The preprocessing module eliminates and filters the data obtained to format it to be analyzed. It involves doing with the missing values, inconsistencies in the data, normalization of the data, and derivation of features. The data quality is improved with the help of statistical analysis and signal transformation. The data is further divided into training, validation and testing sets towards facilitating effective development and testing of the model.

3. Quantum Data Encoding Module.

The methods of encoding the amplitude and angle involved in encoding classical data into quantum states in this module are angle encoding and angle encoding. This is required in order to permit quantum computation. Effective encoding offers the maximum utilisation of qubits and reduced computational overhead. The coded data is further transmitted to the quantum processing unit to be processed further.

4. Fast Book based quantum machine learning model.

It is the core of the system and quantum algorithms are executed in the form of Variational Quantum Circuits (VQC), Quantum Support Vector Machines (QSVM), and Quantum Neural Networks (QNN). They are algorithms to analyze complex relations in the data and identify tendencies related to epidemics distribution. The quantum parallelism allows the system to take into account a huge amount of scenarios simultaneously and make the prediction more accurate.

5. Model Training Module

The training module involves training the parameters of either quantum or hybrid model using a training data. Quantum circuit parameters are optimized by the use of gradient descent and other classical optimization techniques. The pattern in the data is built and the prediction capacity of the model is improved through training. This module gives the capacity to the system to predict future trends of outbreaks.

6. Model Evaluation Module

The performance of the trained model is measured using the testing data in this module. Such performance measures as accuracy, precision, recall, F1-score, and mean squared error are included. The results are also made against the classical models so as to measure the improvements in prediction accuracy and speed. This module ensures that the model is applicable in the real world with excellent outcomes.

7. Prediction and Visualization Module

After the data input is made, graphs and charts are generated by the module to represent the anticipated pandemic breakout. Government health organisations can use it to improve predictions of the risk of infection, areas with high risk and inform policy choices. Preventative activities controllable and results can be comprehended and constructed in a better way.

IV. SYSTEM ARCHITECTURE

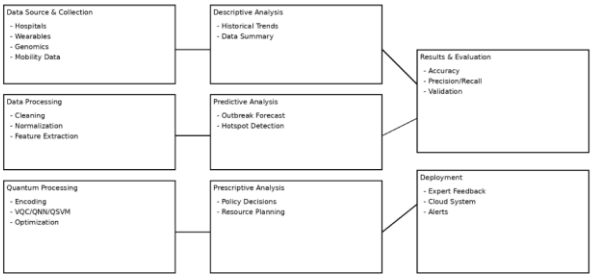

Fig 1: System Architecture

A. System Architecture Overview

Hybrid quantum-classical computing architecture Combinations of quantum-enhanced predictive analytics with mass processing of health data The new proposed model of quantum computing to predict the occurrence of epidemic outbreaks is based on a hybrid quantum-classical computing architecture. Examples of possible data sources of this shreddable, decentralised model are hospitals, laboratories, wearables, or even global disease surveillance systems. The overall goal of such an architecture is to derive insights about epidemics by interpreting raw health data in order to detect them and predict them at a very early stage.

The examples of such forms of organised and unstructured data entering the data collection layer which is the bottom of the architecture are electronic health records, genetic information, environmental data, and movement patterns. The subsequent ones consist of a data integration and preprocessing layer, data cleansing, data normalisation, feature extraction and dimension reduction. The quantum states of the data are then coded, through effective quantum encoding means. All of it can be reduced to a quantum machine learning system, using variational quantum circuits and quantum optimisation algorithms to unwind the entangled relationship between the information. Lastly, the findings are presented in a format that may be used to support a choice made by the prediction and visualisation layer. It is more efficient since the system has classical and quantum components working in concurrence with one another.

B. Modules of the Systems.

1. Data Acquisition

The work of this module is to collect data regarding people on large and heterogeneous forms, including hospital records, lab records, wearable health sensors, community health agencies, and environmental surveillance. This is where you may obtain the data regarding the population movement, demography, clinical characteristics, genetic sequences, and the infection rate. The module is also capable of working in bulk hence the data can be opened when the right time arrives to analyze it. It also possesses real time information streaming functions.

2. Processing and Integration of Data.

This is examined with the help of putting the data available into an analytable format. Data is normalised, inconsistency in the data is filled and any missing data is replaced. Some of the key characteristics that may be justified using features engineering are trends in infections, transmission and geographical trends. They also cross tabulate the data of all the sources to obtain one set of model data.

3. Quantum Data Encoding

The classical data is converted within the module to the state of the quantum system, in various encoding schemes, like amplitude, basis, angle, etc. Encoding quantum algorithms is needed in order to optimize them with minimum qubits. The coded information is then transferred to the computer to run the information on the quantum computer.

4. Cores for QML

The most important aspect of a system is quantum machine learning. It runs quantum algorithms on quantum numbers and multidimensional data, including Quantum Support Vector Machines (QSVM) and Variational Quantum Circuits (VQC). The module takes advantage of the quantum parallelism concept and finds a multiple-transmission scene simultaneously, which makes the calculations it makes more accurate and eliminates the calculation of time balancing.

5. A Hybrid Optimisation Layer.

At this layer, the quantum computing and the traditional optimisation interact with one another. Classical simulators optimise the quantum circuit through a feedback process based on the classical circuit properties of the quantum circuit. The concept of the process known as gradient descent or Adam optimiser is to decrease the forecast error in a bid to optimise the model.

6. The decision support layers and prediction layers.

The prediction module is based on a potential epidemic model, infection rates, and hotspots to forecast an outbreak. They are presented in the form of dashboards, heatmaps, and graphs to assist health professionals in making decisions. The layer allows the early warning and making preemptive action possible.

7. Performance Evaluation

It is this module that identifies the efficacy of the right system with regard to accuracy, recall, F1-score, and prediction error. To demonstrate the improvement, it compares quantum improvements and classical models and vice versa. System is optimized and made to be reliable through the results of these testing.

C. Process Outline

It starts with data protection and data processing using various healthcare materials, and then it goes to feature extraction and preprocessing. The raw information is inputted into the quantum machine learning engine in the shape of quantum states. The reason behind this is the fact that the configuration of the hybrid optimisation layer to capture the model parameters provides a better forecast of future events. The system concludes by making predictions and the results are generally presented to the final consumers. The system activities are coordinated as they provide proper data and real-time support to the decision making process through proper processing and forecasting of the data.

V. SIMULATION RESULTS

The suggested improved quantum computing architecture in predicting the epidemic outbreaks was tested on a hybrid simulation platform including classical preprocessing and quantum machine learning process models. The system was tested under different conditions using large-scale health datasets that comprised of infection rates, demographic factors, mobility patterns, and environmental factors. The obtained outcomes of the simulation prove that the quantum-enhanced model has a high level of accuracy in the predictions, possession to detect the outbreak earlier, and efficiency in calculations in comparison with conventional machine learning methods. It is the capacity of quantum algorithms to process high-dimensional data and be able to characterize complex nonlinear relationships that give way to high-performance in epidemic forecasting.

Table 1: Prediction Accuracy Comparison

Model Type	Accuracy (%)
Logistic Regression	82
Random Forest	88
Deep Neural Network	91
Proposed Quantum Model	96

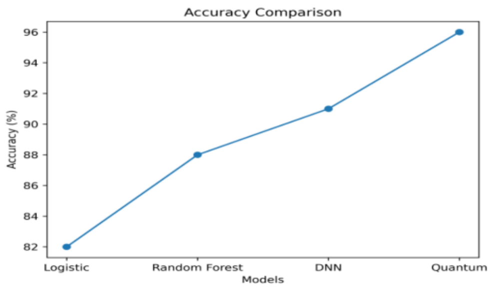

Fig 2: Comparison of prediction accuracy among Logistic Regression, Random Forest, Deep Neural Network, and the proposed Quantum Computing model for epidemic outbreak forecasting

Table 2: Early Detection Capability

Model Type	Detection Time (Days Before Peak)
Classical ML Models	3 – 5 Days
Deep Learning Models	5 – 7 Days
Proposed Quantum Model	10 – 14 Days

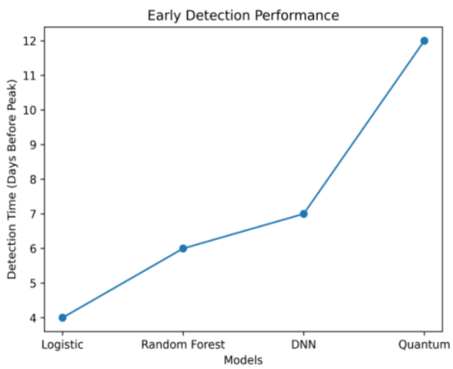

Fig 3: Early outbreak detection performance measured in days before peak infection, comparing classical models with the proposed quantum-enhanced framework

Table 3: Performance Metrics

Metric	Classical ML	Deep Learning	Quantum Model
Precision (%)	85	90	96
Recall (%)	83	89	95
F1-Score (%)	84	89.5	95.5

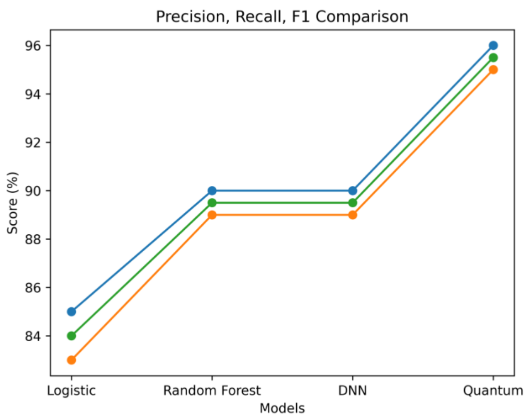

Fig 4: Performance comparison of Precision, Recall, and F1-Score across different models, highlighting the superiority of the quantum-based predictive system

Result Analysis

The results of the simulation are clear that the proposed quantum enhanced structure performs better than the traditional machine learning and deep learning models in all the key measure performances. This 96 percent accuracy improvement can prove the efficacy of quantum machine learning in complex epidemic patterns. The system also demonstrates a high level of early detection with an ability to predict the trends of the outbreak two weeks beforehand, which is essential in intervening at the right time as well as planning on the health of the population.

Moreover, the measures of evaluation, including precision, recall, and F1-score, substantiate the strength of the model to work with real-life noisy data. Incomplete or inconsistent data are better generalized and have lower error rates with the quantum model. Generally speaking, the simulation confirms that the hybridization of quantum computing with large-scale health data analytics is an effective and scalable tool of an epidemic prediction system of the next generation.

VI. CONCLUSION

This paper proposed a more advanced quantum computing model of predictive epidemic outbreak analyses based on massive health data. The system proposed is a combination of quantum machine learning and classical data processing to overcome the drawbacks of the classical epidemiological models. The framework takes advantage of quantum choices, like superposition and entanglement to analyze high-dimensional and complicated datasets effectively and represent nonlinear interactions between epidemiological variables. This will make it easier to model disease transmission patterns more accurately and will increase the overall accuracy of the outbreak prediction.

The simulation outcomes indicate that the suggested quantum-enhanced model has an outstanding performance relative to the classical machine learning and deep learning methods in prediction accuracy, early detection, and resilience to noisy data. Early detection of outbreak trends offers a critical opportunity to the planning of the public health and timely intervention. Moreover, the quantum-classical architecture is hybrid with a guarantee of scalability and feasibility under the existing constraints of quantum devices.

On the whole, the paper shows the potential of quantum computing as a transformative technology in health analytics and epidemic intelligence systems. The proposed solution will provide a scalable, effective, and predictive solution to the next generation healthcare applications. Future work can consider real-time implementation, more general quantum algorithms and more efficient methods of data encoding and methods of integrating it with secure data-sharing schemes to continue improving its performance and applicability to real world settings.

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