International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

Assessing the Impact of Quantum Optimization Algorithms on the Performance of Deep Learning Models for Dengue Fever Detection

Dr. Kiran Kumar M N[1], **Dr. Hiren Dand**[2]

[1,]Head of the Department-Bachelorof Computer Applications,
BMS College of Commerce and Management,Bengalore-560004.
[,2] Department of Computer Applications
Shri Jagdishprasad Jhabarmal Tibrewala University, Vidyanagari, Jhunjhunu, Rajasthan, India

Abstract - Dengue fever remains a major public health burden, and deep learning models are increasingly used for its early detection. Training and tuning such models, however, is computationally expensive. This study assesses whether quantum optimization algorithms, namely quantum annealing and the Quantum Approximate Optimization Algorithm (QAOA), can improve hyperparameter optimization of convolutional (CNN) and recurrent (RNN) neural networks for dengue detection from clinical data. Quantum-assisted tuning is compared with classical grid search and random search in terms of accuracy, precision, recall, F1-score, training time, convergence steps and generalization. The quantum-optimized CNN and RNN reached accuracies of 91.2% and 90.1%, respectively, which is 2.8 percentage points above the strongest classical baseline (grid search). Training time was roughly halved relative to grid search, and the number of optimization steps fell by a factor of about three. Train–test accuracy gaps stayed below one percentage point. These gains are modest, were obtained on a single public dataset, and depend on the maturity of current quantum hardware; the findings therefore indicate promise rather than clinical readiness.

Keywords: ***quantum optimization; QAOA; quantum annealing; deep learning; hyperparameter optimization; dengue fever detection***

1. INTRODUCTION

Dengue fever, a viral illness transmitted by mosquitoes, is a significant public health concern in many tropical and subtropical regions, and its global incidence has risen markedly over recent decades [1, 2]. Early detection and accurate diagnosis are essential for effective case management and for limiting outbreaks. Traditional diagnostic methods rely on clinical symptoms, laboratory tests and manual interventions, which can be time-consuming, costly and prone to human error. Machine learning (ML) and deep learning (DL) have therefore gained momentum in the medical field, offering the prospect of rapid and reliable dengue detection [3].

Deep learning models, which exploit large datasets and complex neural network architectures, can analyze diverse inputs such as medical images, clinical data and environmental factors. Training them, however, is computationally intensive, and optimizing their performance remains challenging when datasets are high-dimensional and feature spaces are complex.

Quantum computing harnesses the principles of quantum mechanics and has attracted interest as a route to accelerating optimization tasks in machine learning [4, 5]. Quantum optimization algorithms such as quantum annealing and QAOA may improve the efficiency of training and tuning deep learning models by exploring complex search spaces differently from classical methods. Reviews of quantum machine learning in healthcare note, however, that most reported applications rely on simulators and simplified datasets, and that evidence of practical advantage remains limited [6, 7].

This study assesses the impact of quantum optimization algorithms on the performance of deep learning models used for dengue fever detection. It examines whether quantum-assisted hyperparameter optimization can improve accuracy, training efficiency and generalization relative to classical search strategies, with particular relevance to resource-constrained settings where timely and accurate detection is critical.

1.1 The Global Impact of Dengue Fever

Dengue is transmitted primarily by *Aedes aegypti* and *Aedes albopictus* mosquitoes. It is characterized by high fever, severe headache, retro-orbital pain, muscle and joint pain and rash, and in some cases by haemorrhagic manifestations that can be fatal.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

The disease is endemic in more than 100 countries across Southeast Asia, Latin America, Africa and elsewhere, and the World Health Organization (WHO) estimates that roughly half of the world's population, about 3.9 billion people, live in areas at risk of transmission [1, 2]. Urbanization, climate change and the proliferation of mosquito breeding sites have contributed to the rising incidence.

Accurate and timely detection is crucial for treatment and containment. Serological tests and polymerase chain reaction (PCR) assays are reliable but can be slow and costly, and they require trained personnel and specialized equipment that may be unavailable where dengue is most prevalent. Researchers have therefore turned to artificial intelligence, using patient symptoms, clinical laboratory values, medical history, environmental factors and vector-monitoring data to improve the speed and accuracy of diagnosis.

1.2 Deep Learning Models in Disease Detection

Deep learning models based on neural networks have transformed many areas of healthcare by automating disease detection from images, patient records and epidemiological data [3]. They can identify complex patterns in large datasets that may be missed by human experts. For dengue, they can analyze structured and unstructured data to identify risk factors, predict outbreaks and support early diagnosis.

The convolutional neural network (CNN) is among the most widely used architectures for medical diagnosis, excelling at image classification and, with one-dimensional convolutions, at extracting local patterns from structured feature vectors [3]. The recurrent neural network (RNN), particularly its long short-term memory (LSTM) variant [11], is designed for sequential data and can be used to predict outbreaks from time-series data such as historical case counts, weather patterns and mosquito population dynamics.

Several challenges remain. Training requires large amounts of labelled data, which are often difficult to obtain for specific clinical settings. Selecting an architecture and tuning hyperparameters such as the number of layers, learning rate and activation functions is time-consuming and computationally expensive. These challenges motivate more efficient optimization techniques that reduce the time and resources needed to train and tune deep learning models.

1.3 Quantum Optimization Algorithms and Their Potential

Quantum computers use quantum bits (qubits), which, unlike classical bits, can exist in superpositions of 0 and 1. Quantum algorithms exploit superposition, entanglement and interference to amplify the probability of correct answers. This does not mean that all candidate solutions are evaluated in parallel and read out at once, and provable speedups are known only for specific problem classes [4, 5].

Quantum optimization algorithms address problems in which the goal is to find the best solution among a very large set of candidates. Well-known examples include the following:

- **Quantum Approximate Optimization Algorithm (QAOA):** a hybrid quantum–classical algorithm that finds approximate solutions to combinatorial optimization problems [8]. Hyperparameter selection for deep learning models can be cast as such a problem.
- **Quantum annealing:** a method related to simulated annealing that seeks the minimum-energy state of a system [9]. It has been explored for machine learning model tuning and image recognition tasks.
- **Grover's search algorithm:** an algorithm that searches an unsorted database with a quadratic speedup over classical search [10]. Although not an optimization method in itself, it can accelerate the search stage of optimization problems.

Because of their potential to explore large search spaces efficiently, these algorithms are attractive candidates for optimizing deep learning models, with possible benefits for training time, resource use and the exploration of better model configurations. Current devices are noisy and of limited scale, the so-called NISQ era [4], and this constrains what can be achieved in practice.

1.4 Quantum Optimization and Deep Learning for Dengue Detection

Combining quantum optimization with deep learning may improve dengue detection systems. Hyperparameter tuning, weight initialization and architecture selection are all optimization problems to which quantum methods can in principle be applied, potentially yielding faster convergence, better generalization and higher accuracy. Quantum optimization may also be applied to feature selection, which improves model efficiency and reduces overfitting. Dengue data are frequently noisy and incomplete, and better-optimized models may be more robust to such variability. If speed improvements can be sustained, they could support near-real-time prediction and help public health authorities respond to emerging outbreaks.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

2. RESEARCH METHODOLOGY

2.1 Research Design

An experimental, comparative design is used to assess how quantum optimization influences deep learning models for dengue detection from medical data. A CNN and an RNN are each tuned with (i) classical hyperparameter search (grid search and random search [12]) and (ii) quantum-assisted optimization (quantum annealing and QAOA). The resulting models are compared in terms of accuracy, speed, convergence and generalization.

2.2 Data Collection and Pre-processing

The dataset consists of medical diagnostic data relevant to dengue fever, obtained from a publicly available repository (the Dengue Fever Dataset on Kaggle). The main steps are:

- **Pre-processing:** cleaning, normalizing and handling missing values.
- **Feature selection:** identifying key clinical indicators of dengue, such as body temperature, platelet count and white blood cell count.
- **Data splitting:** division into training (70%), validation (15%) and test (15%) sets.

2.3 Model Selection

Two deep learning architectures are considered: a convolutional neural network (CNN) and a recurrent neural network (RNN) of the LSTM type [11]. Model weights are trained with standard gradient-based optimizers, namely stochastic gradient descent (SGD) and Adam [13]. The comparison of interest concerns how the hyperparameters, model configuration and weight initialization are selected, as described below.

2.4 Optimization Algorithms

Classical baselines. Grid search exhaustively evaluates a predefined grid of hyperparameter combinations, whereas random search samples configurations at random from the same space [12].

Quantum-assisted optimization. Hyperparameter selection is formulated as a combinatorial optimization problem and solved with quantum annealing [9] and QAOA [8]. Hybrid variational quantum–classical routines, in which a parameterized quantum circuit is evaluated on a quantum backend while a classical optimizer updates its parameters, complement these methods. The quantum components are implemented with a quantum computing framework such as IBM Qiskit [14] or Google Cirq.

2.5 Evaluation Metrics

Models are evaluated on accuracy, precision, recall and F1-score; on training time and number of optimization steps to convergence; and on generalization, expressed as the ratio of the accuracy reported in Table 1 to test accuracy (values close to 1 indicate a small gap).

3. Results and Discussion

Quantum optimization methods are applied to hyperparameter tuning, model selection and weight initialization in a CNN and an RNN for dengue detection, and compared with the classical grid search and random search baselines. Results are presented in Tables 1–5 and discussed below. Percentage-point differences are denoted “pp”.

Table 1: Accuracy of classical versus quantum optimization

Model	Classical (Grid Search)	Classical (Random Search)	Quantum Optimization	Improvement vs. Grid Search
CNN (Dengue Detection)	88.4%	85.7%	91.2%	+2.8 pp
RNN (Dengue Detection)	87.3%	84.1%	90.1%	+2.8 pp

As shown in Table 1, quantum-assisted hyperparameter tuning (quantum annealing and QAOA) produced higher accuracy than both classical approaches for both architectures. The quantum-optimized CNN reached 91.2%, 2.8 pp above grid search and 5.5 pp above random search. The quantum-optimized RNN reached 90.1%, 2.8 pp above grid search and 6.0 pp above random search. A plausible

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

explanation is that quantum optimization explores the high-dimensional hyperparameter space more effectively and so finds better configurations, but this study does not isolate that mechanism.

Table 2: Training time of classical versus quantum optimization (minutes)

Model	Classical (Grid Search)	Classical (Random Search)	Quantum Optimization	Speedup of Quantum Optimization
CNN (Training Time)	120	90	60	2.0× vs. grid; 1.5× vs. random
RNN (Training Time)	110	85	55	2.0× vs. grid; 1.5× vs. random

Table 2 shows a reduction in training time with quantum optimization: about half that of grid search and about two-thirds that of random search for both models. The speedup may reflect faster convergence of the search procedure, as Table 4 suggests. It should not be read as evidence of generic quantum "parallelism", since the advantage of quantum search depends on the algorithm and problem structure [4, 5].

Table 3: Precision, recall and F1-score for dengue detection

Model	Precision (Grid Search)	Precision (Random Search)	Precision (Quantum)	Recall (Quantum)	F1-Score (Quantum)
CNN (Dengue Detection)	0.89	0.86	0.92	0.89	0.90
RNN (Dengue Detection)	0.87	0.84	0.91	0.88	0.89

Table 3 reports precision for each tuning method together with recall and F1-score for the quantum-optimized models. Precision for the CNN rose from 0.89 (grid search) to 0.92, and for the RNN from 0.87 to 0.91. The quantum-optimized CNN achieved a recall of 0.89 and an F1-score of 0.90, and the RNN a recall of 0.88 and an F1-score of 0.89. Recall and F1-score for the classical baselines are not reported, so the effect on the balance between precision and recall, which matters in medical settings where both false negatives and false positives carry costs, cannot be assessed here.

Table 4: Convergence efficiency (optimization steps to convergence)

Model	Quantum Annealing Steps	QAOA Steps	Classical (Grid Search)	Classical (Random Search)	Step Reduction (Annealing vs. Grid)
CNN	300	200	1000	800	3.3×
RNN	280	180	950	780	3.4×

As Table 4 shows, quantum annealing needed 300 steps (CNN) and 280 steps (RNN) to converge, compared with 1000 and 950 steps for grid search and 800 and 780 for random search. QAOA required fewer steps still (200 and 180). Quantum optimization therefore reached convergence in roughly one-third of the steps of grid search. Because a step on a quantum backend and a step of classical search differ in cost, the step counts are not directly comparable to wall-clock time (Table 2).

Table 5: Generalization of quantum-optimized models

Model	Accuracy (Table 1)	Test Accuracy	Accuracy / Test Accuracy
CNN (Dengue Detection)	91.2%	90.5%	1.01
RNN (Dengue Detection)	90.1%	89.4%	1.01

Table 5 summarizes generalization. For the quantum-optimized CNN, accuracy fell from 91.2% to 90.5% on the test set, and for the RNN from 90.1% to 89.4%. Both ratios are close to 1 (below 1.1), indicating no substantial overfitting. Because train–test gaps for the classically tuned models are not reported, it cannot be concluded that quantum optimization reduced overfitting relative to classical search.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

4. LIMITATIONS

Several limitations qualify these findings. First, results are reported as point estimates without confidence intervals, repeated-run variance or significance tests, so differences of a few percentage points should be interpreted with caution. Second, the experiments use a single public dataset; external validation on prospectively collected clinical data from multiple sites is needed before any conclusions on clinical utility can be drawn. Third, classical baselines are limited to grid search and random search, and stronger classical optimizers (for example Bayesian optimization) were not compared. Fourth, current quantum hardware is noisy and limited in scale [4], and reviews note that many quantum machine learning results in healthcare depend on simulation and small problem sizes [6, 7]. Finally, the step counts and run times of quantum and classical procedures are not strictly equivalent in cost.

5. CONCLUSION AND FUTURE WORK

This study examined the effect of quantum optimization algorithms, specifically quantum annealing and QAOA, on the performance of deep learning models for dengue fever detection. In the experiments reported here, quantum-assisted hyperparameter tuning gave higher accuracy (+2.8 pp over grid search for both CNN and RNN), shorter training time and faster convergence than classical grid and random search, with good generalization to held-out data.

These benefits should be viewed in context. Integration of quantum optimization with classical deep learning is at an early stage; hardware limitations, the complexity of adapting quantum algorithms to specific medical tasks and the computational resources required hinder real-world deployment. The performance gains are modest and may be smaller when compared with well-tuned classical approaches.

Future work should (i) evaluate against stronger classical optimizers, (ii) report variance over repeated runs with statistical testing, (iii) validate the models on independent, multi-site clinical datasets, (iv) test the approach on real quantum hardware and quantify the effect of noise, and (v) assess the value of quantum-assisted feature selection and architecture search for dengue detection.

REFERENCES

[1] World Health Organization. Dengue and severe dengue [Fact sheet]. WHO; updated periodically. https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue

[2] Bhatt, S., Gething, P. W., Brady, O. J., et al. (2013). The global distribution and burden of dengue. *Nature, 496*, 504–507. https://doi.org/10.1038/nature12060

[3] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*, 436–444. https://doi.org/10.1038/nature14539

[4] Preskill, J. (2018). Quantum computing in the NISQ era and beyond. *Quantum, 2*, 79. https://doi.org/10.22331/q-2018-08-06-79

[5] Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., & Lloyd, S. (2017). Quantum machine learning. *Nature, 549*, 195–202. https://doi.org/10.1038/nature23474

[6] Gupta, R. S., Wood, C. E., Engstrom, T., Pole, J. D., & Shrapnel, S. (2025). A systematic review of quantum machine learning for digital health. *npj Digital Medicine*. https://doi.org/10.1038/s41746-025-01597-z

[7] Ur Rasool, R., Ahmad, H. F., Rafique, W., Qayyum, A., Qadir, J., & Anwar, Z. (2023). Quantum computing for healthcare: A review. *Future Internet, 15*(3).

[8] Farhi, E., Goldstone, J., & Gutmann, S. (2014). A quantum approximate optimization algorithm. *arXiv:1411.4028*. https://arxiv.org/abs/1411.4028

[9] Kadowaki, T., & Nishimori, H. (1998). Quantum annealing in the transverse Ising model. *Physical Review E, 58*(5), 5355–5363. https://doi.org/10.1103/PhysRevE.58.5355

[10] Grover, L. K. (1996). A fast quantum mechanical algorithm for database search. In *Proceedings of the 28th Annual ACM Symposium on Theory of Computing* (pp. 212–219). https://doi.org/10.1145/237814.237866

[11] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

[12] Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. *Journal of Machine Learning Research, 13*, 281–305.

[13] Kingma, D. P., & Ba, J. (2015). Adam: A method for stochastic optimization. In *International Conference on Learning Representations (ICLR)*. https://arxiv.org/abs/1412.6980

[14] Qiskit contributors. (2023). *Qiskit: An open-source framework for quantum computing*. Zenodo. https://doi.org/10.5281/zenodo.2573505

(This work is licensed under a Creative Commons Attribution 4.0 International License.)