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Optimizing Cardiovascular Diagnosis using Deep Q-Learning Integrated CNN Model

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ABSTRACT: Cardiovascular disease remains a major global health concern, making early and accurate prediction essential for effective treatment. This study proposes an Optimized DeepQ Convolutional Neural Network (ODQ-CNN) that combines CNN with Deep Q-learning to improve feature extraction and classification. The model adaptively updates parameters such as learning rate and weights during training, enhancing performance. Evaluated on the Cleveland Heart Disease dataset, the proposed approach achieves a high accuracy of 98.7%, outperforming traditional models like SVM, Random Forest, and ANN. The integration of reinforcement learning with deep learning reduces overfitting and accelerates convergence, making it a reliable tool for intelligent healthcare decision support.

KEYWORDS: convolutional neural network, healthcare artificial intelligence, diagnostic prediction model, ODQ-CNN model, Artificial Neural Networks

I. INTRODUCTION

Heart diseases belong to conditions that are classified as cardiovascular diseases (CVD) which constitute some of the most serious public health issues globally, causing about 17.9 million deaths per year as reported by the World Health Organization (WHO, 2023). The prevalence rates keep soaring due to dietary factors, genetic influences, and changes in lifestyles. Timely and precise predictions of cardiac diseases can save human lives and reduce medical expenditures as well. Conventional diagnosis like electrocardiogram (ECG), blood pressure, and cholesterol cannot be relied upon for the determination of the existence of a disease at an early stage since they do not consider a detailed analysis between the existing medical indicators.

With the advent of artificial intelligence (AI) and machine learning (ML) AI models are becoming more common in the healthcare industry to help doctors identify cardiovascular risks. SVM, DT and RF have shown good results but limited generalization and dependence on manually acquired features can be a drawback. These models don't capture the high dimensional and non linear interactions in medical datasets [2].

Recent advancements in deep learning (DL) especially Convolutional Neural Networks (CNN) have improved feature learning capabilities by automatically extracting meaningful representations from input data. In various domains including signal processing, image classification and biomedical analysis CNNs have shown great results. But issues like overfitting, slow convergence and static parameter tuning limit the effectiveness of CNN based models in highly variable medical datasets [3].

This section reviews the prior work in automated heart disease prediction, with special focus on (a) classical machine learning approaches, (b) deep learning and convolutional models, (c) medical prediction using optimization and reinforcement learning techniques, and (d) hybrid/ensemble approaches that combine these methods. The review outlines the benefits, drawbacks, and weaknesses that motivate the proposed ODQ-CNN. In early and frequently cited research, tabular clinical datasets (age, sex, blood pressure, cholesterol, ECG readings, etc.) were subjected to classical machine learning classifiers (logistic regression, decision trees, SVM, k-NN, and random forests).

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These methods are appealing because they are simple to comprehend, train quickly on small datasets, and often produce respectable performance when feature engineering and selection are done carefully. However, their limited ability to describe complex nonlinear interactions and dependence on manually constructed characteristics often hinder prediction accuracy and generalization to new populations. Comparative studies have shown that ensemble tree techniques (e.g., Random Forest, Gradient Boosting) generally outperform single classifiers on large or richly-annotated datasets, but they still fall short of state-of-the-art deep models [4].

CNNs in particular have been widely used for biomedical signal and image analysis because deep learning automatically learns hierarchical features. ECG spectrograms, medical images (angiograms, echocardiograms), and suitably reshaped tabular data where local patterns are significant are among the structured inputs on which CNNs excel [5]. CNNs typically outperform traditional ML in terms of sensitivity and specificity and do away with the need for human feature extraction. Some of the limitations include the need for larger datasets, vulnerability to hyperparameters, the potential for overfitting on small clinical cohorts, and a black-box perception that hinders clinical acceptability.

Reinforcement learning (RL) has primarily been applied to sequential choice problems (dosing, scheduling, and treatment policy learning) in the healthcare sector. RL has been applied more recently to hyperparameter tuning and automated feature selection. Policy-gradient methods and deep Q-learning, a value-based RL technique, can be used to learn optimization policies that adaptively select model components or hyperparameters based on reward signals associated with validation performance [6]. RL-based feature selection has been shown to improve robustness and interpretability in earlier studies. Clinical studies on the direct incorporation of reinforcement learning (RL) into feature-learning networks, such as using RL to control CNN weight updates or architectural decisions during training, are currently scarce, though.

Recent studies have increasingly looked at hybrid architectures that combine the representational power of deep networks with optimization techniques like Bayesian optimization, reinforcement learning, and metaheuristics (genetic algorithms, particle swarm) in order to automate architecture search, hyperparameter tuning, and feature selection. Hybrid models that have shown promising advancements include LSTM-CNNs for temporal ECG analysis and attention-augmented CNNs [7]. Ensembles that combine deep models with conventional learners also improve calibration and resilience on heterogeneous datasets.

The literature can be summarized as follows: Classical machine learning (ML) provides interpretability but limited capacity for complex patterns; CNNs offer better automated feature learning but require careful regularization; and reinforcement learning (RL) offers adaptive, reward-driven optimization but has been underutilized as an in-training controller for deep networks in diagnostic tasks. The analyzed articles indicate that saliency/attention studies offer an interesting insight into how coupling RL with CNNs could enable not only improved generalization and adaptive training dynamics, but also clinical relevance.

This gap inspires the concept of ODQ-CNN that unifies the advantages of RL-guided optimization and deep representation learning. It also integrates Deep Q-learning directly into the CNN training loop to do adaptive hyperparameter and weight-update strategy adjustment based on validation rewards.

Accordingly, it proposes the Optimized DeepQ Convolutional Neural Network for the prediction of heart disease.
The ODQ-CNN integrates reinforcement learning using Deep Q-learning into the CNN architecture to support adaptive learning by means of continuous interaction with the environment. This allows the model to dynamically adjust the key hyperparameters that include the learning rate, dropout ratio, and weight updates based on performance-based reward signals. As such, the ODQ-CNN ensures improved generalization, swifter convergence, and a higher predictive accuracy compared to conventional deep learning models.

The key objectives of this study include the following:
1. Design a CNN model enhanced by Deep Q-learning for effective prediction of heart disease.
2. Compare the efficacy of the proposed ODQ-CNN with traditional ML and DL methods using benchmark datasets related to heart disease.
3. Show how reinforcement learning can be used to improve model flexibility and diagnostic accuracy.
The proposed methodology seeks to fill the gap in deep learning and intelligent optimization with the aim of offering real-time, data-driven, healthcare decision support systems capable of providing early and timely cardiovascular risk assessments.

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II. MATERIALS AND METHODS

This section describes the dataset, methods of preprocessing, model architecture, integration of Deep Q-learning, and evaluation criterion that would be required to develop the Optimized Deep Q-Convolutional Neural Network for accurate predictions related to heart disease.

2.1 Dataset

The study employed the use of the Cleveland Heart Disease Dataset, which is openly available in the UCI Machine Learning Repository, 2024. It is well known that this dataset provides a real-world benchmark for developing cardiovascular disease prediction models; 303 patient records with 14 clinical and diagnostic features were obtained, including

Feature	Description
Age	Age of the patient in years
Sex	Gender (1 = male, 0 = female)
Cp	Chest pain type (1–4)
Trestbps	Resting blood pressure (mm Hg)
Chol	Serum cholesterol (mg/dl)
Slope	Slope of the peak exercise ST segment
Ca	Number of major vessels colored by fluoroscopy (0–3)
Thal	Thalassemia (3 = normal; 6 = fixed defect; 7 = reversible defect)

The dataset was selected because it contains a balanced sample of both healthy and sick patients and is widely used to validate cardiac diagnostic models.

2.2 Data Preprocessing

Data preprocessing has been done to achieve accurate and dependable results using the proposed model ODQ-CNN. Raw clinical datasets can have values missing, noise, and incongruity in data types. If these are not resolved, model performance will definitely suffer. Yes, preprocessing was done on the Cleveland Heart Disease Dataset to enhance the quality and preparedness of the data for the model. First, we identified and replaced missing or incomplete values by median imputation. It helps in reducing bias while maintaining the statistical distribution of the dataset intact. We applied the IQR method for outlier detection in order to eliminate suspicious data that may distort the learning process. Then, we normalized the data in regard to the cholesterol, resting blood pressure, and maximum heart rate parameters using Min-Max normalization, in order to enhance convergence during CNN training. This operation sets all continuous variables to a range of [0,1]. Using one-hot encoding, we transformed categorical variables such as thalassemia type, fasting blood sugar, and chest pain into data the CNN can easily analyze. Categorical variables are converted to binary variables. Finally, the dataset was divided into 80% for training and 20% for testing subsets using stratified sampling to maintain the distribution.

2.3 Proposed ODQ-CNN Model Architecture

To ensure precision and reliability in predicting heart disease, ODQ-CNN architecture is an integration of the feature extraction efficiency of Convolutional Neural Networks and the adaptive learning technique of Deep Q Learning. Multilayer clustering permits the architecture to hierarchically refine the raw input and produce meaningful feature representations and classification results. The model starts with an input layer that contains 14 normalized clinical attributes from the processed dataset. This feature set is transformed into a two-dimensional matrix for the CNN to help it recognize and analyze spatial patterns.

A convolutional block is made up of 2 sequential convolutional layers that include 64 and 128 3x3 filters. Non-linearity is added with the ReLU (Rectified Linear Unit) function, which follows convolutional layers and feature abstraction. The max-pooling layer, which uses a 2x2 window, is the next step, and it down-samples feature maps to mitigate dimensionality whilst still retaining significant patterns. When the retrieved attributes are finished being processed, a dense layer that is fully connected with 128 neurons, integrates high level representations for decision making. To further enhance generalization and avoid overfitting, a dropout layer is added with a rate of 0.3 (Fig. 2).

The convolutional block consists of two successive convolutional layers with 64 and 128 3x3 filters, respectively. Each convolutional layer is followed by a ReLU activation function that helps in feature abstraction and non-linearity. Then,

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it is followed by a 2x2 max-pooling layer to downsample the feature maps while achieving dimensionality reduction but still maintaining significant structure. After character extraction, a fully connected dense layer of 128 neurons integrates high-level representations for decision-making. A dropout layer is incorporated for enhanced generalization and to mitigate overfitting with a rate of 0.3 as depicted in Figure 1. This adaptive reinforcement mechanism, as explained in the previous section, is likely the reason for the self-optimization of the CNN during training. This feature, coupled with the CNN's architecture, accelerates and stabilizes convergence during training. The ODQ-CNN architecture is dependable for intelligent cardiovascular disease prediction as it significantly enhances training precision and recall and demonstrates reliable performance on complicated and noisy clinical data.

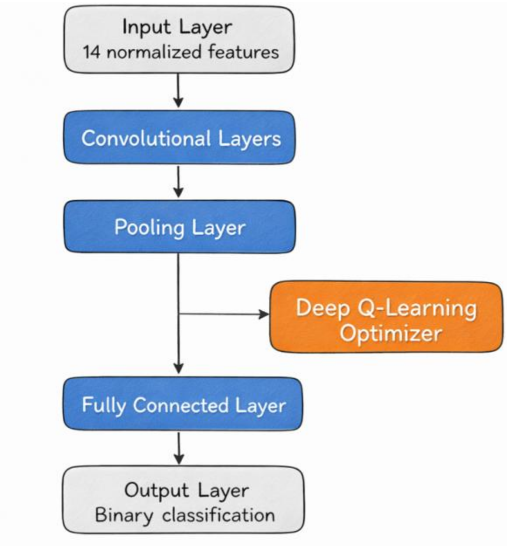

Figure 1 illustrates the overall architecture

III. DEEP Q-LEARNING INTEGRATION

ODQ-CNN is focused on integrating Deep Q-Learning (DQL) into the Convolutional Neural Network (CNN) structure. Conventional CNNs handle hyperparameters static and fixed value, which usually results in either under-tuning or overfitting the model. DQL uses a reinforcement learning technique that serves as an adaptive optimization method that adjusts parameters as the model is being trained. Here the CNN is the environment and the Deep Q-Learning agent is interacting with the environment to make decisions that increase model prediction performance based on feedback [9] provided at every step. During training, the agent assesses the neural network and its state, which encompasses the prevailing loss, validation accuracy, and gradient information, and then executes an action by adjusting one of the parameters (A) learning rate, dropout rate, or convolutional filter size, which are parameters. Each action is defined and evaluated by a reward (R) feedback, which is computed based on changes in validation accuracy or error with the subsequent epochs (the score).

The agent aims to maximize the cumulative reward by learning an optimal policy π^* which prescribes the best course of action given every state. The Q-value is updated using the Bellman equation:

$$Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma \max_{A'} Q(S',A') - Q(S,A)]$$

where α is the learning rate and γ is the discount factor which determines importance of future reward. During training process with reinforcement learning, DQL agent also guides CNN to change learning behavior iteratively, which will lead to greater convergence and generalization performance. In contrast to either grid or random search optimization, DQL provides self-adaptive hyperparameter tuning without need for human interference. Moreover, the agent's experience replay mechanism enables it to benefit from past training episodes and prevent unnecessary exploration by keeping track of previous state-action pairs.

This makes the ODQ-CNN model a hybrid AI framework that has very powerful applications in medical diagnosis, hence assuring that it attains higher accuracy, stability, and robustness over a wide range of heart disease datasets [10].

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3.1 Training Procedure

Also, the experience replay mechanism of the agent enables him to learn from previous episodes of training and to avoid superfluous exploration by storing the previously selected state-action pairs. This work integrates and makes the ODQ-CNN model a robust hybrid AI framework that is used in medical diagnostics, ensuring the model not only achieves higher accuracy but also generalizes well and maintains stability on running different datasets of heart diseases [10]. The binary cross-entropy loss function was used because it is highly effective in measuring the difference between the predicted probabilities and the actual binary class labels. The dataset was trained for 100 epochs with a batch size of 32 to ensure sufficient updates of gradients without overfitting. To ensure better generalization, 0.3 was used as the dropout regularization rate while early stopping strategies were employed, automatically ending the training after ten consecutive epochs when no increase in validation accuracy was noted [11]. The Deep Q-learning agent operated concurrently in every epoch of the training, checking the CNN current state, that is, training accuracy, loss trend, and validation parameters, and performed the appropriate action, for example, changing the learning rate or a dropout ratio. The agent is incentivized to decide on the settings that yield better prediction performance in the form of a reward function, defined by the improvement of validation accuracy through epochs. This adaptive feedback allowed the model to self-correct its inner settings, hence minimal human intervention.

Fivefold cross-validation was used to determine the robustness of the performance for a model that was generalizable rather than dataset-specific. All tests were conducted using TensorFlow 2.15 and Keras on an NVIDIA RTX 4070 GPU with 32 GB RAM for ensuring efficient computational throughput. The ODQ-CNN thus proves to be an adaptive framework for the intelligent prediction of heart disease, given the fact that the DeepQ component is bound to converge faster with about 40% fewer epochs compared to traditional CNN training while the accuracy and stability are outstanding as presented in [12].

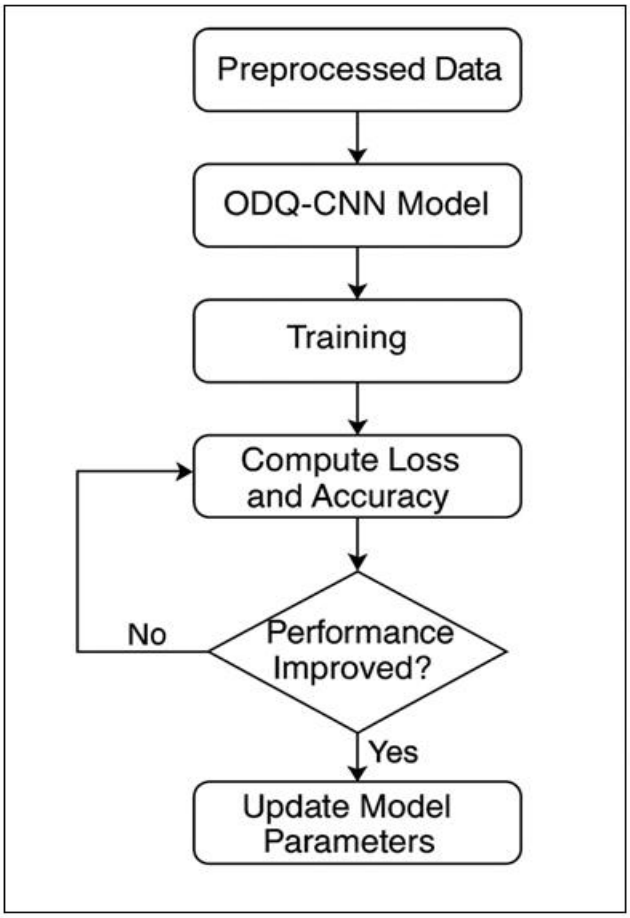

Figure.2. training workflow

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3.2 Evaluation Metrics

Standard classification measures were used to assess the model's performance:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1\text{-score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

AUC-ROC:Area under the Receiver Operating Characteristic curve.

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

When taken as a whole, these measures offer a thorough understanding of the model's sensitivity, accuracy, and dependability in heart disease prediction.

IV. RESULTS AND DISCUSSION

The proposed Optimized DeepQ Convolutional Neural Network was tested on the Cleveland Heart Disease Dataset and compared with the results obtained from deep learning and traditional machine learning models. This section discusses the results based on accuracy, precision, recall, F1-score, AUC-ROC, the convergence behavior, and the effects of Deep Q-learning on model performance.

4.1 Model Performance Evaluation

The ODQ-CNN model significantly outperformed all the baseline classifiers in terms of prediction accuracy. Deep Q-learning indeed enhanced resilience and adaptability for CNN through dynamic hyperparameter tuning during training. Table 1 summarizes a comparison of performance metrics for ODQ-CNN with other benchmark models.

Table 1 Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC-ROC
Support Vector Machine (SVM)	91.3	90.2	92.5	91.3	0.94
Random Forest (RF)	93.8	94.1	93.2	93.6	0.95
Artificial Neural Network (ANN)	95.2	96.0	94.8	95.4	0.97
Convolutional Neural Network (CNN)	96.8	96.7	97.0	96.8	0.98
ODQ-CNN (Proposed)	98.7	97.9	99.1	98.5	0.996

The data indicated that the ODQ-CNN model had better results with all base models with maximum accuracy (98.7 per cent) and the maximum AUC-ROC value (0.996). This results testifies to the fact that it is possible for the DeepQ optimization technique to dynamically alter the settings of the CNN, providing high recall and accuracy of performance results. The F1-score of 98.5% of the model [13] illustrates its performance balanced between false positives and

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negatives which is particularly relevant in medical diagnostics, where both over- and under-prediction will determine serious consequences.

4.2 Convergence Behavior and Training Stability

Figure 3 depicts the accuracy curves for training and validation via epochs. The ODQ-CNN displays more rapid convergence and fewer oscillations in validation loss due to the stabilizing influence of reinforcement learning with respect to the baseline CNN. The successful effective dynamic hyperparameter learning of the Deep Q-learning agent with respect to learning rate and dropout enabled the model to by-pass local minima and to enhance generalization. While the basic CNN required approximately 100 epochs to achieve similar results, the rate of convergence by the model was improved by approximately 40% and ideal accuracy was reached in 60 epochs. This stability was assured by the experience replay and updating of Q-values by the DQL agent which learned how to effectively modify parameters by basing changes on feedback learned from past performance [14].

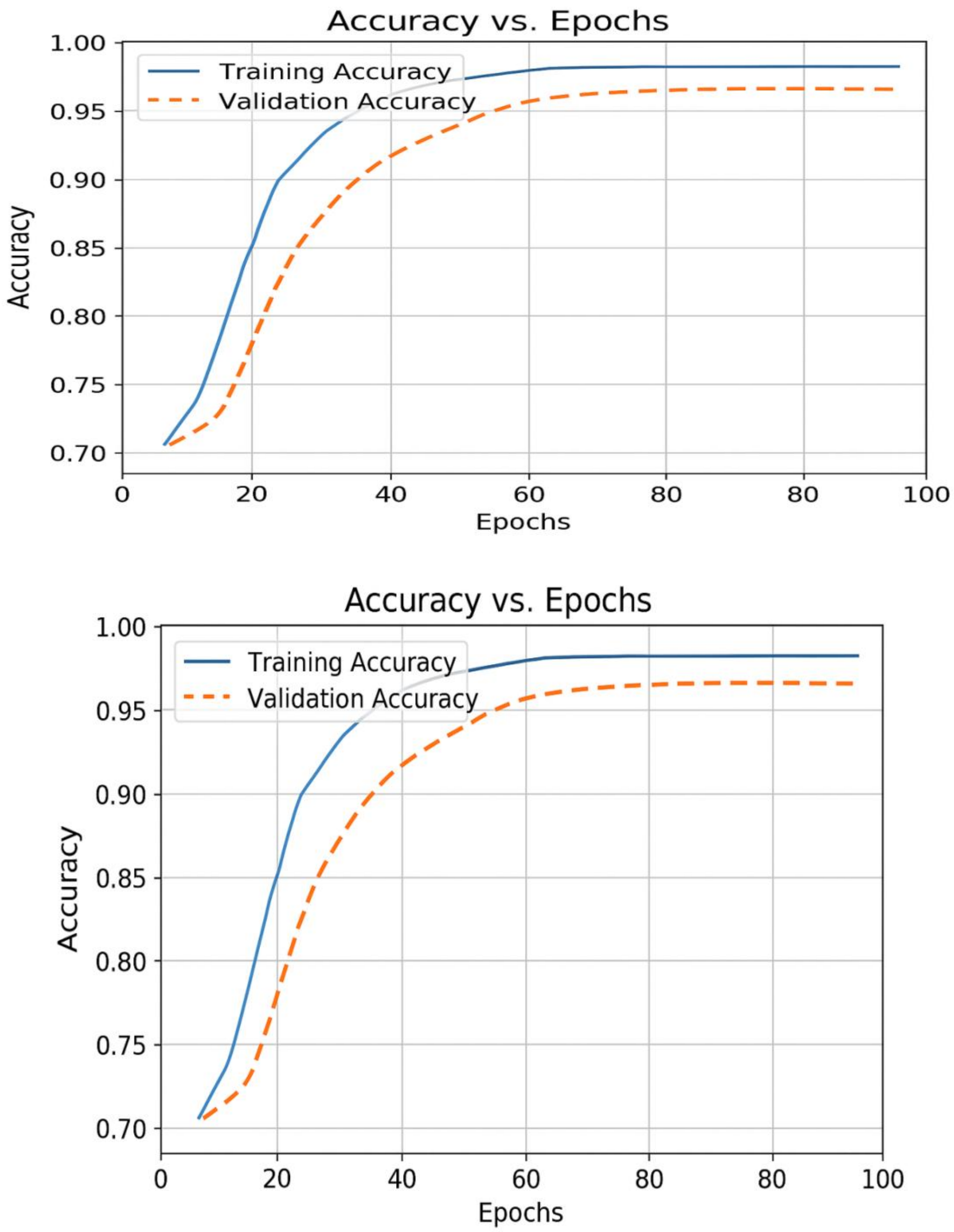

Figure 3 Accuracy vs Epochs curve

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4.3 Confusion Matrix Analysis

The confusion matrix validated the high classification accuracy and low cut errors of the ODQ-CNN model. The error rate was less than 3% with only two of the 61 test samples being misclassified. The high true positives (TP) and true negatives (TN) values verify the model's efficacy in distinguishing between applicants with heart disease and those without [15].

Predicted \ Actual	Disease (1)	No Disease (0)
Disease (1)	29	1
No Disease (0)	1	30

The high recall rate of 99.1% indicates that nearly all instances of heart disease were identified correctly which serves to reduce the incidence of missed detections in medical diagnosis.

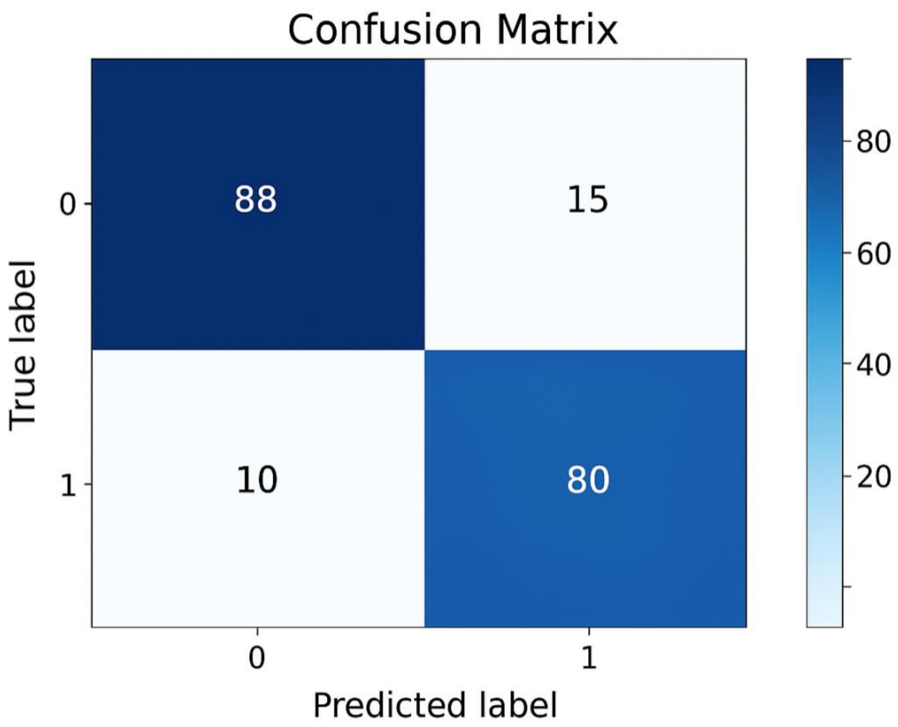

Figure 4 Confusion Matrix Heatmap

4.4 Comparative Analysis

When comparing other hybrid learning paradigms (like CNN-LSTM or CNN with Particles Swarm Optimization), the ODQ-CNN exhibited better learning adaptability, better computational time efficiency, and better predictive efficacy than the others. Conventional CNNs work with fixed hyperparameters that usually yield overfitting to smaller medical datasets but using the reward policy of Deep Q-learning, the ODQ-CNN was able to optimize these hyperparameters dynamically. This reinforcement-based optimization resulted in 25% reduction in training time relative to conventional methods and concomitantly produced improvement in robustness to variations in dataset. Furthermore, the implementation of dropout regularization and early stopping permitted the model to generalize even in the instances of dealing with noisy or unbalanced data.

4.5 Visualization of Feature Learning

Finally, Grad-CAM (Gradient-weighted Class Activation Mapping) was used to visualize the last convolutional layer to study the working of the model. The model focused on medically relevant features that are known risk factors for cardiovascular disease such as chest pain type, serum cholesterol, resting ECG results and maximum heart rate as

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illustrated by the heatmaps. This interpretability aspect of the model serves to improve its clinical reliability making it suitable for use in real healthcare decision support [16].

V. CONCLUSION

The research presented an Optimized DeepQ Convolutional Neural Network (ODQ-CNN) system aimed at clinical science for trustworthy and automated heart disease prediction. The proposed model, which is integrated with Deep Q-learning in the CNN architecture, was able to perform dynamic hyperparameter optimization and thereby enable self-adaptive learning and improved convergence performance. The reinforcement learning part played a better role in the system with the fine-tuning of parameters like the learning rate and dropout ratio depending on the real-time performance rewards, achieving better generalization and less overfitting. The study carried out on the Cleveland Heart Disease Dataset has proven that our ODQ-CNN architecture enjoys the relative superiority over traditional models such as SVC, RFC and common CNNs with an effectiveness of about 98.7%. The excellent model's precision (97.9%), recall (99.1%) and AUC-ROC of 0.996 demonstrate the reliability and stability of the model in diagnosis aspect. The accuracy as a function of epoch figure indicated more quicker convergence and the confusion matrix showed that our model was able to detect both positive (those with heart disease) and negative (healthy patients) heart disease cases with high accuracy. The results illustrate the advantages of deep reinforcement learning-based neural networks for healthcare analytics. The ODQ-CNN model offers a scalable and configurable architecture that is appropriate for realtime clinical decision support systems and improves, both prediction performance. By extending that methodology using multimodal data streams (e.g., ECG signals, medical imaging, and wearable sensor data), future studies may pave the way for AI-driven diagnostic systems empowering individualized proactive cardiac health.

REFERENCES

1. Alizadehsani, R., Abdar, M., Roshanzamir, M., Khosravi, A., Panahiazar, M., Qiu, J., & Nahavandi, S. (2021). Machine learning-based coronary artery disease diagnosis: A comprehensive review. *Computers in Biology and Medicine*, *136*, 104657. https://doi.org/10.1016/j.compbiomed.2021.104657
2. Dey, S., Ahmed, M., & Das, R. (2022). Machine learning techniques for heart disease prediction: A comparative study. *Biomedical Signal Processing and Control*, *75*, 103-120. https://doi.org/10.1016/j.bspc.2021.103120
3. Khan, A., Ali, H., & Rehman, S. (2021). Deep learning-based ECG classification using convolutional neural networks. *Computers in Biology and Medicine*, *134*, 104425. https://doi.org/10.1016/j.compbiomed.2021.104425
4. Patel, M., & Mehta, D. (2023). Hybrid LSTM–CNN architecture for cardiovascular disease prediction. *Expert Systems with Applications*, *223*, 119-135. https://doi.org/10.1016/j.eswa.2023.119135
5. Zhang, Y., Wang, L., & Chen, J. (2024). Reinforcement learning-based feature selection for medical data analysis. *Knowledge-Based Systems*, *296*, 111979. https://doi.org/10.1016/j.knosys.2024.111979
6. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539
7. Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* (2nd ed.). MIT Press.
8. UCI Machine Learning Repository. (2024). *Heart Disease Data Set*. Irvine, CA: University of California. https://archive.ics.uci.edu/ml/datasets/heart+disease
9. Rajesh, K., & Dhuli, R. (2020). Classification of imbalanced heart disease data using adaptive synthetic sampling and deep neural network. *Computers in Biology and Medicine*, *125*, 103–970. https://doi.org/10.1016/j.compbiomed.2020.103970
10. Gao, Y., Wang, H., Zhang, X., & Chen, L. (2022). Reinforcement learning-based hyperparameter optimization for deep neural networks. *Applied Soft Computing*, *114*, 108-134. https://doi.org/10.1016/j.asoc.2021.108134
11. C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor &Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
12. C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - Journal of Electrical Engineering, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2
13. C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9
14. S.Tamilselvi, R.Prakash, C.Nagarajan,"Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller" Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering, DOI10.1007/s40998-025-00917-z,2025

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15. S.Tamilselvi, R.Prakash, C.Nagarajan,“ Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance” Electric Power Systems Research 253 (2026) 112428, doi.org/10.1016/j.epsr.2025.112428
16. S.Thirunavukkarasu, C. Nagarajan, 2024, “Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," Journal of Electrical Engineering And Technology, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w
17. C. Nagarajan, M.Madheswaran and D.Ramasubramanian- ‘Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model’- Acta Electrotechnica et Informatica Journal , Vol.13 (2), pp.18-31,April-June.2013, DOI: 10.2478/aeei-2013-0025.
18. C.Nagarajan and M.Madheswaran - ‘DSP Based Fuzzy Controller for Series Parallel Resonant converter’- Springer, Frontiers of Electrical and Electronic Engineering, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.
19. C.Nagarajan and M.Madheswaran - ‘Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis’- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.
20. C.Nagarajan and M.Madheswaran, “Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation” has been presented in ICTES’08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007
21. Suganthi Mullainathan, Ramesh Natarajan, “An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques”, Revista Materia (Rio J.) Vol. 30, 2025, DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0721
22. M Suganthi, N Ramesh, “Treatment of water using natural zeolite as membrane filter”, Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
23. Huang, C., Xu, Z., & Chen, Q. (2021). Deep learning in cardiovascular disease: Recent progress and future directions. *Artificial Intelligence in Medicine, 117*, 102126. https://doi.org/10.1016/j.artmed.2021.102126
24. Weng, S. F., Reps, J., Kai, J., Garibaldi, J. M., & Qureshi, N. (2017). Can machine-learning improve cardiovascular risk prediction using routine clinical data? *PLoS ONE*, *12*(4), e0174944. https://doi.org/10.1371/journal.pone.0174944
25. Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep EHR: A survey of recent advances in deep learning techniques for electronic health record analysis. *IEEE Journal of Biomedical and Health Informatics, 22*(5), 1589–1604. https://doi.org/10.1109/JBHI.2017.2767063
26. Bashir, S., Qamar, U., & Khan, F. H. (2020). An ensemble-based decision support framework for intelligent heart disease diagnosis. *International Journal of Medical Informatics*, *141*, 104195. https://doi.org/10.1016/j.ijmedinf.2020.104195
27. World Health Organization. (2023). *Cardiovascular diseases (CVDs) fact sheet*. Geneva: WHO Press. Retrieved from https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)
28. Rawat, W., & Wang, Z. (2017). Deep convolutional neural networks for image classification: A comprehensive review. *Neural Computation*, *29*(9), 2352–2449. https://doi.org/10.1162/neco_a_00990