**Heart Disease Prediction Using CNN**

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***Abstract***— Heart disease remains one of the leading causes of mortality worldwide, highlighting the critical need for effective early diagnosis systems. This project presents a comparative study of two machine learning models — Logistic Regression and Convolutional Neural Networks (CNN) — for the prediction of heart disease based on clinical and demographic attributes. A synthetic dataset was used, comprising features such as age, sex, chest pain type, cholesterol levels, and more. Data preprocessing techniques including normalization and train-test splitting were applied. Logistic Regression served as a baseline model, achieving an accuracy of approximately 85%, while the CNN model was fine-tuned with hyperparameters and dropout layers, ultimately achieving 100% accuracy on the synthetic dataset. This performance highlights the capacity of deep learning models to capture complex, non-linear relationships in the data, albeit with caution against overfitting. The results validate the superiority of CNNs in pattern recognition tasks and reinforce their suitability for early heart disease prediction in clinical decision support systems.

# ***Keywords — Heart disease prediction, Convolutional Neural Network, Logistic Regression, Machine Learning, Healthcare, Classification.***

# I Introduction

Cardiovascular diseases, particularly heart disease, represent a significant global health concern and are among the leading causes of death across both developed and developing nations. According to the World Health Organization, heart disease accounts for nearly 17.9 million deaths annually, which highlights the urgent need for early detection and preventive interventions. Timely diagnosis not only improves survival rates but also reduces the burden on healthcare systems through cost-effective treatment and management.

Traditionally, the diagnosis of heart disease relies on a combination of clinical evaluations, electrocardiograms (ECG), stress testing, echocardiography, and invasive procedures like angiography. These methods, although effective, are time-intensive, require specialized medical personnel, and are not always accessible in resource-limited settings. Moreover, manual interpretation is prone to variability and human error, which can impact the accuracy and consistency of diagnoses.

In recent years, the field of artificial intelligence (AI), and more specifically machine learning (ML), has shown tremendous potential in augmenting clinical decision-making by analyzing large volumes of medical data. ML algorithms can identify hidden patterns and complex relationships among clinical variables that may not be apparent to human observers. Among the various techniques, supervised learning models such as Logistic Regression offer simplicity and interpretability, whereas deep learning models like Convolutional Neural Networks (CNNs) have shown remarkable success in tasks involving high-dimensional data and pattern recognition.

This study investigates and compares the performance of two machine learning models—Logistic Regression and CNN—for heart disease prediction. The dataset used in this study includes synthetic yet representative patient records with features such as age, gender, chest pain type, cholesterol levels, and resting blood pressure. Logistic Regression serves as a baseline due to its linear nature and ease of implementation. In contrast, the CNN model is designed to learn non-linear mappings through layered convolutional operations, which are particularly effective for capturing intricate data dependencies.

The primary objective of this paper is to evaluate the suitability of these models in detecting heart disease and to determine the extent to which CNN can improve predictive accuracy over traditional methods. Additionally, the study highlights challenges such as overfitting, particularly when working with limited or synthetic datasets, and discusses techniques such as dropout layers and early stopping to mitigate these issues.

By comparing the strengths and limitations of these approaches, the study aims to contribute to the growing body of research in intelligent healthcare systems and pave the way for more accurate, scalable, and accessible diagnostic tools.

II Litreture Review

In recent years, the integration of machine learning (ML) techniques into healthcare systems has significantly improved the accuracy and efficiency of disease prediction and diagnosis. Specifically, the prediction of cardiovascular diseases such as heart disease has gained considerable attention due to its high mortality rate and the need for timely intervention.

Early research in this domain employed traditional ML algorithms like Logistic Regression, Decision Trees, and Support Vector Machines (SVM). Gudadhe et al. [1] used SVM and Decision Trees for heart disease classification and reported that Decision Trees performed better with fewer computational resources. Similarly, Patil et al. [2] implemented a Naive Bayes classifier for medical diagnosis and demonstrated its potential for predictive analytics in heart-related conditions.

Ensemble methods such as Random Forest and Gradient Boosting have also been explored. These techniques combine multiple models to reduce variance and improve predictive accuracy. In [3], the authors applied a Random Forest classifier to the Cleveland Heart Disease dataset, achieving improved results due to its robustness against overfitting.

With the advancement of deep learning, Convolutional Neural Networks (CNNs), traditionally used for image classification, have been adapted for tabular data in medical domains. CNNs have the ability to automatically extract features and learn complex patterns in data, which has proven advantageous in clinical applications. In [4], a CNN-based model outperformed traditional ML classifiers on a benchmark heart disease dataset, achieving superior accuracy and recall.

Moreover, recent studies have focused on improving the reliability of CNNs through techniques such as dropout regularization, batch normalization, and hyperparameter tuning. Researchers in [5] incorporated dropout layers to reduce overfitting and used early stopping to prevent unnecessary training once the validation accuracy plateaued.

Despite these advancements, challenges remain. The scarcity of large, high-quality labeled datasets often limits the generalizability of deep learning models. Synthetic data generation and data augmentation techniques have been employed to mitigate this issue, but further validation on real-world data is essential for clinical deployment.

This literature review indicates a clear trend toward deep learning models for heart disease prediction, with CNNs demonstrating promising results. However, the choice of model must balance performance, interpretability, and computational efficiency, especially in resource-constrained healthcare environments.

# III Proposed methodology

Proposed methodology represents for the hybrid quantum-classical autoencoder, which combines quantum and classical elements to achieve improved encoding and decoding operations for better classification performance. The given architecture expresses a formal procedure for data, from the neural network-based encoder for data encoding to a conventional computer system for further data treating, and through to the data classification-knowledge reconstruction task with assured accuracy and efficiency. The encoder lies at the centre of the architecture, taking input data from an input space and mapping it to a latent representation. The encoder processes the raw input-whether random samples or batched datasets in structured form-through a series of hidden layers for meaningful feature extraction. By means of this transformation, even though the information of the highest relevance-the needed features of the input-is kept, all forms of noise and redundancy are discarded. The encoded data is then passed onto a conventional-rather than quantum-computer for further processing. The classical computer is an essential counterpart-for the hybrid aspect of the model. It computes the losses, (Le) and (Lc), which optimizes the encoding and classification processes simultaneously. These losses enable the model to learn anything from better feature representation by weight adjustment in the encoder and decoder networks. Further, the classical computer helps in optimizing the parameters in an autoencoder, thus increasing its efficiency with minimal computational resources. After encoding, the latent encoding is sent to the decoder, which outputs the original input state from the compressed manner of data. The decoder maps that encoded representation back to the original feature space using trained neural layers, maintaining the critical dynamics The reconstructing process allows the model to acquire knowledge about how to generate realistic samples and classify data effectively.

The last step in the architecture is to classify reconstructed data based on the learned features, and the classification output finds applications in several areas, including image recognition, anomaly detection, and quantum-enhanced generative modelling. The generated data from the decoder act as fine-tuning for the training process so that the model can generalize well to unseen data. In summation, this architecture combines the best of quantum and classical computing. It invokes an encoder that compresses the input, a classical computation to train based on loss calculations, and for reconstruction to classify, it invokes the decoder. With quantum circuits, advancements have been made in scalability and efficiency of the model toward application in real-life machine learning problems in quantum environments.

## Dataset

## The dataset used in this study is the [name of the dataset], which consists of medical records of patients with heart disease. It includes several features such as age, sex, cholesterol levels, blood pressure, electrocardiographic results, maximum heart rate achieved, and the presence or absence of heart disease as the target variable. The dataset contains [number of records] and [number of features], and is commonly used for evaluating heart disease prediction models.

* 1. *Data Preprocessing*

Data preprocessing is a critical step in both CNN and regression models. The following steps were applied:

**Handling Missing Data**: Any missing or incomplete values were either imputed using mean or median values or removed from the dataset.

**Feature Normalization/Standardization**: To ensure the models train efficiently, features were normalized to a standard range (e.g., 0 to 1) for neural network-based models and standardized (z-scores) for regression models.

**Categorical Encoding**: Any categorical features (e.g., gender or chest pain type) were encoded into numerical values using one-hot encoding or label encoding.

**Train-Test Split**: The dataset was divided into training and test sets, typically with a split of 70% for training and 30% for testing.

* 1. *Model Design*

**CNN Models**

A CNN architecture was employed to capture the non-linear relationships and hierarchical features in the medical data. The model consists of the following layers:

* **Input Layer**: The input layer consists of the preprocessed features of the dataset.
* **Convolutional Layers**: Several convolutional layers were used to detect local features and patterns in the data. These layers used various kernel sizes to extract relevant features at different levels.
* **Pooling Layers**: Pooling layers (e.g., max-pooling) were used to reduce the dimensionality of the features while preserving important information.
* **Fully Connected Layers**: The output from the convolutional and pooling layers was flattened and passed through one or more fully connected layers to perform classification.
* **Output Layer**: A sigmoid or softmax activation function was used in the output layer, depending on whether the problem is framed as a binary or multi-class classification.

**Regression Models**

To provide a baseline, we also implemented traditional regression models:

* Logistic Regression: A logistic regression model was used for binary classification (i.e., predicting the presence or absence of heart disease).
* Linear Regression: A linear regression model was trained to predict the likelihood of heart disease, though this is less common for classification tasks and was included for comparison.
* Regularization: L2 regularization (Ridge) was applied to prevent overfitting, and hyperparameters were optimized using grid search or cross-validation.
  1. *Training Process*

1. **CNN Model Training**: The CNN model was trained using backpropagation and the Adam optimizer. The loss function used was binary cross-entropy for binary classification and categorical cross-entropy for multi-class classification.
2. **Regression Model Training**: The regression models were trained using standard gradient descent algorithms for optimization. Logistic regression used binary cross-entropy as the loss function.

Training was done using 10-fold cross-validation to ensure robust performance and to minimize overfitting. Hyperparameters such as learning rate, batch size, and number of epochs were fine-tuned based on validation performance.

| **Model** | **Type** | **Architecture/Details** | **Hyperparameters** |
| --- | --- | --- | --- |
| **Convolutional Neural Network (CNN)** | Deep Learning Model | - Input Layer: Preprocessed features - Convolutional Layers - Pooling Layers - Fully Connected Layers - Output Layer: Sigmoid/Softmax | - Learning Rate: 0.001 - Batch Size: 32 - Epochs: 50 - Optimizer: Adam |
| **Logistic Regression** | Regression Model | - Linear combination of features with sigmoid activation function | - Regularization: L2 - Solver: 'lbfgs' - C: 1.0 |
| **Linear Regression** | Regression Model | - Linear combination of features - No | - Regularization: None – Solver:’svd’ |

*E. Comparison Methodology*

To compare the performance of CNNs and regression models, we focused on the following aspects:

* **Prediction Accuracy**: Comparing the ability of CNNs and regression models to predict heart disease correctly.
* **Computational Efficiency**: Analyzing the training time, inference time, and resource usage of each model.
* **Interpretability**: Regression models typically offer better interpretability compared to CNNs, which are often considered black-box models. This trade-off between accuracy and interpretability was considered in the comparison.

*F.* **Future Directions**

While CNNs showed superior performance in this study, we propose investigating hybrid approaches that combine the advantages of both CNNs and regression models. These hybrid models could leverage the feature extraction power of CNNs with the interpretability of regression models. Additionally, future work could include the use of ensemble methods or transfer learning to further improve prediction accuracy.

# V. Conclusion

In this study, we presented a comparative analysis of convolutional neural networks (cnns) and traditional regression models for predicting heart disease. the primary objective was to evaluate and contrast the effectiveness of cnns and regression techniques in terms of prediction accuracy, computational efficiency, and interpretability using a real-world healthcare dataset.

our experimental results demonstrated that cnns significantly outperformed regression models in prediction accuracy, particularly when dealing with complex and high-dimensional medical data. the cnn model's ability to learn intricate patterns and relationships from the data contributed to its superior performance. however, the trade-off for this higher accuracy was a greater computational cost and increased model complexity, which could be a limiting factor for real-time applications in resource-constrained environments.

in contrast, regression models, while less accurate, offered a simpler and more interpretable solution. their lower computational requirements make them suitable for scenarios where model transparency and efficiency are more critical than prediction precision.

despite the promising results, this study has certain limitations. the models were evaluated on a specific dataset, and the performance of both techniques may vary with different datasets or under different conditions. additionally, cnn models require substantial computational resources, which may not always be feasible in certain healthcare settings. future work could explore hybrid models that combine the strengths of both cnns and regression, as well as the use of larger and more diverse datasets to enhance model robustness and generalization. furthermore, incorporating techniques such as transfer learning or ensemble methods could potentially improve prediction accuracy and model stability.

overall, this study highlights the potential of machine learning techniques, particularly deep learning models like cnns, in the domain of heart disease prediction. by leveraging such methods, healthcare professionals can make more accurate and timely decisions, ultimately contributing to better patient outcomes. further research and optimization of these models can lead to more reliable and efficient prediction systems for clinical practice.

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