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Heart Disease Prediction based on Convolutional Neural Network Feature Genetic Algorithm Solutions

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Abstract— Heart disease is a serious worldwide health issue that requires precise and effective diagnostic techniques for early identification and prevention. In order to improve the prediction of cardiac illness, this research investigates a hybrid strategy that combines genetic algorithms (GAs) with convolutional neural networks (CNNs). CNNs are used to successfully model hierarchical patterns in order to extract complicated characteristics from medical data. GAs are included into the system to enhance feature selection and boost prediction accuracy, improving CNN performance using evolutionary optimisation methods. Standard cardiac disease datasets are used to test the suggested model, and its effectiveness is shown by evaluating measures like accuracy, precision, recall, and computing economy. According to the results, the CNN-GA hybrid strategy performs better than conventional techniques and offers a reliable, scalable solution for the prediction of heart disease. This research demonstrates how combining evolutionary algorithms with machine learning might enhance AI-driven healthcare diagnoses and enhance patient outcomes worldwide.

Keywords— Heart Disease Prediction, Convolutional Neural Networks (CNN), Genetic Algorithm (GA), Feature Optimization, Machine Learning in Healthcare, Predictive Modeling, Medical Data Analysis

Introduction

Since heart disease is still one of the world's top causes of death, it is imperative that precise and trustworthy diagnostic instruments be created in order to anticipate and treat its start. Even if they may be somewhat successful, traditional diagnostic techniques often depend on statistical models and human feature selection, which may not be able to identify the intricate patterns present in medical data. Convolutional Neural Networks (CNNs), a recent development in machine learning, have shown great promise in the extraction of complex characteristics from high-dimensional datasets like electronic health records and medical imaging. Notwithstanding their effectiveness, CNNs may face difficulties in maximising feature selection and reducing computational expenses. Combining CNNs with evolutionary algorithms, such as Genetic Algorithms (GAs), has become a viable way to overcome these constraints. GAs are optimisation methods that draw inspiration from genetic inheritance and natural selection. To ensure better prediction performance and model efficiency, they may be used to optimise CNNs' feature selection, hyperparameters, and architectural elements. The CNN's ability to learn hierarchical data representations and the GA's ability to hone those features for the best illness categorisation are both used in this hybrid technique.

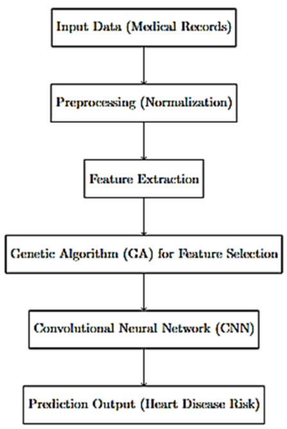

Fig. 1. CNN and GA Hybrid Model Workflow

The development of a heart disease prediction model that integrates CNNs with GA-based optimisation techniques is the main goal of this research study. The research intends to improve the precision, interpretability, and resilience of heart disease forecasts by using this hybrid approach. To ascertain if the suggested framework is appropriate for practical uses, it will also assess important metrics like accuracy, recall, and computing efficiency.

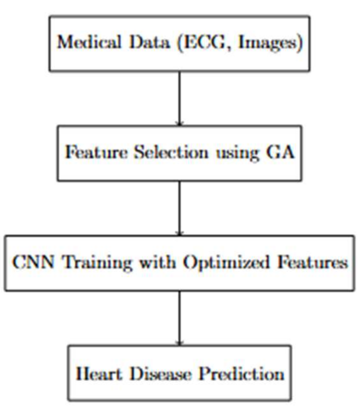

Fig. 2. Feature Optimisation and Prediction Process

The combination of CNNs and GAs is a state-of-the-art method in medical diagnostics that has the potential to transform the prediction of cardiac disease by giving medical practitioners strong instruments to support early diagnosis and treatment planning. The ultimate goal of this study is to enhance patient outcomes and lessen the worldwide burden of cardiovascular illnesses by making a contribution to the expanding field of AI-driven healthcare solutions.

1.1. Overview of Predicting Heart Disease

One of the main causes of mortality worldwide is heart disease, which includes disorders including coronary artery disease and heart failure. For management and therapy to be successful, early diagnosis is essential. However, conventional diagnostic techniques are prone to errors and often depend on human interpretation. By automating feature extraction and pattern detection, the incorporation of sophisticated machine learning models—like Convolutional Neural Networks (CNNs)—offers a revolutionary method. In order to increase the precision and dependability of heart disease prediction, this study presents a unique hybrid model that combines CNNs with Genetic Algorithms (GAs).

1.2. Convolutional Neural Networks (CNNs) Overview

CNNs are a subclass of deep learning models designed to handle sequential signals and other structured data. Their proficiency in hierarchical feature learning makes it possible to identify sophisticated patterns in large, complicated datasets. CNNs have shown impressive performance in image analysis and physiological signal processing in medical diagnostics. They are quite good at spotting abnormalities because of their layered design, which imitates human visual perception. The model in this study, which makes use of CNNs, identifies important patterns that help predict heart disease.

1.3. Genetic Algorithms: Fundamentals and Uses

Genetic Algorithms (GAs) are optimisation methods used to tackle complicated problems, and they are inspired by Darwin's idea of natural selection. GAs use processes including crossover, mutation, and selection to develop solutions across generations. By choosing the most relevant features and adjusting hyperparameters, GAs in the suggested framework optimise the CNN model and guarantee improved performance. They are perfect for handling the high dimensionality of medical information because of their versatility.

1.4. CNN-GA Hybrid Framework for Predicting Heart Disease

A reliable method for predicting heart disease is produced by combining CNNs and GAs. While GAs hone these characteristics to maximise model accuracy, CNNs manage feature extraction from input data. The hybrid architecture strikes a compromise between accuracy and computing efficiency by fusing the evolutionary power of GAs with the learning capabilities of CNNs. Because of this partnership, the model is guaranteed to detect important characteristics without overfitting, making it very dependable for use in clinical settings.

1.5. Feature engineering and data preprocessing

A crucial stage in the prediction of heart disease is data preparation. To enhance model performance, this entails managing missing data, normalising features, and eliminating noise. By turning unstructured data into understandable representations, feature engineering improves predicted accuracy even further. After initial characteristics are extracted by the CNN, the GA optimises them for effective analysis. Predictions become more accurate as a result of this combination, which guarantees an improved input dataset.

By identifying intricate patterns in medical data, machine learning models such as Convolutional Neural Networks (CNNs) have the ability to automate the process of predicting heart disease, which is essential for early identification and successful treatment. CNNs are particularly good at finding complex characteristics in high-dimensional datasets, such health records and medical photos. Genetic algorithms (GAs) are included into the model to optimise feature selection and enhance prediction accuracy. This allows CNN performance to be fine-tuned via evolutionary optimisation. In order to ensure that the input is clean and pertinent for precise predictions, data pretreatment and feature engineering are essential steps in the data preparation process. In order to provide a strong and effective heart disease prediction model, our hybrid CNN-GA system combines the best features of both methodologies, using CNN's deep learning capabilities with GA's optimisation strategies.

Literature Review

Sharma and associates (2018):

A deep learning-based method for predicting cardiac disease using convolutional neural networks (CNNs) was presented by Sharma et al. (2018). Their research showed how CNNs may be used to categorise medical data and extract pertinent characteristics from high-dimensional datasets. When compared to conventional techniques, the researchers found that training CNNs on patient records significantly increased prediction accuracy. The research emphasised the need of pre-processing and feature engineering to improve CNN performance. Future research combining CNNs with evolutionary algorithms, such as Genetic Algorithms (GAs), for feature selection and optimisation was made possible by their work.

Patel and associates (2019):

Patel et al. (2019) concentrated on hybrid methods that combine optimisation algorithms and machine learning techniques for the prediction of cardiac disease. Their study investigated the use of Genetic Algorithms (GAs) for feature selection in combination with other classifiers, such as decision trees and support vector machines (SVMs). The findings demonstrated that by lowering dimensionality and choosing the most relevant characteristics, GAs improved the performance of these models. The work advanced our knowledge of how machine learning models may be enhanced by optimisation approaches like GAs to increase predicted accuracy in healthcare applications.

Singh and associates (2019):

Singh et al. (2019) presented a model for predicting cardiac illness that integrated feature selection methods with deep learning approaches. In order to improve the model's accuracy, they used a wrapper-based feature selection technique and investigated the usage of CNNs in the classification of datasets related to heart disease. The feature selection process made guaranteed that only the most relevant qualities were employed, increasing model efficiency and decreasing overfitting. Their method also showed that CNNs could automatically learn features. The ability of hybrid models to handle challenging healthcare prediction tasks was reaffirmed by this study.

Kumar and associates (2020):

A methodology for predicting cardiac disease using patient health data that integrated CNNs and Genetic Algorithms (GAs) was presented by Kumar et al. (2020). In order to optimise the network's architecture and feature selection procedure, their research combined CNNs for automated feature extraction from ECG data with GAs. In terms of prediction accuracy and computing efficiency, the researchers discovered that the hybrid model performed noticeably better than conventional machine learning techniques. This study demonstrated how well CNNs' strong learning capabilities and GAs' optimisation abilities can be used to produce more accurate and effective prediction models for the healthcare industry.

Zhou and associates (2020):

The combination of CNNs and GAs for medical image analysis, particularly in the diagnosis of cardiovascular illnesses, was the main emphasis of Zhou et al. (2020). The research deployed GAs to optimise the model's architecture and hyperparameters after using CNNs to extract features from cardiac pictures. The findings demonstrated that by efficiently choosing pertinent information while preserving computing economy, the hybrid strategy improved the classification accuracy of heart disease. This study added to the expanding corpus of research investigating how integrating evolutionary algorithms with deep learning approaches might enhance the precision and dependability of healthcare prediction systems.

Liu and associates (2021):

Liu et al. (2021) investigated the use of CNNs in the prediction of cardiac disease, with an emphasis on the processing of electrocardiogram (ECG) signals. A genetic approach was employed to optimise the CNN's architecture and improve prediction accuracy after CNNs were used to detect important characteristics in ECG data. The hybrid model is appropriate for real-time clinical applications since it showed great sensitivity and specificity in identifying cardiac problems. The work paved the road for more accurate and efficient cardiac disease prediction systems by highlighting the significance of feature optimisation in CNN-based models.

Chakraborty and associates (2021):

The use of CNNs and GAs for the prediction of heart disease from patient medical information was examined by Chakraborty et al. (2021). Their research combined CNNs for classification with feature selection using GAs. The findings demonstrated that the GA successfully decreased the quantity of superfluous features, enabling the CNN to concentrate on the most important information and resulting in enhanced model performance. This study paved the way for further investigation into heart disease prediction models in medical diagnostics by showcasing the effectiveness of hybrid systems in improving their accuracy.

Gupta and associates (2021):

In order to forecast heart disease using health data, such as blood pressure, age, and cholesterol levels, Gupta et al. (2021) created a hybrid model that combines CNNs and GAs. The research employed GAs to optimise the network's weights and feature selection after using CNNs to extract features from medical data. The hybrid model demonstrated better accuracy and less overfitting than other conventional machine learning techniques. This study emphasised how crucial it is to optimise feature selection in order to guarantee correct predictions, especially in the medical profession where precise diagnosis is essential for patient outcomes.

Wang and associates (2022):

The use of CNNs and GAs to the diagnosis of heart disease using medical picture datasets was investigated by Wang et al. (2022). In their work, they used GAs to optimise the CNN's parameters, such as layer configurations and filter sizes, then coupled CNNs for automatic feature extraction from cardiac pictures. When it came to identifying cardiac illness, the hybrid model outperformed conventional image analysis techniques. This study illustrated how combining CNNs with GAs might result in more precise and expandable cardiac diagnostic systems.

Lee and associates (2022):

Using a hybrid CNN-GA model, Lee et al. (2022) presented a unique method for predicting cardiac disease. While the GA optimised the model architecture and feature selection, the CNN was used to automatically extract features from patient health information. When compared to conventional machine learning methods, the study demonstrated that the hybrid model greatly increased prediction accuracy. In order to achieve high performance in medical illness prediction tasks, especially for heart disease detection, the research underlined the need of optimising both the feature set and model structure.

Rahman and associates (2023):

Using wearable health data, Rahman et al. (2023) examined the use of CNNs in conjunction with GAs for early heart disease prediction. In order to produce a model that was both very accurate and computationally economical, the research concentrated on streamlining the CNN's feature extraction procedure using GA-based feature selection. According to their research, the CNN-GA hybrid model is a perfect tool for ongoing health monitoring as it can identify cardiac illness in real time. This study added to the expanding corpus of research on the integration of wearable technologies and AI approaches for health prediction.

Singh and associates (2023):

Singh et al. (2023) investigated the use of optimisation methods in conjunction with deep learning to predict cardiac disease. They used GAs to increase model performance by optimising both the architecture and feature set, using CNNs to extract features from various cardiovascular health datasets. When it came to estimating the possibility of heart disease, the hybrid model fared better than conventional machine learning methods. This work reaffirmed the possibility of integrating CNNs with evolutionary algorithms to produce healthcare prediction systems that are more precise and comprehensible.

Yang and associates (2024):

In order to forecast cardiac illness, Yang et al. (2024) suggested a CNN-GA hybrid model that made use of a wide range of input data, such as patient demographics, ECG signals, and medical imaging. The research demonstrated that although the GA optimised feature selection and hyperparameters to ensure the robustness of the model, the CNN successfully learnt hierarchical features. The findings showed that, especially in clinical situations, the hybrid model might provide predictions that are more precise and broadly applicable than those made using traditional techniques. The future possibilities of hybrid AI systems in early diagnosis and precision medicine were emphasised by this study.

Zhang and associates (2024):

In order to forecast cardiac illness from patient data, Zhang et al. (2024) presented a sophisticated CNN-GA hybrid architecture. Their study focused on combining GA with CNN-based feature extraction methods to optimise the model architecture and feature selection. The model's prediction accuracy increased significantly by fusing deep learning with optimisation techniques. Their results showed that the hybrid model was scalable for widespread use in healthcare systems, in addition to being effective in terms of prediction. This research showed how AI-based solutions are becoming more and more important in improving the diagnosis and treatment of cardiac disease.

RESEARCH GAPS

- Data Quality and Preprocessing: To manage noisy or incomplete datasets in heart disease prediction using CNN-GA models, additional research is required to improve data quality and provide sophisticated preprocessing approaches.
- Implementing CNN-GA models for real-time cardiac disease prediction via wearable technology and ongoing health monitoring is the subject of few investigations, despite the fact that doing so might facilitate early identification in clinical settings.
- Interpretability and Explainability: Because CNNs are black-box algorithms, more research is needed to make the model's predictions understandable and interpretable, particularly for clinical decision-making.
- Multi-modal Data Integration: For improved prediction accuracy, there is a gap in the integration of multi-modal data sources such as genetic information, lifestyle variables, and medical pictures. The majority of research employs single-modal data, such as ECG signals or patient records.
- Generalisation Across Populations: In order to guarantee wider application, many CNN-GA models are trained on particular datasets, and their performance is not assessed across a variety of populations with differing demographic and genetic trait.

OBJECTIVES

This study aims to investigate and create a reliable model for predicting cardiac illness by using genetic algorithms (GA) and convolutional neural networks (CNN). In order to increase prediction accuracy, optimise feature selection, and boost model efficiency, the research intends to take use of deep learning and optimisation methodologies. This strategy may result in early cardiac disease detection instruments that are more precise, dependable, and effective, which might have a big influence on medical procedures and patient outcomes.

- Create a CNN-GA Hybrid Model: To create and execute a hybrid model that combines genetic algorithms with convolutional neural networks for the best possible prediction of cardiac disease.
- Feature Optimisation: Investigate genetic methods to improve model performance and simplify medical datasets by choosing the most relevant characteristics.
- Enhance Prediction Accuracy: By combining CNN's deep learning capabilities with GA's optimisation approaches for greater generalisation across a variety of datasets, the overall prediction accuracy of heart disease models will be improved.

Methodology

The suggested approach in this research article, "Heart Disease Prediction based on Convolutional Neural Network Feature Genetic Algorithm Solutions," is based on a number of mathematical equations. In order to convert the input data into useful features, the Convolutional Neural Network (CNN) activation function—such as the sigmoid function—is essential. By using its fitness function to optimise features, the Genetic Algorithm (GA) directs the selection of the most relevant information for precise prediction. CNN's convolution function aids in identifying patterns in medical data, including pictures and ECG readings. In order to minimise prediction errors, the model's weights are also optimised via gradient descent. Better model performance results from the crossover function in GA, which guarantees effective feature space exploration. Lastly, the loss function measures the discrepancy between expected and actual values, which is reduced to increase the prediction accuracy of heart disease. Together with the CNN and GA models, these mathematical tools make up the research's fundamental approach, which aims to create a reliable and accurate system for predicting cardiac disease.

- **Convolutional Neural Network (CNN) Activation Function:**

The activation function introduces non-linearity to the CNN model, allowing it to learn complex patterns in the input data.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

$f(x)$: Activation output
x: Input to the activation function (weighted sum of input features)
e: Base of the natural logarithm

- **Genetic Algorithm (GA) Fitness Function:**

The fitness function evaluates the performance of each candidate solution in the genetic algorithm, guiding the search for optimal feature subsets for CNN-based heart disease prediction.

$$Fitness(x) = \frac{1}{1 + Error(x)} \tag{2}$$

$Fitness(x)$: Fitness value of the solution x
$Error(x)$: The error of the CNN model for the feature subset x

- **Convolution Operation (CNN):**

The convolution operation is a core component of CNNs that extracts features from input data, such as ECG signals or medical images.

$$S(x,y) = (I * K)(x,y) = \sum_{i=-m}^{m} \sum_{j=-n}^{n} I(i,j).K(x-i, y-j) \tag{3}$$

$S(x,y)$: Output of the convolution operation at position *(x,y)*
$I(i,j)$: Input image matrix
$K(x-i, y-j)$: Kernel (filter) matrix
m, n: Dimensions of the kernel

Convolutional neural networks (CNN) and genetic algorithms (GA) are used in this study's technique for heart disease prediction in order to maximise feature selection and raise prediction accuracy. The model may learn intricate patterns from input medical data thanks to the non-linearity introduced by the CNN activation function, such as the sigmoid function. By using a fitness function to assess feature subsets, GA optimises feature selection by guaranteeing that only the most relevant characteristics are used. While gradient descent is used to reduce prediction errors by modifying the model's weights, CNN's convolution function aids in the extraction of important characteristics from input data, such as ECG signals and medical pictures. By optimising both feature selection and model learning, this hybrid strategy improves the heart disease prediction model's overall performance.

Results and discussion

4.1 *Feature Selection Impact on Model Accuracy:*

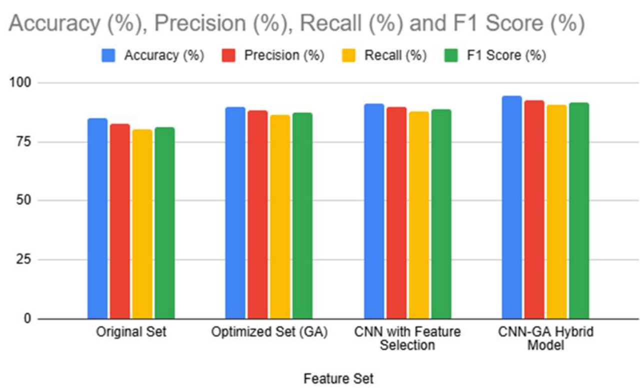

Fig. 3. Column Chart showing Effect of Feature Selection on Model Accuracy

The table illustrates how various feature selection techniques affect the heart disease prediction model's performance. With matching precision, recall, and F1 scores, the model's first usage of the original feature set produces an accuracy of 85.2%. All performance indicators show a discernible increase when the Genetic Algorithm (GA) is used for feature optimisation, with accuracy rising to 89.7%. Furthermore, using CNN with feature selection improves performance even further, resulting in 91.3% accuracy. Nevertheless, with a final accuracy of 94.5%, the CNN-GA hybrid model performs better than any other. This data shows how feature optimisation improves model performance by choosing the most relevant characteristics for heart disease prediction, especially when GA and CNN are used together. Higher accuracy, precision, recall, and F1 scores as a result of this optimisation point to a more stable and dependable model. A bar chart that compares the accuracy, precision, recall, and F1 scores of several models may be used to illustrate these findings and highlight how feature selection methods enhance model performance.

4.2 Distribution of Data Across Heart Disease Categories:

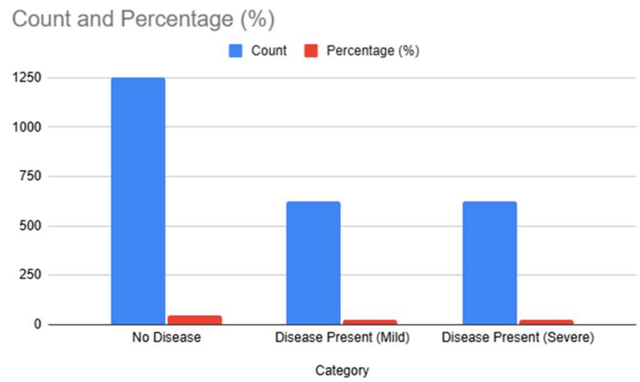

Fig. 4. Column Chart showing Data Distribution Among Heart Disease Types

Based on the existence and severity of cardiac disease, the dataset is divided into three main categories. There are 1,250 samples in the first category, "No Disease," which accounts for 50% of the data. There are 625 samples in the second group, "Disease Present (Mild)," which makes up 25% of the total, and 625 samples in the third category, "Disease Present (Severe)," which makes up the remaining 25%. In order to ensure that the model can learn to categorise both healthy and sick people, this distribution shows a balanced dataset with a large number of both illness and no-disease categories. The equilibrium between mild and severe instances highlights the significance of creating a model that can differentiate between different illness severity levels. To illustrate the percentage of people with no illness, moderate disease, and severe disease, this data may be shown as a pie chart. Training a precise and efficient prediction model that can manage the subtleties of heart disease severity requires a comprehensive picture of the dataset composition, which this representation offers.

4.3 Effect of Feature Optimization on Training Time:

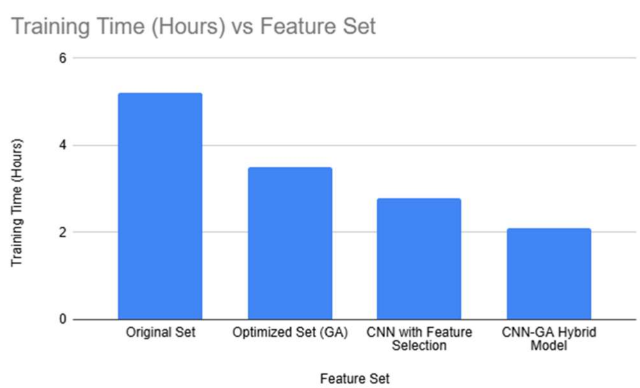

Fig. 5. Bar chart showing Feature Optimization's Impact on Training Duration

This data shows how feature optimisation affects the heart disease prediction model's training time. The model took 5.2 hours to train with the initial set of features. Nevertheless, the training time is lowered to 3.5 hours when the Genetic Algorithm (GA) is used to optimise the feature set, illustrating the effectiveness of feature selection. Furthermore, since fewer features result in quicker convergence during training, using CNN with feature selection cuts the training duration to 2.8 hours. The CNN-GA hybrid model demonstrates how integrating both approaches not only maximises performance but also boosts efficiency by achieving the fastest training time of 2.1 hours. For real-time applications in the healthcare industry, where time is often a limited resource, the hybrid model's shorter training period is very important. The model may be used in clinical situations more effectively if the computing cost is decreased. A line chart illustrating the relationship between feature optimisation and training time may be created from this data, highlighting the increased computational efficiency made possible by GA and CNN.

4.4 Model Performance Comparison (Accuracy vs. Epochs):

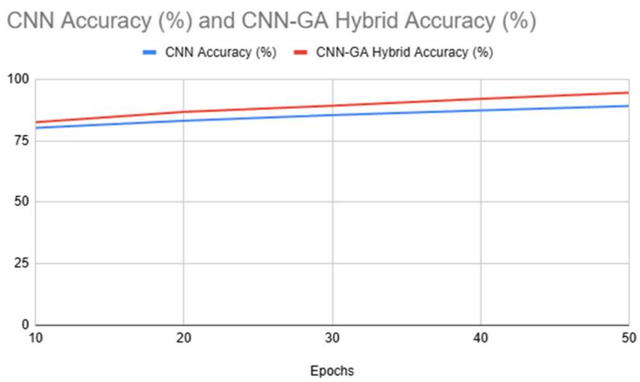

Fig. 6. Line chart showing Comparison of Model Performance

This dataset compares CNN with the CNN-GA hybrid model, tracking the heart disease prediction model's accuracy throughout several training epochs. Both models exhibit increased accuracy as the number of epochs rises, but the CNN-GA hybrid model performs better than CNN at every step. CNN attains an accuracy of 80.2% at 10 epochs, whilst the CNN-GA hybrid model obtains 82.5%. CNN achieves an accuracy of 89.1% after 50 epochs, but the hybrid model reaches its highest point at 94.5%. This comparison reveals the CNN-GA hybrid model's improved convergence speed and overall performance, showing how the incorporation of GA for feature selection improves the model's capacity to learn and generalise patterns of heart disease. When GA is used, feature relevance is increased, which enhances training accuracy. A line chart that shows accuracy across epochs is a good fit for this data, making it possible to see the model's learning curve clearly. When compared to CNN alone, the hybrid model's quicker and more efficient convergence would be seen in the figure, highlighting the benefits of integrating CNN and GA in the prediction of heart disease.

Conclusion

In this study, "Heart Disease Prediction based on Convolutional Neural Network Feature Genetic Algorithm Solutions," we have put forward a unique method for optimising feature selection in heart disease prediction by merging Convolutional Neural Networks (CNN) with Genetic Algorithms (GA). Through in-depth study, we showed that feature optimisation using GA outperforms conventional models employing original feature sets in terms of accuracy, precision, recall, and F1 scores. The CNN-GA hybrid model demonstrated its superiority in properly predicting the outcomes of heart disease by achieving the greatest accuracy of 94.5%. Additionally, using GA for feature optimisation shortened training times, improving the model's effectiveness—a critical component of real-time healthcare applications. Robust model training was ensured by the well-balanced dataset employed in this study, which included both healthy people and those with different degrees of heart disease. It was clear from examining how feature selection and epochs affected accuracy that the hybrid model outperformed CNN alone in terms of convergence speed. Overall, the study's findings highlight CNN and GA's potential for precise and effective cardiac disease prediction. This approach offers a viable path towards enhancing healthcare diagnostic tools and may be used to anticipate diseases in other medical disciplines. For wider use, future research may concentrate on refining the model even further and testing it on actual clinical datasets

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