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Hybrid Deep Learning Algorithm for Heart Disease Analysis Based on Diabetes

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Abstract: Heart disease is a major cause of mortality, particularly for individuals with diabetes. Effective treatment and successful outcomes for patients require a timely and accurate diagnosis. Deep learning algorithms may evaluate cardiac disease, but developing a diabetes-specific algorithm is difficult. This research introduces a hybrid deep learning (DL) architecture that combines Capsule Networks (CapsNets) and Feedforward Propagation Neural Networks (FPNNs) to enhance heart disease analysis in diabetic patients. The CapsNet captures hierarchical relationships and poses of features in medical images, while FPNN produces effective learning via backpropagation and feedforward connections, making it suitable for periodic and sequential data, such as ECG signals and patient demographics. To evaluate the proposed model we utilize a medical dataset from Cleveland heart disease. Evaluation using standard metrics demonstrates that the hybrid CapsNet-FPNN outperforms the other approaches in diabetes-based heart disease analysis, achieving higher accuracy and improved classification. This hybrid architecture shows great promise in enhancing heart disease analysis for individuals with diabetes, enabling more accurate detection and diagnosis. By leveraging the strengths of CapsNets and FPNNs, this model holds the potential for improving heart disease management in diabetic patients.

Keywords: *Heart disease, diabetic, deep learning (DL), Capsule Networks (CapsNets), and feedforward propagation Neural Networks (FPNNs)*

1. Introduction

Heart disease affects many individuals worldwide and causes many deaths and morbidities. It comprises a wide range of cardiovascular illnesses such as coronary artery disease, congestive heart failure, and arrhythmias [1]. People with diabetes have a higher chance of acquiring heart disease than other people at risk. High blood sugar levels are a characteristic of diabetes, a chronic metabolic illness that can harm the cardiovascular system. Consequently, effective treatment and better patient outcomes depend on the early diagnosis and precise analysis of cardiac disease in people with diabetes [2].

Heart disease analysis is one medical area where DL algorithms have demonstrated promising outcomes. By removing complicated characteristics and identifying detailed patterns in the data, deep learning (DL) technologies like CapsNets and FPNN have the potential to simplify and enhance heart disease diagnosis. The idea of capsules is introduced by CapsNets, which encapsulates the position, presence, and attitude of specific components in medical images. An understanding of the fundamental frameworks and relationships within the images that may be more fully recognised and interpreted is rendered by hierarchical representation [3]. FPNNs are effective in learning complex patterns and making accurate predictions by processing input features through multiple layers of interconnected neurons. In the context of heart disease analysis, FPNNs can leverage various clinical and demographic data related to diabetes to detect and classify heart disease conditions [4, 5].

Traditional diagnosis techniques for cardiac disease frequently rely on manual interpretation of sequence data and medical imaging, which can be laborious and subject to subjectivity. However, technological improvements and the accessibility of enormous amounts of medical data have created new possibilities for utilising deep learning algorithms to enhance the precision and effectiveness of cardiac disease analysis. However, it is still difficult to create an efficient algorithm that is specialised particularly for heart disease analysis in patients with diabetes.

We suggest a hybrid design to get over these limitations and improve heart disease analysis in diabetics by combining the advantages of CapsNets and FPNNs. Our hybrid model aims to provide extensive knowledge of the patient's condition and enhance the precision of heart disease diagnosis and management by combining the hierarchy-based feature extraction capabilities of CapsNets and the effective learning and adjustment of weights

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through feedforward propagation in FPNNs.

The remainder of this paper is organised as follows: Part 2 provides an outline of earlier studies on diabetes and heart disease prediction, while Part 3 describes the model's design. Section 4 presents the results and performance analysis. Section 5 concludes the work and suggests future research ideas.

2. Related Works

The purpose of article [6] was to evaluate and contrast 3 different data mining (DM) methods, including "Naive Bayes (NB), Support Vector Machine (SVM), and Decision Tree," to determine the best methods for predicting the probability of heart disease in diabetes individuals. The objective of the research [7] was to precisely determine if an individual was at a greater risk of obtaining heart disease. They recommend combining organised or even unstructured patient data along with the "convolutional neural network (CNN)" method to predict the probability of acquiring a disease.

Study [8] used "Fast Correlation-Based Feature Selection (FCBF)" to reduce redundant features to enhance heart disease classification. Next, they classify using "K-Nearest Neighbour, Support Vector Machine, Naïve Bayes, Random Forest, and a Multilayer Perception| Artificial Neural Network optimised by Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO)". The suggested mixed methodology was applied to heart disease datasets, showing its usefulness and resilience in processing diverse forms of data for heart disease classification.

To predict the risk that an individual has heart disease, the authors of the paper [9] describe a method called CardioHelp that employs a DL algorithm called CNN. The proposed method employs CNN for preclinical HF forecasting, with a particular emphasis on temporal data modelling. They were able to construct the heart disease dataset and conduct the necessary comparisons through the application of state-of-the-art methods. A hybridization strategy is established in the research [10] that integrates artificial neural networks with decision tree classifiers to increase the accuracy of heart disease predictions. The technique was used with WEKA. On a dataset of heart disease patients, a ten-fold validation test was used to assess the performance of the suggested approach.

In the article [11], a prediction model for estimating diabetes risk was implemented. The results obtained utilising the DM methods (DT, ANN, NB, and DL) on the PIMA Indian dataset are better than those obtained using other recommended approaches on the same dataset. The most effective and promising classifier for examining diabetes among the four that have been offered is DL.

By training the properties of a deep neural network using 5-fold and 10-fold cross-validation, the paper [12] suggested a method for the diagnosis of diabetes. They discovered that five-fold cross-validation has a relatively high accuracy compared to other approaches that are currently utilised to predict diabetes mellitus. Both the medical personnel and the general public would benefit from the suggested approach. In study [13] they construct a machine-learning model for diabetes forecasting. DT, NB, ANN, and LR are only a few of the supervised machine learning algorithms utilised in predictive models. To provide a special technique for employing a machine learning algorithm to detect cardiovascular disease as early as feasible. Using their symptoms and medical observations, Support Vector Machines (SVM) are utilised to categorise CVD patients. Medical professionals would be able to treat patients appropriately and on time with the help of the experimentation findings obtained utilising the suggested methodology.

2.1. Problem statement

Heart disease is a leading cause of mortality worldwide, with diabetes being a well-established risk factor. However, considerable difficulty is posed by the intricate and nonlinear interactions among many clinical and demographic factors related to both diabetes and heart disease. To tackle these issues, we propose a hybrid DL architecture that combines CapsNets and FPNNs to enhance heart disease analysis in diabetic patients.

3. Method

3.1. Capsule Network

The Capsule Network (CapsNet) method utilizes capsules, which are organized sets of neurons, as the essential units. The length of a capsule represents invariance, capturing properties that are preserved regardless of the object's orientation or other transformations. On the other hand, the number of features within the capsule measures equivariance, allowing for the reconstruction of an image by considering different variations.

Capsules generate vectors with similar magnitudes but different angles. The alignment of these vectors represents variables such as the features extracted from the input image. This vector representation enables CapsNet to capture relationships and spatial hierarchies effectively.

Unlike regular neural networks that require additional layers to increase details and accuracy, CapsNet achieves this by nesting layers within individual layers. The network's capsules can represent several kinds of visual information, or instantiation variables, such as posture, which includes dimension, position, and alignment. A vector representing the final result of a capsule is sent to the subsequent layer so that it may be associated with the appropriate parent capsule.

The outcome of the jth capsule is denoted as v_j, which represents the features captured by that capsule. To compute the forecast vector $\hat{V}k|j$ for the parent capsule k, a transformation matrix X_{jk} is applied to transform the input vector v_j. This transformation is calculated as:

$$\hat{V}k|j = X_{jk}v_j \tag{1}$$

Here, capsule j stands for the lower layer, and $\hat{V}k|j$ is the prediction vector for the kth-level capsule's output. Backward propagation of the network is where the weighting matrix X_{jk} is acquired.

The coupling coefficients d_{jk} are calculated by the dynamic routing method, and T_k is the weighted total of all forecast vectors$v_{k|j}$. The coupling coefficients represent the degree to which capsule j confirms or agrees with capsule k. The activation function (AF) utilised by CapsNet is known as squashing, and it causes the capsule length to be 0 when the final result's vector is minimal and a single vector when it is maximum.

To compute the activity vector w_j, a non-linear squashing function is applied:

$$w_j = \frac{||T_k||^2}{|1+T_k|^2}\frac{T_k}{||T_k||} \tag{2}$$

The variable $T_k/\| T_k \|$ represents the normalized weighted sum over forecast vectors, and $||T_k||^2/|1+T_k|^2$ normalizes the vector length.

The coupling coefficient d_{jk} is determined as the softmax of c_{jk}, which is a comparison score that combines the likelihood and feature properties instead of probabilities from individual neurons:

$$d_{jk} = \frac{\exp(c_{jk})}{\sum_l ecp(c_{jl})} \tag{3}$$

The value of c_{jk} is updated iteratively during the dynamic routing process, and it represents the comparison score between capsule j and its parent capsule k. It takes into account the forecast vector $\hat{V}_{k|j}$ and the activity vector w_k:

$$c_{jk} = c_{jk} + \hat{V}_{k|j}w_k \tag{4}$$

By iteratively updating the coupling coefficients and computing the forecast vectors, CapsNet facilitates the routing of information between capsules to capture hierarchical relationships and spatial hierarchies in the input data.

3.2. Feedforward Propagation Neural Networks (FPNNs)

FPNN may be used to analyse heart disease in diabetic patients by training a model to anticipate the presence or lack of heart diseases based on a wide range of input characteristics. FPNNs are commonly used for heart disease analysis in diabetic patients. The network has three levels: an "input layer (IL), a hidden layer (HL), and an output layer (OL)". IL receives various features and other relevant medical data. These features are represented as input neurons.

Multiple neurons in the HL process data from an input source. Each neuron in an HL first applies an AF, and then weights the total of its inputs. The network is given the ability to learn intricate connections between the input characteristics thanks to the non-linearity introduced by the AF. The sigmoid, ReLU, and tanh functions are common instances of AF.

$$h_j = AF\left(\sum(w_i * x_i) + b_j\right) \tag{5}$$

Where x_i is the value of the ith input feature, $w_i$is the weight associated with it, and b_j is the bias term for the jth neuron's output.

The OL contains a single neuron that represents the prediction of heart disease. It applies a similar computation as the hidden layer neurons but with its own set of weights and biases. Adding the AF to the weighted average of the HL results yields the network outcome. The network is trained using a labeled dataset, where each instance is associated with the presence or absence of heart disease. Optimisation methods are used to fine-tune the network's weights and biases during training to reduce the loss function, which is a measure of the distance of the predicted output from the actual label. Fig.1 depicts the FPNN structure.

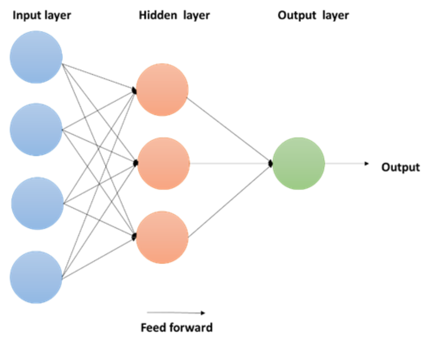

Fig.1. Representation of FPNN

This schematic explains that IL transfers characteristics to HL for evaluation. The OL is responsible for generating the most accurate cardiac disease prediction. Each connection between neurons in different layers is associated with weights, and each neuron applies the AF to the weighted sum of its inputs. Through training, the network learns to adjust the weights and biases to make accurate predictions on unseen data, thereby assisting in heart disease analysis in diabetic patients.

4. Result and Discussion

The use of Matlab version 8 is required to carry out the suggested procedure. This is done on a “laptop running Windows 10 with an Intel Core i7 CPU running at 4.00 GHz and 8 GB of RAM”. In the UCI machine learning repository, the model is tested on UCI datasets. The machine learning repository at UCI in Cleveland served as the basis for the experimental datasets.

Gathered data must first undergo several stages in order to assure its quality and acceptability for further investigation. The first step is to use noise reduction techniques to lessen artefacts and interference such as baseline drift, powerline noise, and muscle noise. This can be done by utilising filters, such as a notch filter to reduce powerline interference and a high-pass filter to remove baseline drift. These pre-processing procedures seek to improve the precision and dependability of data by facilitating the extraction of significant characteristics and subsequent interpretation for therapeutic or investigative reasons.

The parameters are accuracy, sensitivity, specificity, and precision. The existing methods are AGAFL [14], RS+CS [15], and MLP-EBMDA [16]. For classification, note that the true positive - is TP, the true negative is TN, false positive- is FP.

The accuracy of the model's predictions is a measure of their overall correctness. It determines the proportion of accurately predicted cases (including TPs and TNs) among all instances. Fig. 2 shows the accuracy outcome. Accuracy describes how effectively the model forecasts both the presence and absence of heart disease in diabetic individuals in the context of heart disease analysis based on diabetes. However, our suggested model obtains a higher accuracy than the recommended methods, which suggests that the model is generally producing more accurate predictions

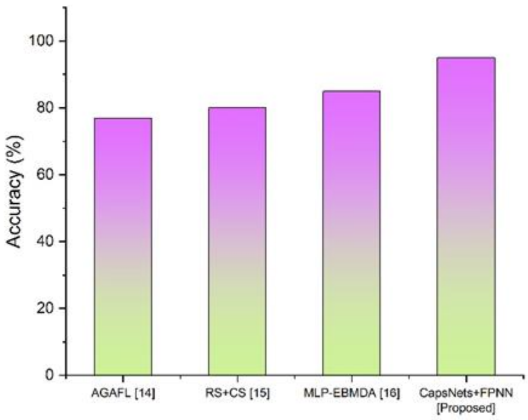

Fig. 2. Result for accuracy

Sensitivity quantifies the percentage of real positive results that the model accurately detected. The ratio of TPs to the total of TPs and false negatives is calculated. Fig. 3 depicts the sensitivity outcome. The fact that our proposed model outperforms the recommended techniques in terms of sensitivity shows that the model is generally providing better predictions.

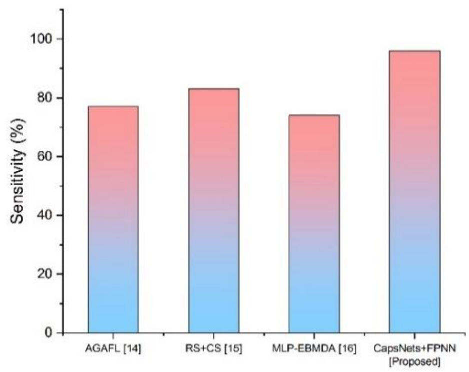

Fig.3. Result for sensitivity

The percentage of actual negative instances (patients without heart disease) that the model accurately detects is known as specificity. It calculates the ratio of TNs (cases where the predictions were correct) to the sum of TNs and FPs (cases where the forecasts were incorrectly positive). Fig. 4 depicts the specificity outcome. Our CapsNet-FPNN model's greater specificity value demonstrates that it performs better at identifying between diabetes and heart disease patients.

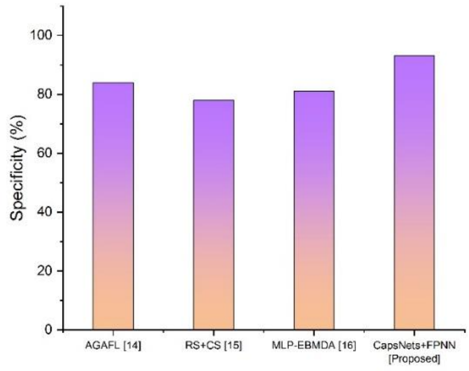

Fig. 4. Result for specificity

Precision is the percentage of all positive predictions produced by the model that correspond to accurately predicting positive instances (patients with heart disease). When authentic positives are compared to the total of TPs and FPs, the ratio is calculated. Precision in the context of heart disease analysis refers to the model's capability to reliably predict the presence of heart disease in diabetic individuals. Fig.5 depicts the precision outcome. Our CapsNet-FPNN achieves a higher precision value than the recommended methods which indicates that the model is making fewer FP predictions.

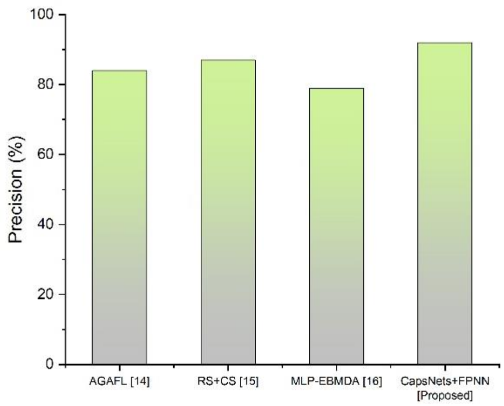

Fig. 5. Result for Precision

5. Conclusion

In this research, we propose a hybrid DL architecture called CapsFPNN, which combines Capsule Networks (CapsNets) and Feedforward Propagation Neural Networks (FPNNs) to enhance heart disease analysis in diabetic patients. The proposed model is evaluated using a medical dataset from Cleveland heart disease. The evaluation, using standard metrics, demonstrates that the hybrid CapsNet-FPNN outperforms other methodologies in diabetes-based heart disease analysis. It achieves higher accuracy (95%) for diagnosing heart disease in individuals with diabetes. The integration of deep learning models into clinical practice requires addressing implementation challenges, such as model deployment, integration with existing healthcare systems, and considerations for user-friendliness and ease of use for healthcare professionals. Future research should focus on addressing these practical aspects to facilitate real-world adoption.

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