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Survey on Ensemble Deep Learning Models for Heart Disease Classification

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ABSTRACT
Ensemble deep learning models have become an effective method. for heart disease classification, leveraging the strengths of multiple neural network architectures to improve diagnostic accuracy. These models combine several deep learning methods to extract different features from intricate medical datasets, including fully connected networks, recurrent neural networks, and convolutional neural networks (CNNs). By integrating different model predictions, ensemble methods can reduce overfitting and enhance generalisation, leading to more robust and reliable heart disease detection. Including clinical records and genetic information, providing a comprehensive assessment of a patient's cardiovascular health. As a result, ensemble Deep learning models have great potential to improve the classification of heart disease. ultimately contributing to better patient outcomes and personalised treatment strategies.

I. INTRODUCTION

Heart disease is a leading cause of death worldwide, responsible for millions of fatalities each year.precise and timely identification of heart problems is critical for improving patient outcomes and reducing healthcare costs. Traditional diagnostic methods, while effective, often require significant time and expertise, which can delay treatment. Recent developments in deep learning and machine learning have created new opportunities for creating automated, efficient, and highly accurate diagnostic tools.This project focuses on utilising ensemble Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep neural networks (DNNs), in particular, are deep learning models. to classify heart disease.Ensemble learning involves creating a diverse set of models and integrating their predictions to form a final decision. This approach enhances the overall performance and robustness of the predictive model. In the context of heart disease classification, ensemble models can combine the spatial learning capabilities of CNNs, the temporal sequence learning of RNNs, and the comprehensive feature extraction of DNNs to improve diagnostic accuracy.

1. A reduction of Dimensions

Methods used in data analysis and machine learning to minimise the number of variables or features in a dataset while maintaining the most crucial information are referred to as "dimension reduction" techniques.

Method of Feature Selection

In deep learning, feature selection is a method for choosing a subset of pertinent features (variables, predictors) for use in model construction. The goal is to improve the model's performance by removing redundant or irrelevant features, which can reduce overfitting and enhance generalisation. Using embedded approaches, feature selection is done. Feature selection helps simplify models, reduce training times, and improve model interpretability.

Method of Feature Extraction

The process of feature extraction is a crucial process in data preprocessing, where raw data is transformed into a group of characteristics that better represent the underlying problem for predictive models. By projecting the initial information onto these components,Correlated variables are transformed using PCA into a collection of uncorrelated ones, thus retaining the most significant information while reducing noise. This simplification enhances the efficiency and performance of machine learning techniques, particularly for high-dimensionaldatasets.

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2. Algorithms

Deep learning

A subset of artificial intelligence called deep learning is motivated by the human brain. It uses artificial multiple-layer neural networks to learn complex patterns from data.

Convolutional Neural Networks (CNNs)

CNNs are designed to efficiently process grid-like data (images) by extracting features and learning hierarchical representations.

Convolution: The heart of a CNN. A filter (small matrix) slides across the input image, performing element-wise multiplication with the corresponding elements in the image. The sum of these products creates a new value in the feature map. Activation Function: Applied after convolution, this function introduces non-linearity into the network.

Pooling: Reduces the dimensionality of feature maps by downsampling. Techniques like max pooling take the maximum value in a local region, summarising the presence of a feature. This helps control overfitting and reduces computational cost.

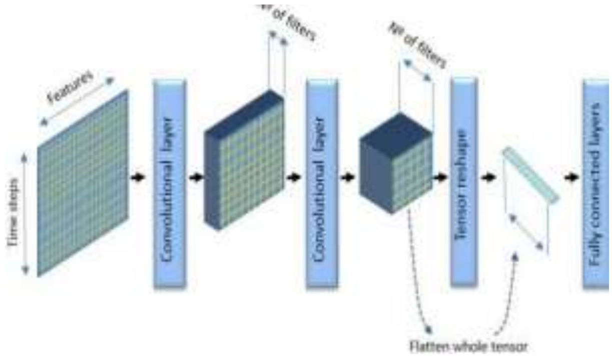

Fig.1.CNN model

Recurrent Neural Networks (RNNs)

RNNs are designed to handle sequential data like text, speech, or time series. They process information one step at a time, incorporating past data to understand the current input.Unlike traditional neural networks that treat each input independently, RNNs have a concept of "memory." This allows them to capture long-term dependencies within sequences.

Calculation:Hidden State (h_t): This vector represents the network's internal memory at a particular time step (t). It captures information from previous inputs.

Input Gate (i_t), Forget Gate (f_t), and Output Gate (o_t): These are additional neural network layers that regulate the information flow within the RNN.

Input Gate: establishes the amount of fresh information (x_t) from the current input is included in the hidden state.

Forget Gate: Decides how much information from the previous hidden state (h_(t-1)) is retained. (Uses sigmoid activation function and element-wise multiplication)

Output Gate: Regulates the amount of the hidden state that is currently in place (h_t) is used as output (y_t). (Uses sigmoid activation function and element-wise multiplication)

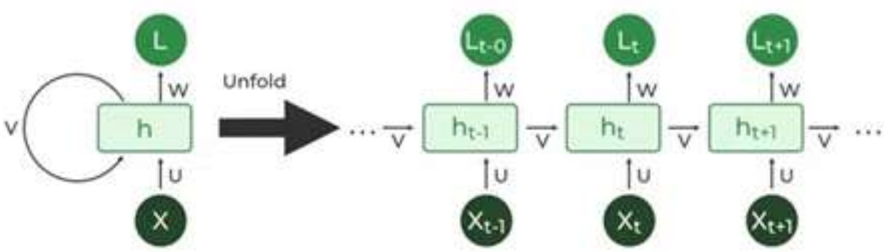

Fig.2.RNN model

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Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs) are a kind of artificial neural network where the input and output layers are stacked with several hidden layers. This allows them to learn complex relationships and patterns in data,making them adaptable to different kinds of work.

Calculations in a DNN: z = W * x + b

z is the total weighted amount (activation input) W represents the weight matrix.
W stands for the matrix of weights. vector from the previous layerb is the bias vector.

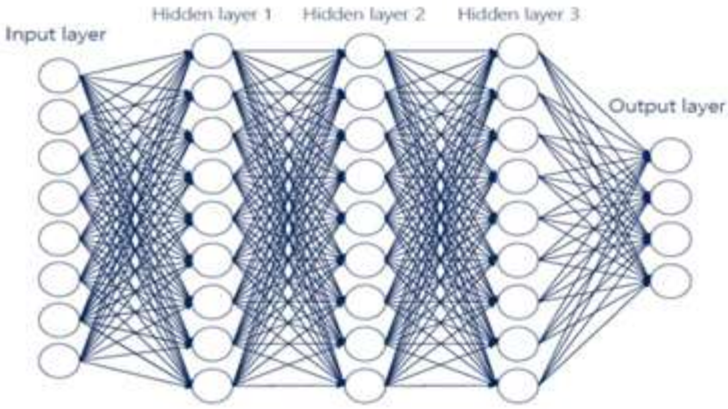

Fig.3. DNN model

3. Metrics of performance

Accuracy

The fraction of accurate predictions among all predictions is known as classification accuracy.It is only helpful when all forecasts and prediction errors have equal weight and each class has the same amount of data.
Accuracy = (Number of Correct Predictions) / (Total Number of Predictions)

confusion matrix

A matrix of confusion is a visualisation tool used in machine learning classification problems to assess the effectiveness of a model. It provides a clear summary of how well the model is dividing data points into various groups.

Key Elements:True Positives (TP): Correctly classified positive examples. (Located on the diagonal from top left to bottom right)

True Negatives (TN): Correctly classified negative examples. (Located on the diagonal from top left to bottom right)

False Positives (FP): Examples incorrectly classified as positive when they are actually negative. (Located above the diagonal)

False Negatives (FN): Examples incorrectly classified as negative when they are actually positive. (Located below the diagonal)

Confusion Matrix

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Fig.5. Confusion Matrix

F1 score

The Formula One score is a metric used in machine learning classification problems to assess the overall correctness of a model while taking both precision and recall. F1 Score Calculatio
F1 Score = 2 * (Precision * Recall) / (Precision +

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Recall)

Recall

Recall a True Positive Rate (TPR), is a metric used for machine learning classification tasks to measure the percentage of real positive instances that were appropriately identified by the model. In simpler terms, it tells you how good your model is at finding all the relevant instances.

Recall = True Positives (TP) / (True Positives (TP) + False Negatives (FN))

Ref	Dataset	Approach	Results	Pros	Cons	Year
[1]	Cleveland heart Disease dataset (304 instances) And Hungarian Heart disease Dataset (1025 instances)	Applied deep learning models,focusing on classification using neural networks,SVM, and KNN.	ET classifier achieved the highest accuracy of 96.74%, followed by GB wit 96.05%.The lowest performance was observed with NB classifier.	High accuracy achieved with deep learning models; significant performance improvement over traditional methods.	Computationall y expensive; requires significant computational resources for training deep learning models.	2022
[2]	Dataset of 1200 Algerian patientswith 20 attributes collected from Mohand Amokrane EHSn Hospital, Algiers, Algeria	Applied machine learning algorithms (Neural Networks,SVM, KNN) to detect heart disease.Data pre-processing involved feature selection using Pearson correlation matrix.	KNN achieved 89.16% accuracy, SVM achieved 84.18% accuracy, and neural networks achieved 85.07% accuracy	Provided a comprehensive approach to feature selection and data pre-processing; validated on a real-world dataset.	Lower accuracy compared to deep learning models; limitedto the specific dataset used in the study	2021
[3]	Cleveland heart disease dataset (S1: 304 instances) and Hungarian heart disease dataset (S2: 1025 instances)	Compared performance of various machine learning algorithms including KNN, DT, ET, GB, RF, SVM, AB, NB, LR, ANN.	ET achieved the highest accuracy of 94.14%, while NB the performance that was least reported.	Comprehensive comparison of multiple algorithms; clear performance metrics provided for each algorithm.	Results are dependent on the dataset used; Performance can change depending ondatasets.	2020
[4]	EHR data from a health system: 3884 HF cases, 28,903 controls (May 16, 2000 - May 23, 2013)	Recurrent neural network (RNN) with gated recurrent units (GRUs)	AUC of 0.777 (12-month window), AUC of 0.883 (18-month window)	Leverages temporal relations, improves performance over conventional methods	Requires extensive EHR data, computationall y intensive	2016
[5]	Heart Disease Dataset 1, Cleveland Datase	Deep stacking ensemble using CNN-LSTM and CNN-GRU with	Dataset 1: ACC=78.81%, PRE=78.1%, REC=78.81%,	High accuracy with both datasets, improved	Complex model, requiressignificant	2022
		SVM as meta-learner	F1=78.81%; Cleveland: ACC=97.17%,	performance over existing models	computational resources	

			PRE=97.42%, REC=97.17%, F1=97.15%			
[6]	Cleveland Heart Disease Database	Ensemble classification (bagging and boosting) with feature extraction	Bagging with Decision Tree and PCA achieved 98.6% accuracy(PCA and LDA)	Significant improvement in prediction accuracy, effective in improving weak classifiers	Limited to the specific dataset used, may require adaptation for other datasets	2019
[7]	Dataset cleaned and preprocessed, features selected via Random Forest Classifier	Deep learning models with various subsets of features, one-hot encoding, Min-Max normalisation	Various subsets of features used, with performance evaluated across different deep learning models	Effective feature selection, normalisation techniques to improve model performance	Potential overfitting due to large number of features, computational complexity	2020
[8]	UCI Heart DiseaseDataset	Ensemble learning combining Logistic Regression, SVM, Decision Tree, KNN, and Gaussian NaiveBayes	Logistic Regression: ACC=82.46%; SVM:ACC=87.34%; Decision Tree: ACC=97.67%; KNN:ACC=89.94%; Gaussian Naive Bayes: ACC=78.57%; Voting Ensemble: ACC=96.10%; Averaging Ensemble: ACC=96.43%	High accuracy, effective combination of multiple models	High accuracy, effective combination of multiple models	2021
[9]	Cleveland heart disease dataset	Ensemble learning using LDA and PCA to extract features, compared with KNN, SVM, NB, DT, and RF classifiers	Bagging ensemble with DT and PCA achieved 98.6% accuracy	High accuracy, effective feature selection	Computationall y intensive, complex ensemble method	2023
[10]	Heart disease dataset from Kaggle	Ensemble methods (boosting and bagging) using LDA and PCA to extract features, comparing multiple classifiers	Bagging ensemble with DT and PCA achieved the highest performance	Improved prediction performance, robust against overfitting	Requires significant computational resources	2021

II. CONCLUSION

This survey demonstrates that ensemble deep learning models offer superior performance in heart disease classification by combining the strengths of multiple neural network architectures. These models, which include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Neural Networks (DNNs), effectively capture diverse features from complex medical datasets, leading to higher diagnostic accuracy. Ensemble methods like boosting and bagging further enhance model performance by reducing overfitting and improving generalisation. Among the methods discussed, the ensemble approach using CNN-LSTM and CNN-GRU with SVM as a meta-learner achieved notable accuracy and robustness, making it the most reliable for predicting heart disease in the surveyed studies.Considering the survey results, ensemble deep learning models stand outas the most efficient technique for heart disease classification. These models not only offer excellent precision but also demonstrate robustness and reliability in detecting subtle patterns indicative of heart disease. Therefore, for practical applications, particularly in medical diagnostics, employing ensemble deep learning approaches is recommended due to their superior performance and ability to handle complex datasets.

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