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RESEARCH ARTICLE - ***Computer***

Diagnosis of heart disease using clinical data of cardiac patients

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Abstract

Heart disease is a leading cause of death worldwide and a major global health concern. For effective treatment and prevention, early and accurate diagnosis is essential. To increase the efficiency and objectivity of heart disease diagnosis, this study investigates the application of machine learning techniques. Large datasets can be analyzed by machine learning algorithms, which can also identify complex patterns that human specialists might overlook. However, since different models have different hypothesis spaces, some patients whose features do not match may be missed. To improve diagnostic accuracy, we propose a novel strategy that combines multiple machine learning methods and professional judgment. To assign appropriate relevance to patient data and expert opinions, we seek to use advanced weighting methods based on artificial neural networks. Our prototype was evaluated on the University of California, Irvine, heart disease dataset and outperformed other techniques including XGBoost, SVC, and decision trees, with a maximum accuracy of 96.65%. The model achieved the highest accuracy, significantly outperforming other methods. Other techniques used include XGBOOST: 79.61, SVC: 73.41, DT: 54.02, RF: 74.92, KNN: 54.21. This strategy has the potential to enhance clinical decision-making frameworks and enhance the recognition of heart disease.

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Keywords: Machine Learning; DT; XGBOOST; RF; SVC; KNN; UCI Dataset.

Nomenclature & Symbols

ML	Machine Learning	KNN	K-nearest neighbors
DT	Decision Tree	IWG	Input weighting gate
RF	Random forest	WDG	Weighted decision gate
SVM	Support Vector Machine		

1. Introduction

Cardiovascular disease is one of the leading causes of mortality worldwide, and early and accurate diagnosis is crucial for effective treatment and prevention. Standard practice used to determine the presence of heart disease involves critically evaluating the results of a battery of tests which can be stressful and the results inconclusive. Machine learning opens up a number of possibilities to increase the effectiveness and accuracy of heart disease diagnosis and rule out intrinsic factors. Thus, this research explores the applicability of machine learning approaches in heart disease diagnosis and the relative advantages of such approaches to patient care.

In a single case of heart disease diagnosis, it is possible to examine a huge amount of different data such as patient records, photographs, laboratory test results, and demographic data. Making a connection between these data and identifying corresponding relationships in heart disease may be a difficult task for a human expert due to the diversity of the phenomenon. Also, widely accepted medical tests can easily be interpreted or evaluated differently by different clinicians. This subjectivity can lead to differences and errors in diagnosis and thus patients can suffer consequences of differences.

The increasing use of electronic health records and various types of medical information results in a huge amount of patient information. Manually reviewing this data can be time-consuming and hinder rapid diagnosis of the disease and subsequent treatment. It can be useful in processing big data and identifying non-linearities that cannot be distinguished by human masters. Machine learning models can use historical data and make the correct prediction and certainly help in early diagnosis and more accurate diagnosis of heart diseases. Moreover, machine learning models make diagnoses based on learned patterns rather than subjective judgments. This helps reduce inter-observer variability and ensures consistent and objective decision-making, leading to more reliable diagnoses.

The primary aim of this research is to propose a novel method for diagnosing heart diseases that leverages the potential of multiple techniques to diagnose a broader range of patients. Additionally, an input weighting gate is used to exclusively weight patient features based on their initial data analysis to enhance expert efficiency. A decision weighting gate is also employed to weight expert decisions based on input data.

The remainder of this paper is organized as follows: Section two reviews related works, section three discusses the methodology, and section four presents the results and evaluation metrics. Finally, the fifth section concludes the paper with discussions on contributions, limitations, and future research directions.

2. RELATED WORK

This paper uses expert aggregation and decision weighting to propose a machine-learning method for identifying cardiac patients. It describes how this proposed method has succeeded in this topic by discussing modern techniques and providing background information. Before outlining the proposed method in this topic, the paper also covers modern techniques as well as background information.

A. Missing Value

In data analysis, missing values refer to a situation where some data is missing for one or more of the measured variables in a given dataset. This can happen in several ways such as; data collection errors, non-response, or early withdrawal of participants from the research. The presence of missing values always affects the results of analysis and learning algorithms as it leads to small sample size, bias, and disruption of relationships between variables. Hence, proper management of these values is needed to provide the correct accuracy and reliability of the models. In the paper [1] this problem was solved by proposing a data preprocessing step, which was preceded by value normalization and applying different algorithms for missing values such as mean value, KNN, MICE, and RF. The data completion challenge in Framingham dataset was addressed using SMOTE approach. The proposed method was performed to classify patients with cardiovascular diseases using different machine learning techniques such as Nu SVM, gradient boosting regressor, extreme gradient boosting, ADA boosting, ExtraTrees, LGBTM, SGD, and clustering algorithm [1]. To overcome this problem, in [2] they tried to solve this problem using a two-layer ensemble model where some ensemble classifiers are used as base classifiers and another ensemble classifier applies a feature selection strategy based on crowd optimization to select the most discriminative feature sets. This is done for each dataset [2].

B. Outlier and unbalanced data:

An abnormality in data sets deforms the learning process of machine learning models making the last point relevant. Outliers refer to data that exist in a random sample and which deviate by a wide margin from other scores within the sample. These data can skew patterns and/or relations, and hence have a bias or overfitting of the models. Also, outliers can produce inaccurate predictions by disproportionately affecting the model and increase the sensitivity of the model to noise. Imbalanced data also affects classification tasks, as models favor the majority class and perform poorly in identifying the minority class. Therefore, it is very important to understand the harm caused by outliers and unbalanced data and to implement appropriate techniques to reduce their negative effects.

Two of the articles studied in this field have presented methods to control the damage that this problem can cause in learning processes [3, 4].

In the article [3], it has been tried by presenting a model consisting of spatial density-clustering of programs with noise to identify and remove outliers, artificial minority oversampling technique-edited nearest neighbor to balance the distribution of training data and XGBoost for prediction. Heart disease, solve this problem. In the research [4], the ensemble method was used, which is one of the most widely used cases. In this research, a set method with three classifiers has been proposed and two feature.

C. Irrelevant Features:

In the field of machine learning, the presence of irrelevant features in a dataset can significantly affect the learning process and the performance of models. Alternatively the irrelevant features are those features that are not informative about the prediction task at hand. Reasons of negative influence of irrelevant features are very important to know in order to develop practical strategies for feature selection or dimension reduction in order to increase the model performance and efficiency.The ideas of the negative impact of irrelevant features with help of feature selection, regularization, and data knowledge are critical for developing powerful and efficient machine learning models. The above mentioned problem states that if models are trained on right features, prediction efficiency would enhance as well as resource utilization since more accurate models would be used In [5], one of them has given a solution to this problem [5]. To enhance the classification efficiency of heart disease diagnosis, this paper has proposed a new hybrid model, the $\chi2$-DNN.

D. Overfitting and underfitting:

There is over fitting when the model of the given dataset is too complex and high prediction rate and low generalization for the new samples. This is one issue with problem when the model recalls a noise or random oscillations instead of the real dynamics of the pattern. The problems associated with overfitting include: Overfitting distorts generalization capability, the model is sensitive to noises, and large variance. That is why in order to decrease overfitting it is possible to use the following methods: overfitting can be avoided by choosing a small value of 'lambda' by cross-validation, by selecting a smaller number of features, by choosing a larger value of 'lambda', or by using a larger amount of training data.

This is where the model that you have used is extremely simple and cannot in the least extract the underlying relations in the data. This results into low efficiency both on the training data set and on new data. Some of the symptoms of poor fit are: small and unsystematic amounts of error and most importantly inability to capture data patterns. When a model is underfitting its relationship with the data results in poor prediction performance and high bias. As a result, approaches for tackling poor fit consist of increasing model capacity and data dimensionality, feature creation and data expansion.

Out of all the studies which offered a solution in this field, there was a proposal for a hybrid algorithm. This paper presents a new approach in predicting heart diseases, known as the swarm-based MLP network (MLP-PSO) and uses the efficiency of the PSO algorithm in optimizing the MLP exercise, including the identification of the best weight and bias values [6].There is a study that proposed the solution to this area and utilized the ensemble method. The proposed study method is a set with Borota-based feature selection algorithm in the study to identify the most relevant features and important features in CAD prediction process in order to reduce the time needed for classification and increase the accuracy level [7].

E. Hyperparameters:

Hyperparameters are important in the process of learning, especially in machine learning the act of determining an outcome from an input. While, the parameters of internal model are learnt during the training process from training data, hyperparameters are decided by the user prior to training the model. Hyperparameters don't influence the model's ability, but they can enhance the rate as well as the quality of the learning procedure. Some hyperparameters are topology and size of the neural network, learning rate, batch size, and other. The problems associated with the hyperparameter tuning involve choosing the right values for these parameters as well as the initialization of these values.

Of the reviewed studies, one offered a solution to this problem, describing a diagnostic system based on the best XGBoost classifier for predicting heart disease. This study is of the view that a correct tuning of the hyperparameters of a ML algorithm must depend on understanding of the algorithm used, practice, and typically, it involves trial and error [8].

F. Processing time:

Time complexity or the execution time of an algorithm measures time taken by the algorithm to execute and come to halt. This concept means time which is needed for algorithm execution and is described as the amount of basic operations performed by this algorithm. Time complexity is a factor in understanding machine learning, since it impacts the rate at which models may be trained and made to make predictions. Diverse parameters including data sample size, model, algorithm performance, required hardware, and the preprocessing of the dataset create computation time. It is thus clear that for a system that is to handle large data sets, the size of the data could be a very significant determinant of the computation time. This is because the bigger the data, the more time it takes to analyze it. There is a positive relation between the size of models and computation time, the larger the model, the more time required to compute. Networks with more parameters or even complex structures like deep learning networks take more time for training as well as prediction. Algorithms selection is another consideration when it comes to calculation time because different algorithms will take different time on processing. Pre-processing step can also have impact on computation time.

There is only one of the reviewed studies that has proposed a solution based on gradual learning to solve this problem. Indeed, this research employed PCA and incremental FSVM for learning the data incrementally to ease the computational time of disease prediction [9].

G. Limited data:

Data is defined as the raw input fed into machine learning models with the intention of training them in an effort to enable them observe tendencies and make proper forecasts. However in real life application this can be of a challenge as obtaining a masses and highly generalized data set may be rather difficult. With limited data, great challenges occur in terms of the reliability, generality, and effectiveness of the machine learning models. Models fail to learn due to a small number of parameters due to less amount of data for training the models.Preliminary data: Large number of parameters increase the risk of over-fitting when there is a small amount of data to learn the parameters. The kind of models are also data hungry to provide good estimates of their parameters. To avoid these problems, investigators are forced to either simplify the model structure or employ the concept of regularization. However, these approaches may lead to low presentation and possibly compromises on performance.

Among all the researches, one of them concentrated on this problem and offered the way how to resolve it [10]. By combining five datasets and increasing the size of the entire dataset, this study has solved the problem of limited data and used two feature selection techniques, Relief and LASSO, to extract the most relevant features based on rank values in medical references.

H. Feature Extraction

In data analysis, feature extraction is the process of removing important details from unprocessed data in order to produce a small feature set, lower dimensionality, and identify important patterns[11]. By identifying and capturing the major components of the data—linear combinations of initial features—Principal Component Analysis (PCA) lowers dimensionality.

The formula C=1/n (∑(4)), where n is the number of observations and xi is a data point, is used to compute the covariance matrix C.

An essential texture analysis technique for evaluating pixel pairings with varying intensity fluctuations at various orientations in images is the Gray-Level Co-Occurrence Matrix (GLCM). It computes the likelihood of coming across two pixels with specified intensity values at a specified spatial offset while capturing textural characteristics. A computer vision technique for object detection called the Histogram of Oriented Gradients (HOG) calculates the orientations and magnitudes of gradients within picture cells, constructs orientation histograms, normalizes them, and combines them to produce a feature vector.

I. Histogram Equalization

One method for lessening the impact of different lighting conditions in ear photographs is the FAST algorithm. By removing the overall impact of ambient lighting, it employs histogram equalization to improve feature recognition by the classifier. The method extracts feature descriptors from pixels surrounding a focus of interest and uses criteria and thresholds to choose significant features[12]. The location of a single point determines the neighborhood pixels' center placement. Ear image representation points that are identifiable and recognizable are called POIs (Points of Interest). The method returns indicators for features compatible with the pair of features after matching features from the first set of coronavirus disease images to the second feature set of the original image. The algorithm entails picking a "p" pixel on the ear image, determining a point of interest, encircling the pixels, measuring the brightness of neighboring pixels, setting the threshold intensity, and repeating the procedure for every pixel in the ear image.

A. Additional features:

A feature is usually considered to have redundancy if there is a correlation between the features. The concept that two features are redundant if their values are completely correlated has been accepted by many researchers, but at the same time, it may not be an easy task to detect feature redundancy when a feature is related to a set of features. According to the definition provided by John and Kohavi, a feature is redundant if it is weakly associated and has a Markov blanket within the current set of features, so it should be removed. Since irrelevant features should be removed anyway, their cleaning is done according to this definition. When additional features are present, they provide additional or overlapping information to the learning algorithm, which can have negative consequences on the learning process and model performance. Effects of redundancy on machine learning models:

- Too fit
- Increasing the complexity of the model

Three research works were conducted among the studies and focused on this issue and proposed their own solutions to solve this issue. [13-15]The first study believed that the excess of features increases the cost of misclassification. For this reason, this study proposed a cost-sensitive ensemble method to improve the detection efficiency and reduce the cost of misclassification. The proposed method includes five heterogeneous classifiers: random forest, logistic regression, support vector machine, extreme learning machine and k-nearest neighbor[13]. Another research in this field has used a set method and the difference is in the type of integration of the primary results of the classifiers[14]. This study proposed a new machine learning model that combines three standard machine learning algorithms to obtain a superior result. The latest research has proposed a feature selection method using evolutionary techniques and then used a set method to design the model[15].

Table (1) compares the classification of heart disease diagnosis using clinical data of heart patients using techniques such as neural networks, machine learning. It shows the factors that affect the performance of each method, such as accuracy, training time. This table 1 is very important for professionals and researchers in heart disease classification, as it helps improve the selection and recruitment process and saves time and effort .

Table (1) shows a comparison between heart disease classification methods.

Study	Year	Disadvantages	Advantages	Methodology	Dataset	Accuracy
[1]	2021	It is not the right decision to choose the best model and not consider the hypothesis space of other models that make decisions based on it and probably do not overlap.	With this method, by filling the missing values, it has increased the efficiency of the model while preserving the samples, which is a better method than removing them.	SVM	UCI	95.83
[2]	2020	-	-	PSO based feature selection And Two-Tier Classifier Ensemble	StatLog dataset Z-Alizadeh Sani datase	93.55 98.13

[3]	2020	It reduces the number of samples and the model may miss some rare but important states.	Using the outlier data detection method based on DBSCAN can be effective in reducing the number of outliers and cause less disturbance in the learning process of the model.	DBSCAN+SMOTE-ENN+XGBOOST	Statlog Cleveland	95.90 98.40
[4]	2021	Classifier models all play the same role in decision-making, and if the performance of one model is bad, the final result will also be affected.	Multi-model ensemble and consensus methods improve the final result	Random over samplim+ smote+ Adasyn	UCI	-
[5]	2019	Reducing the dimensions and, in other words, the details, may cause overfitting or lack of fit.	Removing irrelevant features reduces the dimensions of the sample region and makes the model converge faster.	$\chi2$ -DNN	heart disease dataset	93.33
[6]	2022	The PSO model only receives the MSE error of the last layer and does not consider the error propagation values in the previous layers, which causes a large amount of information to be lost.	Choosing a set of weights from among different options is a better method than propagating linear error in the network.	MLP-PSO	UCI	84.61
[7]	2021	Decreasing input features results in information loss, which increases the likelihood of overfitting and underfitting.	The weighted average was the appropriate method for the final decision that was used in this work, this work makes the impact of the results of the models that have errors less.	ensemble method combining three base classifiers viz., K-Nearest Neighbour, Random Forest, and Support Vector	Z-Alizadeh Sani dataset	98.97%
[8]	2022	The parameter setting works only based on the AUC result, and information such as input data type or its dimensions, which are important parameters, are not considered.	Adjustment based on model output results is a more reliable method than experimental adjustment or by trial and error, which requires more time.	hyper-parameter optimization using Bayesian optimization +XGBoost	Heart disease dataset	91.8
[9]	2020	Adding a clustering step to the method increased the computations.	Reduction of calculation time	PCA+ Fuzzy Support Vector Machine	Statlog dataset Cleveland dataset	97.87 96.06
[10]	2021	Considering that each data set is collected under specific protocols and the possibility of presenting all the selected features of the proposed method is complex, this method will face problems in the clinical stage.	Integrating multiple datasets and selecting effective features can help expand the sample space of the problem and increase the frequency of samples in different cases.	LASSO+ Relief for features extraction DT,KNN	Heart disease dataset	99.05

[13]	2021	Weighting the effect of classifier results causes a negative effect of misclassification on the final result.	Controlling the problems caused by correct learning of models with the group method is an effective method, and reducing the dimensions of the input data also accelerates the learning process.	random forest, logistic regression, support vector machine, extreme learning machine and k-nearest neighbor	Hungarian dataset Statlog dataset	92.02 93.21
[15]	2021	Reducing the dimensions of the sample space in this way increases the probability of overfitting and underfitting.	Using voting controls the negative impact of each classifier's decisions on the final answer, which is a suitable approach	GA+LDA +Voting+Bagging	statlog dataset coronary heart disease dataset SPECTF dataset	93.65 84.95 82.81

1. Methodology

The proposed method in this paper uses the Mixture of Experts framework, which includes 5 different models as experts: XGBoost, Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF) and K-Nearest Neighbor (KNN). Each of these expert models is independently trained on the data. The overall architecture of the model includes an Input Weighting Gate for weighting input features, a Weighted Decision Gate for combining expert opinions, and a multi-layer neural network for final processing and output generation. The input weighting gate uses correlate

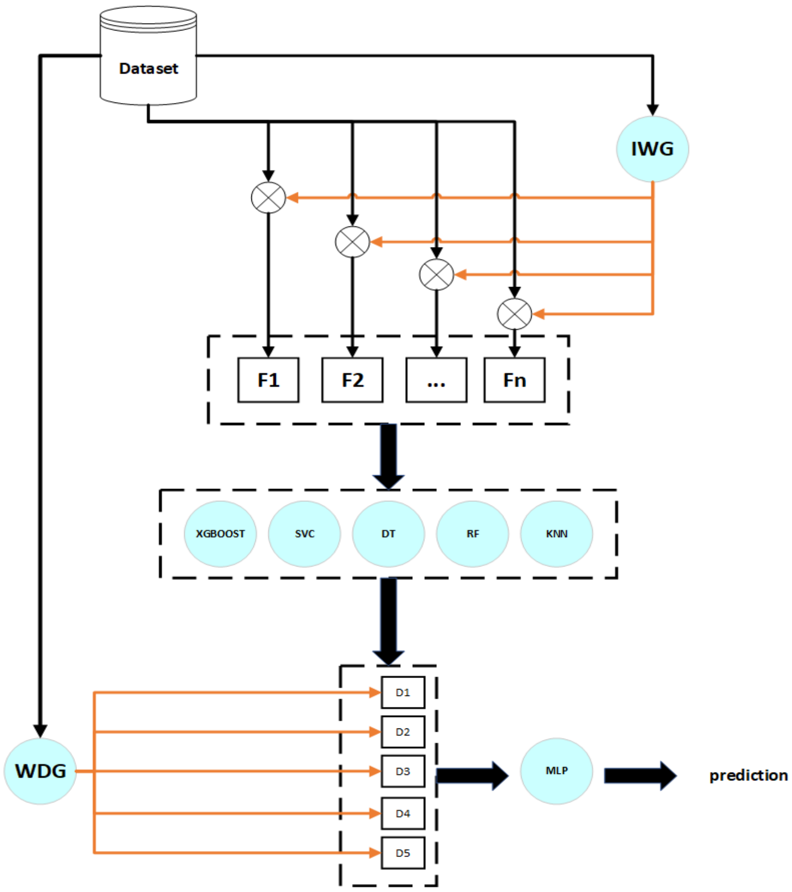

Fig. 1. Recommended model – marked in F1 to Fn of the above model represents features of the proposed dataset, and IWG, represents the input weighting gate while WDG represents the weighted decision gate.

on analysis to weight the input features so that the more important features get more weight. Weighted Decision Gate uses an MLP network to dynamically weight expert opinions based on input data. This kind of architecture attempt to enhance the accuracy of the estimated models concerning the heart diseases and enhance the possibility of the model to generalize well this attempt is done by using several models and incorporating intelligent weights The figure 1 below shows the structure of a hybrid model

A. Input weighting gate (IWG):

The input weighting gate utilises the correlation analysis to weigh the input features. This gate makes the more important features get closer to true mean and have more impact in the decision. This mechanism also enables the model to select relevant features and to neglect the rest of the shorter time intervals. Thus, the performance of the model is enhanced and risk of overfitting minimized among the different techniques being developed.

B. Weighted decision gate(WDG):

Weighted Decision Gate employs an MLP network for weighting the experts' opinions through data on the problem at hand. The gate itself becomes programmed to determine which of the experts is more right and this depends on a particular case. This mechanism enables the model to tap the strengths of each expert in setting and enhance the ultimate decision making.

C. Final composition and output production:

Lastly, the proposed plans and opinions of the different experts are averaged and fed to a multiple layered neural network to provide the solutions. This step enables learning the interaction between the opinions of experts and the final decision as well as to train the model to observe more complex dependencies. This composite architecture attempts to raise the accuracy of recognizing heart diseases and enhancing the generalization capability of the model with the help of several different classifications and smart weighing methods. Using this method, the model can avail of the strengths of each of the experts as well as offset the weaknesses that come with each.

3. RESULTS ANALYSIS

The method presented in this article that has been carried out using the framework The fourth of the three concentric circles, and the components of the mobilization and ordering phase, the framework of gathering experts and input and decision weighting gates, is assessed and quantified. in this part.In order to examine the proposed approach more closely, in this chapter experiments have been designed that evaluate different aspects of the method. According to the purpose of each test, part of the data in the proposed data set is considered as training data and part as test data. In the following section, each of the mentioned experiments will be described.

A. Evaluation Mattress

Accuracy (ACC): Accuracy is a fundamental metric gauging the overall correctness of a predictive model. It is computed as the ratio of correctly predicted instances to the total number of instances in the dataset (As pointed in (1) the…).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \qquad (1)$$

where TP represents the number of true positives, TN denotes true negatives, FP signifies false positives, and FN denotes false negatives.

Precision: Precision focuses on the accuracy of positive predictions and is defined as the ratio of true positive predictions to the total predicted positives (As pointed in (2) the…).

$$Precision = TP(TP + FP) \qquad (2)$$

where TP represents true positives, and FP represents false positives.

Recall (Sensitivity or True Positive Rate): Recall assesses the model's capability to capture all relevant instances within the positive class. It is computed as the ratio of true positives to the sum of true positives and false negatives (As pointed in (3) the…).

$$Recall = TP(TP + FN) \qquad (3)$$

where TP denotes true positives, and FN denotes false negatives.

F1 Score: The F1 score is the harmonic mean of precision and recall, offering a balanced assessment of a model's performance (As pointed in (4) the…).

$$F1score = 2 * \frac{recall * precision}{recall + precision} \qquad (4)$$

The F1 score ranges between 0 and 1, with higher values indicating a model's superior balance between precision and recall. The model under consideration underwent training on the Cleveland dataset, and its performance was systematically evaluated in comparison to 11 contemporaneous state-of-the-art models, as delineated .

B. UCI Heart Disease

The UCI Heart Disease dataset, a publicly available dataset from the Cleveland Clinic Foundation, is a valuable resource for cardiovascular research and machine learning. It contains 303 cases, each representing one patient, with 14 characteristics such as demographics, medical measurements, and laboratory test results. The dataset is accessible to researchers and practitioners worldwide and is used to study and develop predictive models of heart disease. It provides a diverse set of information for analysis and modeling, making it a valuable resource for researchers and practitioners worldwide.

C. Implementation environment

All implementations and evaluations reported in this research have been done with Python programming language, and Python programming language is one of the interpreted languages that is widely used in engineering fields. This programming language has earned its reputation for its ease of use. Furthermore, while implementing the action of the structure of the proposed model, Tensor and Cross packages have been used since they have the relevant potentiality to implement the framework of gathering experts and the mentioned gates.

D. Impact of Expert Aggregation Framework and Weighting Gates in the Method

This section offers a detailed study by offering various computational measures of performance including ACC, Precision, Recall, and F1 Score for all expert models. The evaluation proofs the ability of the expert aggregation method over the standalone selected methods, where all these methods have been trained and evaluated independently of the aggregation framework. A comparison is then made against the criterion adopted by this study to evaluate the performance of each of the identified expert.This multifaceted approach offers a clear understanding of the strengths of individual expert contributions and the holistic predictive effectiveness of the proposed model As shown in Table 2.

Table 2 evaluation of selected methods compared to the method

Methods	Accuracy (%)	precision (%)	Recall (%)	F1-scoer (%)
XGBOOST	79.61	75.31	83.25	78.68
SVC	73.41	73.04	74.82	73.91
DT	54.02	53.18	74.75	62.11
RF	74.92	72.76	80.36	76.32
KNN	54.21	53.12	74.77	62.15
Our model	96.65	83.96	85.66	87.59

The results in Table 2 indicate that the proposed method outperforms the selected standalone methods across all four metrics: accuracy, precision, recall, and F1 score. This suggests that leveraging the hypothesis space of multiple methods can enhance the model's ability to diagnose a broader range of patients effectively.

E. Comparison with Previous Works

Our model was trained on the Cleveland dataset and systematically evaluated against 11 pioneering models, as detailed in Table 3. The empirical findings indicate that the proposed model surpasses its counterparts in terms of prediction accuracy. The observed superiority in accuracy highlights the efficiency of the architectural design and methodology of the proposed model, underscoring its potential as a prominent contender among the studied models As shown in Table 3.

Table 3 comparison with previous works

Authors	Methods	Ensemble	Accuracy (%)
J. Soni et al .[16]	Association rules	False	81.51
A. Khemphila et al .[17]	Back Propagation MLP	False	89.56
M. G. Feshki et al.[18]	PSO and Feedforward neural network	False	91.94
A. K. Paul et al.[19]	Adaptive FDSS	False	95.96
V, Pavithra et al.[20]	NB Net, C 4.5, MLP, PART, Bagging, Boosting, majority voting, Stacking	True	85.48
Latha, C. Beulah Christalin et al.[21]	LR, SVM, KNN	True	87.00
D. Ananey-Obir0i et al.[22]	LR, DT, and Gaussian naïve Bayes (GNB)	True	82.75
F. Rustam ET Al.[23]	Stochastic Gradient Descent Classifiers, LR, SVM, NB, ConvSGLV, and Ensemble methods	True	93.00
Ahamad, Ghulab Nabi ET Al.[24]	LR, KNN, DT, XGB, SVM, RF	True	87.91
N. Chandrasekhar ET al.[25]	RF, KNN, LR, NB, GB, AB, SVE classifier	True	93.44
Our method	XG Boost, SVC, DT, RF, KNN	True	96.98

3.CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a novel approach based on expert aggregation and exclusive input and decision weighting gates to improve the identification of heart disease patients. The proposed method effectively expands the diagnostic range by utilizing multiple hypothesis spaces and emphasizes key features for each specific case through input weighting. Implemented using the UCI Heart Disease dataset, the method demonstrated satisfactory performance and accuracy, surpassing other models in prediction accuracy.

Future research could focus on addressing the limitations identified in this study, such as the use of domestic clinical data to enhance applicability for local patients. Additionally, implementing a multi-stage classification system based on statistical analysis of challenging cases could further improve model accuracy. This would involve using a classifier to identify and separate difficult cases, allowing for independent model training. By integrating two models and a classifier in a pipeline, input data can be directed to the appropriate model for training, enhancing the overall diagnostic capability.

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