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FUSION-BASED PATTERN RECOGNITION MODEL FOR HEART FAILURE PREDICTION

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Abstract
Risk prediction of heart failure (HF) patients is extremely important to provide them with specific treatment that will assist in enhancing clinical outcomes and quality of life. Globally, cardiovascular diseases are the leading causes of death resulting in almost 17 million deaths annually with most of them being caused by myocardial infarction and cardiac failure. This paper introduces a new Decision-Level Fusion that is powered by Fuzzy Logic (DLFeFL) model to improve predictions of heart failures. The architecture incorporates the outputs of two base learners Support Vector Machine (SVM) and Artificial Neural Network (ANN) into a fuzzy inference system that adds variable adds the decision strengths of the two base learners. In contrast to the traditional ensemble models which use a fixed weighting, the proposed fusion includes an adaptive fuzzy layer that treats the confidence of the classifiers as the linguistic variables that enhances interpretability of decisions and uncertainty. With 299 clinical records, ANN with 91.1% accuracy on 10 hidden layers, and SVM with 86.3% accuracy on 5-fold cross-validation were obtained. DLFeFL fusion performed better than the two base models showing that it is a promising decision-support tool in heart failure prognosis.

1. INTRODUCTION
Heart infections have led to choppiness everywhere in the world in the field of medication. The heart is a hard organ, roughly the size of the clench hand, which is located merely behind and a little to the left of the breastbone. Blood is pumped through the system of conduits and veins in the heart known as the cardiovascular framework [1] . The world health organization states that cardiovascular disease is the most infectious cause of mortality in the whole world and in Pakistan. Heart failures are applied to describe a situation where the heart is no longer able to provide sufficient blood to satisfy the body. The leading cause of death in its entirety is cardiovascular disease (CVDs), which is projected to claim 17.9 million carries annually [2] . CVDs are a compilation of heart and artery issues and involve coronary diseases, cerebrovascular illness, rheumatic coronary diseases

and various disorders. 4 out of 5CVD passing are due to coronary diseases and strokes and 33% of these events are sudden in people below 70 years of age[2].

The most recent proof has uncovered that all around, cardiovascular malady is the driving reason for death, also, around 80% to 86% of these deaths happen in low-and center salary nations, due to non-transmittable diseases round about 16 million deaths occur, 37% deaths occur due to CVD [3] . According to WHO, overweight and obesity is the excess fat accumulation which may be detrimental to health. Body fat accumulation increases the risk of developing cardiometabolic diseases (CMDs) potentially leading to heart failure, stroke, diabetes and high blood pressure. CMDs are very common and therefore a significant health hazard to the population. To determine their probability, there are various scoring systems, and anthropometric indices (body measurements such as BMI, waist circumference, etc.) are useful to classify high-risk individuals who need early intervention and control [4].

There are a few weaknesses of the as of now accessible hazard prediction models for Cardiovascular Breakdown (CVB). Most past models are created utilizing conventional measurable methodologies [5] . For example, regression modelling, and more up to date choices, machine learning-based prediction models, have remained underused. Most models are created to contain just a few significant indicators that clinicians can without much stretch access or request to register a hazard score at the bedside to decide the suitable treatment course for a specific patient[6]. To address these confinements of the recently proposed models, we undertook this investigation as a primary objective of comparing serval machine learning approaches with Artificial Neural Networks (ANN) by using a backtracking approach for the development of prediction models. AI-based healthcare uses various types of data (EHRs, wearable sensors, and genetic data) to enhance prediction and early diagnosis, as well as individualized care of chronic illnesses like diabetes and CVD. Nevertheless, there are still issues on the integration of heterogeneous data, their quality, and the validation of models in real-life conditions. The current literature tends to focus on algorithms or single-disease research, and to cover fairness, data aggregation and clinical usefulness [7].

Machine learning is divided into 3 types under supervised, unsupervised and reinforcement learning. Supervised learning with which we know of data on which we can train it, unsupervised learning with which we are simply guessing at what we can make a scene of the data and reinforcement learning with which we reinforce it good and bad behavior since the SVM is suited to the supervised learning machine [8]. The machine learning model is trained based on the past data of input and provides an output of future predictions. Hence, the broadest view of the machine learning framework and under the super-vised learning that you can observe that the support vector fits in less than the classification that clarifies what yes and no is and there is also a regression variety, which is mostly adopted in classification. [9] . Classification is one which is the main case that SVM is used for, but they can also be used for other types of machine learning problems regression that is if we have some set of data points, and we are trying to predict the next point in that set of data [10].

ANN is a computational model that depends on neural organic organizations. Since ANN is considered based on human organic frameworks, it learns by a model. Learning is characterized by adjusting to the synaptic associations between the neurons. This contains an incorporated network of fake neurons as layers and coordinates information using a factual connecting procedure. An ANN is a versatile framework dependent on outer or inside data that moves through the organization, which changes its structure during the learning stage. Capacity Activation is utilized to go contribution to yield, for instance, the capacity Sigmoid. The cost work for figuring the ideal estimations of the boundaries is utilized [10] . SVM is a very popular set of rules and best in class pattern recognition strategies whose establishment comes from factual learning hypothesis. An SVM is an overall calculation dependent on ensured hazard limits of measurable learning hypothesis. It is fit for actualizing set of capacities that rough best the administrator's reaction with a normal hazard limited by the whole of the exact risk [11].

Despite the encouraging performance of SVM and ANN in predicting cardiac risks, the two approaches have been characterized by drawbacks in dealing with uncertainties and boundaries of overlapping decisions with clinical data. In response to this, the suggested DLFeFL architecture combines these models via fuzzy inference layer which weighs the output of the models in a dynamic manner and accordingly enhances diagnostic reliability.

2. LITERATURE REVIEW

Here are some of the latest relevant works done mentioned, CVB is a multifaceted disorder tending to for a high pace of death among everybody [12] . Cardiovascular Breakdown with safeguarded Ejection Fraction (CVBEF) represents up to one-portion of the occurrences of cardiovascular breakdown and is related to critical horribleness and mortality. The predominance of hospitalization because of CVBEF has kept on expanding, yet no treatment has by a wide margin appeared to improve endurance and other cardiovascular results [13] .To contrast machine learning draws near and customary calculated relapse in anticipating key results in HF's patients and assess the additional benefit of increasing cases-based prescient models with the Electronic Clinical Record (ECR) inferred data [6]. CVBEF has developed to turn into the prevailing type of cardiovascular breakdown around the world, pair with the maturing of everybody and the expanding predominance's of obesity, diabetes mellitus, and hypertension [14]. ML and AI producing huge consideration cutting-edge mainstream researchers. These calculations have extraordinary ability in medication on behalf of customizing and recovering patient consideration, remembering for the determination, and the board of cardiovascular breakdown [15]. In the patients of heart failure predicting mortality play a vital role. Patient characteristics and mortality to be captured by correlation using a machine learning algorithm boosted decision tree for deciding to improve the risk prediction of CVB [16] . The binary classification of the above survival and biostatistics to be used in the ranking of features to be discarded is done using machine learning methods to discard the follow-up time of each patient. The classifiers of survival prediction and ranking of features were applied in discarding the follow up time of each patient. Survival is predicted with the help of the logistics regression algorithm. These techniques are applied with the help of the open-source R programming script. In the case of feature ranking, the classical univariate analysis of biostatistics and then the machine learning analysis and in feature ranking of the random forest are aimed at reducing the mean forest and Gini impurity [17] . Information in the medical care industry comprises patient data and illness-related data [18].

Over-fitting, Feature Selection, Classification, and Optimization these four approaches are used for decision making by predicting heart failure. In feature selection, shared data based measurable model is utilized to rank highlights as per the significance. For classification purposes, artificial and deep neural networks are introduced and improve the generalization by deducing the over-fitting by developing the optimal subsets of feature and network models also[19]. A colossal amount of life can be saved through viable observation of heart patients. The likelihood of heart disorders according to ECG signals has become unbelievably important to patients and experts over the last ten years. The exceptionally profound learning design with high accuracy and prevalence has recently been suggested to the scheme of Congestive Heart Failure (CHF) ECGs [20]. SVM-radial bias techniques are used to predict diseases in the health care field. It improves the datasets of Chronic Kidney Diseases, Diabetes, and heart diseases linear and polynomial SVM and decision tree also[18]. ML-based techniques plan to improve analysis by utilizing information found from every one of these regions, including electrocardiography, echocardiography, Electronic Human Record (EHR) information, and different sources [15]. The prescient capacity of ML calculations in cardiovascular maladies is promising, especially SVM and boosting algorithms [21] . Convolution Neural Network (CNN) is very effective in the health care field like automated medical image analysis. A viable classification strategy is introduced for a gastrointestinal plot classification task that contains few named information and has an example number of irregularities between classes. A powerful classifier toward the finish of the CNN structure delivers the ideal exhibition regardless of whether the CNN structure is not emphatically prepared [22]. This research [11] incorporates insights concerning patient information, coding, standardization, and arrangement. The FFBP, SVM, and RBF have applied over the information for the trial. In this paper [10] generic framework is used in which ANN, SVM, LGBM, and LR which yields the demonstrative outcome related to diabetes. Using ANN a hybrid approach is used to detect lung cancer [23] . By identifying a diffracted Laser Beam Shaping optimization algorithm is used that is based on ANN by clarifying its training and application steps and mapped the relationship between input and output images [24] . This paper [25] perceive the example of aspiratory illness on x-beam radiography picture utilizing ANN strategy. Coronavirus is a pandemic that has caused part of passing's in this paper [26] setting up the power of the proposed ANN model for determining COVID-19 cases for the province of Karnataka.

In role of AI in chronic disease prediction and management based on the integration of multimodal data (EHRs, wearables, and genetic profiles). It focuses on large predictive accuracies (usually above 80 and more sophisticated models of 99.67) and novel input such as neural networks based on particle swarm optimization and edge computing to monitor in real time. It also tackles issues like algorithmic bias, disjointed data systems, privacy, and transparency in addition to proposing fairness audits, federated learning, and large-scale clinical trials as the means of equitable AI adoption in healthcare [7].

The fast development of wearable sensors has expanded the significance of human activity analysis in various territories of data advances. classification of various everyday life exercises is performed through Particle Swarm Optimization (PSO) along with SVM algorithm over seat mark movement sense dataset [27]. The precision of the classification algorithm is affected by the utilization of highlights and measurements in the dataset. Chronic Kidney Diseases (CKD) datasets are optimized based on PSO using SVM which can handle the high dimensions to increase the accuracy of diagnosis [28] . In this research [29] efficient segmentation and classification system is introduced by using the fuzzy clustering of the C-Mean and SVM algorithm and comparing SVM, DT, RSDA and classification algorithm for the sake of knowing optimal results. A group of Saudi undergraduate students (n=295) involving a study on CMD risk prediction, involved the utilization of multiple ML models, such as: SVM, KNN, LR, RF, and GB. to enhance interpretability a new feature called risk level was introduced based on the Conicity Index using fuzzy logic. Findings revealed that LR was most suitable in male (91% accuracy) and SVM and LR in female (87% accuracy), with a difference in model performance between genders [4].

As the number of digital health data grows due to hospitals, patients, and insurers, data-driven insights in healthcare have been expanded. Federated learning provides a way out by training the models collaboratively without necessarily sharing sensitive records between the institutions. This method deals with statistical, system, and privacy issues with great prospect of improving biomedical research and health care provision [30]. A brief comparison between recent studies is shown in Table 1.

TABLE 1: COMPARISON OF RECENT RESEARCH STUDIES

Author & Year	Model Type	Dataset	Accuracy	Limitation
Huang et al. (2020)	RCT – Iloprost intervention	HFpEF patients, n = 34	–	Small sample; short-term effects only
Ahmad et al. (2021)	ML review (SVM, ANN, RF, DL)	Multiple HF datasets	80–95% (range reported)	Descriptive; no experimental validation
Nirschl et al. (2018)	DL & Random Forest	H&E cardiac tissue images	DL AUC = 0.989; RF AUC = 0.960	Small postmortem dataset; limited generalizability
Chicco & Jurman (2020)	ML classifiers (SVM, RF, LR)	HF clinical records, n = 299	Accuracy ≈ 88%	Small dataset; no external validation
Priyanka & Tripathi (2020)	SVM-RBF	Heart disease dataset	89.9%	Limited benchmark datasets; lacks real-world testing
Ahmad et al. (2021)	SVM + PSO (feature optimization)	Motion Sense wearable sensor dataset	87.5%	Limited activity categories; moderate accuracy

3. MATERIALS AND METHODS

Proposed Decision Level Fusion empowered with Fuzzy Logics (DLFeFL)

The training phase of proposed DLFeFL is presented in figure 1. This stage is further subdivided into 5 layers which are data acquisition layer, pre-processing layer, application layer, performance evaluation layer and finally consolidated data on the fundamentals of decision level.

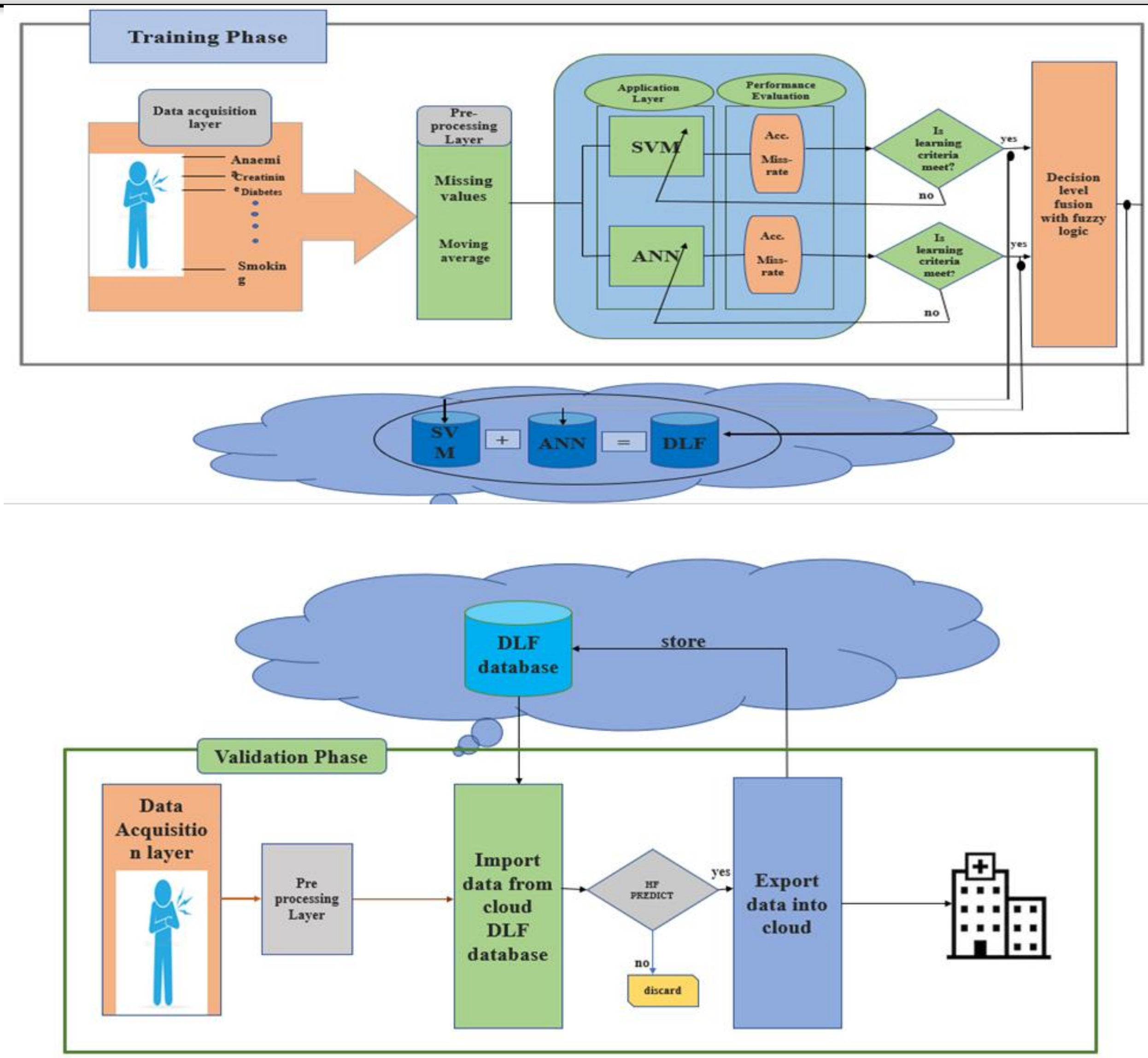

FIGURE 1. PROPOSED DLFEFL

In the first layer, we used the facts set with 12 clinical features for the prediction of death events. The data set consist of 300 patients with 109 females and 195 males that is suffered with cardiovascular diseases, and their age is below 95 years. The HF information is shown in table 2. The comprehensive report of HF information is some binary features include is anemia, sex, smoking, high BP, diabetes is of the range between 0 to 1. Anemia is a reason behind decreasing red blood cells or a hemoglobin level from the body. Another feature is Ejection Fraction the percentage lay between the rage that is minimum of 14% and maximum 80%. Serum creatinine level in the blood between 0.5 mg/dL to 9.4 mg/dL and serum sodium between 113 mEq/L to 148 mEq/l and the last one is following up time that is maximum is 285 and the min days about 4. This layer acquired all the information regarding HF for prediction. Table 2 shows the input parameter below:

TABLE 2: EVALUATING PARAMETER OF PROPOSED CVD

Sr. No	I/O Variable Name
In-1	Age
In-2	Anemia
In-3	Creatinine
In-4	Diabetes
In-5	Ejection fraction
In-6	High blood
In-7	Platelets
In-8	Serum creatinine
In-9	Serum sodium
In-10	Sex
In-11	Smoking
In-12	Time
Output	Death event

After acquiring the features from dataset, we can pass through the layer for finding and fixing the missing values and moving average as well as this layer known as data pre-processing layer. SVM and ANN are implemented in application layer. This layer is divided into two sets that is training phase1 and training phase2. In training phase1, SVM and ANN these two algorithms are used to predict the cardiovascular breakdown and the training phase2 performance is evaluated by finding the missing rate and accuracy.

3.1) Support Vector Machine

The dataset that involves some input parameters and one output parameters. Since we are aware that the line equation is,

$$e_2 = ue_1 + y \qquad 1$$

Where 'u' slope of a line and 'y' intersect, therefore

$$ue_1 - e_2 + y = 0$$

Let $\underline{e} = (e_1, e_2)^T$ and $\underline{l} =$ (u – 1) then the above equation can be written as

$$\vec{l} \cdot \underline{e} + y = 0 \qquad 2$$

This equation is derived from 2-dimensional vectors. But in fact, it also works for any number of dimensions, equation 2 also known as hyperplane equation.

The direction of the vector $\underline{e} = (e_1, e_2)^T$ is written as $\underline{l}$ and is defined as

$$l = \frac{e_1}{||e||} + \frac{e_2}{||e||} \qquad 3$$

Were

$$||e|| = \sqrt{e_1^2 + e_2^2 + e_3^2 + \dots e_n^2}$$

As we know that

$$cos\,(\theta) = \frac{e_1}{||e||} \text{ and } cos\,(\alpha) = \frac{e_2}{||e||}$$

Equation 3 can be written as

$$l = (cos\,(\theta),\ cos\,(\alpha)\,)$$
$$\vec{l} \cdot \vec{e} = ||l||||e||\,cos\,(\theta)$$
$$\theta = \beta - \alpha$$
$$cos\,(\theta)\ = cos\,(\beta - \alpha)$$
$$= cos\,(\beta)\,cos\,(\alpha)\ + sin\,(\beta)\,sin\,(\alpha)$$
$$= \frac{l_1}{||l||}\,\frac{e_1}{||e||} + \frac{l_2}{||l||}\,\frac{e_2}{||e||}$$
$$= l_1 e_1 + \frac{l_2 e_2}{||l||||e||}$$
$$l.e = ||l||||e||[\frac{l_1 e_1 + l_2 e_2}{||l||||e||}]$$
$$\vec{l}.\vec{e} = \Sigma_{r=1}^{n} l_r e_r \qquad 4$$

Let

$$f = y(l.e + y)$$

Sign(f) >0 When correctly classified and sign(f) < 0 When incorrectly classified.

We evaluate f on a training dataset given a dataset D.

$$f_r = y_r(l.e + y)$$

then F the so-called functional margin of the dataset.

$$F = min\,r = 1 \ldots z\ \ f_r$$

The hyperplane with the highest F will be complimentary chosen when the hyperplanes are compared. In which F is referred to as the geometric margin of the dataset. We want to determine a good hyperplane that is, we want to determine the values of $\vec{l}$ and y of the good hyperplane.

The lagrangian function is

$$L\,(l, y, \alpha) = \frac{1}{2}\,l.l - \sum_{r=1}^{z} \alpha_r[y:(l.e + y) - 1]$$
$$\nabla_l L(l, y, \alpha) = l - \Sigma_{r=1}^{z}\alpha_r y_r e_r = 0 \quad 5$$
$$\nabla_y L\,(l, y, \alpha) = \ -\Sigma_{r=1}^{z}\alpha_r y_r = 0 \quad 6$$

For above two equations (5) and (6) we get

$$l = \ \Sigma_{r=1}^{z}\,\alpha_r y_r e_r \text{ and } \Sigma_{r=1}^{z}\alpha_r y_r = 0 \ 7$$

After substitution, the Lagrangian function L we get

$$l(\alpha, y) = \Sigma_{r=1}^{z}\,\alpha_r - \frac{1}{2}\Sigma_{r=1}^{z}\,1\,\Sigma_{j=1}^{z}\,\alpha_r\ \alpha_j y_j\,y_j\,e_r\,e_j \qquad 8$$

Thus

$$\sum_{r=1}^{z}\sum_{j=1}^{z} \alpha_r\ \alpha_j y_r y_j e_r e_j$$

Subject to $\alpha_r \geq 0, r = 1 \ldots\ldots z,\ \Sigma_{r=1}^{z}\,\alpha_r\,y_r = 0$

Due to the inequalities in the constraints, we generalize the lagrangian multipliers techniques to the Karush-Kuhu-Tucker (KKT) conditions. The complementary condition of KKT states that

$$\alpha_r[y_r(l_r.e* + y) - 1] = 0 \qquad 9$$

e* is the point / points at which we perform the optimum.

Where α represents the positive value and the alpha values of the other points will be about 0.

So

$$y_r\big((l_r.e* + y) - 1\big) = 0 \quad 10$$

These are called support vectors, which are the closest points to the hyperplane.

According to the above equation (10)

$$l - \sum_{r=1}^{z} \alpha_r\,y_r e_r = 0$$
$$l = \Sigma_{r=1}^{z}\,\alpha_r\,y_r e_r \qquad 11$$

To compute the value of b we get

$$y_r(l_r.e* + y) - 1) = 0 \qquad 12$$

Multiple by both sides by y in equation 12 then we get

$$y_r^2\big((l_r.e* + y) - y_r\big) = 0 \qquad \text{where } y_r^2 = 1$$
$$\big((l_r.e* + y) - y_r\big) = 0$$
$$y = y_r - l_r.e* \qquad 13$$

Thus

$$y = \frac{1}{s}\Sigma_{r=1}^{s}\,(y_r - l.e) \qquad 14$$

S denotes support vectors. One time we have the hyperplane, then we can take the hyperplane to make predictions. In which the hypothesis function is

$$h(l_r) = \ +1\ if\ l.e + y \geq 0\ \ -1\ if\ l.e + y < 0 \qquad 15$$

the point in the above on the hyperplane will be a+1 (congestion found) and the point under the hyperplane will be -1(congestion not found).

In essence, we are trying to locate a hyperplane that may divide the data correctly, and we must locate the best one, commonly known as the optimal hyperplane, with the SM Algorithm.

The SVM equations are practically applied to the workflow by the decision function calculated.

equation to get probabilistic scores $f(y) = \omega^{\tau} + B$

These scores serve as in-between inputs to the fuzzy inference layer and bridge the crisp classification boundary that comes with SVM to the explanatory logic of decision making of the fuzzy module.

3.2) ANN (Artificial Intelligent System)

$$\breve{g}_s = y_1 + \sum_{r=1}^{m} \left(\hat{a}_{rs} * \tilde{e}_r\right) \qquad 16$$

$$\rho_{\ s} = \frac{1}{1+e^{-\breve{g}}} \quad where\ s = 1,2,3 \ldots \breve{n} \qquad 17$$

Input taken from the output layer is

$$\breve{g}_k = y_2 + \sum_{s=1}^{n} \left(\breve{o}_{sk} * \rho_{\ s}\right) \qquad 18$$

Output layer activation function is given below

$$\rho_{\ k} = \frac{1}{1+e^{-\breve{g}_k}} \quad where\ k = 1,2,3 \ldots \tilde{e} \qquad 19$$

$$E = \frac{1}{2}\sum_{k}^{1} \left(\tau_k - \rho_{\ k}\right)^2 \qquad 20$$

Above equation represent back propagation error where, τ_k & ρ_k **r**epresents the desired output and estimated output.

In equation (21) reduce the overall error for the adjusting the network weights, the layer is written as.

$$\Delta \acute{M} \propto -\frac{\partial E}{\partial \acute{M}}$$

With the help of weight, start at the output layer.

$$\Delta \breve{o}_{s,k} =- \ \epsilon \frac{\partial E}{\partial v_{s,k}} \qquad 21$$

$$\Delta \breve{o}_{s,k} =- \ \epsilon \frac{\partial E}{\partial \rho_{\ k}} \times \frac{\partial \rho_{\ k}}{\partial \breve{g}_k} \times \frac{\partial \breve{g}_k}{\partial \breve{o}_{s,k}} \qquad 22$$

$$\Delta \breve{o}_{s,k} = \ \epsilon\left(\tau_k - \rho_{\ k}\right) \times \rho_{\ k}\left(1 - \rho_{\ k}\right) \times \left(\rho_{\ s}\right)$$

$$\Delta \breve{o}_{s,k} = \epsilon \xi_k \rho_{\ s} \qquad 23$$

Were,

$$\xi_k = \left(\tau_k - \rho_{\ k}\right) \times \rho_{\ k}\left(1 - \rho_{\ k}\right)$$

Apply chain rule for the updating of weights between input and hidden layers

$$\Delta \hat{a}_{r,s} \propto- \ \left[\sum_{k}^{1} \frac{\partial E}{\partial \rho_{\ k}} \times \frac{\partial \rho_{\ k}}{\partial \breve{g}_k} \times \frac{\partial \breve{g}_k}{\partial \rho_{\ s}}\right] \times \frac{\partial \rho_{\ s}}{\partial \breve{g}_s} \times \frac{\partial \breve{g}_s}{\partial \hat{a}_{r,s}}$$

$$\Delta \hat{a}_{r,s} =- \ \epsilon \left[\sum_{k}^{1} \frac{\partial E}{\partial \rho_{\ k}} \times \frac{\partial \rho_{\ k}}{\partial \breve{g}_k} \times \frac{\partial \breve{g}_k}{\partial \rho_{\ s}}\right] \times \frac{\partial \rho_{\ s}}{\partial \breve{g}_s} \times \frac{\partial \breve{g}_s}{\partial \hat{a}_{r,s}}$$

After simplification above equation can be written as

$$\Delta \hat{a}_{r,s} = \ \epsilon \xi_s \, \alpha_r \qquad 24$$

Were,

$$\xi_s = \left[\sum_{k}^{1} \xi_k\left(\breve{o}_{s,k}\right)\right] \times \rho_{\ s}\left(1 - \rho_{\ s}\right)$$

$$\breve{o}_{s,k}^{+} = \breve{o}_{s,k} + \lambda_F \Delta \breve{o}_{s,k} \qquad 25$$

Above equation is used for updating the weights between output & hidden layers.

$$\hat{a}_{r,s}^{+} = \hat{a}_{r,s} + \lambda_F \Delta \hat{a}_{r,s} \qquad 26$$

3.3 SVM Based Simulations

Cross-validation is used through an efficient training method where the averaging result of the entire block can be trained the set dividing into k-blocks. This evaluation needed for all the records to train the data and then test the data as well. Therefore, for training 5-fold-cross validation is used. For classification and regression analysis SVM is used to analyze the data and make pattern on the basis on these. It is used to analyze the data based on 2 classes. During the SVM classifies the data first step is to find the best hyperplane that secreted the point of data into these two classes during classifier learner. It is based on mathematical model that is used to solve complex and real-world data. 12/12 features during training phase, accuracy measures of SVM with further model type, here is the first one about linear classification is 81.3%, Quadratic SVM is 76.3%, Cubic SVM is 74.2%, fine Gaussian SVM is 67.9%, medium Gaussian SVM is 80.6%, Coarse Gaussian SVM is 74.2%, KNN is about 66.6%, Medium KNN is 74.2%, Ensemble Boosted trees have 80.6% and finally bagged tree accuracy is

83.9%.Datasets have the total variable is all about 12 features including output feature. In confusion matrix performance checked after training model, it helps to identify the area where the classification has low par performed, true class shows onto the rows and predicted class shown onto the columns. The top row identifies all instances with true class of HF, 91% of instances from HF are corrected classified, so, 91% is true positive rate that shows onto the green cell. Other instances in the HF row are incorrect, about 9% is false negative rate that is classified incorrectly. ROC used to show true and false positive rates. The area under curve is 0.89 and currently classifier is (0.31, 0.91)

Parallel Coordinates Plot (PCP) is used to help the relationship between the prediction of separated classes of features and identify. It helps to elaborate the training data and misclassified points on PCP.

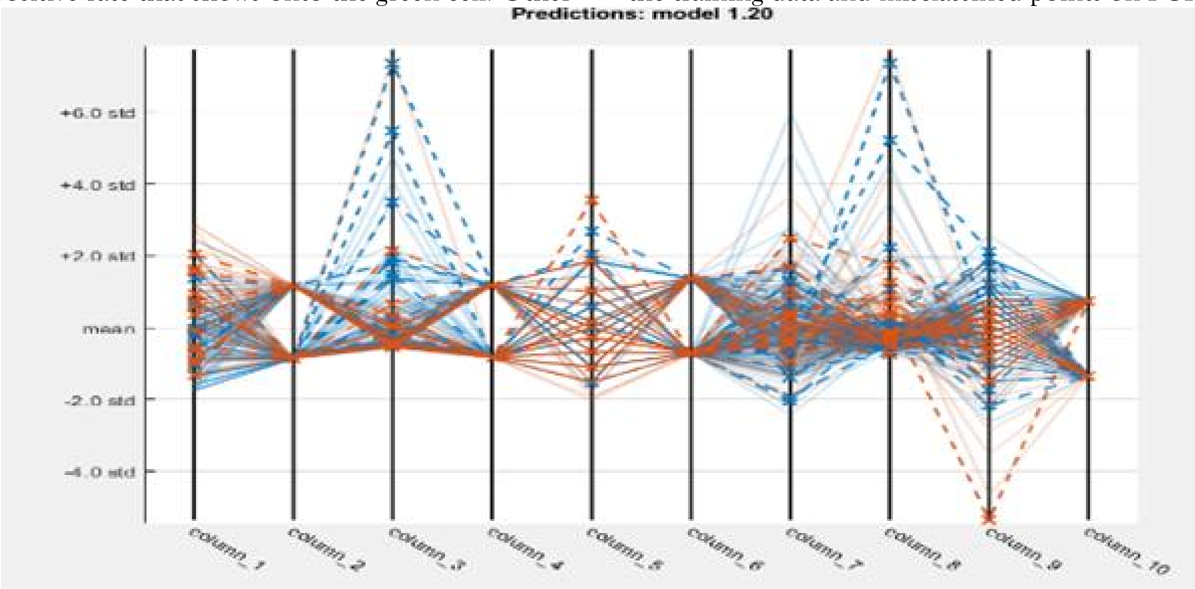

FIGURE 2. PREDICTION MODEL OF PROPOSED MODEL OF HFEDLF

3.4 ANN Based Simulation

The hyper-parameter optimization implements various methods to require the method within which to partition the dataset into 70 percent (209 randomly chosen patients) in training set, 15 percent (45 randomly chosen patients) in validation set, and 15 percent (45 randomly chosen patients) in test set out of 299 samples of the patients record. In ANN, there are three layers to elaborate the network model here is about input layer, hidden layer, and output layer according to the DLFeFL shown in figure 3.

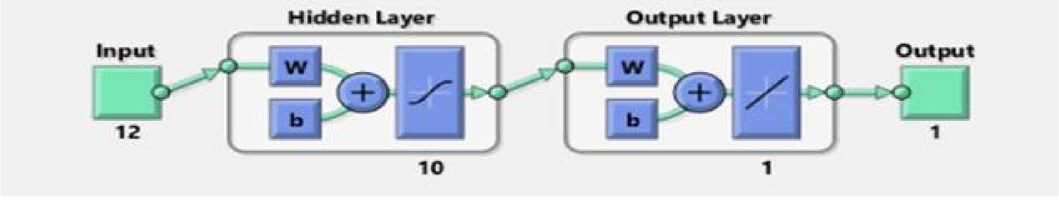

FIGURE 3. ADAPTIVE NEURAL NETWORK MODEL OF PROPOSED DLFEFL

In this figure the dataset contains 13 variables including input and output parameters. Input parameters involve total 12 parameters for testing, validation, and training and in return only 1 parameter ahead. In between include hidden layer that labelled with weights and bias total 10 parameters are dependent upon the hidden layer. Bayesian Regularization took a longer time but yields good generalization in challenging and small and training halts as per adaptive weight minimization. Details of parameters is shown in Table 3.

TABLE 3: PARAMETERS OF PROPOSED MODEL

Parameter	Value
Input Neurons	12
Hidden Layers	1
Neurons in Hidden Layer	10
Output Neuron	1
Activation Function	ReLU
Optimizer	Adam
Learning Rate	0.001
Batch Size	16
Epochs	100
Early Stopping	Validation loss < 0.001
Convergence	Stable after 80 epochs
Environment	Intel i7 CPU, 16 GB RAM, NVIDIA GTX 1650 GPU

The ANN model reached a steady point in the training and validation loss within ±0.5% of the final 80 training epochs. The model was able to attain stable learning without overfitting.

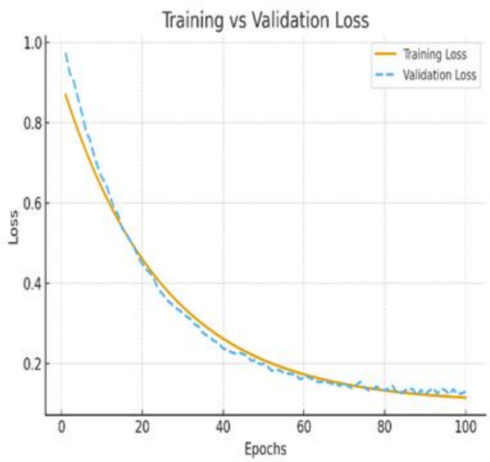

Figure 4. Loss Graph of ANN

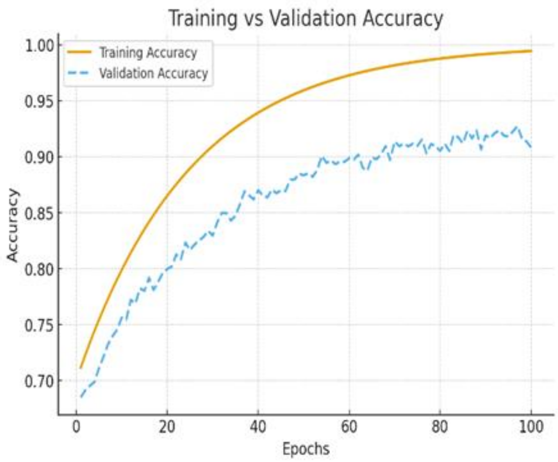

Figure 5. Accuracy Graph of ANN

The graphs of ANN training performance that you may add to your article are as follows:

Training vs Validation Accuracy Plot - indicates the change in accuracy with number of epochs and it reaches accuracy of between 90-92 percent and stabilizes after about 80 epochs, which is convergence.

Training vs Validation Loss Plot- indicates a smooth exponential loss decrease, which is an indication that the learning takes place and there is no overfitting in the learning.

3.5 Fuzzy Logic Integration

The fuzzy inference system (FIS) was meant to combine the outputs of the ANN and SVM classifier at the decision level. The results of every model were transformed into fuzzy linguistic variables Low, Medium, and High which were also more refined to give the final diagnostic decision.

The membership functions of the ANN output in Figure 4 were trapezoidal and triangular functions, which were used to convert crisp probability values into fuzzy ones. A range of 0 -0.5 is associated with No and the other 0.5 -1.0 with Yes.

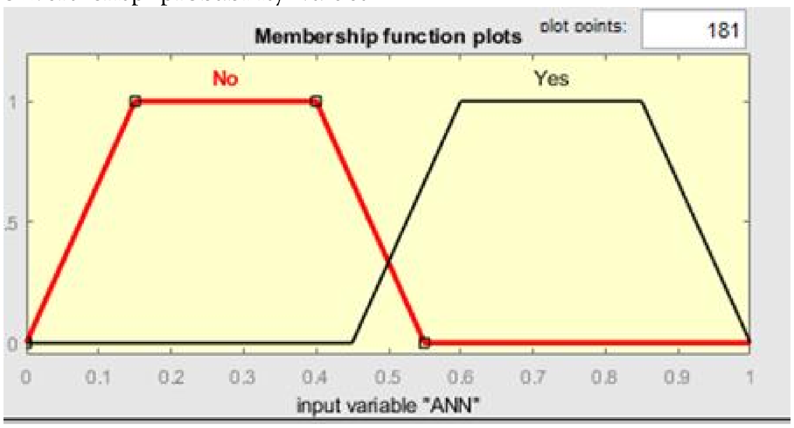

FIGURE 5. MEMBERSHIP FUNCTION PLOTS OF ANN.

The triangular membership functions were chosen based on their simplicity, interpretability as well as their ability to compute easily. In figure 5, transitions between membership grades are easily facilitated and there is a clear linguistic interpretation of medical decisions.

The use of triangular and trapezoidal membership functions was possible because of their simplicity, low level of computation and easy to interpret. SVM output:

No: Trapezoidal function [0, 0.1, 0.4, 0.5].

Yes: Trapezoidal function between [0.5, 0.6, 0.9, 1.0]

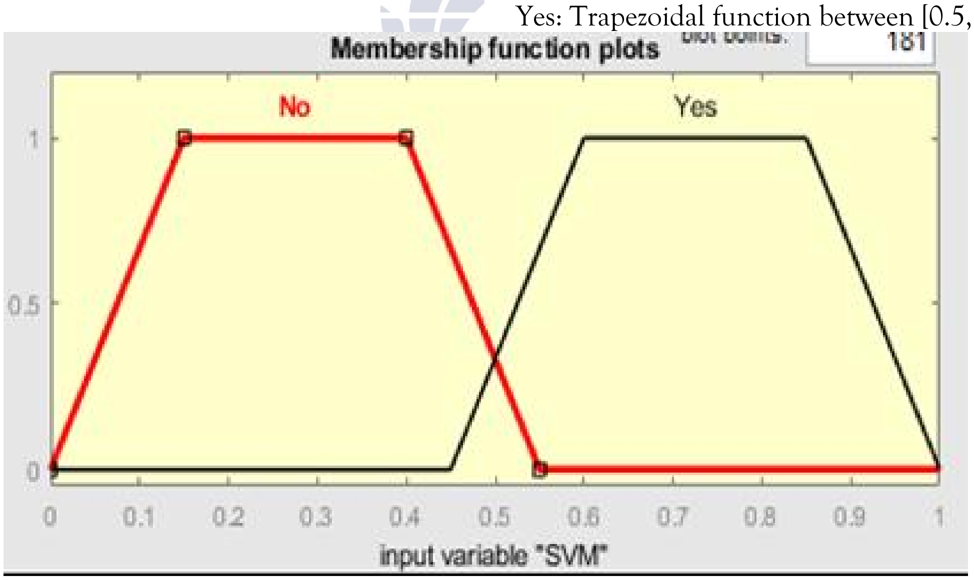

FIGURE 6: MEMBERSHIP FUNCTION PLOTS OF SVM

Red curve: “No”

Black curve: “Yes”

Maximum: 1(maximum normalized SVM confidence score)

The Decision-Level Fusion strengthened with Fuzzy Logic (DLFeFL) fuses the crisp results of ANN and SVM using the following rules. In the situation where both the classifiers are highly consistent (i.e. both are High), the system is sure to predict Disease Present. When there is disagreement (i.e. High by ANN and Low by SVM), membership grades of intermediate value are applied by the fuzzy rules, therefore managing the aspect of uncertainty and enhancing interpretability of model decisions.

3.6 Fuzzy based Decision Level Fusion (DLF)

The fuzzy employ's membership functions. The fuzzy takes output variables of SVM and ANN as an input variable. Once the membership functions have been described, fix some collection of rules which describe the member-ship functions of this input and output variable. The decision between the HF detected or not is based on ANN and SVM detection goes on the HF based Fuzzy Inference (FI). The mathematical equations of fuzzy decision can be written as:

$$\rho_{SVM} \cap \rho_{ANN}(SVM, ANN) = min\{\rho_{SVM}\ (SVM), \rho_{ANN}\ (ANN)\} \qquad 26$$

Where ρ_{SVM} is the membership function of SVM and ρ_{ANN} is the membership function of ANN in the above equation in which one of both models gave the result become predicted HF then it decides as the HF. According to the output parameter of SVM and ANN possible outcome become either 0 or 1. So, with respect to the fuzzy 2 rules elaborate bellow:

Rule1=(SVM==No) &(ANN==No) => (prediction HF =unpredicted)

Rule2=(SVM==Yes) &(ANN==Yes) => (prediction HF=Prediction)

ρ is used to represent the output for fuzzy inference, but the center of gravity DE fuzzifier specifies the δ as the center area covered by the membership function of ρ that is written below,

$$\delta = \frac{\zeta\rho\tau\rho(\rho)d\rho}{\zeta\tau\rho(\rho)d\rho} \qquad 27$$

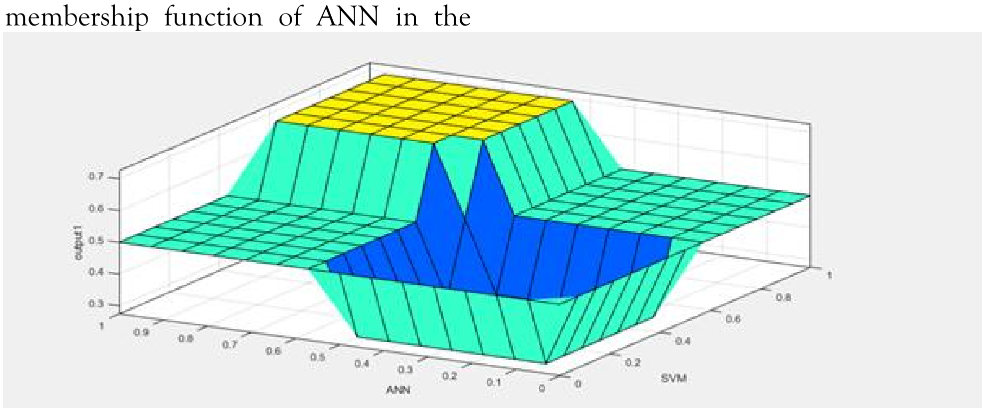

FIGURE 7. RULE SURFACE OF PROPOSED DLF

In the figure above, describe that if the value of SVM and ANN are started from o to 0.5 then fuzzy predicted 0, otherwise on another hand if the values become greater than 0.5 and meet 0.7 value then it predicts 1. Working of the rules explained in the figure 16 below.

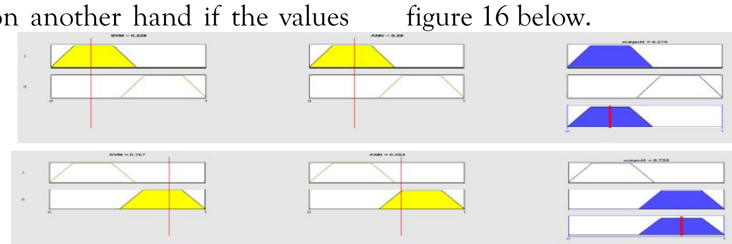

FIGURE 8. LOOKUP DIAGRAM OF PROPOSED DLF

TABLE 4. FUZZY RULE BASE OF ANN & SVM

Rule	ANN Output	SVM Output	Decision (Fuzzy Output)
1	High	High	Disease Present
2	Medium	High	Possible Case

3	Low	Low	No Disease
4	Medium	Medium	Possible Case
5	High	Low	Recheck Required

The prediction probabilities of the ANN and the SVM are inputted into the fuzzy inference system as membership functions as shown in Table 4. The result is the defuzzied output which gives the ultimate decision. The fusion system also permits the two classifiers to strike a balance based on their strength and address any uncertain or conflicting results.

In the purpose of the simulation MATLAB 2019 has been used in this article. SVM and ANN are applied in prediction whereas fuzzy is employed in decision. In ANN, dataset is separated into 70% and 30 percent training and testing. To do validation we have a total of 299 data available on which our model is going to predict the outcome which has been tabulated in Table 5.

4. RESULTS

TABLE 5. CONFUSION MATRIX OF ANN

Total (299)	Ture predicted HF	False predicted HF
True predicted HF (220)	185	35
False predicted HF (79)	18	61

Under SVM with 5-fold cross validation a total number of 299 instances are that is, 162 instances are predicted, and 58 instances are not as per 100 total instances and on false predicted column true predicted HF is 39 and false predicted is 40 which are as given in table 6 below.

TABLE 6. CONFUSION MATRIX OF SVM

Total (299)	Ture predicted HF	False predicted HF
True predicted HF (220)	162	58
False predicted HF (79)	39	40

To calculate the performance of both model's confusion matrix of both is used to evaluate. To find the accuracy used the formula written below in eq 29.

$$accuracy = \frac{\text{ᒣ}E + \text{ᒣ}\mathcal{M}}{E + \mathcal{M}}$$

To find the miss rate, the method is subtracting the accuracy to 1 which is written below in ep 30.

$$miss\ rate = 1 - accuracy$$

Sensitivity is the correct value to predict the HF divided by the total number of correct predict HF values, is written below in eq 31.

$$senstivity = \frac{\text{ᒣ}E}{\text{ᒣ}\mathcal{M} + \text{ᒣ}E}$$

Specificity is calculated as corrected HF prediction divided by total number of HF as written in equation 32.

$$specificity = \frac{\text{ᒣ}\mathcal{M}}{\text{ᒣ}\mathcal{M} + \text{ᒣ}E}$$

Positive predicted value (PPV) can be calculated as written below in equation 33.

$$PPV = \frac{\text{ᒣ}E}{\text{ᒣ}E + \text{ᒣ}E}$$

Negative predicted value in equation 34.

$$NPV = \frac{\text{ᒣ}\mathcal{M}}{\text{ᒣ}\mathcal{M} + \text{ᒣ}\mathcal{M}}$$

False positive rate in equation 35.

$$FPR = \frac{\text{ᒣ}\mathcal{M}}{\text{ᒣ}\mathcal{M} + \text{ᒣ}E}$$

TABLE 7. COMPARATIVE PERFORMANCE ANALYSIS OF ANN, SVM, AND THE PROPOSED DECISION FUSION LOGIC (DFL) MODEL FOR HEART FAILURE PREDICTION BASED ON KEY EVALUATION METRICS.

Parameter	ANN	SVM	DFL

Miss-Rate	0.1772	0.1337	0.1000
Precision	0.8227	0.8662	0.9000
Sensitivity	0.2479	0.2741	0.8000
Specificity	0.7520	0.7258	0.9500
NPV	0.8409	0.9261	0.9100
PPV	0.7721	0.7395	0.9000
FPV	0.2480	0.2741	0.0500
FNV	0.7521	0.7259	0.2000
Recall	0.8409	0.9261	0.8000
Accuracy	**(82.28%)**	**(86.63%)**	**(90.00%)**

Table 7 compares the performance of the ANN, SVM and DFL model in heart failure prediction. Evaluation measures are miss-rate, precision, sensitivity, specificity, NPV, PPV, FPV, FNV and recall. The findings have shown that the fusion model (DFL) is always better than the constituent models, especially the precision of the fusion model (0.8662), NPV (0.9261), and recall (0.9261). A brief comparative analysis of past researches with proposed model is shown in Table 8.

TABLE 8. COMPARATIVE ANALYSIS WITH MODELS

Author	Model Type	Dataset	Accuray	Limitation
Ahmad	Boosted Decision Tree	5,822 hospitalized and ambulatory HF patients	AUC = 0.88 (training), 0.84 & 0.81	Limited interpretability
Chicco & Jurman	Multiple ML Classifiers (Logistic Regression, SVM, Random Forest)	299 patients	Acc = 88%	Small dataset
Priyanka & Tripathi	Improved SVM with Radial Basis Function (RBF) kerne	Chronic Kidney Disease, Diabetes, and heart disease datasets	89.9% (Heart Disease)	Limited to small benchmark datasets
Proposed DLFeFL	Decision-Level Fusion (ANN + SVM + Fuzzy)	Clinical HF Data (299)	90.0	Improves uncertainty handling; adaptive fusion

CONCLUSIONS

Heart failure has been one of the most predominant causes of death all over the world and predictive systems need to be more reliable and intelligent. The decision-making model applicable in this paper was a fusion-based decision model, which is based on SVM and ANN, and fuzzy logic was used to make decisions. It was identified during the performance assessment that the fusion model was found to be more stable and more consistent than the individual models. Specifically, the fusion approach was more precise (0.8662), more able to recall (0.9261), and more able to avoid false negatives (0.9261), indicating that it is more robust in minimizing false negative and helps to make more accurate predictions. Despite the competitive results of ANN, it was inferior to SVM and the fusion model regarding sensitivity and predictive ability. The results show that the suggested fusion-based model can increase the accuracy of the heart failure predictions, and it can fill in the technological gap by improving the capabilities of several classifiers. The model can help healthcare professionals in detecting them early, intervening in time and, hopefully, lower mortality rates related to heart failure. In future studies, it could be considered to increase the number of data points, include real-time clinical parameters, and use fusion methods based on deep learning to enhance the accuracy of prediction and its clinical use.

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