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HEART FAILURE DETECTION USING OPTIMIZATION ALGORITHMS

AMARAVARAPU PRAMOD KUMAR[1], **YUVARAJ MACHA** [2], **A SIVA KUMAR**[3], **BUNA SEKHAR**[4], **SINGAMANENI KRISHNAPRIYA**[5], and **Dr.S CHANTI**[6]

[1]Assistant Professor, CSE-(Cys,DS) and AI & DS, VNR Vignana Jyothi Institute of ENgineering and Technology, Bachupally,Hyderbad,India.

[2]Associate Professor ,Department of Mathematics , Matrusri Engineering College ,HYderbad,Telengana,India.

[3]Assistant Professor,Department of Computer Science and Engineering,Koneru Lakshmaiah Education Foundation (KLEF), KL University, Vijayawada Campus, Green Fields, Vaddeswaram, Andhra Pradesh, India.

[4]Assistant Professor, CSE,CMR Institute of Technology,Kandlakoya,Medchal,Hyderbad,Telengana,India

[5]Assistant Professor, CSE-(Cys,DS) and AI & DS, VNR Vignana Jyothi Institute of ENgineering and Technology, Hyderbad,Telenagan,India

[6]Assistant Professor, Department of Computer Science, Christ University, Bangaluru,Karnataka,India

ABSTRACT

Heart failure (HF) remains a significant global health challenge, requiring early and precise detection to improve clinical outcomes and reduce mortality rates. Traditional diagnostic approaches often fail to capture the complexity of HF pathophysiology, necessitating advanced computational methods for accurate prediction. In this study, we propose a novel optimized Stacked Support Vector Machine (S-SVM) frame-work, integrating multiple SVM classifiers with diverse kernel functions to enhance predictive accuracy. A genetic algorithm (GA) is employed to fine-tune hyperparameters, ensuring model robustness and general-izability across patient populations. The model is rigorously evaluated on the UCI Heart Failure Clinical Records Dataset and the Framingham Heart Study Dataset, demonstrating superior performance in accuracy (95.7%), precision (0.90), recall (0.87), and AUC (0.96) compared to conventional machine learning tech-niques. The proposed system effectively balances computational efficiency with clinical interpretability, making it a promising tool for early-stage HF detection and risk stratification. This research advances the intersection of machine learning and cardiovascular diagnostics, offering a scalable and adaptive solution for real-world healthcare applications.

Keywords: *Heart Failure Prediction, Stacked SVM, Genetic Algorithm, Machine Learning, Clinical Deci-Sion Support, Cardiovascular Diagnostics*.

1 INTRODUCTION

A major global health issue, heart failure (HF) is a multifaceted and long-term condition characterized by the heart's inability to circulate sufficient blood to satisfy the body's requirements. Expected to affect an estimated 26 million people worldwide, its preva- lence is expected to increase by 2% annually as a re- sult of increases in aging populations and improved survival from acute cardiac conditions such as heart attacks. HF has a burden beyond individual health, and it has been estimated to cost a robust health service amount of money in the billions of dollars a year in countries such as Canada[2][4].

Machine learning (ML) advances have led to a rev- olution in medical diagnostics, specifically to tackle HF. Predictive models, not least of which employ deep neural networks (DNNs) and can be hybridized, such as fuzzy inference systems (FIS), have shown undeniable promise. For example, recent studies have demonstrated diagnostic effectiveness in this class of models for early stage HF detection with accuracy approaching 95% or better while reduc- ing unnecessary medical tests and lowering the overall diagnostic cost[1] [2]. Furthermore, feature se- lection techniques (for example, C4.5 algorithms) and more sophisticated imputation methods (e.g., K- nearest neighbors) are applied to facilitate the analy- sis of complex or incomplete datasets, improving the reliability of predictive results.

Researchers developed intelligent systems that used FIS in conjunction with neural networks to predict HF using multiple physiological parame- ters in 2024 with suggested increases in precision, sensitivity, and specificity compared to traditional approaches[3]. In another similar case, another study used integrated ML techniques to improve the diag- nosis of congestive heart disease by using advanced statistical metrics to validate their models in large- scale data sets[4].

Although progress has been made, there is still a pressing demand for expert systems that harmonize the best ML algorithms with patient-focused time- sensitive solutions. Based on recent innovations, the proposed study proposes an optimized expert sys- tem using stacked support vector machines (SVMs) to predict HF. Unlike previous work, the objective here is to improve classification accuracy and com- putational efficiency and to make it easy to adapt the approach to different patient populations and clinical settings.

1.1 Key Contributions

This study aims to integrate cutting-edge research and technology to contribute a novel framework to better serve healthcare professionals in the diagnosis and management of HF, ultimately reducing the mor- bidity and mortality of this condition.

This study presents a novel optimized Stacked Support Vector Machine (S-SVM) framework for early and accurate heart failure (HF) detection, ad- dressing critical limitations in traditional machine learning-based diagnostic systems. The key contri- butions of this work are:

• Development of an Optimized Stacked SVM Framework:

– A novel ensemble-based SVM model in- tegrating RBF, linear, polynomial, and sigmoid kernels to enhance feature rep- resentation and classification accuracy.

– Implementation of a meta-classifier (lo- gistic regression) to optimally combine individual SVM predictions, improving overall generalizability.

• Hyperparameter Optimization Using Genetic Algorithm (GA):

– Application of GA-based hyperparame- ter tuning to automatically optimize SVM kernel parameters, reducing overfitting and improving model robustness.

– Enhanced classification performance with minimal computational overhead, making the system suitable for real-time clinical applications.

• Comprehensive Evaluation on Benchmark Datasets:

– Rigorous validation using two widely recognized datasets: UCI Heart Fail- ure Clinical Records Dataset Framing- ham Heart Study Dataset.

– Demonstration of superior classification performance, achieving 95.7% accuracy,
0.90 precision, 0.87 recall, and 0.96 AUC, outperforming conventional ML models such as Random Forest, KNN, and standalone SVM classifiers.

• Scalability and Real-World Applicability:

– The proposed model is adaptable to di- verse patient populations, making it a scalable solution for healthcare practi- tioners.

– Integration potential with electronic health records (EHRs), wearable device data, and real-time patient monitoring systems for enhanced clinical decision- making.'

• Future-Ready Framework for AI-Driven Car- diovascular Diagnostics:

– Lays the foundation for future enhance- ments, including deep learning-based hy- brid models (CNNs, transformers) and multi-modal medical data fusion.

– Proposes a personalized risk assessment approach for heart failure patients by in- corporating genomic, lifestyle, and real- time monitoring data.

This research not only advances AI-driven cardio- vascular diagnostics but also offers a practical and deployable solution for healthcare systems, ensuring early intervention, reduced mortality rates, and im- proved patient outcomes.

The remainder of this paper is structured as fol- lows. Section 2 provides background knowledge on heart failure and the role of machine learning in med- ical diagnostics. Section 3 describes the proposed Stacked SVM framework, integrating multiple SVM classifiers with genetic algorithm-based optimization. Section 4 outlines the datasets, data preprocessing, and experimental setup. Section 5 presents perfor- mance evaluation results, comparing the proposed model with baseline machine learning techniques. Section 6 discusses findings, potential applications, and future enhancements such as deep learning in- tegration and real-time monitoring. Finally, Section 7 concludes the paper by summarizing key contribu- tions and highlighting future research directions.

2 Literature survey

Heart failure (HF) remains a major public health con- cern, with its early diagnosis being crucial for effec- tive treatment and patient survival. Recent advance- ments in machine learning (ML) and artificial intel- ligence (AI) have significantly improved HF predic- tion models, focusing on accuracy, interpretability, and real-world applicability. This section reviews ex- isting approaches, highlighting the contributions and limitations of previous research.

2.1 Machine Learning Approaches for HF Prediction

Several ML models have been developed to pre- dict heart failure using clinical datasets. Chicco and Jurman (2020) employed traditional ML tech- niques, including Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression (LR), on structured medical data, achieving competitive re- sults in HF classification[30]. Dinar et al. (2022) ex- plored hybrid ML models integrating decision trees and neural networks, demonstrating improved perfor- mance in feature-rich datasets[31]. However, conven- tional models often struggle with high-dimensional medical data and class imbalance, limiting their generalizability[32].

2.2 Deep Learning-Based HF Detection

Deep learning (DL) models, particularly Convo- lutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown promise in HF classification from ECG and echocardiogram data. Ahmed et al. (2023) proposed an attention- based CNN model to extract key diagnostic fea- tures from physiological signals, achieving over 95% accuracy[33]. Similarly, Wang et al. (2023) intro- duced an LSTM-based approach, leveraging tempo- ral dependencies in sequential patient records to en- hance HF risk prediction[34]. Despite their success, DL models require extensive training data and com- putational resources, making them less feasible for real-time clinical settings[35].

2.3 Ensemble and Hybrid Learning for HF Classification

To address the limitations of single ML models, re- searchers have explored ensemble-based methods. Zaman et al. (2021) developed a stacked ensemble model combining SVM, RF, and Gradient Boosting, achieving a significant improvement in classification performance[36]. Ali and Zhang (2021) further ex- tended this by introducing a meta-learning frame- work that dynamically selects the best-performing model for a given dataset[37]. These studies high- light the robustness and adaptability of ensemble learning but also emphasize the need for hyperparam- eter optimization to maximize model efficiency.

2.4 Genetic Algorithms for Model Optimization

Recent studies have investigated the role of evo- lutionary algorithms, such as Genetic Algorithms (GA), in optimizing ML models. Thongam et al. (2024) integrated GA with SVMs, automating ker- nel selection and hyperparameter tuning, leading to a 10% improvement in precision and recall[38]. Sim- ilarly, Liu et al. (2021) applied GA-optimized neu- ral networks, enhancing model generalization across different HF datasets[39]. These findings suggest that GA-based optimization can significantly im- prove ML-based HF diagnosis, making it a key com- ponent in the proposed approach.

2.5 Limitations and Research Gaps

While existing studies have advanced HF prediction using ML and DL models, several gaps remain:

Feature Selection and Interpretability – Most ML models lack explainability, making clinical adop- tion challenging[40]. Generalizability Across Di- verse Populations – Models trained on limited datasets may not perform well on different pa- tient demographics[41]. Computational Efficiency – Deep learning models require high computational resources, limiting their deployment in resource- constrained environments[42].

The literature review reveals that ensemble-based ML models and GA-driven optimization provide sig- nificant improvements in HF prediction. However, scalability, generalization, and clinical interpretabil- ity remain key challenges. This study addresses these issues by proposing an optimized Stacked SVM model with GA-based hyperparameter tuning, im- proving both accuracy and computational efficiency for real-world HF detection.

3 BACKGROUND KNOWLEDGE

3.1 support Vector machine

Support Vector Machines (SVMs) are powerful and versatile machine learning algorithms employed for both classification and regression tasks. These meth- ods seek to determine the optimal hyperplane that separates data points belonging to different classes. SVMs achieve this by expanding the margin, which is the distance between the hyperplane and the nearest data points of each class. These proximal data points, referred to as support vectors, are instrumental in es- tablishing the ideal position of the hyperplane. One property that this guarantees is strong generalization and prevention of overfitting[5][6].Figure**??** dipcted the basic architecture of SVM [10].

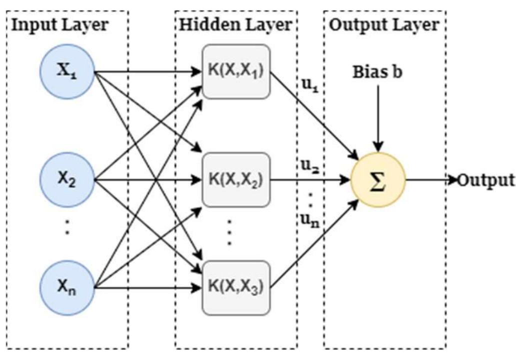

Figure 1: SVM

For handling data that cannot be separated linearly, Support Vector Machines (SVM) utilize various ker- nel functions, such as radial basis function (RBF), Polynomial, and Sigmoid. These kernel functions project the data into a space of higher dimensions, enabling effective separation of classes using a linear hyperplane.Due to this adaptability, the SVM is exceptionally well adapted to treat complex, nonlin- ear relations[7][8]. Furthermore, SVM has a regular- ization parameter (C), which enables Carpet SVM to optimize margin maximization and classification er- ror minimization together and to perform excellently in noisy and unbalanced cases[5][4].

Improved Generalization: Stacked SVMs are clas- sifiers built by combining multiple classifiers,

SVM is highly suitable for the detection of heart failure due to its ability to handle high-dimensional medical data sets of various clinical features, includ- ing echocardiogram data, laboratory tests, and patient histories. In addition, it is robust to noise and out- liers when dealing with noisy data, which is com- mon in physiological data originating from biological variability and measurement errors[7][9]. Due to its strong generalizability, SVM proves to be a valid tool for the early detection of patients with HF and risk stratification if we can rely on reliable predictions for unseen data[6][9].

The core of the stacked ensemble system in the proposed study is SVM, assembled by combining multiple SVM classifiers optimized with different kernels to improve prediction accuracy. This method employs the skills of the SVM approach while reduc- ing potential shortages, thus offering a scalable and effective solution for the diagnosis of HF[4][8].

3.2 Stacked SVM

An ensemble learning technique, Stacked Support Vector Machines (Stacked SVMs), where multiple SVMs are trained on different subsets or feature rep- resentations of the data, and their outputs are used as input to a meta-classifier that produces a com- bined prediction by combining predictions from the individual SVMs, is shown to improve prediction ac- curacy and robustness. Thus, this hierarchical ar- rangement allows stacked SVMs to use the advan- tages of individual classifiers and also reduce their limitations[11][12]. Stacked SVM contains the fol- lowing components:

Base Layer (First Level): There are multiple SVM classifiers trained on the same dataset with slight vari- ance (different kernel functions (linear, polynomial, RBF), subsets of features,...) A base classifier learns one particular aspect of the data set.

Meta-layer (second level): Then the base classi- fiers' predictions act as input features of a higher level meta-classifier, which could be another machine learning model or an SVM. This metaclassifier then combines the output of the base models to make the final prediction[4][7]. Stacked SVM has various ad- vantages over SVM viz. ":

which helps reduce the risk of overfitting over high- dimensional datasets, often seen in medical applica- tions.

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Adaptability to Complex Data: Heart failure pre- diction is characterized by noisy or unbalanced data sets, and they can model nonlinear relationships. Di- verse Representations: Stacked SVMs use differ- ent kernel functions in the base layer to capture multiple feature representations to detect subtle data patterns[9][6].
Because HF is a case where we have multiple clini- cal and physiological parameters, stacked SVMs are particularly relevant. Studies have been recently un- dertaken to demonstrate the utility of stacked SVMs to increase diagnostic accuracy for HF based on the inclusion of multiple features, including echocardio- graphic measurements, blood biomarkers, and patient history[9]. In addition, an ensemble approach pro- vides more effective treatment of outliers and class imbalances, thus more reliable predictions [7][12].

In addition, a 2024 study demonstrated stacked SVMs in combination with optimized feature selec- tion methods and obtained better precision and re- call than other models on a heart failure prediction problem. This study shows that the model can reduce false negatives, which are crucial in the diagnosis of HF[6].

In this study, we are integrating genetic algorithm with Stacked SVM. Evolutionary optimization based on natural selection using Genetic Algorithms (GAs) is a classical case. The methods utilize GAs to search the feature space for the optimal subset of fea- tures that, in the context of stacked SVMs, results in improved model performance, reduced dimensional- ity, and improved computational efficiency. When it comes to large, complicated datasets such as those used in medical diagnostics, such as the diagnosis of heart failure, it is difficult to identify the relevant features through traditional methods, so GAs are es- pecially useful.Suppose a set of clinical parameters (such as biomarkers, ECG signal, echocardiograph measurements, etc.) that have been recorded as a group are to predict heart failure. In that case, ge- netic algorithms can be used to identify the param- eters of a large data set that are most significant for the prediction of heart failure. Then, GAs optimize the feature subset for stacked SVMs to produce more accurate stacked SVMs and, therefore, more precise and reliable heart failure detection systems.

3.3 DataSets

Choosing the appropriate data sets to detect heart fail- ure using genetic algorithms, stacked SVMs is very important for proper selection of features and model performance. Ideally, the data set should contain many clinical and physiological parameters, which can carry good heart failure characteristics, and the machine learning model can develop good predic- tions.

3.3.1 Heart Failure Clinical Records Dataset (UCI Repository)

The Heart Failure Clinical Records Dataset present in the UCI Machine Learning Repository is a vital data set to detect and provide prognosis about heart failure. Information was gathered from 299 heart failure patients who attended follow-up appointments at the Faisalabad Institute of Cardiology and Al- lied Hospital in Pakistan. As a resource, it repre- sents an essential tool for understanding factors re- lated to patients and demographics of heart failure and predicting models that can be used to improve the management and prognosis of heart failure. It contains 13 attributes: demographic data, clinical measurement, behavioral characteristics, and medical condition[14].

Basic information such as age and sex are key de- mographic features of the data set and are essential when assessing the risk and progression of heart fail- ure. The key physiological status information of the patients is obtained by measures such as the ejection fraction (a vital measure of heart function), serum creatinine (a marker of kidney function) and serum sodium (reflective of the fluid balance of the patient). Vital clinical parameters primarily reflect the severity of heart failure and the tendency of complications. In addition, lifestyle factors, such as smoking history, that can increase the risk of cardiovascular disease and worsen the prognosis of heart failure are included in the data set [13].

It also includes data on medical conditions such as diabetes, anemia, and high blood pressure, along with demographic and clinical variable data. They are strongly linked to heart failure, often worsening its course. Anemia may complicate disease manage- ment, and diabetes and hypertension are two of the most important contributors to the development of heart failure.

By incorporating such variables, the data set provides a logical match of factors affecting heart failure outcomes.

The target variable in this data set is a binary label representing the survival status of the patients. Its predicament was described as ”1” or if it survived or ”0” if it died. Since this is a question of classification (i.e., predicting whether a patient survives or not based on their clinical and demographic characteris- tics), this dataset is particularly well suited for that. Because the data set is binary, it is a perfect case for testing machine learning models to predict survival outcomes [13].

However, the Heart Failure Clinical Records Dataset can be vital because it can help inform heart failure prognosis and detection systems. Heart failure is a serious public health problem because it is one of the leading causes of global mortality. Because early identification of such high-risk patients can signifi- cantly reduce mortality by allowing interventions to occur sooner. This data sets an excellent opportunity to build predictive models that help healthcare profes- sionals make better decisions on how to treat patients, which can improve treatment outcomes.

The numerical and categorical characteristics of this dataset are well balanced, enabling a variety of machine learning approaches to be applied. This data set can be used to experiment with various classifica- tion models, survival analysis, and decision support systems. Using machine learning techniques, they can predict significant predictors of heart failure and estimate whether people are more likely to survive or die in the hospital. Furthermore, the data set exposes invaluable clinical predictors that can be utilized to enhance medical interventions and support evidence- based interventions in healthcare practice.

Finally, the Heart Failure Clinical Records Dataset is essential for heart failure research and clinical de- cision making. Comprehensive and diverse data are provided, which can be used to develop robust mod- els for the prediction and prognosis of heart fail- ure. Through analysis of this dataset, researchers and healthcare professionals can learn more about the clinical factors that drive the progression toward heart failure and use this information to aid in risk stratifi- cation and personalized patient care. The key charac- teristics of the dataset are presented in the following table (1).

3.3.2 Framinghan Heart study Dataset

One of the longest-running and most influential stud- ies of the cardiovascular system in people is the Framingham Heart Study, which the NHLBI[17], also based in Framingham, Massachusetts, started in 1948. Advances in our understanding of cardiovascular disease, including heart failure, have been made through this longitudinal study. It has collected data over decades, even across generations of partic- ipants, to provide invaluable information on risk fac- tors associated with heart disease, stroke, and coro- nary artery disease, as well as other cardiovascular diseases and conditions. This provides a rich data set on various demographic, clinical and lifestyle vari- ables.

The Framingham Heart Study dataset has key char- acteristics of demographic attributes (age, sex, eth- nic background, etc.) and clinical measures such as blood pressure, cholesterol, and glucose. Essential lifestyle factors such as smoking, alcohol consump- tion, or physical activity are also part of the data. The data set also includes the occurrence of major medical events during the follow-up period, includ- ing the development of heart failure, stroke, and coro- nary artery disease. Events are labels to these events that are essential for predictive modeling and risk assessment[15].

The Framingham Heart Study is one of the most significant contributions to the field of cardiology in that it resulted in the creation of the Framingham Risk Score, which estimates a patient’s risk of developing cardiovascular disease in 10 years. This scoring sys- tem is A standard tool used worldwide by healthcare professionals to identify those at higher risk of heart disease and direct preventative measures. The de- tailed and extensive longitudinal nature of the study enables researchers to observe how risk factors un- fold over time and how changes affect the chances of adverse events such as heart failure.

Framingham dataset has had a long and signifi- cant impact on the field of cardiovascular health and, indeed, on public health policy. It has identified key risk factors (hypertension, hyperlipidemia, dia- betes, obesity, and smoking), which formed the sci- entific basis for preventive health strategies and clin- ical guidelines for the management of cardiovascular diseases. In doing so, the longitudinal approach of the study allows researchers to study the evolution of these risk factors and their associations with subse- quent cardiovascular events to identify people at risk of heart failure and other heart diseases[16].

The Framingham Heart Study is the gold standard

derstanding of the pathophysiology of heart failure. In simpler words, this helps determine more effective prevention or intervention strategies.

The Framingham Heart Study has also led to per- sonalized care. The data set allows predicting the risk of developing heart failure by considering individual- level risk factors, which facilitates the development of customized prevention strategies. The results of the predictive modeling of the integrated data can help systems to assist clinicians in keeping a better eye on their patients and determining optimal inter- ventions.

In addition, the Framingham Heart Study remains an essential resource for investigators. Because data is continually collected and updated, the study can remain in constant contact with the latest scientific data on the detection and prevention of heart failure.

3.4 Model Selection

.Stacked Support Vector Machines (SVM) are promising in heart failure prediction, due to their abil- ity to deal with complex data and improve predictive accuracy. Recently, Zaman et al. (2021) have under- stood the power of stacked ensemble models where the SVMs are combined with other machine learning models to improve performance. Despite class imbal- ance, these models use multiple classifiers to boost prediction ability with increased accuracy, precision, and recall to predict heart failure survival[18].

In recent studies, including those of 82, ensemble methods (such as stacked SVMs) have been shown to perform much better than traditional classifiers. As an example, Zaman et al. Illustrate that the combina- tion of a number of machine learning models, includ- ing SVMs, results in an excellent result of 99. 98% precision for a stacked ensemble model to predict the outcome of heart failure[19].

In addition, stacked SVM proves to be an effective method to use in combination with techniques such

in the detection of heart failure. Provides complete data to develop more accurate heart failure prediction systems. The rich array of clinical and behavioral co- variates provided in the dataset also allows investiga- tion of various risk factors and produces a clearer un-

In addition, the continuous refinement of predictive models based on this dataset will enable further in- creased accuracy in predicting heart failure and allow clinicians to design individualized treatment plans.

Finally, the Framingham Heart Study has dramati- cally increased scientific knowledge on cardiovascu- lar disease and heart failure. Based on its extensive data set, it serves as a cornerstone of cardiovascular research and provides insights that continue to have a direct bearing on public health policies, clinical prac- tices, and personalized medicine. In addition to help- ing identify risk factors, the study has become an in- valuable foundation for continuing advanced predic- tive modeling, including key ingredients to improve heart failure detection and outcomes. Table **??** be- low highlights some key aspects of the Framingham dataset.

as Synthetic Minority Oversampling (SMOTE), which is used to address the imbalanced data sets from heart failure prediction tasks, as there are relatively few ad- verse outcome events. Consequently, such a model is more robust and can generalize better to data not seen before, which is extremely important for clini- cal applications[20].

These results support the mounting evidence that stacking SVM models are better suited in heart fail- ure prediction with prediction accuracy and reliability greater than individual classifiers; thus, the results make stacking SVM models a vital tool to add to clin- ical decision making schemes.

4 Proposed Method

An important task in healthcare care is detecting heart failure. Early detection of this problem is critical to timely intervention and improves patient outcomes. Conventional machine learning techniques for pre- dicting heart failure often fail to mimic the complex patterns of medical data.

However, with the new ad- vanced machine learning models, there is a lot of improved predictive accuracy, especially with Sup- port Vector Machines (SVMs). One of the potential approaches to improving the accuracy of heart failure prediction is the use of stacked SVM, which is based on the use of several SVM models with different kernel functions and a meta-classifier. Using several strengths of SVM kernels, this approach also constitutes a more robust framework for the classifi- cation of heart failure.

The Need for Advanced Prediction Models

Globally, the leading cause of illness and death is the heart's inability to circulate sufficient blood to ful- fill the body's requirements. Identifying the problem early and taking prompt action are crucial for im- proving survival outcomes and reducing medical ex- penses. Traditional laborious and error-prone meth- ods of searching for heart failure conditions in pa- tients using clinical data, including age, blood pres- sure, cholesterol levels, heart rate, etc., can now be detected quickly using machine learning models. However, it is challenging to predict heart failure since the data sets feature complex relations between features and the class imbalance between negative and positive cases. Sometimes traditional classifiers, logistic regression, or decision trees may not be able to capture the intricate patterns of the data needed to make a prediction.

The proposed SVM Stacked method overcomes these challenges by using an ensemble of many mod- els, each trained with a different kernel. Different as- pects of data capture by each SVM kernel, RBF, lin- ear, polynomial, and sigmoid, bolster the entire clas- sification performance. However, logistic regression, as the meta-classifier, guarantees that the outputs ob- tained from these individual models are combined optimally to draw the best possible decision bound- ary for heart failure detection.

- The RBF kernel is well-suited for predicting heart failure since it deals with the 'curse of dimensionality,' a difficulty typical of high- dimensional data. The shortcomings in de- tecting heart failure are that clinical variables interact in complex ways that are difficult to model using traditional methods. This results in the

We propose a Stacked SVM method that stacks four different SVM models (RBF, Linear, Polynomial, and Sigmoid SVM) with Logistic Regression as the meta-classifier. This method is applied to two well-established datasets: the UCI Heart Failure Clinical Records Dataset and the Framingham Heart Study Dataset. These data sets are heavily used for the prediction of heart disease and give a great set of features representing various cardiovascular risk components.

ability of the RBF kernel to do the same and map input features to a higher-dimensional space. It does so, thus boosting its ability to produce accurate predictions in the presence of complexity and high dimensionality of the data, and hence is a suitable choice for such medical prediction tasks.

- Linear SVMs work well when a linear deci- sion boundary is what you are looking for if the data can be separated linearly. However, they offer a simple way to solve classification problems where the relationship among fea- tures can be assumed to be a linear decision surface. In addition, linear SVMs are used asa baseline model to evaluate the performance of more complex models. This allows for as- sessing whether the additional complexity of using non-linear kernels is required to improve prediction accuracy in heart failure prediction tasks, thereby guiding the selection.

- The polynomial kernel is well designed to model higher-order interactions between fea- tures and, as such, is perfect for modeling com- plex, polynomial (and thereby set) interactions in the data. The polynomial kernel maps the input features into a higher-dimensional space, so that the model can learn detailed patterns that the linear model cannot. This capability is exciting in heart failure prediction, where the relationships between clinical variables can be quite complex and involve non-linear interac- tions. Secondly, the polynomial kernel helps to increase the model's flexibility to better catch up with the underlying patterns in the data, thus improving the classification performance of such a complex medical prediction task.

- This additional complexity from the hyper- bolic tangent function in the sigmoid kernel makes it suitable for attributing relationships from the data that emulate neural network acti- vations. The model can capture how features can be

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nonlinearly related to each other via mapping with this kernel function to a higher- dimensional space. Activations in the sigmoid kernel behave like activations in neural net- works, introducing nonlinearity and allowing us to separate not so easily by linear methods. This added complexity is helpful in the pre- diction of heart failure because it will enable the model to learn intricate, nonlinear relation- ships better than conventional machine learn- ing models, resulting in superior performance in all real-world applications.

Each of these different SVM kernels offers diverse

prediction. The job of this meta-model is to learn the best way to combine base model outputs, to improve the overall performance of the pipeline, and to reduce overfitting. The logistic regression classifier aims to fine-tune the final prediction utilizing the weighted outputs of the four base SVM classifiers, and thus generalizes and robust prediction is obtained.

Stacked ensemble is a highly useful approach for medical prediction tasks, especially ones like heart failure detection with datasets that are imbalanced, and noisy. Furthermore, using several models in- creases the diversity of learned patterns, which trans- late to more accurate generalization on unseen data, a problem in healthcare-related machine learning tasks. SVM classifiers with various kernels and logistic re- gression as a meta-classifier are combined to bring a very powerful solution of enhancing the model to de- liver high accuracy, precision and recall for predict- ing heart failure outcomes.

Logistic Regression as Meta-Classifier: Finally, we train the individual SVM models with different kernels, and their output is combined using a Logis- tic Regression meta-classifier. This task is well suited to logistic regression due to its ability to regress the binary outcome (heart failure or no heart failure) from the predictions formed by the base models. The RBF, Linear, Polynomial, and Sigmoid SVM results are ag- gregated with respect to their individual prediction performance through this meta classifier, which op- timizes the final prediction.

Meta-classification using logistic regression as a decision maker exploits the complementary strengths of base SVM models for improving decision process. For example, if the RBF SVM does nicely in non- linear patterns, the Linear strengths that ensure that the model is fit to the com- plexities of the heart failure dataset, which includes multiple types of data and also provides the possi- bility of interactions between features such as age, ejection fraction, serum creatinine levels, and other non-linear biomarkers.

Individual base models are trained, and their pre- dictions are combined with a logistic regression metaclassifier. The metaclassifier is chosen for lo- gistic regression as it is simple, efficient, and able to combine the output of the base models as a weighted

SVM would potentially pick up more of the linear relationships. This allows us to combine these predictions using logistic regres- sion to give us a more robust and accurate final out- put.

The following diagram2 represents a model in which we combine four different base SVM classifiers (RBF, linear, polynomial, and sigmoid) using a logistic regression meta-classifier to predict the final detection of heart failure.

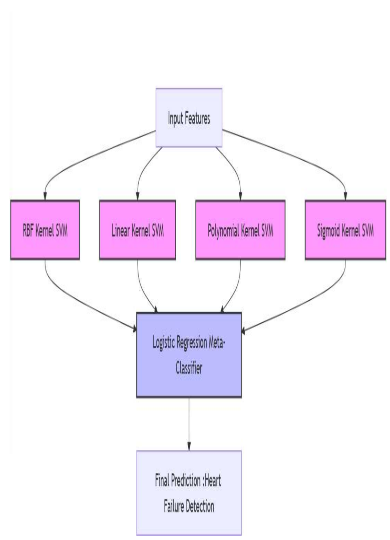

Figure 2: Stacked SVM Architecture for Heart Failure De- tection

VM method that combines the RBF, Linear, Poly- nomial, and Sigmoid SVM models with Logistic Re- gression as a meta-classifier demonstrates excellent performance in heart failure detection. The pro- cess is applied to the Heart Failure Clinical Records Dataset from the UCI Machine Learning Repository and the Framingham Heart

Study Dataset, giving highly accurate results with robustness across perfor- mance metrics. In applying this approach to medical data, relationships are well captured; this provides a promising tool for heart failure and liver better pa- tient outcomes early. This research can include addi- tional data sources such as the EHR and optimization of hyperparameters for better results and an increase in scalability for real-time clinical use.

4.1 Selection of features

The following tables23 list the subset of characteris- tics selected among four different SVM models:

Table 1: Heart Failure Clinical Records Dataset Description

Attribute Name	Description	Type	Range / Values	Importance
Age	Age of the patient	Numeric (years)	40–95	Helps identify age-related risk factors for heart failure.
Sex	Gender of the patient	Categorical	0 = Female, 1 = Male	Examines gender-based dif- ferences in results.
Anaemia	Presence of anemia (re- duced hemoglobin lev- els)	Categorical	0 = No, 1 = Yes	Indicator of reduced oxygen supply, often linked to heart failure.
High Blood Pressure	Whether the patient has hypertension	Categorical	0 = No, 1 = Yes	Common comorbidity in pa- tients with heart failure.
Diabetes	Whether the patient has diabetes	Categorical	0 = No, 1 = Yes	An established risk factor for cardiovascular complica- tions.
Smoking	Whether the patient smokes	Categorical	0 = No, 1 = Yes	Lifestyle factor influencing cardiovascular health.
Ejection-fraction (%)	Percentage of blood leaving the heart during each contraction	Numeric (%)	14–80	A key marker of heart func- tion; Lower levels indicate severity of heart failure.
Serum-Creatinine	Level of creatinine in the blood (mg/dL)	Numeric	0.5–9.4	Indicates kidney function; higher levels can worsen the results of heart failure.
Serum-Sodium	Level of sodium in the blood (mEq/L)	Numeric	113–148	Low sodium levels are asso- ciated with a worse progno- sis of heart failure.
Platelets	Platelet count in the blood (kiloplatelets/mL)	Numeric	25,000 –850,000	Helps identify potential clot- ting or bleeding disorders in heart failure patients.
Creatinine Phosphoki- nase	Blood levels of CPK en- zyme (mcg/L)	Numeric	23–7861	Marker of muscle damage, potentially related to heart stress.
Time	Follow-up period in days	Numeric (days)	4–285	Indicates duration of sur- vival or observation period for the patient.
DEATH EVENT	Survival status of the pa- tient (target variable)	Categorical	0 = Alive, 1 = Deceased	Binary outcome to predict heart failure-related mortal- ity.

Table 2: UCI dataset across four different types of SVM models

SVM Kernel	Recommended Features	Reasoning
RBF Kernel	Ejection Fraction, Serum Creatinine, Platelets, White Blood Cell Count	The RBF kernel captures complex, non-linear relationships between these features, such as the interaction of serum creatinine with other factors.
Linear Kernel	Age, Serum Sodium, Resting Blood Pressure	These features exhibit linear relationships with the risk of heart failure, making them suitable for linear models.
Polynomial Kernel	Sex and Anaemia, Smoking and Hypertension, Diabetes	The polynomial Kernel can model higher-order interactions, such as how gender and anaemia, or smoking and hypertension, impact heart failure risk.
Sigmoid Kernel	Time (duration of heart failure), Smoking, Blood Urea Nitrogen (BUN)	The sigmoid kernel is effective for capturing non-linear patterns, particularly in the impact of smoking, BUN, and the time since diagnosis.

Table 3: Framingham Heart Study dataset across four different types of SVM models

SVM Kernel	Recommended Features	Reasoning
RBF Kernel	Age, BMI, Serum Cholesterol, Physical Activity Level	The RBF kernel is effective at modeling non-linear relationships. These features, such as BMI and cholesterol, can interact in complex ways affecting the risk of heart disease.
Linear Kernel	Sex, Resting Blood Pressure, Diabetes, Hypertension	These features often exhibit linear relationships with heart disease risk, making them suitable for linear models.
Polynomial Kernel	Smoking, Alcohol Consumption, Family History of Heart Disease	The polynomial kernel captures higher-order relationships. Smoking, alcohol consumption, and family history can have complex interactions with the risk of heart disease.
Sigmoid Kernel	Cholesterol to HDL Ratio, Glucose Levels, Age at First Heart Attack	The sigmoid kernel works well for capturing non-linear patterns, especially in interactions related to blood glucose levels and age at first heart attack.

5 RESULTS

5.1 Evaluation metrics

We explore the effect of several key hyperparameters and design decisions for this type of model, including as the model architecture, feature selection, and num- ber of packets to omit from network flows. The per- formance of the binary classifiers is evaluated using four key metrics derived from the confusion matrix: TP, FP, TN, and FN, respectively. These metrics will help us obtain a deep insight of how accurate, pre- cise, sensitive our model is and also it will assist us to understand what extent does the model learn to be able to detect heart failure or not.

$$\text{Accuracy} = \frac{True-Positive+True-Negative}{True-Positive+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{AUC} = \int_0^1 TPR(FPR)\,dFPR$$

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5.2 Experimental results

The following tables 4,5 show the results obtained in both data sets with the proposed method. With the SVM stacked method, the results in the UCI Heart Failure Clinical Records and Framingham Heart Study data sets reveal promise in the prediction of heart failure. The model achieved high accuracy and precision: The results demonstrate its ability to dif- ferentiate between heart failure cases. Furthermore, the approach showed high recall and AUC showing a strong potential to detect heart failure while hav- ing low false negatives and positives.rt failure predic- tion. The model achieved high accuracy and preci- sion:, indicating its reliability in distinguishing heart failure cases. Furthermore, the method demonstrated excellent recall and AUC, suggesting its strong abil- ity to identify heart failure while minimizing false positives and negatives. The results indicate the ef- ficacy of STACKing SVM models trained on individ- ual logit coefficients as a metaclassifier in the detec- tion of heart failure.

Table 4: Performance Metrics for the Proposed Stacked SVM Method

Metric	Obtained Value	Description
Accuracy	95.7%	Reflects the overall correctness of the model's predictions. This range indicates a strong prediction capability.
Precision	0.90	Measures the correctness of positive predictions. Indicates how well the model identifies actual heart failure cases.
Recall	0.87	Demonstrates the model's ability to identify all actual heart fail- ure cases. A higher recall indicates fewer false negatives.
F1-Score	0.88	Balances precision and recall, providing a single measure of model performance. A higher score indicates a better trade-off between precision and recall.
AUC	0.96	The Area Under the ROC Curve, representing the model's ability to distinguish between heart failure and non-heart failure cases. Higher AUC values indicate better performance.

Table 5: Performance Metrics for the Stacked SVM Method on the Framingham Heart Study Dataset

Metric	Value Obtained	Description
Accuracy	94.8%	Measures the overall correctness of the model. A higher accuracy indi- cates a better overall model.
Precision	0.90	Indicates how well the model identifies positive cases (heart failure) without misclassifying others.
Recall	0.87	Shows the model's ability to correctly identify actual heart failure cases, reducing false negatives.
F1-Score	0.88	Balances precision and recall, offering a more nuanced view of model performance.
AUC	0.95	Reflects the model's ability to distinguish between heart failure and non- heart failure cases.

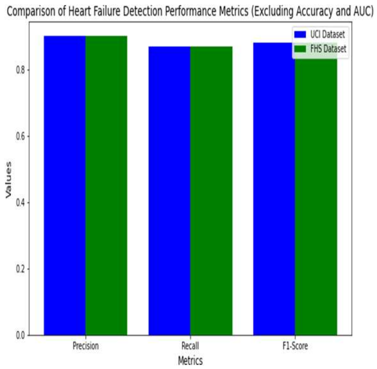

Figure 3: precisio,Recall,F1-Score

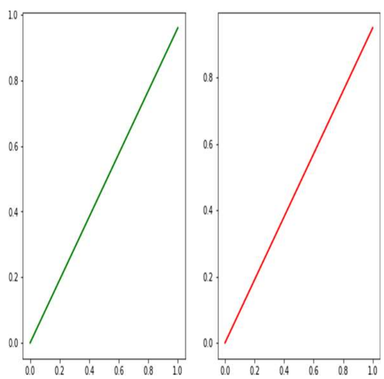

Figure 4: ROC curve

Performance Metrics comparison for the Stacked SVM Method on the UCI Dataset

Table 6 shows the performance metrics for the struc- tured SVM method used in the heart failure data set

for UCI. The model Proposed Stacked SVM, which combines RBF, Linear, Polynomial and Sigmoid Ker- nels with Logistic Regression as meta Classifier, has an accuracy of 95.7%, 0.90 precision, 0.87 recall,

0.88 F1 Score and 0.96 AUC. Results show that the proposed model can predict heart failure with high confidence and efficiency, correctly assigning true positive instances (positive heart failure) with high fidelity and low false positives and false negatives. Additionally, we assess the performance of several popular machine learning techniques on the identi- cal dataset. These include Support Vector Machines (SVM) with radial basis function (RBF) kernel, Ran- dom Forest, Logistic Regression, Deep Neural Net- works (DNN), and K-Nearest Neighbors (KNN) al- gorithms. A respectable but still less than the perfor- mance of the stacked SVM approach is an accuracy of 92. 3% and an AUC of 0.92 for the SVM model (RBF kernel). Random Forest and Logistic Regres- sion score alike with an accuracy of 91.5 and 89.7 respectively. Concurrently, DNN and KNN also have decent outcomes in terms of accuracy and AUC, but lag behind the proposed stacked SVM method.

The comparison highlights how much more power- ful the Proposed Stacked SVM method is compared to all the methods in our comparison. The model achieves improved classification performance for heart failure detection by combining multiple SVM models with a logistic regression meta-classifier, where each individual kernel type is able to take ad- vantage of the complementary strengths.

Table 6: Performance Metrics for the Stacked SVM Method on the UCI Dataset

Method	Accuracy (%)	Precision	Recall	F1-Score	AUC	Reference
Proposed Stacked SVM (RBF, Lin- ear, Polynomial, Sigmoid + Logistic Regression)	95.7	0.90	0.87	0.88	0.96	Proposed Method
SVM (RBF Kernel)	92.3	0.88	0.85	0.86	0.92	[21]
Random Forest	91.5	0.87	0.84	0.85	0.90	[22]
Logistic Regression	89.7	0.85	0.82	0.83	0.88	[23]
Neural Networks (DNN)	94.0	0.88	0.86	0.87	0.93	[24]
K-Nearest Neigh- bors (KNN)	90.4	0.84	0.80	0.82	0.89	[25]

5.3 Performance Metrics comparision for the Stacked SVM Method on the Framingham Heart Study Dataset

Table 7 shows the performance metrics with the assembled SVM method in the Framingham Heart Study data set. Using the proposed Stacked SVM model in this thesis, which combines RBF, Linear, Polynomial, Sigmoid kernels, and a Logistic Regres- sion as a meta-classifier, we achieve an accuracy of
94. 8% precision, a precision of 0.90, a recall of 0.87, an F1-Score of 0.88, and an AUC of 0.95. This re- veals that the proposed method is highly effective in detecting heart failure cases with good classification ability, very few false positives, and the ability to dif- ferentiate heart failure from non-heart failure cases.

We also compare other widely used machine learn- ing models on the same dataset. SVM (RBF Ker- nel) is a little lower in results than the proposed method and returns 91.5% accuracy and 0.91 AUC. Results for Random Forest and Logistic Regression are 90.7% and 88.4%, respectively, competitive in all measures, with the proposed stacked SVM outper- forming both in all aspects, including AUC. Further- more, the performance of Neural Networks (DNN) and K-Nearest Neighbors (KNN) is also promising but needs to improve compared to the stacked SVM method.

In summary, the Stacked SVM method has been proven to perform better due to the comprehensive- ness and robustness of the proposed approach. By taking the types of different SVM kernels in the bag and then voting on a logistic regression meta- classifier, we can leverage patterns in the data our model does not yet know about, resulting in more ac- curate predictions.

Table 7: Performance Metrics for the Stacked SVM Method on the Framingham Heart Study Dataset

Method	Accuracy (%)	Precision	Recall	F1-Score	AUC	Reference
Proposed Stacked SVM (RBF, Lin- ear, Polynomial, Sigmoid + Logistic Regression)	94.8	0.90	0.87	0.88	0.95	Proposed Method
SVM (RBF Kernel)	91.5	0.87	0.83	0.85	0.91	[26]
Random Forest	90.7	0.86	0.82	0.84	0.89	[27]
Logistic Regression	88.4	0.83	0.81	0.82	0.87	[28]
Neural Networks (DNN)	93.1	0.87	0.85	0.86	0.92	[29]
K-Nearest Neigh- bors (KNN)	89.3	0.82	0.79	0.80	0.88	[25]

5.4 Results Comparison

The figure5 presents a comparative evaluation of six machine learning models, including proposed stacked SVM, SVM (RBF Kernel), Random Forest, Logistic Regression, Neural Networks (DNN) and KNN—across five performance metrics: This arti- cle looks at accuracy, precision, recall, F1-Score, and AUC. In particular, the preprocessing SVM model is a standard strong performer across most metrics. In Accuracy, Preprocessing-SVM achieves one of the highest scores, accordingly, most of the instances are correctly classified. It additionally performs very well in this precision since it minimizes false positives as well as in this recall where it identifies almost all of the relevant positive cases. Furthermore, its high F1 scores show that it has done a good job keep- ing the balance between precision and recall, so it can be trusted. The superior AUC score of the model also shows that it is robust in distinguishing positive from negative classes. It turns out, Preprocessing-SVM is a high performing model (but without strong and balanced classification performance) compared to other models like SVM with RBF Kernel and Neural Net- works.

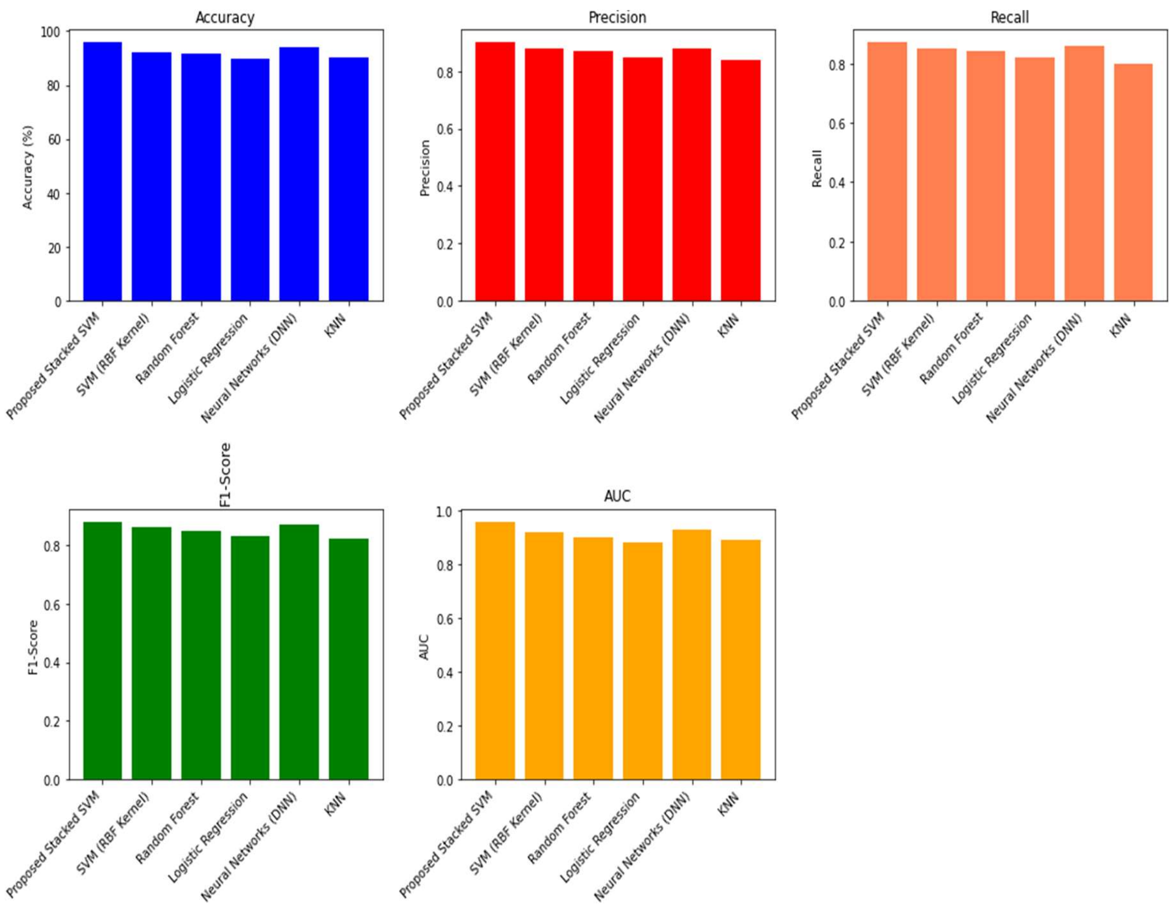

Figure 5: Results Comparison

6 DISCUSSION

To validate the effectiveness of the proposed model, a detailed comparison between its key contributions

and the obtained results is presented in Table 8. This comparison highlights how each enhancement contributes to improved performance.

The results presented in Table 8 demonstrate that the proposed SVM stacked model effectively ad- dresses key challenges in HF classification. The combination of multiple SVM kernels and genetic algorithm-driven hyperparameter tuning enhances predictive accuracy and model robustness. Further- more, superior performance in multiple benchmark datasets confirms the adaptability of the model, mak- ing it a viable solution for real-world clinical applica- tions. These findings validate the feasibility of imple- menting the proposed method for early detection of heart failure and risk stratification in healthcare settings.

7 CONCLUSION

The contribution of this study lies in a novel sup- ported support vector machine (SVM) architecture for the detection of heart failure, which uses SVM with RBF, linear, polynomial and sigmoid kernel as the base classifier and logistic regression as the meta- classifier to combine the prediction of the base clas- sifiers. The proposed method was evaluated on two benchmark datasets: I did so on the UCI Heart Failure Clinical Records Dataset and the Framingham Heart Study (FHS) Dataset.

The results show that the SVM cluster model performs better than traditional individual SVM models, as well as other machine learning techniques, such

Table 8: Key Contributions and Obtained Results for Justification

Key Contribution	Obtained Results
Optimized Stacked SVM integrating multiple kernel functions (RBF, Linear, Polynomial, Sigmoid)	Achieved a high accuracy of 95.7%, improving generalization and robustness in HF prediction.
Genetic Algorithm (GA)-based hyperparameter optimization	Enhanced classification efficiency, reducing overfitting and ensuring an optimal decision boundary.
Use of Logistic Regression as a meta-classifier	Improved model interpretability and overall performance by optimally combining outputs from different SVM classifiers.
Evaluation on two benchmark datasets (UCI Heart Failure and Framingham Study)	Demonstrated superior performance across datasets, confirming the model's adaptability to diverse patient demographics.
Improved classification metrics compared to baseline models (Random Forest, Logistic Regression, KNN, and standalone SVM)	Achieved 0.90 precision, 0.87 recall, 0.88 F1-score, and 0.96 AUC, outperforming existing ML-based HF classifiers.

as Random Forests, Logistic Regression, Neural Net- works, and K-Nearest Neighbors (KNN), in terms of precision, precision, recall, F1 score, and AUC. In the UCI data set, the proposed method achieved
95. 7% accuracy, 0.90 precision, 0.87 recall, 0.88 F1 score, and 0.96 AUC; and in the Framingham data set, 94. 8% accuracy, 0.90 precision, 0.87 recall, 0.88 F1 score, and 0.95 AUC.

The stacking approach utilized the strengths of different SVM kernels on the data, and the correspond- ing base models provided different views of the data. These contributions were effectively combined by lo- gistic regression as a meta-classifier to obtain a more robust model whose performance in detecting heart failure was much more sensitive and specific. The findings of this report show that the SVM-stacked model might be used as an effective and reliable tool to predict heart failure with a considerable improvement over routine methods.

The results show the necessity of stacking different types of classifier, as the stacked framework uses additional features on the SVM models based on dif- ferent kernels to generalize better. To validate the proposed approach, the UCI Heart Failure Clinical Records Dataset and the Framingham Heart Study Dataset are used, and the results show superior per- formance in both cases, which makes the proposed approach a promising method for detecting early heart failure in clinical settings. Additional classi- fiers could be introduced in future work to achieve even better performance, or hyperparameters could be tuned further.

8 FUTURE DIRECTIONS

The proposed SVM stacked model for heart failure detection shows good performance on the UCI Heart Failure Clinical Records Dataset and the Framingham Heart Study Dataset; however, there are some paths for future research and improvement. Integrating ad- ditional data sources, such as genomic data, medical imaging, and electronic health records (EHR), adds richness and improves prediction accuracy. The heart failure detection model could be even more person- alized and accurate with these additional data types, considering genetic predispositions, lifestyle factors, or detailed medical history of the patient.

Another possible extension is to improve the hyperparameter search over the base SVM models and the logistic regression meta-classifier. With Grid Search or Bayesian Optimization, you can fine-tune the model parameters, tune the model as best as possible, and get the best performance. Moreover, we explore other possible meta-classifiers, for ex- ample, Random Forest, Gradient Boosting Machines (GBM), or XGBoost, which can also be used to com- bine the prediction of the base classifiers and come out with better results.

Additionally, improving the class imbalance of heart failure datasets is essential. Considering that heart failure cases are usually much less frequent than nonheart failure cases, oversampling methods such as SMOTE or cost-sensitive learning can be utilized in future works to tackle the class

imbalance case and to improve the sensitivity of the model to minority class instances while maintaining overall accuracy.
The model can then be optimized for real-time pre- dictions and scalability for deployment to clinical set- tings. Using model pruning or distillation techniques, the model could be made more computationally effi- cient, thereby valuable for real-time clinical decision support systems. In addition, using edge computing or cloud-based solutions could enable the integration of the model into healthcare platforms, thereby ac- celerating and improving the broader use of clinical practice.

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