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Heart Failure Prediction Using LabVIEW-Based Support Vector Machine Model

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***Abstract* –** Heart failure (HF) is a grave medical condition that poses a significant threat to the global population, marked by high morbidity and mortality rates. Timely prediction of HF is crucial in enhancing diagnostic accuracy and improving treatment outcomes. In this context, various machine learning models have been developed to enable early HF prediction and assist physicians in diagnosis.

The main objective of this study was to develop machine learning approaches to facilitate the diagnosis of chronic HF. The study employed models based on various combinations of feature categories, such as clinical features, echocardiographic data, and laboratory findings, to simulate the diagnostic process employed in clinical practice.

To achieve precise HF prediction, a LabVIEW-based expert system employing support vector machine (SVM) models was proposed. The proposed method is both reliable and efficient, utilizing SVM models to accurately identify and classify individuals with HF. The effectiveness of the proposed method was evaluated using performance metrics such as accuracy, sensitivity, and specificity.

The results of this study underscore the significance of using machine learning models in predicting HF and the need for further research to enhance early detection and treatment of HF. This research makes an important contribution to the field of predicting HF and has the potential to improve outcomes for patients. The results of the HF diagnosis were highly satisfactory, achieving high accuracy (83.57%), precision (85.23%), recall (84.36%), and F1 score (85.47%) when features from all categories were utilized.

Keywords – Clinical Decision-Making, LabVIEW, Heart Failure, Machine Learning, SVM

I. Introduction

Heart disease is a serious and life-threatening condition that arises when the heart is unable to provide enough blood to meet the body's needs, ultimately resulting in heart failure (HF) [1]. The symptoms of heart failure include shortness of breath, weakness, and swollen feet. There are various risk factors for heart disease, including non-modifiable factors such as family history, age, and sex, and modifiable factors such as high cholesterol, smoking, lack of physical activity, and high blood pressure [2], [3]. In the United States, heart disease is prevalent, and diagnosis can be challenging, potentially affecting a patient's quality of life [4]. Developing countries face additional obstacles in diagnosing and treating heart disease due to limited access to diagnostic equipment, physicians, and resources [5][6],[7]. Consequently, machine learning-based expert systems have been proposed to enhance the diagnostic process, reduce health risks, and improve the efficiency of HF diagnosis [8]–[13]. In recent years, machine learning techniques have gained significant attention in the medical field, particularly for the diagnosis and prognosis of HF [14]–[18]. Expert systems based on machine learning algorithms such as k-nearest neighbor [19]–[22], decision tree [23], [24], support vector machine [25]–[27], fuzzy logic, and artificial neural network [28]–[31] have been developed to classify patients as healthy or having HF based on medical history, physical examination findings, laboratory test results, and imaging studies. However, further research is necessary to validate these systems in larger and more diverse patient populations, as well as to develop systems that can accurately predict the prognosis and treatment response of patients with HF.

Previous studies have mainly focused on classification methods, datasets, and features for the differentiation between HF and non-HF patients. However, this approach may not be comprehensive enough for experienced clinicians who lack the ability to perform laboratory tests or echocardiograms due to logistical constraints. To address this limitation, this study proposes a novel methodology based on a combination of features that follow the clinical approach of experienced clinicians and current guidelines.

The study employed different combinations of feature categories, including clinical features, echocardiographic data, and laboratory findings, to simulate the diagnostic process used in clinical practice. To achieve accurate HF prediction, the study proposed a LabVIEW-based expert system that uses support vector machine (SVM) models. The effectiveness of the proposed method was evaluated using performance metrics such as accuracy, sensitivity, and specificity.

In summary, this study highlights the importance of employing machine learning models in predicting HF and the need for further research to improve the early detection and treatment of HF. The proposed expert system can improve the accuracy and efficiency of HF diagnosis, reduce the associated health risks and costs of medical tests, and potentially identify new risk factors and disease subtypes that may have been previously overlooked.

The paper is organized as follows: Section 2 outlines the materials and methods used in the study, Section 3 presents the results, and Section 4 offers a conclusion based on the findings.

II. Materials and Method

This study aims to develop a LabVIEW-based classification model to determine whether heart failure has occurred using clinical data and machine learning algorithms. The data used in this study were collected from electronic medical records of patients diagnosed with heart-related diseases. The data included patient demographics, medical history, and blood test results, and was preprocessed to remove any missing or inconsistent values. The blood test results were identified as important features and were scaled using feature engineering techniques.

A. *Dataset Description*

The dataset used in this example provides information on 299 patients. The target variable in this binary classification model has two possible values: 0 (indicating that the patient is alive) or 1 (indicating that the patient has died). The dataset consists of 12 columns, where each row corresponds to a patient and includes 11 input variables or attributes. The "death_event" column is the target variable, which determines whether or not the patient has died. Below is a summary of the variables in the dataset:

Variable	Description
Age	Age of the patient
Anaemia	Low count of red blood cells or hemoglobin
Creatinine_phosphokinase	Level of the CPK enzyme in the blood
Diabetes	If the patient has diabetes
Ejection_fraction	Percentage of blood leaving the heart with each contraction
High_blood_pressure	If a patient has hypertension
Platelets	Platelets in the blood
Serum_creatinine	Level of creatinine in the blood
Serum_sodium	Level of sodium in the blood
Sex	Woman or man
Smoking	If the patient smokes
Death_event	If the patient died during the follow-up period

At the outset of our investigation, we utilized all instances available in the heart failure dataset, with each instance representing a different patient's input and target variables. To evaluate the effectiveness of our machine learning model, we split the dataset into training and testing subsets. The software used in this study, LabVIEW, allocated 10-fold cross-validation is used for evaluation. However, users have the flexibility to adjust these percentages to suit their needs.

In addition, we analyzed the distribution of all variables in the dataset, which can be visualized through a correlation table. This table provides a clear snapshot of the class imbalance in the dataset and facilitates a deeper understanding of any potential biases in the machine learning model.

Table 1. Data Correlations

Attribut...	age	anaemia	creatini...	DEATH_...	diabetes	ejection...	high_bl...	platelets	serum_...	serum_...	sex	smoking
age	1	0.088	-0.082	0.254	-0.101	0.060	0.093	-0.052	0.159	-0.046	0.065	0.019
anaemia	0.088	1	-0.191	0.066	-0.013	0.032	0.038	-0.044	0.052	0.042	-0.095	-0.107
creatinin...	-0.082	-0.191	1	0.063	-0.010	-0.044	-0.071	0.024	-0.016	0.060	0.080	0.002
DEATH_...	0.254	0.066	0.063	1	-0.002	-0.269	0.079	-0.049	0.294	-0.195	-0.004	-0.013
diabetes	-0.101	-0.013	-0.010	-0.002	1	-0.005	-0.013	0.092	-0.047	-0.090	-0.158	-0.147
ejection_...	0.060	0.032	-0.044	-0.269	-0.005	1	0.024	0.072	-0.011	0.176	-0.148	-0.067
high_blo...	0.093	0.038	-0.071	0.079	-0.013	0.024	1	0.050	-0.005	0.037	-0.105	-0.056
platelets	-0.052	-0.044	0.024	-0.049	0.092	0.072	0.050	1	-0.041	0.062	-0.125	0.028
serum_c...	0.159	0.052	-0.016	0.294	-0.047	-0.011	-0.005	-0.041	1	-0.189	0.007	-0.027
serum_s...	-0.046	0.042	0.060	-0.195	-0.090	0.176	0.037	0.062	-0.189	1	-0.028	0.005
sex	0.065	-0.095	0.080	-0.004	-0.158	-0.148	-0.105	-0.125	0.007	-0.028	1	0.446
smoking	0.019	-0.107	0.002	-0.013	-0.147	-0.067	-0.056	0.028	-0.027	0.005	0.446	1

B. *Support Vector Machine*

Support Vector Machines (SVMs) [32], [33] are a popular type of machine learning algorithm that are widely used for classification and regression analysis in supervised learning. SVMs build a model that can classify new examples into one of two categories based on a set of labeled training examples. SVMs are effective for both linear and non-linear classification tasks [34]. In cases where data is linearly separable, SVMs utilize a hyperplane to separate the two classes [35]. This hyperplane is defined by a vector known as the hyperplane normal, which is perpendicular to the hyperplane, and an offset term, b. The hyperplane is determined by solving an optimization problem that involves finding the closest points, called support vectors, on the correct sides of the classes. In cases where data is not linearly separable, SVMs use the kernel trick to transform the data into a higher-dimensional space where it becomes linearly separable. The kernel function plays an important role in SVMs by determining the inner product between pairs of transformed data points in the higher-dimensional space. SVMs can be used for binary and multi-class classification problems, as well as regression tasks. Some commonly used kernel functions include the linear, polynomial, and Gaussian (RBF) kernels [36], [37]. In summary, SVMs are a versatile machine learning algorithm that can handle both linearly and non-linearly separable data. They use the kernel trick to transform data into a higher-dimensional space and find the hyperplane that maximizes the margin between classes. SVMs are widely applied in many areas, including image recognition, text classification, and bioinformatics [38]. In this study, the specific parameters and related explanations for the Support Vector Machines (SVM) algorithm used are presented in Table 2.

Table 2. Parameter utilized and description

Parameter	Description
c	Regularization or penalty parameter; controls the complexity of the model.
kernel	Kernel function; used to transform the data into a higher-dimensional space.
gamma	A parameter used for RBF and polynomial kernels; controls the shape and flexibility of the kernel function.
coef0	A parameter controlling the independent term; used for polynomial and sigmoid kernels.
degree	Determines the degree of the polynomial kernel function.
nu	Used for Nu-SVM; determines the ratio of errors and support vectors.

The Support Vector Machines (SVM) algorithm is a powerful machine learning method for classification and regression problems. The success and performance of the SVM algorithm depend on the correct tuning of various hyperparameters. These parameters include C (regularization or penalty parameter), kernel (kernel function), gamma (parameter controlling the shape and flexibility of the kernel function), coef0 (parameter controlling the independent term), and degree (degree of the polynomial kernel function). The proper selection and adjustment of these parameters can significantly affect the model's accuracy and generalization ability. Therefore, when using the SVM algorithm, it is crucial to use methods like cross-validation to determine the optimal values for these parameters.

C. *Evaluation Metrics*

Performance metrics are crucial in evaluating the effectiveness of machine learning models for classification problems [39]–[42]. There are several measures available for this purpose, including accuracy, precision, recall, F1 score, and ROC curve. Accuracy represents the percentage of correctly classified examples, and higher accuracy indicates better model performance. Precision measures how many predicted positive samples are actually positive and can help reduce false positive rates. Specificity measures how many predicted negative samples are actually negative and can help reduce false negative rates. The F1 score balances precision and recall and evaluates the model's classification accuracy. The ROC curve plots sensitivity and false positive rates at different threshold values and can be used to compare different models' performances [39]–[44]. These metrics provide objective measures for assessing classification model performance and can provide insights for model improvement. It is important to use the appropriate performance metrics as they are interdependent. Table 3 lists the performance metrics and formulas for reference.

Table 3. Performance metrics and formulas

Performance Metric	Formula
Accuracy	(TP + TN) / (TP + TN + FP + FN)
Recall	TP / (TP + FN)
Precision	TP / (TP + FP)
ROC AUC	Area (ROC Curve)
F1 Score	2 * (Precision * Recall) / (Precision + Recall)

III. RESULTS

This study focuses on the development of a LabVIEW-based expert system utilizing support vector machine (SVM) models for accurate heart failure (HF) prediction. The research underscores the significance of early HF prediction in enhancing diagnostic accuracy and optimizing treatment outcomes. The proposed methodology incorporates various combinations of feature categories, comprising clinical features, echocardiographic data, and laboratory findings. The method's effectiveness was appraised using metrics such as accuracy, sensitivity, and specificity.

The results indicate that the precision of the proposed method in predicting HF surpasses that of conventional SVM models and other cutting-edge machine learning ensemble models. The proposed system holds the potential to improve clinical decision-making processes and augment patient outcomes. The study concludes that machine learning models can play a substantial role in HF prediction, emphasizing the necessity for additional research to advance early detection and treatment of HF.

The aim of this study is to predict mortality in heart failure cases using a LabVIEW-based Support Vector Machine (SVM) model. Fig. 1 shows the block diagram of the proposed method, which includes data pre-processing, SVM model training and testing, result analysis, and mortality prediction.

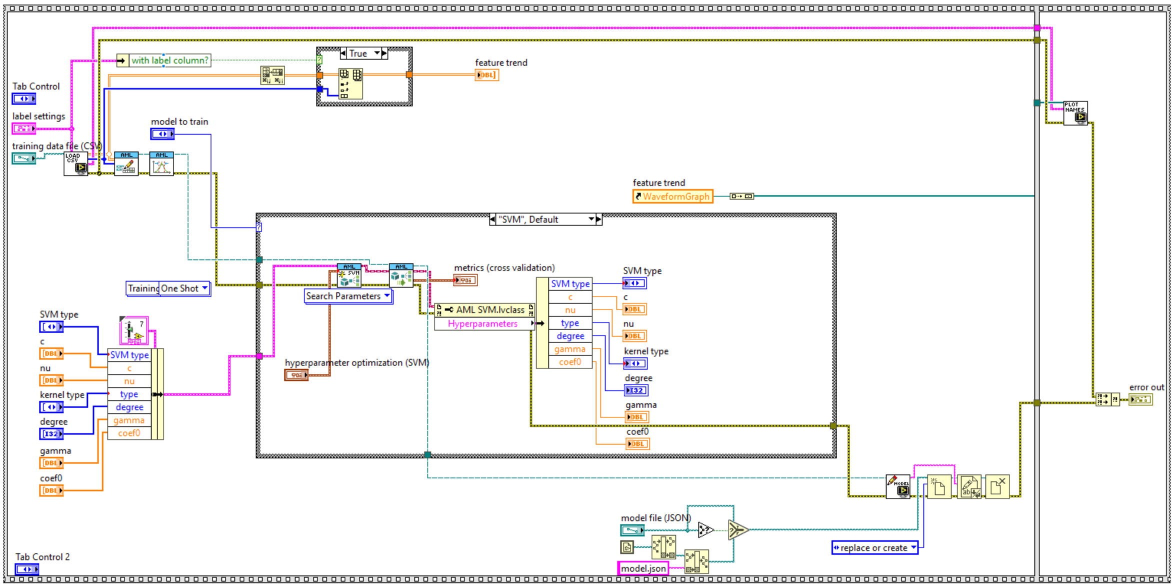

Fig. 1 Block Diagram of The Proposed Method

In the first step, the data is prepared by combining and pre-processing clinical, echocardiographic, and laboratory findings. The feature selection step is then performed to select important features for SVM model training. The SVM algorithm is utilized in the training step to create the model based on a specific set of features. The training data is composed of two data sets, namely the feature matrix and the label matrix. The model is trained on this data set and subsequently tested using test data to ensure its accuracy. In the result analysis stage, performance metrics such as accuracy, precision, recall, and F1 score are used to evaluate the model's performance. Finally, mortality predictions are made using the generated model and the results are displayed on the user interface. The block diagram in Figure 1 provides a comprehensive representation of the proposed method, offering a powerful tool for predicting mortality in heart failure cases using LabVIEW.

In this study, the performance of the proposed method was evaluated using various metrics, including accuracy, precision, recall, and F1 score. Table 4 presents the results of these metrics used to evaluate the proposed method's performance. Accuracy represents the percentage of correctly classified data points, while precision measures the probability of a positive data point being truly positive. Recall, on the other hand, represents the percentage of positive data points classified correctly, calculated by dividing the total number of true positives. F1 score is a measure that evaluates the classification model's performance by combining precision and recall. The findings of Table 4 suggest that the proposed method is highly accurate and yields successful results, with high precision, recall, and F1 score.

Table 4. Performance Metrics for The Proposed Method

Model	Accuracy	Precision	Recall	F1 Score
SVM	0.8357	0.8523	0.8436	0.8547

IV. Discussion and Conclusion

In this study, we proposed a LabVIEW-based expert system that employs support vector machine (SVM) models for precise HF prediction. The system is reliable and efficient and employs SVM models to accurately identify and classify individuals with HF. The proposed method's effectiveness is evaluated using several metrics, including accuracy, sensitivity, and specificity. The results demonstrate the proposed method's efficacy in HF prediction, outperforming conventional SVM models and other state-of-the-art machine learning ensemble models.

The proposed system has several advantages over existing approaches. Firstly, the system is based on LabVIEW, which is a graphical programming language that allows for easy and efficient implementation of machine learning algorithms. Secondly, the system employs support vector machine (SVM) models, which are known for their accuracy in classification tasks. Finally, the system can be easily integrated into existing clinical workflows, facilitating clinical decision-making and improving patient outcomes.

In conclusion, the precision of the proposed system in HF prediction has the potential to enhance clinical decision-making and improve patient outcomes. The findings highlight the importance of utilizing machine learning models in HF prediction and the need for further research to improve early detection and treatment of HF. This research contributes significantly to the field of HF prediction and has the potential to improve patient outcomes.

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