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Enhancing Cardiovascular Diseases Classification using CNN Algorithm

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Abstract

This study focuses on using machine learning algorithms to detect cardiovascular diseases, addressing the critical need for accurate and timely diagnosis of these conditions, which are significant contributors to global morbidity and mortality. The research aims to evaluate the performance of various machine learning algorithms such as Convolutional Neural Network (CNN), Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Gaussian Naive Bayes (GNB), and Gradient Boosting in categorizing patients into 'yes' or 'no' groups for cardiovascular diseases based on a thorough dataset. The methodology includes data preprocessing, feature selection, and model training and assessment. The results indicate that CNN and SVM demonstrate strong and balanced performance, whereas the Decision Tree shows high sensitivity but potential overfitting. These outcomes offer valuable insights for algorithm selection and model improvement in the detection of cardiovascular diseases, setting the groundwork for further research to enhance diagnostic accuracy, clinical relevance, and healthcare outcomes.

Keywords

Cardiovascular Disease Detection, Machine Learning Algorithms, CNN, SVM, Medical Diagnosis

1. Introduction

Cardiovascular diseases (CVDs) have a significant impact on public health globally, being the leading cause of mortality worldwide. They encompass various conditions such as . Ischemic heart disease, stroke, heart failure, and peripheral artery disease are included in this category of diseases, CVDs result in a high burden of premature mortality and disability, affecting individuals, health systems, and countries. The global burden of atherosclerotic cardiovascular diseases (ASCVDs) is particularly concerning, leading to years lost to premature mortality and disability. Inequalities exist between countries and individuals in the risk of ASCVDs. The factors contributing to ASCVDs include unhealthy behaviors, lifestyles, and social components. Adequate prevention and treatment approaches are crucial in addressing the impact of CVDs on public health [1].

Early detection of CVD can significantly improve the chances of a patient's cure. Accurate prediction and timely diagnosis hold significant importance in the realm of clinical investigations and the healthcare sector [2]. Numerous approaches, encompassing machine learning frameworks and ensemble classification models, have been suggested to precisely forecast cardiac ailments in individuals. [3]. Additionally, the use of efficient diagnostic methods, such as the detection of biomarkers and the development of detection models using ECG recordings, can aid in the early diagnosis of CVD [4]. Implementing a comprehensive Enhancing the assessment and care of individuals with diabetes mellitus,

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a high-risk population for CVD, can be improved through the implementation of a comprehensive cardiovascular risk stratification approach that integrates clinical risk algorithms, biomarkers, atherosclerosis imaging, and cardiac stress testing [2]. Consequently, the early detection of CVD assumes a pivotal role in enhancing patient outcomes and alleviating healthcare system's burden. Furthermore, it is important to note that CVD stands as the primary cause of global mortality. accounting for a significant number of deaths globally. CVD includes conditions like ischemic heart maladies, strokes, heart insufficiency, and peripheral arterial conditions [3].

The World Health Organization reports that each year, 17.9 million individuals succumb to CVD, constituting 31% of the total global mortality. The burden imposed by CVD extends significantly to individuals, healthcare systems, and nations, primarily stemming from premature mortality and the disability attributed to these ailments. The economic burden of CVD is also significant, with rising healthcare costs and productivity losses. Therefore, addressing CVD is crucial for reducing mortality rates and improving overall health outcomes globally [4].

The accurate detection of CVD with a high degree of accuracy is important in the medical world for several reasons. Firstly Globally, CVD stands as the foremost cause of mortality. and timely and correct diagnosis is crucial for effective treatment and prevention of complications [9]. Secondly, the majority of cardiovascular disorders are preventable, and accurate detection can help identify individuals at risk and implement preventive measures. Additionally The application of machine learning models in detecting CVD can improve the accuracy of predictive analysis, leading to more effective and personalized treatment plans [5].

Developments in machine learning technology, particularly the CNNs, can contribute to improved detection of CVD. CNNs have been used to accurately detect the presence of diseases such as diabetic macular edema (DME) and CVD, as well as determine their severity. Machine learning models, including CNNs, have been employed to predict cardiovascular risk factors like hypertension, body mass index, and total cholesterol level, achieving high accuracy rates [15]. CNNs have the ability to automatically detect features in images without human intervention, making them efficient for tasks such as face recognition, image classification, and detection of medical problems [16]. Additionally, an improved CNN recognition algorithm has been developed for portable electrocardiographs, enabling the recognition of heart rhythm types and the detection of atrial fibrillation with increased accuracy [6].

Prediction models using CNN in the context of CVD detection are expected to provide accurate and reliable predictions for early disease detection. These models aim to alleviate the situation of CVD by predicting the disease based on the severity of the patient's side effects. The use of CNN in these models allows for the analysis of complex patterns and features in the data, leading to improved prediction accuracy. Compared to other machine learning techniques, CNN has shown promising results in the detection of various medical conditions, including CVD. It has the potential to outperform traditional clinical prediction models (CPMs) that rely on statistical analysis of factors linked to developing CVD. However, further improvements and research are needed before CNN can be implemented over current CPMs [7].

The results of these studies can impact the development of CVD early detection tools in the future by providing insights into effective screening methods and risk prediction models. A study found that community-based self-screening through a mobile health (mHealth) application can be a potential tool for CVD risk assessment, especially during the COVID-19 pandemic when access to healthcare facilities is limited. Another study compared different methods of characterizing prenatal tobacco exposure and highlighted the importance of capturing both between-individual and within-individual variability in exposure for accurate risk detection. A study [22] applied various machine learning algorithms to predict CVD and identified the Random Forest algorithm as the best performer. Additionally, a study developed a simple model based on age and QRS-T angle for the early detection of prevalent CVD in resource-constrained community settings. These findings can inform the development of user-friendly and accurate tools for early detection and risk assessment of CVD [8].

2. Literature Review

ASCVDs are the most common types of CVD globally. These encompass ischemic heart disease, stroke, heart failure, peripheral arterial disease, and other cardiac and vascular ailments. These diseases are caused by atherosclerosis, a chronic arterial disease characterized by the buildup of plaque in the arteries [25]. Symptoms of ASCVDs may differ depending on the specific condition, but common signs include chest pain or discomfort, shortness of breath, fatigue, dizziness, and swelling in the legs or ankles [26]. However, it is important to note that symptoms can differ among individuals and may not always be present. Early detection and management of risk factors are crucial in preventing and treating ASCVDs [9].

The epidemiology of coronary heart disease (CHD) has evolved over time, leading to a greater understanding of its causes and the development of preventive measures. Early investigations in CVD epidemiology established a broadly applicable risk-factor framework, setting the stage for more conclusive preventive trials during the 1980s and subsequent years [2]. Reliable estimates of the prevalence and incidence of CHD have highlighted its significance as a contemporary health hazard. Social determinants of health, such as socioeconomic status (SES), play a crucial role in the development of CHD, and understanding the pathways through which socioeconomic inequalities are translated into CHD is important for prevention [4]. Research indicates that individuals residing in high-poverty areas tend to have elevated rates of CHD, even after adjusting for individual-level factors [31]. emphasizing the importance of both individual and neighborhood attributes in understanding CHD risk [10].

The relationship between risk factors such as smoking, diabetes, high blood pressure, and cardiovascular disease has been documented in previous studies. Smoking has been found to be a major risk factor for CVD, leading to increased levels of triglycerides and low levels of HDL cholesterol [11]. Diabetes mellitus is strongly correlated with cardiovascular disorders, and individuals with diabetes have a higher likelihood of developing heart attacks due to factors such as dyslipidemia, hypertension, and obesity [35]. High blood pressure is also a risk factor for CVD, and its prevalence has been associated with the distribution of body fat mass and fat-free mass in the limbs and trunk [36]. These studies highlight the importance of addressing these risk factors to reduce the long-term cardiovascular complications associated with these conditions [12].

Genetic risk factors significantly contribute to the development of CVD, Large-scale genetic studies have identified numerous genomic loci associated with CVD risk, indicating a strong genetic component. These loci contain common variants that individually have small effect sizes but collectively contribute to disease risk. Experimental research has revealed novel mechanisms underlying CVD pathophysiology, some of which are unexpected. Genetic predisposition is implicated in both CVD and cancer, with shared risk factors and potential mutual promotion of disease onset. Furthermore, genetic variants associated with cardiomyopathies increase the risk of cardiovascular toxic side effects. Missense mutations in specific mediator (MED) subunits have been linked to heart development and CVD. The emergence of findings from genetic association studies has provided insights into the complex genetic puzzle of CVD. These findings have identified novel etiologic mechanisms and have implications for personalized medicine [13].

CNNs process image data by extracting discriminative statistical features from images and classifying them. They are effective in processing visual data because they can learn to classify images based on predictive features within the dataset, even if those features are idiosyncratic or not relevant to human object recognition. Additionally, CNNs can be enhanced by incorporating additional data or filtered responses from established image analysis filters. This augmentation improves the accuracy of CNNs in image classification tasks [14].

Layer convolution, pooling, and activation functions are fundamental components of CNNs. Convolution involves applying filters to input data to extract features and capture spatial relationships. Pooling is a down-sampling process that reduces the dimensionality of feature maps, discarding irrelevant information and selecting global features. A study proposed an automated technique for the identification of eye cancer using a CNN, achieving a high classification rate. Although there is no specific mention of CNNs in the detection of cardiovascular disease, the successful application of CNNs in other medical domains suggests their potential in cardiovascular disease diagnosis [15].

The structure of CNN architecture can be adapted for CVD detection tasks by incorporating various techniques and modifications. One approach is to use convolutional layers with different kernel sizes, such as depthwise temporal convolutions, to explore temporal features more optimally [49]. Another technique is to stack multiple structural units together, Raising the kernel sizes for consecutive depthwise temporal convolutions and incorporating residual connections through feature addition are strategies proposed in [16]. Additionally, the use of neural network architectures that combine different bio-markers, These risk factors include anomalous morphology of ECG waveforms and abnormal Heart Rate Variability (HRV). can enhance the classification of CVD like Coronary Artery Disease (CAD) [17] .

SVM are a machine learning method employed for the detection of CVD. SVM works by creating a hyperplane that separates data points into different classes based on their features. It aims to discover the perfect hyperplane that maximizes the margin between classes, thus improving the classification accuracy. SVM has several advantages in the context of CVD detection. It can handle high-dimensional data and is effective in dealing with small sample sizes. SVM also has good generalization capabilities and can handle non-linear relationships between features. However, SVM has some limitations. It may incur high computational costs, particularly when dealing with extensive datasets. SVM also requires careful selection of hyperparameters and can be sensitive to noise in the data. Additionally, SVM may not perform well when there is significant overlap between classes. [18].

KNN is among the machine learning classifiers employed for the classification of CVD. Comparative evaluations of its performance against other classifiers suggest that KNN might not be the most efficient approach for CVD diagnosis [20]. Random Forest is a machine learning method that can be used to address the problem of class imbalances in CVD datasets. It has several benefits in this context. Firstly, Random Forest can handle imbalanced datasets by constructing a nearly balanced dataset in the uncertainty region, which helps to deal with the class imbalance problem [19].

3. Proposed Method

The proposed model is a neural network based on CNN architecture for internet network intrusion detection [21][22]. The following is the mathematical concept. The Conv1D layer, also known as the first Convolutional layer, operates on one-dimensional time-series data, specifically tailored to a dataset of length “padding value” In this particular layer, there are 128 filters utilized, each with a kernel size of 3 for scanning the input data. The employed activation function in this context is ReLU (Rectified Linear Unit). It imparts non-linearity to the model by converting negative values to zero and preserving positive values unaltered. Conv1D Layer 1 is shown in Equation 1.

$$Conv1D_1(x) = ReLU(W_1 * x + b_1) \qquad (1)$$

In Equation 1, Conv1D Layer 1 uses the symbol x to denote the input to this specific layer. Additionally, it involves the weight matrix represented by W and the bias vector denoted as b.

Incorporating a MaxPooling1D layer, denoted as Pooling Layer 1, this component performs maximum pooling on the data, specifically designed for one-dimensional datasets. It employs a pool size of 2, effectively reducing the dimensionality of the input data by selecting the maximum value within each pair of adjacent elements. This pooling operation aids in capturing the most significant features while reducing computational complexity, contributing to the model's ability to focus on essential patterns within the data. MaxPooling1D Layer 1 is shown in Equation 2.

$$MaxPooling1D_1(x) = max(stride(x)) \qquad (2)$$

MaxPooling1D Layer 1 in Equation 2, $stride(x)$ represents the maximum pooling operation.

The Dropout Layer 1 is a crucial element within the neural network architecture, primarily aimed at mitigating overfitting, a common challenge in machine learning. In this layer, a dropout rate of 30% is applied to the units from the preceding layer. This means that during training, 30% of the units are randomly deactivated, effectively preventing the model from becoming overly reliant on specific connections and features. By doing so, Dropout Layer 1 encourages the network to generalize better and enhance its ability to perform well on unseen data, thereby improving the model's overall robustness and preventing it from memorizing the training data.

The Conv1D Layer 2, also known as the second Convolutional Layer, plays a significant role in the neural network architecture. It is equipped with 256 filters, each with a kernel size of 3, and employs the ReLU activation function. This layer is responsible for further extracting intricate patterns and features from the input data. The 256 filters act as feature detectors, scanning the data for relevant patterns. The utilization of the ReLU activation function brings non-linear characteristics to the network, which enhances its capacity to discern intricate connections within the data. This layer's output contributes to the network's ability to discern and understand the subtle details in the input, making it a crucial component in the process of detecting intrusion patterns in network traffic data. Conv1D layer 2 is shown in Equation 3.

$$Conv1D_2(x) = ReLU(W_2 * x + b_2) \qquad (3)$$

The MaxPooling1D Layer 2, followed by Dropout Layer 2, constitutes a crucial part of the network architecture. In the MaxPooling1D Layer 2, maximum pooling is implemented using a pool size of 2, effectively diminishing the spatial dimensions of the data while preserving the most crucial information. This layer helps in subsampling the features extracted by the previous convolutional layers, focusing on the most relevant details while reducing computational complexity. Subsequently, Dropout Layer 2 randomly drops 30% of the units from the previous layer during training, acting as a regularization technique to prevent overfitting. This dropout mechanism enhances the network's generalization capabilities and ensures that it doesn't rely too heavily on any particular set of neurons. Together, these layers contribute to the network's ability to learn and represent intricate patterns in network traffic data efficiently, aiding in the detection of intrusion patterns.

The Conv1D Layer 3 is a pivotal component of the network architecture, characterized by its substantial number of filters, totaling 512. Employing a kernel size of 3, this layer conducts convolutional operations on the input data, focusing on capturing intricate patterns and features. The activation function used here is ReLU, which introduces non-linearity to the model by transforming negative values to zero and allowing the network to learn complex relationships within the data. This layer plays a crucial role in extracting high-level abstractions from the input, contributing significantly to the network's ability to discern subtle intrusion patterns in network traffic data. Conv1D Layer 3 is shown in Equation 4.

$$Conv1D_3(x) = ReLU(W_3 * x + b_3) \quad (4)$$

The GlobalAveragePooling1D Layer serves as an integral part of the network architecture by executing a global average pooling operation across all the features or time steps. This operation involves computing the average of all the values in the input data, and condensing the information while retaining essential insights. It plays a pivotal role in reducing the spatial dimensions of the data, ensuring that the subsequent layers receive a compact representation of the features, which can aid in efficient and effective pattern recognition. Global Average Pooling 1D layer is shown in Equation 5.

$$GlobalAveragePooling1D(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (5)$$

The Dense Layer 1, also referred to as the Fully Connected Layer 1, plays a significant role in the network architecture with a total of 128 units or neurons. These units are densely connected to the previous layer, creating a fully connected structure. The activation function employed here is ReLU, which introduces non-linearity to the network by allowing only positive values to pass through while filtering out negative values. This non-linearity is crucial for the model's capacity to learn complex relationships within the data. Dense layers are essential for the final stages of feature extraction and abstraction, enabling the network to capture high-level patterns and representations from the previously processed features. These layers are a key component of the Convolutional Neural Network and contribute significantly to its overall performance in network intrusion detection. Dense Layer 1 is shown in Equation 6.

$$Dense_1(x) = ReLU(W_4 \cdot x + b_4) \quad (6)$$

The Dropout Layer 3 is incorporated into the model with a dropout rate of 30%. This dropout rate implies that during each training iteration, approximately 30% of the units or neurons from the preceding layer are randomly dropped or deactivated. This dropout mechanism serves as a regularization technique to prevent overfitting, enhancing the model's generalization capabilities. It encourages the network to rely on multiple pathways, reducing the risk of relying too heavily on specific neurons and thus improving the model's robustness.

The final layer in the network architecture is the Dense Layer 2, commonly known as the Output Layer. In this binary classification problem, a single unit is employed, and the activation function used is Sigmoid. Sigmoid activation maps the network's output to a probability score between 0 and 1, which is interpretable as the likelihood of the input data belonging to the positive class (intrusion) in binary classification scenarios. This layer is responsible for producing the final prediction or decision of whether a network traffic instance is normal (no intrusion) or malicious (intrusion detected). Dense layer 2 is shown in Equation 7.

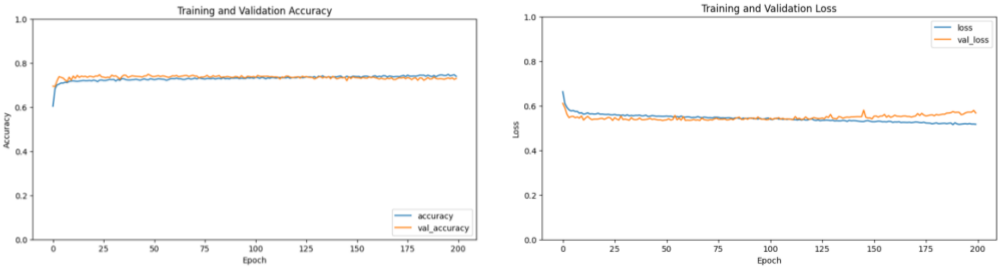
$$Dense_2(x) = Sigmoid(W_5 \cdot x + b_5) \quad (7)$$

This model is then compiled with the specified optimizer ("optimizer"), and the loss function used is binary cross-entropy ("binary_crossentropy"). The model undergoes training for 200 epochs using the training dataset ("X_train" and "y_train") with a batch size of 64.

4. RESULTS

4.1. Training Process

The training process is an integral part of this study's methodology, and it is essential for assessing the performance and convergence of the machine learning model used for cardiovascular disease detection. Figure 1 visualizes critical aspects of the model's training.


Training and Validation Accuracy

Training and Validation Loss

Figure 1. Training and Validation Accuracy and loss

Figure 1 showcases the training accuracy, represented by the blue line, and the validation accuracy, depicted by the orange line, over the course of training epochs. This graph offers insights into the model's ability to. This graph offers valuable insights into the model's learning capabilities, showing its capacity to acquire knowledge from the training data and apply that knowledge effectively to make predictions on new unseen data. The loss values are indicative of the model's performance in terms of minimizing errors during training. By examining the convergence and trend of these loss curves, it becomes possible to gauge the model's learning dynamics and its capacity to optimize its parameters effectively. The two graphical representations provide a comprehensive view of the training process, enabling a thorough evaluation of the model's accuracy and loss patterns as it iteratively refines its predictive capabilities.

4.2. Model Performance

The training phase is accompanied by a comprehensive evaluation process that encompasses the computation of Confusion Matrices and Classification Reports for various machine learning algorithms, including CNN, SVM, Decision Tree, KNN, Gradient Boosting, and GNB.

Table 1. Confusion Matrix

Algorithm	TP	FP	FN	FP2
CNN	851	182	321	646
SVM	827	207	312	655
DT	857	176	340	627
KNN	713	320	293	674
GNB	851	182	375	592
Gboost	796	237	279	688

Table 1 provides a Confusion Matrix for each algorithm, presenting the counts of TP, FP FN, TN. These matrices offer a granular Considering the model's perspective classification regarding its performance, aiding in the assessment in terms of its capability to correctly recognize both positive and negative instances

Table 2. Classification Report

Algorithm	Accuracy	Class	Precision	Recall	F1 score
CNN	0,75	No	0.73	0.82	0.77
		Yes	0.78	0.67	0.72
SVM	0.74	No	0.73	0.80	0.76
		Yes	0.76	0.68	0.72
DT	0.74	No	0.72	0.83	0.77
		Yes	0.78	0.65	0.71
KNN	0.71	No	0.71	0.69	0.70
		Yes	0.68	0.70	0.69
GNB	0.72	No	0.69	0.82	0.75
		Yes	0.76	0.61	0.68
Gboost	0.74	No	0.74	0.77	0.76
		Yes	0.74	0.71	0.73

Table 2, in turn, furnishes a Classification Report for each algorithm, which includes These essential evaluation metrics include accuracy, precision, recall, and F1 score. These metrics offer a holistic perspective on the model's performance, with accuracy indicating the overall correctness of the model, precision quantifying its ability to make accurate positive predictions, recall measuring its capacity to correctly identify all relevant instances, and F1 score providing a harmonic mean of precision and recall, offering a balanced evaluation of the model's effectiveness.

5. Conclusion

Our research delved into the application of various machine learning algorithms, including CNN, SVM, Decision Tree, KNN, GNB, and Gradient Boosting, for detecting cardiovascular diseases (CVD). The study provided valuable insights into the performance of these algorithms, showing that CNN and SVM achieved robust and well-balanced outcomes, while the Decision Tree displayed high sensitivity but some signs of overfitting. These results emphasize the importance of carefully selecting algorithms and refining models in the realm of healthcare diagnostics. While our study made significant contributions to the field, it also highlighted the need to address limitations such as dataset quality and feature selection in future research endeavors. Recommendations for further studies include exploring ensemble methods, data augmentation techniques, and real-time monitoring systems, as well as conducting clinical validations and cost-effectiveness analyses to drive the practical applications of cardiovascular disease detection models forward.

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