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Review on the use of PPG Signals for Deep Learning based CVD Classification

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***Abstract*—Heart disease has emerged as one of the leading killers in the world in recent years. Statistics show that this disease claims the lives of almost 17 million people annually. Electrocardiograms (ECGs) are typically used to diagnose cardiac problems, but they are exceedingly expensive and difficult for individuals to afford, especially in rural regions. However, it is simpler, non-invasive, and less expensive to use Photoplethysmography (PPG) signals to find cardiac conditions and other bodily problems. Researchers have developed a low-cost, precise method using ECG data and artificial intelligence (AI) technology to overcome the issues with conventional invasive-based techniques for the detection of cardiac illness. Therefore, this research discusses low-cost AI-based methods for cardiovascular disease (CVD) detection utilizing PPG signal. This review will contribute to a more accurate classification of CVD from PPG Signals and the severity of CVD disease.**

***Index Terms*—PPG, CVD, AI, deep learning**

I. Introduction

The biggest cause of death in the world is CVD, which includes heart illnesses. The World Health Organization (WHO) report states that CVD is the most common chronic illness and the leading cause of the world's disease burden. According to the analysis, CVDs are to blame for 31% of deaths worldwide [1]. The inability of the heart or blood arteries to function normally is a highly significant medical condition [2][3]. Numerous cardiovascular conditions affect the blood vessels [4].
For the detection of CVD, numerous techniques have been developed. The results of physical examinations, a patient's medical history, and any accompanying symptoms form the foundation for conventional intrusive procedures. [5]. Among the standard approaches, angiography is regarded as one of the most accurate methods for detecting heart issues. However, there are significant disadvantages of angiography, including its high cost, variety of adverse effects, and technical complexity [6]. When the heart contracts and relaxes, an ECG captures this electrical activity. The ECG can identify irregular heartbeats, some damage, insufficient blood supply, and enlarged hearts. The blood test procedure then looks for enzymes or other compounds that are released as cells start to die. They serve as "markers" of the extent of your hearts damage. The injured heart tissue that is not receiving blood flow is then discovered by a nuclear scan examination. It may also indicate issues with the heart's pumping mechanism. The test looks at your heart's blood flow using radioactive tracers. The procedure known as coronary angiography uses dye and specialized X-rays to reveal the inner of your coronary arteries. 90% of CVD, according to estimates, can be avoided. Due to human error, conventional approaches frequently result in inaccurate diagnosis and take more time. Additionally, it is a time-consuming, expensive, and computationally

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intensive approach to disease diagnosis [7].
A developing device called PPG provides a straightforward, affordable, and inconspicuous way to continually monitor the vascular system [8]. In earlier research, several PPG-based techniques for the identification of CVD have produced encouraging results [9–11].
Since PPG signals and a low-cost gadget are the main components of this study, CVD identification using them is the main goal. Using a variety of analytical methods, we had carefully evaluated PPG signals for CVD detection. The essay is organized as follows for the remaining sections: Section 2 talks about PPG Signal; Section 3 is devoted to a review of the literature. Section 4 describes different deep learning classifiers, and Section 5 represents the discussion and conclusion which includes proposed methodology and gap analysis with concluding remarks.

II. PHOTOPLETHYSMOGRAPHY

The PPG formula, developed in the 1930s, can be used to estimate how much light is reflected or absorbed by blood vessels in live tissue. The PPG signal responds to changes in blood volume rather than blood vessel pressure because the amount of blood in the optical pathway determines the degree of optical absorption or reflection.
A pulse oximeter functions by emitting light onto the skin and monitoring the changes in light absorption. The pressure pulse-induced change in volume is detected by shining an LED on the skin and measuring the amount of light reflected or transmitted by a photodiode. Infrared technology is used by the device to scan the skin and determine the amount of oxygen present in the blood. The pulse oximeter provides information on the heart rate and blood oxygen saturation (SpO2) [12].
Changes in volume are measured by plethysmographs. Blood flow can be calculated by using the formula $F = dV/dt$ to convert volume change. In other circumstances, such as when determining the heart's pulse rate, only relative volume must be known. In that situation, the timing rather than the amplitude or structure of the signal contains the information.
PPG technology is an affordable and beneficial technology that can be used to monitor several cardiovascular parameters, including heart rate, blood pressure, blood oxygen saturation, respiration, cardiac output, endothelial function, arterial aging, microvascular blood flow, and autonomic function [13]. Various PPG waveform patterns have been associated with cardiovascular pathology and aging [14-15]. As the pressure in arteries may be related to their volume and distension, the PPG signal produces pulse waveforms that resemble pressure waveforms generated by tonometry. Furthermore, the PPG signal can be continuously monitored using compact, affordable, and wearable optical devices.

III. LITERATURE REVIEW

The following is a collection of some of the literature on PPG analysis and methods for categorizing heart disease. The primary goal of the literature review is to list the different strategies and methodologies the researcher created, along with any benefits and drawbacks.
In prior investigations, PPG signals were used to detect CVD using machine learning (ML) or deep learning techniques. The PPG waveform is used in ML-based approaches to determine the manually constructed features for CVD diagnosis from PPG signals. In order to discriminate atrial fibrillation (AF), normal sinus rhythm (NSR), and PPG signals, McManus et al. devised a linear detection approach that integrated two statistical features obtained from the interbeat interval sequences [16]. This method had 96.8% accuracy.
According to Andrius Sološenko et al investigation of a feed-forward artificial neural network design, they were able to determine Premature ventricular contraction (PVC) from Sinus rhythm (SR) in PPG data with a sensitivity [17]. Polania et al. developed a novel approach utilizing support vector machine (SVM) technique, which integrates frequency-domain and nonlinear dynamics features extracted from interbeat intervals series and pulse amplitude data of PPG signals, to differentiate between various types of arrhythmias. The proposed method demonstrated remarkable accuracy in identifying PVC and VT, distinguishing them from NSR and SVPC in photoplethysmography signals with an accuracy of 96.0% and 93.9%, respectively. The experimental findings done on two patients. However, the focus of these ML-based studies has been on the distinction between 2 rhythm types. Multiple arrhythmia kinds' of identification has not received much attention [18].
Deep learning methods, exemplified by DCNN, have shown considerable success in computer vision in recent years [19].

These methods offer a complete solution for disease classification and streamline i.e., autonomously learn features from the original signal without using feature engineering is a method known as feature extraction [20].A promising use of deep learning is the detection of various arrhythmias from photoplethysmography signals.
Aliamiri et al. developed a model that combines a convolutional neural network and recurrent neural network to differentiate between noise, AF, and non-AF segments using PPG data [21]. The model successfully achieved an area under the curve of over 99% for identifying AF. However, these experiments did not demonstrate the model's ability to distinguish between different types of arrhythmias in PPG signals. Z constructed a deep learning model utilizing VGGNet-16 architecture.
Liu et al. used photoplethysmography signals to distinguish between different forms of arrhythmia. The findings indicated that the proposed model outperformed the machine learning-based models in identifying various rhythms from photoplethysmography signals. The authors achieved an accuracy of 85.0% in classifying five different forms of arrhythmia (PVC, PAC, VT, SVT, and AF).Slow arrhythmias were excluded from the study. The model's PAC, PVC, SVT, and VT detection accuracy could yet be enhanced [22].
Munasingha et al proposed a reliable machine learning-based approach for screening endothelial dysfunction by utilizing features derived from a combination of PPG, digital temperature monitoring, biological factors (age and gender), and anthropometry (BMI and pulse pressure). The study, which included 45 individuals with clinically confirmed cardiovascular diseases and 55 healthy subjects, was a case-control analysis. Following dimension reduction and 5-fold cross-validation, the Logistic Regression and Linear Discriminates models yielded the highest accuracies of 84% and 81%, respectively [23].
A novel deep learning system has been developed by T.R. Kulkarni and N. Dushyant et al. for detecting five different forms of arrhythmias using PPG signals. Low signal quality is the primary factor in erroneous arrhythmia identification with a PPG signal. The first goal is to choose good quality PPG signals from the available dataset before using the PPG signal for arrhythmia diagnosis. The second task involves looking at the selected PPG signals to find five different types of arrhythmias. The author demonstrated that the suggested architecture outperforms earlier, well-known arrhythmia detection methods substantially and adapts effectively even when the training and testing datasets have different distributions [24].
The ability of characteristics taken from signals to detect systolic and diastolic blood pressure levels was studied by S. Maqsood et al. Studies have shown that combining and ECG can directly help calculate blood pressure, albeit it can be challenging to synchronize both signals at the same time. Additionally, it is a complicated process to compute blood pressure because it requires the implantation of multiple sensors on the body. Therefore, it becomes harder to calculate blood pressure the more sensors we have. As a result, the author had conducted study on the use of PPG signals alone to monitor blood pressure. To do this, the authors carried out a thorough analysis to determine the most effective feature extraction method and machine learning algorithm. The results of this investigation showed that time domain-based features outperformed other feature extraction methods in terms of accuracy. More importantly, deep learning algorithms outperformed other methods to estimate SBP and DBP with high accuracy and low error [25].

Algorithm	Advantages	Limitations
Screening for endothelial dysfunction. VenoScreen (medis) software was used to process PPG signals. [23]	The accuracy of the logistic regression model was 84%. The study had combined the usage of , Digital Thermal Monitoring, and Biological Features.	For diagnosis, just BMI and pulse pressure were used. The model has poor accuracy.
A brand-new deep learning system that uses PPG signals to identify five different types of arrhythmias. [24]	Recognising high-quality signals to distinguish them from noise and seeing 5 different types of arrhythmia.	The range of features is constrained.
The author had done research into employing PPG signals alone to measure blood pressure. To do this, the authors carried out a thorough analysis to determine the most effective feature extraction method and machine learning algorithm. [25]	Time domain-based features outperformed other feature extraction methods in terms of accuracy.	PPG signals and on the one feature they had studied to detect blood pressure.
Using PPG signals to detect various arrhythmia types using a deep learning model based on VGGNet-16. [22]	With an overall accuracy of 85.0%, the author (s) classified five different types of arrhythmias (PVC, PAC, VT, SVT, and AF).	Low accuracy and no pre-processing of signals are being done.
To identify noise, SR, ectopy rhythm, and AF from PPG inputs, convolutional neural network architecture with six dense blocks is used. [21]	Reported a 96.1% overall accuracy.	These studies did not support how well their model performed in identifying other types of arrhythmias from

Algorithm	Advantages	Limitations
		data.
Support vector machine algorithm that uses pulse amplitude information from PPG signals along with frequency-domain and nonlinear dynamics properties to differentiate between various arrhythmia types. [18]	The suggested method was 96.0 percent and 93.9% accurate at differentiating PVC and VT from SR and PAC in signals, respectively.	Multiple arrhythmia kinds have not received much attention when it comes to detection.
Algorithm for linear detection that incorporated two statistical features derived from sequences of interbeat intervals. [16]	Achieved a 96.8% accuracy in separating AF from SR from signals.	A limited number of features and application of Neural Network is missing.

IV. DEEP LEARNING METHODS FOR CLASSIFICATION OF CVD

A. Support vector machine

Supervised machine learning is used to learn from training sets of labeled tuples in order to locate the optimal hyperplane that can separate different classes. The aim is to identify the hyperplane that maximizes the distance between classes and has the largest margin, even though there may be several hyperplanes that can do the same job. Using the hyperplane, new data points can be classified with ease. However, the datasets may vary [24].

B. K – Nearest neighbour

The KNN model, one of the easiest and most used supervised classification algorithms, was proposed by Fix and Hodge. It operates by determining its closest neighbors by computing the distance between the tests and training data points. The class of the new sample's closest neighbor is then chosen. KNN's closest neighbors are represented by the number K [26]. The classification is substantially impacted by this K value. KNN analyses numerical data using a number of metrics, such as Euclidean, Manhattan, and Minkowsky [27].

C. Decision tree

One supervised learning method that can handle both continuous and categorical features is the decision tree. The dataset is split into two or more similar sets in accordance with the most important predictors to start the classification [28-29]. The efficiency of each attribute is then calculated. The splitting attribute is chosen based on its maximum information gain or lowest entropy. Recursively applying the same technique to more properties.

D. Artificial neural network

A "neural network," often known as an artificial neural network (ANN) (NN). It is a multi-level system that mimics the neurons found in human anatomy to carry out computations and numerical models. It performs the same role as one neuron in the human brain [30]. It has different levels, and each level contains different perceptron’s. The weight assigned to each perceptron affects the output. Additionally, it has several input layers that carry out calculations and weight reassignments, as well as an output layer that creates the result [31].

V. GAP ANALYSIS

Although accuracy and other parameters have been in the region of 85% to 95%, there is room to improve the model's accuracy whereby a more precise CVD diagnosis together with the levels of various forms of CVD would be achievable. In none of the aforementioned studies has several types of characteristics, such as time domain and frequency domain analysis, been integrated. Only a few features had been studied for the prediction of CVD. By applying various types of filters, noise removal in signals will improve model performance.

VI. PROBLEM STATEMENT

To design and implement a novel approach using deep learning by the implementation of right feature extraction methodology using PPG signal for prediction of CVD.

VII. PROPOSED SYSTEM

In order to assess the precision of classifying various CVDs using photo plethysmography, a proposed system incorporates a deep convolutional neural network (DCNN) for the detection and classification of multiple rhythm classes from raw PPG waveforms. Clinical annotations of rhythm, based on ECG as the reference standard, are utilized within this framework. The generalized block diagram of the proposed model is shown in

Fig. 1, it is observed that from raw PPG signals noise can be removed to get smooth signal. Time domain and frequency domain analysis is combined for best feature selection technique which will help to classify different types of CVD.

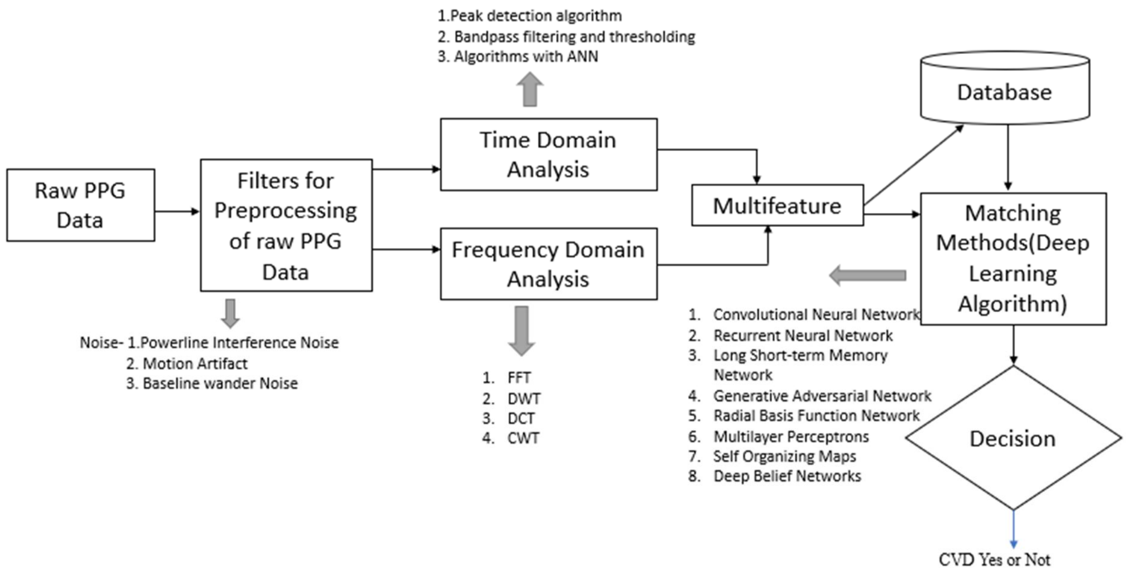

Figure 1. Block diagram of proposed system

VIII. Discussion and Conclusions

Several researchers had used deep learning and machine learning to implement CVD prediction. The majority of research had only used one or two characteristics, such as temporal domain analysis features and BP, which were useful for the study of CVD via PPG Signals. Numerous methods, including feature selection and optimization, had been employed. Researchers who employed PPG signals to do various investigations on the level of CVD detection, such as arrhythmia detections, also used feature extraction.

The study focuses on the use of photoplethysmography (PPG) signals for detecting cardiovascular diseases (CVD). It investigates various machine learning and deep learning algorithms that have been applied to classify different cardiac conditions using PPG signals and analyzes the strengths and limitations of each approach based on the existing literature.

The research findings suggest that combining different types of features from the time and frequency domains can enhance the accuracy of CVD detection using PPG signals. By leveraging advanced deep learning techniques, these features can potentially enable the assessment of various heart diseases. The study highlights the need for further research to address the current gaps in PPG signal classification and improve the effectiveness of CVD detection methods.

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