Public Health Initiatives of Wearable Sensors for Health Monitoring and Early Heart Disease Detection

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ABSTRACT

The science of preserving and enhancing individual and community health is known as public health. In order to accomplish this task, healthy lifestyle promotion, disease and injury prevention research, and the detection, prevention, and management of infectious diseases are used. Early detection and treatment of health disease can improve the prognosis for the condition worldwide. However, the massive volume of data needed poses a problem to the current automatic algorithms for diagnosing health illness. This study presents a medical gadget that uses the Internet of Things to gather cardiac data from individuals both before and after of heart illness. Technology is developing at a quick pace, leading to the establishment of many methodologies and ongoing research into solutions for problems that arise in a variety of industries. Preprocessing techniques are employed to effectively classify collected health data because the human body generates enormous amounts of data all the time. Furthermore, the most important phase is accurately classifying health data, which is necessary for diagnosis. The Deep Convolutional Neural Network (DCNN) is among the greatest and most efficient methods for categorising medical data. The results of the simulation in experimental research demonstrate that following this advise improves classification accuracy.

1. Introduction

Everyone is occupied with work in today's environment, and time is passing by extremely quickly. The fast-paced nature of today's world has made taking care of one's health an overwhelming undertaking. In terms of heart rate monitoring, manual cardiac activity entries began to be digitalized in the late 20th century in order to provide automated monitoring systems. These methods gained popularity in the sports industry early on and were employed by a wide range of athletes from various sports-related fields and industries [1]. This ultimately led to the development of wearable technology in the present day, which tracks and logs a person's daily physical activity—even while they sleep. This was maintained as a foundation by major companies in the cardiovascular market to transfer electrocardiography (ECG) technology from large devices used in hospitals and emergency rooms to non-invasive wearable ECG modules that provide real-time analytics (report) of any detected cardiac abnormalities. These studies might point to the need for an early diagnosis of heart failure, arrhythmia, or potential cardiac arrest, which could notify patients beforehand [2]. These reports might be accurate, but since the wearers of the ECG modules are exposed to outside noises on a regular basis, there's a good chance that the data the sensors collect will be tainted, leading to a decisive inaccuracy in the beat identification process. In these situations, the sounds could mostly be human-caused by limb movement during daily activities, wireless signal transmission, or baseline movement, all of which would eventually dilute the quality of the ECG data that was obtained. According to a World Health Organisation (WHO) report, heart disease, or more specifically cardiovascular disease, is a major contributing factor to the high death rate worldwide [6]. One of the body's components, the heart pumps and circulates blood to every area of the body, including the brain, playing a crucial role for all other sections. The heart can cease pumping blood to the brain and other bodily nerves, which can lead to the death of the nervous system, which means that all of the body's tissues and nerves will stop functioning and eventually die [3]. As a result, the heart is the only organ in a living being. Therefore, each person needs their heart to work properly in order to live a healthy life. To lower the death rate, it's critical to detect the illness at an early stage and administer the proper care when needed.

2. Literature Review

In recent years, the analysis of ECG signals has gained popularity as a research subject [11]. There are numerous studies in the topic of ECG signal processing that have been published by various researchers. My understanding of the hardware implementation of signal processing techniques based on ECG is inspired by a number of research ideas [4]. While slope significant characteristics are obtained by the application of derivative filters, digital filters are employed to eliminate artefacts in the cardiac signal [13]. The author of [5] created a real-time QRS detection technique using waveform characteristics including amplitude, slope, and width in order to identify the QRS waves. The suggested model employs the Band Pass Filter (BPF) to eliminate noise, 5-point derivation to derive waveform slop, and squaring function to extract non-linear amplification. Moreover, the QRS wave is detected using the threshold technique. The suggested model is unable to accurately detect heartbeats and has a higher Detection Error Rate (DER). The author of [12] used digital filtering and optimisation techniques in another work to improvise the pre-processing stage in a year. Additionally, the author created threshold-based logic-based decision rules to improve the accuracy rate of heartbeat detection. Though at the expense of time inaccuracy, the suggested method successfully raised the detection accuracy. In order to address this problem and locate the R peak on the ECG waveform, the author of [7] suggested the Hilbert Transform technique (HTM), which makes use of the initial differential signal. Additionally, the author used the MIT/BIH Arrhythmia dataset's Kaiser-Bessel window (KBW) based FIR filter to eliminate artefacts. Because the signals need to have a Brand Pass Filter, the improved HTM has a high load. Furthermore, using derivative filters, the suggested method's detection of QRS is not reliable. Additionally, it is adaptable to ECG signals with variable noisy times.

The main goal of this research project is to create a QRS detection algorithm with increased PPV and sensitivity. The created algorithm should have minimal power requirements and need few resources, including registers, DSPs, and LUTs, which are fundamental components of real-time monitoring systems. Once the corresponding R-peaks of an ECG signal are identified, heart rate may be calculated with ease. Therefore, the authors must create a reliable algorithm that can accurately extract the heart rate from the ECG information.

3. Methodology

Whether an aberration has a possibility of living on its own can be ascertained by the completely automated Computer Aided Diagnosis system (CAD). In terms of accuracy, the CAD system genuinely faces off against professionals in the diagnostic sector. The most persuasive use of tumour detection technology that gives radiologists confidence is the CAD. The technology acts as a second reader, thus after utilising it, radiologists' performance must increase. A CAD framework makes the jobs of damage diagnosis and representation easier by enhancing the physician's skills and cutting down on the time needed for precise analysis. Figure 1 shows the standard CAD architecture.

In terms of aggregated data and Internet of Things devices, this study use worn watches as IoT devices to collect a variety of data. The gadget monitors the patients' pulse rates and tracks their physical activity since it offers valuable information for tracking patients' cardiac ailments. A Bluetooth connection is subsequently used to transmit this data to the medical facility. Information on the wearable gadget is gathered from http://insight4wear.com/#three. The UCI machine learning repository data set is utilised for analysis since it consists of patient data collected from an Internet of Things wearable device [10]. The gadget captures the patient's ECG, blood pressure, cholesterol, vascular data, kind of chest pain, heart rate during rest and peak activity, angina, and depression symptoms.

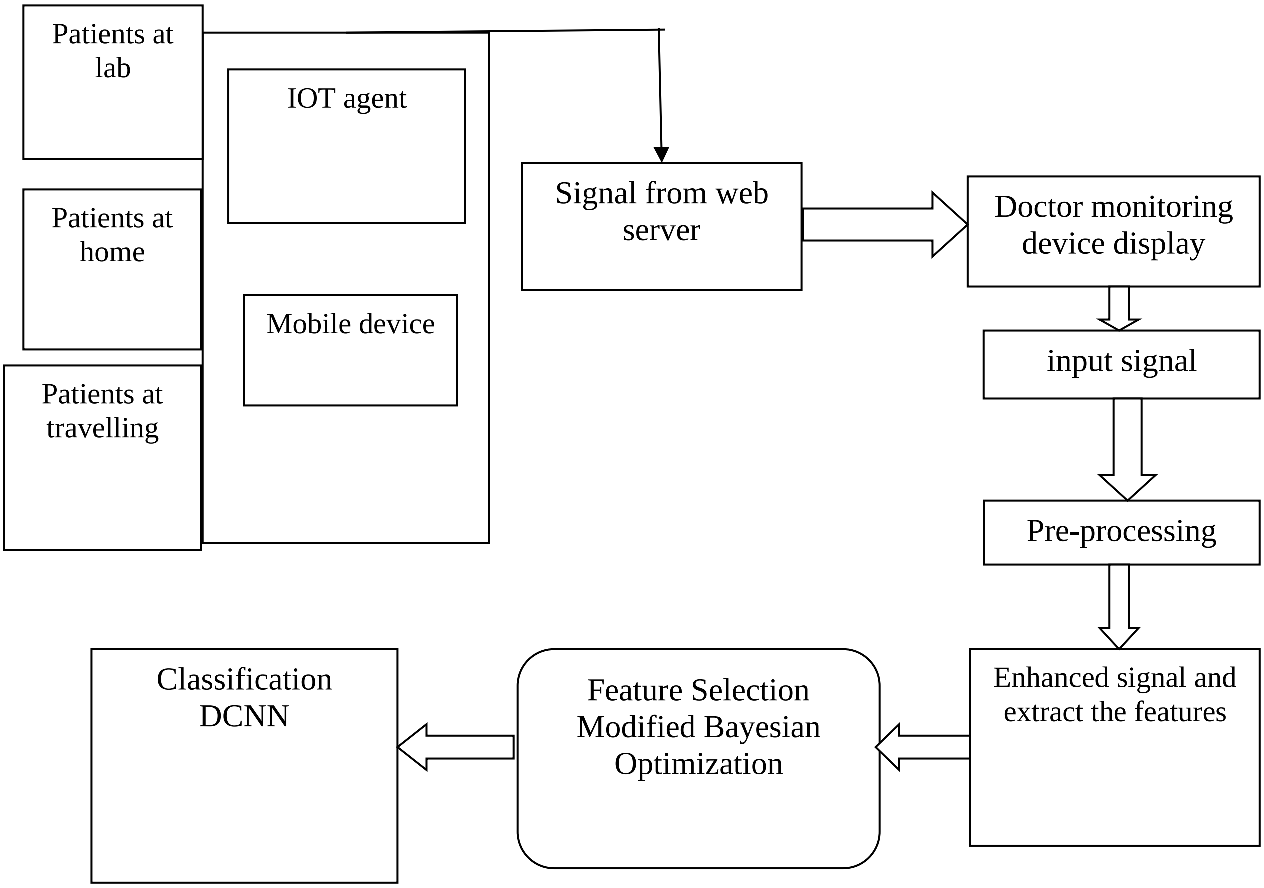


Figure 1: overall proposed framework

The measured vital sign values are compared to a medically acceptable range, like the Modified Early Warning Scores (MEWS), in order to forecast when a patient's health will deteriorate [8]. An efficient filtering technique needs to be used in order to remove noise. Bayesian Optimisation is used further for feature selection. Given a finite input set X, the primary goal of Bayesian optimisation is to find the least value of the function g\(x). To make use of the approximation function, Bayesian optimisation constructs an acquisition function q. The two approaches that are most frequently used are average pool and maximum pool. The three layers of the CNN model are the pool, activation, and convolution layers [14]. To incorporate recently obtained data into the network, a number of filters are employed. These filters are similar to those found in conventional HR filters. They are discovered by impartial inquiry rather than being made public. By employing feature detector maps with different kernel sizes or visual input at various locations, the convolution layer is able to capture local characteristics. Among the benefits of the convolution layer are the target alignment stability, strong approach, and local connection. Usually, the pooling layer comes after the convolution layer [9]. Usually, the fully connected classification layer in the final pool layer simulates a neural network [15]. In the convolutional layer, which is composed of convolutional nuclei, each neuron performs the role of a convolutional nucleus. The convolution action becomes a correlation operation if the kernel is symmetric. The receptive fields that the convolutional kernel generates are tiny fragments of the original image. This is how the convolution operation is depicted:

$$f_1^k(p,q) = \sum_c \sum_{x,y} i_c(x,y) \,.\, e_1^k(u,v) \qquad (1)$$

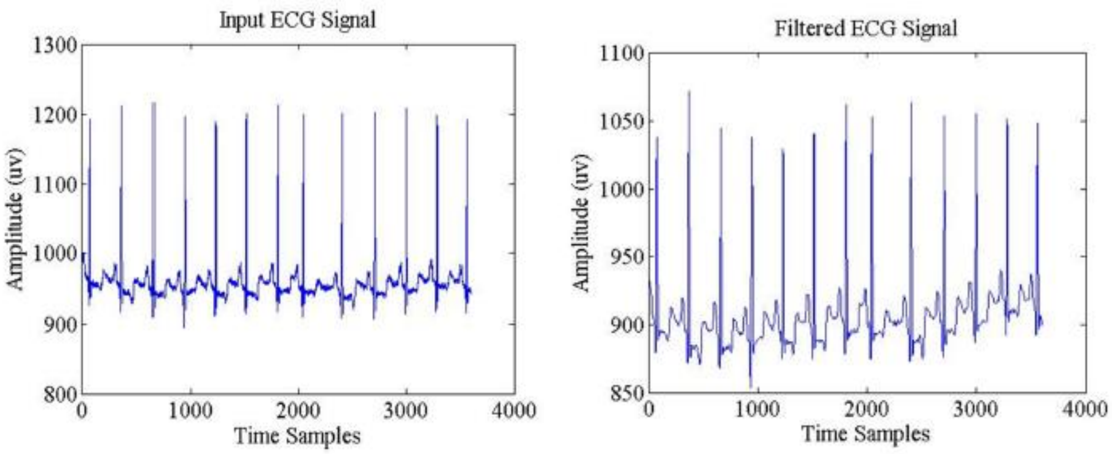
$$F_1^k = [f_1^k(1,1), \ldots (f_1^k(p,q), .. f_1^k(P,Q))]. \qquad (2)$$

$$N_l^k = \frac{F_l^k - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{3}$$

In this instance, the index of the k convolution kernel of the first layer is multiplied by each element of the input image tensor.

4. Results and discussion

Data pre-processing techniques used in the proposed research include removing noisy data, removing missing data, filling default values when applicable, and classifying predictive and decision-making features at different levels. Using methods like classification, accuracy, sensitivity, and specificity analysis, the diagnosis model's performance is assessed. This approach provides a prediction model to identify cardiac disease and provide advice or information about it. By comparing the accuracy of applying rules to the particular outcomes of various algorithms used in a region, an accurate model of disease prediction in patients is presented. The filters are used by the health monitoring team to process the incoming signal. The ECG signal is seen in Figure 2(b) following filtering.



(a) (b)

Figure 2: (a) Input ECG signal (b): filtered ECG signal

Determining the emotion's peak was an essential first step. This was accomplished by using the recommended DL algorithm.

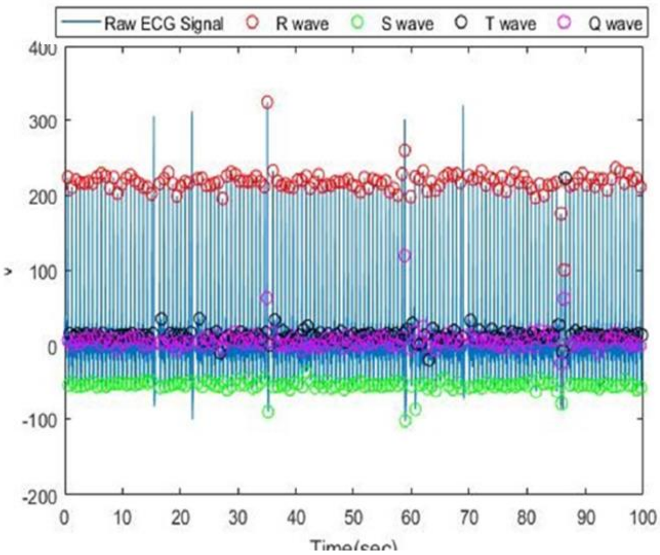


Figure 3: Detected peak signal for heart disease

Figure 3 displays the ECG peaks of a congenital cardiac disease. It was evident that a sad person's R peak value was lower than a healthy person's. The ECG's amplitude value was much less than its average, as seen in Figure 3. The impact of CNN-based RBF on the effectiveness of semi-supervised sickness detection algorithms in smart IoT devices is depicted in figure 4. The accuracy of the model we suggested was very good. As shown in Figure 4, we compared our results with those obtained using alternative methods. In comparison with current techniques, our suggested approach yields 96.5% accuracy.

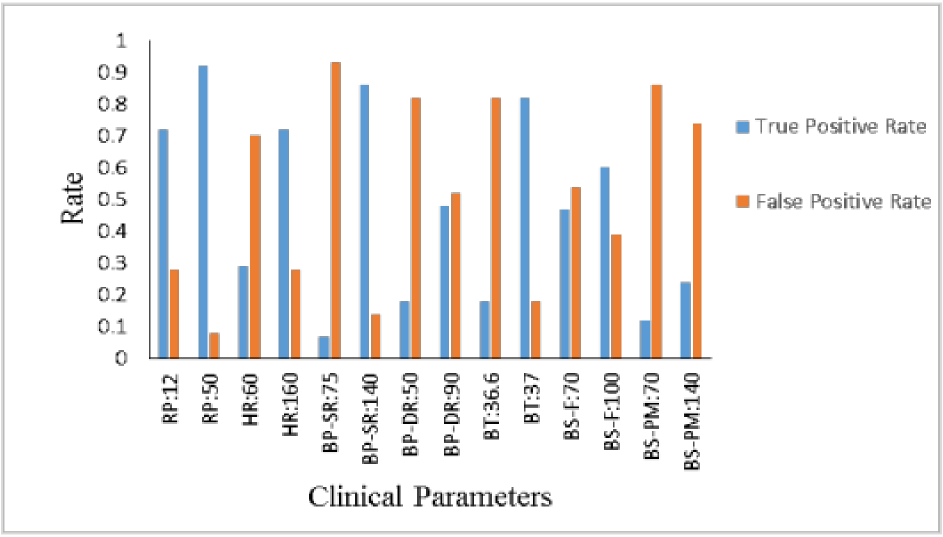


Figure 4: detection ratio for DCNN

Diseases	Models	Accuracy (%)	Specificity (%)	Sensitivity (%)	F1-Score	Precision (%)	Recall (%)
Heart disease	*RNN*	80	82	81	0.75	80	79
	CNN	92	94.16	91.15	0.89	92	80.85
	BO based DCNN	96.5	92.05	93	0.90	92.15	95.05

Using information and communication technology, the proposed solutions aim to provide an integrated IOT and DL strategy that addresses the patients' real health demands. In conclusion, this endeavour also brings in money for the health control items that are incorporated into the systems to make treatment monitoring easier.

5. Conclusion and future scope

One of the leading causes of death is heart disease, for which an accurate early diagnosis is essential to therapy. Deep learning algorithms are employed in the diagnosis of illnesses. This is how the suggested methodology uses a deep learning algorithm to predict heart disease before it becomes worse. The suggested method pre-processes the input data before feeding it into feature selection in order to select the relevant feature. The optimal unsupervised feature selection algorithm is used in this method to identify the relevant feature. When the suggested DCNN is used to choose features for the heart disease model's diagnostic outcome, the BO performs better. The effectiveness of the suggested BO-based DCNN model was confirmed through the use of medical data. The study indicates that the recommended model attains maximum accuracy of 96.5%.

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