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Original scientific paper

Performance Evaluation of Wrist Pulse Signals by using Hybrid Artificial Bee Colony with Feed Forward Neural Networks

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Abstract: People are increasingly suffering from various health issues, with a noticeable rise in frequency. This has created a substantial global demand for health assessments, as these problems are affecting all socioeconomic groups more widely. Technological advancements in disease prevention and health maintenance have led to the development of new fields, such as monitoring systems. Heart rate, which is the average number of times the heart beats per minute, reflects various physical states, including workload, stress, attention levels, drowsiness, and the activity of the nervous system. Deployment of IoT based pulse sensor devices is a more effective way of detecting pulse signal from wrist that is termed wrist pulse signal. Using the SN11574 model pulse sensor, real-time signals from both healthy and unhealthy individuals can be collected with the help of an Arduino controller. The captured signals are processed such as noise removal, signal normalization and signal quantization etc. The sensor's analog pulse rate readings are converted into digital data, which is then analyzed using the Fast Fourier Transform (FFT). This method has an advantage over traditional FFT approaches in reducing the influence of breathing patterns and avoiding the mixing of breathing and heartbeat signals. The classification of pulse signals for healthy and unhealthy individuals is done using a combination of the Hybrid Artificial Bee Colony and a Feed Forward Neural Network (HABCFFNN) to predict the individual's health status.The pulse databases are implemented in this HABCFFNN for performance evaluation. The wrist pulse signal databases, POLYU and Wojcikowski, are used in this method. The output of the neural network is fed into an analysis report, where some statistical notations are considered. Performance measurements such as accuracy, precision, sensitivity, specificity, etc., are used to highlight the effectiveness of this method compared to other related work.

Keywords: disease prevention technology; health monitoring; heart rate detection; neural network classification; pulse signal analysis

1 INTRODUCTION

The emergence of the ubiquitous sensor network is currently being attributed to the aging and ill-health of the global population. Pervasive networks within the home and nursing homes may help residents and their carers by offering ongoing medical monitoring, memory improvement, control over household appliances, access to medical data, and emergency communication. The most significant concern is the long-term home healthcare service for senior individuals, which is also a result of the aging society. To realize the broad vision of healthcare, numerous studies are being conducted in the disciplines of computers, networking, and medicine [1].

Researchers described the development and evaluation of a PVDF-based pulse sensor for obtaining three pulses from the radial artery [2]. All of the participants had a clean bill of health and no history of cardiovascular disease. The subjects were split into the vata, pitta, and kapha kinds based on their physical traits, and the morphologies used amplitude and frequency analysis to analyse the pulses. In addition, they found that the pulses vary throughout the day, from dawn to afternoon to night.

A creative compound system for multichannel pulse signal capture has been developed to address issues related to sensor positioning. Our system offers an advantage over earlier designs by providing a methodical approach to sensor placement and accurately detecting pulse width. Study results show that, in certain situations, multichannel signals outperform single-channel signals in terms of classification performance. For the analysis of pulse signals and the separation of patients from healthy individuals, two methodologies, the wavelet approach and the autoregressive prediction error (ARPE) method, have been developed. After gathering distinctive properties, the SVM is used to classify pulse signals. The researchers choose a wearable, affordable real-time pulse monitoring device to determine the patient's status in real time [3-5].

2 RELATED WORKS

An automated method for continuous, non-invasive Pulse Transit Time estimation may be utilized to correlate with other metrics, such as systolic and diastolic blood pressure. While lying down in the standard lying down posture, 25 healthy individuals (aged 22 to 5 years) had their continuous pulse data from the brachial artery, the radial artery, and the digital artery taken [6]. The simultaneous peak from several pulse signals, the inter peak to peak transit time, and the intra peak to peak transit time from one pulse signal to another have all been calculated for the blood pressure computation.

A Doppler ultrasonic equipment, wrist-pulse data from healthy people and patients with gastritis and cholecystitis were collected. Transformations breakdown and obtain wavelet characteristics from the pulse signals once the envelopes of an ultrasonic pulse contour have been obtained [7-9]. The researchers were able to distinguish between the ill and healthy as well as individuals with various ailments by using a two-category classifier along with multiple Doppler ultrasonic diagnostic measurements like the STI, RI, and other parameters.

Information can be derived from wrist pulse signals used methods for signal processing to retrieve information. They had non-invasively collected radial artery pulse signals at the wrist position for a number of interesting cases in order to achieve this. The wrist pulse waveforms' spatial characteristics had been investigated. The researchers were successful in getting clear results in one instance when wrist pulse signals were recorded for many people before and after exercise [10-12]. To distinguish between the groups, a support vector machine classifier is employed, and a high classification accuracy of 99.71 percent is attained.

The device gathers the necessary data and reports on patients by capturing nadi pulses. The pulses for various patient types will vary, as will the waveforms collected from the sensor depending on the conditions of the experiment. These pulse signals need to be amplified and filtered because they are too weak to be of any value. Three infrared sensors are attached to the wrist and are able to distinguish between the vata, pitta, and kapha types of pulses.A signal processing circuit that included a signal amplifier, a filter, and a noise reduction circuit was used to process the pulse signals after they were collected from the IR sensor [13-15].

A DTW approach with IUI enhancements for identifying pulse waveforms. They are able to avoid the abnormal alignment that the original DTW algorithm and DDTW algorithm can create thanks to their method. To demonstrate the efficacy of our method, we conducted a significant number of experiments employing 1000 pulse waveforms [16-22]. Our method greatly lowers the FRR and FAR values when compared to the original DTW and DDTW algorithms. Calibration models have been used for classifying BMI values, but they show only a narrow ability to discriminate values and offer limited algorithmic implementation. Another approach considered acoustic signals with a new method of handling waveforms, but the results were affected by noise, leading to poor and inconsistent classification. Some methods have focused only on specific diseases like polycystic ovary syndrome, neglecting the generalization needed for broader wrist pulse classification, and were also time-consuming. Other works have demonstrated the use of approximate sample entropy and diabatic sample entropy, but faced issues with the non-stability of the generated internal metric feature set. IoT-based systems utilizing tridosha signals have been proposed, yet they still require significant improvements in accuracy and sensitivity.

From an extensive analysis of the various existing wrist pulse classification methods, the novelties of this paper are proposed as follows. Real-time and standard existing datasets are utilized, and a new HABCFFNN model is efficiently developed. Compared to the cited works, HABCFFNN offers higher sensitivity, quicker response, and more effective disease prediction for conditions such as hypertension, coronary heart disease, pregnancy, liver malfunction, kidney irregularity, psychological disorders, and others.

3 PROPOSED METHODOLOGIES

In this paper, a new HABCFFNN system architecture is proposed and implemented in two ways: one using pulse sensors and the other using a pulse dataset, as shown in Figs. 1 and 2. The overall system architecture is divided into three sections: input signal capturing module, HABCFFNN, and performance evaluation.

Data processing involves cleaning, organizing, and transforming raw data into a usable format for analysis, often using statistical techniques and specialized software tools depending on the type of data collected, selecting a representative subset of the population to study, such as random sampling, stratified sampling, or convenience sampling, and applying appropriate statistical methods to analyze patterns and trends in the data.

3.1 System Architecture for Real Time Pulse Acquisition System

The Arduino Due processor from the IoT toolbox is used to record the wrist pulse signals. The setup includes a laptop, Arduino kits, and a pulse sensor. The Pulse Sensor is an excellent low-power, plug-and-play heart rate sensor for Arduino applications. The system architecture is shown below in Fig. 1.

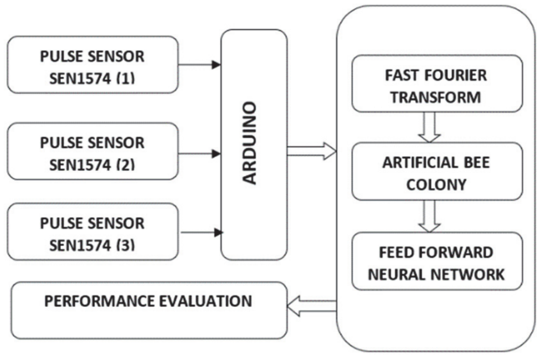

Figure 1 System architecture for real time pulse acquisition system

For classification tasks, accuracy is a standard metric. It measures the proportion of correct predictions to the total number of predictions. Precision, Recall, and $F1$-Score: In classification, especially with imbalanced datasets, other metrics like precision (correct positive predictions), recall (ability to identify all positive instances), and $F1$-score (harmonic mean of precision and recall) are important for evaluating model performance. For regression or approximation tasks, *MSE* (Mean Square Error) is used to measure the average squared difference between predicted and actual values. Convergence speed refers to how quickly the hybrid optimization approach converges to an optimal or near-optimal solution. Overfitting occurs when the model learns noise in the training data rather than general patterns. A hybrid approach like HABCFNN might reduce overfitting by improving the exploration of the search space and refining the model's parameters using BCO's local search. Given that ACO and BCO are both population-based optimization methods, training can be computationally expensive compared to traditional gradient-based approaches like backpropagation. The performance of the HABCFNN model can be influenced by the number of weights and parameters in the FFNN. The depth and width of the FFNN (number of layers and neurons per layer) can affect both the model's learning capacity and its computational efficiency.

3.2 System Components

Pulse Sensor: It is evident that a pulse sensor operates by setting it to search mode and then applying slight pressure with a finger. This allows the sensor to detect vibrations from the pulse as it moves through the body and display the results in beats per minute (BPM). Fig. 2 illustrates the front and back views of the pulse sensor used for obtaining readings from a person.

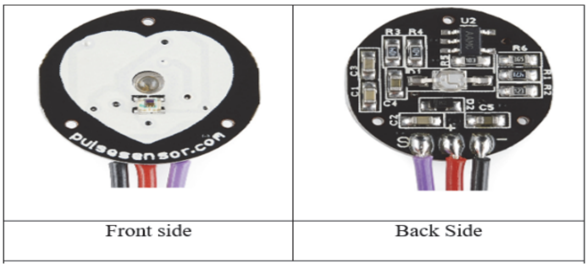

Figure 2 Pulse sensor

Arduino Tool Kit: The open-source electronics platform Arduino features a programmable circuit board and software, that are simple to use. It is currently one of the most widely used platforms in the industry for creating robots and smart home automation [23]. The Arduino board is utilized in this suggested system to collect data from the wearer's wrist pulse sensor via an input port. Fig. 3 below depicts the Arduino's basic structure.

Easy deployment, especially in global settings, is pivotal. Controlling the IoT data pipeline is crucial for ensuring the efficient and reliable transmission of data between IoT devices and the cloud. A well-engineered IoT platform can help businesses create a flexible architecture for developing elastic IoT applications that can support the ever-increasing number of devices, users, and data volumes.

IoT Establishing safe, private, and secure communications can be complex due to the different components that converge on the network node. IoT security is multi-faceted, encompassing physical protection, control issues, and privacy concerns. Robust security protocols, regular audits, and compliance with regulations like GDPR are essential. Consider network capacity, solution architecture, software infrastructure, automated bootstrapping, and controlling the data pipeline.

The SN11574 sensor might detect multiple compounds or environmental factors that interfere with the intended measurement. High temperatures might cause sensor materials to degrade or lead to falsereadings, while low temperatures could slow down sensor reactions or lead to poor sensitivity. If the sensor is sensitive to moisture, high levels of humidity or condensation might cause malfunction or erroneous readings.

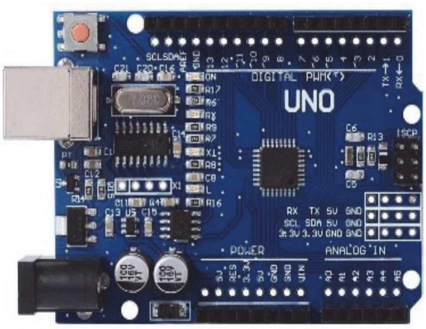

Figure 3 Arduino

The sensor might be vulnerable to electromagnetic fields from nearby equipment, electrical devices, or high-voltage infrastructure in industrial or urban environments. This interference can distort or affect the signal processing, leading to inaccurate readings. If the sensor is deployed in environments with moisture, like in marine or agricultural settings, it might be prone to biofouling where mold, bacteria, or other microorganisms attach to the sensor.

3.3 System Architecture for Database Pulse Acquisition System

For each wrist pulse signal in existing database, four individual wrist pulse signals are produced using four data augmentation functions. By including original wrist pulse signal before data augmentation, the total number of wrist pulse signals after data augmentation is five. Data augmentation is the process of creating the new dataset from the existing dataset to improve the wrist pulse signal classification rate. This data augmentation is required only for training the proposed system and it is not required in testing of the proposed system as illustrated in Fig. 4. In this work, the following data augmentation functions are applied on the input wrist pulse signal from the existing database.

$$\text{Shiftedright} = \text{rightshift}(x(n)) \tag{1}$$

$$\text{Shiftedleft} = \text{leftshift}\ (x(n)) \tag{2}$$

$$\text{Rotateright} = \text{rightrotate}(x(n)) \tag{3}$$

$$\text{Rotateleft} = \text{leftrotate}(x(n)) \tag{4}$$

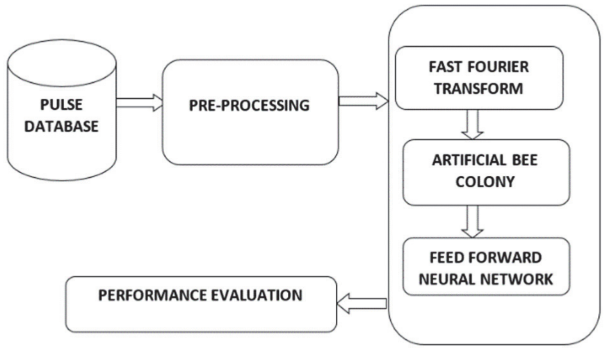

Figure 4 System architecture for pulse acquisition system using database

The existing POLYU database consists of 320 wrist pulse signals and Wojcikowski database consists of 1024 wrist pulse signals. In this paper, 60% of signals from the existing database are used for training the proposed system and the remaining 40% of signals are used for testing the proposed wrist pulse signal classification system. After data augmentation process in this work, POLYU database contains 960 wrist pulse signals and Wojcikowski database contains 3070 wrist pulse signals including source wrist pulse signals also.

3.4 Fast Fourier Transform

By applying FFT the system can separate the signal into distinct frequency components. The breathing signal typically falls in the low-frequency range (around 0.1 - 0.5 Hz), while the pulse signal will have higher frequency components (e.g., 1 - 3 Hz). After transforming the signal into the frequency domain, the system can identify and isolate the frequency components associated with breathing, which are much lower than those associated with the pulse. Once the signal is represented in the frequency domain, the system can apply a band-pass filter or high-pass filter to remove or attenuate the unwanted low-frequency components corresponding to breathing. After filtering, the remaining frequency components (which correspond to the wrist pulse signal) are reconstructed back into the time domain using the Inverse FFT (IFFT). In more advanced systems, an adaptive filter could be used in conjunction with FFT to dynamically adjust the filter parameters. For instance, the system could track the frequency range of breathing signals over time and continuously adjust the filter to effectively suppress breathing interference. FFT and filtering techniques are typically applied in real-time systems so that users can monitor their pulse without significant delays. By continuously monitoring the frequency domain and updating the signal processing parameters as needed, the system can continuously minimize the impact of breathing interference.

3.5 Artificial Bee Colony (ABC) Algorithm

A worker bee at a food source that has been abandoned becomes a scout. The artificial bees' search results can be summed up as follows.

Step 1: Initialize Population.

Step2: Repeat.

Step 3: Place the hired bees near their sources of food.

Step 4: Depending on how much nectar they provide, place the watchful bees on the food sources.

Step 5: Scouts should be sent out to look for new food sources.

Step 6: Keep in mind the best food source so far.

Step 7: until requirements are met.

Following this, decide where to choose food source regions, exchange nectar information about food sources, and assess the nectar content of the food sources. The bees choose a set of food sources at random during the initiation phase, and their nectar output is calculated. These bees enter the hive at the beginning of the cycle and advise the bees awaiting in the dance area of the sources of the nectar.

Rapid discovery and effective use of the best food sources are essential for the bee colony's survival and growth. Similar to this, finding effective solutions to challenging engineering problems quickly is important, especially when solving problems that must be solved immediately. To improve the outcome of signal categorization, apply the Feed Forward Neural Network (HABCFFNN) once the pulse signal has been optimized.

3.6 Feed Forward Neural Network

In a training example, the output node j level of inaccuracy in the nth data point can be represented by:

$$e_j(n) = d_j(n) = y_j(n) \tag{5}$$

where $y_j(n)$ is the desired goal value for the nth data point at node j, and $d_j(n)$ is the value generated at node j when the nth data point is supplied. The node weights can then be changed based on adjustments that reduce the error in the overall output for the nth data point.

$$E(n) = 1/2 \sum_{outputnodej} e_j^2(n) \tag{6}$$

The change in each weight w_{ij} is:

$$\Delta w_{ji}(n) = -n \frac{\partial e(n)}{\partial v_j(n)} y_i(n) \tag{7}$$

where $y_i(n)$ represents the output neuron i before it, and stands for the learning rate, which is chosen to make sure that the weights are equal. In the preceding phrase, $\frac{\partial e(n)}{\partial v_j(n)}$ represents a partial derivation of the error $E(n)$ based on the weighted sum $v_j(n)$ of the input connections of neuron i.

The induced local field v_j, which is variable in and of itself, determines the derivative that must be determined in Fig. 6 as the Pseudo code Feed forward neural network. It is straightforward to show that this derivative can be reduced for an output node based on changes in the weights of the kth nodes, which represent the output layer.

The data collection criteria for selecting healthy and unhealthy datasets were based on recommendations from medical practitioners. For the healthy portfolio is like that: Normal blood pressure: systolic < 120 mmHg, diastolic > 80 mmHg Blood, Glucose: Fating Glucose < 100 mg/dL, Healthy Weight: BMI within the range of 18.5 - 24.9, Cholesterol: Cholesterol < 200mg/dL, LDL < 100 mg/dL, LDL < 100 mg/dL, History of Healthy patient: i. smoking habbits, ii. alcohol consumption / usage, iii. balanced diet, iv. adequate sleep, v. mental health statues vi. physical exercise, vii. History of medical port if any. The unhealthy portfolio is like that: Obesity: (BMI > 30), Hypertension: Systolic > 130 mmHg, diastolic > 80 mmHg, Blood Glucose: Prediabetes (100-125 mg/dL or Diabetes (> 126 mg/dL) and history of unhealthy patient: i. Smoking, Alchohol, ii. alcohol consumption / usage, iii. Poor diet iv. sleeping disorder, v. mental health status vi. physical carelessness, vii. health issues, chronic condition etc.

4 PERFORMANCE EVALUATION

4.1 Performance Evaluation using Database

The performance of the proposed wrist pulse classification system is evaluated with respect to the parameter indexes Normal Wrist Pulse Detection Rate (NWRDR) and Abnormal Wrist Pulse Detection Rate (AWRDR). The NWRDR is defined as the ratio between the count of correctly detected normal wrist pulse signals and the total normal wrist pulse signals. The AWRDR is defined as the ratio between the count of correctly detected abnormal wrist pulse signals and the total abnormal wrist pulse signals. These performance metrics are illustrated by the following equations.

$$NWRDR = \frac{Correctly\ detected\ normal\ wrist\ pulse\ count}{Total\ normal\ wrist\ pulse\ count} \tag{8}$$

$$AWRDR = \frac{Correctly\ detected\ abnormal\ wrist\ pulse\, count}{Total\ abnormal\ wrist\ pulse\, count} \tag{9}$$

In this work, both NWRDR and AWRDR are measured in percentage and they are varied between the numerical values 0 and 100.

In this proposed wrist pulse classification system, the 98 normal wrist pulses are correctly detected over 100 normal wrist pulses and obtain 98% NWRDR. Also, 215 abnormal wrist pulses are correctly detected over 220 abnormal wrist pulses and obtain 97.7% AWRDR in POLYU database. Similarly, the 746 normal wrist pulses are correctly detected over 750 normal wrist pulses and obtain 99.4% NWRDR. Also, 271 abnormal wrist pulses are correctly detected over 274 abnormal wrist pulses and obtain 98.9% AWRDR in POLYU database. The measurements of the performance metrics NWRDR and AWRDR are depicted in Tab. 1.

Table 1 NWRDR and AWRDR computations

Database	Normal wrist pulses count	Abnormal wrist pulses count	Correct detected normal wrist pulses count	Correctly detected abnormal wrist pulses count	NWRDR / %	AWRDR / %
POLYU	100	220	98	215	98	97.7
Wojcikowski	750	274	746	271	99.4	98.9

Moreover, the performance of the proposed wrist pulse classification system is analyzed using True Positive (X), True Negative (Y), False Positive (Z) and False Negative (P) with the aid of the following equations in this work.

$$PulseSensitivity\left(Pse\right) = \frac{X}{X+P} \tag{10}$$

$$PulseSpecificity\left(Psp\right) = \frac{Y}{Y+Z} \tag{11}$$

$$PulseClassificationAccuracy\left(PCA\right) = \frac{X+Y}{X+Y+Z+P} \tag{12}$$

$$PulsePositiveValue\left(PPV\right) = \frac{X}{X+Z} \tag{13}$$

$$PulseNeagtiveValue\left(PNV\right) = \frac{Y}{Y+P} \tag{14}$$

The terms X and Y represent the actual abnormal pulse signal with positive test result and the actual normal pulse signal with negative test result, respectively. The terms Z and P represent the actual normal pulse signal with positive test result and the actual abnormal pulse signal with negative test result, respectively.

The *Pse* defines the correctly detected pulse signal ratio with respect to positivity and the *Psp* defines the correctly detected pulse signal ratio with respect to negativity in this work. The *PCA* defines both correctly detected pulse signals with respect to positivity and negativity. The *PPV* defines the number of normal wrist pulse signals incorrectly detected by the system and the *PNV* defines the number of abnormal wrist pulse signals incorrectly detected by the system. All these parameters are evaluated in percentage and vary between 0 and 100 in this work.

The correlation between these terms is illustrated by a matrix which is called as Confusion Matrix (*CM*), as depicted in Tab. 2.

Table 2 Confusion matrix illustrations of the proposed system

Confusion matrix / cm	Abnormal pulse	Normal pulse
Positive test result	X	Z
Negative test result	P	Y

Tab. 3 shows the performance estimation of the proposed wrist pulse classification system on POLYU and Wojcikowski databases. The proposed wrist pulse classification system achieves 98.5% Pse, 99.1% Psp, 98.9% PCA, 98.6% PPV and 95.1% PNV on the wrist pulse signals available in POLYU database in this paper. The proposed wrist pulse classification system achieves 99.1% Pse, 98.9% Psp, 99.1% PCA, 98.7% PPV and 96.3% PNV on the wrist pulse signals available in Wojcikowski database in this paper.

Table 3 Various parameters

Parameters	Databases	
	POLYU	Wojcikowski
Pse	98.5	99.1
Psp	99.1	98.9
PCA	98.9	99.1
PPV	98.6	98.7
PNV	95.1	96.3

4.2 Performance Evaluation using Real Time Systems

The sensitivity and accuracy of the proposed system is compared with other algorithms and the rate of sensitivity and accuracy is highly appreciable rate of growth which is shown below in Tab. 4.

Table 4 Classification result for accuracy and precision

Algorithms	*Pse*	*PCA*
SVM	77.5	78.3
CNN	80.5	83.1
FFNN	81.35	85.6
HABCFFNN	90.32	91.2

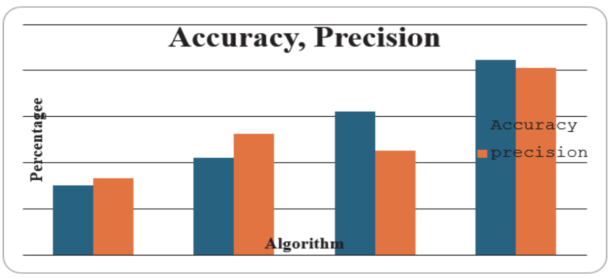

Figure 5 Graph result for accuracy and precision

The results values from the suggested system, HABCFFNN, which achieves 91.2% accuracy and 90.32% precision, are explained in Table 4 above. Figure 5 illustrates that the suggested approach delivers accuracy and precision gains of 5.6% and 8.97%, respectively, over conventional methods.

Normally we analyse the sensitivity and specificity of the new methods as good rate of change which is shown in Tab. 5 and Fig. 6.

Table 5 Classification result for sensitivity and specificity

Algorithms	Sensitivity	Specificity
SVM	79.15	75.8
CNN	81.4	85.0
FFNN	82.5	86.7
HABCFFNN	92.32	90.1

The pulse sensor module comes with a portable device that aids in measuring heart rate. The amount of blood in the capillary blood vessels can change depending on where we place our finger on the heartbeat gadget. Any health situation anomalies can be directly known and communicated to the specific person. It uses Waveform technology to respond to medical emergencies. Finally, the table below indicates the report of the patients with various diseases which is identified in both real time and database as shown below in Tab. 6.

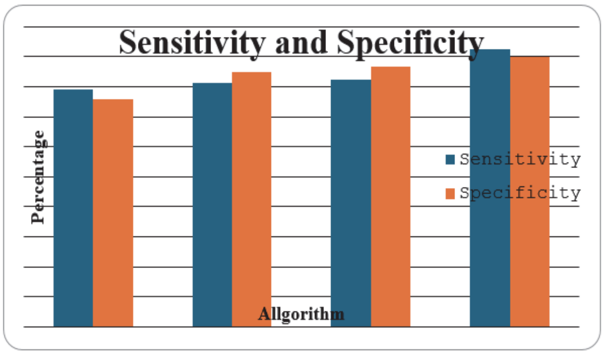

Figure 6 Graph result for sensitivity and specificity

Table 6 Classification result

S. No.	Total	Real Time	Database
	Types of diseases	No. of Pulse classification	
1	Healthy	275	175
2	Hypertension	25	30
3	coronary heart diseases	17	22
4	Pregnancy	16	14
5	liver cirrhosis	08	05

The results values from the suggested system, HABCFFNN, which achieves 98.5% accuracy and 99.1% precision, are explained in Tab. 7 below. Fig. 6 illustrates that the suggested approach delivers sensitivity and specificity respectively, over conventional methods. The graphical representation of the above table is depicted in Fig. 6.

Table 7 Comparison result of Wojcikowski database

Methods	Experimental values / %				
	Pse	Psp	PCA	PPv	PNV
HABCFNN	98.5	99.1	98.9	98.6	95.1
Chang et al.	95.2	96.3	95.9	95.3	95.9
Quanyu et al.	94.9	93.1	94.7	94.3	94.1
Zhang et al.	93.9	94.2	94.7	94.1	94.9
Wojcikowski	93.9	94.1	94.8	94.2	93.2
Fischer et al.	94.3	94.2	94.3	94.1	93.1

Digital pulse sensors can measure pulse waveforms with high precision, capturing a detailed spectrum of information, including pulse rate, rhythm, and subtle variations. Implement real-time feedback mechanisms for patients and doctors, enabling instant health status alerts. In telemedicine-based platforms patients can connect with practitioners remotely using video conferencing or specialized sensors. Use real-time analytics to detect sudden changes or anomalies in pulse patterns that may indicate acute health issues (e.g., heart attack, stroke), enabling quicker interventions.

Development of new screening methods allow for earlier identification of diseases like cancer, heart disease, and neurodegenerative conditions. Findings related to genetics, AI, or biotechnologies may bring about ethical concerns regarding privacy, consent, and equity in healthcare.

The comparative analysis of various authors' percentages of evaluation used POLYU databases much higher percentages shown in our proposed methods shown in Tab. 8.

Table 8 Comparison result of POLYU database

Methods	Experimental values / %				
	Pse	*Psp*	*PCA*	*PPv*	*PNV*
HABCFNN	99.1	98.9	99.1	98.7	96.3
Chang et al.	96.7	96.9	96.3	95.3	95.2
Quanyu et al.	95.1	96.3	95.2	94.2	94.5
Zhang et al.	94.3	94.9	94.2	95.1	94.9
Katayama	94.7	94.3	93.9	95.2	94.1
Wojcikowski	94.8	95.1	94.9	94.7	93.9

Health data privacy is one of the most sensitive aspects of healthcare. This includes both personally identifiable information (PII) and health information (PHI). AI and machine learning models used in healthcare can perpetuate or amplify existing biases if trained on skewed or unrepresentative data, leading to inequitable outcomes. Health data security is paramount. Breaches of sensitive health data can lead to serious harm, including identity theft, financial loss, and even harm to an individual's health if the data is altered or misused. Implement strong security measures, including encryption, secure authentication, and access controls. Artificial Intelligence (AI) and data analytics are transforming healthcare by providing insights that can lead to better diagnosis, treatment plans, and personalized medicine.

5 CONCLUSION

The pulse rate sensor is a versatile device critical for monitoring cardiovascular health. Its non-invasive nature, compact design, and real-time data collection capabilities make it invaluable across healthcare, fitness, and sports. By accurately measuring heart rate, it aids in diagnosing cardiovascular conditions and provides athletes with insights into exercise intensity and recovery. Integration with wearable technology and smartphones has further enhanced accessibility, empowering individuals to take charge of their health. Future advancements should focus on improving accuracy, reliability, and user-friendliness to maximize its impact. This paper proposes a resource-efficient deep learning framework for automatic wrist pulse detection and classification. The method is applied to two independent databases, POLYU and Wojcikowski, with experimental results analyzed using various performance metrics, including time consumption. The proposed method demonstrates superior wrist pulse classification accuracy compared to existing approaches. However, wrist pulse diagnosis for different severity levels was not addressed, highlighting a limitation and future scope for this work. The study's extension focuses on signal acquisition using full-body sensors and explores parameters related to AYUSH principles to promote natural healing. The ultimate goal is to inspire a next-generation approach centered on natural medicine, practices, and well-being, aligning technology with holistic health practice.

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