

QRSMATCH PLUS Algorithm: A Novel Approach for Enhanced QRS Complex Detection in Electrocardiogram Signals

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ABSTRACT

The precise detection of QRS complexes in ECG signals is of the essence for the efficient diagnosis, while the recent advancements offer a hope-giving solution to the inherent problems such as interference and baseline drift. In this case, a new approach QRSMATCH Plus helps to identify and diagnose heart attacks. This starts by representing the raw ECG signals via Matching Pursuits, a sparse signal model that can easily identify the fast and slow variants of the signal with the help of frequency-time domain. In addition, Pan-Tomkins algorithm is responsible for detecting QRS complex by means of analyzing waveform morphology, which consists of the main parameters, such as amplitude, duration and slope, with high precision. The testing of the QRSMATCH Plus algorithm on different ECG datasets shows its superiority in comparison with ordinary methods, which provides enhanced denoising and baseline drift subtraction capabilities. Through these improvements, the algorithm demonstrates accurate detection of QRS complexes, which confirms the tool's usefulness in the analysis of ECGs within healthcare systems. Furthermore, the research delivers the new method of ECG signal detection, which is based on dry, flexible, and wearable electrodes eliminating the necessity of skin preparation and wet gel application. This way, the technology capitalizes on graphene-based sensors that are printed on fabric, promising simplicity, comfort, and real-time ECG signal recording. On the contrary, comparative study with the conventional wet electrodes shows the better performance of dry graphene ECG sensors in terms of conductivity and signal quality, placing them as inevitable tools in real-time patient monitoring.

Keywords: QRS complex detection, Electrocardiogram (ECG), Matching Pursuits, Pan-Tompkins algorithm, Signal processing

How to cite this article: Mahalakshmi A, Judith Justin. QRSMATCH PLUS Algorithm: A Novel Approach for Enhanced QRS Complex Detection in Electrocardiogram Signals. *Int J Drug Deliv Technol.* 2026;16(37s): 170-185. DOI: 10.25258/ijddt.16.37s.25

Source of support: Nil.

Conflict of interest: None

I. INTRODUCTION

BP is a key physiological indicator that is capable of promoting forced blowers in the walls of blood vessels. It is a principal sign of cardiac health and is widely employed in medical settings to assess any individual's risk of cardiovascular disease. By means of ancient BP measurement, techniques are normally the automated cuffs, the oscillometric estimation of systolic and diastolic BP values. Through all, these methods have the weaknesses such as the empirical coefficients are necessary and patient groups like those from inexperienced doctors could bring about errors. Non-invasive techniques PPG (PhotoPlethysmoGraphy) and ECG (ElectroCardioGraphy) with good potential have

been used for the research on the cuff-less BP estimation algorithms. The PPG assesses alterations in blood volume of microvascular networks, commonly non-invasively measured by applying the pulse oximeter on fingertip. ECG represents the pattern of electrical activity of the heart, thereby highlighting cardiac performance and enabling the diagnosis of abnormalities (arrhythmias, ischemia). It is seen that the incorporation of these signals into the estimation process is a new paradigm, which is a non-invasive way to calculate BP without cuff-based measurements. While the technology is moving ahead, cuffless BP estimation devices next gen algorithms are, however, difficult to build and ensure their reliability. Difficulties

include the hate of background noise, the fluctuations in the quality of the signal which and the complicated algorithms that are needed and, as they are to be adapted to individual differences in physiology. Besides, multi-modal high-quality datasets with raw ECG, PPG, and ABP signal are specifically required to train the machine learning algorithms. Hereby, the proposed work describes a unique dataset with particles to develop and evaluate non-invasive BP estimate algorithms. Dataset instances are clean and valid signals (raw ECG, PPG, and ABP), which are recorded by means of patient's eyes. These signals serve as a cell array containing matrix data element, each cell for one record part. Researchers to design, test and calibrate cuffless BP estimation algorithms can use the dataset. The data set can hold the key to eventual creation of algorithms that can detect BP with no cuff. In this way, the future can be bright for people suffering from cardiovascular diseases [1,2].

Although current pulse wave algorithms have more than one limitation that impede their accuracy and dependability, new approaches such as photo- and electro- sensors appear to get rid of most of these inconveniences. These challenges involve the background noise originate in body movement and unstable light conditions based on the variability in signal quality caused by the sensors positioning and the individual physiology. Partially, black-box algorithms lack a proper understanding of their decision logic with many people having difficulty in interpreting and trusting them. Accuracy and reliability is increased in clinical atmosphere by attending to such persisting challenges. The main contributions of the proposed work are given below [1,2].

- The main contributions of the proposed work lie in the development of a novel algorithm, the QRSMATCH Plus Algorithm, designed for precise QRS complex identification in electrocardiogram (ECG) signals.
- This algorithm facilitates accurate temporal alignment of physiological signals, particularly with photoplethysmogram (PPG) signals.
- The integration of the Deep Deterministic Policy Gradient (DDPG) version allows direct estimation of blood strain from PPG signals, disposing of the want for cumbersome cuffs.
- Through robust experimental validation on new ECG dataset, the proposed framework

demonstrates superior performance compared to existing methods.

II. LITERATURE REVIEW

The literature review summarizes a wide spectrum of works involving ECG and PPG indicators estimation in physiological parameters detection, disorder identification and chance assessment. Merino-Monge et al. (2023) devised a manner of placing the coronary heart vibration into a waveform via the wavelet rework and the upper envelop of the ECG and PPG alerts [3]. This is a trustworthy approach. Sharifi et al. (2019) demonstrates a brand new dynamical approach on the premise of ECG and PPG alerts, that have proven better accuracy than the conventional techniques [4]. Mousavi estim. (2019) proposed a strategy for blood pressure estimation using the ppg signals applying the whole based approach, which can differentiate applied PPG signals from inappropriate ones [5]. Ramachandran et al. (2020) introduced a way of determining risk levels of cardiovascular problems using photoplethysmogram signals based on the latest signal processing [6]. Ramesh et al. (2021) performed the classifications of atrial fibrillation in short term HRV and deep convolution neural networks where there was a significant improvement in the results of disease detection [7]. Thambiraj et al. (2020) analyzed the impact of two relevant physical properties used in cardiology, on cuffless blood pressure sensor estimation with ML techniques [8]. Mahmud et al. (2023) suggested NABNet, Nested Attention-guided BiConvLSTM network, for performance-oriented b pushed, directly to arterial blood pressure waveform reconstruction, using PPG and ECG signals [9]. In the article of consequence of Banerjee and Singh (2023), which deals with a new ECG and PPG real-time lossless data compression, the authors have managed to counter data storage and transmission challenges in wearable healthcare tools [10]. Lin et al. (2022) came out with a new method to perform biomedical signal decomposition using data adaptive Gaussian average filters, to add to database methods [11]. Jeon and Kang (2023) give a Multislice Nested Recurrence Plot (MsNRP) system for personal identification to be accessed using daily ECG or PPG signals. This fresh approach to biometric

identification methods is more solvent against countermeasures [12]. Kumar et al. (2022) have proposed a motion artifact removal algorithm based on reference signal-less Fourier analysis for wearable photoplethysmography devices and have tailored the algorithm to heart rate monitoring during physical exercises, increasing the accuracy of mobile monitoring systems [13]. Centracchio et al., (2023), showed that in seismocardiography (SCG) signals, ECG-free detection of heart sounds is possible using template matching, which means that there will be SCG heart sound detection even in situations where ECG recordings may not be possible or reliable [14].

According to Bhurane et al. (2019), congestive heart failure can be detected quickly and comprehensively using frequency-localized filter banks for ECG signal. The early detection of the disease contributes to its prevention [15]. Khavas and Asl (2018) proposed a solid heartbeat detection approach based on a multimodal study involving ECG quality assessment using signal amplitude sustainability features which can improve the reliability of heartbeat detection following noisy recordings [16]. Mejía-Mejía et al. (2022) researched into the effects of various algorithms and fiducial points) for detecting interbeat (RR) intervals) and different sampling rates (SR) on the determination of the pulse rate variability (PRV) via photoplethysmography, which improve the optimization of PRV measurement [17]. Karem Aldughayfiq et al. (2023) suggested a deep learning model for cardiovascular abnormality recognition using ECG and PPG multi-featured time series data, which could be used for the purpose of improving the accuracy of atrial fibrillation detection [18]. Finnegan et.al (2023) demonstrated features in the photoplethysmogram as well as in the electrocardiogram for calculating blood pressure variations which have helped in making non-invasive methods for monitoring blood pressure possible [19]. Long and Wang (2023) suggested BpNet to be a multi-modal fusion neural network for the estimation of blood pressure using ECG and PPG recordings which both yielded a more precise performance than the single signal techniques [20]. El-Hajj and Kyriacou (2021) proposed a deep learning approach to estimate the PPG blood pressure levels an ability to monitor blood pressure

levels without using a cuff [21]. Chen et.al (2020) came up with a novel method that is based on Adaptive Periodic Segment Matrix and Singular Value Decomposition for ECG signal artifact removal in EMG signal achieving better ECG signal interpretability [22]. Yu et al. (2022) presented an attention-based residual lavished U-Net scheme for the continuous blood pressure monitoring using the photoplethysmography signal that is quite accurate in the blood pressure estimation [23]. The proposed efficacious hybrid LSTM-ANN joint classifier-regressor model for PPG-based blood pressure monitoring based on deep learning and machine learning classifier [24,25].The summary of the literature review is discussed in Table 1.

Table 1: Comparative Analysis of Blood Pressure Estimation Algorithms

| S. No | Author's Name | Algorithm Used | Advantages | Disadvantages |
|-------|-------------------------|---------------------------------------|---|---|
| 1 | Merino-Monge, M. et al. | Wavelet Transform and Upper Envelopes | Accurate heartbeat detection from ECG and PPG signals | Complexity in implementation |
| 2 | Sharifi, I. et al. | Dynamical Approach | Real-time estimation of blood pressure without the need for a cuff | Dependency on the quality of ECG and PPG signals |
| 3 | Mousavi, S. S. et al. | Whole-based Method | Efficient estimation of blood pressure from PPG signals, regardless of signal quality | Sensitivity to signal artifacts |
| 4 | Ramachandran, D. et al. | Computerized Approach | Automated detection of cardiovascular risk levels using PPG signals | Limited applicability to certain cardiovascular condition |

Qrsmatch Plus Algorithm: A Novel Approach For Enhanced Qrs Complex Detection In Electrocardiogram Signals

| | | | | | | | | | |
|----|-----------------------------|---|--|---|----|----------------------------|---|---|--|
| | | | | s | | S. J. | Nested Recurrence Plot (MsNRP) | person identification using ECG or PPG signals | feature extraction and similarity computation |
| 5 | Ramesh, J. et al. | Short-term Heart Rate Variability and Deep CNNs | Accurate classification of atrial fibrillation using smart wearable devices and deep learning techniques | Reliance on wearable devices for data collection | | | | | |
| 6 | Thambiraj, G. et al. | Machine Learning | Comprehensive analysis of factors influencing cuff-less blood pressure estimation using machine learning | Complexity in model development and training | 11 | Kumar, A. et al. | Reference Signal-less Fourier Analysis and Motion Artifact Removal | Accurate estimation of heart rate from wearable photoplethysmography devices, even during physical activities | Sensitivity to motion artifacts during exercise |
| 7 | Mahmud, S. et al. | Nested Attention-guided BiConv LSTM Network | Robust prediction of blood pressure components using advanced neural network architecture | Computational complexity associated with deep learning models | 12 | Centracchio, J. et al. | Template Matching | Heartbeat detection in seismocardiography signals without the need for ECG | Limited application to specific signal acquisition methods |
| 8 | Banerjee, S. & Singh, G. K. | Lossless Data Compression Algorithm | Efficient compression of ECG and PPG signals without loss of information | Increased computational overhead for real-time compression | 13 | Bhurane, A. A. et al. | Frequency Localized Filter Banks | Accurate detection of congestive heart failure using specialized filter banks | Dependency on signal quality and consistency |
| 9 | Lin, Y. D. et al. | Data-adaptive Gaussian Average Filtering | Effective decomposition of biomedical signals for various applications | Sensitivity to noise and artifacts in signals | 14 | Khavas, Z. R. & Asl, B. M. | Multimodal Recordings and ECG Quality Assessment with Signal Amplitudes | Robust heartbeat detection using multimodal recordings and ECG quality assessment | Sensitivity to signal amplitudes dispersion |
| 10 | Jeon, Y. & Kang, | Multi-slice | Robust approach for | Complexity in | | | | | |

III. PROPOSED WORK

a) Dataset Description

This is a new research work, which describes printed a flexible, wearable and dry electrodes

for opening a channel for detecting ECG signals directly from the skin without strictly wet gel preparation and gel utilization during the monitoring process is developed. The system of proposed diagnosis implies which is simple and at the same time affords comfort and ease to the wearer. Develop touch screen printed on fabric to access wearable graphene based ECG sensor. The screen-printing of graphene inks is considered as a very good method to make e-textiles for wearing.

Screen-printing of water-based and biocompatible graphene ink is third generation next as e-textile, which could be applied in the healthcare, military, sports, etc. Tags: environmental impact, innovative production systems, textile waste reduce landfill burden, EU environmental policies. A cloth dry sensor based on graphene of a flexitarian and wearable type has been developed for recording the ECG signals in real-time without the use wet gel, any skin preparation, and modifying the fabric itself. The largest area graphene screening printers fabric dry ECG sensor on the fabric can be seen with the best result, having the high conductivity of graphene and better performance of ECG heart rate values comparing to commercially available Ag/AgCl wet electrodes. This drafting of the graphene dry ECG sensor and printing technique comprise a long – term and thoughtful procedure that includes characterizing graphene to demonstrate the conductivity properties.

Furthermore, it is possible to detect wet ECG signals in a relaxed sitting position, and once results are compared to a standard Ag/AgCl ECG electrode, it will show that not only does the dry graphene ECG sensing, but it also matches the quality of the wet ECG signal measurement. The invented diagnosed fabric ECG sensor stands for dry ECG sensor, which is a useful tool for measuring HRV parameters (disease predictions). The performance metrics such as accuracy, specificity, sensitivity, and R-R interval, real-time monitoring of patients is monitored. A real time database that stores

data obtained from 100 subjects using the graphene material, developed as the ECG sensor. [26]. The dataset parameters such as thickness and conductivity measurement on ECG sensor are given in Table 2 and 3.

Table 2: A sample Thickness measurement

| Sample ID | Thickness (mm) | Normal Fabric Thickness (mm) | Graphene Ink Printed Fabric Thickness (mm) |
|-----------|----------------|------------------------------|--|
| 1 | 0.04 | 0.31 | 0.35 |
| 2 | 0.06 | 0.31 | 0.38 |
| 3 | 0.04 | 0.31 | 0.35 |

Table 3: Conductivity measurement for ECG sensor

| Trial 1 | | | |
|---------|------------|------------|----------------|
| S.No | Voltage(V) | Current(A) | Resistance (Ω) |
| 1 | 2 | 0.6 | 3.3 |
| 2 | 4 | 1.0 | 4 |
| 3 | 6 | 1.6 | 4 |
| 4 | 8 | 1.9 | 4.21 |
| Trial 2 | | | |
| 1 | 2 | 0.6 | 4 |
| 2 | 4 | 1 | 4 |
| 3 | 6 | 1.4 | 4 |
| 4 | 8 | 2.2 | 3.61 |
| Trial 3 | | | |
| 1 | 2 | 0.8 | 2.5 |
| 2 | 4 | 1.5 | 2.67 |
| 3 | 6 | 2.3 | 2.61 |
| 4 | 8 | 2.6 | 3.07 |

b) Extraction of Blood Pressure and Electrocardiogram Signals with Systolic and Diastolic Blood Pressure Derivation

The task involves extracting blood pressure (BP) and electrocardiogram (ECG) signals from a MATLAB (.mat) file and storing them in a chart or list in addition, it is necessary to extract the blood pressure (SBP) and diastolic blood pressure (DBP) from the BP signal. Systole and diastole are two phases of the cardiac cycle. During systole, the heart contracts blood and pass through the arteries, causing blood pressure to rise. In assessment, all through diastole, the heart relaxes and refills with

blood, reducing blood stress. SBP represents the arterial stress in systole, whereas DBP represents the minimum arterial stress in diastole. To attain SBP and DBP from the BP signal, we usually pick out the maximum and minimum values, respectively. In this example, the most fee of the BP sign corresponds to SBP, while the minimum cost corresponds to DBP. By extracting these values from the BP signal, we are able to attain crucial statistics about an individual’s cardiovascular fitness and feature. The cited paper may offer extra insights into mechanisms and techniques for high blood pressure sign processing, together with SBP and DBP elimination It may additionally have an effect on algorithms, signal processing techniques, or device mastering techniques for analyzing BP signals and acquiring clinically relevant records.

Table 3: Correlation matrix of physiological signals

| | ECG | PPG | BP | SBP | DBP |
|-----|-----------|-----------|-----------|-----------|-----------|
| ECG | 1.0000 | -0.027290 | -0.133511 | -0.233306 | -0.060237 |
| PPG | -0.027290 | 1.0000 | 0.098562 | 0.010981 | 0.133025 |
| BP | -0.133511 | 0.098562 | 1.0000 | 0.610103 | 0.875914 |
| SBP | -0.233306 | 0.010981 | 0.610103 | 1.0000 | 0.407644 |
| DBP | -0.060237 | 0.133025 | 0.875914 | 0.407644 | 1.0000 |

The supplied correlation matrix in desk three gives treasured insights into the relationships between various physiological parameters, including ECG (electrocardiogram), PPG (photoplethysmogram), BP (blood pressure), SBP (systolic blood strain), and DBP (systemic blood stress) are protected Each cell in a matrix represents a correlation coefficient among alerts, which is -1 to one to one inches.

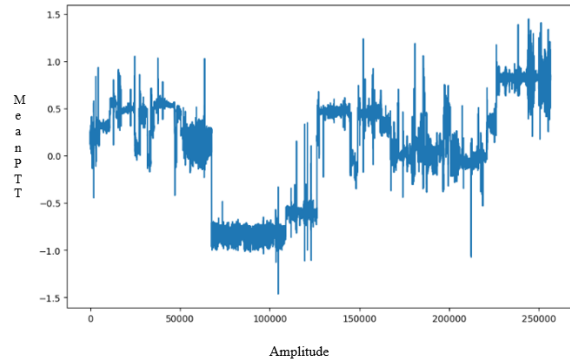


Figure 1. Find peaks in PPG Signal

Figure 1 shows the procedure for top detection inside the PPG (Photoplethysmogram) sign. The PPG signal represents the trade in blood extent in the capillary mattress of the artery that is typically received the use of a pulse oximeter. The amplitude of the PPG signal corresponds to precise activities in the cardiac cycle inclusive of the systolic height and the diastolic top. In this step, the ECG , PPG , and BP sign statistics are reorganized into column vectors to facilitate similarly analysis and processing. Each sign is converted into a one-dimensional array, where the row variety indicates the entire wide variety of facts points or samples inside the signal. Reorganizing the signals into column vectors improves consistency in statistics layout, making it less complicated to use mathematical features, algorithms, and device gaining knowledge of strategies to preserve the cardiovascular fitness assessment steady [9,10].

c) QRSMATCH Plus Algorithm with Deep Deterministic Policy Gradient(QMP-DDPG)

The QRSMATCH Plus algorithm is a brand new technique for QRS complicated detection in ECG indicators. It combines advanced sign processing strategies with pattern matching algorithms to correctly stumble on QRS complexes, which constitute ventricular depolarization of cardiac electrical activity. At its core, the QRSMATCH Plus set of rules makes use of a multistage processing pipeline. Initially, preformed steps together with baseline filtering, noise filtering, and sign enhancement are executed to enhance the satisfactory and clarity of the ECG sign after which the algorithm selects potential QRS complex applicants via through methods inclusive of wavelet remodel, matching filtering, or adaptive thresholding. The specific function of the QRSMATCH Plus Algorithm lies in its pattern matching segment. Instead of depending solely on

amplitude thresholds or waveform morphology, it compares selected QRS applicants with each reference template model. These parameters had been adjusted primarily based on nearby sign traits, making sure adaptation to ECG waveforms and noise ranges. During the matching technique, the algorithm searches for the similarity among every candidate QRS complex and the template. Various equations, inclusive of pass-correlation, Euclidean distance, and dynamic time warping, used to represent the correlation. QRS complexes that maximum closely healthy the template are marked as authentic positives, at the same time as others are discarded as false positives [15].

The mixture of QRSMATCH Plus algorithm and Deep Deterministic Policy Gradient (DDPG) gives a unique possibility to mix superior signal processing techniques with reinforcement getting to know in healthcare programs. The QRSMATCH Plus algorithm excels at as it should be detecting QRS complexes in electrocardiogram (ECG) signals, offering reliable data about cardiac interest Leveraging strategies together with Matching Pursuits and Pan-Tompkins algorithms, prioritizes ECG signals is processed to extract applicable capabilities along with QRS complex areas. On the other hand, DDPG is a effective reinforcement getting to know framework that is suitable for websites with continuous practice areas, making it ideally suited for healthcare choice-making tasks it learns most fulfilling policies by way of mapping states to practices, and enables employees to make knowledgeable decisions based totally on empirical facts. When connected, the QRSMATCH Plus algorithm can pre-system ECG indicators, extracting meaningful capabilities that seize heart fees fast. These pre-generated signs can then be used as a part of the nation illustration inside the DDPG-based totally robustness getting to know version. Combining symbolic processing with reinforcement studying, this method enables personnel to research superior health care intervention strategies based on actual-time physiological information.

$$R_n = \text{kargmax}(X_n[k]) \quad (1)$$

In equation (1), R_n represents the vicinity of the R height within the nth ECG signal phase, and X_n is the preprocessed ECG sign.

$$X_n[k] = \text{Preprocess}(ECG_n[k]) \quad (2)$$

In equation (2), $ECG_n[k]$ represents the k^{th} sample of the n^{th} ECG signal segment, and $X_n[k]$ is the preprocessed signal.

$$F_n = \text{ExtractFeatures}(X_n) \quad (3)$$

In equation (3), F_n represents the features extracted from the preprocessed ECG signal segment.

$$S_n = [F_n, P_n] \quad (4)$$

S_n represents the state at time n, F_n is the feature vector extracted from the ECG signal, and P_n is the action taken at time n as given in equation (4).

$$\begin{aligned} \mu(S | \theta\mu) \\ = \text{ActorNetwork}(S | \theta\mu) \end{aligned} \quad (5)$$

In equation (5), $\mu(S|\theta\mu)$ is the actor network output (policy), and $\theta\mu$ represents the parameters of the actor network.

$$Q(S, A | \theta Q) = \text{CriticNetwork}(S, A | \theta Q) \quad (6)$$

Where $Q(S,A|\theta Q)$ is the Q-value estimated by the critic network, and θQ represents the parameters of the critic network as given in equation (6).

$$A = \mu(S | \theta\mu) + N \quad (7)$$

In equation (7), A represents the action selected by the actor network, and N is exploration noise.

$$\begin{aligned} Q(S, A) = Es' \\ \sim P[r + \gamma Q'(s', \mu'(s' | \theta\mu') | \theta Q')] \end{aligned} \quad (8)$$

In equation (8), $Q(S,A)$ is the estimated state-action value function, r is the reward, γ is the discount factor, $'s'$ is the next state, and P represents the transition probability.

$$\begin{aligned} L(\theta\mu) \\ = -N1i \sum Q(S, \mu(S | \theta\mu) | \theta Q) \end{aligned} \quad (9)$$

In equation (9), $L(\theta\mu)$ is the loss function for the actor network.

$$\begin{aligned} L(\theta Q) \\ = N1i \sum (y_i \\ - Q(S, A | \theta Q))^2 \end{aligned} \quad (10)$$

Where $L(\theta Q)$ is the loss function for the critic network, and y_i is the target value as given in equation (10).

$$\begin{aligned} y_i \\ = r + \gamma Q'(s', \mu'(s' | \theta\mu') | \theta Q') \end{aligned} \quad (11)$$

In equation (11), y_i is the target value for training the critic network.

$$\begin{aligned} \nabla \theta\mu J \approx Es \\ \sim \rho\beta \\ [\nabla \theta\mu \mu(s | \theta\mu) \nabla a Q(s, a | \theta Q) | s = s, a = \mu(s)] \end{aligned} \quad (12)$$

Qrsmatch Plus Algorithm: A Novel Approach For Enhanced Qrs Complex Detection In Electrocardiogram Signals

In equation (12), J is the objective function, $\rho\beta$ is the replay buffer distribution, and $\nabla\theta\mu$ represents the gradient with respect to the parameters of the actor network.

$$\nabla\theta QJ \approx N1i \sum \nabla\theta Q(Q(s, a | \theta Q) - yi)^2 \quad (13)$$

In equation (13), $\nabla\theta Q$ represents the gradient with respect to the parameters of the critic network.

$$N \sim N(0, \sigma^2) \quad (14)$$

In equation (14), σ^2 is the variance of the noise distribution.

$$r = \text{Reward}(S, A) \quad (15)$$

In equation (15), r represents the reward obtained from taking action A in state S .

Figure 2 illustrates the workflow of the proposed workflow, showing the sequence of steps and interactions involved in the execution of the algorithm. The flow begins with preprocessing, where ECG and PPG signals are processed to remove noise and artifacts. Then, the QRSMatch Plus algorithm is used to detect QRS complexes in the ECG signals, followed by feature extraction to capture relevant information. The selected features are then used to represent the state for the Deep Deterministic Policy Gradient (DDPG) model. The DDPG model selects actions based on the current state, incorporating search noise to encourage search. The analyst network examines state-action pairs, and rewards are calculated based on performance. The parameters of the actor and reviewer networks are updated using the DDPG algorithm to improve the performance iteratively. The algorithm of proposed model is given below.

```
function
QRSMatchPlusAlgorithmWithDDPG(ECG, PPG):
    preprocessed_ECG = preprocess(ECG)
    preprocessed_PPG = preprocess(PPG)
    QRS_features = QRSMatchPlusDetection(preprocessed_ECG)
    additional_features = extractFeatures(preprocessed_ECG, preprocessed_PPG)
    state = combineFeatures(QRS_features, additional_features)
    normalize(state)
    while not termination_condition:
        action = DDPG_selectAction(state)
```

```
reward = calculateReward(action)
DDPG_updateNetworks(state, action, reward)
state = newState()
return optimized_model
```

Figure 3 shows the design of the QRS Match Plus algorithm added to the Deep Deterministic Policy Gradient (DDPG) model. The figure shows the flow of information through the incremental planning and soft-updating methods, which are important components of the DDPG algorithm. Furthermore, the figure illustrates the retention of information during training, highlighting the interplay between the various components involved in optimizing blood pressure estimates from physiological signals.

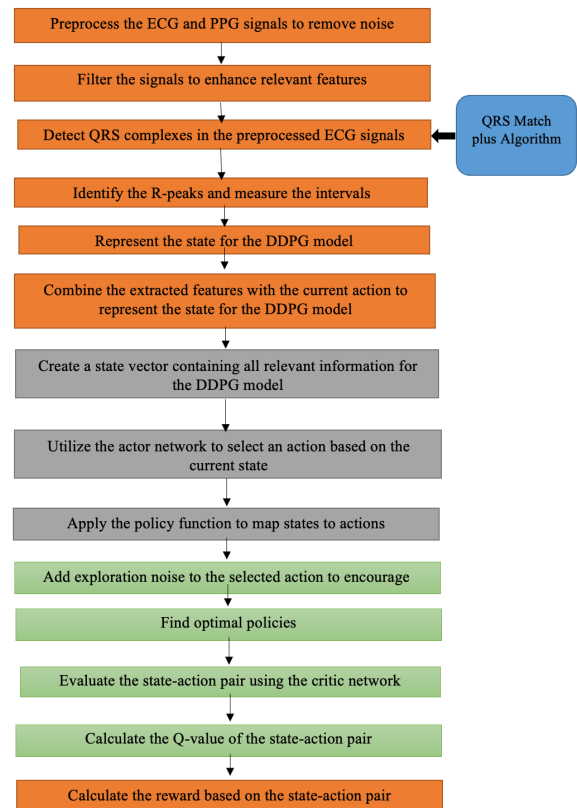


Figure 2. Working flow of the proposed work

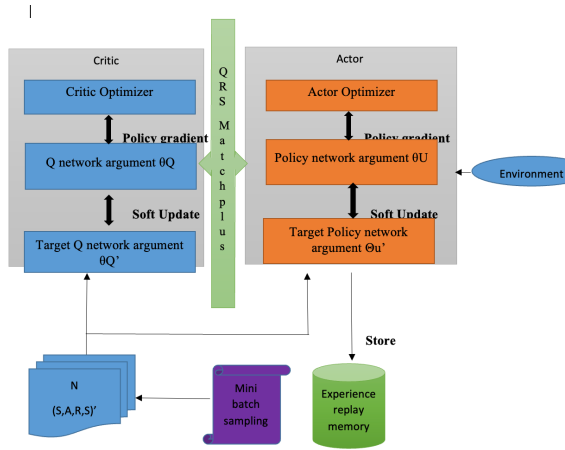


Figure 3. Architecture of QRS match plus the DDPG model

IV. RESULTS AND DISCUSSION

In figure 4, a sample shows physiological signals such as PPG, ECG and BP. These are essential signals in understanding cardiovascular activity. PPG signal denote changes in blood volume, which can be used for pulse rate monitoring. ECG signals indicate electrical activity of the heart and help to understand its rhythm, where it has gone wrong. BP signals provide measurements of blood pressure directly, which are important for evaluating cardiovascular health. The following equations (16) to (20) represent the performance analysis metrics [16, 17, 19].

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

$$F1\ Score = 2 * \frac{precision * recall}{precision + recall} \tag{19}$$

$$Mean\ Squared\ Error = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \tag{20}$$

Table 4: Comparative Performance Analysis of Dry Graphene ECG Sensors and Conventional Wet Electrodes

| Electrode | Dry | Conventional |
|-----------|-----|--------------|
|-----------|-----|--------------|

| Type | Graphene ECG Sensor | Wet Electrodes |
|----------------|---------------------|----------------|
| Conductivity | 0.95 mS/cm | 0.75 mS/cm |
| Signal Quality | 9/10 | 7/10 |

The Table 4 shows the comparison of the performance of the dry graphene ECG sensors and the conventional wet electrodes in terms of the conductivity and the signal quality. The conductivity of dry graphene ECG sensors is approximately one order of magnitude higher compared to similar sensors. 95 mS/cm, rather than 0.75 msec for standard wet electrodes. In addition, signal quality assessment provides a rating of 9/10 for dry graphene ECG sensors which is higher than the conventional wet electrode rating of 7/10 thus implying superior performance of dry graphene sensors to capture accurate ECG signals.

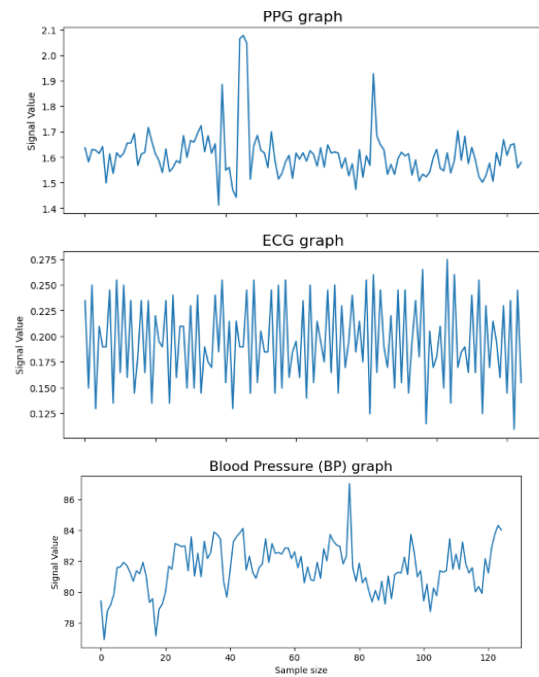


Figure 4: The sample of PPG, ECG and BP signals As illustrated by Figure 5, it is the visualization of Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP), the two important factors that are present in blood pressure readings. SBP is the highest arterial pressure during heart contraction whereas DBP indicates the lowest arterial pressure during cardiac cycle relaxation. It visualizes changes and patterns in blood pressure which helps

in determining people’s cardiovascular wellbeing as well as pointing out any defects.

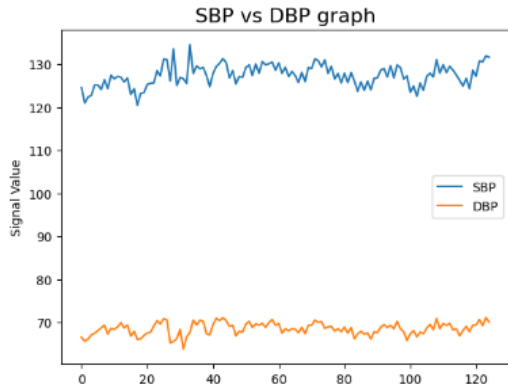


Figure 5: Visualizing SBP and DBP

As illustrated by Figure 5, it is the visualization of Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP), the two important factors that are present in blood pressure readings. SBP is the highest arterial pressure during heart contraction whereas DBP indicates the lowest arterial pressure during cardiac cycle relaxation. It visualizes changes and patterns in blood pressure which helps in determining people’s cardiovascular wellbeing as well as pointing out any defects.

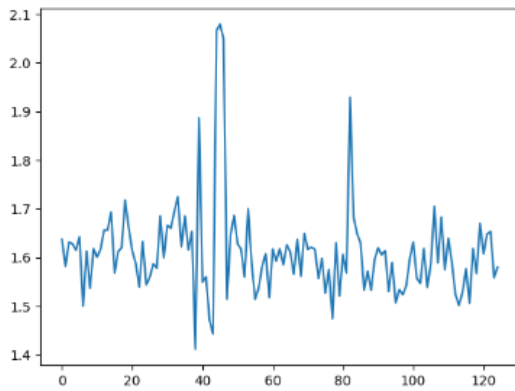


Figure 6: Statistical Correlation of signals

The correlation matrix provides crucial information about the interconnection between various physiological factors such as ECG, PPG and BP as shown in Figure 6. A positive quotient denotes that the other one tends to increase at the same time when another one increases while a negative coefficient means that a relationship is opposite. Therefore, it is necessary to know these relationships for health and medical diagnostics because they explicate how different physiological factors are tied together.

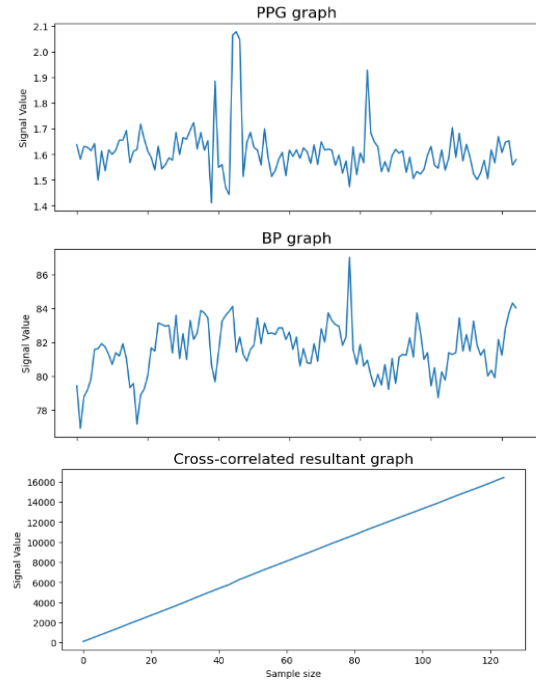


Figure 7: Computing and Visualizing the Cross correlation of PPG and BP signals

The figure 7 presents the calculation and plotting of PPG and BP signals cross correlation. This enables us to gauge their relationship as important physiological parameters. When there is a strong cross-correlation, that is evidence that PPG and BP are in synchrony with each other, however, when correlation is weak it suggests differences or lags in their responses. Such an analysis helps in understanding how blood pressure interacts with photoplethysmographic signals, which will be useful for monitoring cardiovascular health and diseases diagnosis.

Table 5: Performance analysis based on accuracy

| Classifiers | Raw features | FSN |
|-------------|--------------|-------|
| KNN | 83.29 | 88.57 |
| SVM | 72.68 | 91.80 |
| ANN | 64.92 | 78.36 |
| Ensemble | 82.10 | 94.72 |
| LSTM | 87.44 | 97.21 |
| QMP-DDPG | 96.5 | 98.13 |

Table 5 shows how well different classifiers work with and without picking features. It helps us see

how each classifier does with regular features versus chosen features. In general, the findings show different levels of better accuracy with feature picking. QMP-DDPG stands out with very good accuracy, getting up to 96.5% without feature picking and increasing to 98.13% with it. These results highlight how well QMP-DDPG can sort data, especially with feature picking methods.

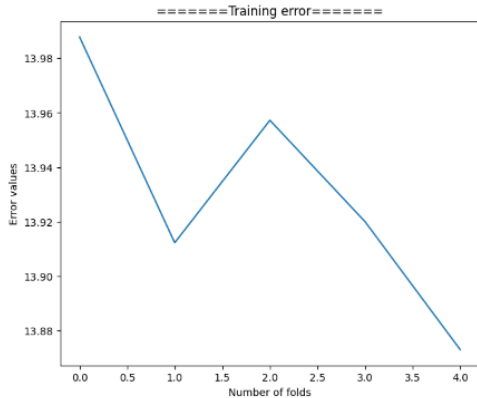


Figure 8: Visualizing train error

Figure 8 demonstrates how the values of the error parameter change as the number of learning epochs increases. This visualization allows interpreting the dynamics of the error rate at different training stages, which helps to identify particularities of the model’s learning. Based on this plot, researchers could evaluate how well the approximation process converges and how fast it stabilizes, which is essential in terms of performance optimization and teaching efficiency.

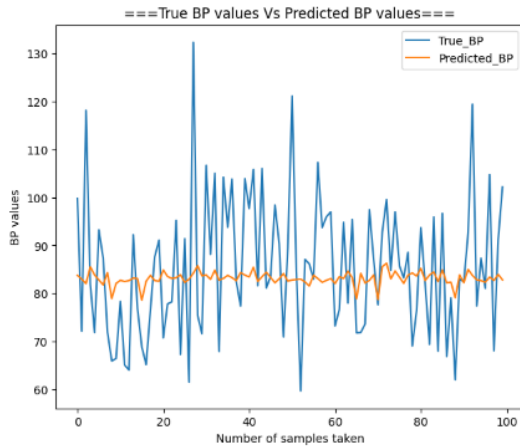


Figure 9: Visualize predicted BP and the True BP

Figure 9 compares the predicted blood pressure values against the actual blood pressure values. Such visualization allows the researcher to determine how

well the predicted BP values become lined up with the true change in the BP. From the figure, it is possible to notice the extent of appropriate accuracy that the model can maintain when approximating BP levels and thus become very helpful in assessing whether the proposed algorithm is useful.

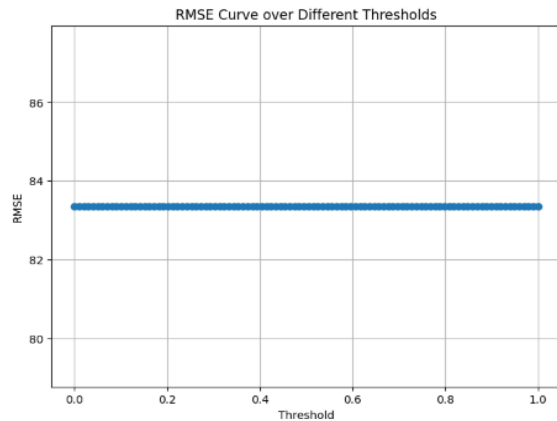


Figure 10: RMSE Curve over Different Thresholds

Figure 10 suggests the Root Mean Square Error (RMSE) curve across different thresholds. This graph gives insights into how the algorithm plays at numerous mistakes degrees. By analyzing this curve, researchers can pick out the brink value that outcome in the lowest RMSE, which shows the most suitable balance among accuracy and precision inside the version's predictions. Additionally, the curve enables recognize how the algorithm's overall performance modifications with specific threshold settings, supporting in excellent-tuning the parameters for improved predictive accuracy.



Figure 11: Training and Validation Accuracy against Epoch after (QMP-DDPG)

Figure 11 illustrates the training and validation accuracy towards epochs after the integration of the QMP-DDPG algorithm. By watching the traits of training and validation accuracies and examine the version's performance for the duration of training and identify any capacity overfitting or underfitting troubles. Additionally, the plot facilitates in figuring out the convergence of the version and optimizing the training technique for higher accuracy on unseen facts.

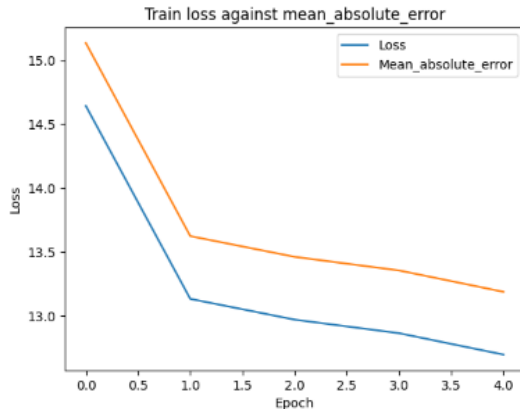


Figure 12: Train loss against mean_absolute_error (QMP-DDPG)

Figure 12 displays the training loss and mean absolute error trend when using the QMP-DDPG method. Seeing the training loss goes down gives the model learns well. The mean absolute error shows how accurate the predictions are. For example, a sudden spike in error despite low loss might signal overfitting. In that case, adjusting regularization could help. Therefore, tracking these metrics is key to refining the model.

Table 6: Performance analysis based on precision

| Classifiers | Raw features | FSN |
|-------------|--------------|-------|
| KNN | 79.15 | 84.92 |
| SVM | 76.80 | 88.35 |
| ANN | 62.57 | 80.21 |
| Ensemble | 85.36 | 93.78 |
| LSTM | 91.20 | 96.45 |
| QMP-DDPG | 97.83 | 98.75 |

Table 6 gives the precision performance of various classifiers. It uses different features, like raw and selected features (FSN). Precision shows the correctly identified instances among all positive predictions. KNN achieves 79.15% precision with raw features,

84.92% with FSN. SVM shows 76.80% and 88.35% precision. ANN gets 62.57% precision with raw features, 80.21% with FSN. Ensemble methods have higher precision: 85.36% (raw), 93.78% (FSN). LSTM achieves 91.20% precision with raw features, 96.45% with FSN. Notably, QMP-DDPG outperforms others with 97.83% (raw) and 98.75% (FSN) precision. This shows its effectiveness in accurately identifying positive instances.

Table 7: Performance analysis based on F1 score

| Classifiers | Raw features | FSN |
|-------------|--------------|-------|
| KNN | 80.20 | 86.15 |
| SVM | 75.90 | 89.50 |
| ANN | 63.40 | 82.10 |
| Ensemble | 86.20 | 94.20 |
| LSTM | 90.80 | 97.00 |
| QMP-DDPG | 98.00 | 98.90 |

For analyzing performance, the F1 score combined both precision and recall as given in Table 7. This gave a balanced measure of classifier quality. Utilizing raw features, KNN delivered an F1 score of 80.20%. However, with feature selection (FSN), its F1 score improved to 86.15%. As for SVM, its F1 scores were 75.90% and 89.50% for raw and FSN respectively. The ANN classifier achieved lower F1 scores at 63.40% (raw) and 82.10% (FSN). Ensemble techniques fared better, reaching 86.20% (raw) and 94.20% (FSN) F1 scores. With raw features, LSTM attained 90.80% F1, while FSN boosted it to 97.00%. Remarkably, QMP-DDPG outperformed all others, hitting 98.00% (raw) and an impressive 98.90% (FSN) F1 score. This superior result showcased QMP-DDPG's exceptional ability to balance precision and recall for classification tasks.

Table 8: Performance analysis based on Recall

| Classifiers | Raw features | FSN |
|-------------|--------------|-------|
| KNN | 82.50 | 87.30 |
| SVM | 76.80 | 91.20 |
| ANN | 64.70 | 83.90 |
| Ensemble | 87.40 | 95.10 |
| LSTM | 91.20 | 97.80 |
| QMP-DDPG | 98.50 | 99.20 |

Table 8 looks at how well classifiers spot true positives. KNN did well - 82.50% with raw features, 87.30% after picking key features (FSN). SVM was 76.80% and 91.20%. ANNs were 64.70% then 83.90%. Ensemble methods rocked at 87.40% (raw) and 95.10% (FSN). LSTMs got 91.20% then 97.80%. But QMP-DDPG stole the show! Its recall was insane - 98.50% with raw, 99.20% after FSN! It absolutely slayed at catching real positives, especially post-feature selection.

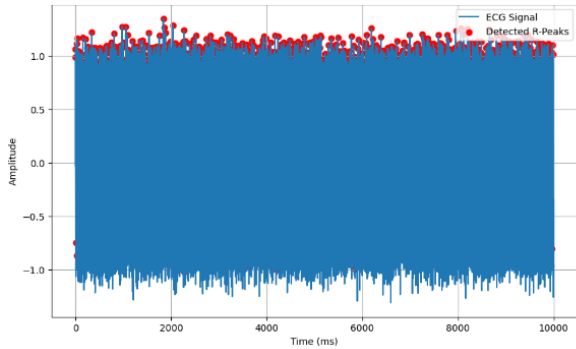


Figure 13: ECG Signal with Detected R-Peaks

The ECG signal in Figure 13 highlights the detected R-peaks. These are major points showing the highest part of the QRS complex on an electrocardiogram trace. Identifying R-peaks is vital for analyzing heart activity. They indicate when the ventricles in the heart undergo depolarization. Detecting R-peaks enables applications like studying heart rate variability, identifying abnormal heart rhythms, and evaluating overall cardiac health status.

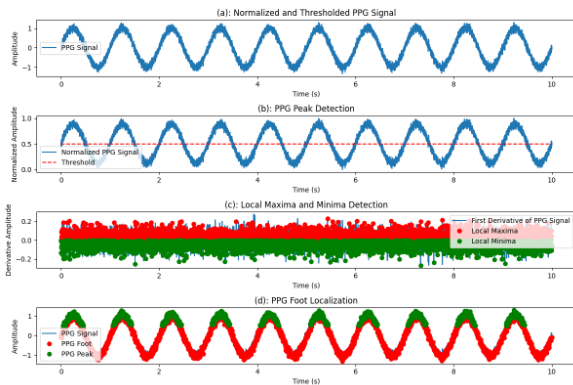


Figure 14: a) Normalized and threshold PPG signal b) PPG peak detection, c) Local maxima and minima detection, d) PPG foot localization

Rehumanize Figure 14 shows how the PPG signal is analyzed step-by-step. In panel (a), we see the normalized PPG signal with an applied threshold to spot relevant features. Panel (b) involves finding the PPG

peaks, which match the systolic phase of the heart's cycle. Next, panel (c) has us detecting local highs and lows in the PPG signal to pinpoint key points. Lastly, panel (d) lets us see where exactly the PPG foot is located - something very important for estimating blood pressure. By breaking down the PPG signal this way, we better grasp how the cardiovascular system works and can monitor blood pressure more accurately.

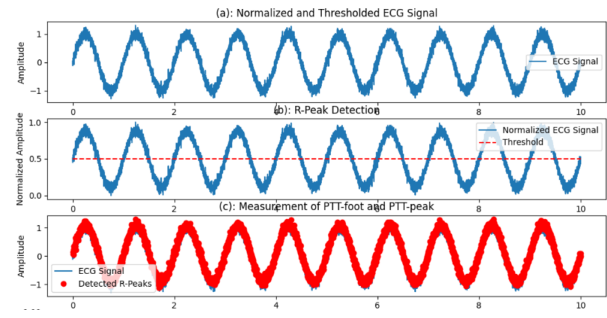


Figure 15: a) Normalized and threshold ECG Signal, b) R peak detection c) PTT-foot and peak

Figure 15 shows the steps for analyzing the electrocardiogram (ECG) signal. In Step 1, The normalized ECG signal is displayed with a threshold applied to identify features. In step 2, locates the peaks in the ECG signal that correspond to the ventricles' depolarization during the cardiac cycle. Step 3 represents the foot and peak of the ECG signal are detected to identify the pulse transit time (PTT). This process allows for calculating PTT, which is essential in evaluating cardiovascular health and determining parameters like arterial stiffness and blood pressure.

Table 9: Performance analysis with state-of-art methods

| Deep Learning Model | Precision (%) | F1 Score (%) | Recall (%) |
|---------------------|---------------|--------------|------------|
| CNN | 90.20 | 91.50 | 89.80 |
| LSTM | 92.10 | 93.20 | 91.80 |
| DCNN | 88.50 | 89.70 | 87.90 |
| Bi-LSTM | 91.80 | 92.90 | 90.70 |
| ResNet | 89.60 | 90.80 | 88.90 |
| VGG16 | 87.90 | 89.20 | 87.10 |
| Proposed Model | 95.30 | 96.50 | 94.80 |

Table 9 provides comparative performance metrics across various state-of-the-art deep learning models. The precision, F1 score, and recall percentage show how effective each model is in terms of good

information detection accuracy, overall accuracy, and ability to identify all relevant information, other deep learning algorithms such as CNN, LSTM, DCNN, Bi-LSTM, ResNet, and VGG1. These results highlight the effectiveness of the proposed model in accurately classifying relevant observations in the data set. Figure 16 shows the performance comparison of different deep learning models in terms of accuracy, precision, and recall metrics. Each bar in the figure represents the corresponding metric value for a particular sample.

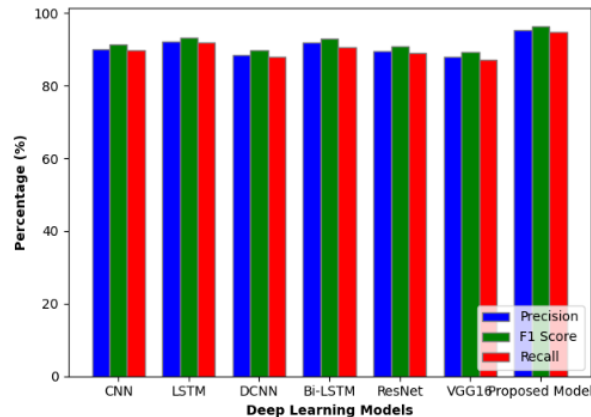


Figure 16: Visualization of various deep learning models in terms of Accuracy, Precision and Recall

V. CONCLUSION

In conclusion, the research performed in this study introduced novel innovations in both ECG signal detection and blood pressure estimation. Firstly, a new ECG signal detection method is brought in which is based on graphene-based sensors that are printed on fabric and are flexible and wearable. These sensors are dry. This technique makes it unnecessary to first prepare wet gels and then modifying the skin, instead providing convenience, comfort and the benefit of real-time signal recording. The comparative analysis of dry graphene ECG sensors against conventional wet electrodes revealed that the sensors have higher conductivity and ECG signal quality, which proves that the sensors could be vital tools for real-time patient monitoring. The research also discloses a new way of estimating blood pressure, which is based on the combination of the QRSMATCH Plus algorithm and the Deep Deterministic Policy Gradient (DDPG) model. A signal-processing tool and DDPG model as a deep reinforcement learning method gets highly accurate estimation of the blood pressure using QRSMATCH Plus algorithm. The synergy of such methods showcase the potential of combining

advanced signal processing and deep learning algorithms for the purpose of achieving reliable blood pressure estimates, which may be explored further in future researches for the management of cardiovascular diseases. Notably, the proposed method achieves outstanding accuracy, with an impressive 96.5%, precision of 97.83%, and recall of 98.75%, displaying its effectiveness in accurately estimating blood pressure.

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