Hybrid ResNet and Bidirectional LSTM based Deep Learning Model for Cardiovascular Disease Detection using PPG Signals

[1]Kalaiselvi Balaraman and [2]S P Angelin Claret
[1]Department of Computer Science, College of Science and Humanities
[2]Department of Computational Intelligence, Faculty of Engineering and Technology
[1,2]SRM Institute of Science and Technology, Kattankulathur, Chennai.
[1]kb1291@srmist.edu.in, [2]angelins@srmist.edu.in

Correspondence should be addressed to Kalaiselvi Balaraman : kb1291@srmist.edu.in.

Article Info
Journal of Machine and Computing (http://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202303030
Received 25 January 2023; Revised from 10 May 2023; Accepted 30 May 2023.
Available online 05 July 2023.

Abstract – Hypertension is the major root cause of blood pressure (BP) which in turn causes different cardiovascular diseases (CVDs). Hence BP need to be regularly monitored for preventing CVDs since it can be diagnosed and controlled through constant observation. Photoplethysmography (PPG) is identified as an important low-cost technology for facilitating a convenient and effective process in the early detection of CVDs. Different cardiovascular parameters such as blood oxygen saturation, heart rate, blood pressure, etc can be determined using the PPG technology. These cardiovascular parameters when given as input to the deep learning model are determined to diagnosis CVDs with maximized accuracy to an expected level. In this paper, Hybrid ResNet and Bidirectional LSTM-based Deep Learning Model (HRBLDLM) is proposed for diagnosing CVDs from PPG signals with due help in supporting the physicians during the process of continuous monitoring. This deep learning model mainly concentrated on the diagnosis of stage 1 hypertension, stage 2 hypertension, prehypertension, and normal CVDs with maximized accuracy using PPG signals. The PPG signals determined from PPG-BP dataset for investigation were recorded using IoT-based wearable patient monitoring (WPM) devices during the physical activity that includes high intensity, medium and low intensity movements involved driving, sitting and walking. The experiments conducted for this proposed deep learning model using PPG-BP dataset confirmed a better classification accuracy of 99.62% on par with the baseline PPG-based deep learning models contributed for detecting CVDs.

Keywords – Cardiovascular Diseases (Cvds), Photoplethysmography (PPG) Signals, Wearable Patient Monitoring (WPM), Resnet, Bidirectional LSTM, Hypertension.

I. INTRODUCTION

The advent of wearable patient monitoring (WPM) devices-based Internet of things (IoT) electronic component and wireless communication technology wide opened the way for remote healthcare in the modern world[1]. These models are highly impact in the domain of telemedicine, robotic and artificial intelligence. Diversified number WMP devices are existing in the market for transmitting the medical information to wen and mobile applications using a wireless network[2]. But they possesses the challenges of reliability, precision, and accuracy. According to the report of world health organization (WHO), hypertension is identified as the major risk factor of cardiovascular diseases[3]. CVDs are identified as one of the main chronic diseases which contributes around 31% of the deaths around the globe [4]. This CVDs need to detect primarily through regular and continuous monitoring of Blood Pressure (BP). This BP monitoring complete depends on the three vital parameters of evaluation that includes mean arterial pressure (MAP), diastolic blood pressure (DBP)[5], and systolic blood pressure (SBP)[6]. In general, invasive and non-invasive methods of finding BP is more common. Cuff-based readings were used for non-invasive measurements, but they are not comfortable for overweight, injured and infants [7]. Moreover, the results of non-invasive measurements are discrete which means that they lie withing some set of intervals making it non-ideal for the patients. On the other hand, invasive procedure for continuous monitoring of BP necessitates arterial lines management[8]. But they are highly prone to infections. Thus cuff-less, non-invasive and continuous BP measurement system is essential [9].

At this juncture, Photoplethysmography (PPG) is an innovative option used for continuous monitoring of BP without the need for inflatable cuff. This PPG technology uses the vessels of human skin to identify the changes in the transmitted light or reflection identified using the photoelectric sensor [10]. It is also considered to the low-cost and versatile technology which plays an indispensable role in identifying the deviation of human blood volume and difference between the diastolic and systolic processes of the heart which are completely related to BP. In PPG technology, photodiode and light emitting diode are utilized for estimating the variations in the amount of light reflected. In specific, PPG-based BP estimation is highly authentic [11]. It can be extensively used in exploring the different dimensions of cardiac surveillance that includes the identification of autonomic function, microvascular blood flow, endothelial control, diabetes [12], arterial aging[13], respiration, cardiac output, BP estimation [14], continuous monitoring of heartrate [15] and blood oxygen saturation[16], [17]. It furthermore does not require any specified method for connecting it to sensors existing at any particular locations in the body. It can be simply extracted from the earlobe, finger or wrist. This simplicity inherent with the PPG has made it a potential wearable applications-based bio-signal which is useful for estimating the heart rate during the movement of physical activities [18].

In this paper, Hybrid ResNet and Bidirectional LSTM-based Deep Learning Model is proposed for diagnosing CVDs from PPG signals with due help in supporting the physicians during the process of continuous monitoring. This deep learning model mainly concentrated on the diagnosis of stage 1 hypertension, stage 2 hypertension, prehypertension, and normal CVDs with maximized accuracy using PPG signals. The PPG signals determined from PPG-BP dataset for investigation were recorded using IoT-based wearable patient monitoring (WPM) devices during the physical activity that includes high intensity, medium and low intensity movements involved driving, sitting and walking.

II. RELATED WORK

In this section, the recently proposed PPG-based CVDs detection mechanisms of the literature are presented with the merits and limitations.

Brophy et al. [19] proposed a federating learning-based framework for detecting heart disease using single optical photoplethysmogram (PPG) sensor for determining the arterial blood pressure. This learning framework adopted a time-series-to-time-series generative adversarial network (T2TGAN) which can estimate the arterial blood pressure with the standard deviation of 19.33 and mean error rate of 2.95 mmHg, respectively. It was proposed as the first method which adopted GAN for generating continuous arterial blood pressure from the input signal of PPG through the inclusion of federated learning methodology.

Then Huang et al. [20] proposed a deep learning model termed MLP mixer which combined the merits of MLPlstm-BP and gMLP-BP networks for detecting heart disease from PPG signals. It utilized a preprocessing approach called multi-filter to multi-channel (MFMC) for the objective of filtering put the factors that handles the signals of PPG to a remarkable manner. It further used the merits of multi-channel data for estimating BP directly. The experiments of the MLP mixer deep learning model conducted using MIMIC II dataset confirmed a SD of 5.10 mmHg, MAE of 3.52 (4.18) mmHg with respect to systolic pressure. On the other hand, this deep learning model evaluated using MIMIC II dataset confirmed a SD of 3.07 mmHg, MAE of 2.13 mmHg with respect to diastolic pressure.

Putra et al.[21]proposed a feature selection method for diagnosing heart disease using PPG signals using Recursive Feature Elimination (RFE), Pearson Correlation, and Analysis of Variance (ANOVA). This adopted feature selection method of ANOVA, PC and RFE helped in determining the potential features from the input PPG signals. It also adopted a classification algorithm that utilized K-Nearest Neighbors for constructing the machine learning model using the features of PPG. The results of the experiments with respect to PC method confirmed an accuracy of 90.9%, specificity of 99.12% and sensitivity of 97.98% during the process of CVD detection.

Ismail et al. [22] proposed a deep learning model using Convolutional-Recurrent Regressor for determining heart rate from the signals of PPG. The PPG considered for heart beat rate detection is extracted during the movement of different exercises. It initially extracted the features that presents the signal such that the extracted feature sequences can be fed to an integrated regression framework that includes the merits of convolutional-recurrent neural network (C-RNN). The experiments conducted using signal processing cup dataset confirmed minimized error rates with respect to subject independent and subject dependent protocols used for evaluation.

Al Fahoum et al. [23]proposed a practical feature selection process from PPG for diagnosing coronary artery diseases. It achieved classification process by extracting the statistical, measure of mean and standard deviation with respect to time domain properties. It explored the search space in a more extensive manner for selecting the comprehensive subset of features. It further used the merits of HF, DVT and AF for determinising the conditions of cardiac activities.

The review of the above mentioned works clearly confirmed that still a scope of improvement in terms of classification exists during the diagnosis of CVDs, and moreover, the features considered during multiclass classification need to be comprehensive for better precision, recall and F-measure during the diagnosis process.

III. PROPOSED HYBRID CNN BiLSTM MODEL

The proposed Hybrid ResNet and Bidirectional LSTM-based Deep Learning Model mainly targets on detecting the cardiac diseases that include normal, stage 1 and stage hypertension, and prehypertension classes. In this deep learning system, the signals of PPG are recorded using IoT-assisted WPM nodes which is capable in capturing the physical activities that includes the high, medium and low intensity arm movement during sitting, walking and driving.

Dataset used for CVDs detection

The data set used for CVDs detection using the proposed Hybrid ResNet and Bidirectional LSTM-based Deep Learning Model is the PPG-BP Data Set. This PPG-BP dataset is the publicly available and accessible dataset which comprises of PPG and BP. This dataset consists of comprehensive set of anonymous and clinical patients' data admitted in the Guilin People's Hospital, China. The data available in this PPG-BP dataset is clearer and hence it wide opens the option of conducting clinical investigation which helps in understanding the association between the cardiovascular health and PPG signals. It comprises of PPG-BP data collected from 219 patients which were in the age group of 21 and 86 years. Out of this entire dataset, the percentage of male subjects were 48%.

Hybrid ResNet and Bidirectional LSTM-based Deep Learning Model

Ahybrid scheme that combines CNN and bidirectional-Long Short-Term Memory (CNN-BiLSTM) is proposed for better classification. On performing several experiments, it is seen that CNN is efficient in determining spatial characteristics and performs well in case the circumstantial information with former sequence is not mandatory. RNNs are efficient in determining information when contiguous elements' context is significant for classification. Initially, multi-dimensional data is given to CNN as low-level input. In case of pooling as well as convolution, substantial features are determined in each layer. Compared to conventional CNN, output layer is completely linked to hidden layer. Accuracy is enhanced by employing more amounts of convolutional and pooling layers, and convolution kernel improvements. With risk of over-fitting, the network may become complex. A network of recurring neurons that are time-based is designed, wherein LSTM is combined with CNN to handle sequence problem. Comparable and unusable information is obtained by employing kernels and significant information is saved for prolonged duration in state cell. Leading outcomes are attained by combining CNN with BiLSTM. Subsequently, CNN-BiLSTM is employed, wherein convolutional layer enables determination of less dimensional semantic attributes from text and reduces amount of dimensions. Furthermore, BiLSTM deals with text as input. Numerous 1-Dimensional (1D) convolutional kernels are employed for offering improved performance on input vectors.

Sequential data is considered as mean of embedding vectors comprising of words as presented in Equation (1). The single-level, bi-level and multi-level feature characteristics are determined using diverse kernel sizes by implementing them on X_1:T using 1D-CNN. The attributes produced in 't^th' convolution involve a window with 'd' features being expanded from t: t+d. Convolution produces window features as shown in Equation (2).

$$X_1 : T = [Y_1, Y_2, Y_3, \ldots . Y_T] \tag{1}$$

$$h_d, t = tan\, h(W_d Y_{t:t+d-1} + b_d) \tag{2}$$

Where,

$\mathrm{Y}_{\mathrm{t:t+d-1}}$ - Embedding word vector in context window

$\mathrm{W_d}$ - Factors with matrix showing learnable weight

$\mathrm{b_d}$ - Bias

As text is convolved with each filter, produced feature map of filter has a convolution (size 'd') as shown in Equation (3),

$$fm_d = \left[fm_{d_1}, fm_{d_2}, fm_{d_3}, \ldots . Y_{T-d+1}\right] \tag{3}$$

By using diverse convolutional kernels with different widths, there is a scope of CNN to determine latent association amid numerous contiguous words. The most significant feature of convolution filter for extracting features from text is to lessen the amount of trainable factors in feature learning. Max pooling layer is used ensuing convolutional layers[24]. Input is handled through numerous convolutional channels. Each channel comes with its own distinctive collection of values. Maximum value from every convolutional layer during max pooling is chosen and pooled to build a collection of fresh attributes. Max pooling is implemented on feature maps in every kernel with convolutional size 'd' as shown in Equation (4). Attributes of every window are determined by concatenating 'p_d' for each filter of size 'd' = [1, 2, 3] and hidden attributes of obtained unigram, bigram and trigram as represented in Equation (5).

$$p_d = Maxt(fm_{d_1}, fm_{d_2}, fm_{d_3}, \ldots . Y_{T-d+1}) \tag{4}$$

$$fm_d = [p_1, p_2, p_3] \tag{5}$$

The substantial benefit in using feature extraction based on CNN over conventional LSTM is that complete amount of attributes is significantly lessened. The attributes are employed by a forecast model subsequent to feature extraction. LSTM framework makes it overcome 'Vanishing Gradient' by involving sequential data using input, output and forget gates together with states that work as complete long-term memory as well as additional connections amid states. At time 't' for a cell with 'Y_t' and intermediary state, its output state (fm_t) is determined as shown in ensuing Equations.

$$f_t = \varphi(P_f.Y_t + Q_f.fm_{t-1} + a_f) \quad (6)$$
$$i_t = \varphi(P_f.Y_t + Q_i.fm_{t-1} + a_i) \quad (7)$$
$$c_t = \varphi(PW_c.Y_t + Q_c.fm_{t-1} + a_c) \quad (8)$$
$$g_t = tanh(P_g.Y_t + Q_g.fm_{t-1} + a_g) \quad (9)$$
$$m_t = f_t.c.m_{t-1} + i_t.c.g_t \quad (10)$$
$$fm_t = c_t.c.tanh(m_t)$$

Where,
P, Q and a - Learnable factors
φ - Sigmoid function
c - Convolution operator
m_t - Memory or Cell state

LSTMs gate includes Forget (f_t), Input (i_t) and Output (o_t) gates respectively. Cell state enables LSTMs to get long-term dependences in data offered in input and implemented on data with lengthier sequences. The CNN portion of network includes 3 convolution layers with adjustable amount of filters. Initial 2 layers involve 128 filters with kernel of size 3×3 including sigmoid as well as Rectified linear activation unit (Relu) as Activation Functions (AFs). The 3rd convolution layer includes 64 filters including kernel and sigmoid AF. It is trailed using Max pool layer of 4×4 kernel. Lastly, biLSTM is used with less variant concealed computations. As computations are performed in forward as well as backward directions, the drawbacks of RNN are considered, that is information from former computations is employed in ensuing step. A 'dropout layer' is used with 'keep probability=0.1' to overcome overfitting on training data. In the output layer, Relu activation is employed and model training is performed on 'binary_crossentropy' loss as well as 'Root Mean Squared propagation (RMSprop)' optimizer.

Algorithm.

Input: Training features (Y_train), targets (X_train)
Hyper-parameters: Total no. of filters, Total no. of Epochs, Pool size, Embedding size, LSTM units, Batch size, Kernel size, Strides, Kernel type, Optimiser, Loss function, Dropout rate
Arbitrarily set the model
Prepare CNN model using BiLSTM for PPG-based heart rate estimation
Train the model for 50 epochs
Embed input
Set Sequential model
Include Embedding layer as input layer involving vocabulary & Embedding size
Include first Convolution layer involving Total no. of filters, Kernel size, Sigmoid AF
Include second Convolution layer involving Total no. of filters, Kernel size, Relu
Include third Convolution layer involving Total no. of filters, Kernel size, Sigmoid AF
Include Max pooling layer involving Pool size, Strides
Include biLSTM layer involving LSTM units, Recurrent activation, AF, Return sequences, Dropout
Include dropout involving dropout rate
Include dense layer involving Kernel type, Total no. of units, Relu
Compile the model using Loss function, RMSprop optimizer
Train the model using X_train, Y_train, Total no. of Epochs, Batch size

ResNet-50

Residual Network-50 (ResNet-50) is a CNN with 50 layers. It differs from ResNet model with 48 Convolution layers along with 1 Max pool and 1 Average Pool layers. It involves3.8 x 〚10〛^9 Floating points operations. It is a typical neural network that is employed as a backbone in several computer vision jobs. The essential breakthrough is that it allows training exceedingly DNNs with more than 150 layers. It is an advanced NN that was first introduced by [10].

CNNs face 'Vanishing Gradient Problem'. In backpropagation, the gradient value significantly drops, thus enabling rare changes to weights. ResNet overcomes this issue by using 'skip connection'.

The algorithms train on output (O), but ResNet trains on F(X). ResNet tries making F(X)=0 such that O=X.

'Skip Connection' aids in establishing direct connection which skips over layers of model. Output varies owing to 'skip connection'. Without this connection, input 'X' will be multiplied by layer weights followed by including a bias term.
AF is expressed as,

$$F\,(w * x + b) = F(X) \quad (11)$$

With skip connection, the output varies

$$F\ (w * x + b) = F(X) + x \tag{12}$$

ResNet-50 includes two types of blocks namely, identity block and convolutional block.Value of 'X' is added to output layer if input and output sizes are the same. If not, a 'convolutional block' is added in the shortest path to make the sizes equal by padding the input volume or performing 1*1 convolutions.

The output layer size is given by,

$$\left[\left(\frac{n+2p-f}{s}\right)+1\right]^2 \tag{13}$$

Where,
n - Size of input image
p - Padding
s - Stride
f - Number of filters

For 1*1 convolutional layer, the output layer is of size (n/2)×(n/2)
Pooling is used for reducing the image size in CNN. Stride takes the value '2' instead.

The overall architecture diagram of the proposed Hybrid ResNet and Bidirectional LSTM-based Deep Learning Model (HRBLDLM) is presented in **Fig 1**.

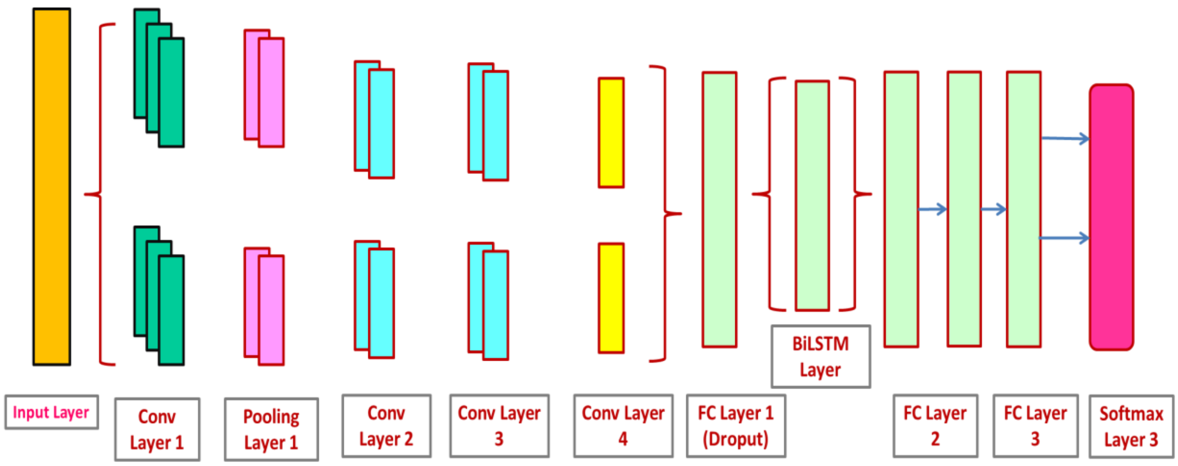

Fig 1. Architecture diagram of the proposed HRBLDLM Model

The PPG signals from the PPG-BP dataset is considered for processing using the bandpass filter whose value lies between 0 and 4 Hz of frequency. This signal is down-sampled to 500 Hz such that it could be potentially applied over the PPG data. Then the signals are partitioned into 20 segments. In this present work, number of signals segments were considered using the classification process. This work adopted PPG segmentation utilized the minimums of signals. The label class true and false was assigned with the value of 0 to 4. The data of PPG and its related labels are represented as a equal sized matrices of dimension. 1100 × 10,000. Initially the imbalance between two labels are identified during the process of preliminary investigation conducted over the experimental data. It further utilized the weights of the parameter preventing the problem of imbalanced data. In specific, the weights assigned to the samples of corresponding liable 0 and are 1.85 and 0.68, respectively. In, specific, these values of weights are determined after the analysis conducted on tuning of weights.

In this model, CNN and RNN (Bi-LSTM) is used for processing time-series data since they are potential in extracting the deep and time-dependent features that helps in better predictions. With the time series data, CNN, and Bi-LSTM with respect to PPG waveform detection is identified to establish better performance. CNNs on one end are capable inn extracting time-dependent deep features, while Bi-LSTM on the other end being a regularization method helps in reducing the problem of data imbalance. This model utilized a sample-by-sample classification approach rather than a classical complete signal segment processing. The entire data is partitioned into 70% and 30% with respect to training and testing. In specific the validation of 20% is introduced, then the data are reshaped for it to be fed into the Bi-LSTM model. Moreover, SSFT and PPG are flattened into two and single columns, respectively. Which are related to the real and imaginary spectrum region.

IV. RESULTS AND DISCUSSION

The Performance evaluation of the proposed Hybrid ResNet and Bidirectional LSTM-based Deep Learning Model (HRBLDLM) is conducted confusion matrix, ROC Curve and accuracy. Initially the confusion matrix is utilized for evaluating the performance of the deep learning model using the parameters of true positive, true negative, false positive and false negative rate. Then curve of ROC is determined by plotting the false positive rate against true positive rate.

Initially, **Fig 2** presents the confusion matrix of the proposed HRBLDLM model determined during the detection of CVDs with respect to PPG-BP dataset. The result presented using the confusion matrix clearly proved that the HRBLDLM model is efficient enough in attaining proper classification depending on the practical features extracted from PPG signals to the expected level. It also portrayed how the four classes of CVDs are identified during the implementation of the proposed deep learning model.

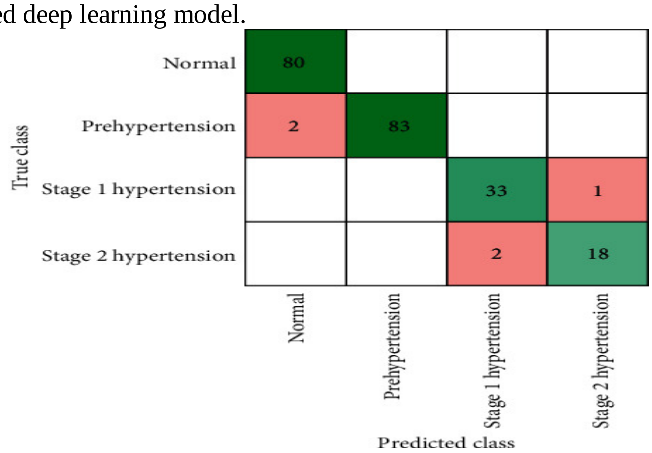

Fig 2. Confusion matrix of the Proposed HRBLDLM Model with respect to PPG-BP Dataset

Then **Table 1** demonstrates the comparative results of the proposed HRBLDLM model and the reviewed works of the literature using the PPG-BP dataset. The results evidently proved that the proposed HRBLDLM model confirmed a better classification accuracy of 99.61%, which is comparatively better than the competitive deep learning models contributed to the literature for PPG-based CVDs detection. This potential performance of the proposed HRBLDLM model is mainly due to adoption of practical features from the input PPG signals and the application of multi-level classification process that helped in significant diagnosis process.

Table 1. Classification accuracy attained by the Proposed HRBLDLM model with respect to PPG-BP Dataset

Authors	Deep learning model adopted	Classification accuracy (in %)
Brophy et al. [19]	Federated Learning Approach	99.48
Huang et al. [20]	Multilayer Perceptron Back Propagation (MLP-BP)	99.53
Sinnapolu et al. [23]	Novel COMMA-Z classifier and GPU Framework.	99.41
Ismail et al.[25]	Convolutional-Recurrent Regressor	99.54
Proposed model	**ResNet and BiLSTM**	**99.61**

Further, **Table 2** portrays the comparative results of the proposed HRBLDLM model and the reviewed works of the literature evaluated using precision, recall and F-measure with respect to the experiments conducted using the PPG-BP dataset. The results confirmed that the proposed HRBLDLM model is predominant in attaining maximized precision, recall and F-measure of 98.21%, 99.16% and 97.86%, respectively independent to the number of features determined from PPG signals.

Table 2. Precision, Recall and F-measure attained by the proposed HRBLDLM model with respect to PPG-BP dataset

Authors	Precision	Recall	F-Measure
Brophy et al. [19]	97.12	98.45	97.16
Huang et al. [20]	96.86	99.12	96.78
Sinnapolu et al. [23]	97.52	99.04	97.19
Ismail et al.[25]	97.64	98.98	97.42
Proposed model	**98.21**	**99.16**	**97.86**

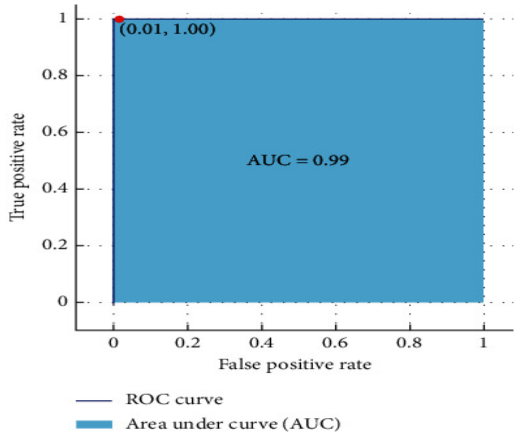

Fig 3. ROC Curve of the Proposed HRBLDLM model with respect to PPG-BP Dataset

The results from **Fig 3** confirmed that the proposed deep learning model adopted for CVDs detection has performed well in terms of ROC curve which is plotted between false positive rate and the true positive rate.

Furthermore, **Fig 4** portrays the comparative investigation of the proposed HRBLDLM model, and the baseline ResNet, ResNet-LSTM, CNN-LSTM, CNN-LSTM-AM and GoogleNet deep learning models with respect to specificity, sensitivity, F1-Score and MCC. The results confirmed that the proposed HRBLDLM model is remarkable in determining the essential parameters that attribute towards better classification process. Thus the proposed HRBLDLM model on an average improved the F1-Score by 17.51%, better than the baseline deep learning architectures used for investigation.

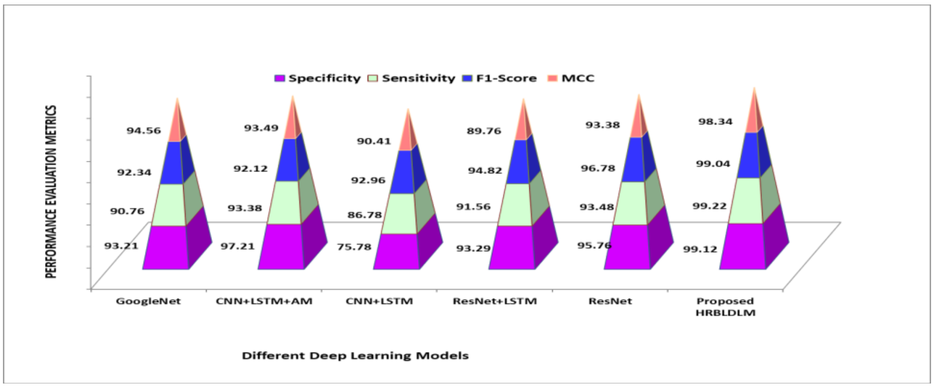

Fig 4. Comparative Investigation of the Proposed HRBLDLM Model and the Baseline Deep Learning Models Used for Evaluation

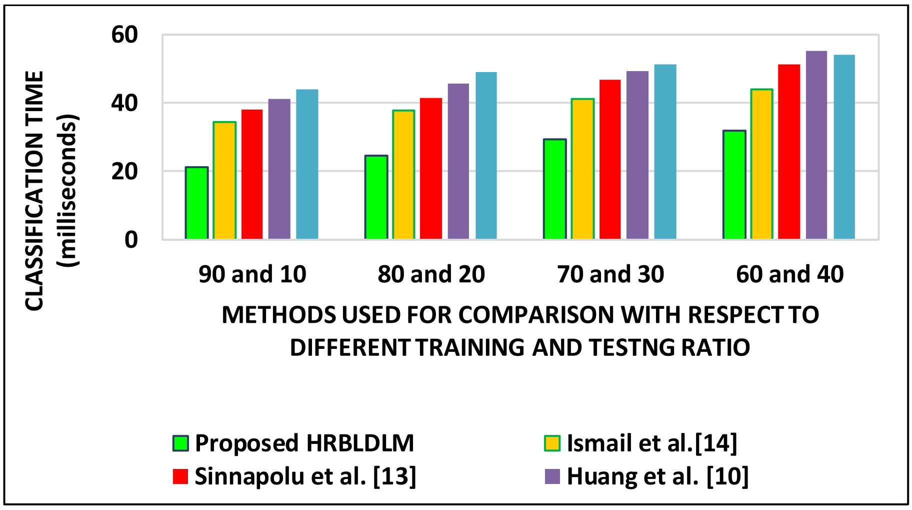

Fig 5. Comparative Investigation of the Proposed HRBLDLM Model and the Baseline Deep Learning Models Based On Classification Time

In addition, Figure 5 presents the results of the Comparative investigation of the proposed HRBLDLM model, and the baseline deep learning models conducted based on classification time. The results clearly proved that the proposed HRBLDLM model is excellent in attaining the processing of multi-class classification with reduced amount of time, since it was able to extract potential features from the PPG-BP dataset with maximized optimality. Thus the proposed HRBLDLM model on an average minimized the classification time by 18.42%, better than the baseline approaches used for investigation.

V. CONCLUSION

The proposed HRBLDLM model attained better detection of CVDs from PPG signals using the merits of ResNet and Bi-LSTM from PPG signals extracted from PPG-BP dataset. It classified the stages of CVDs into normal, pre-hypertension, stage 1 hypertension and stage 2 hypertension by exploring and exploiting the features that contribute towards diagnosis process. The experiments of the proposed HRBLDLM model conducted using PPG-BP dataset confirmed a better classification accuracy of 99.62% on par with the baseline PPG-based deep learning models used for investigation. The results confirmed that the proposed HRBLDLM model is predominant in attaining maximized precision, recall and F-measure of 98.21%, 99.16% and 97.86%, respectively independent to the number of features determined from PPG signals.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding was received to assist with the preparation of this manuscript.

Ethics Approval and Consent to Participate

The research has consent for Ethical Approval and Consent to participate.

Competing Interests

There are no competing interests.

References

[1]. M. F. Ihsan, S. Mandala, and M. Pramudyo, "Study of Feature Extraction Algorithms on Photoplethysmography (PPG) Signals to Detect Coronary Heart Disease," 2022 Int. Conf. Data Sci. Its Appl., pp. 300–304, 2022, doi: 10.1109/ICoDSA55874.2022.9862855.

[2]. S. Aziz, M. Awais, K. Iqtidar, and U. Qamar, "Classification of cardiac disorders using 1D local ternary patterns based on pulse plethysmograph signals," no. April 2020, pp. 1–5, 2021, doi: 10.1111/exsy.12664.

[3]. S. E. Kjeldsen, "Hypertension and cardiovascular risk: General aspects," Pharmacol. Res., vol. 129, pp. 95–99, 2018, doi: 10.1016/j.phrs.2017.11.003.

[4]. A. Alharbi, W. Alosaimi, R. Sahal, and H. Saleh, "Real-Time System Prediction for Heart Rate Using Deep Learning and Stream Processing Platforms," vol. 2021, 2021.

[5]. F. Schrumpf, P. Frenzel, C. Aust, G. Osterhoff, and M. Fuchs, "Assessment of deep learning based blood pressure prediction from PPG and RPPG signals," IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work., pp. 3815–3825, 2021, doi: 10.1109/CVPRW53098.2021.00423.

[6]. M. Nitzan, A. Patron, Z. Glik, and A. T. Weiss, "Automatic noninvasive measurement of systolic blood pressure using photoplethysmography.," Biomed. Eng. Online, vol. 8, p. 28, 2009, doi: 10.1186/1475-925X-8-28.

[7]. H. Elwahsh, E. El-shafeiy, S. Alanazi, and M. A. Tawfeek, "A new smart healthcare framework for real-time heart disease detection based on deep and machine learning," PeerJ Comput. Sci., vol. 7, pp. 1–34, 2021, doi: 10.7717/PEERJ-CS.646.

[8]. S. González, W. T. Hsieh, and T. P. C. Chen, "A benchmark for machine-learning based non-invasive blood pressure estimation using photoplethysmogram," Sci. data, vol. 10, no. 1, p. 149, 2023, doi: 10.1038/s41597-023-02020-6.

[9]. W. Ho, C. Liao, Y. J. Chen, K. Hwang, and Y. Tao, "Quickly Convert Photoplethysmography to Electrocardiogram Signals by a Banded Kernel Ensemble Learning Method for Heart Diseases Detection," IEEE Access, vol. 10, pp. 51079–51092, 2022, doi: 10.1109/ACCESS.2022.3173176.

[10]. P. P. G. Bio-signals, J. Yu, S. Park, S. Kwon, K. Cho, and H. Lee, "AI-Based Stroke Disease Prediction System Using," IEEE Access, vol. 10, pp. 43623–43638, 2022, doi: 10.1109/ACCESS.2022.3169284.

[11]. G. Georgieva-tsaneva and E. Gospodinova, "Cardiodiagnostics Based on Photoplethysmographic Signals," 2022.

[12]. E. Susana, K. Ramli, P. D. Purnamasari, and N. H. Apriantoro, "Non-Invasive Classification of Blood Glucose Level Based on Photoplethysmography Using Time–Frequency Analysis," Information, vol. 14, no. 3, p. 145, 2023, doi: 10.3390/info14030145.

[13]. L. Dall'Olio et al., "Prediction of vascular aging based on smartphone acquired PPG signals," Sci. Rep., vol. 10, no. 1, pp. 1–11, 2020, doi: 10.1038/s41598-020-76816-6.

[14]. N. Hydro, "Norsk Hydro: Successful placement of new sustainability linked bonds," Norsk Hydro, 23-Nov-2022. [Online]. Available: https://www.globenewswire.com/news-release/2022/11/23/2561741/0/en/Norsk-Hydro-Successful-placement-of-new-sustainability-linked-bonds.html. [Accessed: 09-Jun-2023].

[15]. H.A, A. R and S. M, "Smart Sensor Networking and Green Technologies in Urban Areas," Computing and Communication Systems in Urban Development, pp. 205–224, 2019. doi:10.1007/978-3-030-26013-2_10

[16]. B. Koteska, H. Mitrova, A. M. Bogdanova, and F. Lehocki, "Machine learning based SpO2 prediction from PPG signal's characteristics features," 2022 IEEE Int. Symp. Med. Meas. Appl. MeMeA 2022 - Conf. Proc., pp. 1–6, 2022, doi: 10.1109/MeMeA54994.2022.9856498.
[17]. T. Y. Abay and P. A. Kyriacou, "Photoplethysmography for blood volumes and oxygenation changes during intermittent vascular occlusions," J. Clin. Monit. Comput., vol. 32, no. 3, pp. 447–455, 2018, doi: 10.1007/s10877-017-0030-2.
[18]. P. Ashish, K. Rama, and K. Manjeet, "A Review on Computation Methods Used in Photoplethysmography Signal Analysis for Heart Rate Estimation," Arch. Comput. Methods Eng., vol. 29, no. 2, pp. 921–940, 2022, doi: 10.1007/s11831-021-09597-4.
[19]. E. Brophy, M. De Vos, G. Boylan, and T. Ward, "Estimation of Continuous Blood Pressure from PPG via a Federated Learning Approach," pp. 1–12, 2021.
[20]. B. Huang, W. Chen, C. Lin, C. Juang, and J. Wang, "Biomedical Signal Processing and Control MLP-BP : A novel framework for cuffless blood pressure measurement with PPG and ECG signals based on MLP-Mixer neural networks," Biomed. Signal Process. Control, vol. 73, no. December 2021, p. 103404, 2022, doi: 10.1016/j.bspc.2021.103404.
[21]. F. A. Putra, S. Mandala, and M. Pramudyo, "Study of Feature Selection Method to Detect Coronary Heart Disease (CHD) on Photoplethysmography (PPG) Signals," vol. 4, no. 2, pp. 1018–1026, 2022, doi: 10.47065/bits.v4i2.2259.
[22]. C. Regressor, S. Ismail, I. Siddiqi, and U. Akram, "Heart rate estimation in PPG signals using," Comput. Biol. Med., vol. 145, no. December 2021, p. 105470, 2022, doi: 10.1016/j.compbiomed.2022.105470.
[23]. A. S. Al Fahoum, A. O. Abu Al-Haija, and H. A. Alshraideh, "Identification of Coronary Artery Diseases Using Photoplethysmography Signals and Practical Feature Selection Process," Bioengineering, vol. 10, no. 2, 2023, doi: 10.3390/bioengineering10020249.
[24]. S. R. Sinnapolu, GiriBabu and Alawneh, Shadi and Dixon, "A Method to Compute Electrical Activity of the Heart: Prediction and Analysis of Heart Diseases Using Novel Comma-Z Classifier and Gpu Framework (August 2, 2022). Available at SSRN: https://ssrn.," https://ssrn.com/abstract=4179609, 2022.
[25]. C. J. Nichols et al., "Wearable Seismocardiography- - Based Heart Disease," vol. i, 2022, doi: 10.1161/JAHA.122.026067.