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BLOOD PRESSURE PREDICTION FROM PHOTOPLETHYSMOGRAM SIGNAL USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Blood pressure measurement in current medical practice relies on manual methods with the most widely used modality being sphygmomanometers. Utilizing the principle of Photoplethysmography, it is possible to provide an accurate reading of one's blood pressure through light signals and photodetector devices. This research paper introduces a new Artificial Intelligence driven approach to predict Blood pressure levels and classify them according to the updated ACC (American College of Cardiology) criteria as Normal, Elevated, Stage I, and II Hypertension from the given PPG signal values using Machine Learning Models. This research paper aims to accurately read the Systolic and Diastolic Blood Pressure using Artificial Intelligence, place them into the correct value bins and further prove that the blood pressure values differ based on different skin tones in different light wavelengths such as red, infrared, and green. Machine Learning models such as the Support Vector Machine have shown an accuracy of 70.58% for Systolic Blood Pressure and Decision Tree with an accuracy of 74.4% for Diastolic Blood Pressure classification. The models used in this research are Support Vector Machine, Decision Tree and K-Nearest Neighbor. This research study has future applications and extensions to predict blood pressure levels for patients with different skin tones under different light radiations and PPG signal readings. Neural Network models will be developed to compare the blood predictions from this work.

Keywords: Artificial Intelligence, Machine Learning, Blood Pressure, Hypertension, Photoplethysmography (PPG) Signal, Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Time Series data.

1. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular disease is the main chronic disease that causes around 32% of deaths worldwide [1] with hypertension being the highest medical risk factor as it currently affects 1.28 billion people [2]. According to the updated ACC guidelines in 2017 [1], Blood pressure categories are now classified as normal (<120/80 mm Hg), elevated (120-129/<80 mm Hg), stage 1 (130-139/80-89 mm Hg), stage 2 (>140/90 mm Hg) and finally, Hypertensive crisis (>180/>120 mm Hg). The three components of blood pressure- Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Mean Arterial Pressure (MAP) are essential to understanding the working apparatus of the heart [3]. The purpose of this work was to develop a deep-learning model to predict SBP and DBP directly from PPG signals from publically available dataset.

2. MATERIALS AND METHODS

This research process involves the use of a publically available dataset, its pre-processing, and the training of 3 machine learning models for the prediction of the blood pressure bins.

2.1 Dataset

The Pulse Transmit Time PPG dataset used for this research is from a publically available open-access database that contains recordings of 22 healthy subjects that have performed 3 physical

activities – run, walk, and sit- with over 40000 heartbeats [4]. This dataset also contains numeric values for systolic, and diastolic blood pressures and blood oxygenation saturation levels from which only systolic and diastolic blood pressure readings along with PPG signal values under red wavelength for the distal phalanx (first segment) of the left index finger are used to train and test machine learning models for the classification problem.
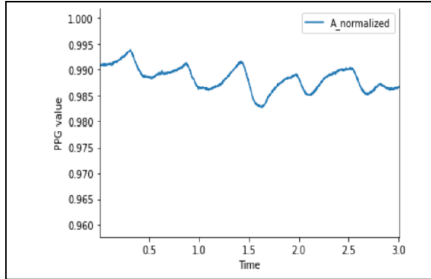

FIGURE 1: PPG SIGNAL WAVEFORM OF DATA

2.2 Data Pre-processing

The Blood pressure values are first divided into 4 bins and the dataset is accordingly divided as well based on the 4 blood pressure value ranges as shown in Table 1.

TABLE I.   BIN VALUES FOR SYSTOLIC AND DIASTOLIC BLOOD PRESSURE VALUES

Bin No.	Systolic BP Value (mmHg)	Diastolic BP Value (mmHg)
1	Normal: <120	Normal: <80
2	Prehypertension: 120 - 139	Prehypertension: 80 - 89
3	Stage I: 140 - 159	Stage I: 90-99
4	Stage II: >=160	Stage II: >=100

The final dataset comprised of blood pressure values of all the 22 subjects in ***red wavelength*** performing all the 3 activities. The pre-processing involved removal of missing values (NAN), and scaling(standardization) of the PPG signal values for effective learning of the machine learning models. The features selected for training these models are Weight, Height, Age along with Activity, and Gender which were One Hot encoded together with other features which resulted in a total of *242134* feature columns. These features were selected as a baseline for initial analysis.

2.3 Machine Learning Models

This is a classic Multiclass classification problem where the goal is to use the time series PPG signal value of each subject for each activity to classify into the defined four bins of Systolic and Diastolic blood pressures. The entire dataset is divided into training and testing data with 75% for training and 25% for testing the model. Three machine learning models- Support Vector Machine (SVM), Decision Tree, and K-Nearest Neighbor (KNN) - are trained and tested using this data where the Bin is the target column to be classified into.

3. RESULTS AND DISCUSSION

The 3 machine learning models are evaluated on the prediction of the test data based on the accuracy metric. The following Table 2 shows the accuracy score for each of these three machine learning models based on their prediction of the 25% test data.

TABLE II. MACHINE LEARNING MODEL ACCURACIES

	Support Vector Machine	Decision Tree	K-Nearest Neighbor
Diastolic	65%	74.47%	64.7%
Systolic	70.58%	64.7%	52.9%

4. CONCLUSION

This research paper provides evidence and a baseline for use of Artificial Intelligence in the prediction of Blood Pressure using Photoplethysmogram signal values under different light wavelengths. This research paper is a proof that Artificial Intelligence, when trained with enough data can be used for the automatic prediction of Blood Pressure values based on PPG waveforms and signal data that has immense clinical utility.

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