Blood pressure class estimation using CNN-GRU model

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***Abstract*—Blood pressure (BP) estimation can add on great value in emergency medicine, especially in case of mass casualty situations. The presented research aims to create a model for BP class estimation using electrocardiogram (ECG) and photoplethysmogram (PPG) waveforms. We focus on developing a BP classification model as a convolutional neural network (CNN) - gated recurrent unit (GRU) hybrid model, containing both CNN and GRU layers. The used dataset is the publicly available UCI Machine Learning Repository dataset. We have achieved f1 score of 0.83, 0.73 and 0.74 respectively according to the BP classes and 78% overall accuracy.**

Keywords*—*blood pressure (BP) estimation, triage, electrocardiogram (ECG), photoplethysmogram (PPG),gated recurrent unit (GRU), artificial neural network, deep learning, CNN-GRU hybrid model

I. Introduction

Blood pressure (BP) is an important metric to determine a patient's hemodynamic stability. While primary triage (ex. START) does not include blood pressure in the decision making process, this metric is important in the secondary triage. Blood pressure is usually measured noninvasively by using a cuff-based measuring device or invasively, in a specialized hospital setting. Using the first method (cuff-based), the values are obtained on demand or in regular intervals thus are non-continuous. The second method requires specific conditions, equipment and highly-trained staff. Furthermore in case of mass casualty event it may not be possible to repeatedly measure blood pressure with both of the methods.

The goal of our research is to estimate BP in real-time given the embedded electrocardiogram (ECG) and photoplethysmogram (PPG) signals' values. ECG represents the electrical activity of the heart, while PPG shows the changes of blood volume in the microvascular tissue. The ECG and PPG values will be obtained by using patch-like combined multi-sensor attached to a human's chest. Both of them are low cost sensors that can be used as integrated sensors on a patch. The sensors will obtains basic signals and vital parameters necessary for triage process [1]. The correlation among BP, ECG and PPG has been researched in other studies [2] [3] [4] [5].

The ECG and PPG signals are given in a time series. Recurrent neural networks are a type of neural networks that specialize in processing sequential information that are specifically built to be able to follow long term dependencies. This type of network are typically slow and difficult to train. Because of the nature of the problem the classification needs to be continuous. To further increase the efficiency of the model it's combined with a CNN layer which essentially performs feature selection. The model our paper proposes is a CNN-GRU neural network.

The rest of the paper is organized as follows. Section 2 presents an overview on similar papers or related researches. The methodology is described in Section 3. The results of the experiments and the discussion are presented in Section 4, including the introduction of the dataset, the preprocessing part and the used methods. Section 5 presents the conclusion.

II. Related Work

In this section, an exploratory analysis of related work is done. Estimation of blood pressure from ECG and PPG is a theme that has vastly been researched. There are mainly two approaches used in similar papers: the first one is extracting relevant features from the signals and the other one is building neural networks that can process raw signals. In this paper it's opted to go with the second approach because of lack of assurance that the PPG and ECG signals in this dataset have been recorded in sync.

The most commonly used features with the highest information gain are pulse transit time (PTT) and pulse arrival time (PAT). PTT is more prominent in recent work. The features are similar, however a study done on this topic shows that PAT is not unable to detect subtle BP changes as well as PTT [6]. PTT forms the basis for continuous BP estimation in many works [4] [7]. Often time the features are combined with others in an attempt to get better results. One such features is photoplethysmogram intensity ratio (PIR), a measure for the arterial diameter change [8]. The strong correlation between the ratio and BP is explored in a different study that also states that patient with hypertension have a higher mean PIR with higher variance for this value [9]. Another study performs a complexity analysis to extract features from ECG. The machine learning model of that study achieves mean absolute error (MAE) of 8.64 mmHg for SBP, 18.20 mmHg for DBP, and 13.52 mmHg for MAP [10]. These results are further improved with model calibration. The features are not always limited to what can be extracted from the PPG and/or ECG signal. For example a study focusing on features extracted from PPG and combining them with demographic characteristics achieves root mean square error (RMSE) of 6.74 mmHg for SBP and 3.59 mmHg for DBP.

The bio signals that a body emits are depended on many factors such as: medications, circulatory system diseases and interaction between the different physiological systems. This contributes to patient-specific morphological contours for the signals. This is the main problem with using the approach with feature extraction. Other studies focus on building model capable of estimating blood pressure from raw signals. One such study's proposed solution is a hierarchical ANN-LSTM neural networks, where the lower level extract the features and the higher ones track time distributed dependencies. The proposed network's results are RMSE of 1.56 mmHg for SBP and 0.85 mmHg for DBP [11]. A hybrid CNN-LSTM network that works with a similar approach with the previously mentioned one achieves MAE of 4.43 ± 6.09 mmHg for SBP and 3.23 ± 4.75 mmHg for DBP [12]. A study attempts to predict the blood pressure in hemodialysis patients using a CNN-GRU neural network [13]. Another study attempts to utilize the difference between PPG and ECG to feed to a neural network with a CNN-LSTM architecture [14]. This difference is used to calculate PAT and it allows the network to learn PAT information.

III. Materials and Methods

In this section we describe the dataset, data preprocessing procedures, the developed CNN-GRU model and the used evaluation metrics.

A. Dataset

Most of BP studies utilise the MIMIC database or some subset of it. However because of a current memory storage constraints, in this study the "Cuff-Less Blood Pressure Estimation Data Set" published in the UCI Machine Learning Repository [15] is used. This dataset is consisted of 12000 instances, each having three recorded signals of variable length. The signals correspond to PPG, ABP, and ECG recorded with a 125 Hz frequency. There is no other information in the dataset, nor patient identifiers, so it's impossible to identify whether two separate instance are signals from the same patient.

1) PPG: Photoplethysmograph, PPG, measures the blood volume changes in microvascular tissue by detecting changes of light absorption on the skin. It's a technology that has gotten prominence in the medical field in recent years because of it's low-cost and it's usability in understanding the cardiovascular system [3].

2) ABP: Arterial blood pressure, ABP is a waveform representing blood pressure measured from within an artery. Measurements of this kind can only be taken in a hospital setting. Blood pressure is the pressure created in the blood vessels of a cardiovascular system as the heart pumps the blood. The positive peaks of the waveform represent the moment when the heart contracts and the blood pressure is at it's highest and the negative peaks represent the moment when the heart relaxes after a contraction and the blood pressure is at it's lowest. The blood pressure in these moments are known as the systolic blood pressure, SBP, and dyastolic blood pressure, DBP.

3) ECG: The heart plays a vital role in the circulation of blood. Electrocardiogram, ECG, measure the electrical activity of the heart. While it's measured no electricity is send to the body. It only tracks the polarization wave caused by the heart as it beats. The ECG in this study is a 1-channel one. With each beat an electrical impulses coordinate the heart's contraction. An ECG simply records these impulses as they move through different parts of the heart.

On Figure 1 a 8 second electrocardiogram is visualized and the peaks characteristic to ECG are marked.

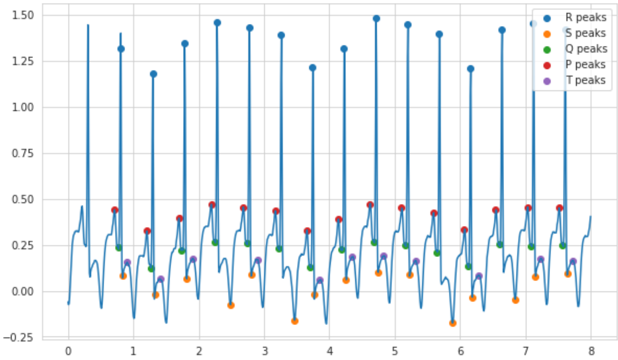

Fig. 1. 8s ECG waveform with annotated peaks

B. Preprocessing

1) Data Validation: The data is validated according to the two following criteria: 1. There aren't missing values in any of the three signals, PPG, ABP and ECG; 2. The pulse pressure is above 20 and less than 80. No data instance is taken into consideration when building the models if both of the criteria weren't met.

The average pulse pressure, i.e. the difference between SBP and DBP is between 40 and 60. Too low pulse pressure indicates poor heart function, while too high pulse pressure indicates a health problem. Valid data are considered to be in the range (20 , 80). It is also worth noting that the signal quality is mediocre. The values calculated from signals with extremely low or high pulse pressure may be a result of a sensor noise. This problem can be remedied with a larger dataset of higher quality signals in future work.

2) Data Segmentation: The signals per patient in the dataset are with variable length, within the range [1000, 74000] data points. The signals are recorded with frequency of 125 Hz, concluding that the shortest signal length in the dataset is 8 seconds and the longest - 9.9 minutes long.

Different studies suggest and work with segments of different length, usually within the range of 5-30 seconds [10] [12]. In this study it is decided to use 8 seconds (8s) segment length. This decision was influenced by the aforementioned fact that the shortest signal has a length of 8 seconds and if we were to work with longer signal per instance, we would have had to exclude the shorter signals, reducing the already small datase. To further increase the number of samples, multiple segments are taken from the longer signals. The segments are taken sequentially with no overlap. The decision to use this type of segmentation was influenced by a similar study [16], where the same approach was used. It should be noted that by taking multiple samples from the same patient we introduce bias due to the patients specific morphological contours. However this approach was deemed as necessary since this dataset is quite limited.

3) Normalization: The PPG and ECG signals are normalized by scaling the values into decimals between 0 and 1, with 0 being the minimum value of the signal and 1 being the maximum. Normalizing the data before training the models is a common practice and generally leads to better convergence in machine and deep learning models.

4) Filtering: Noise is a common problem with sensors. It can appear in a signal for a variety of reasons such as - noise caused by the electrical activity of the muscles, breathing, loss of contact with the skin, etc. Often, the noise has the same frequency as the signal and thus it's difficult to completely remove it without distorting the signal.

Filtering is the process of removing unwanted component from the signal. For the filtering of biological signals the most commonly used filters are notch and bandwidth filters. The decision to use this type of filters was made based on the results presented in previous works in this field which show that bandwidth filters are suitable for both PPG and ECG [11].

However, the PPG is filtered by a filter of the fourth order and the ECG by a filter of the fifth order.

5) BP categorization: For the purposes of this study it's necessary to transform the ABP waveform into 2 scalars, SBP and DBP, used for the blood pressure categorisation. To avoid possible outliers it's decided that instead of taking the min and max value in the segment, it's better to calculate the average of the local extremes, maxima for SBP and minima for DBP [17].

An illustration of the extraction process is presented on Figure 2.

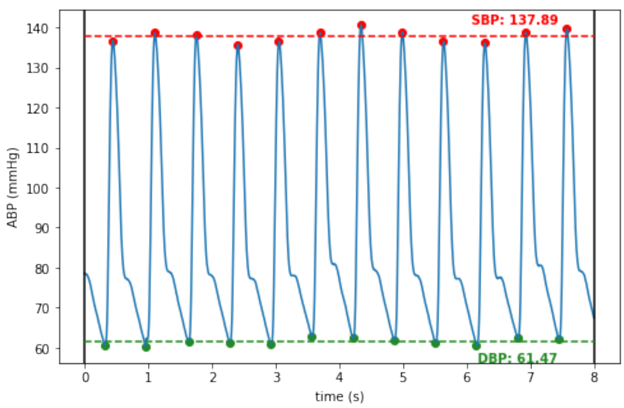

Fig. 2. Illustration of SBP and DBP extraction from ABP waveform

The European Society of Hypertension and the American College of Cardiology have different classifications schemes for blood pressure categorization. In this study it's decide to use the latter. Following the scheme there are four blood pressure: normal, elevated, stage 1 hypertension and stage 2 hypertension [18]. Since the dataset is small and the hypertension classes are under represented, it is decided to merge them into a single class. The elevated blood pressure class in this study is referred to as prehypertension. In Table I can be seen the conditions for division and the number of samples per class.

As shown in Table I, there is a class imbalance in the dataset used in this study. The results of models trained on an imbalanced dataset often favor the more common classes. Many solutions have been developed to counteract this problem. The most common and widely used are oversampling of the minority classes and undersampling of the majority classes. The most popular type of oversampling, SMOTE is not applicable to this problem, since the input vectors are time distributed sequences. Undersampling methods were also considered. These methods are useful in some specific cases, but usually achieve lower classification performance because the loss of data negatively impacts the models ability to learn. A problem with their adaptation for he purpose in this research, is the problem of measuring the similarity between two signals. There is a undersampling method that removes samples at random, however this method is unlikely to yield good results because of the above mentioned problem.

TABLE I
BLOOD PRESSURE CATEGORIZATION

Category	SBP	DBP	Number of Samples
Normal	< 120	< 80	118644
Prehypertension	$120 - 139$	$80 - 89$	102927
Hypertension	≥ 140	≥ 90	49948

A simple solution of the problem of dealing with an imbalanced dataset is the method of assigning weight to the classes. The weights are assigned so that the training samples of the majority classes have a lesser impact and the minority classes have greater impact while training. The less represented a class is, the higher weight value is appointed and vice versa. The formula used to calculate the weights is $weight\_class\_i = \frac{total\_num\_samples}{num\_classes*num\_samples\_i}$. The calculated weights for the classes are: 0.76 for Normal, 0.88 for Prehypertension and 1.81 for Hypertension.

C. Model Structure

Recurrent Neural Network (RNN) is a type of neural networks designed to be able to follow temporal dependencies through temporal sequence. A main problem with these networks is the vanishing gradient problem. The gradient disappears or explodes after a few timesteps, thus preventing learning long term dependencies. To overcome this problem several solutions have been developed. The most popular one is the Long Short Term Memory, LSTM. The cells in a LSTM layer have a internal state and the flow of data is strictly controlled through the use of three gates: input gate, output gate, and forget gate. Gated recurrent units, GRU are recurrent network layers that are similar to LSTM, however they have fewer parameters and lack a forget gate. Even with this simplification they perform comparably on a variety of problems [19]. The gates in a GRU cell are called an update gate and a reset gate. They control the flow of data. A GRU cell has the capacity to keep information in the form of a cell state for a long time without overwriting it.

A simple way to improve a recurrent neural networks is the use of bidirectional layers. A bidirectional layer is made up of two different layers linked to the same output layer. The time-distributed sequence the network is processing is passed once forwards and once backwards. By passing the sequence backwards, the network attempts to use future context to explain the present by looking at the previous data points. The same is true for GRU layers. Networks that utilize bidirectional layers are more computationally expensive than networks of the same size that utilize only single directional recurrent layers [20].

Convolutional neural network, CNN, is a type of neural network that uses the mathematical concept of convolution, an operation on two functions that produces another function. It's a popular network that's most often used in problems involving computer vision and picture analysis. It should be noted that ability to extract patterns from data also makes applicable for solving other types of problems than those mentioned above such as processing natural languages, recommending systems, brain-computer interfaces and any other where patterns can be found.

The input vector consist of 2000 real numbers and it enters the network in the format (100, 10, 2), where the values correspond to (length of subsequences, number of timesteps, number of features). There are 2 features: PPG and ECG. The size of the subsequences and the size of the timesteps are inversely proportional. If the subsequences are too small the CNN won't be able to find patterns in them, while if there are too few timesteps the ability to track longterm dependencies granted by the GRU won't be fully utilized. Keeping that in mind it's empirically decided on previously mentioned values.

We use a multivariate CNN-GRU architecture. A CNN-GRU is a hybrid neural network that contains both CNN and GRU layers. The first layer is a time distributed 1d convolutional layer that receives the input vector. This layer processes the subsequences attempting to find usable features. Convolutional layers are typically followed by max pooling ones, such is the case in our model. Max pooling layers perform downsampling of the inputs from the previous layer retaining only the most salient features. A batch normalization layer normalizes the inputs and stabilizes the learning process. After this step, the data is passed to a bidirectional GRU layer. This layer attempts to follow the temporal dependencies of the features generated by the convolution layer. The network ends with a dense layer with three neurons, one for each class, with a Softmax activation. In the proposed model, each of the classes (Normal, Prehypertension, Hypertension) is represented as 0, 1, 2, respectively.

The model is somewhat similar to CNN-LSTM models given in related work, with the main difference being that most of those models are geared to solving regression, while ours works with classification, as well as the use of a GRU instead of an LSTM layer. The goal of this study is to aid in the development of a lightweight algorithm for blood pressure category classification. Since GRU layers are simpler and therefore faster yet comparable to LSTM, they are used as a part in this architecture.

D. Evaluation Metrics

In this section, the metrics that evaluate the performance of this model are explained. This model attempts to classify the category of blood pressure, hence the classification evaluation metrics are used:

1) Accuracy is the ratio of correctly predicted samples against the total number of samples;
2) Precision is the ratio of the number of correctly classified samples and the total number of samples classified as such;
3) Recall is the ratio of the number of correctly classified samples and the total number of samples of that class regardless of whether they where accurately classified;
4) F1 score is the harmonic mean of precision and recall.

After the aforementioned metrics were calculated, averaging schemes were used obtaining a single performance value. The schemes used in this paper are:

1) Macro average is a schema often used for multi-class classification that first calculates the above mentioned metrics independently and averages their results;
2) Weighted average is a schema that averages the other metrics by assigning them weight with regard to their class representation. The less represented a classes is in the testing dataset the higher its weight.

The support is just the number of testing samples for each class from which the other metrics are calculated. The metrics are presented via a classification report from the sklearn python package.

IV. Results and Discussion

In this section, the achieved results are presented and discussed. The proposed model has a CNN-GRU architecture that predicts the BP category using ECG and PPG signals.

A. Model Training

The dataset is split into training and testing sets with a ratio of 85:15. A further 10% from the training set is designated for a validation dataset. By using a keras tuner, it is concluded that ADAM optimizer with a learning rate of 0.001 is suitable for this specific problem. The most successful model structure so far was trained with a batch size of 512 for 22 epochs.

B. Model Evaluation

In Figure 3 a classification report of the model's performance is shown. The testing dataset has 40728 samples divided in three categories - 17673 as normal BP, 15466 have prehypertension and 7589 have hypertension. The model has overall accuracy of 0.78. The most distingushable class for the model is the normal class. It has a precision of 88%. The prehypretension class has the lowest f1-score, that leads us to a conclusion that the model struggles to learn the class boundaries between the normal and the prehypretension class, and the prehypretension and the hypretension class.

	precision	recall	f1-score	support
0	0.88	0.79	0.83	17673
1	0.72	0.75	0.73	15466
2	0.69	0.81	0.74	7589
accuracy			0.78	40728
macro avg	0.76	0.78	0.77	40728
weighted avg	0.78	0.78	0.78	40728

Fig. 3. Classification report

In Figure 4 the training and validation accuracy per epoch are shown and in Figure 5 the training and validation loss per epoch are shown.

C. Discussion

The proposed model obtains overall accuracy of 78%, which is higher than our previous best results with different LSTM models. While there is an improvement, the model would still require further development in order to be applicable.

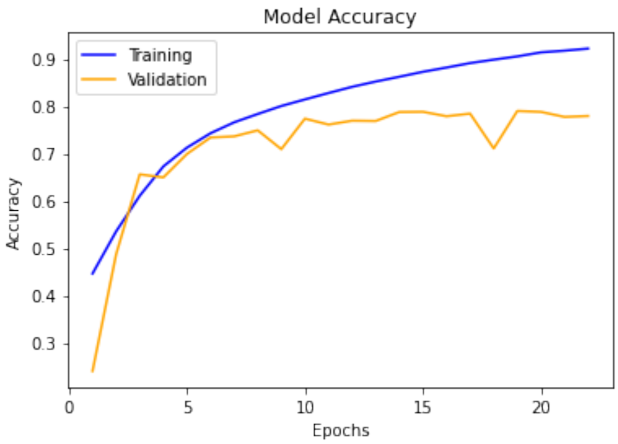

Fig. 4. Results - Training and validation accuracy

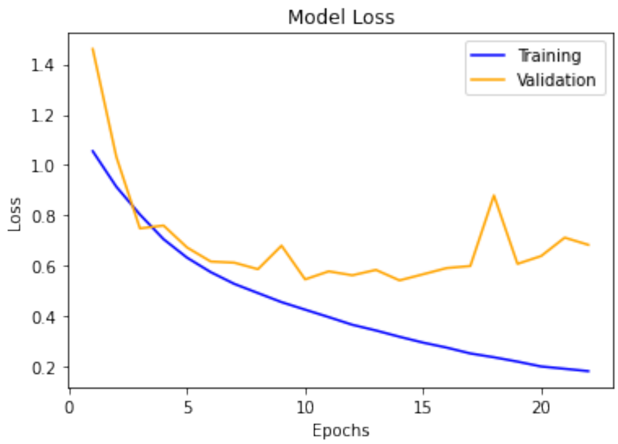

Fig. 5. Training and validation loss

Most of the studies listed in related work utilize regression models. Thus making direct comparison with our classification model impossible. It should also be taken in to account that the results the model achieves are somewhat influenced by the bias introduces during the segmentation phase. In future work a larger dataset will be used to reduce the bias and enhance the development of a generalized algorithm for blood pressure classification, as well as extending the model's pulse pressure limits to include abnormal cases.

One important aspect that is not considered in the current model are the demographic characteristics, since the information gain from these characteristics is significant. Arteries stiffen with age and as a result the blood pressure needed to deliver the blood rises, meaning older people have on average higher blood pressure.

Other aspect that may impact the model is the short segment size (8 sec). Our further research will focus on both of these aspects. The results show that the proposed model can distinguish between the different categories. This is important trait, since they indicate that using a larger dataset can improve the results. Hence we assume that using an much larger dataset from different sources will help to overcome the pointed aspects.

V. Conclusion

Our research is focused on blood pressure category estimation, given ECG and PPG signals. The idea is to use the embedded sensors placed on a patch in order to obtain the aforementioned signals, and using a tablet or a remote server to utilise our developed model. The whole system should be used in emergency and mass casualty situations. In these situations it is not practical to measure BP values manually with cuff-based devices for each subject in order to estimate the subject's hemodynamic state in conjunction with the other vital parameters obtained by the sensor. Other important aspect is that BP varies and thus the BP measurement should be continuous to enhance the second triage process. Given large number of subjects in situations with high number of casualties, it would not be possible to regularly manually measure BP and effectively trace changes in subject's health state. Hence BP category estimation can be an important future in the triage process and increase the survival rate.

In this paper we propose building and training of CNN-GRU model. The input form the model are sequences of ECG and PPG signals and output is the BP category. An important aspect is the preprocessing stage, given that we have raw signals. We normalize and filter the ECG and PPG signals from the dataset we use. Since the dataset contains ABP signals, we extract SBP and DBP from these signals. The model learns by adjusting its weights.

For imminent future work we plan on refining our model using much larger dataset, as MIMIC III, and including other futures and characteristics. Later we also plan to work on refining of the results by developing regression models for BP estimation with deep learning approach, using Big Data for selection of different features from the ECG and PPG signals.

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