Blood pressure classification using CNN-LSTM model

Ivan Kuzmanov[1], Anastasija Vasilevska[1], Ana Madevska Bogdanova[1], Nevena Ackovska[1], Magdalena Kostoska[1], and Fedor Lehocki[2]

[1] University Ss. Cyril and Methodius,
Faculty of Computer Science and Engineering,
Rugjer Boskovikj 16, 1000 Skopje, N. Macedonia
[2] Institute of Measurement Science,
Slovak Academy of Sciences and Faculty of Informatics and Information Technologies,
STU, Slovakia
`{ivan.kuzmanov,anastasija.vasilevska}@students.finki.ukim.mk`
`{ana.madevska.bogdanova,magdalena.kostoska,nevena.ackovska}@finki.ukim.mk`
`fedor.lehocki@stuba.sk`

Abstract. Blood pressure (BP) estimation can aid the triage process and help prioritizing and helping injured, especially in a situation of multiple casualties. 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 (LSTM) hybrid model, containing both CNN and LSTM layers. The used dataset is the publicly available UCI Machine Learning Repository dataset. We have achieved stable AUCROC for each class - 0.89, 0.83, and 0.89 respectively and overall accuracy of 83%.

Keywords: electrocardiogram · photoplethysmogram · blood pressure estimation · triage · LSTM · artificial neural network · deep learning · CNN-LSTM hybrid model.

1 Introduction

The humankind faces threats from all sorts of agents: viruses, natural disasters etc. Not only the COVID-19 pandemic, but also many terrorist threats, wars, hurricanes, earthquakes, droughts in the last decade have made huge impact in nearly all aspects of human lives. This created pressure for finding new effective solutions for use in healthcare, especially among the first responders, personalized therapies, medicament distribution, as well as in the economy, transportation, education, culture, and many other aspects of our lives. Many solutions are offered to assist all of these domains in the new era, shaping the new normal. Among the solutions that are getting a lot of attention are the affordable solutions for the first responders on sites where many victims appear - mass disasters or war conflicts with many casualties. In those situations the first responders need to have effective systems to easily recognize the severity of the person's injuries.

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, in order to follow the health status of the injured, whether internal bleeding has occurred. 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 the BP in real-time given the embedded electrocardiogram (ECG) and photoplethysmogram (PPG) signals' values. ECG signals represent the electrical activity of the heart, while PPG manifests 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 signals are given in a time series. The patch-like sensor will obtain basic signals and vital parameters necessary for triage process [14]. The correlation among BP, ECG and PPG has been researched in other studies [15] [9] [5] [18].

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 networks are typically slow and difficult to train. Because of the problem's nature, the classification needs to be a continuous process. 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-LSTM neural network.

The rest of the paper is organized as follows. In section 2 is presented an overview on similar papers or related researches. Section 3 describes the used methodology. 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. The conclusion is presented in Section 5.

2 Related Work

Noninvasive and continuous blood pressure monitoring is a popular research subject because of the prevalence of hypertension and recent wide availability of low cost sensors. The correlation among blood pressure, ECG and PPG has been explored in other works. Most of the studies follow the standards outlined by The Association for the Advancement of Medical Instrumentation (AAMI) and British Hypertension Society (BHS) [12].

The most common method of cuffless blood pressure estimation is by using some manually extracted features from the raw signals such as pulse wave velocity (PWV), pulse transit time (PTT) and pulse arrival time (PAT). PWV is a measure of arterial stiffness and is estimated from PTT since pulse transit time is an indirect indicator of blood pressure. It is the time interval required for the heartbeat to reach the periphery of the body. ECG represents the electrical activity of the heart, while PPG is often measured by oscillometer attached on the fingertip and it shows the changes of blood volume measured in the microvascular tissue. PAT is a feature that is simpler to measure, however it isn't an adequate substitute for PTT [22]. These features are typically accompanied by others depending on the type of the study. Some focus on the signals complexity [19] based on the theory that loss of complexity is a sign of an abnormality. Another useful feature is pulse intensity ratio (PIR) [6]. This feature estimates the arterial diameter and its correlation with blood pressure has been shown [3].

While the dependency between the above-mentioned features and blood pressure has been proven in numerous studies [7][18], one of the main challenges of blood pressure estimation are the patient specific morphological contours. These differences are a result of the patient specific characteristics that influence their cardiovascular systems, which are caused by diseases, medication, lifestyle, interaction with other systems etc. Calibration could be used to attempt to overcome this problem, however this is not always possible, since frequent calibration would be necessary to allow for continuous and long-term estimations [12].

Some studies suggest a deep learning approach where typically the lower layers of the deep learning models are used for feature extraction. This study [20] uses an ANN-LSTM type of model and achieves MAE of 1.10 mmHg for SBP and 0.58 mmHg for DBP and RMSE of 1.56 mmHg for SBP and 0.85 mmHg. These approaches are more computationally expensive. However, they are free of the human bias that can happen during manual feature extraction. The features with the most information gain, PTT and PAT, can be found in the differences between the ECG and PPG signals. There is a study that focuses on this aspect and uses the difference in the signals as an input in a CNN-LSTM neural network. This study [10] achieves the predictive accuracies of 0.0 ± 1.6 mmHg and 0.2 ± 1.3 mmHg for SBP and DBP, respectively. It should be noted that this attempt requires synchronisation of the signals [16].

Another study [17] similar to ours in the sense that it focuses on classification, achieves f1 scores for normotension versus prehypertension of 84.34%, the scores for normotension versus hypertension of 94.84%, and the scores for normotension plus prehypertension versus hypertension of 88.49%. The best results of the study were achieved with the dataset containing both PAT and PPG features in addition to the features extracted by the ECG.

3 Materials and Methods

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

3.1 Dataset

In this study we use the "Cuff-Less Blood Pressure Estimation Data Set", published in the UCI Machine Learning Repository [11]. This dataset consists 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.

Important characteristics For the purpose of our research, several important signals and measurements are used. We shortly give their description here.

Photoplethysmograph, PPG, measures the blood volume changes in microvascular tissue by detecting changes of light absorption on the skin. It's a low-cost technology that has gotten prominence in the medical field in recent years because of its usability in understanding the cardiovascular system [9]. Visualisation of a PPG is given in Figure 1.

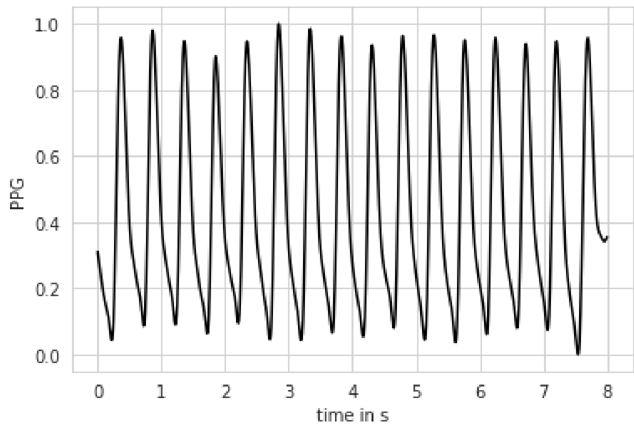

Fig. 1. Visualization of a PPG waveform

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 its highest and the negative peaks represent the moment when the heart relaxes after a contraction and the blood pressure is at its lowest. The blood pressure in these moments are known as the systolic blood pressure, SBP, and dyastolic blood pressure, DBP. Visualisation of an ABP waveform is shown in Figure 2.

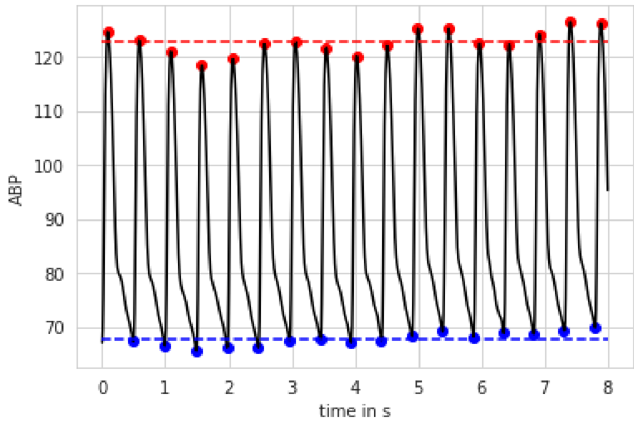

Fig. 2. Visualization of an ABP waveform

Electrocardiogram, ECG, measures the heart's electrical activity, nevertheless no electricity is sent 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, the electrical impulses coordinate the heart's contraction. An ECG simply records these impulses as they move through different parts of the heart. Visualisation of an 8 second electrocardiogram is presented in Figure 3.

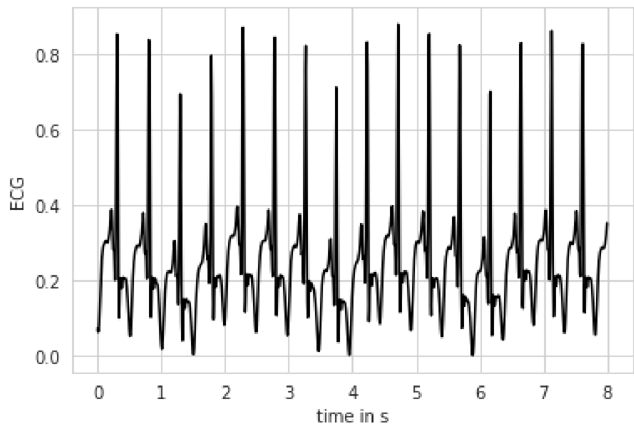

Fig. 3. Visualization of an ECG waveform

3.2 Preprocessing

Signal Selection The used dataset contains signals with varying quality. The decision whether an ABP signal is usable is made by the following criteria: if the difference between the SBP and DBP, the pulse pressure, is larger than twenty and less than eighty units, than the signal is valid. We recognize that this limits the model building process. However, we believe it's necessary because of sustaining the signal quality. Abnormal values may be caused by sensor malfunction.

The consistency of the ECG and PPG signals is checked by calculating the beat-to-beat interval ratio and the peak ratio. If any of these values are larger than 1.5, the signal is invalid.

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 [21][19]. 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 dataset. Multiple segments are taken from the longer signals to further increase the number of samples. The segments are taken sequentially with no overlap. The decision to use this type of segmentation was influenced by a similar study[2], 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.

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 the machine and deep learning models.

Filtering Noise is a common problem with a sensor utilization. It can appear within a signal for a variety of reasons - 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 components from the signal. For the filtering of biological signals the most commonly used filters are notch and bandwidth filters. The decision to use these 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[20]. However, the PPG is filtered by a filter of the fourth order and the ECG by a filter of the fifth order.

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. In order to avoid possible outliers, it is 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[1].

The European Society of Hypertension and the American College of Cardiology have different classifications schemes for blood pressure categorization. In this study the second (ACC) scheme is used. Following the scheme there are four blood pressure categories: Normal, Elevated, Stage 1 hypertension and Stage 2 hypertension [4]. Since the dataset is small and the Hypertension classes are underrepresented, it is decided to merge them into a single class, since it does not interfere with the second triage process in the emergency situations. The elevated blood pressure class in this study is referred to as Prehypertension. In Table 1 the conditions for division per class are shown, as well as, the number of samples per class.

Table 1. Blood Pressure Categorization

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

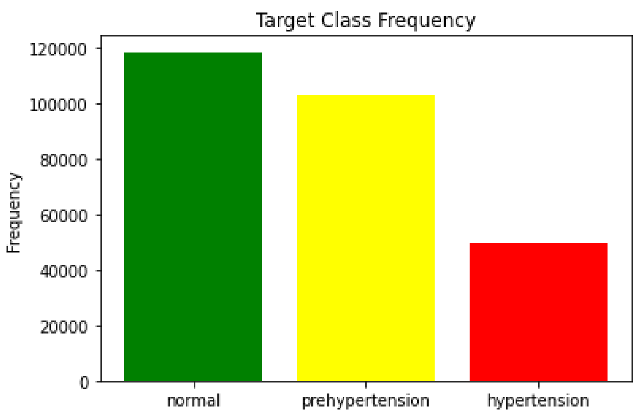

Fig. 4. Class imbalance

As shown in Figure 4, there is a class imbalance in the used dataset. 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 dependant 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 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 given in (1).

$$weight\_class\_i = \frac{total\_num\_samples}{num\_classes * num\_samples\_i} \tag{1}$$

The calculated weights for the classes are: 0.75 for Normal, 0.87 for Prehypertension and 1.93 for Hypertension.

3.3 Model Structure

Recurrent Neural Network (RNN) is a type of a neural network 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. The cells are capable to recall values over arbitrary interval of time.

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.

The input vector for the model is in the format (100, 10, 2) where the values are length of subsequences, number of timesteps and number of features, respectively. The features used are PPG and ECG. The model has around 450,000 trainable parameters.

For the model architecture, we use a multivariate sequential CNN-LSTM architecture. It is a hybrid neural network that contains CNN layers as well as LSTM layers. The first two layers of the model are time-distributed 1D convolutional layers, each with a convolution kernel of size 5 and a rectified linear (ReLU) activation function. The convolutional layers are then followed by a max pooling layer with a pool size of 2. The max pooling layer performs downsampling of the outputs of the previous layer, keeping only the features with the maximum value. After the max pooling layer we have a time-distributed flatten layer, which flattens the data making it suitable for the inputs of the LSTM layers. The next layer is a batch normalization layer that normalizes the outputs of the previous layer, significantly reducing the number of training epochs required to train the model. The batch normalization layer is then followed by 3 LSTM layers each with 128 neurons. Each of the LSTM layers attempts to learn the long-term dependencies of the features generated by the outputs of the previous layers. Between the LSTM layers there's also dropout layers with a rate of 0.2, used to help prevent overfitting. The model architecture ends with two dense layers, separated by one more dropout layer. The first dense layer has 128 neurons and ReLU as the activation function, while the second one has 3 neurons with the softmax activation function. Each of the 3 neurons in the last layer represent one of the classes of the model: Normal (0), Prehypertension (1) and Hypertension (2). The best results for the model were obtained when using the Adam optimizer with a learning rate: 0.0005 and decay 0.000001.

A generalised image of the described model is presented in Figure 5. We depict only the top view, obscuring the pooling, batch normalization and dropout layers for simplicity.

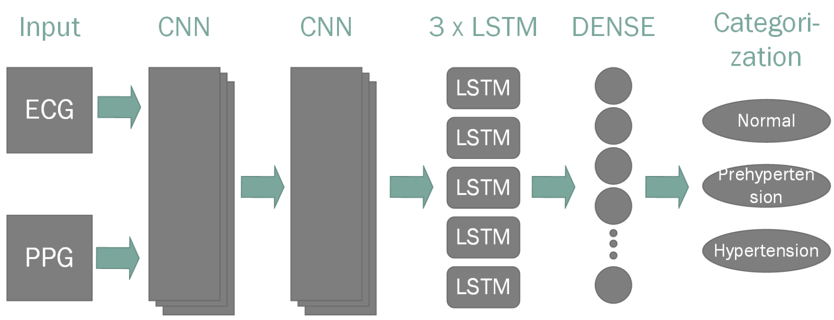

Fig. 5. Simplified overview of the developed CNN-LSTM model architecture

3.4 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 samples number 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.

4 Results and Discussion

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

4.1 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 0.0005 and decay of1e-6 is suitable for this specific problem.

4.2 Model Evaluation

In Figure 6 a classification report of the model's performance is shown. The testing dataset has 18966 samples divided in three categories - 8564 as Normal BP, 7161 have Prehypertension and 3241 have Hypertension. The model has overall accuracy of 0.83. 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. The evaluation metric values are calculated from the confusion matrix generated by the model, as shown in Figure 7.

The AUCROC for each class are 0.89, 0.83, and 0.89 respectively.

	precision	recall	f1-score	support
0	0.88	0.88	0.88	8564
1	0.80	0.78	0.79	7161
2	0.78	0.83	0.81	3241
accuracy			0.83	18966
macro avg	0.82	0.83	0.83	18966
weighted avg	0.83	0.83	0.83	18966

Fig. 6. Classification report for the developed model

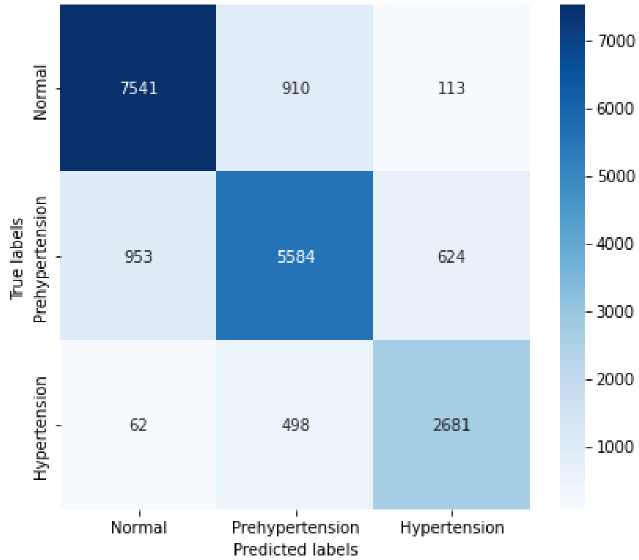

Fig. 7. Confusion Matrix

4.3 Discussion

The proposed model obtains overall accuracy of 83% and stability in all metrics among the classes, which is a big improvement compared to our previous best results with different LSTM models [13]. The improvement over the previous work [13] lies mainly in the model structure and the preprocessing. A second CNN layer and a third LSTM were added, which empirically improved the result. It should be noted that some changes in the preprocessing were made as well, in regard to signal selection. The criteria for signal selection are more restrictive, which improves the signal quality while it decreases the size of the dataset. These results are emphasizing the conclusion that this model can be used in the development of the new patch, though it still requires further development in order to be applicable.

The difference between our study and other published results for the BP classification is in the specific CNN-LSTM model architecture, as well as in the preprocessing part. This type of a problem is usually framed as a regression problem instead of a classification, which makes direct comparison with others difficult. The authors in the study [10] propose same type of model that attempts to use the difference between the ECG and PPG signals to generate PAT information. For comparison, our model uses the signals directly. Compared to the reported results with a similar CNN-LSTM model for BP classification [8] - the classification of Normal vs Hypertension yields accuracy 67.76, which is slightly higher than Normal vs Prehypertension, our CNN-LSTM model achieves higher scores of the evaluation metrics (accuracy and AUROC).

It should also be taken in to account that the results the model achieves are somewhat influenced by the bias introduced 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. In addition we aim to extend 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 an important trait, since it indicates 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.

5 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 patch. Other important aspect is that BP varies and thus the BP measurement should be continuous to enhance the second triage process. Given there are 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 feature in the triage process that can increase the survival rate.

In this paper we propose building and training of CNN-LSTM 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.

The proposed model obtains overall accuracy of 83% and stability in all metrics among the classes (AUCROC for each class are 0.89, 0.83, and 0.89 respectively), which is a big improvement compared to our previous best results with different LSTM models. This model can be used in conjunction with the patch and used as described in the beginning of this section. 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 producing regression models for estimation of blood pressure with deep learning, using Big Data for selection of different features from the ECG and PPG signals.

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