Localization and Classification of Myocardial Infarction Based on Artificial Neural Network

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***Abstract*—In this article, has been developed Convolutional Neural Network (CNN) architecture for classifying and determining the localization of myocardial infarction based on electrocardiogram (ECG). Training process is carried out on deep learning toolbox of MatLab. For the training, the database based on a 12-lead ECG device is developed. Database consisted of 11 classes: 10 classes belong to patients of myocardial infarction and one class's data taken from healthy persons. All data of total classes saved on .mat file form, and each class consisted of different amount of .mat files. For each class, network accuracy calculated separately and average result determined. The training result achieved at 98.47%. The results also compared to the obtained results of other researchers. The specifics of each taken results are also discussed.**

Keywords-CNN; ECG; class; myocardial infarction; localization; classification

I. INTRODUCTION

According to the analytical data provided by the Food and Drug Administration (FDA), cardiovascular diseases (CVDs) cause 17.3 million annual deaths among the worldwide population. This figure could reach to 23.6 million people by 2030 [1]. Most important thing is that, in recent years, among CVDs the highest death rate shows myocardial infarction (MI). Last decade MI is observing among young people, and the number of heart attacks and sudden deaths is increasing among population. As a result of the inability to make a correct diagnosis on time and failure to provide the necessary treatment MI deaths among people is increasing year by year. The MI causes damage or kills heart muscle.

If it is not provided emergency to damaged muscles on time, it causes permanent damage. Therefore, by early detection of MI and the correct diagnosis, it can be provided with immediate medical care.

There are different determining methods of MI in medicine such as laboratory analysis, MRT, ultrasound and ECG. In laboratory analysis, precise data can be obtained through myocardial protein in the blood, including myoglobin and the cardiac troponin. In turn, this process requires a long time. However, laboratory results may indicate the presence of a heart attack, but the location of MI cannot be determined [2]. Based on data taken from the 12-lead ECG system, diagnosis of myocardial infarction is a relatively easy, cheap, rapid and proven method.

It is possible determining not only MI but also, other types of CVDs by interpreting ECG data. Moreover, MI occurrence, the damaged level and location can be detected by deep learning of ECG features. Risk is assessed by identifying the affected part of the heart. Last years for equalize the patient-doctor ratio automatic detection of CVDs, especially MI, is becoming more and more relevant. In this paper, only CNN based algorithm is considered for detecting of MI.

In general, algorithms have following steps: pre-processing, feature extraction and classification.

- In the pre-processing step, filtration and normalization of ECG signals are carried out.
- The feature extraction step is a key process for detecting heart rate. The process of correct extraction of ECG signals' features depends on the classification

accuracy, otherwise, it may increase the loss rate and consequently reduce the classification accuracy [3]. In recent years, for the feature extraction of MI many mathematic algoritms and methods [4, 6, 7, 8, 9] are used. Among these methods, CNN algorithm is more suitable than others.

- The final step is a classification step that currently classification algorithms such as Thresholding [8], Discriminant analysis, Support vector machine [10], Decision tree [11], Naive Bayesian [12], K-nearest neighbor (KNN) [13], Simple differential equations [15], Polynomial approximation [16] are widely used. Hovewer many algorithms of Artificial neural network [14] are more suitable for deep learning, exactly CNN [18]. Because training results in deep learning may reach almost at 100% on CNN networks. Most importantly, deep learning not requires pre-processing and feature extractions before classification of ECG signals [17].

Last years, deep learning algorithms are becoming popular for voice, image, video and object recognition processes [10-16]. In CNN network, It is possible to classify multidimensional signals, and even to achieve at on-demand expected results. As mentioned above, pre-processing, feature extractions and decreasing noise levels are not required for an input signal of CNN network. Network parameters and output weight become very small than other neural networks algorithms. This causes decreasing the training process time with a simple form of CNN architecture.

In 2012, CNN network was first developed by Alex Krajewski. While the classification error was 15% at that time, then the error rate decreased to 2.9% in 2018. The sensitivity level of CNN network achieved a degree of precision beyond the human eye in terms of image classification [19], object recognition [20] and semantic segmentation [21]. CNN algorithms are then used effectively in the classification of Magnetic resonance imaging, Ultrasonography, X-ray, radioactive and ECG images in medicine [22-23].

CNN is one of the algorithms of neural network that it differs its convolution layers. The convolution layer is the core layer of CNN network. As the filters are used in CNN layers, the resolution decreases step by step. As a result, the total number of parameters of the network decreases than the usual network, and the speed of the network increases. As network performance is improved by increasing the layers of CNN, so that “the deep learning” term uses for CNN.

It is known from the medical experiences, CVDs could be determined by the features in ECG signals' wave. Automatic detection of myocardial infarction determines in the same way as conventional methods. Currently, the process of detecting myocardial infarction by some ECG applications is not fully justified but uses as a decision-making system. Based on ECG images, MI detecting process still not uses as an independent system, meaning there are many gaps to fill. Based on ECG images, MI detection process is showing remarkable results in narrow fields. This is because the symptoms of MI do not always occur in ECG images, but they could be seen in the blood laboratory tests without any changes in ECG.

In this paper, CNN network architecture for localization and classification of MI by interpreting ECG signals has presented.

Current researches in medicine show that CNN is widely used in the interpretation of ECG images, QRS complex detection, ST-segment scanning, and heart diseases detection. ECG classification have studied by [24-26]. In this review, only ECG based MI has analyzed.

Detecting MI by CNN network based on a single lead ECG signals data was proposed in [27-28] and also Rule Inference and synthesis Bayesian approaches were used for CNN deep learning [29]. For detecting 12-lead data simultaneously, the multiple-feature-branch CNN was also tested.

The results of the researcher Baloglu [31] were much closer to the results obtained by Acharya, and, in particular, the network’s architecture, which is very similar to Acharya's architecture. In the classification method proposed by Baloglu, MI is classified based on a single lead. Distinctive feature than Acharya's research, is that network trained not only on lead I but on all 12-lead, one-by-one [27]. In other paper [32], Fully CNN, ResNet and LSTM-CNN networks used and training process carried out with relatively small database. Obtained results were compared and concluded that Fully CNN has better performance to diagnosis of MI than other two networks.

Many researchers use PhysioNet database, which is open source. Proposed database has very limited ECG data. As deep learning requires huge amount of data for high accuracy, each data fragmented into single heartbeats to augment the number of the data. As heartbeats have very little difference between them, they can be supposed as data augmentation. If too much heartbeat of the same patient is used for database this can be cause to overfitting of the network. Most of researcher, we look in, used almost all heartbeat (more than 150 heartbeats) of the full ECG signal, while we used only 40 heart beats of the signals for preventing overfitting. It seems it will be gold balance between data augmentation and overfitting.

II. Database

In this work, PTB database was used, and then limited amount of ECG data fragmented into single heartbeats to increase training data.

To obtain optimum size, only 652 samples (which is equal to 0.651 second duration) is taken as an input signal. For separating PQRST properly, R peaks are determined first. Then, 200 intervals from right and 451 intervals from left side of R peaks cut. Data of patients with tachycardia and bradycardia are not used in the database. The total database size reached to 19904 samples.

We know that CNN require more data for high accuracy, however using each heartbeats of the same patient as a new data not always help to increase accuracy but it can cause to mistakes. At the same time with only 149 data of PTB one cannot train the network. So we try to use as less as possible heartbeats of the same patient when augmenting data.

Before the training, MI data were split into 11 classes: anterior (A), anterior lateral (AL), anterior septal (AS), inferior (I), inferior lateral (IL), inferior posterior (IP), inferior posterior lateral (IPL) lateral (L), posterior (P), posterior lateral (PL) and healthy heart data. All 11 classes saved in separated folders. The number of files per class given in Table I. Database split into three parts: 70% for training, 20% for validation and 10% for the test. All samples saved in the .mat file format, the *imageDatastore* method was used.

TABLE I. DEDICATED CLASSES AND AMOUNT OF DATA FOR EACH CLASSES

Number of class	Total number of .mat file data for each class
A	2517
AL	1989
AS	3550
H	3450
I	4271
IL	2494
IP	148
IPL	885
L	150
P	200
PL	250
Total	19904

Each .mat file size organized as 12x652 samples for the input layer of CNN.

III. CNN ARCHITECTURE

For designing and training CNN architecture deep learning toolbox of Matlab R2018a (version 9.4.0.813654) used. In this CNN network, Adam optimizer was used as the network optimizer [4]. This parameter consists of gradient (β_1) and its square values (β_2), summarizes as follow,

$$m_l = \beta_1 m_{l-1} + (1-\beta_1)\nabla E(\theta_l) \tag{1}$$

$$v_l = \beta_2 v_{l-1} + (1-\beta_2)[\nabla E(\theta_l)]^2 \tag{2}$$

where, m_ℓ - average moving value of the gradient, v_l - average moving quadratic value of the gradients, $\nabla E\theta_l$ - loss function of the gradient, l - number of repetitions, θ - parameter of the vector. These coefficients set at 0.9 and 0.99, respectively. As a result, changes in network parameters is expressed by the following way:

$$\theta_{l+1} = \theta_l - \frac{a_{m_l}}{\sqrt{v_l + \epsilon}} \tag{3}$$

where α - the training speed and ϵ - the coefficient is defined as 0.01 and 1, respectively. Also, the number of iterations per epoch and epochs number are 128 and 22, respectively.

In most case, RELU layer uses for storing image data. Because proposed CNN network has negative and positive signals, RELU converts all negative values to zero and may result in desired data loss. Therefore, the Leaky RELU layer used to achieve the desired results. In this layer any negative numbers less than zero is multiplied by a certain constant *x*.

$$f(x) = \begin{cases} x, & x \geq 0 \\ scale * x, & x < 0 \end{cases} \tag{4}$$

The last layers of the network are fully connected, SOFTMAX and classification output.

Because image Datastore is for storing images, additional @readFcn1 function used for reading .mat files.

Training and testing processes were performed on a computer with Intel (R) Core (TM) i5-7200U CPU @ 2.50GHz 2.71 GHz.

Other specifities of network are given in the Table II.

TABLE II. PARAMETERS OF PROPOSED CNN ARCHITECTURE

Name of the layers	The parameter of layers
INPUT	12x652
CONVOLUTION 2D	Filter size = [2 12], Number of filters = 64, Number of stride=2
BATCH NORMALIZATION	64
LEAKY RELU	Scale - 0.01
MAXPOOLING	Pooling size = 2, Number of stride = 2
CONVOLUTION 2D	Filter size = [3 9], Number of filters = 16, Number of stride =1, PADDING = 2
BATCH NORMALIZATION	16
LEAKY RELU	Scale0.01
MAXPOOLING	Pooling size = [1 2], Number of stride = 2
CONVOLUTION 2D	Filter size = [2 3], Number of filters = 8, Number of stride = 2
BATCH NORMALIZATION	8
LEAKY RELU	Scale - 0.01
MAXPOOLING	Pooling size = [1 2] Number of stride = 2
FULLY CONNECTED	Fully connected = 11
SOFTMAX	SOFTMAX
CLASSIFICATION OUTPUT	Crossentropyex with 'A' and 10 other classes

TABLE III. RESULTS FROM TESTING OF THE NETWORK ON PROPOSED ARCHITECTURE

Class name	Specificity (%)	J –stat (%)	Accuracy (%)
A	97,2	96	98
AL	94,9	92,9	96,5
AS	99,4	95,7	97,9
H	97,3	94,4	97,2
I	99,3	98,1	99,4
IL	96	93,6	98,8
IP	100	100	100
IPL	100	100	100
L	100	93,3	96,7
P	100	100	100

PL	96	96	98
Total	98,2	96,4	98,4

It can be seen from the result (Fig. 1) sensitivity of the network for IP, IPL, P and PL classes, as well as its precision for IP, IPL, L and P classes was 100%. The sensitivity for other class were less, for example, the results for the healthy class reached 97,1%. The reason for that can be their close appearance. For example, ECG wave shape of AL class and healthy class distinguish very little, where the shape of AS class very different from that of healthy. So, none of ECGs of healthy class isn't classified as AS. Using parameters (*sensitivity* – green numbers on the bottom of the table, *precision* - green numbers on the right side of the table, *overall test accuracy* – green number on the right bottom corner of the table) given in the table, specificity, Juden's J-statistics and accuracy for each class are calculated using the following formulas and the results are summarized in Table III.

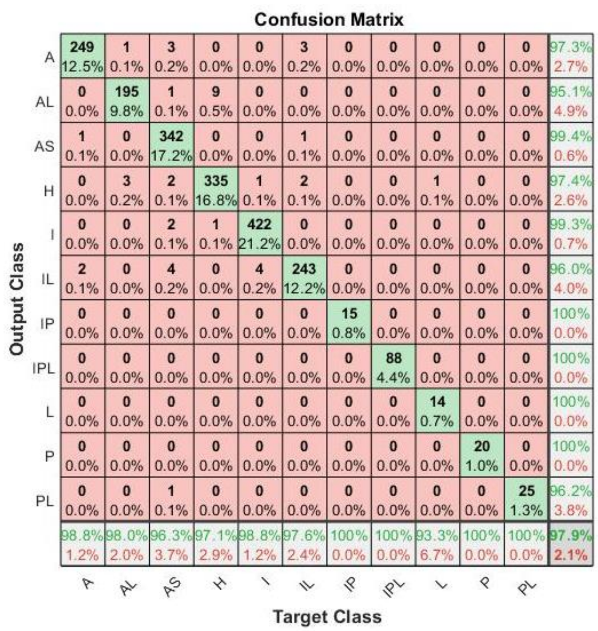

Figure 1. Confusion matrix

$$Acc = \frac{TP + TN}{TP + FP + TN + FN} \quad (5)$$

$$Spe = \frac{TN}{TN + FP} \quad (6)$$

$$J\ stat = Specifity + Sensivity - 1 = = \frac{TN}{TN + FP} + \frac{TP}{TP + FN} - 1 \quad (7)$$

where, TN - true-negative results, TF - true-positive results, FN - results in false negative, FP - false-positive results.

So far, different approaches for the localization and classification of myocardial infarction based on a single ECG [27, 28] or more ECG leads [28, 29, 30, 31, 32, 33] have been developed. In most cases, medical professionals use 12-lead ECG data detecting myocardial infarction, and the reliability of the classification are also provided by such data. Through a single lead it is indeed difficult to provide complete information about myocardial infarction, which occurs in different parts of the heart.

TABLE IV. Developed Solutions for Detecting Myocardial Infarction and Their Comparative Analysis

Proposed CNN architecture	**Num. of sample**	**Num . of leads**	**Accuracy (%)**	**Num. of classes**
R. Acharya [27]	50728	1	93.53	2
T. Reasat [33]	6277	3	84,54	2
D. Lingpen [29]	150000	8	86.22	(10+)
B. Baloglu [31]	611404	12	99,78	11
N. Strodthoff [32]	207	8	80,3	3
V. Liu [30]	59336	12	99,81	6
W. Lui [28]	150000	1	94,62	4
Proposed method	19904	12	98,47	11

IV. Discussions

Our first achievement is that we used 12-lead ECG data compared to [27, 28, 29, 32, 33]. Secondly, all 12-lead ECG data were analyzed simultaneously, however, [30] analyzed separately (network trained for each lead independently) which is almost the same as a single lead diagnosis. Thirdly, even [31] used 12-lead ECG data and achieved more accuracy than ours, they classified data into 6 classes which are almost twice as less as ours with triple more data. Fourthly, the weight of our network was very lighter than others because the small size filter were used. Fifthly, we used as much as less data than others. Moreover, the number of classes was more than [27, 30, 33].

V. Conclusion

In this work, CNN architecture is developed. This network could detects myocardial infarction based on 12-leas ECG and identify the localization of myocardial infarction. During the training, overfitting is prevented.

Although obtained results by V. Liu and B. Baloglu are reached above to 99%, they used too many data in the training. The proposed method, compared to the above approaches, supports more classes and less data to achieve nearly 100%.

The obtained results from proposed work may use as an application to inform physicians about the localization and classification the extent of myocardial infarction. Moreover, It can be applied to Holter or mobile applications, which allow controlling patients from distance.

References

[1] R. Narayan, “Encyclopedia of biomedical engineering.”, Amsterdam, Elsevier publisher, vol.1, 2019

[2] S. Smith, D. Zvosec, “The ECG in acute MI: an evidence-based manual of reperfusion therapy.” 1st ed. Philadelphia: Lippincott, Williams and Wilkins; 2002, pp. 98-112.

[3] L. Le, Z. Yefeng, C. Gustavo, Y. Lin, “Advances in computer vision and pattern recognition, precision medicine, high performance and large-scale datasets”, Springer International Publishing Switzerland, 2017, pp. 512-517,

[4] H. Pereira and N. Daimiwal, "Analysis of features for myocardial infarction and healthy patients based on wavelet," *Conference on Advances in Signal Processing (CASP)*, Pune, 2016, pp. 164-169.

[5] S. Banerjee and M. Mitra, "Application of Cross Wavelet Transform for ECG Pattern Analysis and Classification," in *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 2, pp. 326-333, 2014.

[6] Qibin Zhao and Liqing Zhang, "ECG Feature Extraction and Classification Using Wavelet Transform and Support Vector Machines," *International Conference on Neural Networks and Brain*, Beijing, 2005, pp. 1089-1092.

[7] H. T. Geoffrey, Z. Jeffrey, N. D. Francesca, and C. D. Rahul, “Automated and interpretable patient ECG profiles for disease detection, tracking, and discovery,” Circulation: Cardiovascular Quality and Outcomes, Vol. 12, No. 9, 2019.

[8] R. Rodríguez, A. Mexicano, J. Bila, R. Ponce and S. Cervantes, "Adaptive Threshold and Principal Component Analysis for Features Extraction of Electrocardiogram Signals," *2014 International Symposium on Computer, Consumer and Control*, Taichung, 2014, pp. 1253-1258.

[9] K. K. Jen, Y. R. Hwang, “ECG feature extraction and classification using cepstrum and neural networks,” Journal of Medical and Biological Engineering, 28 (1): 2008, pp. 31-37

[10] A. K. Dohare, V. Kumar, R. Kumar, “Detection of myocardial infarction in 12 lead ECG using support vector machine,”. Applied Soft Computing, 64, 2018, pp. 138-147

[11] J. Mair, J. Smidt, P. Lechleitner, F. Dienstl, B. Puschendorf, “A decision tree for the early diagnosis of acute myocardial infarction in nontraumatic chest pain patients at hospital admission,” Chest Journal, Volume 108, Issue 6, pp. 1502-1509, 1995.

[12] M. G. Devika, C. Gopakumar, R. P. Aneesh and G. R. Nayar, "Myocardial infarction detection using hybrid BSS method," *International Conference on Communication Systems and Networks (ComNet)*, Thiruvananthapuram, 2016, pp. 167-172.

[13] A. Muhammad, A.M. Ijaz, A.A. Fayyaz, "Detection and Localization of Myocardial Infarction using K-nearest Neighbor Classifier", Journal of Medical Systems, Volume 36, Issue 1, pp 279–289, 2012.

[14] J. Kojuri, R. Boostani, P. Dehghani, F. Nowroozipour, N. Saki, “Prediction of acute myocardial infarction with artificial neural networks in patients with nondiagnostic electrocardiogram," Journal of Cardiovascular Disease Research, Vol 6, Issue 2, pp. 51-59, 2015.

[15] G. Zewdie, M. Xiong, “Fully automated myocardial infarction using ordinary differential equations,” Proc. 8th int. Conf. Bioinforma. Comput. Biol. BICOB., 2016, pp. 17–22

[16] P. Chang, J.J. Lin, Y.C. Wu, “Myocardial Infarction Classification Using Polynomial Approximation and Principal Component Analysis”, 2011. doi.org/10.1115/1.859735.paper30

[17] S. Kiranyaz, T. Ince and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," in *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 3, pp. 664-675, March 2016. doi: 10.1109/TBME.2015.2468589

[18] X. Zhai and C. Tin, "Automated ECG Classification Using Dual Heartbeat Coupling Based on Convolutional Neural Network," in IEEE Access, vol. 6, pp. 27465-27472, 2018. doi: 10.1109/ACCESS.2018.2833841

[19] A. Vishali “A review: deep learning technique for image classification,” ACCENTS transactions on image processing and computer vision, Vol 4(11), pp. 465–472, 2017.

[20] Xin Jia, "Image recognition method based on deep learning", 29th Chinese Control And Decision Conference, 2017, pp. 212–217

[21] https://medium.com/@arthur_ouaknine/review-of-deep-learning - algorithms-for-image- semantic-segmentation-509a600f7b57

[22] O. Emad, I. A. Yassine and A. S. Fahmy, "Automatic localization of the left ventricle in cardiac MRI images using deep learning," 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, 2015, pp. 683-686.

[23] H. Chen, Y. Zheng, J.H. Park, P.A. Heng, S.K. Zhou, “Iterative multi-domain regularized deep learning for anatomical structure detection and segmentation from ultrasound images,” In: Proceedings of international conference medical image computing and computer assisted intervention, 2016, pp. 574–586

[24] B. C. Luis, M. R. Sergio, G. C. Alicia, L.R. José, “Review Deep Learning and Big Data in Healthcare: A Double Review for Critical Beginners,” Applied. Science. 2019, pp. 401–407.

[25] A. Haya, “Convolutional Neural Network Application in Biomedical Signals,” Journal of Computer Science and Information Technology, Vol. 6, No. 2, pp. 45-59, 2018.

[26] G. Nagarajan, S. Ramakrishnan, M. D. Thomas, “Deep learning on 1-D Biosignals: a taxonomy-based survey,” CC BY-NC-ND 4.0 · Yearb Med Inform , 27(01): pp. 098-109, 2018.

[27] U. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J.H. Tan, M. Adam, “Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals,” Inf Sci, 2017, pp. 415–416,

[28] H. W. Lui, K. L. Chow, “Multiclass classification of myocardial infarction with convolutional and recurrent neural networks for portable ECG devices,” Informatics in Medicine Unlocked, 13, 2018, pp. 26-33.

[29] J. Linpeng, D. Jun “Normal versus abnormal ECG Classification by the Aid of Deep Learning,” Artificial Intelligence - Emerging Trends and Applications, 2018, pp. 295-316.

doi.org/10.5772/intechopen.75546

[30] L. Wenhan, H. Qijun, Ch. Sheng, W. Hao, H. Jin, “Multiple-feature-branch CNN for myocardial infarction diagnosis using electrocardiogram,” Biomedical Signal Processing and Control 45, 2018, pp. 22–32.

[31] U. Baloglu, M. Talo, Ö. Yıldırım, R. S. Tan, U.R. Acharya, “Classification of Myocardial Infarction with Multi-Lead ECG Signals and Deep CNN,” Pattern Recognition Letters, 2019.

10.1016/j.patrec.2019.02.016.

[32] N. Strodthoff, C. Strodthoff, “Detecting and interpreting myocardial infarctions using fully convolutional neural networks,” Physiological measurement Journal, Vol. 40, Num.1, 2018.

[33] T. Reasat and C. Shahnaz, "Detection of inferior myocardial infarction using shallow convolutional neural networks," *IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, Dhaka, 2017, pp. 718-721. doi: 10.1109/R10-HTC.2017.8289058