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RESEARCH ARTICLE

PREDICTING MYOCARDIAL INFARCTION COMPLICATIONS AND OUTCOMES WITH DEEP LEARNING

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ABSTRACT

Early diagnosis of cardiovascular diseases, which have high mortality rates all over the world, can save many lives. Various clinical findings and past histories of patients play an important role in diagnosing these diseases. These days, the prediction of cardiovascular diseases has gained great importance in the medical field. Pathological studies are prone to misinterpretation because too many findings are studied. For this reason, many automatic models that work with machine learning methods on patients' findings have been proposed. In this study, a model that predicts twelve myocardial infarction complications based on clinical findings is proposed. The proposed model is a deep learning model with three hidden layers with dropouts and a skip connection. A binary accuracy metric is used for measuring the performance of the proposed method. Rectified Linear Unit is set to the hidden layers and sigmoid function to the output layer as an activation function. Experiments were performed on a real dataset with 1700 patient records and carried out on two main scenarios; training on original data and training on augmented data with 100 epochs. As a result of the experiments, a total accuracy rate of 92% was achieved which is the best accuracy rate that has been proposed on this dataset.

Keywords: Deep Learning, Myocardial Infarction, Data Augmentation, Artificial Intelligence, Prediction

1. INTRODUCTION

Cardiovascular diseases (CVD) are one of the main reasons for death and disability in Europe. CVD reduce people's quality of life. Most deaths in Europe are due to CVD. In 2019, deaths from cardiovascular diseases in Europe accounted for 43% of total deaths [1]. Myocardial infarction (MI) is one of the most important cardiovascular pathological conditions [2].

Damage to the heart muscle occurs when blood flow is reduced or stopped. This damage leads to myocardial infarction or popularly known as heart attack. MI, a disease predominantly seen in developed countries, is becoming more common in developing countries. In proportion to the strong evidence base that cares for acute myocardial infarction is currently practiced records show a reduction in mortality [3-9]. Studies are showing that MI is preventable and curable. If a rapid recovery is not initiated, it can cause serious health problems and even death [18]. Therefore, early diagnosis of MI is very important. Early diagnosis can be achieved with various clinical findings and laboratory test results. Among these results, markers such as hypertension, diabetes, chronic heart disease, etc. play an important role in diagnosing MI [10-12]. Considering these values, myocardial infarction can be predicted and prevented.

Deep learning is a machine learning method based on artificial neural networks [12,13]. The deep neural networks (DNN) recognize the complex patterns of the test data given as inputs. A DNN aims to classify the outputs with high success, after a few epochs on the training data. [14]. Previous studies have shown that deep neural network methods have been used successfully for problems in the medical field. [15-

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17] The condition of applicants who might be classified as patients, could be predicted by training a deep neural network model on clinical features.

There are many input features in CVDs. These features are derived from the results of a series of laboratory results and medical imaging processes (ECG, etc.). In addition to these features, the patient's family history, medical history, risk factors, and physical examination findings can be counted. [18] We could predict the presence or absence of disease with statistical data containing these input features. The deep learning method could be trained with these inputs to predict the results and support the decision-making process of medical doctors.

There are several studies for predicting heart diseases with deep neural networks. One of the studies hired an autoencoder-based neural network for predicting heart disease [19]. This study consists of two parts. At the first stage, Moenye and friends trained an unsupervised neural network with a sparse autoencoder and at the second stage, they used an artificial neural network for prediction. The Heart Disease UCI dataset from Kaggle (https://www.kaggle.com/ronitf/heart-disease-uci, date of access is 09.01.2022) was used for this study. Several algorithm results were compared, as a result, they reached maximum 90% accuracy with the proposed method.

Another study aimed to predict coronary heart disease with convolutional neural networks. Dutta and friends trained and tested their approaches on data which is curated from National Health and Nutritional Examination Survey (NHANES) dataset. They propose a two-step approach: first for feature weight assessment and extracting important features. At the second step of the approach, they trained a fully connected layer and then classified tests. They had overall 79.5% accuracy with their proposed model [20].

Golovenkin et al. mentioned that the results of myocardial infarction may be too uneventful to be discovered even by experienced professionals, and they mentioned that the use of artificial neural networks in the diagnosis of this disease would be beneficial [24]. They used the "Myocardial infarction complications Database of University of Leicester" as a dataset [21] which is also used in this paper. They offered both 1 and 3 hidden layered ANN structures. The results they obtained with the model they proposed in their study have a total accuracy value of approximately 91.6%.

Study [22] was proposed by the same authors as study [24]. [22] was presented as a further study of [24] to predict more positive outcomes. Dorrer and friends aimed to predict the course of CVD with data augmentation. They used the same dataset [21] as in [24]. Due to the scarcity of positive output data, the authors proposed a data augmentation method and performed their testing on various deep neural network models. The authors had 72.14% total accuracy score from their final proposed model [22].

In this paper, we proposed an efficient deep neural network model for predicting MI complications and outcomes using the Myocardial infarction complications Database of the University of Leicester dataset. We performed our experiments both using augmented dataset and original dataset. All feature values in the dataset were trained and tested on all possible outcomes and complications. Results were compared with studies using the same dataset as in this study. The model optimized with adaptive moment estimation (Adam) algorithm, batch normalization, and dropout layers are also used against overfitting problem and improve performance. The proposed model in this study has better performance than the state-of-the-art literature approaches [19, 20, 22, 24].

2. MATERIALS AND METHODS

In this study, we used the Myocardial infarction complications database of the University of Leicester dataset to make our predictions [21]. This dataset has 1700 patients with MI. The database was collected in the Krasnoyarsk Interdistrict Clinical Hospital in Russia. The dataset has total 124 attributes. The first

112 attributes are about patients' clinical and laboratory data which were used as input features. The last 12 attributes hold the complications and outcomes information. The dataset has numerical and binary attributes. Most of the values consist of binary data. A total of 7.6% of data is missing in the database. The summary of complications and outcomes is presented in Table 1.

Table 1. The summary of complications and outcomes

Complication	Number of Cases	Fraction
Atrial fibrillation	170	10.0%
Supraventricular tachycardia	20	1.18%
Ventricular tachycardia	42	2.47%
Ventricular fibrillation	71	4.18%
Third-degree AV block	57	3.35%
Pulmonary edema	159	9.35%
Myocardial rupture	54	3.18%
Dressler syndrome	75	4.41%
Chronic heart failure	394	23.18%
Relapse of the MI	159	9.35%
Post-infarction angina	148	8.71%
Lethal outcome (cause)[1]	271	15.94%

[1]Converted to binary attribute: dead or alive.

The gender distribution of the patients is 37% female and 63% male. Figure 1 shows the age and gender distribution. According to Figure 1, female patients admitted to the hospital with MI are older than male patients.

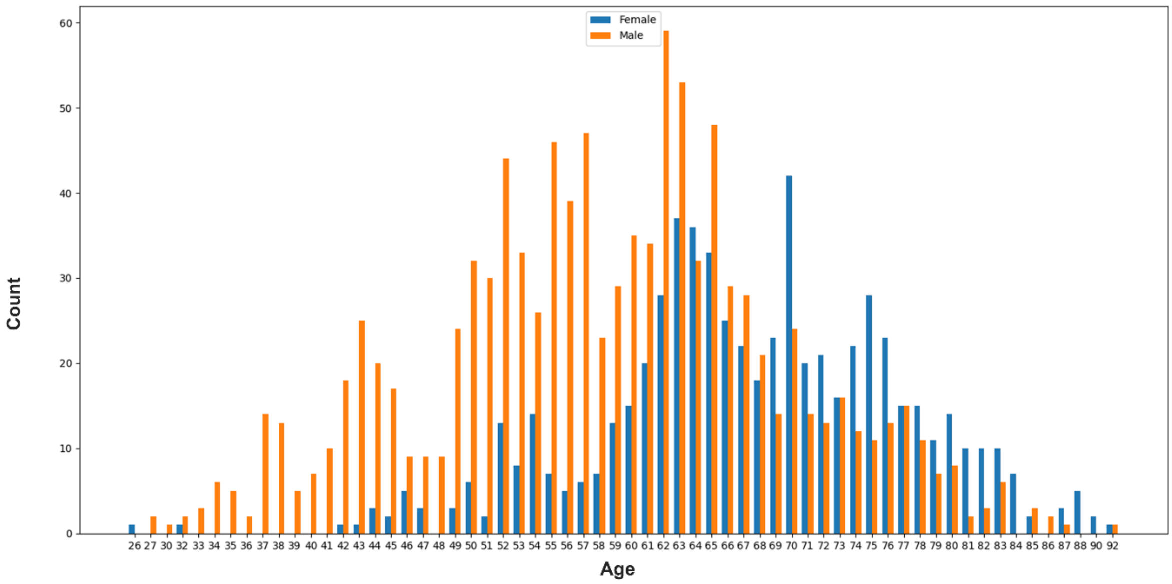

Figure 1. Age and Gender Distribution of dataset. (Blue bars – women, Orange bars – men)

Distributions of mortality depending on some important input features are shown in Figure 2.

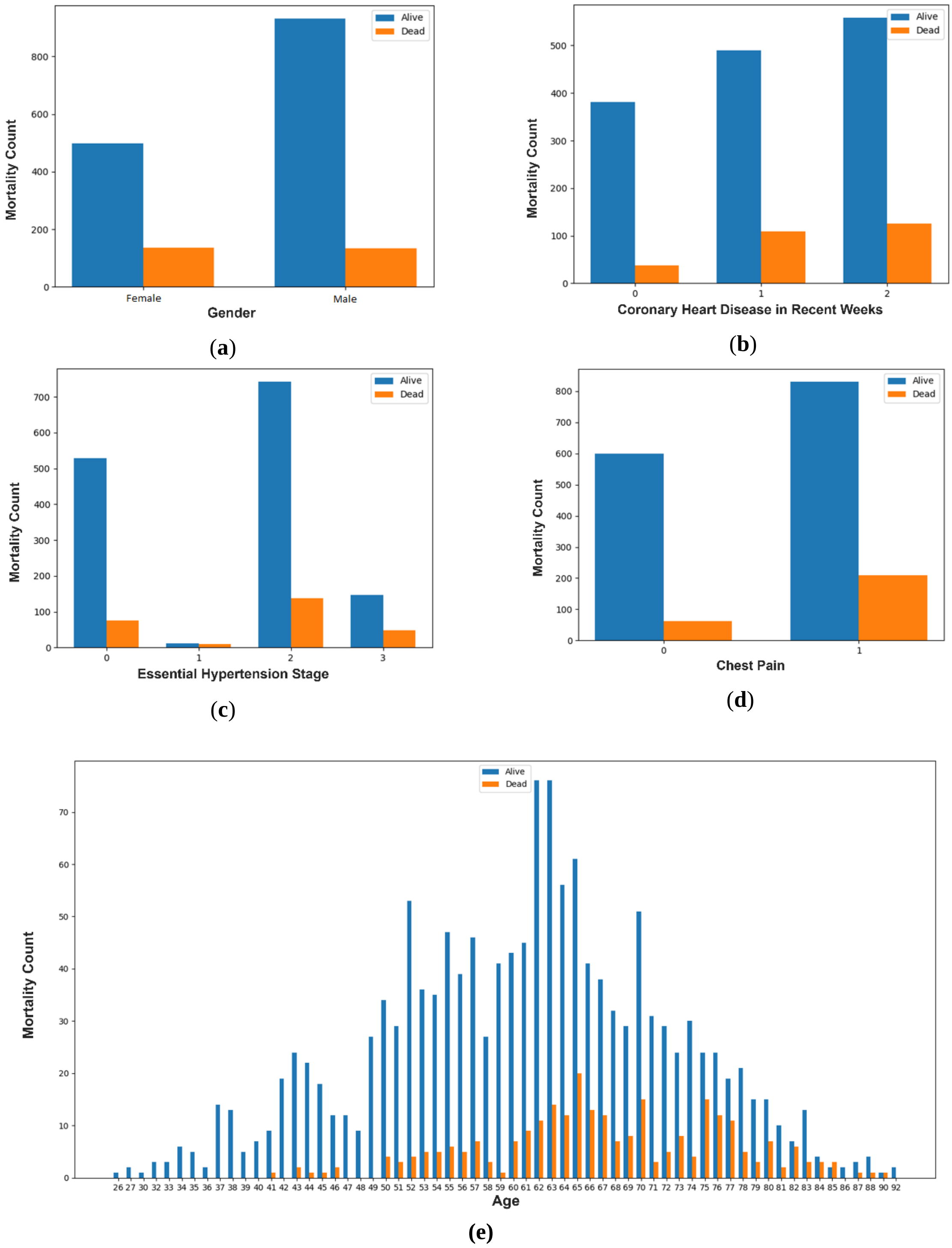

Figure 2. Distributions of mortality depending on some important input features: The blue bars indicate the number of deaths, and the orange bars indicate the number of alives.

Explanations of the charts in Figure 2 as follows; (a) Distribution of mortality rate according to gender; (b) Distribution of mortality rate according to coronary heart disease in recent weeks, days before hospital admission (0: There was no CHD, 1: Exertional angina pectoris, 2: Unstable angina pectoris); (c) Distribution of mortality rate according to essential hypertension (0: There is no essential hypertension,1: Stage 1 Hypertension, 2: Stage 2 Hypertension, 3: Stage 3 Hypertension); (d)

Distribution of mortality rate according to exertional angina pectoris in the anamnesis (0: There is no chest pain,1: There is chest pain); (e) distribution of mortality rate by age.

Figure 2 (a) shows the number of female and male patients in terms of mortality rate. Although the number of male patients admitted to the hospital with MI is high, the mortality rate is higher in female patients. The number of patients with coronary heart disease (CHD) in the last weeks, days before hospital admission, is shown in Figure 2 (b). Patients with CHD before hospital admission have a higher mortality rate. Figure 2 (c) shows the mortality rate in terms of the presence of essential hypertension. Accordingly, applicants with 2nd and 3rd stage essential hypertension have a higher death count, but also without any essential hypertension, applicants are in the risk group. The number of patients who have exertional angina pectoris in the anamnesis is shown in Figure 2 (d) [23]. Chest pain due to coronary heart disease is called angina pectoris. It is an important sign for MI. The figure shows that patients with chest pain have a higher mortality rate. Figure 2 (e) presents the distribution of mortality rate by age. The death rate increases with age.

While carrying out this study, Keras, TensorFlow, and scikit-learn (sklearn) machine learning frameworks and numpy, pandas utility libraries were used in the Python development environment. The dataset was accessed from the University of Leicester website (https://leicester.figshare.com/articles/dataset/Myocardial_infarction_complications_Database/12045261?file=23581310, date of access is 09.01.2022). As mentioned above, there were some missing values. These missing values were filled with the mean of the attribute in which they were found. Lethal outcome (cause) (LET_IS) which is one of the important outcomes shows the patient is dead or alive after the hospital admission. LET_IS feature was a categorical attribute and it is converted to a binary attribute (0: Alive, 1: Dead) before calculations. After that, the first attribute of the dataset was dropped, which was patient ID.

All of the input features were transformed with sklearns' preprocessing method StandardScaler and then composed with the ColumnTransformer method. The proposed deep neural network architecture in this paper has three fully connected hidden layers with dropouts and a skip connection. The model is shown in Figure 3.

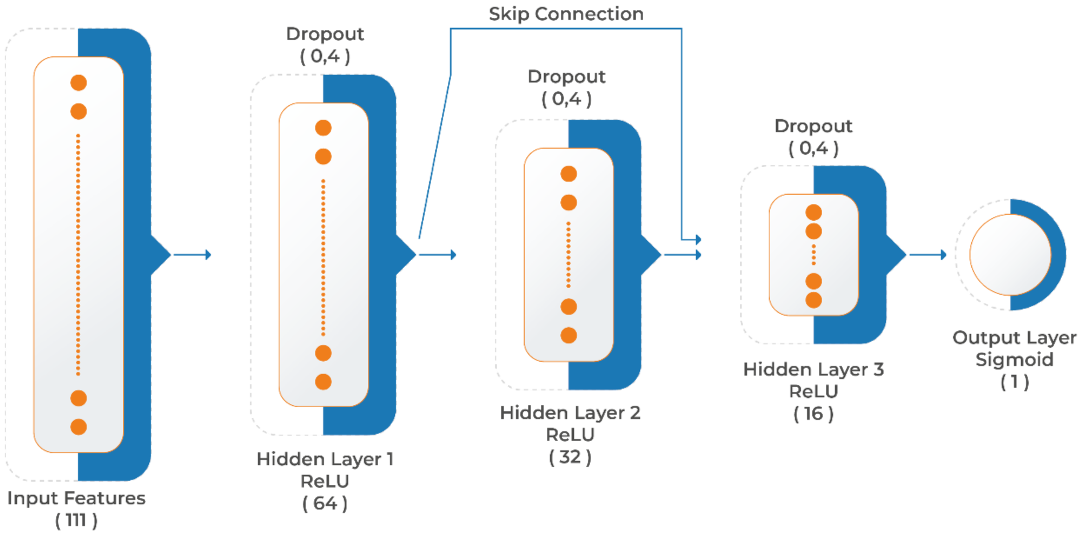

Figure 3. The proposed deep neural network architecture.

A dropout layer with a 0.4 rate was added after each hidden layer to prevent overfitting. Each hidden layer had Rectified Linear Unit (ReLU) as an activation function which is proposed in (1). X is a neuron input in (1).

$$f(x) = x^{+} = \max(0, x) \tag{1}$$

If x is negative then the result will be zero, else whatever the input is, so is the output.

The training process was held through 100 epochs. However, it is known that if the number of epochs increases overfitting could occur, if the number of epochs decreases underfitting could occur. EarlyStopping API of Keras was hired to prevent overfitting and underfitting caused by epoch number. EarlyStopping API monitors validation loss value and stops the training when the model performance stops improving on the validation data. EarlyStopping API's parameters were as follows: monitor='val_loss', patience=5, restore_best_weights=True. EarlyStopper monitored validation loss with the patience of 5 epochs when the model performance stops improving. After stopping epochs, it restored the best weights.

The proposed deep neural network model also had a skip step. Skip step was originated from the first hidden layer to the third hidden layer. The third hidden layer took its inputs as a concatenation of the first and second layer's output. This skipping approach provided an uninterrupted gradient flow from the first layer to the third layer, which deals with the vanishing gradient problem. Concatenative skip connections, which were used in the proposed method, ensured the same size feature reusability from the first layer.

Sigmoid activation function was used at the output layer, shown in (2); where x_0 is the x value of the sigmoid's midpoint, L is the curve's maximum value and k is the logistic growth rate of the curve.

$$f(x) = \frac{\mathrm{L}}{1 + e^{-\mathrm{k}(\mathrm{x}-x_0)}} \tag{2}$$

The Adam optimization algorithm was used to optimize the weight matrices and bias vectors. The default values provided by Keras for the Adam optimization algorithm (β1 = 0.9, β2 = 0.999, epsilon = None, decay = 0.0, amsgrad = False) have been preserved, just learning rate was modified as 0.0001. Binary cross entropy was used as a loss function. A binary accuracy metric function was used to judge the performance of the proposed model. Model parameters are proposed in Table 2.

Table 2. Deep neural network parameters.

Layer	Shape	Number of Parameters	Connected to
Input Layer	111	0	-
Hidden Layer 1	64	7168	Input Layer
Dropout Layer 1	64	0	Hidden Layer 1
Hidden Layer 2	32	2080	Dropout Layer 1
Dropout Layer 2	32	0	Hidden Layer 2
Concatenate	96	0	Hidden Layer 1, Dropout Layer 2
Hidden Layer 3	16	1552	Concatenate
Dropout Layer 3	16	0	Hidden Layer 3
Output Layer	1	17	Dropout Layer 3

The total trainable parameter count is 10.817 and the non-trainable parameter count is 0.

3. RESULTS AND DISCUSSION

The proposed architecture was evaluated on a PC with 2.9 GHz 4 core CPU, 8GB of memory, and without a GPU card. All experiments have been executed using PyCharm IDE with Python 3.8, Keras 2.7.0, and TensorFlow 2.7.0 on Windows 10 Pro x64.

Accuracy (3), Sensitivity (4), and Specificity (5) measures were used to assess the performance of the proposed method. Where, true positives (TP) were the number of cases correctly identified as sick or dead, false positives (FP) were the number of cases incorrectly identified as sick or dead, true negatives (TN) were the number of cases correctly identified as healthy or alive and false negatives (FN) were the number of cases incorrectly identified as healthy or alive.

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}\ x\ 100 \tag{3}$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN+FP}}\ x\ 100 \tag{4}$$

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP+FN}}\ x\ 100 \tag{5}$$

Experiments were handled in two main scenarios. In the first scenario, after the data preprocessing and model creation, the dataset was divided into three parts as training (60%), testing (20%), and validation (20%) data. The deep neural network model (DNN) was trained through 100 epochs. Our results and the results from the study [24] are presented in Table 3.

Table 3. First experiment results on complications and outcomes

Complication	Accuracy rates from our first scenario	Accuracy rates from [24]
Atrial fibrillation	**90,85%**	89,94%
Supraventricular tachycardia	98,53%	**98,76%**
Ventricular tachycardia	97,35%	**97,47%**
Ventricular fibrillation	**96,67%**	95,64%
Third-degree AV block	**96,76%**	96,59%
Pulmonary edema	**90,29%**	90,11%
Myocardial rupture	96,47%	**96,70%**
Dressler syndrome	**96,17%**	95,53%
Chronic heart failure	74,70%	**75,57%**
Relapse of the MI	87,64%	**90,64%**
Post-infarction angina	**93,23%**	91,23%
Lethal outcome (cause)[1]	**86,47%**	73,69%
Average	**92,09%**	90,98%

[1]Converted to binary attribute: dead or alive.

As can be seen in Table 3, the average accuracy of our study was 92,09% which is slightly better than [24]. Total average specificity on all outcomes was 99,31% and total average sensitivity was just 4.09% in our study. It was very hard to predict true positive values due to the lack of positive outcomes. In study [24], authors made several experiments and had maximum 92,32% average specificity rate and there were no information about sensitivity rate.

In the second scenario, data was augmented as proposed in [22]. The main goal of the data augmentation was the augment the positive outcomes. The data augmentation process was handled instance by instance. The first instance was selected as an active instance and was extracted from the dataset. After that, the instances with positive results in the data set were found. The number of positive instances was subtracted from the total number of instances and divided by the number of positive instances. Thus, the number of the count was found that how many times each positive instance would be duplicated in the dataset. After the data was copied to the end of the dataset, the DNN was retrained for each row. It was guaranteed that all copies of the relevant row were removed from the dataset before training to prevent the formation of bias. The augmentation structure is presented in Figure 4.

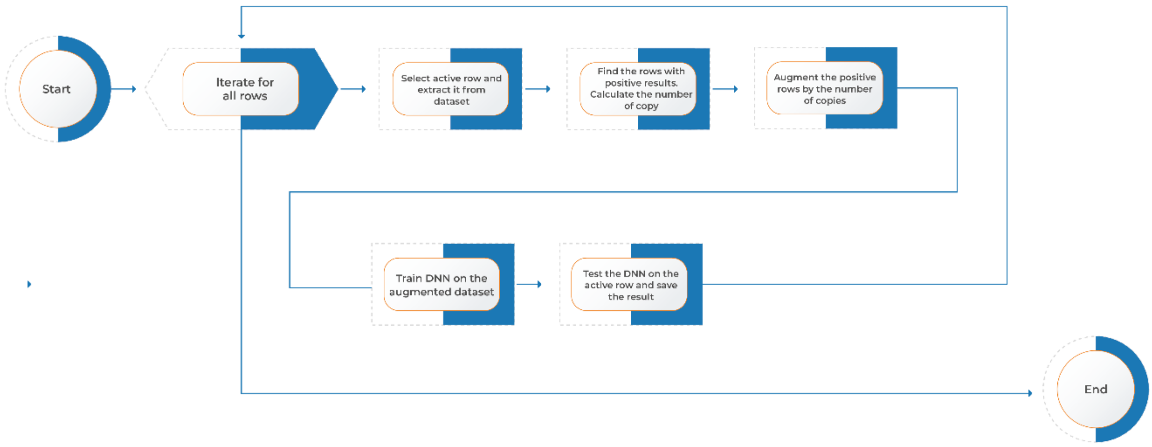

Figure 4. Data augmentation structure

Experiments results with the augmentation process are given in Table 4.

Table 4. Experiments results on the augmented dataset

Complication	Accuracy	Specificity	Sensitivity	Training Time in Seconds	Prediction Time in Seconds
Atrial fibrillation	71,79%	74,08%	51,17%	8082,45	93,13
Supraventricular tachycardia	89,04%	89,93%	10,00%	14872,19	93,42
Ventricular tachycardia	87,33%	89,13%	16,67%	12857,95	94,80
Ventricular fibrillation	82,27%	84,27%	36,62%	11433,16	99,66
Third-degree AV block	87,22%	89,09%	33,34%	12264,68	101,56
Pulmonary edema	76,20%	78,96%	49,36%	9386,78	95,47
Myocardial rupture	86,63%	88,44%	31,48%	12091,11	94,57
Dressler syndrome	80,04%	81,88%	40,00%	9850,98	95,78
Chronic heart failure	54,71%	53,83%	57,61%	3981,74	95,83
Relapse of the MI	66,49%	68,29%	49,06%	7251,57	96,53
Post-infarction angina	71,02%	72,96%	50,68%	7382,58	96,17
Lethal outcome (cause)[1]	76,38%	77,67%	69,51%	9318,83	94,63
Average	77,49%	79,71%	51,52%	118774,02	1151,55

[1]Converted to binary attribute: dead or alive.

It was observed that the accuracy and specificity were decreased by the augmentation method. However, the number of positive outcome predictions was increased. In this way, the sensitivity value was increased approximately 11.6 times. Even if the accuracy and specificity were decreased with the presented method, it is clear that the results obtained in this study are more successful when compared to the results in [22]. Table 5 shows the results from [22] and the results presented in this study.

Table 5. First experiment results on complications and outcomes

Method	Overall Accuracy	Overall Precision	Overall Recall
Results in this study with 100 epochs	77,49%	17,88%	51,52%
Results in this study with 200 epochs	78,31%	18,68%	51,70%
Results from [22] with 100 epochs	72,14%	6.09%	29,57%
Results from [22] with 200 epochs	75,02%	5,86%	24,69%

As can be seen in Table 4, our overall accuracy result is 7.42% better with 100 epochs and 4.39% better with 200 epochs . Overall precision and recall are also 2.94 and 1.74 times better with 100 epoch and 3,19 and 2,09 times better with 200 epochs, respectively.

Differences between our model and the model proposed in [22] is given in Table 5.

Table 6. Differences between our model and the model proposed in [22]

Model Feature	Proposed in this study	Proposed in [22]
Activation Function on hidden layers	ReLU	Sigmoid
Optimizer	Adam	RMSProp
Metrics	Binary Accuracy	Accuracy
Dropout Rate	0.4	0.2
Skip Connection	Yes – From 1st to 3rd Hidden Layer	No

4. CONCLUSION

Coronary diseases affect people's quality of life. However, these diseases could be treated. One of the most important Coronary diseases is myocardial infarction. Early diagnosis is very important in such diseases. To make the diagnosis, the laboratory results, physical examination results, and ECG of the samples taken from the patients are evaluated.

In this study, it was tried to predict the diseases of the patients based on these types of values. Comparisons were made with the results obtained in previous studies. Results have improved when compared to previous studies. An average of 77.49% accuracy was achieved in the DNN architecture trained on the augmented dataset, and 92.08% accuracy was achieved in the DNN architecture trained with the original data set. Better results were obtained from the last study [22] working on the same dataset.

As presented in Table 3, the results of the first experiment were compared with the study in [24]. The model we presented in this study achieved better accuracy than the model presented in [24]. Compared with [24], this study showed obvious success on specificity values in the first scenario.

In the second scenario involving data augmentation, the effects of the model we proposed on accuracy, specificity and sensitivity were observed. Our proposed model has been tested in two stages, 100 epochs and 200 epoks. In both cases, more successful results were obtained than in [22], as presented in Table 5. Our proposed model achieved relatively better results at 200 epochs.

It has been observed that the skip connections between the first and third layers of our proposed DNN model, which prevents the loss of features, provide a better learning.

As further work, even more, successful results can be achieved by selecting input features that are considered more relevant (reducing the size of the input layer). In addition, separate models could be developed for each outcome and complication. Thus, more successful results can be obtained.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

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