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Detection of Cardiovascular Diseases with CNN-LSTM Based Model Using Different Evaluation Parameters

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Abstract – Heart diseases are one of the most common diseases in the world. Many deaths can be prevented with early detection of heart disease. In addition, patient care costs decrease with early diagnosis. There is a shortage of specialists in many places and the diagnosis of heart disease cannot be made early. In order to make early diagnosis of heart diseases, computer-aided systems should be developed and used for automatic diagnosis. In this study, a CNN-LSTM based model was developed to detect heart diseases. In order to compare the performances of the developed model, seven various machine learning classifiers that have been utilized in the literature were used. When the results obtained in the proposed CNN-LSTM based model and different classifiers are compared, it is seen that higher success rates are obtained in the proposed CNN-LSTM based model.

Keywords –Cardiovascular Diseases, CNN, LSTM, Machine Learning, Classifiers

I. Introduction

According to the World Health Organization (WHO), heart diseases are very dangerous diseases that cause 17.9 million deaths each year. The rate of heart attack and stroke is higher in cardiac patient death, usually under the age of 70 [1]. Since the heart has the task of pumping blood to the body, the obstacles that will arise during the fulfillment of this function also cause heart diseases. These include sedentary life, smoking, obesity, and alcohol [2]. According to experts, if patients at high risk of developing heart disease can be identified, their chances of survival may increase. In recent years, artificial intelligence techniques have been widely used in the field of classification of diseases in the biomedical industry. The high performance achieved is the main source of this popularity. The fact that there are not enough experts in this field around the world makes it difficult to find people who are at risk of contracting this disease or have heart disease. For all these reasons, in this study, it has been tried to classify heart diseases with the CNN-LSTM-based model developed in order to alleviate the workload of the specialists and to identify the patients. The performance of our proposed model has been compared with the best-known machine learning classifier.

The remainder of the work is organized as follows. The dataset used and the proposed CNN-LSTM based model are detailed in Section 2. In Section 3, experimental results are given. In Section 4, the conclusion of the study is summarized.

II. BACKGROUND

The dataset and methods used in the study are examined in this section. The dataset used in the study is a dataset consisting of 70000 patient records and published publicly on the Kaggle platform. In the relevant dataset, there are 11 features for each sample and the class to which these features belong. The characteristics in each sample were determined as Height, Age, Weight, Diastolic blood pressure (DBP), Gender, Systolic blood pressure (SBP), Cholesterol, Glucose, Smoking, Alcohol, Physical activity (PA), and Classes [3].

In this study, the model was built using long short term memories (LSTM) and convolutional neural networks (CNN). Due to their outstanding performance in computer vision, CNNs are often used in research on image identification, signal processing, natural language processing, emotion recognition, segmentation, classification, and object recognition [4]. One of the most popular deep learning architectures is this one. The application of CNNs has increased recently, particularly in the field of biomedicine [5].

The feature extraction issue in traditional machine learning architectures has been resolved in CNN architectures, which is another factor contributing to CNN architectures' increased use in recent years. In classical machine learning methods, feature extraction is a very troublesome process. In this process, experts in the field are needed. This situation has negative aspects both in terms of cost and time. CNN architectures, unlike classical machine learning methods, perform the learning process directly on the model and make feature extraction automatically.

Hochreiter and Schmidhuber suggested LSTMs in their studies. Cells in LSTM networks store input data and prior state [6]. These cells in LSTM architectures decide which data to keep and which data to delete. In this way, LSTM architectures pave the way for learning patterns in temporal data [7].

In the CNN-LSTM based model developed for the detection of cardiovascular disease, 2 convolution layers 1D, 2 maxpooling layers 1D, 2 Dropout, 2 LSTM, flatten, and dense layers were used to prevent overfitting. In the proposed model, RELU is preferred as the activation function and ADAM is preferred as the optimizer. The block diagram of the proposed model is presented in Figure 1.

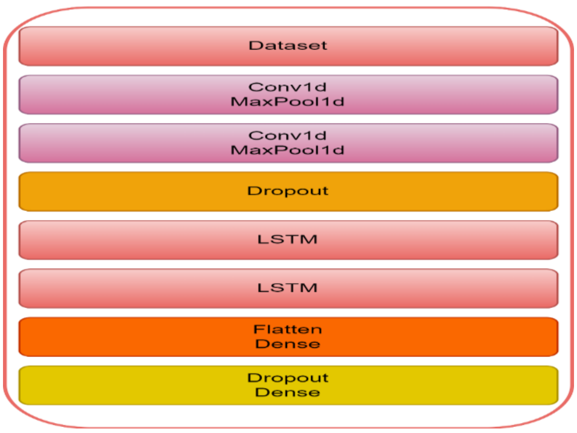

Fig.1 CNN-LSTM based model

While the proposed model was being trained, 56000 of the data in the data set were used for training and 14000 for testing.

III. Results

In the study, the results of the application for the diagnosis of cardiovascular disease were taken in the Python environment. While 80% of the data in the data set used in the study was reserved for training, 20% of the data in the dataset was reserved for testing the models. In the study, a CNN-LSTM based hybrid model was developed to diagnose cardiovascular disease. Results from 7 other machine learning classifiers were also gathered in order to compare the performance of the proposed model. The performance of the models utilized in the study was evaluated using a variety of performance measurement indicators. Accuracy, precision, recall, and f1-score are metrics used to evaluate the performance of models [8].

The confusion matrix, ROC/AUC curve, KNN learning curve, and Precision-Recall curves obtained in the K-nearest neighbors (KNN) [9] classifier during the diagnosis of cardiovascular disease are presented in Figure 2.

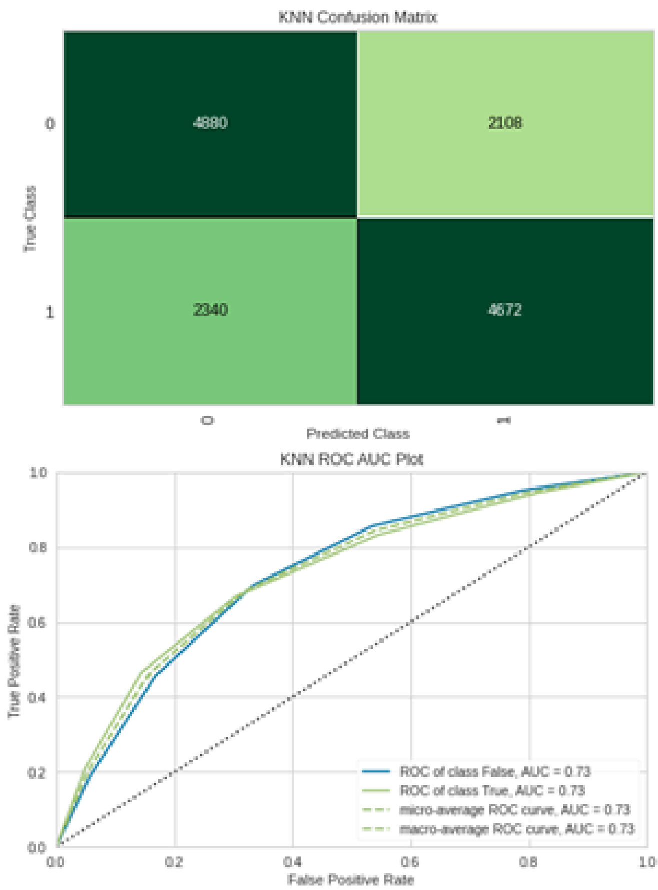

Fig. 2 Results obtained in the KNN classifier

When the confusion matrix given in Figure 2 is examined, the KNN classifier correctly predicted 4880 out of 6988 non-cardio data, while it incorrectly predicted 2108 as cardio. The accuracy value of the KNN classifier in the classification of non-cardio data is 69.83%. While the KNN classifier predicted 4672 of the 7012 test data belonging to the cardio class correctly, it estimated 2340 of them incorrectly. The accuracy value obtained by the KNN classifier in the cardio class is 66.62%. The KNN classifier estimated 9552 correctly and 4448 incorrectly out of a total of 14000 test data. The accuracy value of the KNN classifier is 68.22%.

The confusion matrix, ROC/AUC curve, SVM learning curve, and Precision-Recall curves obtained in the Support Vector Machine (SVM) [10] classifier during the diagnosis of cardiovascular disease are presented in Figure 3.

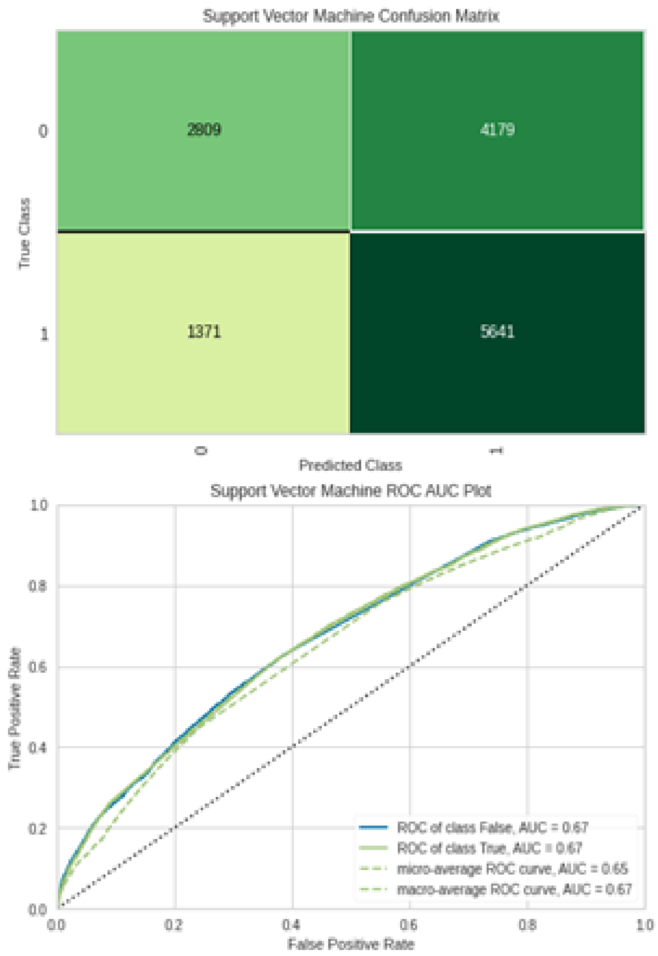

Fig. 3 Results obtained in the SVM classifier

When the confusion matrix given in Figure 3 is examined, the SVM classifier correctly predicted 2809 out of 6988 non-cardio data, while it incorrectly predicted 4179 as cardio. The accuracy value of the SVM classifier in the classification of non-cardio data is 40.19%. While the SVM classifier predicted 5641 of the 7012 test data belonging to the cardio class correctly, it predicted 1371 of them incorrectly. The accuracy value obtained by the SVM classifier in the cardio class is 80.44%. The SVM classifier estimated 8450 of the 14000 test data correctly and 5550 of this data incorrectly. The accuracy value of the SVM is 60.35%.

The confusion matrix, ROC/AUC curve, LR learning curve, and Precision-Recall curves obtained in the Logistic Regression (LR) [11] classifier during the diagnosis of cardiovascular disease are presented in Figure 4.

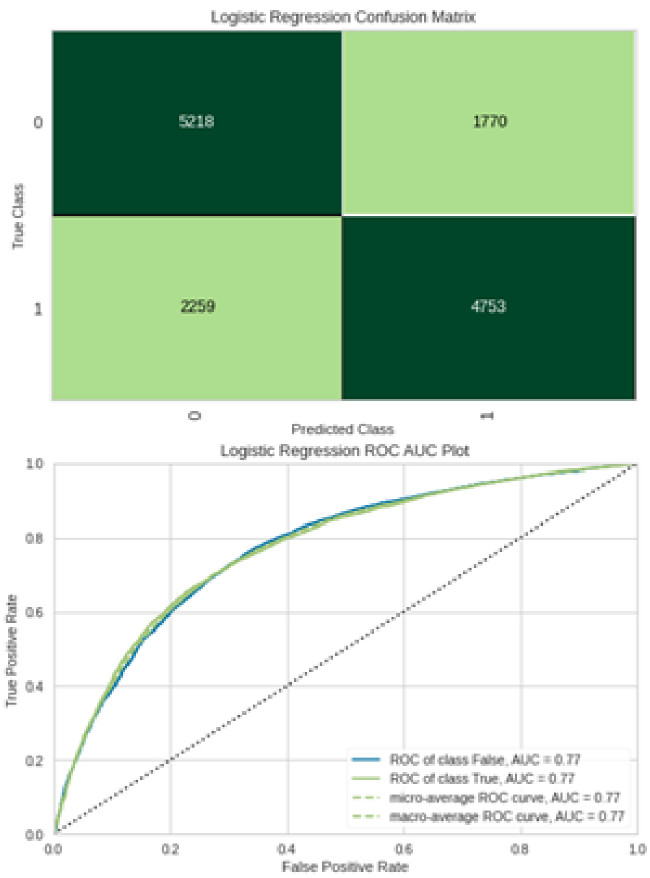

Fig. 4 Results obtained in the LR classifier

When the confusion matrix given in Figure 4 is examined, the LR classifier correctly predicted 5218 out of 6988 non-cardio data, and incorrectly predicted 1770 as cardio. The accuracy value of the LR classifier in the classification of non-cardio data is 74.56%. While the LR classifier predicted 4753 of the 7012 test data belonging to the cardio class correctly, it predicted 2259 of them incorrectly. The accuracy value obtained by the LR classifier in the cardio class is 67.78%. The LR classifier predicted 8450 correctly and 5550 incorrectly of the total 14000 test data. The accuracy value of the LR classifier is 71.22%.

The confusion matrix, ROC/AUC curve, NB learning curve and Precision-Recall curves obtained in the Naive Bayes (NB) [12] classifier during the diagnosis of cardiovascular disease are presented in Figure 5.

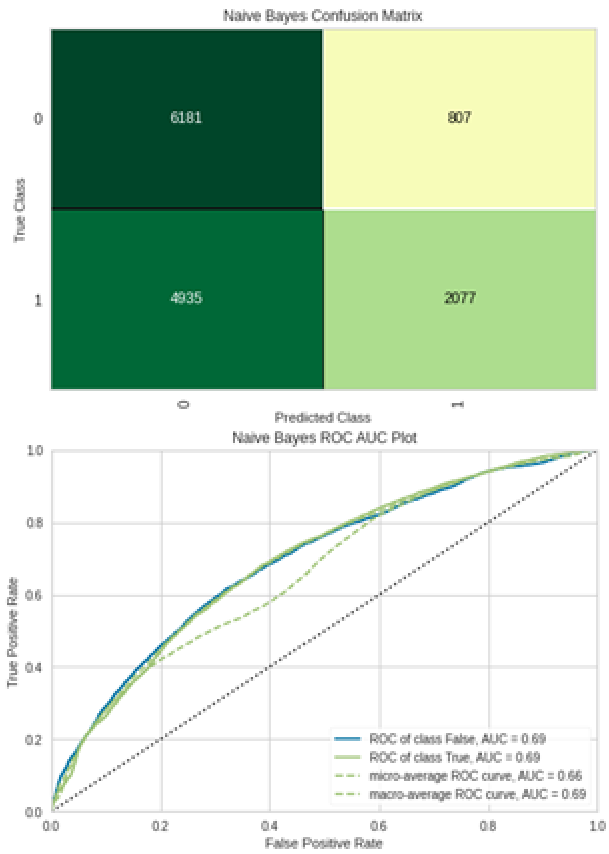

Fig. 5 Results obtained in the NB classifier

When the confusion matrix given in Figure 5 is examined, the NB classifier predicted 6181 out of 6988 non-cardio data correctly, while it incorrectly predicted 807 as cardio. The accuracy value of the NB classifier in the classification of non-cardio data is 88.45%. While the NB classifier predicted 2077 of the 7012 test data belonging to the cardio class correctly, it predicted 4935 of them incorrectly. The accuracy value obtained by the NB classifier in the cardio class is 29.49%. The NB classifier estimated 8258 of 14000 test data correctly and 5742 of this data incorrectly. The accuracy value of the NB classifier is 58.98%.

The confusion matrix, ROC/AUC curve, RF learning curve, and Precision-Recall curves obtained in the Random Forest (RF) [13] classifier during the diagnosis of cardiovascular disease are presented in Figure 6.

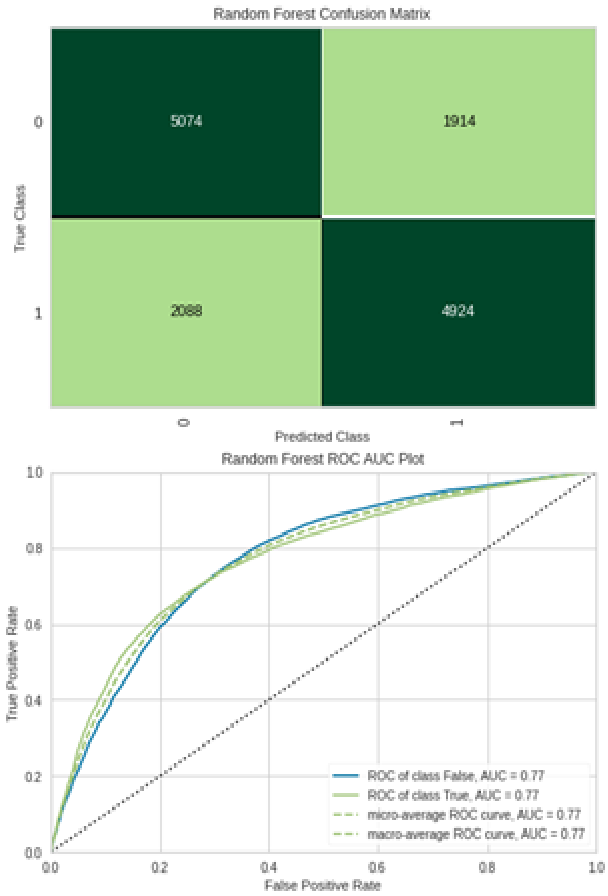

Fig. 6 Results obtained in the RF classifier

When the confusion matrix given in Figure 6 is examined, the RF classifier correctly predicted 5074 out of 6988 non-cardio data, while it incorrectly predicted 1914 as cardio. The accuracy value of the RF classifier in the classification of non-cardio data is 72.61%. While the RF classifier predicted 4924 of the 7012 test data belonging to the cardio class correctly, it predicted 2088 of them incorrectly. The accuracy value obtained by the RF classifier in the cardio class is 70.22%. The RF classifier estimated 9998 correctly and 4002 incorrectly out of a total of 14000 test data. The Adaboost classifier was more successful at classifying non-cardio data than it was at classifying cardio data. The accuracy value of the RF classifier is 71.41%.

The confusion matrix, ROC/AUC curve, DA learning curve, and Precision-Recall curves obtained in the Discriminant Analysis (DA) [14] classifier during the diagnosis of cardiovascular disease are presented in Figure 7.

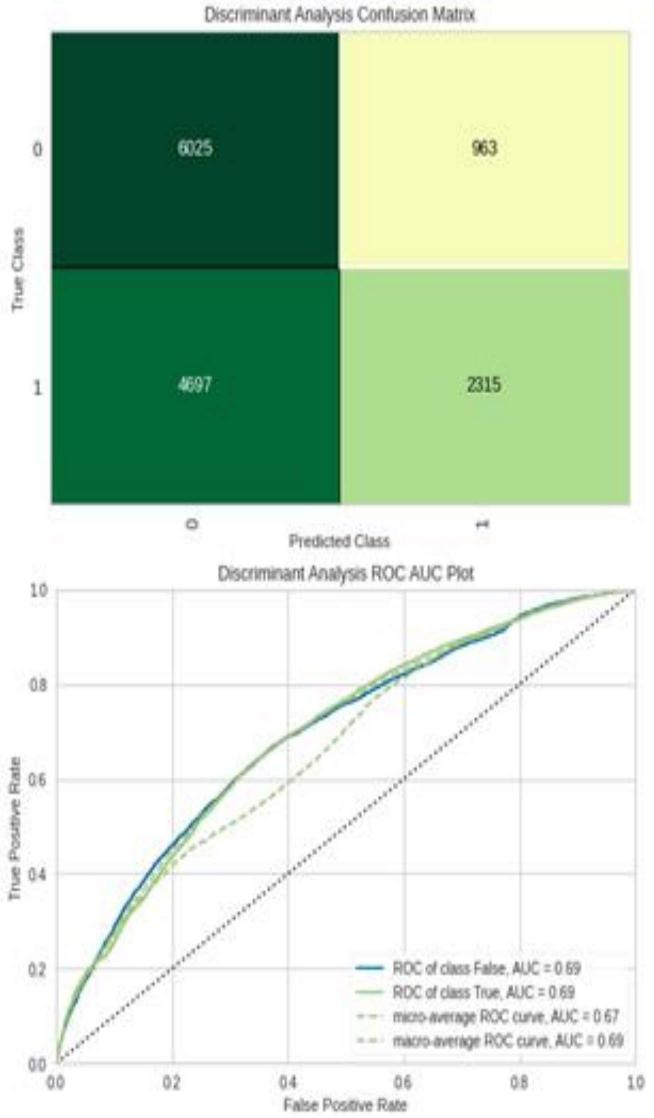

Fig. 7 Results obtained in the DA classifier

When the confusion matrix given in Figure 7 is examined, the DA classifier correctly predicted 6025 out of 6988 non-cardio data, and incorrectly predicted 963 as cardio. The accuracy value of the DA classifier in the classification of non-cardio data is 86.21%. While the DA classifier predicted 2315 of the 7012 test data belonging to the cardio class correctly, it predicted 4697 of them incorrectly. The accuracy value obtained by the DA classifier in the cardio class is 33.01%. The DA classifier estimated 8340 of the 14000 test data correctly and 5660 of this data incorrectly. The accuracy value of the DA classifier is 59.57%.

The confusion matrix, ROC/AUC curve, Adaboost learning curve, and Precision-Recall curves obtained in the Adaboost[15] classifier during the diagnosis of cardiovascular disease are presented in Figure 8.

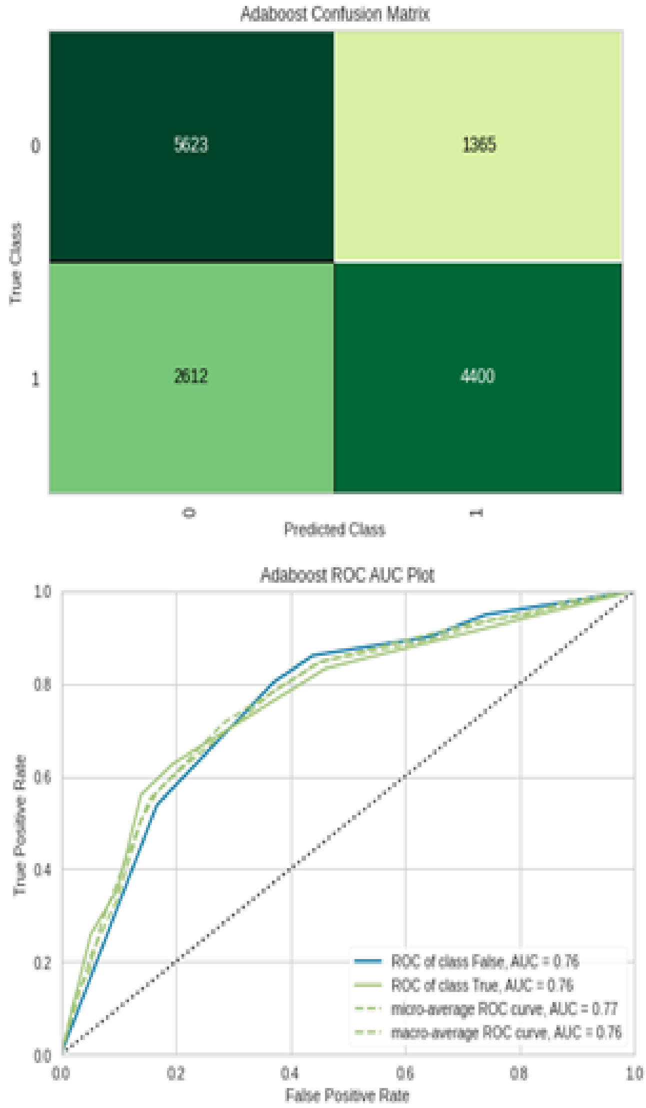

Fig. 8 Results obtained in the Adaboost classifier

When the confusion matrix given in Figure 8 is examined, Adaboost classifier correctly predicted 5623 out of 6988 non-cardio data, and incorrectly predicted 1365 as cardio. The accuracy value of the Adaboost classifier in the classification of non-cardio data is 80.46%. Adaboost classifier correctly predicted 4400 of the 7012 test data of cardio class, while it predicted 2612 incorrectly. The accuracy value obtained by the Adaboost classifier in the cardio class is 62.74%. Adaboost classifier estimated 10023 correctly and 3977 incorrectly of the total 14000 test data. The Adaboost classifier was more successful at classifying non-cardio data than it was at classifying cardio data. The accuracy value of Adaboost classifier is 71.59%.

The accuracy and loss curves obtained in the developed model are presented in Figure 9.

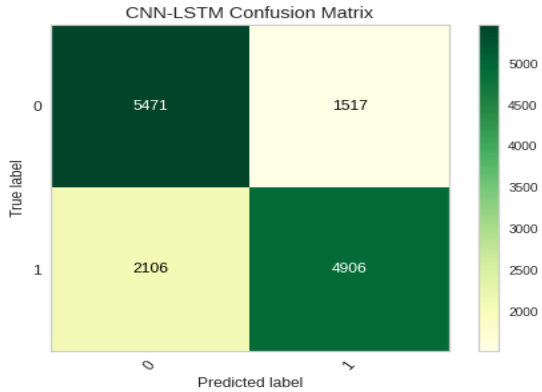

Fig. 9 The results obtained in the proposed model

When the confusion matrix given in Figure 9 is examined, the proposed CNN-LSTM based model predicted 5471 out of 6988 non-cardio data correctly, while it incorrectly predicted 1517 as cardio. The accuracy value of the proposed model in the classification of non-cardio data is 78.29%. While the proposed model predicted 4906 of the 7012 test data belonging to the cardio class correctly, it predicted 2106 of them incorrectly. The accuracy value of the proposed model in cardio class is 69.96%. The proposed model estimated 10023 correctly and 3977 incorrectly of the total 14000 test data. The accuracy of the proposed model is 74.12%.

In the process of diagnosing cardiovascular disease, the accuracy values obtained in the classifiers used in the study and the proposed model are presented in Figure 10 comparatively.

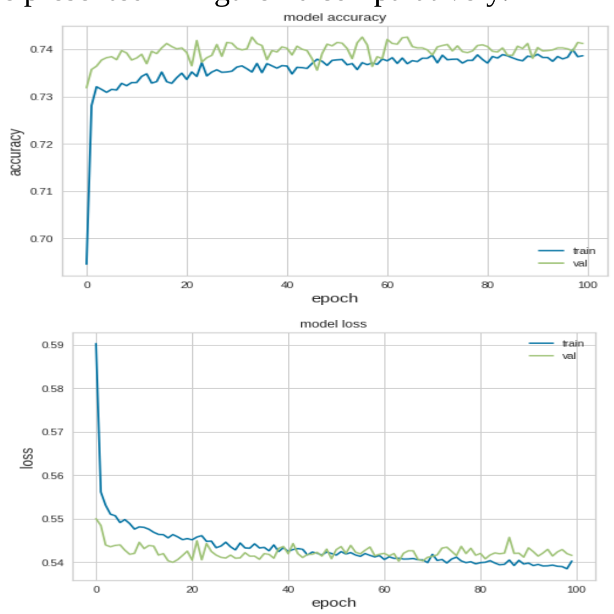

Fig. 10 The accuracy and loss curves of the proposed model

The accuracy values of the proposed model and classifiers are presented in Table 1.

Table 1. Accuracy Rates

KNN	SVM	LR	NB
68.22%	60.35%	71.22%	58.98%
RF	**DA**	**Adaboost**	**Proposed Model**
71.41%	59.57%	71.59%	74.12%

When the results of seven different classifiers and the proposed model were examined, a higher accuracy value was obtained in our CNN-LSTM based model.

IV. CONCLUSION

Heart diseases are increasing due to the sedentary lifestyle that arises from the use of both public transport and private vehicles for transportation in today's conditions. Obesity, which is caused by excessive consumption of fast food, is an important factor that triggers heart disease. Alcohol and cigarette use of people is another important factor that causes these diseases to occur at an earlier age. Classifying the diseases using artificial intelligence techniques and directing the patient to early treatment is extremely important for treatment. In this study, a new CNN-LSTM-based model that reveals heart disease is proposed. The model we proposed in our study was found to have a 74.12% accuracy in the classification of cardiovascular disease. In future studies, it is planned to detect cardiovascular disease with higher accuracy values on the dataset containing more data.

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We thank the owners of the dataset.

CONFLICT OF INTEREST

There is no conflict of interest.

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