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Heart Disease Prediction Using Modified Version of LeNet-5 Model

Shaimaa Mahmoud*
Computer Science Department, Faculty of Computers and Information, Menoufia University, Shebin Elkom 32511, Egypt
E-mail: sh.mahmoud600@gmail.com
ORCID iD: https://orcid.org/0000-0001-9132-5684
*Corresponding Author

Mohamed Gaber
Computer Science Department, Faculty of Computers and Information, Menoufia University, Shebin Elkom 32511, Egypt
E-mail: m.gmalhat@yahoo.com
ORCID iD: https://orcid.org/0000-0002-0136-4805

Gamal Farouk
Computer Science Department, Faculty of Computers and Information, Menoufia University, Shebin Elkom 32511, Egypt
E-mail: gamal.farouk@ci.menofia.edu.eg
ORCID iD: https://orcid.org/0000-0002-8498-8727

Arabi Keshk
Computer Science Department, Faculty of Computers and Information, Menoufia University, Shebin Elkom 32511, Egypt
E-mail: arabikeshk@yahoo.com
ORCID iD: https://orcid.org/0000-0002-8389-7989

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Abstract: Particularly compared to other diseases, heart disease (HD) claims the lives of the greatest number of people worldwide. Many priceless lives can be saved with the help of early and effective disease identification. Medical tests, an electrocardiogram (ECG) signal, heart sounds, computed tomography (CT) images, etc. can all be used to identify HD. Of all sorts, HD signal recognition from ECG signals is crucial. The ECG samples from the participants were taken into consideration as the necessary inputs for the HD detection model in this study. Many researchers analyzed the risk factors of heart disease and used machine learning or deep learning techniques for the early detection of heart patients. In this paper, we propose a modified version of the LeNet-5 model to be used as a transfer model for cardiovascular disease patients. The modified version is compared to the standard version using four evaluation metrics: accuracy, precision, recall, and F1-score. The achieved results indicated that when the LeNet-5 model was modified by increasing the number of used filters, this increased the model's ability to handle the ECGs dataset and extract the most important features from it. The results also showed that the modified version of the LeNet-5 model based on the ECGs image dataset improved accuracy by 9.14 percentage points compared to the standard LeNet-5 model.

Index Terms: Heart disease, Deep learning, LeNet-5, Prediction.

1. Introduction

A cardiovascular disease is a form of heart disease that affects the heart or blood vessels. According to WHO statistics, cardiovascular disease accounts for around 30% of fatalities globally [1]. Heart disease can take many different forms, including cardiomyopathy, congenital heart disease, arrhythmias, heart failure, and diseases of the heart valves [2]. Cardiovascular illness is regarded as the leading cause of death both in the United States and globally [1]. It is also the most significant kind of heart disease (source: American Heart Association, Data from the World Health

Organization, 2013 [3]). The prevalence of cardiovascular disease and its high mortality rate pose serious threats to and costs to global health care systems. Early detection of cardiovascular disease can help to minimize the disease's effects, perhaps lowering mortality rates.

Computer vision [4] is a field of computer science capable of creating intelligent programs that can understand image content much like a human. The image data may be in different forms, such as sequential images, scenes from several cameras, or multi-dimensional data collected from different types of electronic devices, for example, ECGs of heart disease patients. Deep learning [5] is a subset of machine learning, which is a neural network of three or more layers. These neural networks aim to replicate how the human brain functions while falling far short of being able to "learn" from vast amounts of data. Even while a single-layer neural network can still generate rough predictions, the accuracy can be increased with additional hidden layers. Convolutional neural networks are a special type of multi-layer neural network. Like almost any other neural network, they are trained on a version of the backpropagation algorithm, but they differ is in the architecture.

Convolutional Neural Networks are intended to identify visual patterns without much preprocessing, straight from pixel images [6]. When Hubel and Wiesel released a study on the visual cortices of primates and birds, it marked the beginning of CNN's development. Then, in the 1980s, Kunihiko Fukushima presented the CNN field with a convolution technique called recognition that was influenced by the work of Hubel and Wiesel. However, Yann Le Cunn, who developed the LeNet-5 convolutional network employing backpropagation and adjustable weights for different parameters, was largely responsible for elevating CNN to its current state [7]. In [8], the authors proposed a model for the early prediction of heart problems through the predictive analysis of ECG signals. The authors use the benchmark MITDB. However, this model suffers from the small size of the data. In [9], the authors used Logistic Regression [10,11], KNN [12], SVM [13,14], Naïve Bayes [15], Random Forest [16], and deep neural networks (DNN) [5] to predict heart disease patients. However, the achieved results are not accurate enough to be a reliable model. In [17], the authors used SVM [13,14], Artificial Neural Network (ANN) [18], NB [15], DT [19], LR [10,11], and K-Nearest Neighbors (KNN) [12] to implement the Cleveland heart disease dataset, however, this model suffers from the high dimensionality of data.

Many machine and deep learning methods are employed to predict (CVDs), and while these models perform well, they are limited by the high dimensionality of the data. The achieved accuracy wasn't similar across all of the authors' classifiers and wasn't accurate enough to be a dependable model. The majority of authors have resorted to using limited, standard datasets to study cardiovascular problems. Additionally, the abundance of features in the datasets led to machine learning algorithms misinterpreting the data and failing to recognize the most crucial elements. To enhance the effectiveness of the prediction process, the applicable models must train with additional datasets related to cardiovascular disease as well as the opposite. According to the above problems, the aim of the present study is to build a modified version of the LeNet-5 model for improving the prediction of cardiovascular diseases using a patient’s ECG image dataset. LeNet-5 and a modified version are tested using an ECG image dataset of cardiac patients created under the auspices of Ch. Pervaiz Elahi Institute of Cardiology Multan, Pakistan that aims to help the scientific community in researching cardiovascular diseases [20]. and evaluated using four evaluation metrics: accuracy, precision, recall, and F1-score. The experimental results show that LeNet-5 as a transfer model achieved an accuracy of 89.24% and a modified version achieved an accuracy of 98.38%.

This paper is organized as follows: In section 2, some related works in heart disease prediction are introduced. The methods are presented in section 3. The experiment setup and results of our approach are presented in section 4. Conclusions and future work are put forward in section 5.

2. Related Work

Detecting cardiovascular problems is a challenging task that requires more skills and knowledge [21,22]. Therefore, implementing deep learning models for the early identification of cardiac issues based on patient-related ECG has attracted the interest of many researchers in trying to solve this issue. The current research publications on this issue are listed in this part, along with a description of their advantages and disadvantages. In [8], the authors proposed a model for the early prediction of heart problems through predictive analysis of ECG signals. The authors use the benchmark MITDB database [23] acquired from Physionet [24], which includes 48 ECG recordings collected from 47 individuals. The MITDB dataset is split into a training dataset (DS1) and a test dataset (DS2), each containing 22 records with a relatively balanced number of samples for four classes [25]. The proposed method achieved a classification accuracy of 96.6%. However, this model suffers from the small size of the data and needs to implement different deep learning models to verify the validity of the results achieved by the used model.

In [26], the authors proposed a model for heart disease prediction using deep learning neural network. The following methods are used: Logistic Regression [10,11], KNN [12], SVM [13,14], Naïve Bayes [15], Random Forest [16], and deep neural networks (DNN) [27]. The authors used the Heart Diseases datasets collected from the UCI repository [28]. Their experimental results showed that accuracy of 85.25%, 90.16%, 81.97%, 85.25%, 85.15%. 90.78% was obtained for Logistic Regression, KNN, SVM, Naïve Bayes, Random Forest, and DNN respectively. The evaluated algorithms work well in the case of KNN and DNN. However, this model suffers from the high dimensionality of data. In addition, the traditional machine learning algorithms cannot extract the important features from the used standard dataset. Therefore, the applied models are not able to train well with the used dataset.

In [29], the authors proposed an IoT framework for improving heart disease prediction based on the Modified Convolution Neural Network (MDCNN) classifier. The authors compared the performance of MDCNN with that of Deep Learning Neural Network (DLNN) [29] and Logistic Regression (LR) [10,11]. Data from the UCI machine learning repository, Framingham, Public Health, and Sensor Data [30,31] were used to train and evaluate the disease. Accuracy, precision, sensitivity, recall, and F1 Score metrics were used to evaluate the performance of the MDCNN and the other employed methods. It was found that the proposed model achieved the best results compared with other methodologies. The MDCNN achieved 98.2% accuracy. In contrast, the existing LR and DLNN have lower accuracy of 88.3% and 81.6%, respectively. However, this model suffers from the high dimensionality of data. The achieved results need to be improved because it is not good enough to use with heart disease prediction.

In [17], the authors proposed a heart disease identification method using machine learning classification in healthcare. Researchers study the impact of using two feature selection methods (i.e., Relief [32] and LASSO [33]) on the performance of six standard machine learning techniques. These techniques are SVM [13,14], Artificial Neural Network (ANN) [18], NB [15], DT [19], LR [10,11], and K-Nearest Neighbors (KNN) [12]. The Cleveland heart disease dataset [28], which was extracted from the UCI machine learning repository is used. Accuracy, sensitivity, specificity, precision, and Matthews Correlation Coefficient (MCC) metrics are used to evaluate the performance of the employed techniques. The accuracy of SVM with their feature selection algorithm was achieved at 92.37%. However, this model suffers from the small size of the data. In addition, the large number of features presented in the data set caused machine learning algorithms to be misleading and unable to extract the most important features from the data.

Table 1. Summary of the related work

Year	Reference Number	Methods Used	Dataset	Best Accuracy Achieved	Advantages	Disadvantages
2019	[8]	Global classifier, and subsequent personalized classification.	MITDB dataset which includes 48 ECG recordings collected from 47 individuals.	96.6%	The accuracy achieved good results in the evaluation.	This model suffers from the small size of the data and needs to implement different deep learning models.
2020	[9]	Logistic Regression, KNN, SVM, Naïve Bayes, Random Forest, and deep neural networks (DNN).	Heart disease contains 303 instances and 14 attributes.	90.78%	The evaluated algorithms work well in the case of KNN and DNN	This model has a high dimensionality of data.
2020	[29]	Deep Learning Neural Network (DLNN), Logistic Regression (LR), and Modified Deep Convolutional Neural Network (MDCNN).	UCI machine learning repository, Framingham, Public Health, and Sensor Data	88.3%, 81.6%, and 98.2% when using LR, DLNN, and MDCNN respectively.	The MDCNN achieves 98.2% accuracy which is the best result compared with other methodologies.	This model suffers from high dimensionality of data.
2020	[17]	Support vector machine, Artificial neural network, Naïve bays, Decision tree, Logistic regression, and K-nearest neighbor.	Heart disease contains 303 instances and 75 attributes.	92.37%	Researchers presented a comprehensive test using machine learning classifiers and Artificial neural network	This model suffers from the small size of data.
2021	[34]	Logistic Regression, KNN, SVM, Decision Tree, and Deep Learning (DL).	Cleveland, Hungary, Switzerland, and the VA Long Beach	94.2%	The accuracy was achieved well using the deep learning model.	The used models suffer from the small size and high dimensionality of data.
2022	[35]	Random Forest, Decision Tree, Naive Bayes, and Weighted Average Ensemble model.	A combined dataset from Cleveland, Long Beach VA, Switzerland, Hungarian, and Stat log datasets are used.	precision, recall, and F1-score are all 0.93%. MAE, MSE, and RMSE of 0.07, 0.07, and 0.27.	A huge amount of datasets from the UCI repository are used. In addition, using different evaluation metrics to evaluate their model.	The dataset has a limited number of data. And the obtained results are not accurate enough to be a reliable model.

In [34], the authors proposed a model for the prediction of heart disease based on a combination of machine and deep learning techniques. The four databases they used were Cleveland, Hungary, Switzerland, and Long Beach V, and the Public Health Dataset [28]. The following methods are used: Logistic Regression [10,11], KNN [12], SVM [13,14], Decision Tree [19], and Deep Learning (DL) [27]. Accuracy, Specificity, and Sensitivity metrics were used to evaluate the employed algorithms. Their experimental results show that accuracy of 83.3%, 84.8%, 83.2%, 80.3%, 82.3%, and

94.2% was obtained for Logistic Regression, KNN, SVM, Decision Tree, and Deep Learning respectively. The deep learning model achieved better accuracy compared to the used machine learning models. However, the used models suffer from the small size and high dimensionality of data. And the obtained results are not good enough to be a reliable model for heart disease prediction. Therefore, the applied models need to train with other heart disease datasets to improve their performance.

In [35], the authors proposed a novel machine learning model called the Weighted Average Ensemble that achieves a superior result by combining three standard machine learning techniques (Random Forest [16], Decision Tree [19], and Naive Bayes [15]). Researchers used a combined dataset from Cleveland, Long Beach VA, Switzerland, Hungarian, and Stat log datasets [28]. The performance of the Weighted Average Ensemble model was evaluated using the following metrics: Accuracy, Precision, Recall, F1-score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) metrics. It was found that the average ensemble model's precision, recall, and F1-score are all 0.93. And, when compared to the other six algorithms, MAE, MSE, and RMSE of 0.07, 0.07, and 0.27, respectively, are the best performance results. However, the dataset has a limited number of data points. And the obtained results are not accurate enough to be a reliable model for heart disease prediction.

Table 1. lists the discussed related work in summary. It shows the year of publication, methods used, employed datasets, advantages, disadvantages, and accuracy achieved for each related work. It was found that these models work well but suffer from the high dimensionality of data. The achieved accuracy wasn’t stable on all classifiers used by the authors and was not accurate enough to be a reliable model.

3. Methods

In this work, we propose a modified version of the LeNet-5 model to be used as a transfer model for cardiovascular disease patients. So, we start the explanation with how LeNet-5 was applied in the used ECG data set. Next, how we modified the LeNet-5 architecture to improve the accuracy of cardiovascular disease prediction using the ECG dataset.

3.1. LeNet-5

In 1998, Yann LeCun, one of the forerunners of deep learning, invented LeNet-5 in his work "Gradient-Based Learning Applied to Document Recognition" [36]. Using the MNIST dataset as a base, banks used LeNet-5 to recognize handwritten checks. Fully connected networks and activation functions were previously known in neural networks.

LeNet-5 as shown in Fig.1 consists of 7 layers – alternatingly 2 convolutional and 2 average pooling layers, and then 2 fully connected layers and the output layer with an activation function called softmax. Fig.2 shows how LeNet-5 as a transfer model has been applied to ECG dataset with four classes.

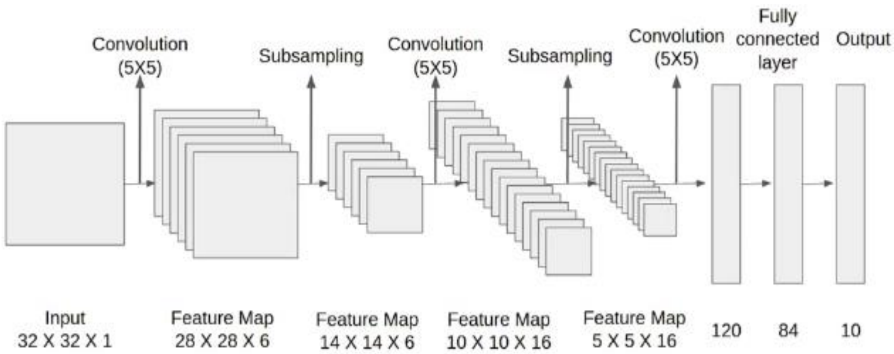

Fig.1. LeNet-5 architecture [36]

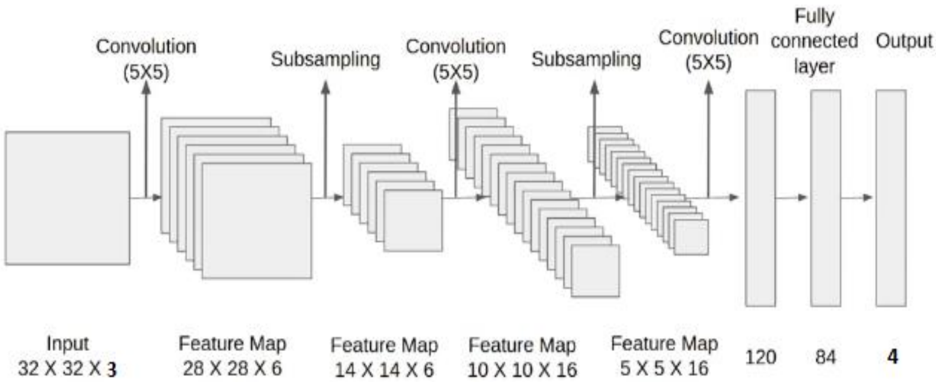

Fig.2. LeNet-5 as a transfer model architecture

LeNet-5 consists of 7 layers, 2 convolutional and 2 average pooling layers, and then 2 fully connected layers and the output layer as follows:

- *From Fig.2 the feature extraction layers are:*
  - Layer (1)

    Conv2D(filters=6, kernel_size=(5, 5), activation='tanh')
  - Layer (2)

    AveragePooling2D()
  - Layer (3)

    Conv2D(filters=16, kernel_size=(5, 5), activation='tanh')
  - Layer (4)

    AveragePooling2D()
- *From Fig.2 the fully connected layers are:*
  - Layer (5)

    Dense (units=120, activation='tanh')
  - Layer (6)

    Dense (units=84, activation='tanh')
  - Layer (7)

    Dense (units=4, activation = 'softmax')

As shown below in Fig.2, the LeNet-5 model architecture contains: -

- First layer: The first layer of LeNet-5 is a 32x32 input image layer. It passes through a convolutional block with six filters of size 5x5. The resulting dimensions are 28x28x6 from 32x32x3.
- Second layer: The pooling layer also called the subsampling layer has a filter size of 2x2 and a stride of 2. Image dimensions are reduced to 14x14x6.
- Third layer: This is again a Convolutional Layer with 16 feature maps, a size of 5x5, and a stride of 1.
- Fourth layer: It is a pooling layer with a filter size of 2x2 and a stride of 2 with an output of 5x5x16.
- Fifth layer: It is a fully connected convolutional layer with 120 feature maps and size being 1x1 each.
- Sixth layer: It is a fully connected layer with 84 units.
- Finally, the output layer is a softmax layer with four possible values corresponding to each digit.

3.2. Modified Version of LeNet-5

A modified version of LeNet-5 as shown in Fig.3 consists of 7 layers – alternatingly 2 convolutional and 2 max-pooling layers, and then 2 fully connected layers after each one dropout (0.2) is used, and the output layer with activation function softmax.

- *Feature extraction as shown in Fig.3.*
  - Layer (1)

    (Conv2D(32, kernel_size=(3,3), strides=(2,2), padding='same', activation='relu', input_shape=(350,350,3))
  - Layer (2)

    MaxPool2D(pool_size=(2,2)))

- Layer (3)

  Conv2D(64, kernel_size=(3,3), strides=(2,2), padding='same', activation='relu'))

- Layer (4)

  MaxPool2D(pool_size=(2,2)))

- *Output as shown in Fig.3.*

  - Layer (5)

    Dense (64, activation='relu')

  - Layer (6)

    Dense (32, activation='relu')

  - Layer (7)

    Dense (4, activation='softmax'))

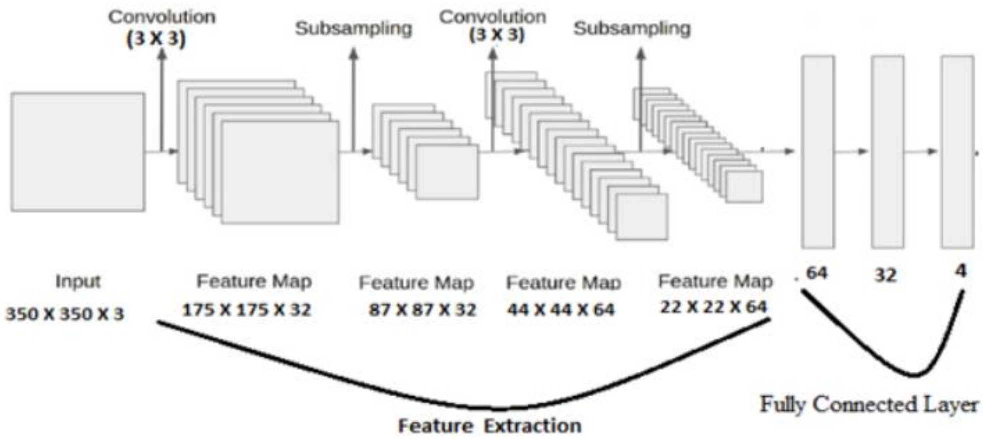

Fig.3. Modified version of LeNet-5 architecture

As shown below in Fig.3, a modified version of LeNet-5 architecture contains:

- First layer: The first layer of LeNet-5 is a 350x350 input image layer. It passes through a convolutional block with 32 filters of size 3x3. The resulting dimensions are 175x175x32 from 350x350x3.
- Second layer: The pooling layer also called the subsampling layer has a filter size of 2x2 and a stride of 2. Image dimensions are reduced to 87x87x32.
- Third layer: This is again a Convolutional Layer with 64 feature maps, a size of 3x3, and a stride of 2.
- Fourth layer: It is a pooling layer with a filter size of 2x2 and a stride of 2 with an output of 22x22x64.
- Fifth layer: It is a fully connected convolutional layer with 64 units.
- Sixth layer: It is a fully connected layer with 32 units.
- Finally, the output layer is a softmax layer with four possible values corresponding to each digit.

LeNet-5 suffers from the small size of the used filters and didn't apply the dropout technique. So, comparing the modified version of LeNet-5 to the LeNet-5 model, it achieved better performance as discussed below in the performance evaluation section. Increasing the number of filters in the modified version helped to extract the most important features from the ECG images. In addition, the use of the maxpooling2D and dropout technique led to a reduction in the number of parameters used and deleted the irrelevant features from the used dataset.

4. Experimental Setup

In this section, we present dataset information, evaluation metrics, and performance comparison between LeNet-5 and a modified version of LeNet-5.

4.1. Dataset

We have used the publicly available ECG images dataset of Cardiac Patients created under the auspices of Ch. Pervaiz Elahi Institute of Cardiology Multan, Pakistan that aims to help the scientific community in researching cardiovascular diseases [20]. This dataset contains four classes as shown in Fig.4:

- ECG Images of Myocardial Infarction Patients.
- ECG Images of Patients that have an abnormal heartbeat.
- ECG Images of Patients that have a history of Myocardial Infarction (MI).
- Normal Person ECG Images.

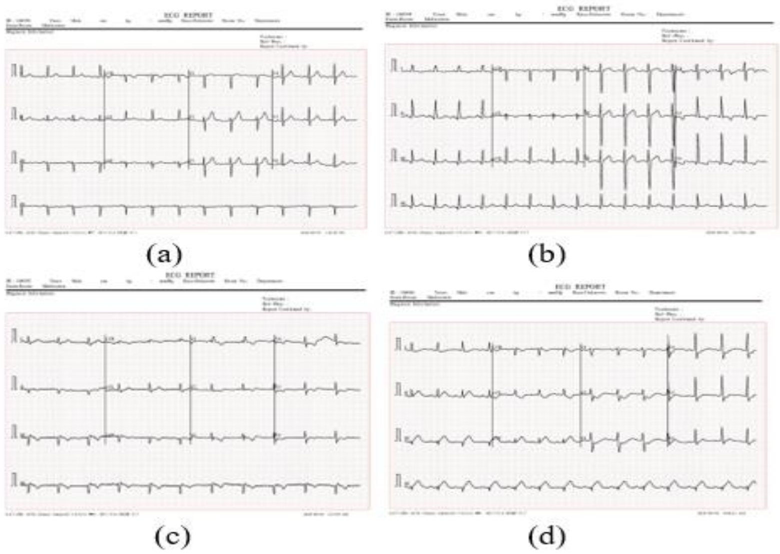

Fig.4. Samples of ECG dataset, (a) Normal, (b) Abnormal, (c) History of MI, and (d) Infarction patients

As shown in Table 2. this dataset contains 928 ECG images divided into four classes: normal, abnormal, history of MI, and infarction patients. Then it is split with the ratio of 80:20, where 80 is used for training used models and 20 is used for testing.

Table 2. Distribution of the ECG dataset.

Type	Normal	abnormal	History of MI	Infarction	Total
Train	227	186	138	191	742
Test	57	47	34	48	186

4.2. Evaluation Metrics

The evaluation metrics used for evaluating the employed classifiers are accuracy, precision, recall, and F1_score are discussed in this section.

- Accuracy refers to the proximity of the measurements to a specified value. The higher the accuracy value, the better the performance of the model used as defined in Eq. (1)[1].

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Postive + True\ Negative + False\ Positive + False\ Negative)} \tag{1}$$

- Precision as defined in Eq. (2)[1] quantifies the number of positive class predictions that belong to the positive class.

$$Precision = \frac{(True\ Positive\ )}{(True\ Postive + \ False\ Positive\ )} \tag{2}$$

- Recall quantifies the number of positive class predictions made out of all as defined in Eq. (3)[1].

$$Recall = \frac{(True\ Positive\ )}{(True\ Postive + \ False\ Negative)} \tag{3}$$

- In Eq. (4)[1], the F1 score combines precision and recall to a given positive class - The F1_score can be thought of as a weighted average of precision and recall, with 1 being the highest and 0 being the worst.

$$F1\text{-}score = \frac{2(Precision * Recall)}{(precision + Recall)} \tag{4}$$

Terminologies that are used in the evaluation metrics equations:

- *True Positive:* Consider the time when the model's heart disease was accurately recognized.
- *True Negative:* When the model successfully identified the opposing class, such as patients who do not have any heart problems.
- *False Positive:* Refer to when the model incorrectly identified heart disease patients i.e., identifying non-heart disease patients as heart disease patients.
- *False Negative:* When the model wrongly identifies the opposite class, such as heart disease patients as normal patients.

4.3. Performance Evaluation

In the case of using the LeNet-5 model as a transfer model the accuracy of 89.24% was obtained and as shown in Table 3. LeNet-5 model achieved precision, recall, f1-score: 81%, 100%, and 90% respectively in the normal class, 100%, 55%, and 71% respectively in the abnormal class, 85%, 100%, and 92% respectively in the history of myocardial infarction class, and 96%, 100%, and 98% respectively in the infarction class.

Table 3. Confusion matrix of LeNet-5 model for each class.

Class	Precision	Recall	F1_Score
Normal	0.81%	1.00%	0.90%
abnormal	1.00%	0.55%	0.71%
History of MI	0.85%	1.00%	0.92%
Infarction	0.96%	1.00%	0.98%

- After modifying the LeNet-5 model the accuracy of 98.38%.was obtained and as shown in Table 4. modified version of LeNet-5 model achieved precision, recall, f1-score: 95%, 100%, and 97% respectively in the normal class, 100%, 94%, and 97% respectively in the abnormal class, 100% for all in the history of myocardial infarction class, and the infarction class, which are better than LeNet-5. A modified version of LeNet-5 obtained better performance than LeNet-5 for many reasons:

  - LeNet-5 receives the images with size 32 X 32 but this size is not good enough for our dataset. So, increasing the image size during the processing step before entering it into the used model led to an improvement in the model's ability to identify the most important features in the images.
  - The use of the maxpooling2D led to a reduction in the number of parameters used while retaining the most important features in the images through the use of strides and thus speeding up the model used while maintaining performance.
  - Dropout is a technique that certain neurons are dropped at random during training. It is an easy method for the deep neural network to become less dependent. Dropout effectively addresses the overfitting issue in neural networks and improves the performance of applied models. So, using dropout in a modified version of LeNet-5 improved the model performance.

Table 4. Confusion matrix of a modified version of LeNet-5 model for each class.

Class	Precision	Recall	F1_Score
Normal	0.95%	1.00%	0.97%
abnormal	1.00%	0.94%	0.97%
History of MI	1.00%	1.00%	1.00%
Infarction	1.00%	1.00%	1.00%

As shown in Fig.5, Fig.6, and Fig.7, comparisons between LeNet-5 and a modified version of LeNet-5 using precision, recall, and f1_score respectively for each class with the used ECG dataset. And as shown in Table 5. and Fig.8, performance comparisons between LeNet-5 and a modified version of LeNet-5 using all evaluation metrics and used time for each model during the implementation.

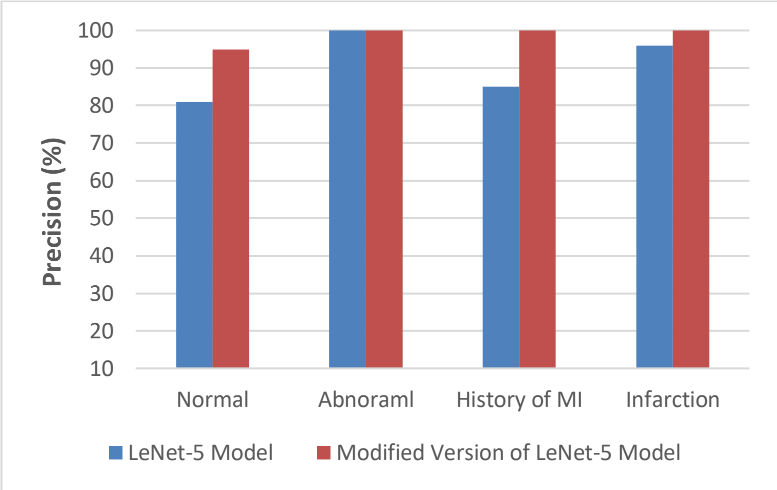

Fig.5. Comparison between LeNet-5 and a modified version of LeNet-5 using precision for each class

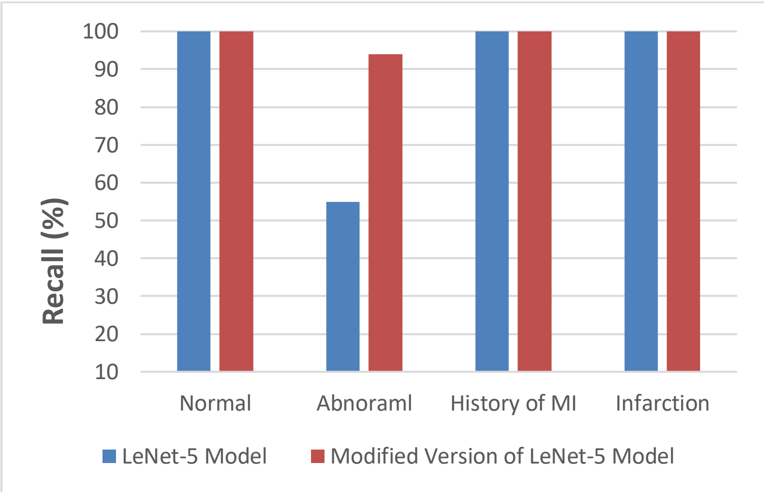

Fig.6. Comparison between LeNet-5 and a modified version of LeNet-5 using recall for each class

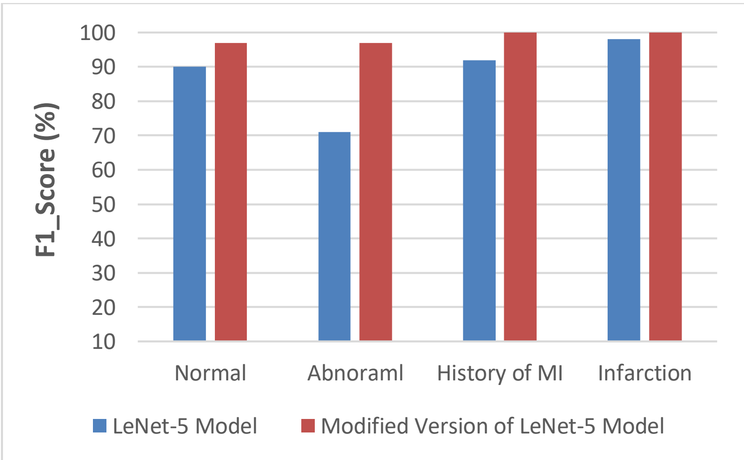

Fig.7. Comparison between LeNet-5 and a modified version of LeNet-5 using f1_score for each class

As shown in Table 5. LeNet-5 achieved precision, recall, f1_score, loss error, and accuracy of 91%, 89%, 88%, 0.70, and 89.24%. In addition, it took time of 41.95 seconds during the training process. The modified version of LeNet-5 achieved precision, recall, f1_score, loss error, and accuracy of 99%, 98%, 99%, 0.07, and 98.38% which are better than LeNet-5. In addition, it took time of 144.62 seconds during the training process.

Table 5. Performance comparisons between LeNet-5 and a modified version of LeNet-5.

Model	Precision	Recall	F1_Score	Loss	Accuracy	Time
LeNet-5	91%	89%	88%	0.70	89.24%	41.95 Seconds
Modified Version of LeNet-5	99%	98%	99%	0.07	98.38%	144.62 Seconds

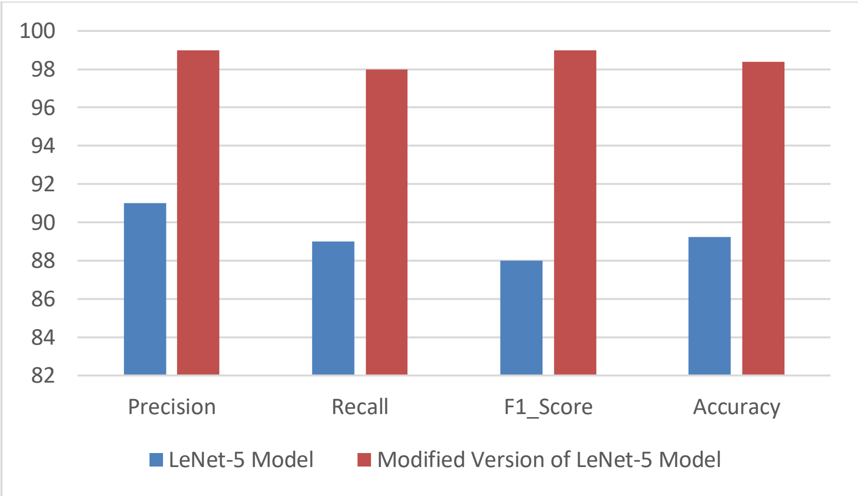

Fig.8. Comparison between LeNet-5 and a modified version of LeNet-5

5. Conclusions and Future Work

Heart disease is one of the most dangerous diseases that lead to death. It results from the lack of early detection of heart patients. Many researchers analyzed the risk factors of heart disease and proposed machine and deep learning models for the early detection of heart patients. However, these models suffer from the high dimensionality of data and need to be improved to obtain highly accurate results. In this work, LeNet-5 as a transfer model is used to detect cardiovascular patients. Then we modify its architecture and have a new version of LeNet-5. The used dataset contains 928 ECG images divided into four classes: normal, abnormal, history of MI, and infarction patients. Then it is split with the ratio of 80:20, where 80 is used for training used models and 20 is used for testing. Modifying LeNet-5 architecture by increasing the number of used filters helped to extract the most important features from the ECG images. In addition, the use of the maxpooling2D and dropout technique led to a reduction in the number of parameters used and deleted the irrelevant features from the used dataset. Our experimental results show that LeNet-5 as a transfer model obtains a classification accuracy of 89.24%, a precision of 0.91%, a recall of 0.89%, and an f1_score of 0.88%. A modified version of the LeNet-5 model obtains a classification accuracy of 98.38%, a precision of 0.99%, a recall of 0.98%, and an f1_score of 0.99%, which are better than the results of the LeNet-5 as a transfer model.

In the future, we will plan to build a new CNN model and compare its performance with other CNN models such as ResNet-50 and DenseNet.

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Authors’ Profiles

Shaimaa Mahmoud is a PhD student at Menoufia University, Egypt. She received her B.Sc. in Computer Science from 6 October University, Faculty of Computers and Information in 2017 respectively. And received her M.Sc. in Computer Science from Menoufia University, Faculty of Computers, and Information in 2020. Her main research interest includes Data Mining, Computer Vision, Machine and Deep Learning.

Mohammed G. Malhat received his B.Sc., M.Sc., and PhD in Computer Science from Menoufia University, Faculty of Computers, and Information in 2010, 2014, and 2019, respectively. His research interest includes Distributed Systems, Data Mining, Machine Learning, Data Privacy, and Security, Cloud Computing, intelligent agent, Software engineering.

Gamal. F. Elhady received the B.Sc, M.Sc and PhD degree in Computer Science at Faculty of Science, in 1998 and 2006, Mansoura University, Egypt. During 1998 and 2006, he works as the researcher student and Lecturer Assistance in Faculty of science computer science Dept. He is member of IAENG in USA (# 108463). His research interest includes software programing, software testing, distributed system, data mining, database, Artificial intelligent, image processing and bioinformatics.

Arabi Keshk received the B.Sc. degree in electronic engineering and the M.Sc. degree in computer science and engineering from the Faculty of Electronic Engineering, Menoufia University, in 1987 and 1995, respectively. He received his Ph.D. degree in electronic engineering from Osaka University, Japan in 2001. His research interests include software testing, software engineering, distributed systems, cloud computing, machine learning, the IoT, big data analytics, and bioinformatics.

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