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Heart Attack Prediction using CNN

Jithina Jose, Pavan Mishra, Jay Bansod, Twinkle Pingat, Paramanand Malvadkar
Department of Computer Engineering
Dr. D. Y. Patil Institute of Technology, Pimpri, Pune, India
jithina.jose@dypvp.edu.in, pavanmishra719900@gmail.com, jaybansod678@gmail.com
twinklepingat04@gamil.com, param.malvadkar@gmail.com

Abstract: *The study represents a significant advancement in cardiovascular disease detection by employing deep learning techniques, particularly focusing on Electrocardiogram (ECG) data analysis. By utilizing transfer learning with pretrained deep neural networks like SqueezeNet and AlexNet, alongside a novel convolutional neural network (CNN) architecture tailored for cardiac abnormality prediction, the researchers demonstrated remarkable accuracy in identifying four major cardiac conditions. This approach not only capitalizes on the strengths of deep learning but also addresses the challenges posed by limited medical datasets, showcasing the potential of artificial intelligence in revolutionizing healthcare diagnostics.*

The results are highly promising, with the proposed CNN model outperforming previous methods, achieving exceptional accuracy, recall, precision, and F1 score. Furthermore, employing the CNN model for feature extraction in tandem with traditional machine learning algorithms highlights its versatility and potential for integration into clinical practice. Overall, this study underscores the pivotal role of deep learning in early detection and classification of cardiovascular diseases, offering healthcare professionals a powerful tool to improve patient outcomes and save lives

Keywords: Cardiovascular, Electrocardiogram (ECG), Machine Learning, CNN.

I. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular diseases, also known as heart diseases, are the primary cause of death globally. They claim approximately 17.9 million lives each year, accounting for 32% of all deaths worldwide. Heart attacks, or myocardial infarctions (MI), are responsible for about 85% of all heart disease-related deaths. Detecting cardiovascular disease at an earlier stage can save many lives. Various techniques, such as electrocardiogram (ECG), echocardiography (echo), cardiac magnetic resonance imaging, computed tomography, and blood tests, are used in the healthcare system to detect heart diseases. The ECG is a widely used, cost-effective, and noninvasive tool for measuring the heart's electrical activity. It helps identify heart- related cardiovascular diseases. However, the manual process of interpreting ECG waves can lead to inaccurate results and is time-consuming. The advancement of artificial intelligence in healthcare offers great potential to reduce medical errors. Machine learning and deep learning techniques can be used for automatic prediction of heart diseases. These methods require experts to extract and select the appropriate features before applying the classification phase. Feature extraction involves reducing the number of features in a dataset by transforming or projecting the data into a new lower-dimensional feature space while preserving the relevant information.

The idea behind feature extraction involves creating a fresh set of features that are a combination of the original features, resulting in a lower-dimensional space that captures most, if not all, of the information present in the input data. The principal component analysis (PCA) is the most well-known technique for feature extraction. On the other hand, feature selection aims to eliminate irrelevant and redundant features (dimensions) from the training data set in machine learning algorithms. There are various methods available for feature selection, which can be classified as unsupervised or supervised. Unsupervised methods do not require the output label for feature selection, while supervised methods utilize the output label. Within supervised feature selection, there are three methods: the filter method, the wrapper method, and the embedded method.

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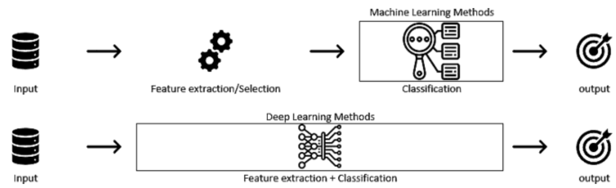

Fig. 1. Abstract concept of machine learning and deep learning.

Machine learning models, including decision tree (DT), Naïve Bayes (NB), K-nearest neighbors (K-NN), and neural network (NN), were evaluated on the UCI Cleveland heart disease dataset. The study found that DT achieved the highest accuracy of 89%. Dissanayake and Md Johar investigated the impact of feature selection techniques on machine learning classifiers for heart disease prediction using the same dataset. Various methods such as ANOVA, Chi-square, forward and backward feature selection, and Lasso regression were examined. Six classifiers, namely DT, random forest (RF), support vector machine (SVM), K-NN, logistic regression (LR), and Gaussian NB (GNB), were applied. Through feature selection, the classification accuracy improved significantly, with the highest accuracy of 88.52% achieved using the backward feature selection method with the DT classifier. Another study focused on NB, SVM, and DT algorithms for heart disease detection using ten-fold cross-validation on the South African heart disease dataset comprising 462 instances. NB showed the best performance with an accuracy rate of 71.6%, sensitivity of 63%, and specificity of 76.16%. Kim et al. compared NN, SVM, and classification based on multiple association rules (CMAR), DT, and NB algorithms for cardiovascular disease prediction using ultrasound images of carotid arteries (CAs) and heart rate variability (HRV) datasets. The combined features from the CAs+ HRV dataset yielded higher accuracy compared to separate features of CAs and HRV. SVM and CMAR classifiers outperformed others with accuracies of 89.51% and 89.46%, respectively. Additionally, deep learning, a subfield of machine learning, automatically extracts crucial features and patterns from training datasets for classification without external intervention.

II. LITERATURE REVIEW

Numerous studies have been carried out to automatically predict cardiovascular diseases using machine learning and deep learning techniques with ECG data as digital or image representations. Bharti et al. [28] conducted a comparison between machine learning and deep learning methods on the UCI heart disease dataset to predict two classes. The deep learning approach achieved the highest accuracy rate of 94.2%. Their deep learning model architecture included three fully connected layers: the first layer with 128 neurons, followed by a dropout layer with a rate of 0.2, the second layer with 64 neurons, followed by a dropout layer with a rate of 0.1, and the third layer with 32 neurons. Machine learning methods, combined with feature selection and outlier detection, achieved accuracy rates as follows: RF at 80.3%, LR at 83.31%, K-NN at 84.86%, SVM at 83.29%, DT at 82.33%, and XGBoost at 71.4%. Research in concluded that deep learning has shown to be a more accurate and efficient technology for various medical issues such as prediction, potentially replacing traditional machine learning based on feature engineering. Kiranyaz et al. introduced a CNN with three layers of adaptive one- dimensional (1-D) convolution layers. This network was trained on the MIT-BIH arrhythmia dataset to classify long ECG data streams, achieving accuracy rates of 99% and 97.6% in classifying ventricular ectopic beats and supraventricular ectopic beats, respectively. Additionally, the study in [31] presented a CNN with three 1-D convolution layers, three max- pooling layers, one fully connected layer, and one softmax layer. The filter size for the first and second convolutional layers was set to 5, and a stride of 2 was used for the first two max-pooling layers. They achieved an accuracy rate of 92.7% in classifying EsCG heartbeats using the MIT-BIH arrhythmia dataset

III. PROPOSED SYSTEM

The CNN model proposed consists of various layers, including 2-D convolutional layers, fully connected layers, max-pooling layers, leaky ReLU layers, batch normalization layers, dropout layers, depth concatenation layers, and a softmax layer. In total, there are 38 layers. The architecture of this model is depicted in Figure 4. Additionally, the proposed CNN model comprises two branches, namely the stacked branch and the full branch, which aid in extracting

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more representative features. The input image size accepted by the model is 227x227x3, and it flows into both branches simultaneously.

The stack branch is composed of three stacked 2-D 3x3 convolutional layers. Each of these layers is followed by a leaky ReLU layer, a batch normalization layer, and a max-pooling layer. The leaky ReLU layer utilizes a leaky ReLU activation function with a scale of 0.1, which helps address the issue of dying neurons. The batch normalization layer normalizes the inputs for each minibatch, resulting in faster model training and increased accuracy. The max-pooling layer applies the max-pooling operation to the feature map, reducing its spatial size and the number of parameters and the computational cost in the model. The max-pooling layers in this branch have a filter size of 6x6 and a stride of 3. For the first, second, and third convolutional layers, 64, 128, and 224 filters are employed, respectively. The output size at the end of the stack branch is 2x2x224. Conv04 is a 32x2x2 convolutional layer with a stride of 1 and a padding of 1, while conv05 is a 64x3x3 convolutional layer with a stride of 2 and a padding of 2. The feature maps of these two convolutional layers are combined to create a feature map of 2x2x96. Following the combination of features, a dropout layer is utilized to diminish the impact of correlated features and prevent overfitting.

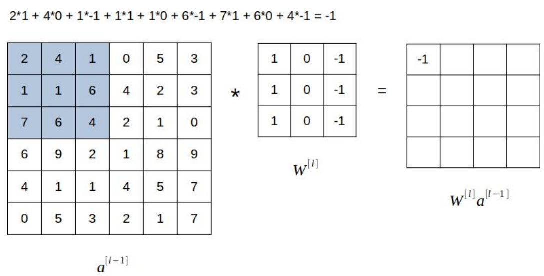

Fig. 2. Example of a convolution operation.

The outputs from the two branches are merged to form a feature map of 2x2x320. Subsequently, a dropout layer is introduced to address overfitting in the model. An 11-convolutional layer with 256 filters is included to enhance the nonlinearity of the model and decrease the depth or quantity of feature maps to lower computational expenses. A fully connected layer with 512 neurons is integrated to reinforce the classification process. For the final output, a fully connected layer with four neurons corresponding to the four classes for classification is added, followed by a softmax layer to obtain the predicted output. The evaluation of the trained network for the proposed CNN model is detailed.

The diagram illustrating the application of the proposed CNN model for the classification of ECG images of cardiac patients is presented in Fig. 5. Initially, the input images undergo preprocessing steps such as cropping, resizing, and augmentation. Subsequently, the preprocessed images are stored in the image datastore. The proposed model is trained using the specified training parameters with the ECG images stored in the image datastore. The model learns the features and adjusts its parameters accordingly. Upon completion of training, the model is prepared to evaluate ECG images to classify cardiac abnormalities into one of the four categories: NP, AH, MI, and H.

IV. METHODS

4.1 Convolutional Neural Networks (CNN)

In the domain of deep learning, a Convolutional Neural Network (CNN) is a specialized type of artificial neural network that is specifically designed for image classification and processing. The neurons within CNNs are organized in three dimensions: height, width, and depth (channel). For instance, an input image may have dimensions of 227x227x3, indicating that the width and height of the image are both 227, while the depth (channel) is 3. The primary objective of CNNs is to extract significant features from the input images. The two key components of CNNs are the convolutional layers and pooling layers. The upper layers of CNNs can consist of fully connected layers, and the final layer typically employs a sigmoid or softmax activation function to obtain the predicted output. The convolution process, which utilizes convolutional layers, involves applying a filter or kernel to the input data to generate a feature map that represents the detected features of the input. This process entails sliding the filter across the input and performing matrix multiplication at each position, with the results being summed onto the feature map. Figure 2 provides a simple example of a convolution process for an input with a depth of 1. It is important to note that the convolution process is linear. To introduce nonlinearity to the output, an activation function layer, such as ReLU or its

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variations, is applied after the convolution layer. Following the convolution layer, a pooling layer, such as a max-pooling layer, can be utilized to downsample the feature map and reduce computational costs. Figure 3 illustrates a straightforward example of max-pooling for an input with a depth of 1.

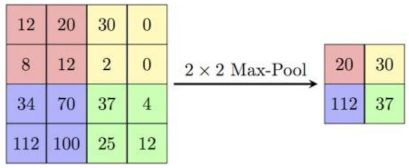

Fig. 3. Example of 2 × 2 max-pooling with stride = 2.

4.2 Pretrained Deep Learning Models

The utilization of pre-trained deep neural networks (NNs) extends to transfer learning, feature extraction, and classification. This article employs low-scaled SqueezeNet and AlexNet pre-trained convolutional neural network (CNN) models that can run efficiently on a single CPU for transfer learning and feature extraction purposes

Transfer learning is a widely adopted strategy involving pre-trained deep NNs when applied to a new dataset. Leveraging a pre-trained network that has already acquired a diverse set of features can prove advantageous for transferring knowledge to similar tasks. The majority of pre-trained networks have undergone training with over a million images and possess the capability to classify images into 1000 object classes. When implementing transfer learning, the final layers of the pre-trained network are substituted with new layers to capture the specific features of the new dataset. Subsequently, the model undergoes fine-tuning by training it on a fresh training dataset with tailored parameters, followed by evaluating its performance on a new test dataset.

Pretrained deep NNs can also serve as an efficient feature extraction tool, eliminating the need to invest time and effort in training from scratch. In this study, features extracted from the pre-trained networks are utilized to train conventional machine learning classifiers, such as SVM, K-NN, DT, RF, and NB. Further elaboration on the utilization of pretrained networks is provided in the subsequent sections.

4.3 Proposed CNN Architecture

The CNN model proposed consists of various layers, including 2-D convolutional layers, fully connected layers, max-pooling layers, leaky ReLU layers, batch normalization layers, dropout layers, depth concatenation layers, and a softmax layer. In total, there are 38 layers. The architecture of this model is depicted in Figure 4. Additionally, the proposed CNN model comprises two branches, namely the stacked branch and the full branch, which aid in extracting more representative features. The input image size accepted by the model is 227x227x3, and it flows into both branches simultaneously.

The stack branch is composed of three stacked 2-D 3x3 convolutional layers. Each of these layers is followed by a leaky ReLU layer, a batch normalization layer, and a max-pooling layer. The leaky ReLU layer utilizes a leaky ReLU activation function with a scale of 0.1, which helps address the issue of dying neurons. The batch normalization layer normalizes the inputs for each minibatch, resulting in faster model training and increased accuracy. The max-pooling layer applies the max-pooling operation to the feature map, reducing its spatial size the number of parameters, and the computational cost in the model. The max-pooling layers in this branch have a filter size of 6x6 and a stride of 3. For the first, second, and third convolutional layers, 64, 128, and 224 filters are employed, respectively. The output size at the end of the stack branch is 2x2x224. Conv04 is a 32x2x2 convolutional layer with a stride of 1 and a padding of 1, while conv 05 is a 64x3x3 convolutional layer with a stride of 2 and a padding of 2. The feature maps of these two convolutional layers are combined to create a feature map of 2x2 x96. Following the combination of features, a dropout layer is utilized to diminish the impact of correlated features and prevent overfitting.

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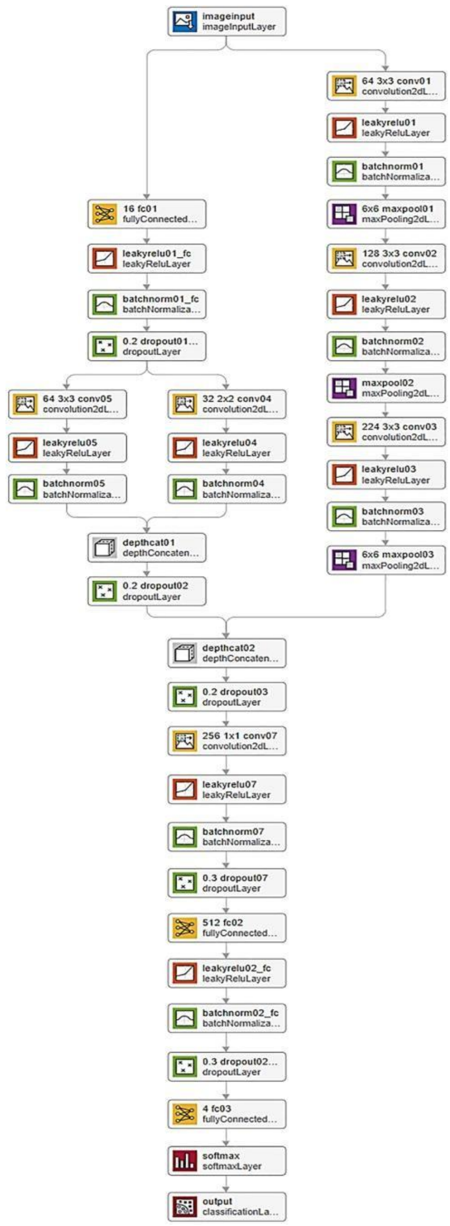


Fig. 4. Representation architecture of the proposed CNN model.

V. EXPERIMENTS

5.1 ECG Images Dataset of Cardiac Patients

The methods mentioned were validated using the ECG Images dataset of cardiac patients [23]. This dataset comprises 928 unique patient records categorized into 4 distinct classes, as outlined in Table II. These classes include NP, AH, MI, and H. MI. In Fig. 6, there are examples of samples from this dataset. An NP refers to a healthy individual without any heart irregularities. An AH (arrhythmia) occurs when the heart's electrical impulses are too fast, too slow, or irregular, resulting in an irregular heartbeat. MI, also known as a heart attack, happens when blood flow in the heart's coronary artery decreases or stops, leading to heart muscle damage. Patients classified as H. MI have recently recovered from a heart attack or MI.

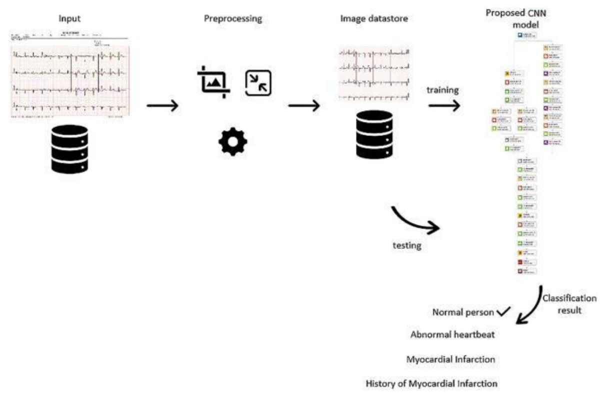


Fig. 5. Schematic of using the proposed CNN model for ECG images of cardiac patients' classification.

5.2 Experimental Settings

Preprocessing. As illustrated in Figure 6, the ECG images within the dataset include header and footer information that is irrelevant to the necessary features. Consequently, cropping has been implemented on all images to concentrate on the essential features, as depicted in Figure 7. Furthermore, all ECG images were resized to a uniform resolution of 227 x 227 with 3 channels (RGB) before commencing model training.

TABLE II:PUBLIC ECG IMAGES DATASET DESCRIPTION

No	Class	Number of Images
1	Normal Person	284
2	Abnormal Heartbeat	233
3	Myocardial Infarction	239
4	History of Myocardial Infarction	172

Data augmentation. To enhance the robustness and accuracy of the developed model, data augmentation was utilized on the dataset. This process aids in increasing the number of images in the dataset and mitigating the impact of training the model on an imbalanced dataset. Three augmentation techniques (rotation, flipping, and translation) were applied to the dataset, resulting in a total of 4700 images.

Deep learning training parameters. Due to the computational intensity of hyperparameter optimization, all experiments were conducted using the training parameters outlined in Table III. The Adam optimizer was employed to train the model for 16 epochs with a minibatch size of 128. Notably, the initial learning rate value (LR) is a critical hyperparameter, and various LR values were tested in the experiments, as detailed in the subsequent section. Based on these parameters, there are 29 iterations per epoch and a total of 464 iterations for training the model.

For reliable testing and evaluation of the model, a fivefold cross-validation approach was implemented. This method involves dividing the dataset into five parts, with four parts allocated for training and one part for testing (3760 images for training and 940 images for testing). Consequently, five distinct training and testing splits were conducted, and the results represent the average performance across the five folds.

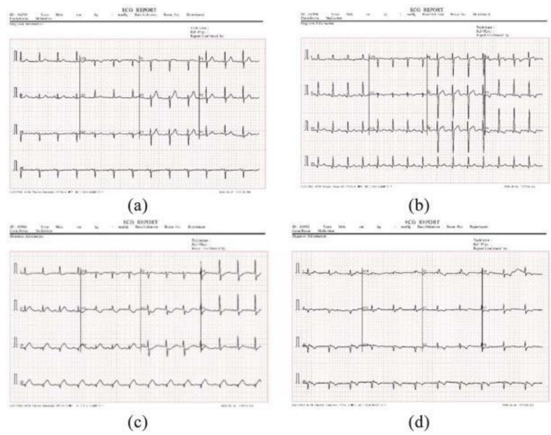


Fig. 6. Samples from the ECG images dataset. (a) NP. (b) AH. (c) MI. (d) H.MI.

Network	No of Layers	No of Connections	No of Parameters (million)
SqueezeNet	58	75	1.24
AlexNet	25	24	61
Proposed CNN	38	39	3.43

VI. RESULTS

In order to analyze the performance of the experiments, several measurements were utilized, including accuracy, precision, recall, F1 score, as well as training and testing times. These measurements were derived from the analysis of the data in a confusion matrix. Accuracy refers to the percentage of correctly predicted observations in relation to the total number of observations. Recall represents the proportion of correctly predicted observations in the true class, while precision signifies the proportion of correctly predicted observations in the predicted class. The F1 score is a weighted average of both recall and precision, taking into account both false negatives and false positives. The semantics of the confusion matrix for our specific case, which involves a dataset of ECG images of cardiac patients, can be observed.

6.1 Results of Transfer Learning and Proposed CNN Model

The advanced architectures of the pretrained networks SqueezeNet and AlexNet were utilized to implement the transfer learning method in our research. Originally trained for classifying 1000 image classes, we retrained these networks to classify a new set of ECG images in the dataset by replacing the last layers with new ones tailored for the task at hand. In the case of AlexNet, the last fully connected layer was substituted with a new fully connected layer containing 4 neurons to match the number of predicted classes. On the other hand, since SqueezeNet does not utilize fully connected layers, we replaced the last convolutional layer, which was designed for identifying 1000 classes, with a new convolutional layer containing 4 1x1 filters. For both pretrained networks, a new classification layer was added to generate an output based on the probabilities computed by the softmax layer.

Each model underwent training with varying learning rates (LR) of 0.01, 0.001, and 0.0001. Notably, our proposed CNN model achieved the highest success rate, with an average accuracy of 98.23%, when the LR was set to 0.0001. The average accuracy rate of the proposed CNN model consistently yielded high results across different LR values. Conversely, the pretrained SqueezeNet and AlexNet models exhibited subpar performance when trained with LR values of 0.01 and 0.001, but showed slight improvements when the LR was adjusted to 0.0001. This disparity can be attributed to the fact that in transfer learning, the weights of pretrained models are not initialized from scratch.

Hence, in order to prevent getting trapped in local minima, it is advisable to commence with a lower learning rate (LR) of 0.0001 when implementing transfer learning techniques.

The confusion matrices of the proposed CNN model for the classification of heart diseases in the ECG images dataset for each fold, with an RL of 0.0001 and other hyper-parameters as specified.

The average accuracy rates for AlexNet and SqueezeNet are 96.79% and 95.43% respectively, with an RL of 0.0001. Additionally, the proposed CNN model surpasses other models in terms of time cost.

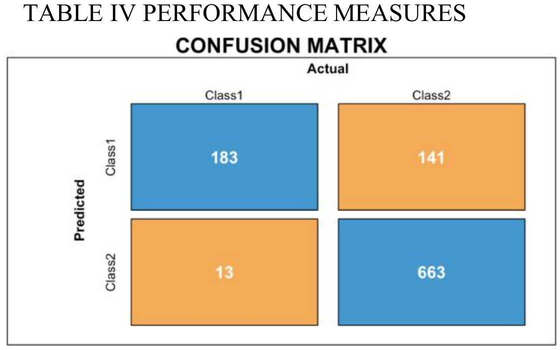
Despite SqueezeNet having the fewest parameters and being a fully convolutional neural network (CNN), it exhibits the poorest performance in terms of time cost. This is due to the high number of computations in the convolutional layers, resulting in longer processing time, particularly when executed on a single CPU platform. The accuracy rate gradually increases with each iteration, while the loss steadily decreases and reaches 0.0043.

In that study, the dataset was divided into 80% for training and 20% for testing They utilized a batch size of 24 and a learning rate of 0.0002 during the model training process. The training period extended to nearly 4 days. As per their publication, they attained a high precision rate of 98.3% for class MI. Conversely, our suggested CNN model surpasses their performance with a precision rate of 99.4% for class MI.

6.2 Results of Using Pretrained Deep Learning Models As a Feature Extractor

The ECG images in the dataset were processed using the pretrained SqueezeNet and AlexNet networks to extract their features. Additionally, our proposed CNN model was utilized as a feature extractor, and the outcomes were compared. Deep learning proves to be powerful in extracting image features without the need to retrain the entire network. The network's activations are computed through forward propagation of the input images up to the specific feature layer. For SqueezeNet, AlexNet, and our proposed CNN model, the activation feature layers used were conv10 (layer number 64), fc7 (layer number 20), and fc02 (layer number 32), respectively. Subsequently, these extracted features were employed to train various machine learning algorithms, including SVM, k-NN, DT, RF, and NB. Notably, when our proposed CNN model was used as the feature extractor, the NB algorithm achieved the most successful result with an accuracy, recall, precision, and F1-score rate of 99.79%. The SVM algorithm attained accuracy rates of 99.47%, 97.87%, and 97.66% when our proposed CNN model, SqueezeNet, and AlexNet were utilized to extract the features, respectively. Consequently, our proposed CNN model yielded the best results for all performance measures. When comparing SqueezeNet and AlexNet, the features extracted from SqueezeNet led to higher accuracy rates for the SVM, RF, and NB algorithms. However, the training and testing times for SqueezeNet-based algorithms were longer due to the larger size of the extracted features. Despite having the smallest extracted feature size, our proposed CNN model achieved the best results across all performance measures, as demonstrated. Hence, this serves as evidence that our suggested model is designed to grasp the essential characteristics of the ECG images dataset. Consequently, the benefits of our proposed model encompass not only improved accuracy rates but also reduced computational expenses in comparison to existing studies. Nevertheless, the performance of the proposed model could be further enhanced by employing optimization algorithms to ascertain the optimal values for its hyperparameters.

TABLE IV PERFORMANCE MEASURES



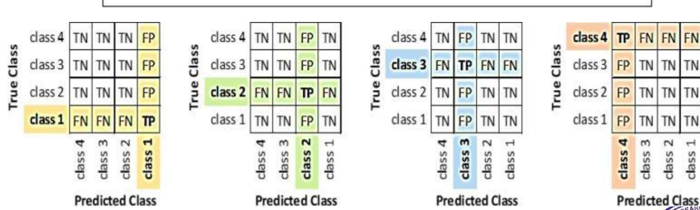


Fig. 8. Semantic of the confusion matrices for four classes results.

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R: initial learning rate, A.: accuracy, R.: recall, P.: precision, F1: F1 score, T1: training time, T2: The bold values indicate the best results.

		A. (%)	R. (%)	P. (%)	F1 (%)	T (r
Squeeze-Net (Transfer learning)	0.01	24.79	25.00	NaN	NaN	24
	0.001	24.15	25.00	NaN	NaN	21
	0.0001	95.47	95.43	96.07	95.40	21
AlexNet (Transfer learning)	0.01	24.15	25.00	NaN	NaN	19
	0.001	37.00	37.88	NaN	NaN	20
	0.0001	96.79	96.80	97.02	96.78	19
	0.01	97.24	97.24	97.31	97.22	**18**

Measures	Defined as
Accuracy	*(TP+TN)/(TP+FP+FN+TN)*
Recall	*TP/(TP+FN)*
Precision	*TP/(TP+FP)*
F1 score	*(2 × Recall × Precision)/(Recall+Precision*

VII. CONCLUSION

In this article, we present a lightweight CNN-based model that can effectively classify the four major cardiac abnormalities: AH, MI, H. MI, and NP classes. This model utilizes a publicly available dataset of ECG images from cardiac patients. The experimental results demonstrate that our proposed CNN model achieves outstanding performance in the classification of cardiovascular diseases. Additionally, it can serve as a valuable tool for feature extraction in traditional machine learning classifiers. Consequently, this CNN model can assist clinicians in the medical field by enabling the detection of cardiac diseases from ECG images, eliminating the need for manual processes that are prone to inaccuracies and time-consuming.

In future research, optimization techniques can be employed to obtain optimized values for the hyperparameters of our proposed CNN model. Furthermore, the versatility of our model allows for its application in predicting other types of problems. Given that our model falls under the category of low-scale deep learning methods in terms of layers, parameters, and depth, it would be worthwhile to explore its utilization in the Industrial Internet of Things domain for classification purposes

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