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ECG Images-based Cardiovascular Disease Classification utilizing a Deep Learning Model

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ABSTRACT

Early and accurate cardiovascular diseases detection is indispensable in specifying efficient treatment and prohibiting life-threatening complications. Traditional detection schemes that depend on manual interpretation of electrocardiograms (ECGs) are generally subject to inter-observer variability and are time-consuming. In this paper, a deep learning model is proposed for classifying cardiovascular diseases relying on two benchmark publicly available datasets of “twelve-lead ECG images”. In order to improve signal diversity, distinct pre-processes and augmentation are adapted on these datasets of cardiac patients. The proposed deep learning model of Convolutional Neural Network (CNN) encompasses distinct blocks of layers (Extensible and detachable convolutions) that are intended to possess morphological patterns and wider spatial dependencies in ECG images. Furthermore, multiple layers of batch normalization and dropouts were employed for stabilizing training and achieving generalization. Experimental results revealed a superior classification accuracy for the proposed system with augmentation utilizing the two datasets, outperforming existing related systems. These results demonstrated the capability of the proposed system to assist cardiologists in early diagnosis and preventive treatment.

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1. Introduction

Through people of old age, unhealthy lifestyles, and poor mental health, the hazard of cardiovascular diseases is increasing. Accordingly, early diagnosis is pivotal for the survival of people with cardiovascular diseases [1]. In the cardiovascular disease’s diagnosis, “ECGs” is the abbreviation for electrocardiograms, and “PCGs” is the abbreviation for phonocardiograms, which supply prominent, albeit different, diagnostic information. PCG signals represent beneficial valvular defects and murmurs detection; they are highly susceptible to interference and lack support from high-quality and large public datasets, limiting their efficiency in robust deep learning [2]. However, ECGs remain the preferred approach for detecting cardiac arrhythmias, conduction disturbances, ischemic changes, and other electrophysiological abnormalities. This is because ECGs directly capture the heart's electrical activity, offer abundant datasets, and offer clear clinical classification [3] [4].

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Even though the models of deep learning demonstrated outstanding potential in the cardiovascular diseases auto-detection, distinct recent systems come with more restrictions (like insufficient extraction for essential features, noise sensitivity, and restricted generalization). Most of these systems revolve around ECG signals or images, without exploring the potential of sophisticated deep learning structures, optimized training strategies, or advanced pre-processes to improve accuracy and effectiveness [5]. Further, many of the recent deep learning-based systems, despite the high detection accuracy reported, lack practical implementation mechanisms to support their immediate clinical utilization. The applicability of such systems in real-world healthcare demands the integration of diagnostic support tools. Thus, there is an essential requirement for high-performance and effective systems capable of accurately detecting cardiovascular diseases out of ECG signals or images [6].

This paper employs two-dimensional representations of ECG signals (ECG images) suited for deep learning to increase ECG diagnostic sensitivity, improve dataset availability, and enhance the performance in detecting cardiovascular diseases. The principal contributions of this proposed system are as follows:

- Applying an effective sequence of image pre-processes (cropping, resizing, normalization, and standardization), and augmentation on the two benchmark ECG images datasets.
- Proposing a deep learning model of hybrid block structure of Extensible and detachable convolutions to enhance responsiveness to morphological ECG modifications accompanying cardiovascular abnormalities. Additionally, batch normalization, pooling, and dropout layers are added for hindering overfitting and stabilizing model training.
- Supplying comparative experiments with current relevant systems, exhibiting the superior results of the proposed deep learning model across utilized measures.

The continuing sections of this article are systematically organized as follows: The currently existing relevant systems are introduced in the second section; The proposed system and its structural elements are expounded in detail in the third section; The experimental outcoms, an in-depth analysis of the model's ability for classifying ECG images, and comparisons are detailed in the fourth section. Ultimately, the article's conclusions and recommendations for improvements are enumerated in the fifth section.

2. Related Works

Current developed deep learning models have substantially advanced the cardiovascular diseases classification utilizing ECG images. Additionally, distinct schemes have been progressed to deal with class misbalancing and computational efficiency difficulties, also strengthening classification performance.

A. H. Khan et al., 2021, [7] suggested a cardiovascular diseases classification system utilizing a benchmark dataset of “928” twelve-lead ECG images for patients with Cardiac” with unstandardized formats that is collected manually from distinct devices. In this suggested classification system, the dataset was first resized and labeled, and then a lightweight architecture of MobileNetV2-Single-Shot classification was exploited to auto-extract essential features and classify cardiovascular diseases into normal and multiple cardiac abnormalities. This generalized image-based system attained 98% classification accuracy across distinct ECG formats. However, the imbalance issue might influence the generalization of the minority classes. Moreover, training the system on a moderately small dataset led to an increase in overfitting.

L. Mhamdi et al., 2022, [8] exhibited a cardiovascular diseases classification system utilizing distinct deep learning models relying on the dataset of “twelve-lead ECG images”. The technique of ECG image augmentation was applied in this classification system to strengthen the quantity and diversity of inadequate data. Before being supplied to deep learning models, ECG images were resized and normalized. Afterwards, VGG16 and MobileNetV2 models were fine-tuned, and their ultimate layers were adapted to yield 4 classes. These two models produced a high accuracy, reaching more than 95%, relying on the validation set. Nevertheless, this classification system missed an independent testing set for strong validation, and it definitely indicated that it should not replace the work of a doctor.

L. Aversano et al., 2023, [9] suggested a cardiovascular diseases classification system based on deep learning utilizing the dataset of “twelve-lead ECG images” considering both binary and multi-class classification. The first stage in this system was to segment every ECG image into three isolated bands relying on the electrodes. Then, considering all the ECG images, these bands were cropped and reshaped. After that, the obtained images were separated into 60% train, and 40% test and validation sets. In order to classify these images, a two-dimensional CNN was suggested, which involved two blocks of distinct layers (each encompassing convolution with activation, batch normalization, and dropout). The pooling layer takes place in the middle of these blocks. These two blocks were followed by several dense layers with a final Softmax activation for classification. Although the image segmentation strategy could be regarded as innovative, it is not medically validated and needs more studies to verify its reliability. In addition, the pre-resize process that was carried out to minimize resolution may result in the loss of essential information and thus inaccurate findings. This system achieved an accuracy of 80% for 4-class classification and 91% for binary classification.

A. Ashtaiwi et al., 2024, [10] presented a vectorization method for converting ECG images into vectors, with the aim of obtaining a vector representation that accurately embodies the distinctive characteristics of the heart signal. This method involves several operations (including cropping the image, scanning the grid lines, and allocating pixels to recognize the heart signal from its background. The extracted vector of features using this method was extremely shorter than the vector yielded via the VGG16 model, which considerably reduced the memory required, increased the convergence speed of the algorithm, and lowered the computing power requirements. The obtained feature vector was then fed to an artificial neural network, and the attained findings were approximately 88% for multi-class and 98% for binary cardiovascular diseases classification. This classification system was able to conquer feature imbalances, minimize their dimensions, and improve classification accuracy. However, its generalizability is restricted, and its performance in distinguishing between multiple classes is weaker in contrast to binary classification.

3. Proposed Classification System

In this paper, a developed deep learning-based system for cardiovascular diseases classification is presented to enable persons to realize cardiac abnormalities. This system encompasses distinct stages, including inputting and pre-processing ECG images, optional data augmentation, and performing an extensible and detachable CNN model to extract essential features and provide classification. Fig 1 illustrates the structure of the proposed system.

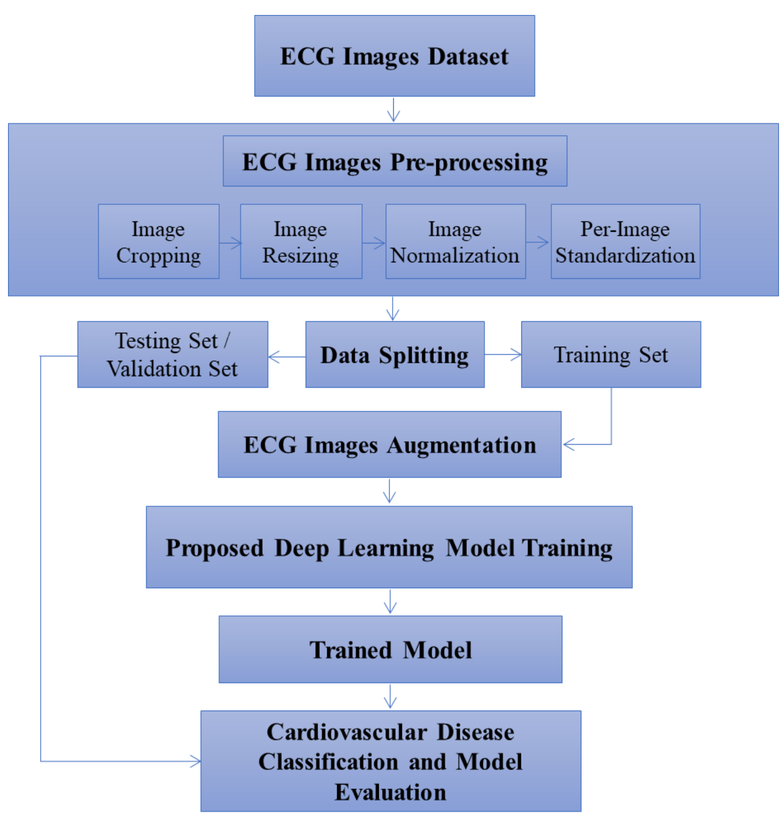


Fig. 1 - Structure of the proposed cardiovascular diseases classification system.

3.1. Utilized datasets of ECG images

Two benchmark datasets of "twelve-lead ECG images" are employed in this proposed classification system. The first utilized dataset includes 928 images [11], while the second dataset includes 3,951 images [12] of individuals suffering from cardiac conditions. These datasets provide 4 classes (normal (3), abnormal heart beats (2), myocardial infarction (1), and prior history of myocardial infarction (0)). Some samples from its classes are shown in Fig 2.

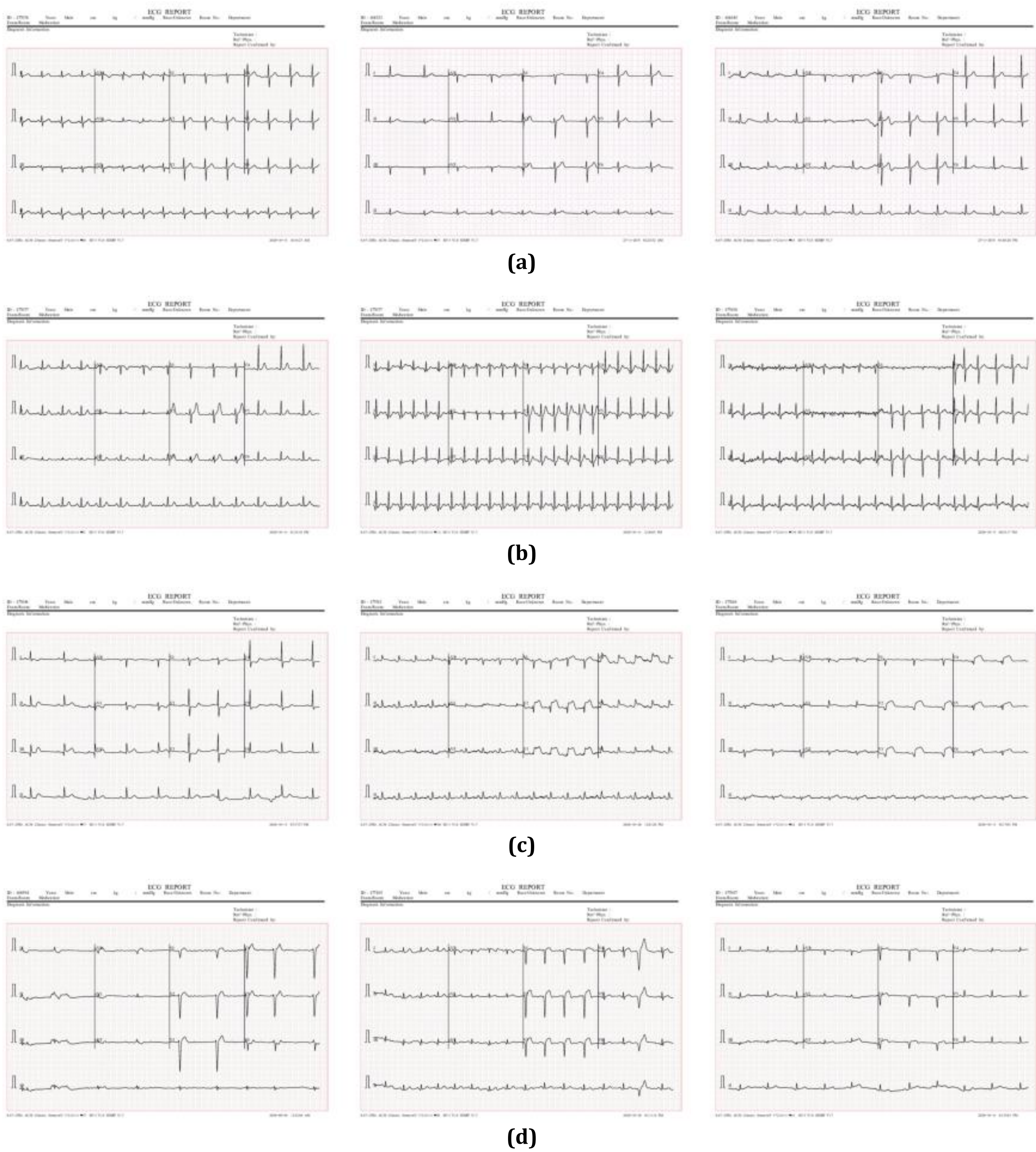


Fig. 2 - Samples of 4 ECG image classes: (a) Normal heart beats, (b) Abnormal, (C) Myocardial infarction, and (d) Prior history of myocardial infarction.

The following are the 4 classes of heart conditions as seen in ECG images:

- The condition of "normal heart beats" indicates healthy individuals who are not affected by heart diseases, and the heart rate of adult individuals should range from sixty to one-hundred beats/per minute.
- The condition of "abnormal heart beats" indicates irregular, too slow, or too fast patterns of electrical impulses, resulting from multiple factors and underlying medical conditions.
- The condition of "myocardial infarction", also called a heart attack, is a serious condition caused by a blockage of blood flow to a heart portion, leading to the death of the heart muscle.
- The condition of "a prior history of myocardial infarction" indicates people suffered from a prior heart diseases.

3.2. Data pre-processing and separation

ECG image inputting and pre-processing is the term used to describe actions that are implemented at the most fundamental abstraction levels. Although these procedures do not enhance the amount of information contained in ECG images, they do reduce the amount of information. Pre-processing is an approach works on improving the data by minimizing undesirable distortions or improving certain visual attributes that are essential for succeeding analysis task. Image cropping, resizing, normalization, and standardization represent distinct types of pre-processing procedures for images, all of which make images more efficient for input into the next stage. Table 1 provides the details of the pre-processes. After this stage, the dataset is partitioned into "80%" training and "20%" testing/validation sets.

Table 1 – A detailed pre-processes with description.

ECG Images Pre-Processes	Description
Cropping	This process works on removing the ECG images' borders via cropping portions of their width and height based on the crop percentage.
Resizing	This process works on resizing the ECG images to a width of 512 pixels and a height of 256 pixels to guarantee consistency of input dimensions for the proposed CNN model.
Normalization	This is accomplished by adjusting the scale of the measurements. Normalizing data helps generate consistency across features and creates uniformity, which is especially significant when datasets contain characteristics with widely varied sizes. While there are several methods available for normalizing data, the min-max normalization approach is utilized in this stage.
Standardization	After the process of standardization, the distribution of a sample of data is determined to obtain a mean value of "0" and a standard-deviation value of "1". It is possible to determine the mean and standard-deviation for each image individually.

3.3. Data augmentation

In order to increase the ECG images dataset diversity and enhance the generalizability of CNN models, augmentation techniques can be implemented. Augmentation assists in simulating the potential variations in ECG images and inhibiting the model from overfitting. Table 2 explains the augmentation techniques employed in our proposed system.

Table 2 – A detailed description of augmentation techniques.

Techniques	Description	Parameters
Re-scaling	Normalizing pixel values to the range [0,1]	1./255
Rotating	Presenting rotational variations	±15°
Width and Height Shifting	Simulating horizontal and vertical translations	±10%
Shearing	Applying geometric distortion	±10%
Zooming	Presenting scale variations	±10%
Horizontal Flipping	Mirroring images	True

After implementing this optional stage, the total count of training samples turns into 1484 in the first dataset and 3020 in the second dataset, while the count of the test and validation samples remains without any alteration, as depicted in Fig 3.

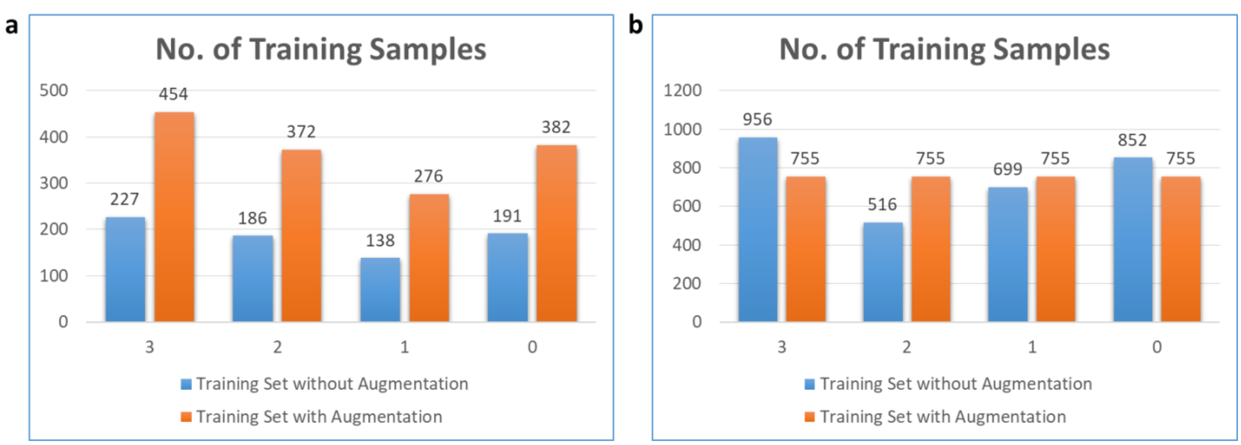


Fig. 3 - ECG images training set with and without augmentation for (a) first dataset; (b) second dataset.

3.4. Proposed deep learning model

The proposed model structure encompasses distinct convolution blocks for the gradual extraction of higher-level distinctive features, attended by the stage of regularization and classification, as depicted in Table 3. Extensible and detachable convolutions are extensively unified with multi-scale receiving fields to reinforce time pattern extraction and maintain efficiency of computations. Fig 4 depicts the architecture with detailed layers of the proposed model.

Table 3 – A detailed description of deep learning blocks.

Blocks	Description
First Block	It takes the fundamental temporal and spatial features (wave contours and edges) from the inputting images, via inserting two convolution layers (each utilizing 32-filter and “3×15” kernel size), batch normalization, and an average pooling layer (of size "2×2").
Second Block	It adds extensible convolution layers (each utilizing 64- filter and “3×21” kernel size) with a dilation rate of (1, 2) to refine the field of temporal receptive, and batch normalization after every layer. Ultimately, an average pooling layer is applied to attain

	miniaturized feature maps.
Third Block	It utilizes two wide detachable convolutions (each utilizing 128-filter and "3×31" kernel size) to detect complex spatio-temporal features. After that, batch normalization is applied to those convolutions. Ultimately, an average pooling layer (of size "2×2) is applied to further decrease the feature maps.
Forth Block	It introduces a deeper convolution (encompassing 192-filter, "3×41" kernel size, and dilation rate of (1, 4)) to integrate long-range dependencies and minor distortions in parts of the ECG signal.
Fifth Block	It applied to refine model performance by inserting a spatial dropout layer (0.15) to de-correlate the spatial feature maps, and global average pooling with another dropout to convert the feature maps into a simplified representation.
Sixth Block	In encompasses two fully-connected layers, the first is a dense layer (256 neurons), ReLU, and dropout of "0.3", and the second is a final output layer (Softmax) representing 4 disease classes.

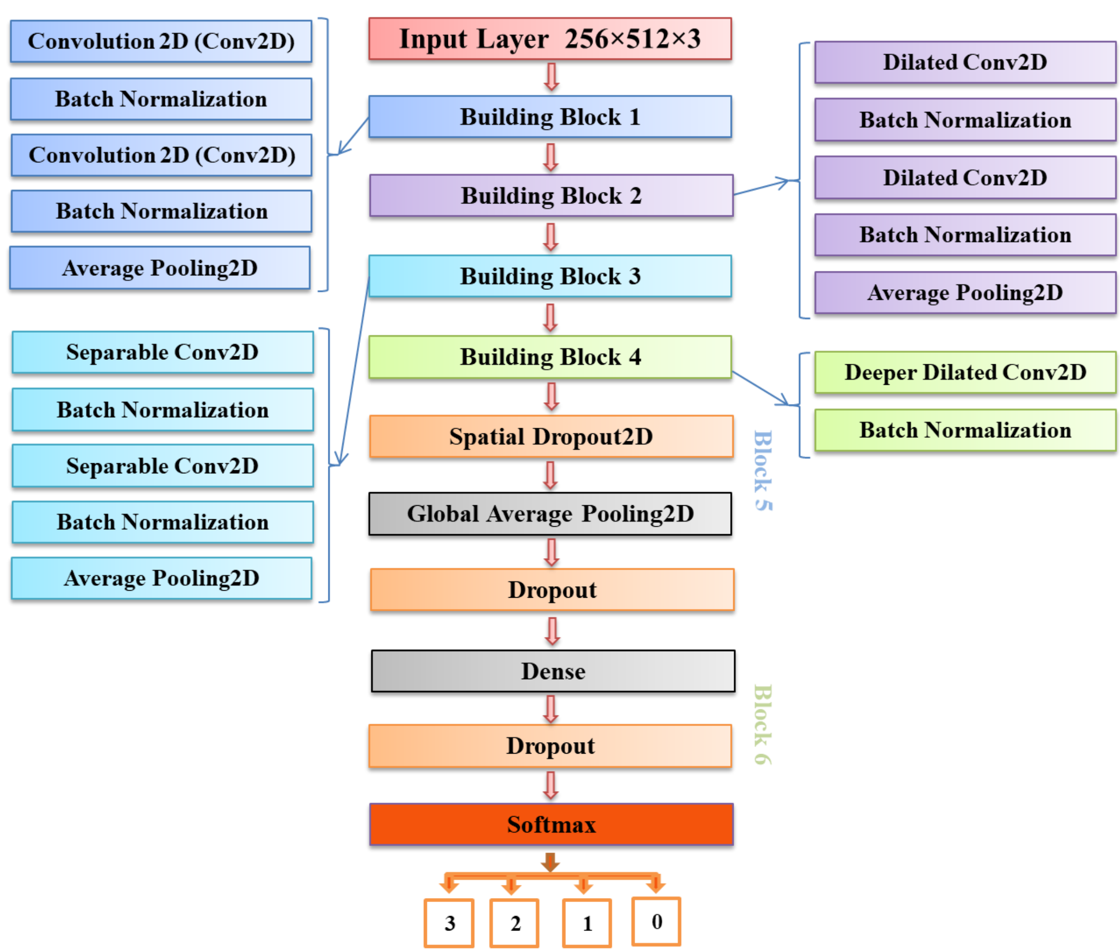


Fig. 4 - The proposed model architecture.

4. Experimental Outcomes

In order to examine the performance of the proposed classification system, distinct assessment measures are exploited. Here, the main job of the proposed system is to categorize ECG images into 4 classes; accordingly, several measures are exploited to precisely reflect the system capability in classifying those classes.

Accuracy (Acc) is the most straightforward and common assessment measure, which obtains the proportion of right predictions over all normal and abnormal classes. In the classification of multiple cardiovascular diseases, Acc can be measured as the percentage of all right predictions from the total count of ECG instances in the ECG images dataset. It is given as follows:

$$Acc = \frac{True_{Negative}+True_{Positive}}{True_{Negative}+True_{Positive}+False_{Negative}+False_{Positive}} \tag{1}$$

Where $True_{Negative}$ and $True_{Positive}$ indicate negative and positive ECG instances that were rightly predicted, respectively. $False_{Negative}$ and $False_{Positive}$ indicate negative and positive ECG instances that were non-rightly predicted, respectively.

Precision (Pre) is a beneficial measure, especially when the percentage of $False_{Positive}$ predictions is high. It can be measured as the percentage of positive predictions that are actually right. For every "i" class, Pre is given as follows:

$$Pre = \frac{True_{Positive}(i)}{False_{Positive}(i)+True_{Positive}(i)} \tag{2}$$

Sensitivity (Rec) is a beneficial measure, especially when the percentage of false negative predictions is high. It can be measured as the percentage of actual positive ECG instances that are rightly detected by the proposed model. For every "i" class, Sen is given as follows:

$$Rec = \frac{True_{Positive}(i)}{False_{Negative}(i)+True_{Positive}(i)} \tag{3}$$

The F1 score ($F1$) is a beneficial measure, especially when some classes are underrepresented. It can be measured as the harmonic mean of Sen and Pre, providing a balance between these measures. For every "i" class, $F1$ is given as follows:

$$F1_i = 2 \times \frac{Rec_i \times Pre_i}{Rec_i + Pre_i} \tag{4}$$

By utilizing the above-mentioned assessment measures, we obtain that the proposed deep learning model (with augmentation) achieved higher outcomes across 4 classes. These outcomes are specified in Table 4 and Table 5.

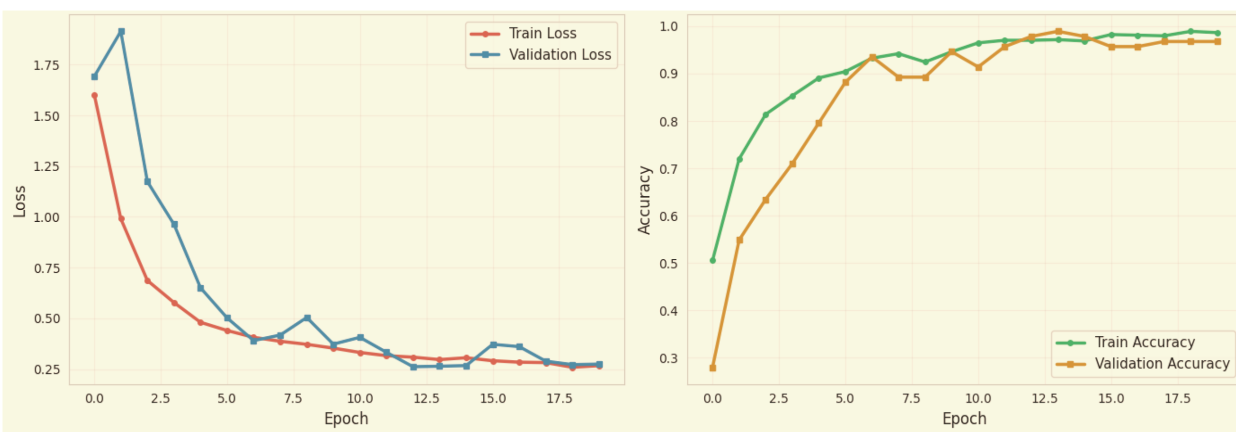
Table 4 – Outcomes of the proposed model with and without augmentation utilizing the first dataset.

Classes	Proposed Model without Augmentation				Proposed Model with Augmentation				Support
	Pre	Rec	$F1$	Acc	Pre	Rec	$F1$	Acc	
0	0.8148	0.9167	0.8627	0.9167	1.0000	1.0000	1.0000	1.0000	24
1	0.9286	0.7647	0.8387	0.7647	0.8947	1.0000	0.9444	1.0000	17
2	0.9524	0.8333	0.8889	0.8333	1.0000	0.9167	0.9565	0.9167	24
3	0.7419	0.8214	0.7797	0.8214	1.0000	1.0000	1.0000	1.0000	28
Acc	0.8387				0.9892				93

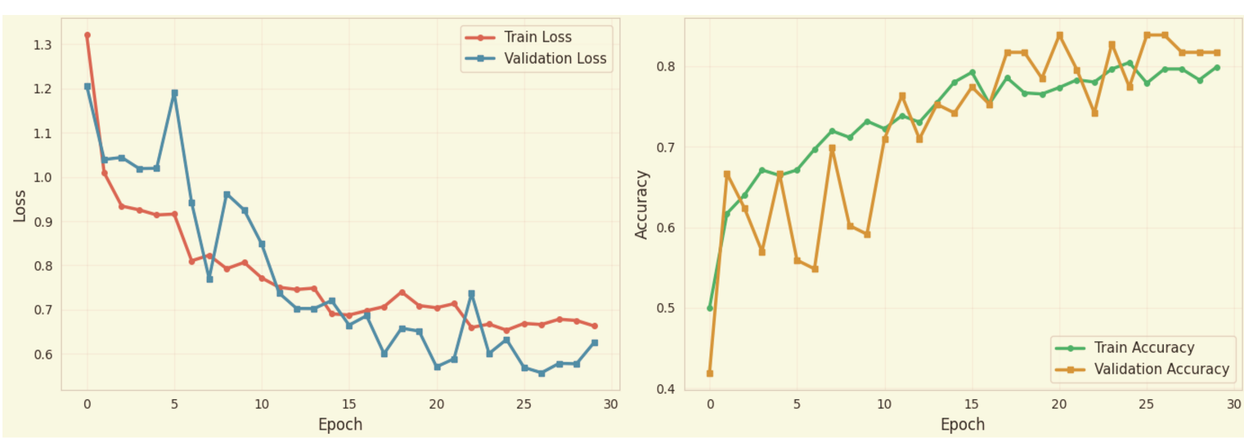
Table 5 – Outcomes of the proposed model with and without augmentation utilizing the second dataset.

Classes	**Proposed Model without Augmentation**			**Proposed Model with Augmentation**			**Support**
	Pre	***Rec***	***F1***	***Pre***	***Rec***	***F1***	
0	1.0000	0.8996	0.9471	1.0000	1.0000	1.0000	239
1	0.6853	1.0000	0.8132	0.9247	1.0000	0.9609	172
2	0.8730	0.9442	0.9072	1.0000	0.9399	0.9690	233
3	1.0000	0.7394	0.8502	1.0000	1.0000	1.0000	284
Acc		0.8804			0.9849		928

The outcomes of all applied assessment measures showed that the proposed deep learning model with augmentation for both datasets of ECG images performed better in processing the four categories, with outstanding performance. The curves of training-validation losses and accuracies for the proposed model with and without augmentation are shown in Fig 5 and Fig 6.

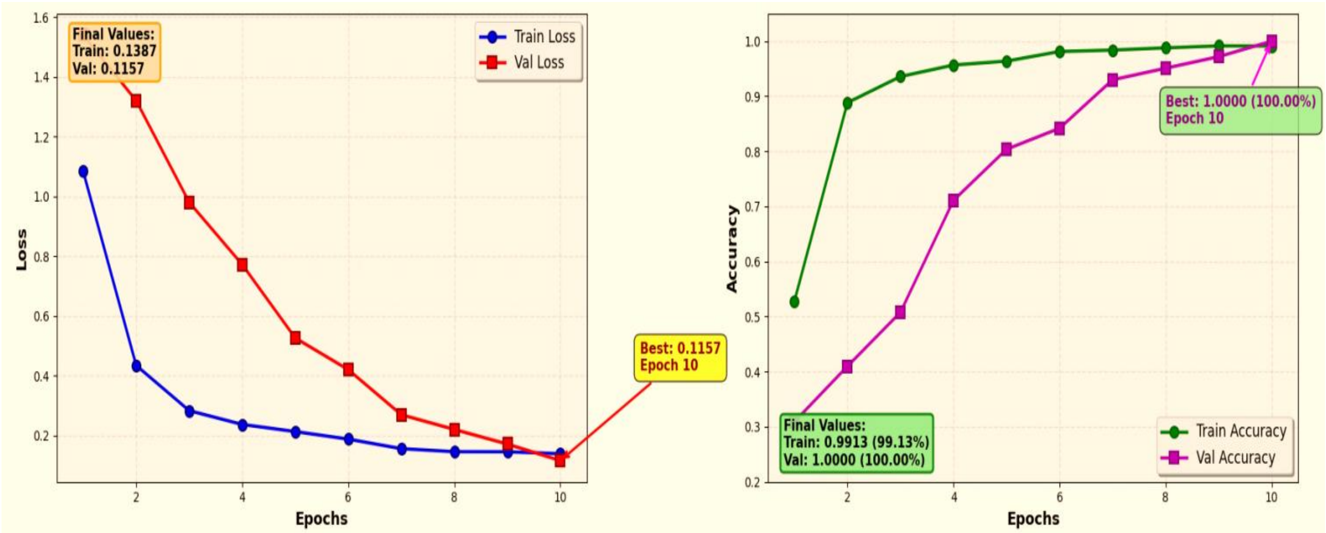


(a)

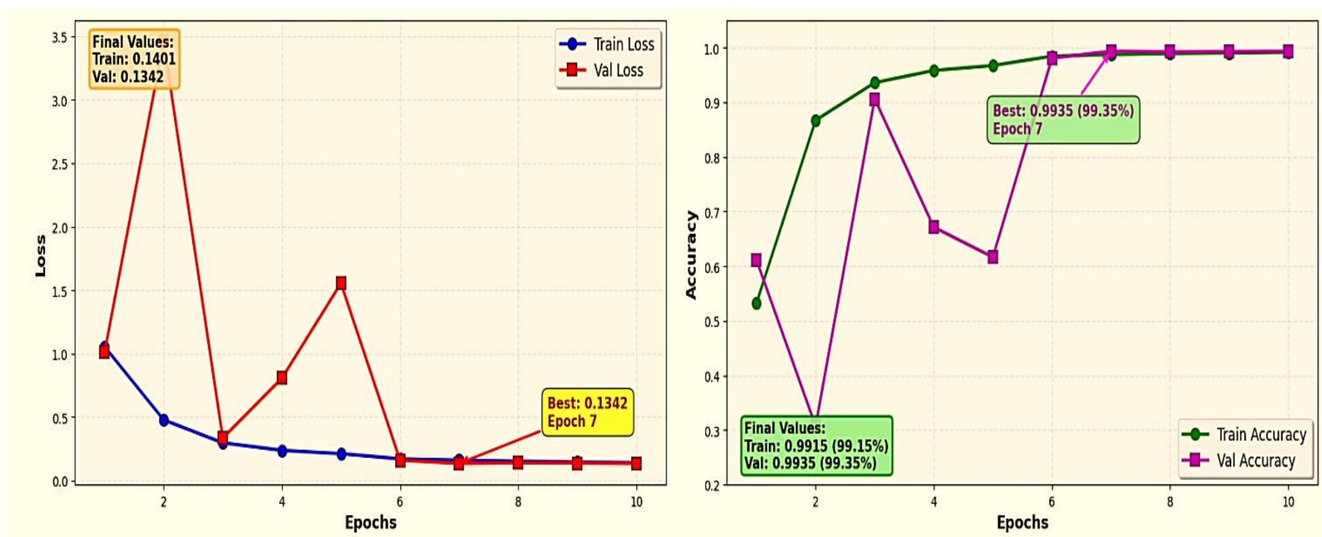


(b)

Fig. 5 - The behavior of learning for the proposed system utilizing first dataset; (a) with augmentation; (b) without augmentation.



(a)



(b)

Fig. 6 - The behavior of learning for the proposed system utilizing second dataset; (a) with augmentation; (b) without augmentation.

The training and validation loss curves for the proposed model with data augmentation demonstrated that it rapidly learned the features of the training ECG data. However, it may encounter some challenges when generalizing the results to the validation sets. The training accuracy curves rose rapidly and stabilized at nearly 99%, indicating that the proposed model with data augmentation matched the training data well. In contrast, the validation accuracy curves rose slowly, with a perceptible plateau suggesting the possibility of overfitting and the requirement for early stopping. These curves provide strong evidence for the feasibility of utilizing early stopping to ensure the proposed model generalization to unseen new data and evade overfitting. The proposed model with data augmentation supplies better performance, as depicted in Fig 7 and Fig 8.

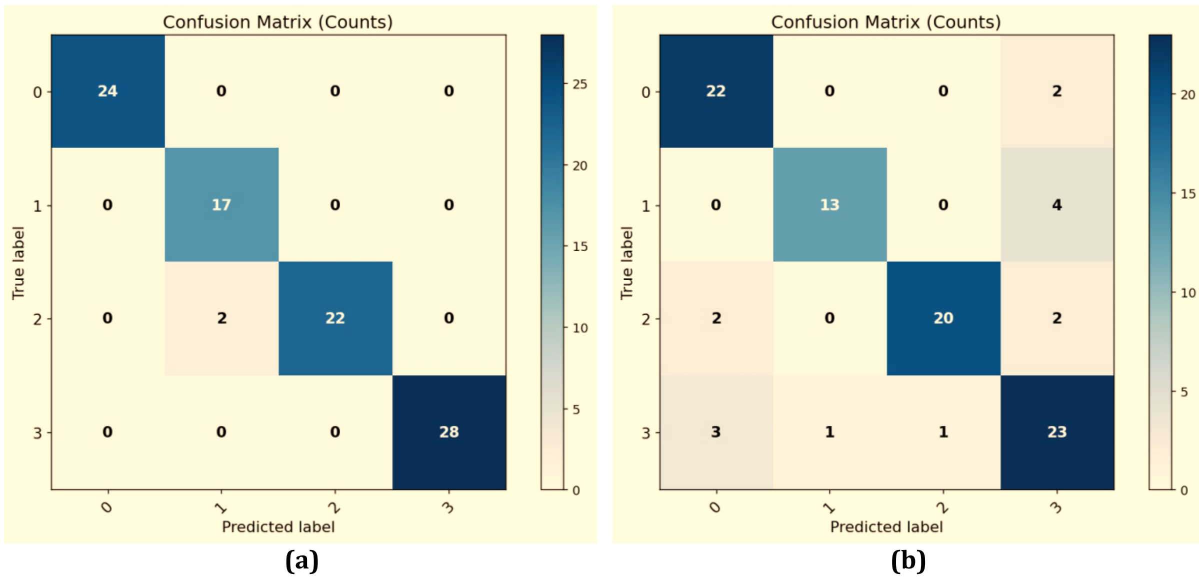


Fig. 7 - Confusion Matrix of the proposed system utilizing the first dataset (a) with augmentation; (b) without augmentation.

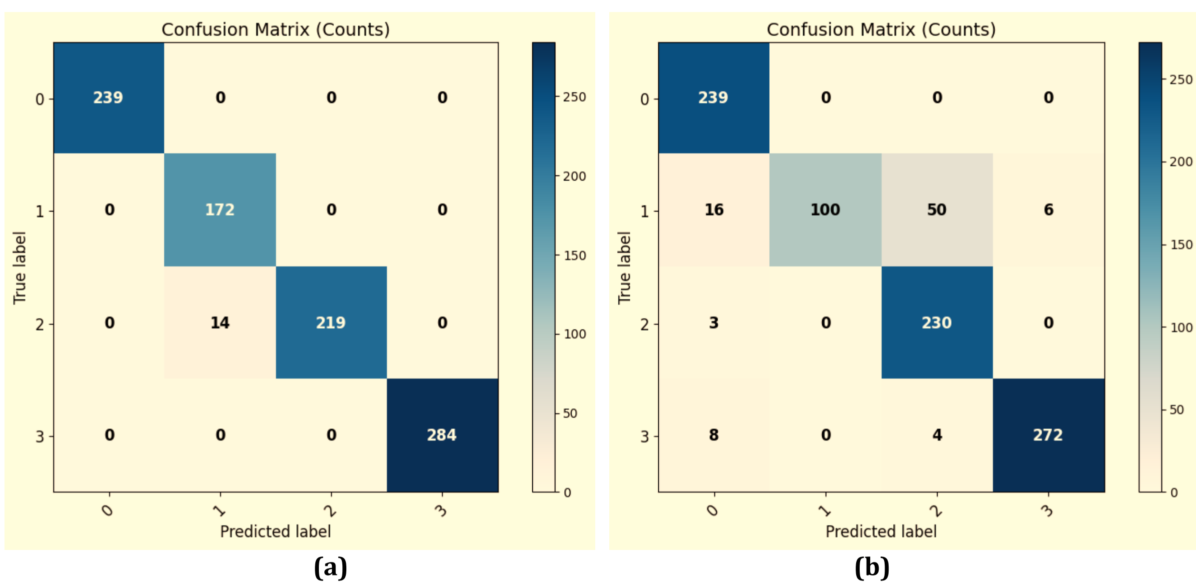


Fig. 8 - Confusion Matrix of the proposed system utilizing the second dataset (a) with augmentation; (b) without augmentation.

Compared to other works, the proposed classification system demonstrates a high degree of discrimination between the four classes. It achieves near-perfect performance, particularly considering the low number of misclassifications, which indicates its effectiveness in learning the unique features of each class. Fig 9 presents a comparison between our proposed classification system and closely related works that employed the first dataset of ECG images.

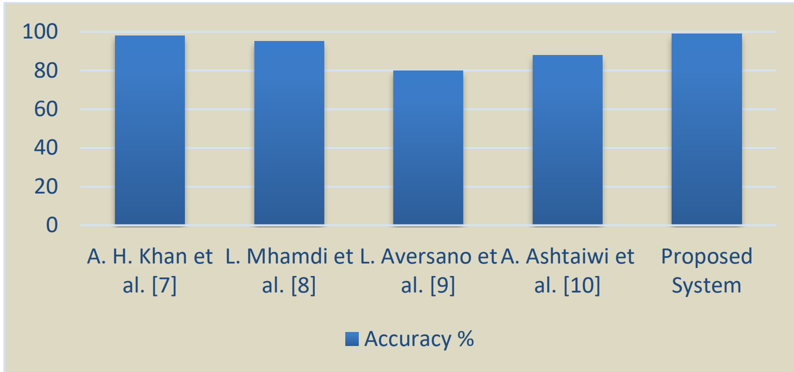


Fig. 9 - Comparison with related works utilizing the first dataset.

5. Conclusion

This paper exhibits a new architecture of deep learning for cardiovascular disease detection from ECG images. The proposed CNN model efficiently acquires spatial and temporal information utilizing extensible and detachable, and deep convolution layers. It achieved superior classification performance, surpassing the existing related architectures. These outcomes demonstrate that leveraging ECG image representations with an effective deep learning model can allow a reliable foundation for computer-aided diagnosis of cardiovascular diseases. Distinct pre-processing and augmentation were applied, led to enhance the generalizability and robustness of the proposed system. The dataset should be expanded in future works to incorporate ECG images (of multiple leads) with comprehensive demographic diversity to enhance the system's generalizability to diverse clinical contexts. Also, CNN should be incorporated with transformers to improve the comprehension of temporal dependencies among ECG images. Furthermore, the proposed system should be combined with wearable devices and expanded interpretable AI-visualizations to facilitate real-world applications in cardiovascular health-care.

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References

[1] G. Muhammad, S. Naveed, L. Nadeem, T. Mahmood, A. R. Khan, Y. Amin, S. A. O. Bahaj, "Enhancing Prognosis Accuracy for Ischemic Cardiovascular Disease Using K Nearest Neighbor Algorithm: A Robust Approach," in IEEE Access, vol. 11, pp. 97879-97895, (2023).
[2] S. Singhal and M. Kumar, "Cardiovascular Diseases Classification Using High- Resolution Superlet Transform on ECG and PCG Signals," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, (2023), pp. 1-5.
[3] J. Li, K. Li, D. Qiang, D. Xiaodi, C. Xiangmin, "Research on the Classification of ECG and PCG Signals Based on BiLSTM-GoogLeNet-DS," Applied Sciences, vol. 12, no. 22, (2022).
[4] S. Karimi, A. J. Shah, G. D. Clifford and R. Sameni, "Bidirectional Translation Between ECG and PCG," 2025 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI), Atlanta, GA, USA, (2025), pp. 1-5.
[5] R. Studer, C. Sartini, K. Suzart-Woischnik, R. Agrawal, H. Natani, S. K. Gill, S. B. Wirta, F. W. Asselbergs, R. Dobson, S. Denaxas, D. Kotecha, "Identification and Mapping Real-World Data Sources for Heart Failure, Acute Coronary Syndrome, and Atrial Fibrillation," Cardiology, vol. 147, no. 1, pp:98-106, (2022).
[6] F. Asadi, R. Homayounfar, Y. Mehrali, C. Masci, S. Talebi, F. Zayeri, "Detection of cardiovascular disease cases using advanced tree-based machine learning algorithms," Scientific Reports, vol. 14, (2024).
[7] A. H. Khan, M. Hussain, M. K. Malik, "Cardiac Disorder Classification by Electrocardiogram Sensing Using Deep Neural Network", Complexity, vol. 2021, pp. 1-8, (2021).
[8] L. Mhamdi, O. Dammak, F. Cottin, I. B. Dhaou, "Artificial Intelligence for Cardiac Diseases Diagnosis and Prediction Using ECG Images on Embedded Systems", Biomedicines, vol. 10, no. 8, (2022).
[9] L. Aversano, M. L. Bernardi, M. Cimitile, D. Montano, R. Pecori, "Early Diagnosis of Cardiac Diseases using ECG Images and CNN-2D," Procedia Computer Science, vol. 225, pp. 2866-2875, (2023).
[10] A. Ashtaiwi, T. Khalifa, O. Alirr, "Enhancing heart disease diagnosis through ECG image vectorization-based classification", Heliyon, vol. 10, no. 18, (2024).
[11] https://data.mendeley.com/datasets/gwbz3fsgp8/2.
[12] https://www.kaggle.com/datasets/evilspirit05/ecg-analysis.