Evaluation of Heart Disease Risk Using Deep Learning Technique with Image Enhancement

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Abstract

This study emphasizes the significance of the heart in the human body. Numerous serious vascular conditions exist in the heart and the blood. The dataset, study goals, methodology, approach, and efficient algorithms for identifying and classifying electrocardiogram (ECG) data are all covered in this paper. Picture scaling, grayscale conversion, and training/testing dataset segmentation are part of the cardiovascular ECG image-processing process. To assess ECG images, researchers used a convolutional neural network. Iterations in model training increase the accuracy. We examined generalization and model recall using an additional dataset. The accuracy, F1 score, confusion matrices, and ECG pattern identification must all be evaluated to diagnose heart disease. We used a Cardiovascular ECG Image Collection that was openly accessible. The system was constructed in Python using Matplotlib, NumPy, and Keras. The GPU-based machine learning platform was Google Colab. Photos were analyzed, categorized, and processed using MobileNet-V2. With a remarkable accuracy rate of 99.3 %, the developed model offers a viable basis for further hyperparameter investigation. Additionally, to demonstrate the efficacy of the selected method, we present a graphic depiction of ECG data. Overall, this study combines advanced machine learning algorithms, strict assessment criteria, and ECG image analysis to enhance the diagnosis of heart-related disorders.

Keywords: Electrocardiogram (ECG), convolutional neural network (CNN), heart disease, MobileNet-V2

1. Introduction

The human heart is an important and complex organ that is necessary for life because it pumps blood throughout the body. Blood is continuously pumped through the chest by the heart, which is a strong organ of the size of a fist. The body's hormones, nutrients, and oxygen are supplied by the four chambered hearts, which consist of two atria and two ventricles. Muscle contractions and relaxations, which occur 60–100 times per minute, are perfectly timed by an internal electrical system to assist this essential function. In addition to its medical significance, the heart has a significant cultural and emotional value as a representation of love and strong human emotions. Throughout history, this has inspired many authors, painters, and artists [1]. As an organ that sustains life and represents our deepest emotions, the heart is a remarkable and significant part of who we are. The intricate structure of blood circulation and carefully controlled functions are essential for maintaining human health. Symbolic values are deeply ingrained in human emotions, culture, and artistic expression. One of the most important and aesthetically pleasing parts of the human body is the organ [1], [2], [3]. This general phrase covers a wide range of conditions that affect the functioning of the heart and blood vessels. A person's general health and well-being may be significantly affected by disease-related cardiac dysfunction [4]. Numerous modifiable and non-modifiable risk factors are associated with heart disease.

Diet, physical inactivity, high alcohol use, and smoking significantly increased the risk of heart disease. Additionally, the likelihood of developing heart disease may be increased by age, genetics, and certain medical conditions [5], [6]. The effects of heart disease are extensive and often include major health problems, a reduced quality of life, and early mortality. For patients to make informed decisions about their cardiovascular health and for healthcare professionals to deliver high-quality treatment, patients must be informed about the causes, symptoms, prevention measures, and therapies of heart disease [7]. On Electrocardiogram (ECG), these impulses are clearly seen as waves. Electrocardiograms (ECGs) are used by cardiologists to diagnose heart disease, track the health of known cardiac patients, and evaluate symptoms, including palpitations and chest discomfort [8]. Many elements of the ECG waveform, including the QRS complex, P-wave, T-wave, and ST segment, provide vital details regarding the rhythm and operation of the heart. Every type of ECG is intended for a specific clinical situation. While resting ECGs are used for everyday monitoring, Holter and event monitors are crucial for recognizing uncommon arrhythmias because they collect continuous data over extended periods. While exercise stress tests examine how the heart reacts to physical effort, ambulatory electrocardiograms (ECGs) record a patient's whole cardiovascular activity over the course of several weeks or months. With its noninvasive analysis of the electrical activity of the heart, ECG is an essential tool in cardiology that helps doctors diagnose, monitor, and treat cardiac conditions [9]. A technique called Deep Learning allows a computer to recognize visual inputs without explicitly removing any aspect [10]. In terms of accuracy, deep-learning models outperform human-level abilities. Labeled massive data was used to train deep learning models. The architecture of a traditional neural network consists of several layers. Levels with many hidden levels are referred to as deep layers. Similar to machine learning, deep learning comprises several layers with nonlinear processing units. The characteristics of the tiers above provide the input to the lowest layer. A Convolutional Neural Network (CNN) is an algorithm used for deep learning. These networks consisted of completely connected layers and several convolutional layers. In addition, the layers were clustered together. The use of Boltzmann machines is restricted to Deep Belief Networks (RMBs). Deep networks can be trained using (RMB)/RMB/auto-encoders [11], [12], [13]. The prize for the best object recognition performance is given by the CNN. Deep neural networks outperform all other machine learning methods in terms of efficiency. Convolutional neural networks, particularly deep neural networks, have shown excellent performance in image recognition. Picture categorization has undergone a paradigm shift owing to recent developments in computer vision and machine learning [14], [15]. By thoroughly examining the dataset's real-world variability and using appropriate preparation approaches, a CNN-based system can be trained to accurately recognize ECG data and make better generalizations to other scenarios [16], [17]. To demonstrate the superiority of the current ECG classification approaches, including deep learning-based and classical methods, a comparative study using a CNN-based methodology was conducted. The results of this study have broad implications for ECG classification and computer vision applications. The proposed method will enhance the medical sector by empowering healthcare providers to automate ECG grading tasks. Finally, our research will help create automated ECG identification systems for the medical industry by addressing the problems of ECG categorization and using state-of-the-art machine learning algorithms. The methodology, experimental data, and comments are covered in more detail in later chapters, which will provide a comprehensive assessment of the ECG classification system. The use of deep learning techniques to categorize ECG images is the main advantage of the proposed method [18].

This study has initiated the development of the previously discussed objectives that were outlined and implemented regarding the requirements of the research question and expected results. One of these was to develop a deep learning-centric ECG recognition and classification model and an exhaustive review of the literature. An important contribution of our study is: 1) assessment of the effectiveness of the machine learning model, 2) use of image datasets as image dataset suits modern research better, and 3) identifying which machine learning algorithm performed best when classifying heart disease based on performance.

2. Methodology

It is important to select an effective and optimal methodology for identifying and classifying ECG. We can then accurately process our data and train the machine using this limited dataset. Here, we choose the type of methodology and algorithm workflow that we use in this study, which gives us a good result in the output. This chapter describes the research objective, the algorithm we used, and our data with some analysis, along with the proposed workflow. We analyzed the ECG classification dataset of Cardiovascular ECG Images using appropriate data preprocessing. In the preprocessing step, the effects of resizing, grayscale conversion, and labeling were examined. Subsequently, a deep learning model called MobileNet-V2 [18] is trained and implemented. Predictions were performed using the aforementioned algorithms. Each step is described in detail below: The proposed approach for ECG classification consists of five main processes and supporting steps: Fig. 1 shows a flowchart of our methodology.

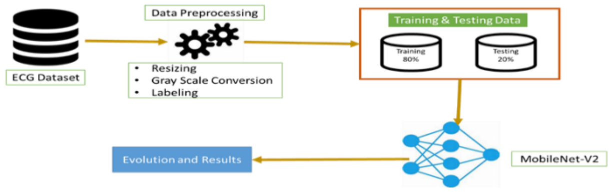

Fig. 1. Flow Chart.

2.1. *Dataset Collection*

The Cardiovascular ECG Image dataset chosen for the proposed study is freely accessible at Kaggle [14]. Because the dataset used was not proprietary or self-compiled, it was taken from an online source, so there was no relevant population of the study from which the dataset was collected. The cardiovascular ECG image collection included four ECG combinations. ECG images of patients with abnormal heartbeats and ECG images of a normal person are the only two categories of ECG that were used to support the theory. By selecting these two categories, I narrowed down the dataset to what was relevant for their research or analysis. This filtering process yielded a dataset comprising 741 ECG images. The primary objective was to create a dataset suitable for training and testing the machine learning models.

2.2. *Data Preprocessing*

This is a crucial phase in the preprocessing workflow that prepares the ECG images for training. Because preprocessing ensures that the input is in a format suitable for training models, it is crucial to machine learning and computer vision. The initial step was to resize the ECG images to standard resolution. This is important because machine-learning algorithms often demand constant dimensions in the input data. Resizing makes processing the model easier by keeping the width and height of each photograph consistent. By removing the color information, grayscale conversion also simplifies the images, which may help reduce the complexity of the model and improve its generalizability. Finally, splitting the dataset into training and test subsets is a crucial machine-learning stage for precisely assessing the model's performance. While the training subset was used to train the model, the test subset was kept separate for evaluation to ensure that the model could generalize well to new data. These steps maximize the training process and eventually enhance the performance of the model in ECG interpretation tasks by standardizing, cleaning, and organizing the data. Fig. 2 shows the processed image.

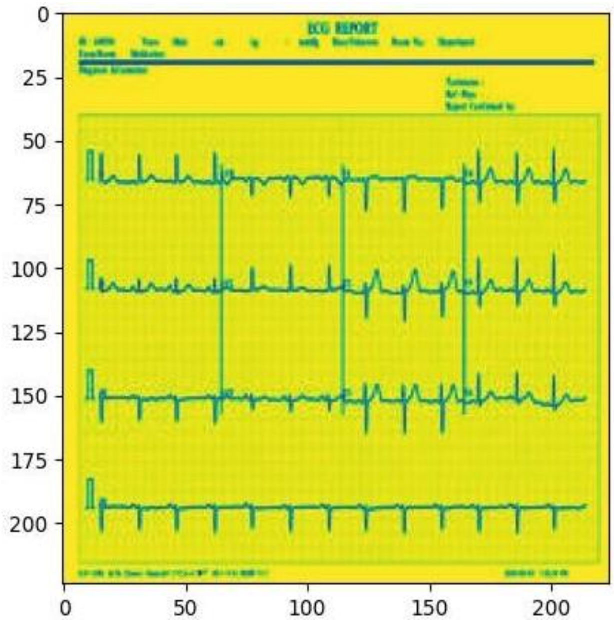

Fig. 2. Processed Image.

2.3 *Model Architecture Design*

Building an appropriate architecture for a convolutional neural network for ECG image processing is one of the critical tasks in medical imaging analysis. Intelligent architecture is important in the acquisition of critical information as well as avoiding problems like overfitting and underfitting. The first set of layers in a CNN model for processing ECG images is comprised of a series of convolutional layers. Filters are used in these layers to explore the input images and capture low-level features such as edges and curves. For ECG analysis, detection of waveform patterns and structures can be included in the process.

2.4 *Model Training with Training Dataset*

Training a CNN model using preprocessed fruit images. This involves feeding the training dataset through a CNN model, computing loss (a measure of the model's prediction error), and optimizing the model's weights using an optimizer and a predetermined learning rate. Repeated updates were made until the model achieved an acceptable degree of accuracy on the training dataset. To train the model using the training dataset, the system used 593 ECG images. For training purposes, we selected the MobileNet-V2 model.

2.5 *Model Testing*

Testing the performance of a trained Convolutional Neural Network model with a separate test dataset is a critical step in the machine learning pipeline. The model has never seen a portion of the data, such as the test dataset, which serves as an independent and hidden subset. This replicates real-world situations in which the model discovers previously undiscovered data. The main goal of this testing step is to evaluate the model's ability. to generalize or how well it can make accurate predictions on data that it has not been explicitly trained on. During this evaluation, key performance metrics such as accuracy were computed. These metrics provide a quantitative evaluation of the model's performance by analyzing how well it categorizes objects or patterns in the test data. The model is a reliable tool for a variety of tasks because it can effectively apply the significant qualities and patterns learned from the training data to new, uncovered data, as indicated by the high recall and accuracy levels in the test dataset.

2.6 *Model Evaluation*

Understanding the operational efficiency of deep learning models requires understanding their accuracy and efficacy. These models are similar to highly clever computers that have access to large volumes of data. To measure how well people perform at certain jobs, such as identifying cardiac patterns in ECG readings, we require specific technology. We used a device called "accuracy." This provides details regarding the accuracy rate of the model. However, sometimes, particularly when one type of material dominates over another, the accuracy is not sufficient to capture the whole picture. Therefore, we also utilized a statistic called the "F1 score." This score allowed us to evaluate the accuracy of the model in identifying relevant data while reducing the number of errors produced. The next kind of graphic called “confusion matrix," lists all of the advantages and disadvantages of the model's operation. It is simpler to identify areas on a map where the model is doing well and those that require improvement. By using these techniques, we will be able to assess the extent to which our deep learning models help physicians identify heart anomalies, particularly when interpreting electrocardiograms. Patient care has improved, and everyone has more access to healthcare.

OpenCV Python was chosen for use in the software part for user detection. Processing a video implies executing it.

3. Results and Discussion

In computer vision and machine learning, preprocessing is essential to ensure that the data are suitable for model training. The greatest effort is to resize the ECG pictures to a standard resolution. This technique is essential because uniform-dimensional input data are required for machine-learning algorithms. Scaling helps the model to handle data by ensuring that the picture dimensions are the same. The research also shows how the grayscale conversion of photographs expanded the collection. The removal of color information from photos allows the model to handle larger datasets with less complexity owing to this conversion. Dividing the dataset into training and test subsets is another essential machine-learning step necessary to correctly examine the model's performance. While the training subset is used to train the model, the test subset is set aside to assess how well the model generalizes to data that has never been seen before. Google created the MobileNet-V2 modular convolutional neural network (CNN) architecture in response to the need for rapid and portable computer vision models. MobileNet-V2 is an ideal choice for low-processing-power applications because it is faster and requires less effort than its predecessor. This efficiency might be the result of cutting-edge technology, such as depth-wise separable convolutions, which use a single filter for each input channel to significantly reduce the processing burden. Deeper network topologies may be built using the paradigm's inverted residual blocks without significantly increasing processing complexity. MobileNet-V2 also includes global average pooling for spatial compression, and squeeze-and-excitation blocks for channel-wise feature correction. The model is often retrained using huge picture datasets, such as ImageNet, after which it is adjusted to suit specific demands. This widely used alternative is often used for mobile apps and edge device inference in real-time. It can be adjusted to fit specific applications and take a variety of input sizes. The novel CNN architecture, known as MobileNet-V2, combines accuracy and efficiency. Its unique design choices, such as depth wise separable convolutions and inverted residual blocks, may allow it to attain competitive accuracy with fewer parameters. Therefore, it can compete well in deep learning applications, even in systems with constrained resources. The fact that it is widely used in industry attests to its efficacy in satisfying the requirements of real-time inference in embedded and mobile applications, while producing excellent quality results. Matplotlib is one of these libraries that is used for picture plotting and presentation. NumPy is used to represent matrices and perform the operations required to build convolutional neural networks. The keras. layers, keras. preprocessing and keras.models modules of the TensorFlow Keras API were imported. These were used by the automatic learning processes of the system. In addition, I have included some specialized modules for minor system tasks, such as glob, which allows me to expand Unix pathname patterns and operating systems (OS), giving me access to some fundamental system operations. The efficiency or composition of the CNN was not affected by these modules. A systematic approach was adopted to comprehensively execute the experiment aimed at classifying various ECG patterns. Initially, a baseline model was trained to establish a fundamental performance benchmark. The effectiveness of the model as a whole is then evaluated through a series of controlled experiments to determine how certain hyperparameters affect it. The preliminary results of our training indicated a remarkable achievement, with our model achieving an impressive accuracy rate of 97.6 %. This exceptional baseline performance not only serves as a solid starting point but also paves the way for insightful investigations into how individual hyperparameters can further enhance the model's classification capabilities. Through these rigorous experiments, we aimed to refine our model and develop a robust ECG classification system. We displayed each class's annotated ECG individually using the matplotlib plot function after importing all our modules to verify that the photos would display and test the annotations. Fig. 3 displays the script used to display the normal and abnormal ECG images of the dataset.

```
#image of abnormal heartbeat
img = mpimg.imread('E://train//HB(1).jpg')
imgplt = plt.imshow(img)
plt.show()

#image of normal heartbeat
img = mpimg.imread('E://train//Normal(1).jpg')
imgplt = plt.imshow(img)
plt.show()
```

Fig. 3. The Script Used to Display the Dataset's Normal and Abnormal ECG Pictures.

Subsequently, the data were scaled by dividing each feature value by 255, which is a common practice when working with image data, to rescale the values from a range of 0 to 255 to a normalized range of 0 to 1. This scaling helps ensure that the features are on a similar numerical scale, facilitating the training of the machine learning models. This preprocessing is crucial for building and evaluating predictive models that aim to classify data as "normal" or "abnormal" based on the provided features. Fig. 4 shows that the dataset was split into training and testing groups at an 80:20 ratio.

Fig. 5 and Fig. 6 shows that our model successfully learns the ECG images with the highest validation accuracy of 99.3 %.

A confusion matrix was used to verify the MobileNet-V2 model. The prediction rate of the proposed image processing model was 99.3 %. Fig. 7 shows the confusion matrix for the MobileNet-V2 model.

```
#Train Test Split
X = normal_abnormal
Y = np.asarray(labels)
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
print(X.shape, X_train.shape, X_test.shape)

# scaling the data
X_train_scaled = X_train/255

X_test_scaled = X_test/255
print(X_train_scaled)
```

Fig. 4. Data Training and Testing.

```
Final Train Accuracy: 0.9763513803482056
Final Validation Accuracy: 0.9932885766029358
Final Train Loss: 0.0958276018500328
Final Validation Loss: 0.07850576937198639
Precision: 1.0
Recall: 0.9764705882352941
F1 Score: 0.988095238095238
```

Fig. 5. Model Training Result.

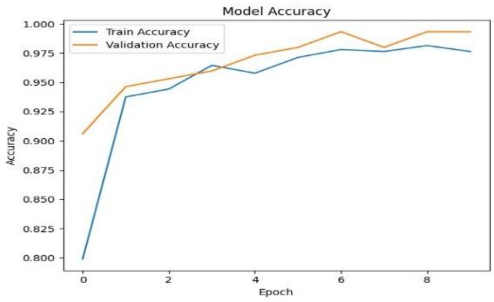

Fig. 6. Model Training and Testing Accuracy Result.

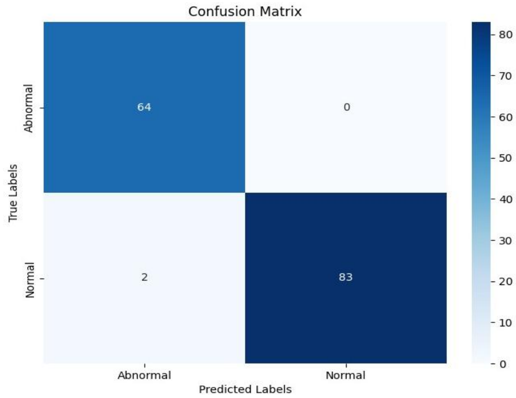

Fig. 7. Confusion Matrix Derived from the Outcome of the Developed MobileNet-V2 Model.

In this study, we presented a systematic approach to ECG pattern categorization using the CNN architecture of MobileNet-V2. We begin by examining an essential method for ECG estimation from the system viewpoint. Subsequently, we thoroughly analyzed the data in our dataset using conceptual and statistical methods to identify and compile patterns. Effective photo preprocessing, such as scaling to a consistent resolution, grayscale conversion, and dataset splitting for training and testing, ensured the best possible data preparation for our machine-learning model.

Our classification model is built on top of the widely known and flexible MobileNet-V2, which has innovative features, such as inverted residual blocks and depth-wise separable convolutions. We draw attention to the critical role that basic libraries and modules play in our methodology, which streamlines the process of creating models and conducting tests. Thorough model training, which involves establishing a high-accuracy baseline, improved our approach. As a result, testing could identify ECG patterns with an amazing 99.3 % accuracy. Furthermore, we used a confusion matrix to evaluate the accuracy, precision, and recall of the proposed model. These findings demonstrate the potential of this method for use in medicine by providing better clinical ECG classification accuracy and indicating future research possibilities for larger and more diverse datasets.

4. Conclusion

In this study, we built and evaluated an ECG classification system using MobileNet-V2 architecture. The importance of evaluating the ECG pattern at the beginning of the inquiry was highlighted through a thorough methodical evaluation. The following step was data analysis when the data were carefully examined and analyzed to identify any noteworthy trends. This method was supported by statistical data and conceptual tools. The research's main discovery was the benefits of picture preprocessing for computer vision and machine learning. Equitable sizing of ECG images made it possible to provide machine-learning models with comparable input sizes and processing speeds. Grayscale picture conversion was made easier by removing color information from the dataset, which reduced the model complexity and improved generalization. More specifically, the training and testing portions of the dataset were separated, which is a critical step in machine learning that allows for the consistent evaluation of model performance. The main goal of this study was to make use of Google's MobileNet-V2, a thin CNN architecture that offers significant processing reductions. MobileNet-V2 is considered the best option for applications with low resources because of its special characteristics, which include depth-wise separable convolutions and inverted residual blocks. The baseline model's amazing 99.3 % accuracy rate was reached after extensive testing, providing a solid basis for further research on how hyperparameters affect the model's classification performance. ECG imaging data were visually evaluated and confirmed using matplotlib. Data scaling was used to normalize the features during the training phase once the dataset was completely divided into the training and testing sets. During the model assessment phase, a system's remarkable 99.3 % prediction performance is emphasized via the use of a confusion matrix. The findings of this study highlight the potential of the MobileNet-V2-based ECG classification system as a useful tool for medical diagnosis and treatment, even if additional development and improvement are required to increase its accuracy and efficiency.

In the future, the ECG categorization methods may change. Currently, 741 images from ECGs are used to train the algorithm to understand them. However, we still have potential. Initially, we had more ECG pictures to speed up the learning process of the system. Modifications to computer program 31 might result in even greater accuracy. As an alternative, we may ask the machine to explain why it determines whether a certain ECG is good or terrible. Physicians may be asked to test a computer to ensure that it functions properly in actual hospitals. We may also make the required adjustments if the equipment interprets certain ECGs incorrectly. We also guarantee that computers will maintain and protect the privacy of people's medical records. We may also consider using more medical data to enhance computer performance. Finally, we may try to utilize a computer to track people's heart rates in real time in an attempt to identify issues early on. All these factors will impact the usefulness of the ECG computer system for physicians and patients.

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Authors Introduction

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He has over 20 years of teaching experience and is now a day HOD at NUML University. He possesses a robust enthusiasm for research and innovation in the fields of information science, information technologies, and IT management, with a particular emphasis on IT/IS research domains such as machine learning, data sciences, AI, deep learning, and network computing applications.

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