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Image-Enhanced Heart Disease Risk Assessment using CNN Algorithm

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Abstract: The study delves into the profound dual nature of the heart, as both a vital organ sustaining human life and a powerful symbol deeply interwoven in human culture and emotions. It acknowledges the pervasive global challenge of heart disease, encompassing a myriad of heart and blood vessel disorders with severe health implications. The study's research methodology emphasizes the crucial selection of effective techniques for identifying and categorizing electrocardiogram (ECG) data, outlining research objectives, chosen algorithms, dataset description, and the proposed workflow. In this research, an analysis of the Cardiovascular ECG Images dataset is conducted, with a focus on data preprocessing steps, including image resizing, grayscale conversion, and dataset division for training and testing.

Keywords: Convolutional Neural Convolution (CNN); Confusion Matrix; Dataset Collection; ECG; FCN layers; Heart Diseases; Machine Learning.

1. Introduction

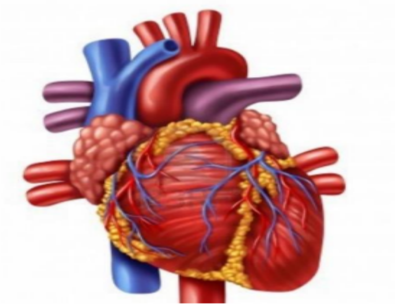
1.1. Introduction to Heart & Heart Disease

The human heart is an incredibly intricate and vital organ that pumps blood throughout the body to maintain life. The size of a closed fist, this muscular powerhouse is tucked away inside the chest and is in charge of the blood's regular circulation. With its two atria and two ventricles, the heart's four chambers control the continuous flow of hormones, nutrients, and oxygen to every area of our body. It's precisely coordinated contraction and relaxation, guided by an internal electrical system, drives this essential process, which occurs approximately 60 to 100 times per minute. Beyond its physical significance, the heart has deep cultural and emotional value as a symbol of love and deep human emotion, inspiring countless artists, poets, and writers throughout history.

Heart disease, also known as cardiovascular disease (CVD), is a widespread and life-threatening medical condition that affects millions of people worldwide. It is a broad term that includes many disorders that affect the heart and blood vessels, ultimately affecting their ability to function effectively. Cardiovascular disease is the leading cause of morbidity and mortality worldwide a major public health challenge. When heart function is affected by disease, it can have devastating consequences on a person's health and well-being. Coronary artery disease, Figure 1 shows: Heart veins and arteries 3 arrhythmias, heart failure, valvular heart disease and congenital heart defects are just a few of the different ways that heart disease can present itself.

Electrocardiography, commonly called EKG or ECG, is a basic medical procedure used to assess the electrical activity of the heart. It involves placing electrodes on the skin, which detected record the heart's electrical impulses as it contracts and relaxes. Specific components of the ECG waveform, such as the QRS complex, P-wave, T-wave, and ST segment, provide important insight into heart rhythm and function.

There are different types of ECGs, tailored to specific clinical scenarios Figure 2 shows the Heart ECG image. Resting ECGs are standard for routine checkups, while Holter monitors and event monitors capture continuous data over long periods of time, making them useful for detecting intermittent arrhythmias. The



ECG is a cornerstone of cardiology, helping healthcare professionals diagnose heart conditions, monitor patients, and treat patients through noninvasive assessment of the heart's electrical activity.

Figure 1. Heart Veins and Arteries

1.2. Machine Learning

Machine learning is one area of artificial intelligence. Artificial intelligence (AI) is a subset of intelligence that enables knowledge to be absorbed by frameworks and enhanced without being explicitly changed.

Using machine learning, large amounts of data can be sent to a computer program, which analyzes it and makes decisions and recommendations based only on the data provided. Artificial intelligence is the study of building computer programs that can take data and use it to solve problems on their own.

Machine learning calculations are used in a variety of applications, such as email filtering and PC viewing, where performing traditional calculations is impractical or impossible.

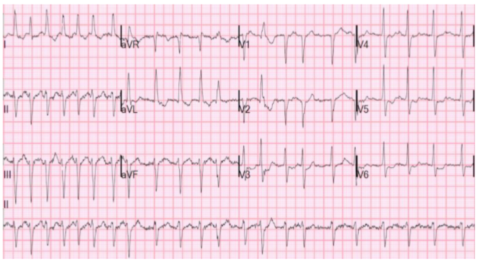


Figure 2. Heart ECG Image

1.3. Convolutional Neural Network

An artificial neural network that uses convolutional neural networks falls into this category. Also known as CNN Convent. Evaluate visual images during data processing at some point. A popular deep learning method called Convolutional Neural Convolution (CNN) teaches a model how to perform classification tasks using images, video, text, or audio. An active neural network can have dozens or even hundreds of layers, and each layer specifies how to recognize different features in an image. Figure 3: shows the CNN layer structure.

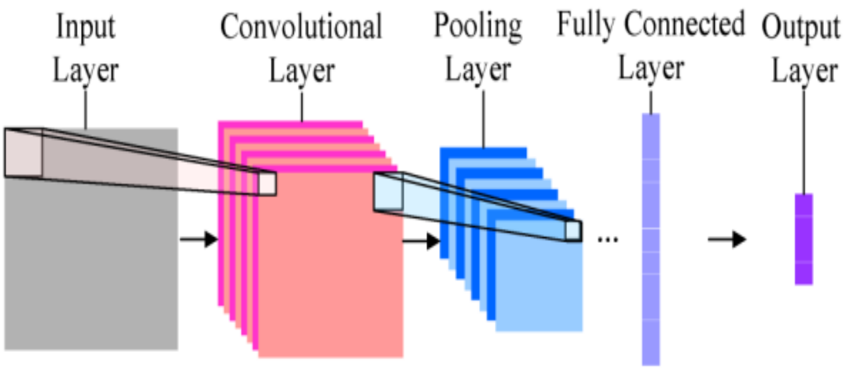


Figure 3. CNN Layer Structure

The main objectives of our study are mentioned below:

1. To assess the effectiveness of machine learning model.

2. Utilize Image dataset because the image dataset is more suitable for modern research.
3. To determine that machine learning algorithm is most effective for classification of heart disease based on performance.

1.4. Significance of the Study

The proposed study holds significant importance for several reasons:

1.5. Early Detection and Prevention

Detecting heart disease early is important because it can help prevent serious health problems. Cardiovascular disease is one of the top reasons of death worldwide, so catching it early can make a big difference. Identifying the signs and getting timely medical attention can save lives and improve outcomes.

1.6. Improved Accuracy and Efficiency

ML algorithms have the potential to deal with the large amount of data and identify the complex patterns that are not easily recognizable by humans alone. By leveraging these algorithms, the study aims to develop a model that can enhance accuracy and efficiency in heart disease prediction.

1.7. Resource Allocation and Planning

Accurate prediction of heart disease can assist policymakers and healthcare organizations in resource allocation and planning.

1.8. Advancement in Machine Learning Techniques

The study contributes to the field of ML by applying algorithm in the context of heart disease prediction.

1.9. Decision Support for Healthcare Practitioners:

The developed model will help healthcare practitioners as a valuable decision support too.

2. Literature Review

CNN models for ECG classification tasks have been the subject of much research in the past few years. The part that follows examines a few current literature studies that are relevant to our field of study.

2.1. Background of the Study

A significant global health concern is heart disease, also known as cardiovascular disease. This includes many conditions, including heart failure, coronary artery disease and arrhythmias, and is responsible for a significant number of deaths worldwide. Machine learning techniques are becoming increasingly popular in healthcare and have shown promise in predicting and diagnosing various diseases, including heart disease. Healthcare professionals may be able to spot patients who are more likely to contract a disease even before symptoms appear by utilizing machine learning. This early detection allows for the implementation of preventive measures, personalized treatment plans, and lifestyle modifications to mitigate the progression of the disease.

2.2. Literature

Heart disease is a common, potentially fatal condition that affects a lot of people worldwide. A key factor in enhancing patient outcomes and lowering mortality rates is the early identification and accurate prediction of heart disease. Healthcare professionals can now make educated decisions and offer individualized treatment plans thanks to the powerful tools that machine learning techniques have developed as in recent years. The goal of this literature review is to investigate developments and trends in machine learning-based heart disease prediction.

The electrocardiograms (ECGs) are useful in identifying cardiovascular diseases, particularly myocardial infarction (MI). ECGs are used to record the electrical activity of the heart, but because of their short amplitude and duration, they can be difficult to visually interpret.93.53% for ECG beats with noise and 95.22% for those without noise removal were the high accuracy rates attained by the CNN. The few ECG classification findings using 1D convolutional neural network (CNN) models with FCN layers and time-series data that had already been processed. The patient-specific ECG heartbeat classifier using an adaptable implementation of 1D Convolutional Neural Networks (CNNs), which are able to combine feature extraction and classification—the two main building blocks of the conventional ECG classification—into a single learning body [1-3].

The automatic classification of single-lead ECG signals using restricted Boltzmann machines and deep belief networks. Using the MIT-BIH Arrhythmia and Supraventricular Databases. A deep learning model architecture and assess it. The results obtained demonstrate that both of our models have significantly outperformed the state-of-the-art performance for supraventricular (SVEB) and ventricular (VEB) arrhythmia classifications on the unseen testing dataset without using any complicated data pre-processing or feature engineering methods. A 33-layer CNN architecture is followed by an NCBAM module suggested technique. The MIT-BIH arrhythmia database yields an average F1 score of 0.9664 for the suggested technique and an AUC of 0.9314 [4-6].

An application that utilizes neural networks, the most accurate and reliable algorithm in machine learning, to predict heart disease symptoms like age, sex, and pulse rate [7].

The heart disease prediction model employing a variety of variables and classification methods was introduced. This improved model can forecast heart disease outcomes more accurately [8].

A dataset with 12 parameters, assess the effectiveness of several machine learning methods, such as SVM, Decision Tree, Naive Bayes, Logistic Regression, Random Forest, 11 and KNN, for predicting heart disease. The 13 features, including age, blood pressure, gender, cholesterol, cp, and obesity etc implemented a user-friendly Heart Disease prediction framework. The 14 parameter UCI Heart disease dataset to forecast the likelihood of heart disease. They sought to identify correlations between variables and precisely forecast the risk of heart disease by using a variety of machine learning techniques, such as Naive Bayes, Random Forest, Support Vector Machine, and Decision Tree [9-11].

To assess patient performance a dataset core comprising 12 parameters and 70000 unique data values were used. The main objective of this study is to improve heart disease diagnosis accuracy using an algorithm. The Cleveland heart disease dataset was used in a research that used regression and classification methods, notably the Random Forest and Decision Tree algorithms [12-13].

Using data from the University of California, Irvine, conducted a comparison of cardiovascular disease prediction methods [14].

A database of 303 individuals' health test results and associated risks of heart disease to build five prediction models, including Support Vector, Logistics Regression, Random Forest, K Nearest Neighbors, and Decision tree Model [15].

A small machine learning (TinyML)-based classification (also known as Tiny CES), in which the ECG monitoring equipment does the classification on its own using a machine learning model [16].

Deep convolutional neural networks, provide a method for categorizing heartbeats that can correctly identify five distinct arrhythmias in line with the AAMI EC57 standard. A reliable and effective 12-layer deep one-dimensional convolutional neural network used to diagnose arrhythmia, created unique techniques. The abstract differentiating characteristics from dual-lead and three-lead ECGs, respectively, may be extracted using the DLCCANet and TL-CCANet algorithms introduced in this study [17-19].

A completely automated, semi-supervised ECG classification system that offers good VEB and SVEB prediction sensitivity and specificity. They maintain up to 300 estimated N beats, or about the number of beats anticipated throughout a 5-minute recording. Convolutional Neural Network (CNN), a DL method effective in classifying signals, is used. CNN is used to automatically train features from time domain ECG data that are obtained from the MIT-BIH Database via Physiobank.com [20-21].

A novel deep-learning approach based on adversarial domain adaptation is proposed for the classification of electrocardiograms (ECGs) [22].

Investigation of the UCI Machine Learning Heart Disease dataset, several machine learning algorithms and deep learning techniques are used to compare the findings. The deep learning method resulted in 94.2% accuracy [23].

2.3. Literature Gap

A multitude of insights into different approaches and models used for this crucial medical task can be gained from the literature review in the area of machine learning-based heart disease prediction. But there is a clear difference when we look at the suggested work, which makes use of the MobileNetV2 architecture and achieves a remarkable accuracy rate of 99.3%. This MobileNetV2-based method differs from previous research in a number of significant ways, offering a novel and exciting direction in the field of heart disease prediction.

Second, the accuracy of 99.3% recorded is far higher than the greatest documented accuracies in the examined literature, which are usually between 86% and 98.67%. Given its exceptional performance, it is possible that the MobileNetV2 model has revolutionized the field of cardiac disease prediction by setting a new standard for accuracy [24-25].

Furthermore, it is essential to investigate the generalization capabilities of MobileNetV2. The literature mentions the use of various datasets, but it is unclear whether MobileNetV2 can consistently achieve its remarkable accuracy across different datasets, including those representing diverse patient populations. Validating the model's robustness and reliability in clinical practice is vital for its adoption in real-world healthcare scenarios. In conclusion, the MobileNetV2-based heart disease prediction approach, with its reported 99.3% accuracy, represents a promising development in the field [26-27].

3. Research Approach and Methodology

3.1. Research Methodology

It is important to choose an effective and optimal methodology to identify and classify ECG. From this little quantity of data, The system can then be trained after we precisely process our data. Here, select an approach and algorithm workflow type that will help us achieve a high-quality outcome for our project.

3.2. Research Design

The ECG classification dataset Cardiovascular ECG Images with appropriate data preprocessing. The impacts of scaling, grayscale conversion, and labeling were investigated during the preprocessing stage. After that, a machine learning model called MobileNet V2 was trained and implemented. Predictions are made using the mentioned algorithms. Figure 4 shows the flow chart of our methodology.

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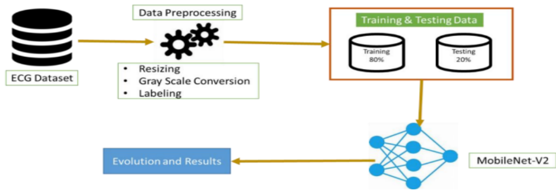

Figure 4. Flow chart methodology

3.3. Dataset Collection

Collect a representative ECG image dataset for testing and training. The Cardiovascular ECG Images collection includes 4 different ECG combinations. ECG images of patients that have abnormal heartbeat and ECG images of normal person are the only two categories of ECG that is used to support my theory. This resulted in 741 ECG images in my chosen dataset. For the training and testing, dataset will be divided into two groups.

The primary objective is to create a dataset suitable for both training and testing machine learning models. A Kaggle dataset named "Cardiovascular ECG Images" must be accessed in order to do this. This dataset appears to contain various ECG combinations, which could represent different aspects of heart health or condition. Plan to split this dataset into two separate groups in front of the machine learning tasks: one for training the model and the other for evaluating its efficacy. This partitioning is a standard practice in machine learning.

3.4. Data Preprocessing

This is a crucial step in the process of preparing Electrocardiogram (ECG) images for training, known as pre-processing. With regard to machine learning and computer vision, pre-processing plays a crucial role in ensuring that the data is in a suitable format for model training. The first task is resizing the ECG images to a uniform resolution. This is important because machine learning models often require input data to have consistent dimensions. Resizing ensures that all images have the same width and height, making it easier for the model to process them. Figure 5 shows the processed image of data. Additionally, the lines touch upon enhancing the dataset by converting the images to grayscale. Grayscale conversion simplifies the images by removing color information, which can help reduce the complexity of the model and improve its generalization.

3.5. Model Architecture Design

Designing the structure of a Convolutional Neural Network for processing ECG (Electrocardiogram) images is a critical task in medical image analysis. To effectively capture relevant features and mitigate issues like overfitting and under fitting, a well-thought-out architecture is essential. The CNN model for ECG images typically begins with a series of convolutional layers. These layers employ filters to scan the input images and detect low-level features such as edges and curves.

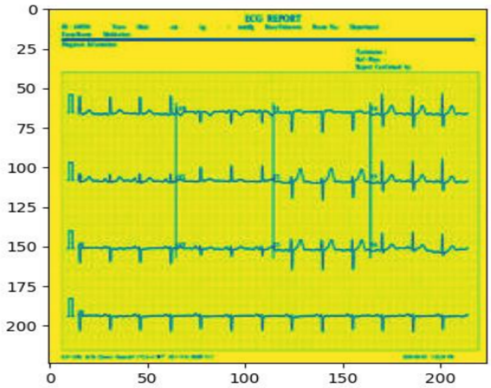

Figure 5. Processed Image

3.6. Model Training with Training Dataset

Train a CNN model using pre-processed 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 making use of the optimizer and a predetermined learning rate. Until the model achieves an acceptable degree of accuracy on the training dataset, repeated 18 updates are made. To train the model with training dataset system used 593 ECG images. For training purpose, we selected mobilenet_v2 model.

3.7. Model Testing

Testing a trained Convolutional Neural Network model's performance with a separate test dataset is a critical step in the machine learning pipeline. This test dataset serves as an independent and unseen subset of the data, one that the model has never encountered during training. By doing this, it replicates situations from the actual world in which the model runs across fresh, unexplored data. The primary goal of this testing phase is to assess the model's generalization ability, determining how well it can make accurate predictions on data it hasn't been explicitly trained on.

3.8. Model Evaluation

Finding out how accurate and efficient deep learning models are is essential to truly understanding how well they perform. These models are like super-smart computers that can learn from lots of information. They require specialized tools to assess their performance on tasks such as cardiac pattern recognition in ECG images. One of our instruments is "accuracy." It tells us how often the model gets things right. But accuracy doesn't always tell the whole story, especially when there are more of one kind of thing than another. In light of this, we also employ the "F1 score."

This score lets us determine how well the model finds the correct stuff while avoiding making too many mistakes. Then, there's the "confusion matrix," which is like a chart showing all the good and bad things the model does. Find out more about how successfully our deep learning models help doctors diagnose heart problems by using these tools, particularly when analyzing ECG images.

3.9. Data Collection

Cardiovascular ECG Images, a publicly available dataset at https://www.kaggle.com/datasets/jayaprakashpondy/ecgimages, was selected for the suggested study. We will use this dataset to get our experiment ready. Figure 5 and 6 shows the Normal and Abnormal images of ECG.

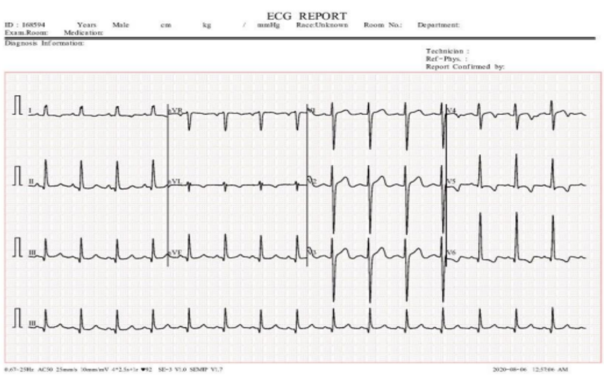

Figure 6. Normal ECG

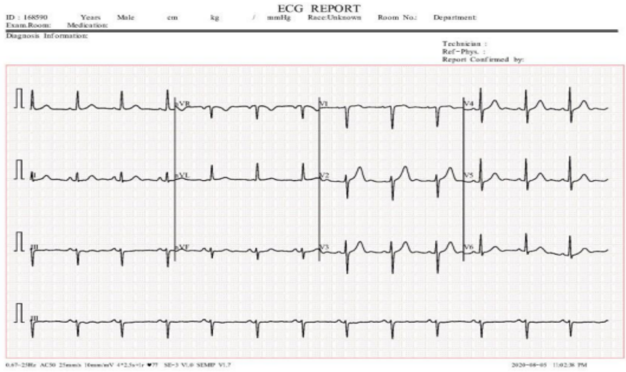

Figure 7. Abnormal ECG

3.10. Software and Tools

The first choice for developing the system was Python since it's one of the easiest languages to write in and it's easy to use with TensorFlow. A couple of Python libraries are also available that might help me achieve my objective.

- Matplotlib: Static or moving visualizations, as well as visual representations of mathematical facts, can be created with a Python tool called Matplotlib. You can make polar plots, scatter plots, line plots, histograms, 3D charts, and more with it. It also has an object-oriented API. To show ECG images on my system, I would use matplotlib.
- NumPy: To generate, examine, and manipulate matrices and multidimensional arrays, utilize the NumPy library for Python. This would help with convolution and data pooling procedures, as well as handle and analyze the array data for the project.
- Keras: One part of TensorFlow is the high-level object-oriented API known as Keras. Its applications in industry and research are extensive and it facilitates fast prototyping. Because it's easily extendable, intuitive, and modular, users can design their own components to use in their applications. Another high-level TensorFlow API that isn't as popular is called the Estimator. Training, assessing, forecasting, and exporting to services were all major capabilities of the estimator.
- PyCharm: In order to establish a simple environment for effective Python, web, and data science development, PyCharm is a specialized Python Integrated Development Environment (IDE) that offers a large range of critical tools for Python developers.
- Sklearn: The most effective and potent Python machine learning library is called Skearn (Skit-Learn). It offers a range of effective machine learning technologies. This Python-based library is based on NumPy, SciPy, and Matplotlib.
- Population and Sampling: Since the dataset used is not a proprietary or self-compiled dataset, it is taken from an online source, so there is no relevant population of the study from which the dataset was collected.

4. Results and Discussions

A: Data Analysis

This is the next stage that we will take; in order to illustrate, demonstrate, describe, and condense our dataset as well as recognize patterns, we have employed a methodical strategy as well as statistical and conceptual tools.

B: Image Pre-Processing

In the realm of machine learning and computer vision, pre-processing assumes a pivotal role in ensuring that the data is appropriately formatted for model training. Initially, the primary task involves resizing the ECG images to a consistent resolution. This task holds significance because machine learning models typically demand input data with uniform dimensions. Resizing ensures that all images share identical width and height, simplifying the model's data processing.

C: Classification Model MobileNet-V2 (CNN)

Google created MobileNetV2, a flexible convolutional neural network (CNN) architecture, in response to the need for effective and lightweight computer vision models. For applications with constrained computing resources, MobileNetV2 is the best option due to its superior speed and lower computational requirements. Innovative methods such as depth wise separable convolutions, which apply a single filter per input channel and greatly lower the computing load, are responsible for this efficiency.

D: Materials & Methods MobileNet-V2 (CNN)

All required libraries and modules have been imported for this round of system development. Among these libraries is Matplotlib, which is used for plotting and displaying images. NumPy handles matrix representation and the operations required to build convolutional neural networks. The TensorFlow keras API modules keras.layers, keras.preprocessing, and keras.models were also imported.

E: Displaying the Dataset

After importing all of our modules, used the matplotlib plot function to display the annotated ECG for each class individually in order to check that the photographs would appear and to test the annotations. In Figure 8 and 9 displays the script for displaying the dataset's normal and abnormal ECG images.

Figure 8. Plot abnormal image

Figure 9. Plot abnormal image

F: Split Dataset Training & Testing

This work prepares a dataset of photos with labels indicating whether they are "normal" or "abnormal" for machine learning analysis. The dataset is divided into two sets using the 'train test split' function and a random seed set: a training set (20% of the data) and a testing set (80% of the data). The data is then scaled, as is typical when working with image data, by dividing each feature value by 255. This causes the values to be rescaled from a range of 0 to 255 to a normalized range of 0 to 1. By ensuring that the characteristics are on a comparable numerical scale, this scaling makes it easier to train machine learning models. In figure 10 split dataset is shown:

Figure 10. Split dataset into training and testing groups

G: Model Training

Figure 11 shows that our model successfully learns the ECG images with the highest accuracy of 97%.

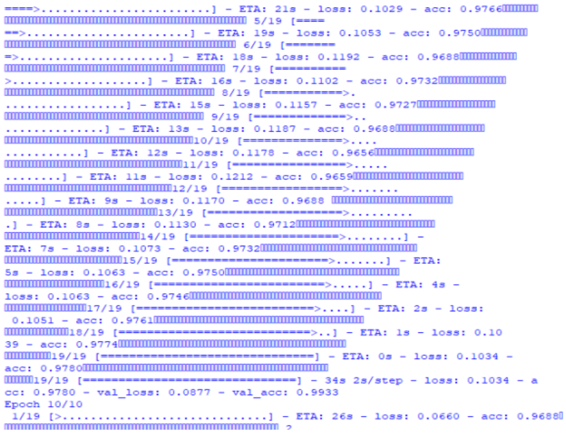

Figure 11. Model training result

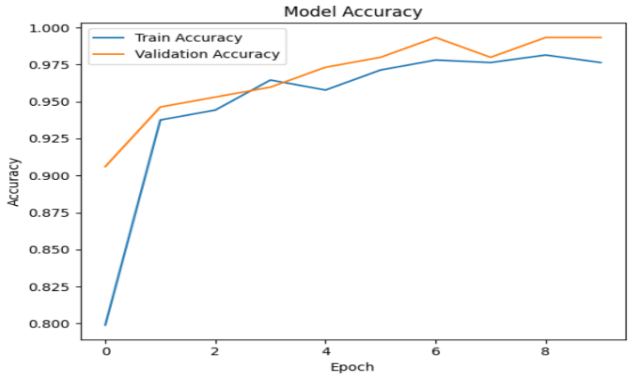

Figure 12. Training and testing loss results

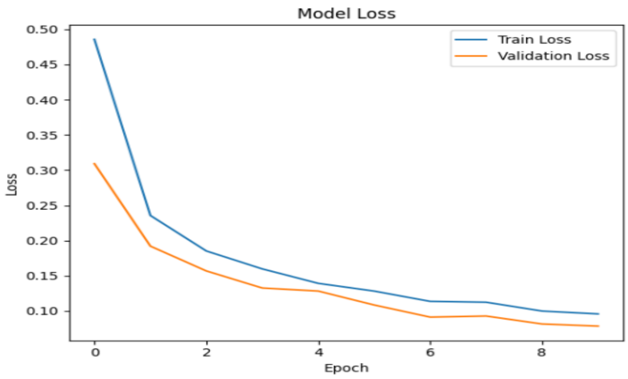

Figure 13. Training and testing loss results

The training and testing results for model accuracy and loss are shown in figures 12 and 13.

H: Evaluation

The confusion matrix was used to display the effectiveness of the MobileNet-V2 (CNN) algorithm. Confusion Matrix. This tool assesses a deep learning classification model's performance using a test dataset. Figure 14 shows how to find confusion matrix.

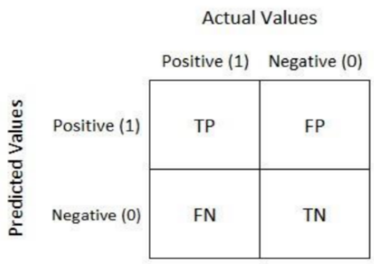

Figure 14. How to find confusion matrix

(TN) True Negative: The model predicted False, while the actual result was False.
(FP) False Positive: The model predicted True, but the actual value was False.
(FN) False Negative: The model predicted False, but the actual result was true.
(TP) True Positive: The model predicted True and the actual value was true.
Confusion matrix also can present precision, recall, and accuracy in figure 15:

To verify the MobileNet-V2 model, we used the confusion matrix. The prediction rate of the proposed image processing model is as high as 99.30%.In figure 16 you can see the confusion matrix.

$$\text{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total}}$$

Figure 15. Formulas Sheet

I: Discussions

In this work, we offer a systematic method for ECG pattern classification using the convolutional neural network (CNN) architecture of MobileNet-V2. The crucial method for ECG estimation is the primary emphasis of our system approach research. After that, we conduct a thorough data analysis using conceptual and statistical methods to identify and condense patterns within our dataset. The best possible data preparation for our machine learning model is ensured by efficient image pre-processing, which includes dataset partition for training and testing, grayscale conversion, and scaling to a uniform resolution. The foundation of our classification model is the MobileNet-V2 CNN, which is well known for its effectiveness and adaptability. It has cutting-edge features including depth-wise separable convolutions and inverted residual blocks.

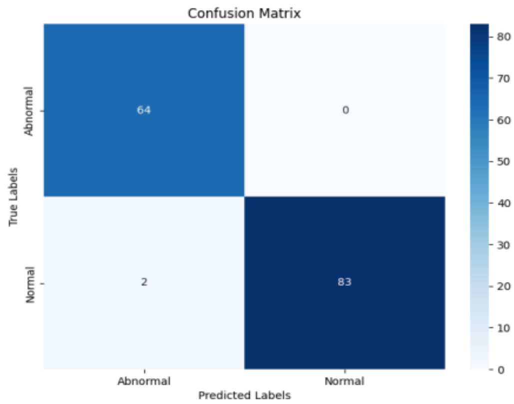

Figure 16. Confusion Matrix

We emphasize the crucial role of essential libraries and modules in our methodology, which streamline model development and experimental execution. Rigorous model training, including establishing a high-accuracy baseline, complements our approach, ultimately resulting in a remarkable 99.3% accuracy in ECG pattern recognition during testing. We also evaluate our model using a confusion matrix, demonstrating its precision, recall, and accuracy. These findings underscore the potential of our methodology in medical applications, promising enhanced ECG classification accuracy for clinical use, and suggest avenues for further research on larger and more diverse datasets.

5. Conclusion and Future Work

The MobileNet-V2 convolutional neural network (CNN) architecture was used in this study to construct and test an electrocardiogram (ECG) categorization system. The research commenced with a systematic overview of the methodology, emphasizing the critical role of ECG pattern estimation. A data analysis phase followed, wherein a methodical strategy, supported by statistical and conceptual tools, was employed to process and understand the dataset, thereby recognizing significant patterns. Crucially, the study underscored the importance of image pre-processing in the context of machine learning and computer vision. ECG images were uniformly resized to ensure consistent input dimensions for machine learning models, enhancing data processing efficiency.

The core of this study centered on the utilization of MobileNet-V2, an efficient CNN architecture developed by Google, renowned for its lightweight design and high computational efficiency. MobileNet-V2 was introduced as an ideal choice for resource-constrained applications, thanks to its innovative features such as depth wise separable convolutions and inverted residual blocks. Through rigorous experimentation, the baseline model achieved an impressive accuracy rate of 99.3%, setting a strong foundation for subsequent investigations into the influence of Hyperparameters on the model's classification performance.

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