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# Enhancing Heart Disease Detection in Echocardiogram Images Using Optimized EfficientNetB3 Architecture

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**Abstract:** Despite the progress in treatment options available for heart disease, it remains one of the most common causes of death worldwide emphasizing a necessity to identify informative and effective diagnostic protocols. This paper proposed an efficient deep learning model, EfficientNetB3, to detect Critical Congenital Heart Disease (CCHD) from echocardiogram images and provides accurate predictions. EfficientNetB3 is further fine-tuned specifically for the heart disease diagnosis in echocardiogram images using advanced techniques like dropout, momentum, and batch normalization to improve overall accuracy of our model. To improve our model architecture and hyperparameters, we carried out a set of experiments. The first experiment conducted was of a baseline model having the pre-training weight, getting the test accuracy as 91.80%. Later improvements, such as the dropout and momentum addition increased this accuracy to 94.14% Finally, the best model configuration with fine-tuned dropout rates and dense layer tweaks yielded a test accuracy of 94.53% Accuracy metrics, confusion matrices and F1 scores were used to assess the performance of the model which outperformed current implementations. This research suggest that the optimized EfficientNetB3 model can be powerful to classify different heart diseases with high accuracy, which has a bright outlook for early and accurate diagnosis. This work is a significant addition to the field of computer-aided diagnostic systems for cardiology and promises to improve clinical practice by offering robust, timely diagnostics assistance in cases where expert echocardiogram interpretation resources may not be readily available. Moving forward, additional deep learning architectures, and multi-modal data will be integrated to enhance diagnostic proficiency.

**Keywords:** Echocardiography; Convolutional Neural Network (CNN); EfficientNetB3; Heart Disease Classification; Deep Learning.

## 1. Introduction

Despite advancements in healthcare, heart disease remains a leading cause of death globally, placing significant strain on healthcare systems worldwide. In 2019, the World Health Organization (WHO) reported that cardiovascular Dis-eases (CVD) accounted for approximately 32% of all deaths globally, totaling around 17.9 million annuals [1]. These conditions, including Coronary Artery Disease (CAD), Angina, and Hypotension, impose substantial economic and societal burdens [2]. Early detection of cardiovascular diseases (CVD) is crucial for effective treatment, which can significantly reduce morbidity and mortality rates.

Prompt diagnosis is also important in treating heart disease. This one is simple: if you catch it early and get into intervention more quickly patients will do better. Diagnosis mainly depends on clinical assessment, electrocardiogram, advanced cardiac imaging and echocardiographic approaches are crucial in diagnosis of structural heart diseases [3]. An Echocardiogram allows evaluation of the size and function of the heart, valves, leaves enlargement [4]. Despite this, reading these images is slow and laborious work that must be done by someone with training in medical imaging. This in turn has driven the development of automatic methods to help clinicians interpret quicker and more accurately.

Echocardiography is a non-invasive imaging modality that employs ultrasound to provide images of the heart. It is crucial for the diagnosis and treatment of many heart diseases. Echocardiograms evaluate the function of the heart as well, and can detect structural abnormalities which are important for guiding treatment [5]. Echocardiography is valuable, but it requires expert interpretation and this might be challenging especially in countries where access to skilled cardiologists may be limited [6]. The respective high level of complexity has kindled interest in applying more sophisticated algorithms, such as deep learning approaches for the analysis of echo images.

This research attempts to tackle the problem of precision diagnosis for heart disease from echocardiogram images, using a deep learning architecture EfficientNetB3. Our study has three key contributions: We got EfficientNetB3 architecture fine-tuned for echocardiogram image analysis, which led to improved classification of different heart conditions. We performed various experiments to finalize the model and achieved better accuracy in prediction heart disease using dropout, momentum, batch normalization techniques. We showed an extensive evaluation of our model via a set metrics; accuracy, confusion matrices and F1 scores which hailed it above all the previously proposed techniques.

Our research results suggested that deep learning model could accurately identify different cardiac diseases in echocardiography images. This high classification accuracy shows bright prospects that deep learning models could contribute to enhancing the diagnostic value of echocardiography. We finish up by checking the strength of our model using confusion matrix and classification report to see what it excels at, as well areas where we can improve.

Finally, this study ends with results that illustrates the deep model for classifying heart diseases on echocardiography. While This approach is still in the development stage, due to its automation of diagnostic procedure it can enable more precise and efficacious diagnosis for cardiac disease that one day benefit patients. Future research should build on these findings by examining the extensibility of other deep learning architectures, integrating multimodal data and performing longitudinal validation studies to evaluate the impact of automated diagnostics in practice.

## 2. Literature Review

Detecting heart disease early and enhancing patient outcomes have made medical imaging one of the focal points for research. The Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRI) and echocardiogram are used to diagnose heart problems. These methods nevertheless have their limitations. Very often they rely on interpreting these images with the doctor's skill level sometimes resulting in difficulty or interpretation errors. Because of this human-dependence, the chance for error is higher and inconsistent results are more common. Hence, there is a big rush to find out better and accurate means of diagnosing heart diseases.

Recent years have witnessed the increasing popularity of deep learning, a method for automatic feature extraction from raw data and especially in medical imaging. CNNs, a type of deep learning model is particularly power full at image recognition. Last year, CNNs were able to detect heart failure using MRI images with a higher ac-curacy than the classical ways [7]. CNNs have also been studied for image type echocardiography images in valvular and coronary heart diseases diagnosis. In general, deep learning models with superior convolutional architecture could accurately detect specific cardiac conditions as shown in this study and it may lessen the diagnostic workload of clinicians while at times enhancing consistency [8]. A similar study applied CNNs to identify heart murmurs from phonocardiogram recordings with an ac-curacy of more than 90%, proving the feasibility and practicability of deep learning in different types of cardiac images [9] [15].

Deep learning has brought new ways to train neural networks from scratch through deep structures with high accuracy. The study [10] provides an overview of how advances in traditional machine learning-based models advanced into state-of-the-art forms that we have nowadays for modern artificial neural network such as CNN and Recurrent Neural Networks (RNNs), which outperformed tasks like image classification, segmentation and detection methods over biomedical imaging data due to large quantities annotated image materials were shared between global research groups. For instance, models using CNNs employed to localize-regions-of-interest have reported state-of-the-art results in breast cancer detection from mammograms [11]. In another study [12], deep learning was employed to automatically recognize common echocardiography views and diagnosing congenital cardiac anomaly children. The model developed by the researchers strikes a balance between high accuracy and efficiency needed for it to be used in clinical settings, showing that AI could correct errors in this skill& diagnostic. Nevertheless, more studies are needed to address limitation in available data quality and quantity, as well methodological issues before AI can be adequately employed for pediatric cardiology practice.

In the last few years, deep learning techniques have been applied to medical image analysis and resulted in a big leap forward regarding diagnostic accuracy. The work [13] attempts to merge state-of-the-art deep neural networks with Internet of Things (IoT) technologies in order to improve standard echocardiogram classification using available ultrasound images. Authors utilized pre-trained recurrent convolutional neural networks (RCNNs) to predict CVD risk, illustrating the potential of integrating IoT with advanced neural networks (NN) architectures in enhancing diagnostic precision and real-time analysis capacities. The strategy emphasizes an emerging trend to employ complex neural network models and IoT platforms aimed at solving problems in medical diagnosis, which is essentially part of the larger change towards more accurate and effective techniques for predicting cardiovascular disease [16] [17].

This review illustrated that the literature concluded mainly with deep learning architecture like CNNs, which are beginning to massively transform cardiac imaging by making useful diagnostic strategies more accurate as well efficient and reliable. Data quality and interpretability are possible limitations, as well as generalizability to public health or clinical decision-making applications before these models can be effectively harnessed in practice. These findings suggest that the Deep Learning (DL) technologies will still evolve for better patient outcomes and earlier detection of cardiac disease.

## 3. Materials and Methods

### 3.1. Dataset

Our primary dataset comprises a set of 2404 images from echocardiogram, where classes are introduced as Angina Disease, Cardiovascular Disease (CVD), Coronary Artery Disease (CAD) and Hypotension. Dataset We used a Kaggle dataset with annotations from Marian Cardiac Centre heart specialist, Poland. We made some histograms to look at things like how our dataset looks. The histograms show how the images are distributed over each class. Figure 1 to check our dataset it should be balance and visually accessible from each class this is a visualization. Then we split the data into three subsets: training, validation, and test sets, with a ratio of 70%, 12%, and 18% respectively Figure 1

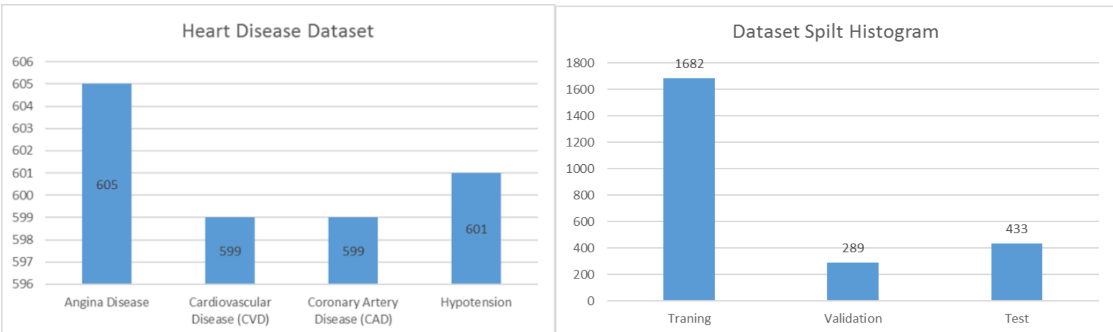


**Figure 1.** Histogram showing the number of images in each class & Data Split for Training, Validation, and Test Sets

### 3.2. Setup for Experiment

Absolutely, this paragraph depicts how exactly the classification of cardiovascular diseases looks like if we try to do it from Echocardiogram (ECG) images. This experiment was run with Kaggle's P100 Graphics processing unit (GPU) in Python. Python was used to train and deploy the model, with 100 epochs of training. P100 GPUs enabled fast processing & training, leading to better model performance and accuracy.

To examine how well our algorithm generalizes for this task, we ran different experiments with differing configurations. Here, we show the results and analysis of only few experiments which has best accuracy. The use of EfficientNetB3 in different configurations conducted experiments provided helpful insights into the classification of heart disease from echocardiogram images. Below diagram (Figure 2) is showing the architecture of the EfficientNetB3 source of the diagram ResearchGate **[14]**.

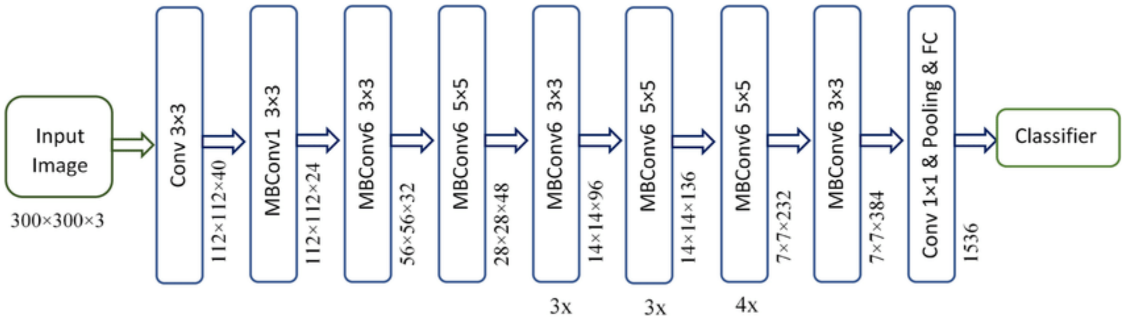


**Figure 2.** EfficientNetB3 Architecture

3.3. First Experiment

In the first experiment with EfficientNetB3, we tested a model where pre-trained weights were frozen, and a new classification layer was added. We incorporated a Global Average Pooling 2-dimensional (2D) layer followed by a dense layer. This setup achieved a test accuracy of 91.80%, establishing a baseline for comparison with other configurations. The training and validation accuracy over epochs were plotted. These plots help us to understand how the model did compare it's in previous epochs They allow us to see how quickly the model is learning and how well it generalizes to data that's outside of what was visible Figure 3. During the experiments we have generated the confusion matrices of validation set. The confusion matrix gives you a detailed breakdown of the model's performance, and shows how many of each class label were correct vs. incorrect predictions.

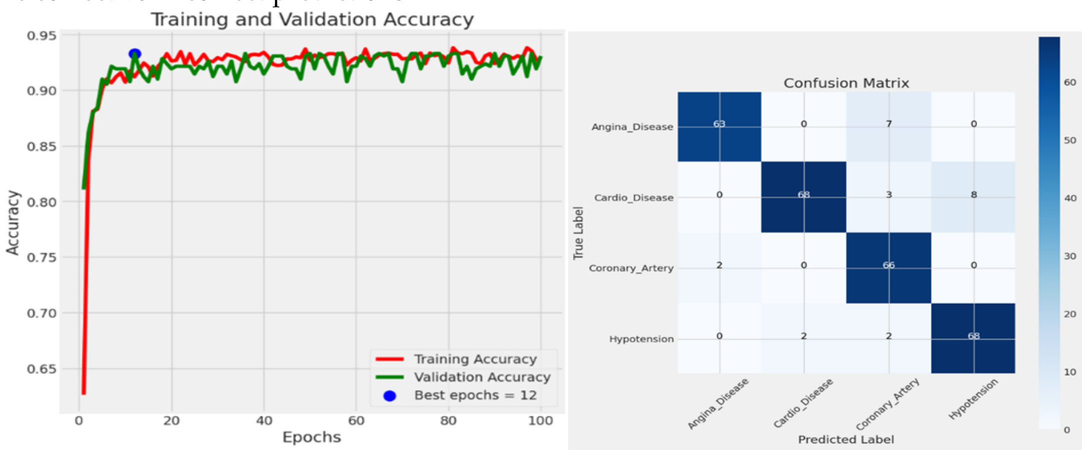


**Figure 3.** Training and validation accuracy over epochs & Confusion Matrices ( Experiment 1)

3.4. Second Experiment

For the second experiment, we enhanced the model by adding Dropout (0.2) and applying Momentum (0.99). The configuration included Batch Normalization and a sequence of dense layers: one with 512 units, another with 256 units, followed by Dropout and a final dense output layer. This setup resulted in a test accuracy of 94.14%, demonstrating improved performance over the baseline. Like the previous experiments, these plots can give some ideas of how well this model learns, and how it behaves in generalization. The training and validation accuracy over epochs & confusion matrix were plotted Figure 4.

3.5 Third Experiment

In the third experiment, we applied Dropout (0.4) and maintained Momentum (0.99). The model featured Batch Normalization, a dense layer with 256 units, Dropout, and a final dense output layer. This configuration achieved a test accuracy of 94.53%, the highest among the tested setups, indicating the most effective balance of dropout and layer structure. This exceeded performance of the original base model and shows you how seemingly small hyperparameter tuning differences affect final accuracy. Similar to 1st & 2nd experiment the training and validation accuracy over epochs & confusion matrices were plotted Figure 5.

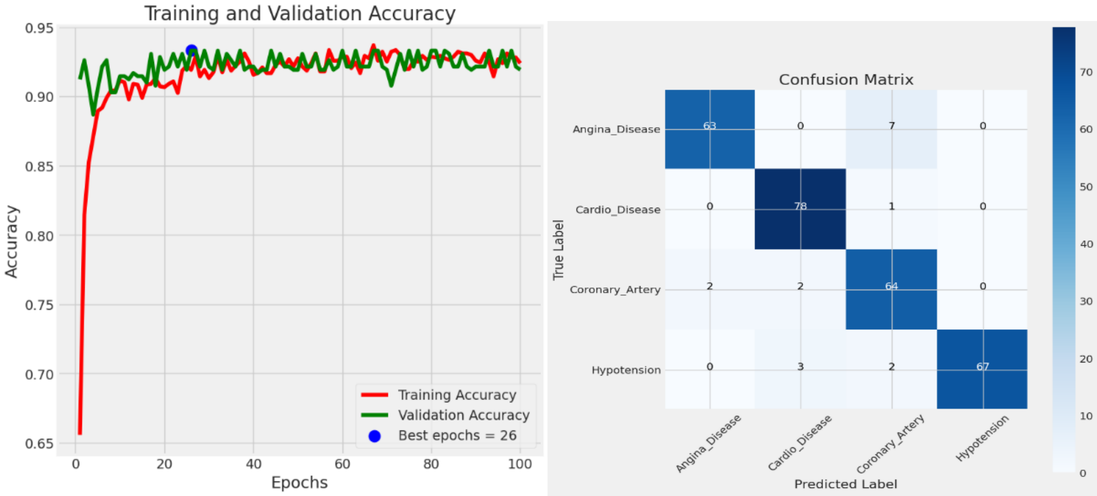


**Figure 4.** Training and validation accuracy over epochs & Confusion Matrices ( Experiment 2)

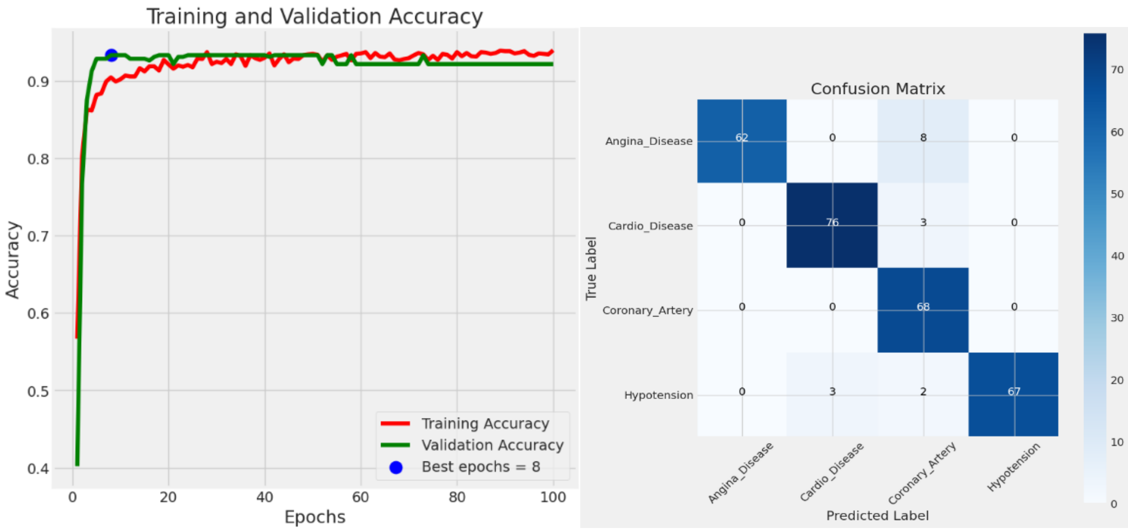


**Figure 5.** Training and validation accuracy over epochs & Confusion Matrices ( Experiment 3)

## 4. Discussion

So as a conclusion the experiments show that the model is getting better in performance with each incremental improvement. The first experiment, with EfficientNetB3 and a simple classification layer, reached test accuracy of 91.80%.The test accuracy of the second experiment, without freezing any layers and adding Dropout (0.5), Momentum (0.99) with a slightly tweak in dense layer design reached 94.14%, showing better results thanks to improved regularization and depth of architecture above all else: The third experiment with improved dense layer configuration and dropout rate of 0.4 had accuracy of 94,53% Did this result demonstrate that fine-tuning hyperparameters, and model architecture can really improve the overall performance dramatically. I think YES, which is very clear with third experiment where we reached proper balance of giving right adjustments. Please see the Table 1 for the details.

**Table 1.** Accuracy and F1 score

| Experiment # | Accuracy | Classification Report | F1-score Angina Disease | F1-score Cardiovascular disease | F1-score Coronary Artery | F1-score Hypotension |
|---|---|---|---|---|---|---|
| 1 | 91.79% | 289 | 93% | 91% | 90% | 92% |
| 2 | 94.14% | 289 | 93% | 96% | 90% | 96% |
| 3 | 94.53% | 289 | 91% | 96% | 91% | 96% |

Further research can be extended by replacing different architectures like Visual Geometry Group (VGG-16) or Inception network to get more improvements in the model. VGG-16 and VGG-19 offer far greater capacity in feature extraction via their deeper, more structured convolutional layers. Therefore, considering the multi-scale convolutional nature of Inception networks, such architectures may facilitate feature extraction at different granularities Level. Overall, the enhancement of these architectures would open new research and developments helping to improve performance beyond what is achieved by existing models.

**5. Conclusion**

We have shown how state-of-the-art deep learning models can transform the detection power of heart disease utilizing echocardiogram images in this paper. Our model achieved significant better classification accuracy and efficiency by using EfficientNetB3 architecture than existing approaches. The experiments results show that by carefully tuning the hyperparameters and distilling knowledge of proper model architectures, small improvements can be made in performance resulting in a solid test accuracy of 94.53% after our final education configuration. We demonstrated that deep learning using convolutional neural networks (CNN), such as EfficientNetB3, is equipped to manage the complex echocardiographic image modality. With an increased necessity for fast and precision diagnostic tools in cardiology this technological evolution is vital. Overall, the high classification accuracy and improved F1 scores of our model are promising meaning that in future work this classifier could be used to help clinicians diagnosing heart conditions earlier and with greater precision. Although these results are encouraging, more complex deep learning architectures can be further investigated for improved performance. The human observers benchmark in our study may serve as a baseline for future work with models like VGG and Inception networks to offer sophisticated feature extraction, improved diagnostic ability etc. Future work will be necessary to validate the clinical utility of automated diagnostics in more varied real-world settings, including data fusion with other forms (multi-modal) and longitudinal studies.

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