INTERNATIONAL JOURNAL OF RESEARCH IN COMPUTER APPLICATIONS AND ROBOTICS
ISSN 2320-7345

CARDIOMEGALY DETECTION WITH EFFICIENTNETB7 CNN

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Abstract

The enlargement of the heart, known as cardiomegaly, serves as a vital indicator for various cardiovascular conditions and can be discerned through chest X-ray images. In this study, we propose a novel deep learning methodology for the automated detection of cardiomegaly from chest X-ray images. The dataset utilized has been obtained from Kaggle, encompasses True and False class images. Subsequently, the dataset was evenly partitioned into training and testing subsets, ensuring an equitable representation of both classes. Leveraging transfer learning with the EfficientNet architecture, particularly EfficientNetB7, we developed a convolutional neural network (CNN) tailored for cardiomegaly classification. Experimental findings showcase the efficacy of our approach in accurately discerning cardiomegaly from chest X-ray images, yielding promising performance metrics on the testing subset. This research contributes to the advancement of automated medical image analysis, fostering early detection and diagnosis of cardiovascular ailments, thereby enhancing patient care outcomes.

Keywords: Cardiomegaly, Chest X-ray images, Transfer learning, EfficientNet.

1.Introduction

Cardiomegaly is a medical condition where the heart's chambers become abnormally larger than their normal size. This condition can be caused by various factors such as chronic health issues like hypertension, coronary artery disease, or valve disorders. Lifestyle choices like obesity, excessive alcohol intake, and certain medications can also contribute to its development. While temporary enlargement may occur due to factors like intense physical exertion, persistent enlargement can lead to compromised heart function, resulting in symptoms such as shortness of breath, fatigue, and irregular heartbeats. Timely diagnosis and appropriate treatment are crucial to manage cardiomegaly effectively and reduce the risk of complications, highlighting the importance of understanding its causes and impact on overall cardiovascular health.

Cardiomegaly can be diagnosed through a series of medical evaluations. Doctors typically use imaging techniques like X-rays and echocardiograms to assess the heart's size and structure. They may also conduct electrocardiograms to measure the heart's electrical activity, looking for irregularities that could indicate cardiomegaly. Symptoms such as shortness of breath and irregular heartbeat are considered during physical examinations. Additionally, doctors review the patient's medical history and lifestyle factors to help determine the presence of cardiomegaly. Identifying cardiomegaly from a chest X-ray involves examining several visual cues. Radiologists carefully analyze the size and shape of the heart, looking for any abnormalities or enlargement beyond normal boundaries. One significant parameter they assess is the cardiothoracic ratio (CTR), comparing the heart's width to that of the chest cavity. An elevated CTR, typically above 0.5, indicates possible cardiomegaly. Moreover, they scrutinize the lung fields for signs of pulmonary congestion, like pronounced blood vessel markings or vascular congestion, which can further suggest an enlarged heart. These observations, combined with the patient's medical history and symptoms, facilitate the accurate identification of cardiomegaly, guiding subsequent diagnostic and treatment protocols.

The detection of cardiomegaly is vital for society as it enables early identification of cardiovascular issues, allowing for prompt intervention and better patient outcomes. Early detection helps prevent serious complications like heart failure or arrhythmias, ultimately reducing the strain on healthcare systems. In essence, it improves healthcare outcomes and fosters a healthier society overall. Through this research endeavour, we aim to contribute to advancement of automated medical image analysis, offering valuable insights for improving patient care outcomes and enhancing healthcare delivery in the realm of cardiology.

2.Literature Review

The literature review section of this paper delves into the existing body of research surrounding the detection of cardiomegaly from chest X-ray images. It provides an in-depth examination of methodologies, findings, and trends in this area, aiming to identify gaps and opportunities for further investigation. By synthesizing insights from previous studies, this review sets the stage for the proposed research, offering a comprehensive understanding of the current state of knowledge and informing the development of novel approaches for cardiomegaly detection.

Li et al. (2019) present a study introducing a novel deep learning algorithm for automatically calculating cardiothoracic ratio (CTR) from chest X-rays. The results show promising agreement between the deep learning method and manual measurements, with reduced measurement time. However, the study notes limitations regarding the model's performance with rare pathologies due to dataset imbalances, highlighting the need for further validation and comparison with alternative methods to evaluate its clinical utility effectively.

The research conducted by Arsalan et al. addresses the importance of automating chest anatomy segmentation in chest X-rays (CXRs) for diagnosing cardiac and related diseases. Their study introduces two novel multiclass residual mesh-based networks, X-RayNet-1 and X-RayNet-2, aimed at achieving accurate segmentation with reduced computational complexity. Evaluation on publicly available datasets demonstrates promising results, highlighting the potential for improved diagnostic assistance. However, further clinical validation and addressing dataset biases are essential for real-world applicability and reliability.

Bouslama, Laaziz, and Tali (2020) proposed a method for automatically detecting cardiomegaly disease using a Deep Convolutional Neural Network U-Net architecture trained on Chest X-ray images. Their approach achieved a diagnostic accuracy of over 93% and enabled precise localization of cardiomegaly, outperforming previous methods. However, limitations include the potential biases in the dataset and the need for further validation on larger and more diverse datasets to ensure generalize ability. Additionally, reliance on deep learning models may pose challenges related to interpretability and computational resource requirements.

Sogancioglu et al. (2020) conducted a study comparing segmentation-based and classification-based approaches for detecting cardiomegaly on frontal chest radiographs. They found that the segmentation-based approach achieved higher performance with an AUC of 0.977 compared to 0.941 for the classification-based model. However, the study acknowledges limitations such as the dataset's single-institution source and the exclusion of lateral view chest radiographs. Further research is needed to address these limitations and explore the applicability of the segmentation-based approach to other diagnostic tasks.

Rajaraman et al. (2020) proposed a modality-specific ensemble learning approach for detecting abnormalities in chest radiographs. Despite its improved performance, the method has drawbacks such as computational intensity, longer training times, and increased memory requirements. Additionally, while ensemble visualization aids interpretation, it may not fully compensate for model errors. Further research is needed to address these limitations and compare the approach with alternative strategies.

Chamveha et al. (2020) introduced an automated algorithm for cardiothoracic ratio (CTR) calculation and cardiomegaly detection using deep learning. While the method demonstrates promising results in terms of time savings and diagnostic assistance, it faces challenges such as the requirement for labelled data and potential segmentation difficulties. Future research should focus on addressing these limitations and evaluating the algorithm's performance across diverse datasets and clinical settings.

Lee et al. (2021) examined the feasibility of using segmentation-based deep learning methods for automated detection of cardiomegaly on chest X-rays. They trained DL models on a dataset of PA chest X-rays for lung and heart segmentation and evaluated their performance. Results showed high accuracy in CTR calculation and diagnostic performance across the dataset, with variations observed in cases with thoracic pathologies. The study highlighted the potential of DL-based methods in assisting with cardiomegaly detection but acknowledged limitations, including dataset diversity and model variability.

Saiviroonporn et al. (2021) conducted observer and method validation studies to assess the feasibility of using artificial intelligence for cardiothoracic ratio (CTR) measurement. They found that while AI-assisted methods improved inter-observer agreement and reduced operation time compared to manual methods, the AI-only approach exhibited higher variation, suggesting it may not be suitable for fully automated measurement.

The study by Yoo et al.(2021) proposes a diagnosis support model for cardiomegaly utilizing Convolutional Neural Networks (CNNs) with ResNet architecture and explainable feature maps. By integrating deep learning algorithms with explainable feature maps, the model aims to enhance the accuracy of cardiomegaly diagnosis while providing transparency into the neural network's decision-making process. While the model demonstrates potential for improving disease diagnosis using medical imaging data, it may face challenges such as the need for large datasets for training, potential biases in the training data, and limitations in generalize ability across different patient demographics. Additionally, the complexity of interpreting explainable feature maps and the computational resources required for training deep learning models could be considered as potential drawbacks of the proposed approach.

Lin et al. (2022) introduced a multilayer 1D CNN-based classifier for automatic cardiomegaly level screening using frontal posteroanterior chest X-ray images. Despite its promising results in accuracy and efficiency, challenges such as dataset heterogeneity and generalize ability to diverse patient populations may need to be addressed for broader applicability in real-world clinical settings. They highlighted the significance of early cardiomegaly screening and the potential of their classifier, while recognizing the need for further refinement to overcome these challenges.

In Sarpotdar's (2022) investigation, a deep learning methodology for identifying cardiomegaly using chest X-ray images is introduced, employing a tailored retrained U-Net model. The strength of their approach lies in its ability to achieve impressive diagnostic metrics, including a high accuracy of 94%, sensitivity of 96.2%, and specificity of 92.5%, surpassing previous pre-trained model results. This underscores its potential for effective and precise early detection of cardiomegaly, essential for timely intervention and management. However, obstacles such as dataset variability and model interpretability persist, limiting its widespread implementation in real-world clinical scenarios. To overcome these challenges and ensure broader adoption, further investigation and validation of the approach are warranted.

Wu et al. (2022) propose a novel method for rapid cardiomegaly screening using a hybrid 2D and 1D convolutional neural network (CNN) applied to chest X-ray (CXR) images. Manual inspection of CXR images is time-consuming, prompting the need for automated tools. Their classifier integrates 2D and 1D CNN processes to improve image quality and pattern recognition. Leveraging the NIH CXR image dataset, the classifier shows promising performance metrics for rapid screening, validated through cross-validation tests. This approach offers superior performance, reducing computational time while maintaining high accuracy in cardiomegaly detection, with potential for real-time clinical applications.

Kim, Kim, and Lee (2023) investigate how varying amounts of training data impact the performance of convolutional neural network (CNN) models for cardiomegaly classification in X-ray images. Despite challenges in acquiring large medical image datasets, they utilize data augmentation techniques. Results indicate that datasets with over 1000 cases yield favourable performance, with the InceptionV3 model showing notable accuracy. Their findings provide valuable insights into addressing data scarcity in medical AI tasks, particularly in X-ray image classification for cardiomegaly.

Kumar et al. (2023) present a novel approach for automated cardiomegaly detection from chest X-ray (CXR) images using a combined 2D and 1D convolutional neural network (CNN) classifier. Their method integrates 2D and 1D CNN processes for feature extraction and noise reduction, achieving promising performance metrics for rapid screening. By leveraging this approach, they aim to enhance efficiency and reliability in medical image analysis, particularly in CXR interpretation. However, potential drawbacks may include the need for extensive computational resources and further validation across diverse datasets to ensure robustness and generalize ability.

Sorour et al. (2024) introduce a DL-based approach for early cardiomegaly detection using CXR images, showcasing the potential of AI in cardiovascular health intervention. Their methodology involves pre-processing and augmentation techniques, leading to the development of CNN and modified ResNet50 models. Evaluation with various optimizers demonstrates superior performance with AdaMax for CNN and AdaGrad for ResNet50, achieving impressive accuracies. Despite notable achievements, challenges such as dataset biases and the complexity of ResNet50 architecture are acknowledged. Future efforts aim to address biases, enhance interpretability, and optimize deployment strategies for practical use in healthcare settings.

In conclusion, recent studies have shown promising results in using deep learning techniques for early cardiomegaly detection from chest X-ray images. These advancements highlight the potential of AI in improving cardiovascular diagnostics and patient outcomes. However, challenges such as dataset biases and model complexity remain to be addressed for practical deployment in clinical settings. Continued research efforts are crucial for refining these models and advancing cardiovascular health care.

3.System Implementation Methodology

3.1.Dataset Description

The dataset used in this study was sourced from Kaggle ,which is pre-processed from the original dataset provided by the NIH Clinical Centre. Notably, the NIH Clinical Centre is widely recognized for offering one of the largest publicly available chest X-ray datasets to the scientific community. This dataset is structured into separate directories for training and testing, with each directory containing subdirectories labelled "true" and "false." The "true" directory comprises images indicating the presence of cardiomegaly, while the "false" directory contains images without this condition. Both the training and testing datasets are evenly distributed, maintaining a balanced ratio of positive and negative instances. In total, the dataset consists of 5552 files, including images and associated metadata. Its primary purpose is to facilitate the training and evaluation of machine learning models, particularly convolutional neural networks (CNNs), for predicting cardiomegaly from chest X-ray images in academic research and publications.

3.2.Data Preparation And Pre-processing

The data preparation and pre-processing steps involve several techniques aimed at optimizing the dataset for subsequent analysis and model training. Initially, the dataset, comprising chest X-ray images, is sourced from Kaggle. This dataset is then divided into distinct training and testing subsets, each containing two subdirectories: one indicating the presence of cardiomegaly (true) and the other without (false). Both subsets maintain an equal distribution of images, ensuring a balanced representation of classes.

To standardize the dataset for model training, several pre-processing techniques are employed. Firstly, the images are resized to a uniform dimension of 224x224 pixels, facilitating consistency across the dataset. Additionally, the colour representation of the images is standardized to RGB format. Although X-ray images inherently lack colour due to the nature of the imaging process, representing them in RGB format allows the model to learn and extract features not only from pixel intensity values but also from colour variations. Normalization of pixel intensities is performed to ensure numerical stability and convergence during model training. Furthermore, real-time data augmentation techniques, such as rotation, shifting, and flipping, are implemented using the Keras `ImageDataGenerator` class., leading to improved model generalization. Overall, these data preparation and pre-processing techniques are crucial for optimizing the dataset's quality, ensuring its suitability for training and evaluating machine learning models.

3.3. Efficientnetb7 Architecture

In this study, a Convolutional Neural Network (CNN) architecture is employed for the task of cardiomegaly prediction from chest X-ray images. The model architecture is built upon the efficient and powerful EfficientNetB7, a variant of the EfficientNet family known for its superior performance in image classification tasks. EfficientNetB7 is used as a feature extractor, where the pre-trained weights are leveraged to capture rich hierarchical representations from input images. These representations are then fed into additional layers, including batch normalization, dense, and dropout layers, to learn task-specific features and make predictions.

3.3.1. Base Model: EfficientNetB7

The EfficientNetB7 serves as the backbone of the model, responsible for extracting meaningful features from the input images. This model is pre-trained on the ImageNet dataset, enabling it to capture rich hierarchical representations of features from diverse images across various categories. By leveraging transfer learning, the pre-trained weights of EfficientNetB7 are utilized to initialize the model's weights, thereby facilitating faster convergence and better generalization.

3.3.2. Additional Layers

Following the base model, a series of additional layers are added to perform classification based on the extracted features:

Batch Normalization Layer: Batch normalization is applied after the base model to normalize the activations of the previous layer, enhancing the stability and convergence speed of the training process.

Dense Layers: Dense layers are incorporated to perform the final classification. These densely connected layers utilize the rectified linear unit (ReLU) activation function to introduce non-linearity into the model, enabling it to learn complex patterns and relationships within the data.

Dropout Layer: Dropout regularization is applied to the dense layers to mitigate overfitting by randomly deactivating a fraction of neurons during training. This regularization technique helps prevent the model from relying too heavily on specific features and improves its robustness.

Output Layer: The final layer of the model is a dense layer with softmax activation, which outputs the probability distribution over the classes. This layer enables the model to make predictions regarding the presence of cardiomegaly in the input chest X-ray images.

3.3.3. Regularization Techniques

To further enhance the model's generalization performance and prevent overfitting, various regularization techniques are employed.L2 and L1 regularization terms are added to the dense layers to penalize large weights and encourage sparsity, respectively. These regularization terms help prevent the model from memorizing noise in the training data and improve its ability to generalize to unseen data.

3.3.4. Training Procedure

The model is trained using the Adamax optimizer ,with a learning rate of 0.001 and categorical cross-entropy loss function. The Adamax optimizer is a variant of Adam optimizer .While Adam calculates the adaptive learning rates for each parameter based on estimates of the first and second moments of the gradients, Adamax is a modification that simplifies the computation of the adaptive learning rates. The training process is conducted over 15 epochs, with validation data used for monitoring model performance and preventing over fitting.

3.3.5. Evaluation and Performance Metrics

Following training, the model's performance is evaluated on both training and validation datasets using metrics such as loss and accuracy. Additionally, the model's performance is assessed on a separate test dataset to evaluate its generalization ability. Confusion matrix and classification report are utilized to further analyze the model's performance across different classes.

The proposed model architecture integrates the EfficientNetB7 convolutional neural network as the primary feature extractor, augmented with additional layers for regularization and classification. Through the use of the Adamax optimizer, the model is trained to accurately classify chest X-ray images for cardiomegaly detection. Evaluation metrics such as accuracy, loss, confusion matrix, and classification report provide insights into the model's performance and its potential for clinical applications. Overall, the architecture showcases a robust framework for automated cardiomegaly detection, offering promising results for medical image analysis.

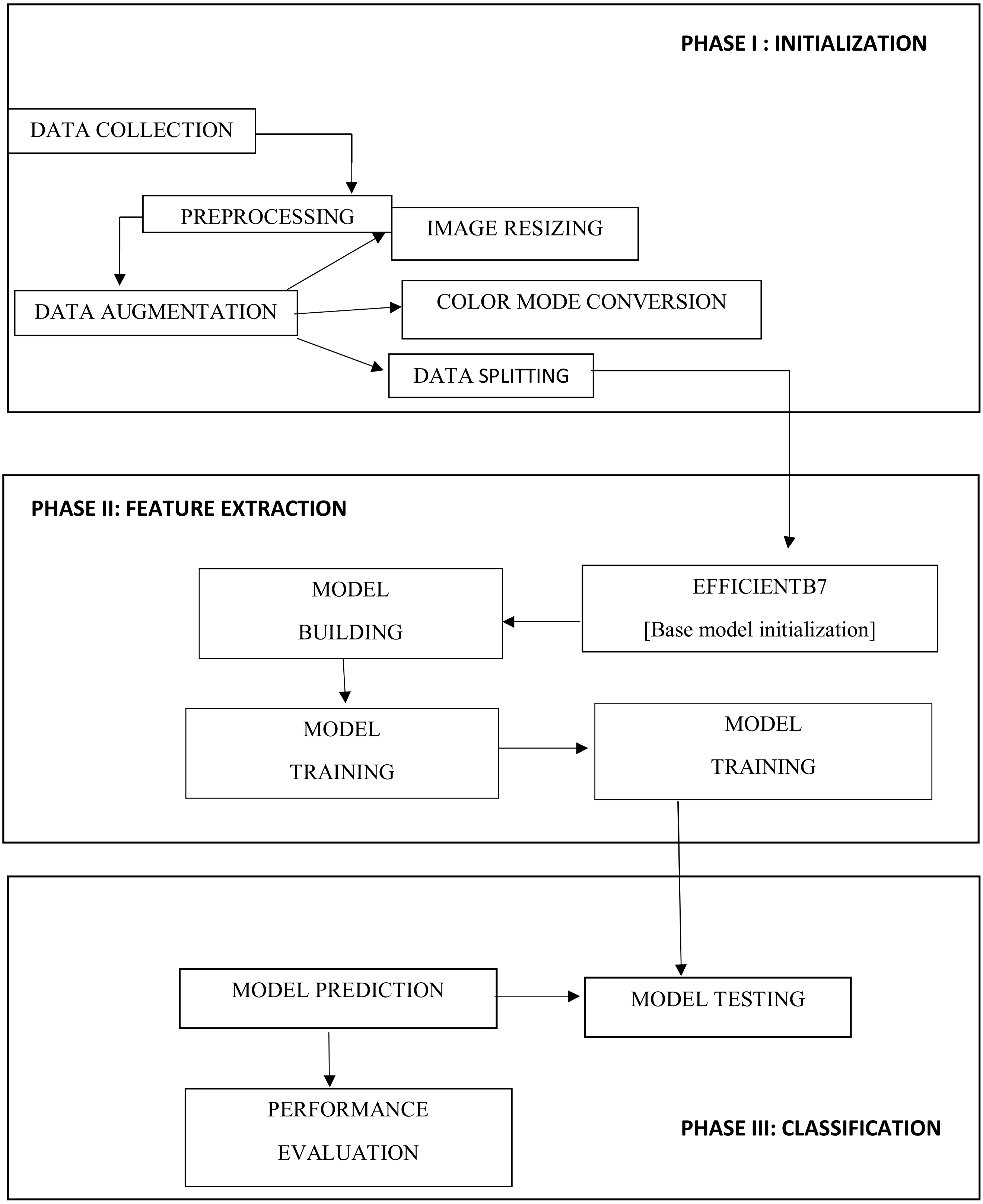

Figure 1:Phases of methodology

4. Results And Discussion

In the final stages of model training, our CNN model displayed significant improvements in both training and validation performance. Over the course of 15 epochs, the model consistently reduced both training and validation losses while steadily increasing accuracy. Notably, in the final epoch, the training loss reached 0.1534 with an accuracy of 98.07%, while the validation loss decreased to 0.1098 with an accuracy of 99.55%. These results highlight the model's robust learning ability and its capacity to generalize well to unseen data.

Evaluation on the test dataset yielded equally impressive outcomes. The test loss was recorded at 0.1075 with an accuracy of 99.61%, affirming the model's effectiveness in accurately predicting cardiomegaly from chest X-ray images. These findings validate the model's reliability and efficacy, indicating its potential utility in clinical settings to aid medical professionals in diagnosing cardiovascular diseases.

Graphical representations of the model's performance, depicting loss and accuracy trends throughout the training epochs, offer further insights. These visualizations illustrate the model's convergence during training, showcasing consistent enhancements in both loss reduction and accuracy improvement. Such graphical insights provide a clear depiction of the model's learning progression.

Additionally, a confusion matrix and a classification report provide detailed assessments of the model's performance. The confusion matrix visually summarizes the model's predictions against the true labels, demonstrating high agreement between predicted and actual values. Furthermore, the classification report offers comprehensive metrics such as precision, recall, and F1-score for each class, offering a thorough evaluation of the model's predictive capabilities.

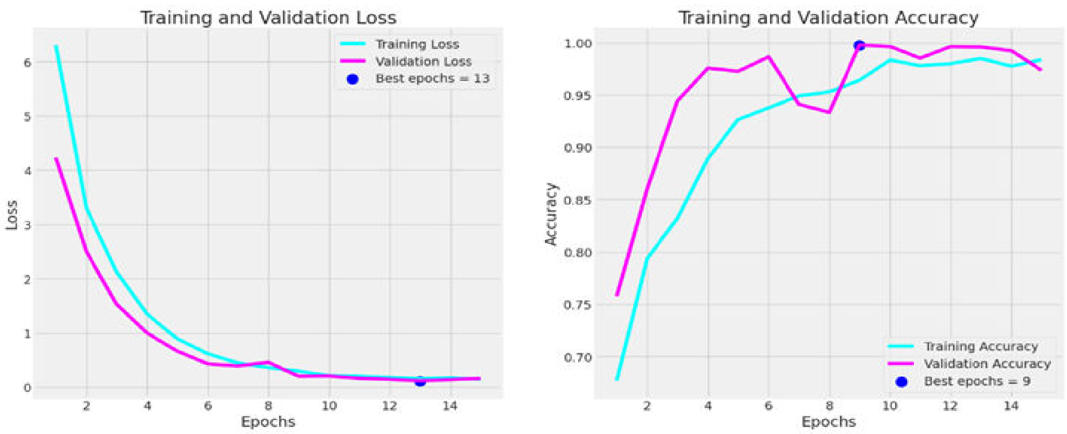

Figure2:Training and validation accuracy

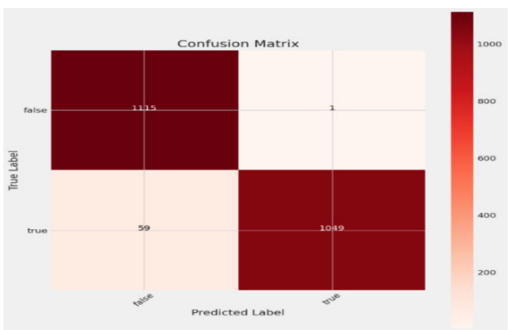

Figure 3:Confusion matrix

	Precision	Recall	F1-Score	Support
False	1.00	0.99	0.99	1116
True	0.99	1.00	0.99	1108
Accuracy			0.99	2224
Macro avg	0.99	0.99	0.99	2224
Weighted avg	0.99	0.99	0.99	2224

Table 1 : Classification report

In summary, the results of our study underscore the effectiveness of the CNN model in accurately detecting cardiomegaly from chest X-ray images. With its impressive performance metrics and robust generalization capabilities, the model holds promise as a valuable tool for assisting healthcare professionals in diagnosing and managing cardiovascular diseases.

5.Conclusion

Our study demonstrates the effectiveness of a CNN model utilizing the EfficientNetB7 architecture in accurately detecting cardiomegaly from chest X-ray images. The model exhibits robust learning ability, achieving high accuracies and low losses on both training and validation datasets. Moreover, its performance on an independent test dataset reaffirms its reliability and potential utility in clinical settings. These findings highlight the promise of deep learning models in medical image analysis, with implications for enhancing diagnostic capabilities and ultimately improving patient care.

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