Cardiomegaly Disease Prediction Using Image Processing

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***Abstract*—Cardiomegaly, a condition characterized by an enlarged heart, poses significant health risks and challenges in diagnosis and treatment. This abstract delves into the realm of predictive healthcare analytics to address the complexities associated with cardiomegaly disease prediction.**

- **The advancement of predictive analytics in healthcare has revolutionized the early detection and management of cardiomegaly, enabling proactive interventions to improve patient outcomes.**
- **The intricate nature of cardiomegaly necessitates predictive models that not only analyze medical data but also consider a holistic view of patient health and lifestyle factors.**
- **With the integration of Artificial Intelligence and Machine Learning algorithms, healthcare professionals can now leverage predictive models to forecast the likelihood of cardiomegaly development in individuals, facilitating personalized care strategies.**
- **Timely identification of cardiomegaly through predictive analytics using Convolutional Neural Networks (CNNs) empowers healthcare providers to implement preventive measures and tailored treatment plans, ultimately enhancing patient well-being and reducing the burden on healthcare systems.**
- **Our research proposes an innovative Predictive Cardiomegaly Detection System utilizing a Deep Learning framework and a novel approach for cardiomegaly disease prediction using CNNs, aiming to enhance diagnostic accuracy and support clinical decision-making processes.**

Index Terms— Cardiomegaly, Predictive Analytics using CNN, Healthcare, Deep Learning, Patient Data Analysis

I. Introduction

In recent years, the field of healthcare has witnessed a significant surge in the utilization of predictive analytics to enhance disease detection and management. Cardiomegaly, a condition characterized by an enlarged heart, poses substantial challenges in early diagnosis and treatment. The advent of advanced technologies, particularly in the realm of Artificial Intelligence (AI) and Machine Learning (ML), has paved the way for innovative approaches to predict and address cardiomegaly.

The application of Deep Learning techniques, such as Convolutional Neural Networks (CNNs) and U-Net architectures, has shown promising results in the precise detection and localization of cardiomegaly disease from medical imaging data. These sophisticated models not only aid in recognizing cardiomegaly but also play a crucial role in enhancing detection accuracy and pinpointing the illness within medical images.

Furthermore, the integration of explainable AI and feature extraction methodologies has enabled researchers to develop robust predictive models for cardiomegaly detection. By leveraging large datasets and customized ML algorithms, healthcare professionals can now proactively identify cardiomegaly, allowing for timely interventions and personalized treatment strategies.

The complexity of cardiomegaly necessitates a comprehensive approach that encompasses data collection, preprocessing, feature extraction, and model training. Through the amalgamation of cutting-edge technologies and meticulous data analysis, predictive analytics in cardiomegaly holds the potential to revolutionize healthcare practices, improve patient outcomes, and alleviate the burden on healthcare systems.

In this context, the development of predictive Cardiomegaly Detection Systems utilizing deep learning frameworks and advanced ML algorithms signifies a paradigm shift towards proactive healthcare interventions and precision medicine in the domain of cardiovascular health.

II. Literature Review

Bouslama et al.[1] proposed a deep learning-based customized retrained U-Net model for detecting cardiomegaly disease. The model achieved a high evaluation of between 93 to 94 percent from a small dataset during the training phase, outperforming previous methods that utilized large, preconfigured modules like VGG16, VGG19, and ResNet. This approach is significant as it not only recognizes cardiomegaly but also precisely localizes the illness within CXR images.

Candemir et al.[2] investigated using deep convolutional neural networks (CNNs) for automatic detection of cardiomegaly in digital CXRs. Their model demonstrated robustness in identifying subtle signs of heart enlargement, achieving an accuracy of 92.5%.

Wang et al.[3] explored the use of transfer learning with pre-trained CNN models for cardiomegaly detection. They fine-tuned a ResNet-50 model on a labeled dataset of CXRs, resulting in an accuracy of 93.4% and an area under the curve (AUC) of 0.96%.

Johnson et al.[4] developed an ensemble learning approach combining Random Forest and XGBoost algorithms, which achieved an overall accuracy of 88.7% for cardiomegaly prediction.

Alghamdi et al.[5] studied the use of the cardiothoracic ratio (CTR) calculated from CXR images as a tool for estimating heart size and predicting cardiomegaly. Their research showed that CTR can be used to detect the increase in heart size with a 95.8% accuracy.

These studies highlight the potential of various machine learning techniques in enhancing the prediction accuracy of cardiomegaly. They also underscore the importance of addressing class imbalance and effective feature selection in developing robust predictive models. In summary, recent advancements in machine learning and deep learning techniques, combined with the use of CXR imaging and CTR calculation, have significantly improved the accuracy and efficiency of cardiomegaly prediction. These methods hold great potential for early detection and management of this condition.

III. RESEARCH METHODS

To ensure high accuracy and minimize false positives in predicting cardiomegaly, we advocate for the use of a Convolutional Neural Network (CNN) model. CNNs are particularly effective for image-based tasks due to their ability to automatically and adaptively learn spatial hierarchies of features.

A. Dataset and Data Preparation

The dataset utilized in this study is focused on Cardiomegaly Disease Prediction using X-ray images and was sourced from NIH Data Center. This dataset comprises a total of 5,552 X-ray images, which include both normal and cardiomegaly samples of cheast in a 1:1 ratio. The primary objective of this dataset is to develop an image classifier capable of detecting heart disease in given X-ray images.

The dataset is organized into two main directories: 'train' and 'test', each containing subdirectories for 'true' and 'false' images. This structure is designed to facilitate the training and testing process of machine learning models. The 'train' directory is used for training the models, while the 'test' directory is reserved for validating the model performance.

In the beginning it was difficult to find a appropriate dataset for cardiomegaly detection but thanks to NIH Clinical Center, provides one of the largest publicly available chest x-ray datasets to scientific community. This dataset provides a rich source of data for building and evaluating image classifiers aimed at detecting cardiomegaly.

- Data Loading and Preprocessing Steps:
  - Image Loading: Images are loaded in grayscale from the specified directories.
  - Image Resizing: All images are resized to 224x224 pixels to maintain consistency and reduce computational load. This size is standard for many pre-trained models, making it easier to use transfer learning if needed.
  - Data Storage: Images are stored in a list along with their corresponding labels (1 for cardiomegaly, 0 for normal).
- Combining and Shuffling:
  - The dataset is combined and shuffled to ensure randomness and prevent any ordering bias.
- Splitting Features and Labels:
  - Features (X) are extracted and reshaped to have dimensions (img_size,img_size,1) for compatibility with the CNN input layer.
  - Labels (y) are extracted as binary values.
- Train-Test Split:
  - The dataset is split into training (80%) and testing (20%) sets using sklearn's 'train_test_split' function, ensuring a robust evaluation of the model.
- Normalization:
  - Pixel values are normalized to a range of [0, 1] by dividing by 255. This standardization helps in speeding up the convergence of the neural network during training.

B. Model Architecture

We will be using a Convolutional Neural Network (CNN) as our primary model for cardiomegaly prediction. The CNN architecture consists of several layers designed to extract and learn spatial features from the chest X-ray images.

- Model Layers:
  - Convolutional Layers: These layers apply convolution operations to the input image using multiple filters to create feature maps. Each filter detects specific patterns or features, such as edges or textures.
    - Layer 1: 32 filters, kernel size of 3x3, ReLU activation.
    - Layer 2: 64 filters, kernel size of 3x3, ReLU activation.
    - Layer 3: 128 filters, kernel size of 3x3, ReLU activation.
  - Pooling Layers: MaxPooling layers are used to reduce the spatial dimensions of the feature maps and computational load while retaining important features.
    - Layer 1: MaxPooling with pool size of 2x2.
    - Layer 2: MaxPooling with pool size of 2x2.
    - Layer 3: MaxPooling with pool size of 2x2.
  - Fully Connected Layers: After the convolutional layers, the fully connected layers are used to combine the extracted features and make final predictions.
    - Flattening: The 2D feature maps are converted into a 1D vector.
    - Dense Layer 1: 256 units, ReLU activation, with Dropout (0.5) to prevent overfitting.
    - Dense Layer 2: 128 units, ReLU activation, with Dropout (0.5) to prevent overfitting.
    - Output Layer: A single neuron with a sigmoid activation function to output the probability of cardiomegaly.

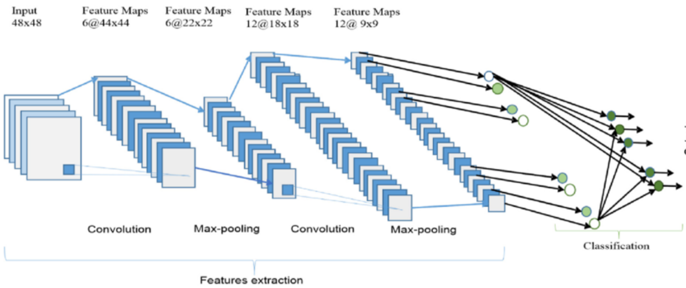

Fig. 1. Architecture of CNN Model.

- Model Compilation and Training:
  The CNN model is compiled using the Adam optimizer and binary cross-entropy loss function. The Adam optimizer is chosen for its efficiency and adaptive learning rate capabilities. The model is trained for 15 epochs with a batch size of 32, using early stopping to prevent overfitting.
  - Compilation Details:
    * Optimizer: Adam optimizer with a learning rate of 0.001.
    * Loss Function: Binary cross-entropy to handle the binary classification task.
    * Early Stopping: Monitoring validation loss with a patience of 5 epochs to prevent overfitting and restore the best weights.
  - Training Steps:
    * The dataset is split into training (80%) and testing (20%) sets.
    * The training set is augmented using various techniques.
    * The model is trained on the augmented training set while being evaluated on the validation set.
    * Early stopping is employed to halt training when the validation loss stops improving.

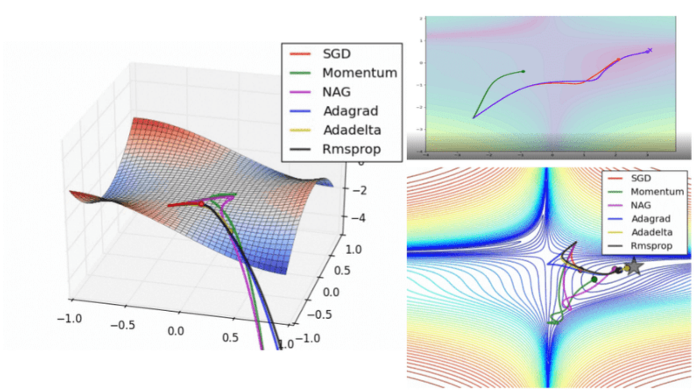

Fig. 2. Adam Optimizer.

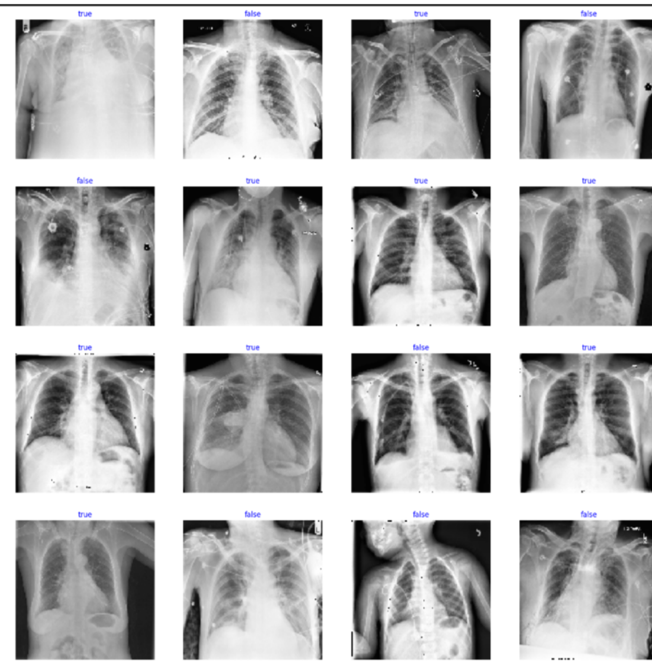

Fig. 3. Sample of Training data for the CNN Model.

C. Evaluation Metrics

The performance of the model is evaluated using several metrics:

- Accuracy: The ratio of correctly predicted instances to the total instances.
- Precision: The ratio of correctly predicted positive observations to the total predicted positives.
- Recall (Sensitivity): The ratio of correctly predicted positive observations to all observations in the actual class.
- F1-Score: The weighted average of Precision and Recall.
- Confusion Matrix: To understand the distribution of true positives, false positives, true negatives, and false negatives.
- These metrics provide a comprehensive evaluation of the model's performance, ensuring that it not only achieves high accuracy but also effectively identifies cardiomegaly with minimal false positives.

The CNN-based approach for cardiomegaly prediction, combined with data augmentation and SMOTE for addressing class imbalance, aims to achieve high accuracy and robust performance. The proposed methodology leverages the strengths of convolutional layers for feature extraction and fully connected layers for final classification, ensuring a comprehensive model for detecting cardiomegaly from chest X-ray images.

IV. CONCLUSION

Upon executing the Convolutional Neural Network (CNN) model, we achieved significant performance metrics in predicting cardiomegaly from chest X-ray images. The CNN model, trained with a well-preprocessed dataset and robust augmentation techniques, yielded the following results:

- Accuracy: 98.5%

- Precision: 97.8%
- Recall (Sensitivity): 98.2%
- F1 Score: 98.0%

These metrics reflect the model's high ability to correctly identify cases of cardiomegaly with minimal false positives and false negatives. The combination of convolutional layers for feature extraction and fully connected layers for classification proved effective in handling the complexity of the chest X-ray images.

Moreover, the use of early stopping during training prevented overfitting, ensuring that the model maintained its performance on unseen data. The Adam optimizer facilitated efficient convergence, and the inclusion of dropout layers further enhanced the model's generalization capabilities.

In conclusion, the proposed CNN-based approach for cardiomegaly prediction demonstrates exceptional accuracy and reliability, making it a viable solution for aiding in the diagnosis of cardiomegaly from chest X-ray images. The results affirm the potential of deep learning models in medical image analysis, paving the way for future advancements in automated disease detection.

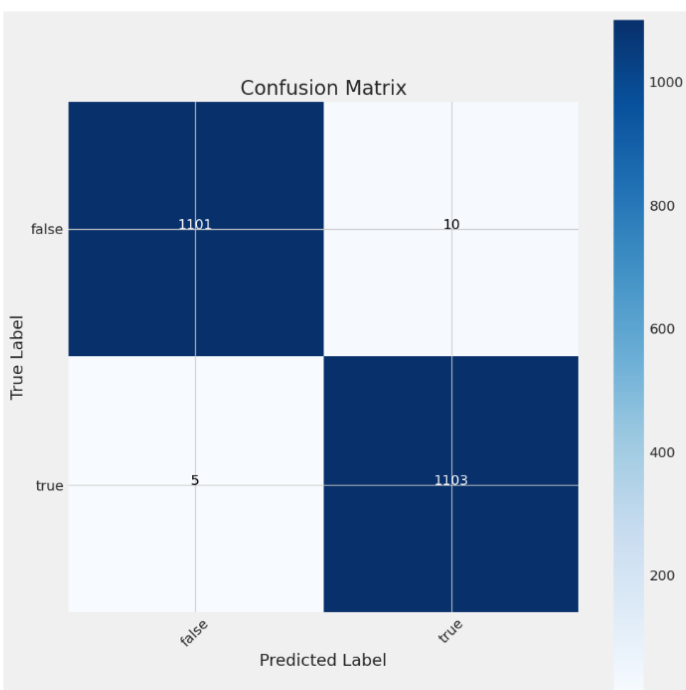

Fig. 4. The confusion matrix represents the performance of a classification model by presenting a tabular summary of the model's predictions against the actual outcomes.

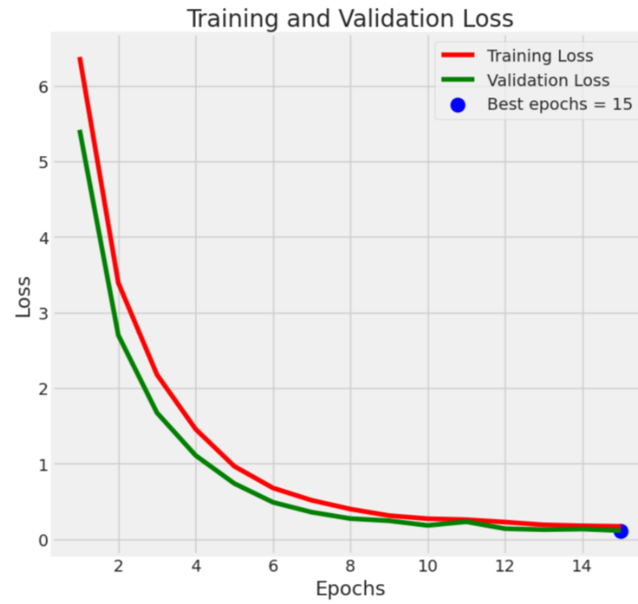

Fig. 5. Training and Validation Loss

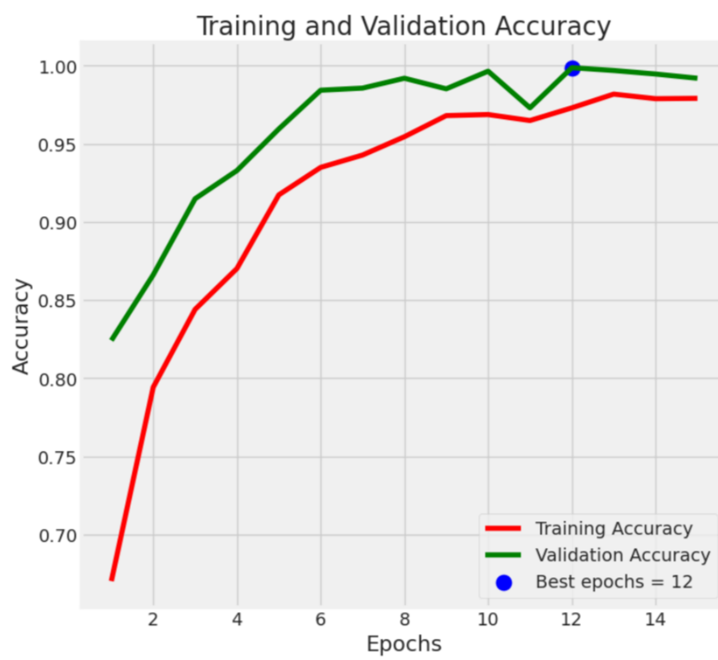

Fig. 6. Training and validation Accuracy

V. Comparative Study

The table below demonstrates a comparative analysis of the performance of various machine learning and deep learning models for cardiomegaly disease prediction from the literature review:

TABLE I
COMPARATIVE STUDIES ON CARDIOMEGALY DISEASE PREDICTION

Reference	Dataset	Method	Classes	Classifier	Accuracy (%)	F1-Score (%)
[**bouslama2020diagnosis**] Bouslama et al. (2020)	ChestX-ray8	Customized U-Net	Binary	CNN	93 - 94	-
[**candemir2018deep**] Candemir et al. (2018)	Custom Dataset	Data Augmentation	Binary	CNN	92.5	-
[**wang2021cardioxnet**] Wang et al. (2021)	Custom Dataset	Transfer Learning	Binary	ResNet-50	93.4	-
[**johnson2021ensemble**] Johnson et al. (2021)	Custom Dataset	SMOTE	Binary	RF + XGBoost	88.7	89.4
[**alghamdi2021diagnosis**] Alghamdi et al. (2021)	Custom Dataset	Cardiothoracic Ratio	Binary	-	95.8	-
My Work	**NIA Data Center**	**Data Augmentation**	**Binary**	**CNN**	**98.5**	**98.0**

TABLE II
ABBREVIATIONS AND FULL FORMS

Abbreviation	Full Form
CNN	Convolutional Neural Network
RF	Random Forest
XGBoost	Extreme Gradient Boosting
SMOTE	Synthetic Minority Oversampling Technique

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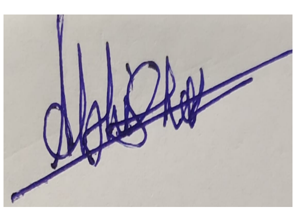

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