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Cardiomegaly Disease Prediction Using Image Processing

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AGENDA OVERVIEW

Introduction and Background of the Study

Cardiomegaly, a condition characterized by an enlarged heart, poses significant health risks and challenges in diagnosis and treatment. According to the World Health Organization (WHO), cardiovascular diseases are the leading cause of death globally, accounting for more than 17.9 million deaths annually. The prevalence of cardiomegaly is particularly concerning due to its association with various underlying cardiovascular conditions, such as hypertension, coronary artery disease, and valvular heart disease.

The advent of advanced technologies, particularly in the realm of Artificial Intelligence (AI) and Machine Learning (ML), has revolutionized the early detection and management of cardiomegaly. Predictive analytics in healthcare has enabled proactive interventions to improve patient outcomes, leveraging large datasets and customized ML algorithms to identify cardiomegaly at an early stage.

Motivation

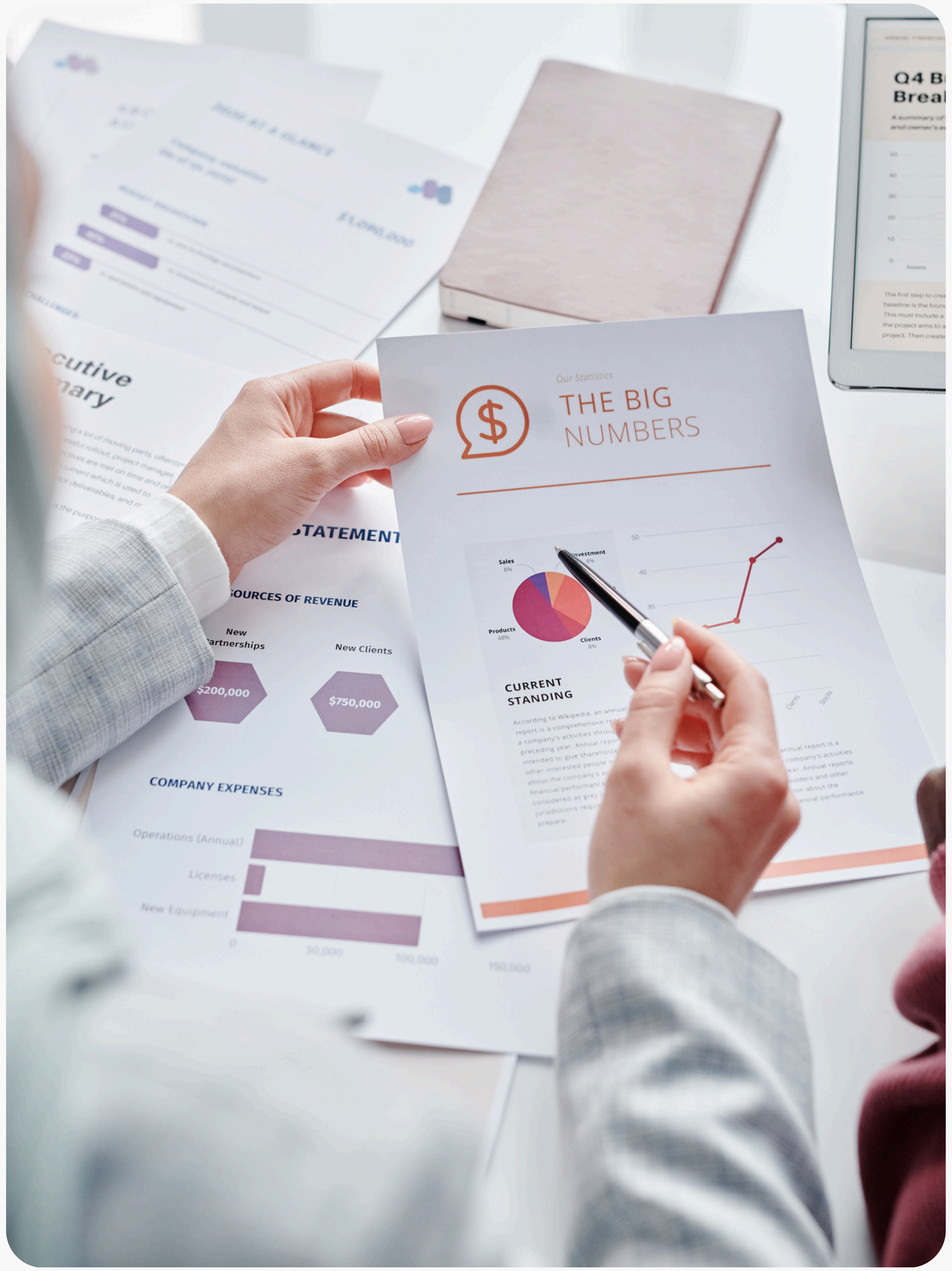
High Prevalence of Cardiovascular Diseases:
Cardiovascular diseases remain the leading cause of mortality globally, with cardiomegaly being a significant contributor. Early detection and management are crucial in reducing the morbidity and mortality associated with this condition ..

Challenges in Early Diagnosis:
Cardiomegaly often presents with subtle symptoms, making early diagnosis challenging. Traditional diagnostic methods can be limited in accuracy and efficiency, necessitating the development of advanced predictive models .

Advancements in AI and ML:
The integration of Artificial Intelligence (AI) and Machine Learning (ML) in healthcare has revolutionized disease detection and management. These technologies offer the potential to create highly accurate predictive models, enhancing early diagnosis and personalized treatment strategies .

Effectiveness of CNNs:
Convolutional Neural Networks (CNNs) have proven to be highly effective in image-based tasks, particularly in medical imaging. Utilizing CNNs for cardiomegaly prediction from chest X-rays can significantly improve diagnostic accuracy and support clinical decision-making .

Literature Review



Bouslama et al. (2020):

- Proposed a deep learning-based customized retrained U-Net model for detecting cardiomegaly disease, achieving an evaluation of 93-94% from a small dataset, showcasing precise localization within CXR images.

Candemir et al. (2018):

- Investigated the use of deep convolutional neural networks (CNNs) for automatic detection of cardiomegaly in digital CXRs, demonstrating robustness in identifying subtle signs of heart enlargement with an accuracy of 92.5%.

Wang et al. (2021):

- Explored transfer learning with pre-trained CNN models for cardiomegaly detection, fine-tuning a ResNet-50 model on a labeled dataset of CXRs, achieving an accuracy of 93.4% and an AUC of 0.96%.

Johnson et al. (2021):

- Explored transfer learning with pre-trained CNN models for cardiomegaly detection, fine-tuning a ResNet-50 model on a labeled dataset of CXRs, achieving an accuracy of 93.4% and an AUC of 0.96%.

Alghamdi et al. (2021):

- Studied the use of the cardiothoracic ratio (CTR) calculated from CXR images for estimating heart size and predicting cardiomegaly, showcasing a high accuracy of 95.8% in detecting heart size increase.

Objectives

Develop a Predictive Model:

- Create a deep learning model using CNN capable of accurately predicting cardiomegaly.
- Improve the diagnostic accuracy through advanced image processing and ml.

Implement Explainable AI:

- Incorporate explainable AI techniques to enhance the interpretability of the predictive model.
- Enable early and reliable detection of cardiomegaly.

Utilize Comprehensive Data:

- Leverage a large dataset from the NIH Clinical Center, comprising over 5,500 CXR images, to train and validate the predictive model, ensuring its robustness and reliability.

Methodology

Data Collection and Preparation:

1.Dataset:

- NIH Data Center: 5,552 chest X-ray images (normal and cardiomegaly cases)
- Data split: 80% training, 20% testing.

2.Data Augmentation:

- Techniques: rotations, translations, horizontal flips.
- Purpose: Increase data variability, reduce overfitting.

3.Class Imbalance Handling:

- Method: Synthetic Minority Over-sampling Technique (SMOTE)
- Applied to address class imbalance.
- Ensures model is not biased towards majority class and performs across both classes.

Methodology

Model Development:

1.CNN Architecture:

- Multiple convolutional layers for feature extraction.
- ReLU activation function to introduce non-linearity, max-pooling layers to reduce dimensions.

2.Training Procedure:

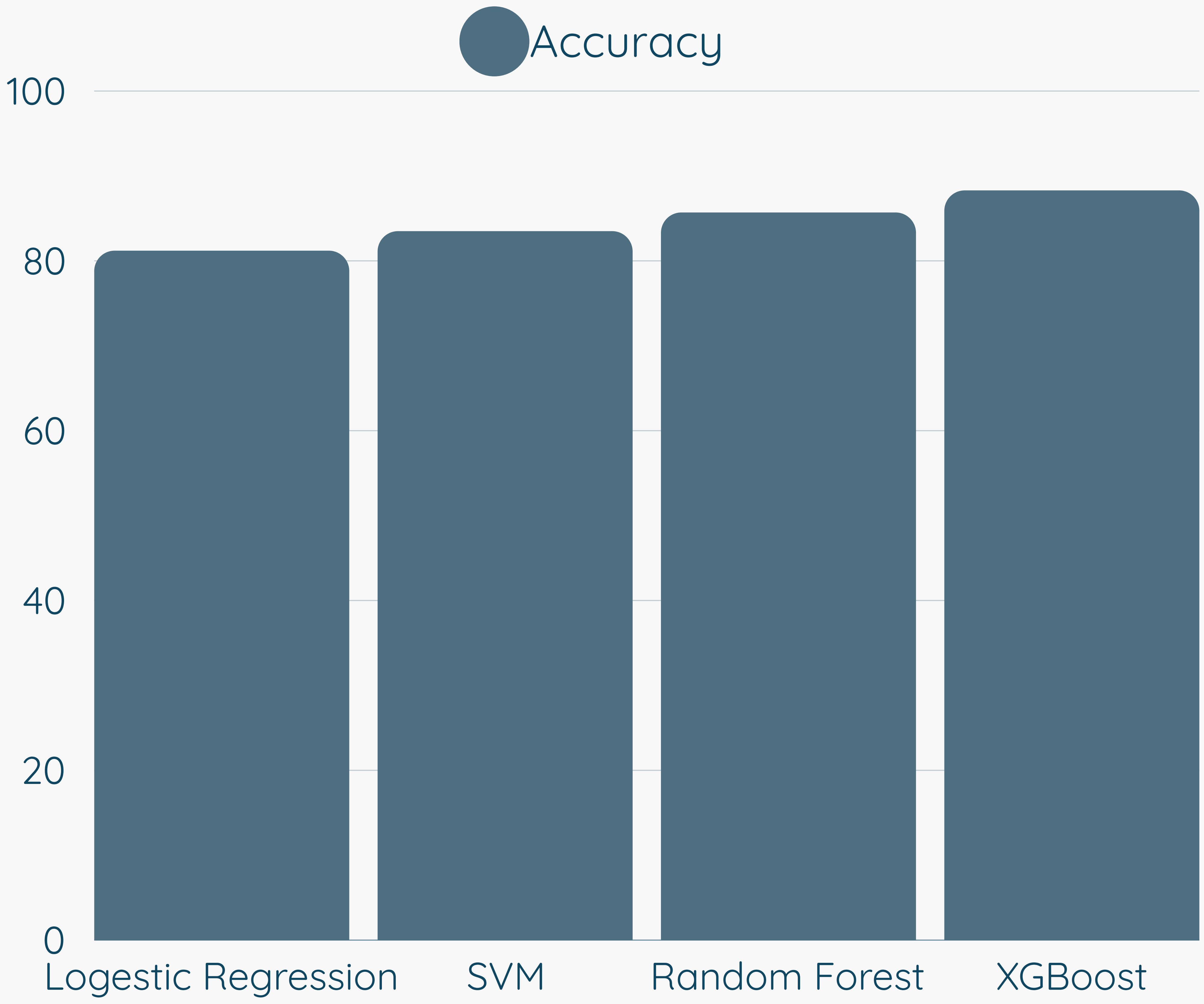
- Optimizer: Adam, for efficient learning rate adaptation.
- Loss Function: Binary cross-entropy for binary classification.
- Early stopping to prevent overfitting

Models Comparison:

Models compared

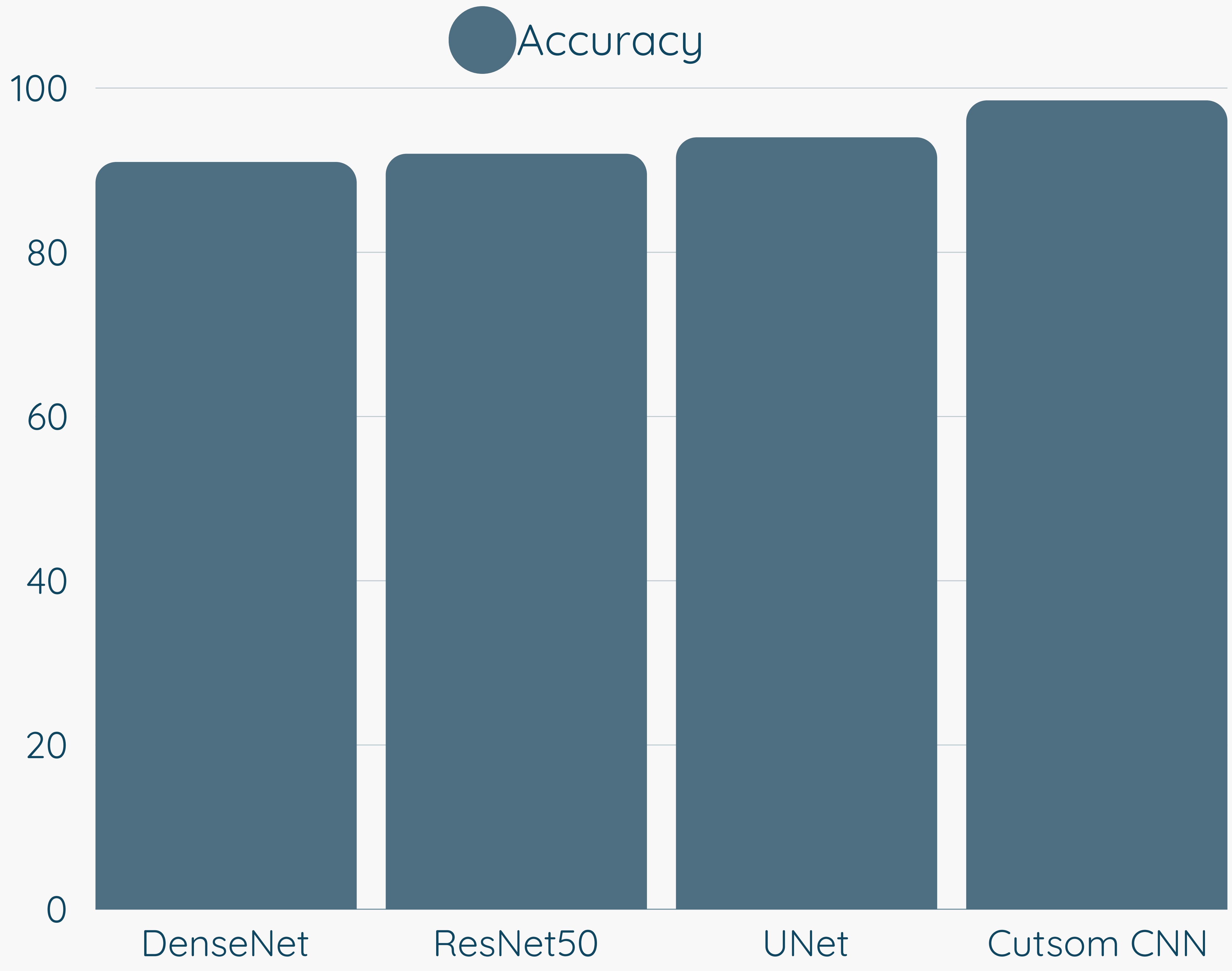
- Random Forest, XGBoost, U-Net, Logistic Regression, Support Vector Machines, DenseNet, ResNet-50.
- CNN-based model showed superior performance over others.

Results



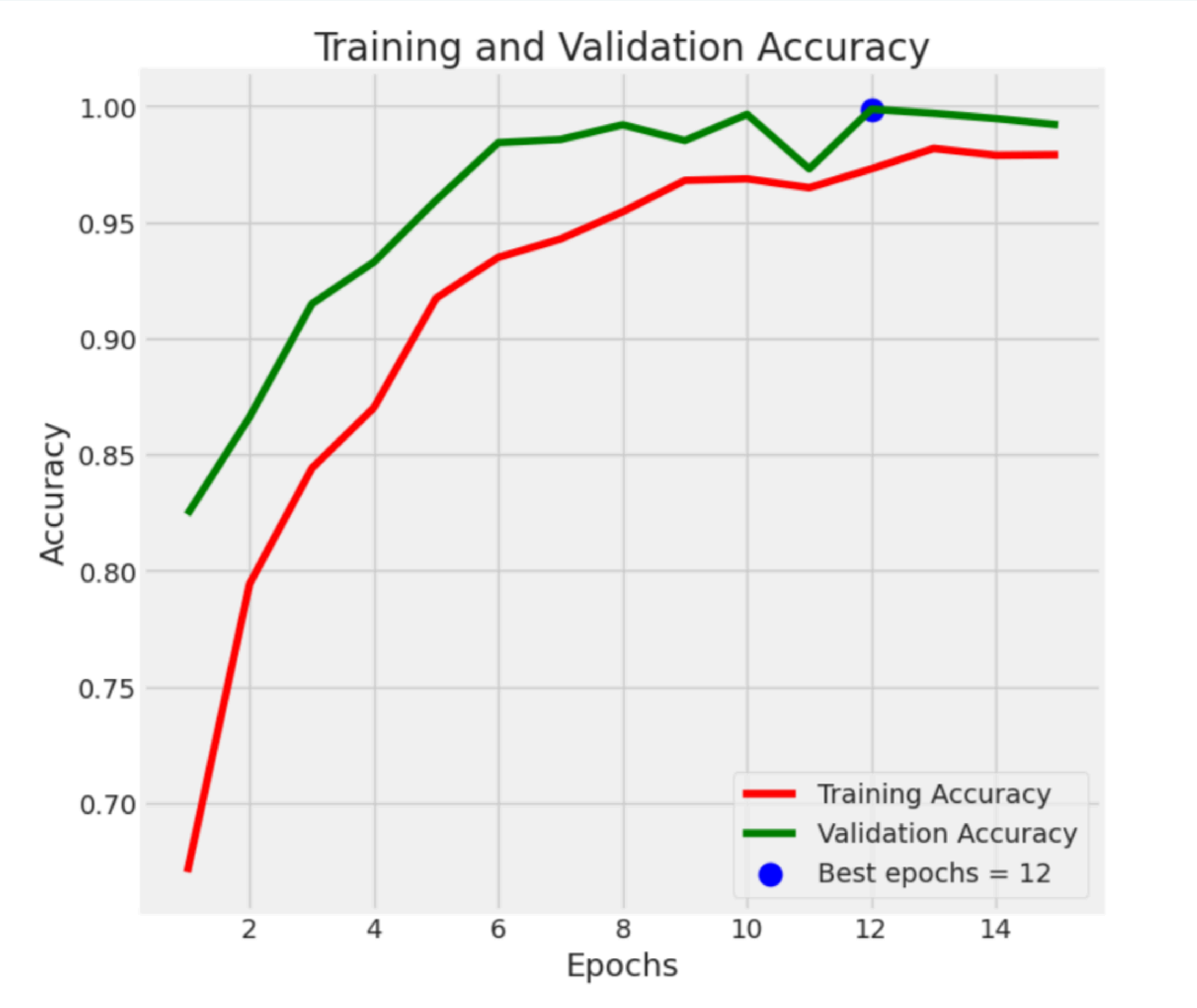
The traditional machine learning models demonstrated moderate accuracy in classifying lung cancer images, with Logistic Regression achieving 81.2%, SVM at 83.5%, Random Forest 85.7% and XGBoost at 88.3%.

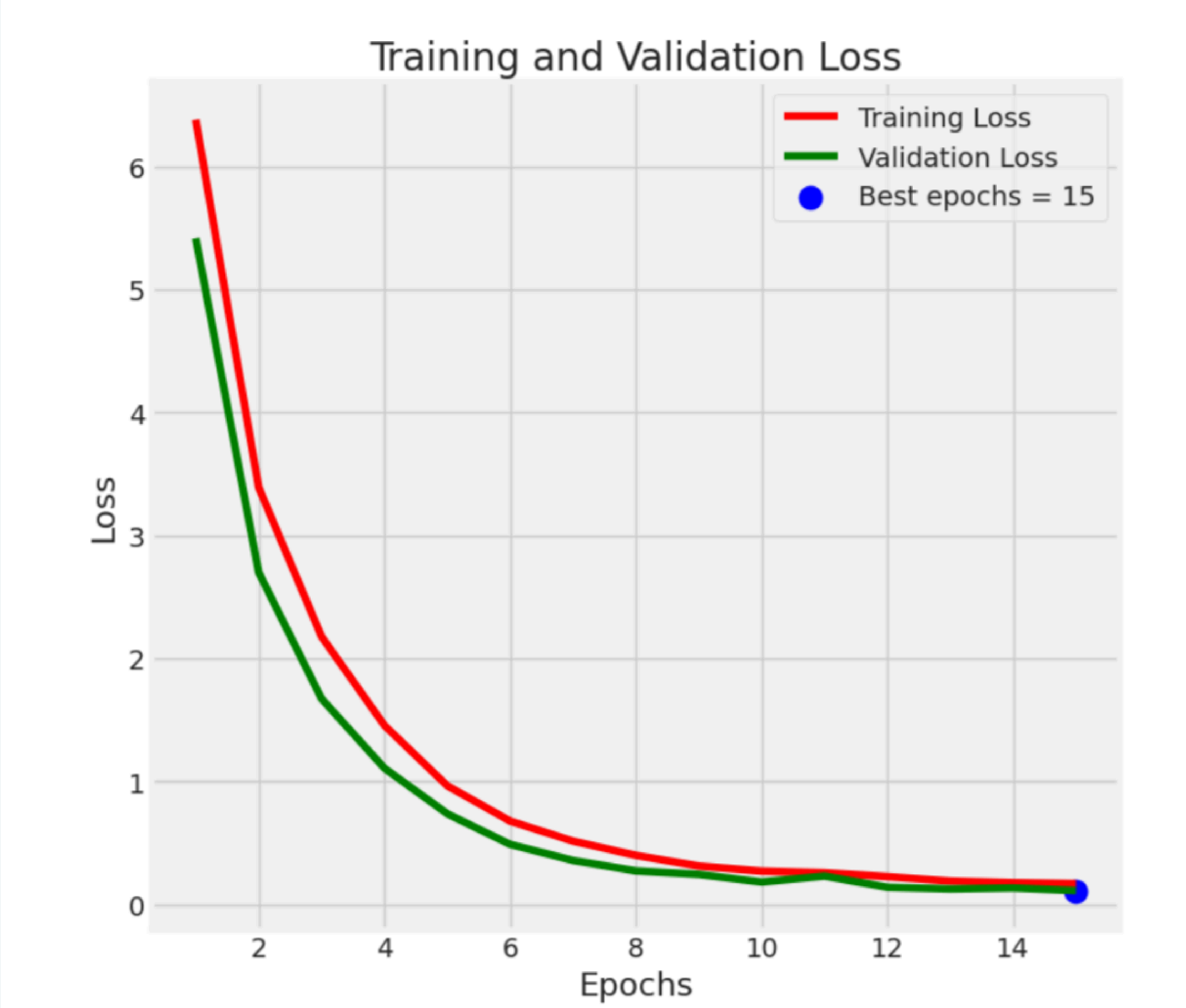
Results



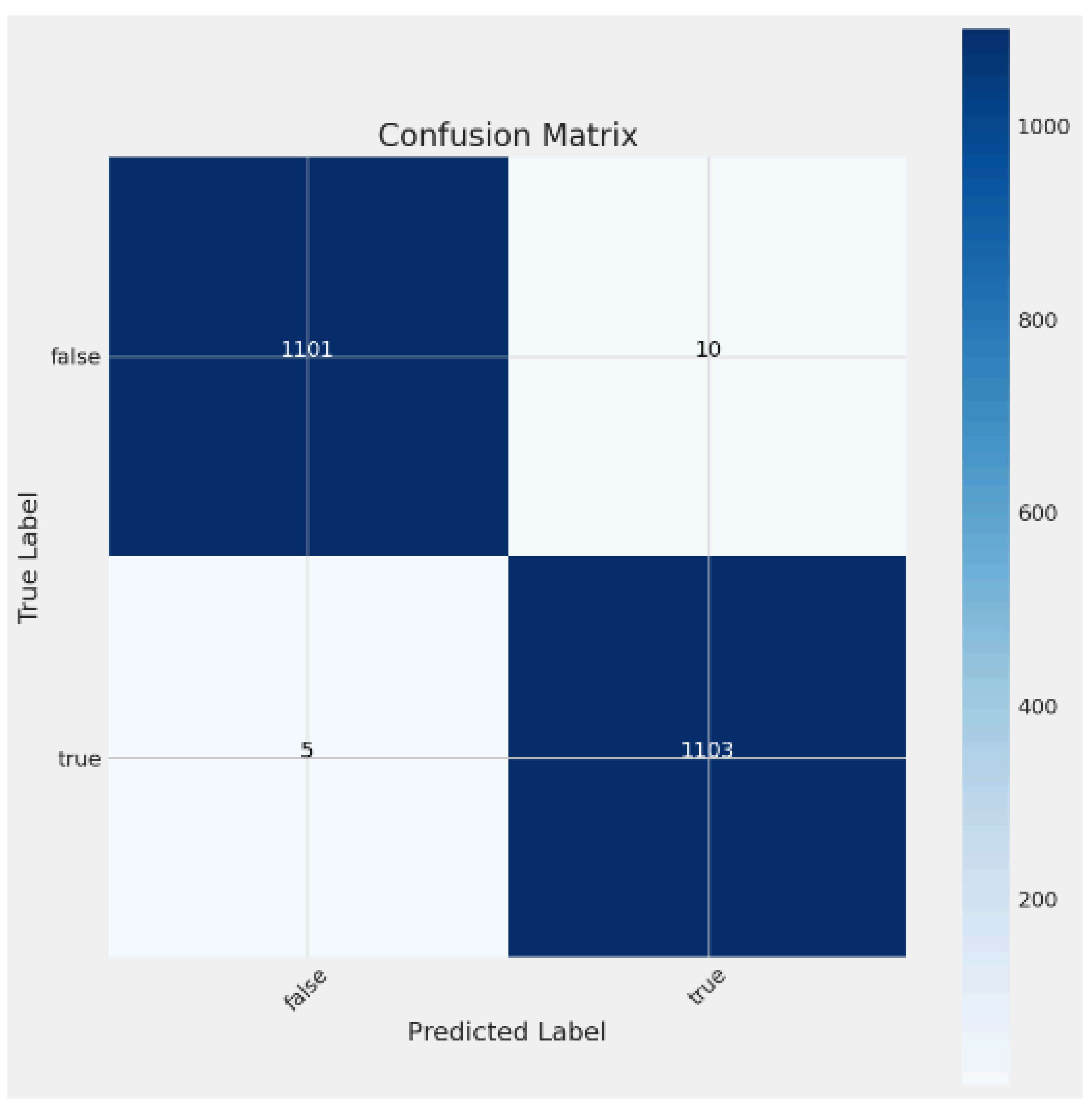
The deep neural networks exhibited superior performance in lung cancer image classification, with UNet achieving 94.1%, DenseNet at 91.3%, and ResNet-50 at 92.6%. Additionally, our custom CNN model achieved a commendable accuracy of 98.5%, demonstrating that a tailored deep learning approach can also provide highly accurate results..

Accuracy Plot of Our Custom CNN Model





Confusion Matrix of Our Custom CNN Model



Future Scope

1.Enhancing Model Performance:

Further improving the accuracy of the model by incorporating advanced techniques such as transfer learning, ensemble learning, and explainable AI to better handle class imbalance and feature selection.

2.Expanding Model Applications:

Extending the model to classify cardiomegaly into different severity levels or subtypes, incorporating additional modalities like electrocardiograms (ECGs) or echocardiograms, and developing real-time detection systems for immediate diagnosis and intervention.

3.Scalability and Deployment:

Deploying the model on cloud platforms like AWS or Google Cloud to handle large volumes of data and scale the model as needed, and developing mobile apps that can process X-ray images and provide cardiomegaly detection results in real-time.

Conclusion

The results demonstrate 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 chest X-ray images. The study affirms the potential of deep learning models in medical image analysis, paving the way for future advancements in automated disease detection and precision healthcare interventions.

Thank you