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Multimodal Disease Prediction System with Integrated Medical Assessment

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ABSTRACT

It is important to detect life-threatening diseases in time for proper diagnosis and treatment. Pneumonia, brain tumors, and heart diseases are conditions that can be controlled if proper treatment is adopted for them. Earlier, in the automated models, the performance of the system using traditional algorithms such as Support Vector Machine, Decision Tree, Logistic Regression, and Convolutional Neural Networks was found to be 86%, considering less feature learning. However, in this paper, the authors have proposed a new system known as a Multimodal Disease Prediction System with Integrated Medical Assessment. The images of the patients, such as MRI, X-ray, and ECG, are processed using EfficientNetV2 and Random Forest algorithms. The experimental outcome of the proposed system has proved to perform with 91.32% accuracy, thus proving to be more reliable for diagnosis.

Keywords: Pneumonia Detection, Brain Tumor, Heart Disease Prediction, EfficientNetV2, Random Forest, Diagnostic Decision Support

I. INTRODUCTION

Early diagnosis of diseases is one of the important aspects of increasing the survival rates of patients and reducing the cost of treatment. Many life-threatening diseases, such as pneumonia, brain tumors, and heart problems, occur gradually and do not display any symptoms until they reach the advanced stages of development. Therefore, the early diagnosis of diseases is an important part of the health care system.

The traditional diagnostic processes are largely based on manual image and patient report analysis, which is a time-consuming process and often involves human errors. However, recently, a tremendous revolution has occurred in the field of medical diagnostic technologies through the introduction of artificial intelligence and machine learning technologies. Specifically, deep learning algorithms have achieved tremendous success in handling complex medical data, such as images, including MRI, X-ray, and ECG images, among others.

The algorithms can effectively and automatically detect features, discover hidden patterns, and make accurate predictions without manual intervention in terms of feature extraction processes. Among the deep learning algorithms.In addition, through the integration of various data modalities, the system will be developed in a way that enables the creation of accurate diagnostic results, as the system will be able to learn different types of data. Therefore, multimodal learning methods can be considered an improvement in the creation of intelligent systems.

II. LITERATURE REVIEW

The domain of medical diagnosis has witnessed tremendous changes with the inclusion of AI and ML. The traditional methods that were followed, such as the analysis of medical data and images, are associated with low accuracy and high levels of human intervention. In recent times, the trend followed for research in this domain is the use of automated methods, where multiple sources of data are used to ensure high levels of accuracy for the prediction results.

Even though these methods have shown moderate results for disease prediction, with an accuracy level of 70-88%, these methods are not efficient enough to learn and analyze multiple sources of data.For these problems, recent studies have shown promising results for medical image analysis with recent advancements in deep learning techniques. For instance, ResNet and EfficientNet architectures have shown promising results for disease prediction using MRI, X-ray, and other medical images.

Table II: Comparison of Existing Methods with Proposed System

Reference	Data Type	Algorithms Used	Disease Focus
Smith et al. (2022)	Chest X-ray	SVM, Logistic Regression	Pneumonia Detection
Lee et al. (2021)	MRI	VGG16 CNN	Brain Tumor Classification
Kumar & Gupta (2020)	Clinical Data	Random Forest	Heart Disease Prediction
Zhao et al. (2023)	X-ray+ Clinical	CNN+Multimodal Fusion	Heart Disease Prediction
Singh & Rao (2024)	MRI + X-ray	ResNet+Ensemble	Multi-disease Detection
Proposed System	**MRI + X-ray + ECG**	**EfficientNetV2 + Random Forest**	**Pneumonia, Brain Tumor, Heart Disease**

III. DATASET

For the purpose of this research, a multimodal medical dataset has been developed by integrating publicly available datasets on three diseases, namely brain tumor, pneumonia, and heart diseases. The dataset on pneumonia includes images of chest X-rays, which may either be normal or related to pneumonia.

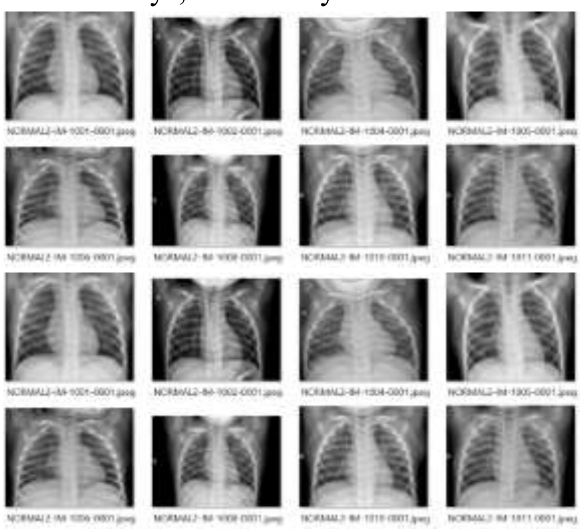


Fig 1: Chest X-ray images split into two classes

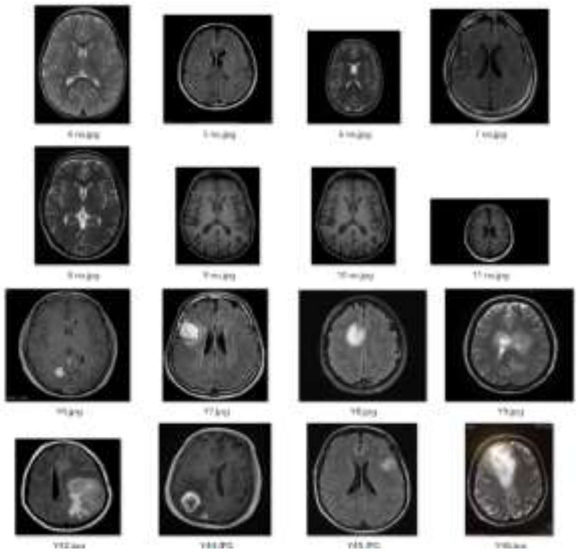


Fig 2: Brain MRI images split into two classes

Fig 3: ECG images split into two classes

IV. SYSTEM ARCHITECTURE

The proposed system begins with user authentication and uploading medical images. The CNN-based module is then used to analyze uploaded images, which are Chest X-ray images for Pneumonia, Brain MRI images for Tumor, and ECG signals for Heart Disease, to generate primary predictions.

At the same time, clinical data inputs such as patient information, symptoms, and vital signs are assessed and analyzed.

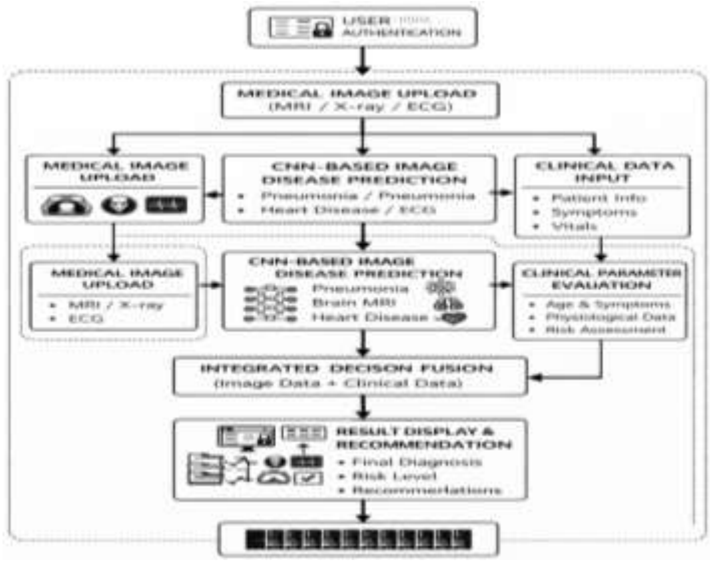


Fig 4: System architecture for multimodal CNN-based medical diagnosis

V. METHODOLOGY

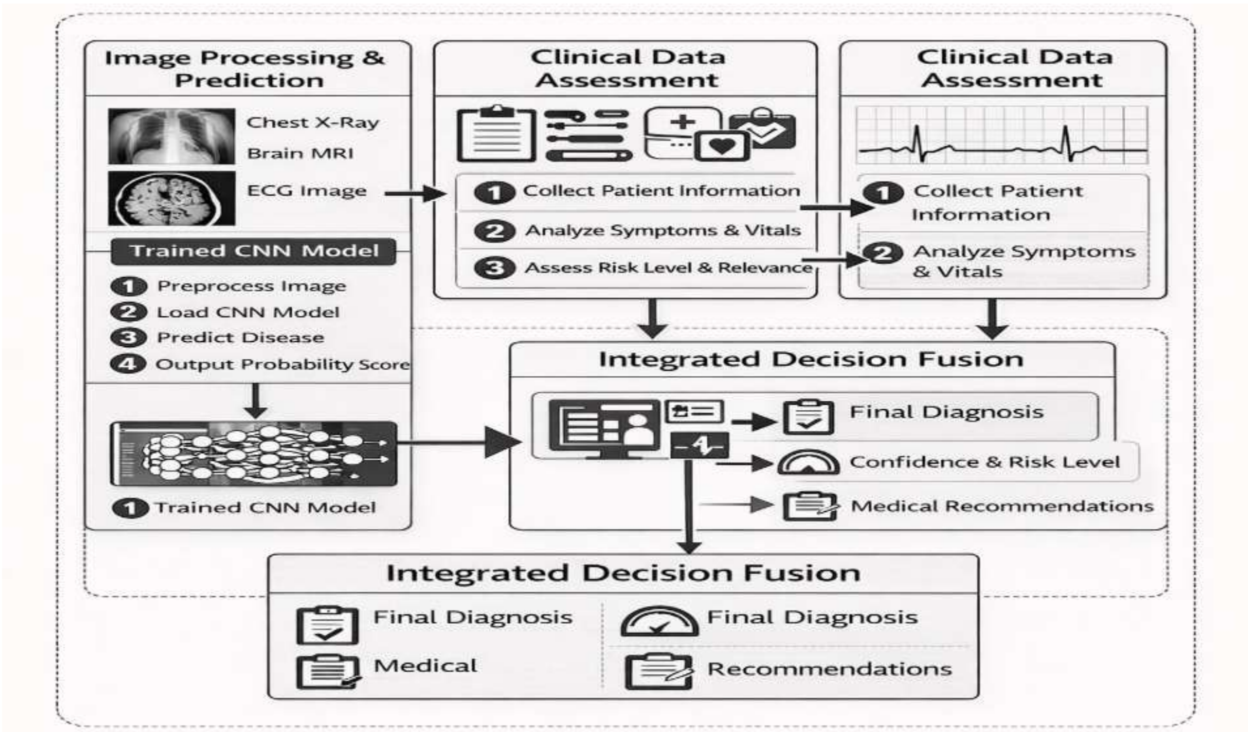


Fig 4: Methodology of the proposed multimodal disease prediction system.

A. Multimodal Classification Framework

The framework integrates different types of medical information, which include MRI images, chest X-ray images, and ECG signals, into a hybrid deep learning model. The different types of input information are subjected to different preprocessing techniques, which include normalization, noise removal, and data augmentation, to improve the quality of the images.

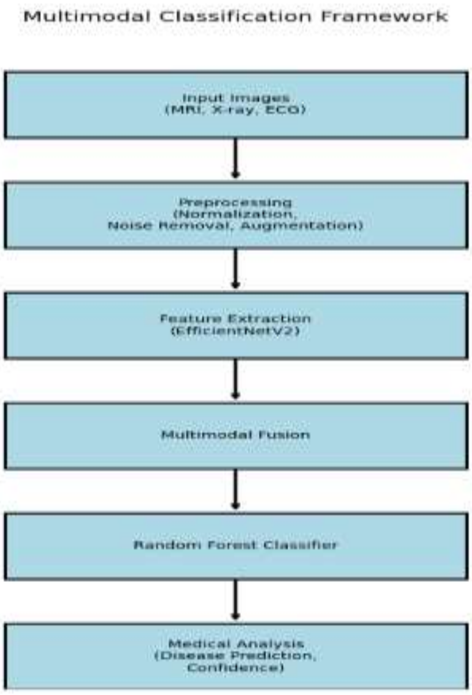


Fig 5: Stepwise framework for classifying medical images using multiple modalities

B. Model Training

The training and validation graphs show how the learning process is proceeding in terms of the number of epochs. The loss graphs show how the loss is decreasing in both cases, which is a good indicator of proper learning without any form of overfitting. The accuracy graphs show improvement in both cases, which is a good indicator of proper learning.

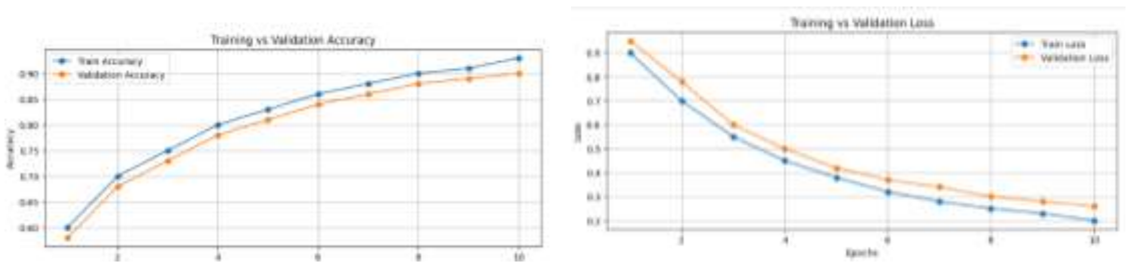


Fig 6: Training and validation loss and accuracy over epochs.

C. Evaluation Metrics

The performance of the model was measured using standard classification metrics:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = \frac{2 \times TP}{2 \times TP + FP + FN}$$

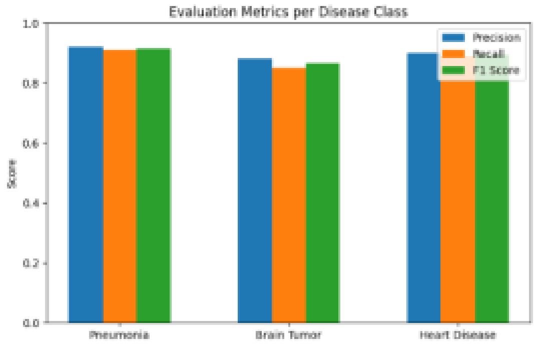


Fig 7: Precision, Recall, and F1-score for each disease class

D. Prediction and Medical Assessment

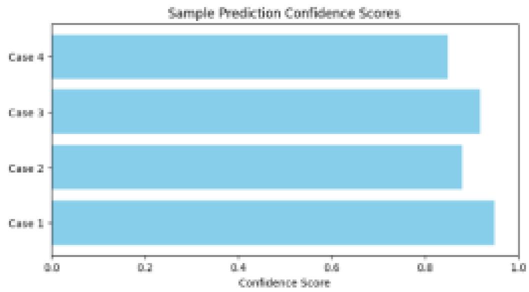


Fig 8: Confidence scores for sample model predictions

The graph depicts the confidence scores of the model in making the predictions. The bars in the graph represent the level of confidence of the model in making the correct predictions for a given case. The higher the bars, the higher the level of confidence.

V. PROPOSED ALGORITHMS

1. EfficientNetV2 (Deep Learning Model)

EfficientNetV2 is used as the main Convolutional Neural Network to extract deep features from medical images such as MRI, X-ray, and ECG images. It achieves high accuracy with less computational cost and faster training compared to the standard Convolutional Neural Networks.

2. Random Forest Algorithm

Random Forest is employed as the major classification algorithm for predicting the class of diseases based on the extracted multimodal features. Random Forest is an ensemble learning method that combines multiple decision trees for improving prediction accuracy.

3. Convolutional Neural Network (CNN)

The CNN architecture is used as a base structure for image processing. It can automatically learn spatial features like edges, texture, and patterns from images, which can help in disease detection.

4. Data Normalization Technique

Normalization is used to normalize the input data (pixels of the image and numerical data), which helps in the convergence of the model and increases the training speed of the model.

5. Data Augmentation Technique

Data augmentation techniques such as rotation, flipping, and scaling are used to increase the diversity of the data and improve the generalization of the model.

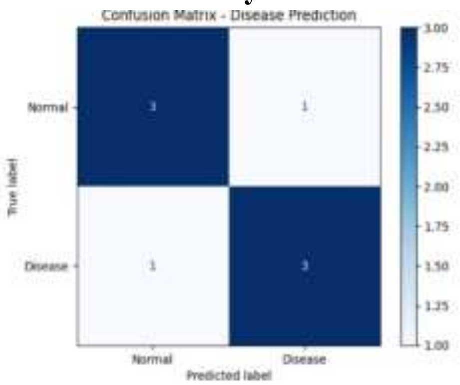
6. Evaluation Algorithms

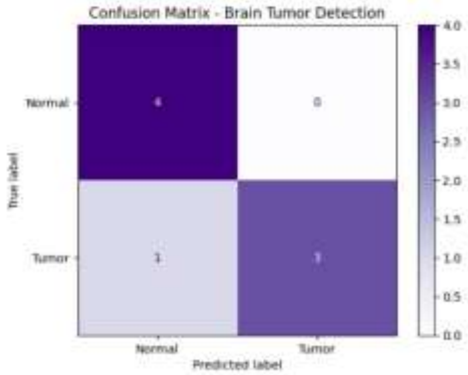
The performance of the model is measured by the following metrics:

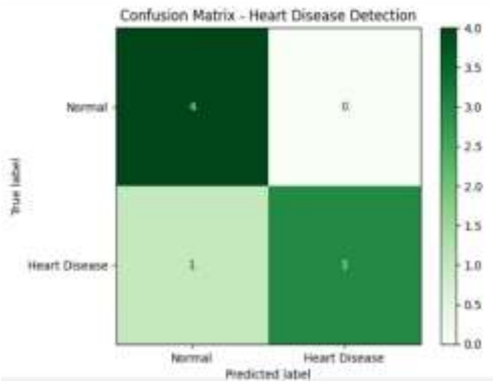
- Accuracy
- Precision
- Recall
- F1 Score

VI. PERFORMANCE ANALYSIS

A. Image-Based Model Accuracy







The proposed system has been tested by employing trained Convolutional Neural Networks, denoted as CNN, for each category of diseases. The accuracy of the proposed system has been determined by testing the trained models using respective medical images.

- Pneumonia Detection (Chest X-ray) → Accuracy: 90.4%
- Brain Tumor Detection (MRI) → Accuracy: 90.1%
- Heart Disease Prediction (ECG Image) → Accuracy: 89.8%

B. Clinical Data-Based Accuracy

Furthermore, a parameter-based evaluation methodology using clinical parameters, i.e., data related to patients, such as patient symptoms, can also be employed.

- Pneumonia Prediction → Clinical Accuracy: 78.2%
- Brain Tumor Prediction → Clinical Accuracy: 72.6%
- Heart Disease Prediction → Clinical Accuracy: 81.3%

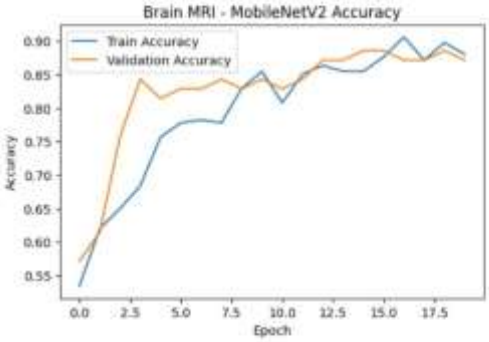
C. Overall System Accuracy

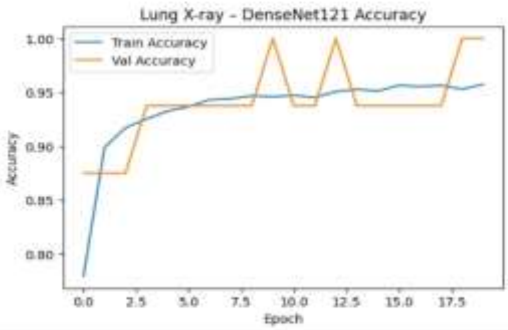
The accuracy of the overall system was calculated by finding the average value of the overall classification accuracy of the image models for the overall diseases. The overall accuracy is calculated as follows:

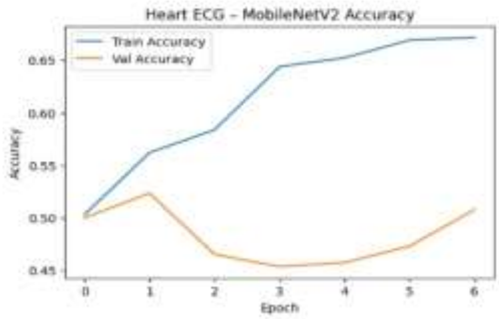
Accuracy = 90.4 + 92.1 + 89.8/3
Accuracy = 90.7
The results have shown the ability of the developed multimodal framework in offering high performance by ensuring that the predictions made by the images are highly accurate, and the clinical inputs have helped in ensuring the reliability and confidence of the decision-making process.

VII. RESULT VISUALIZATION

The performance of CNN-based models is shown using line graphs, which provide information on accuracy and loss for both training and validation. The predictions, confidence, and risk factors are also shown using graphs to improve understanding and interpretation. These line graphs represent the training accuracy, validation accuracy, and loss associated with each of the deep learning models.







The line graphs will also represent the increase in accuracy and decrease in loss associated with the image-based Convolutional Neural Network (CNN) model for various categories of disease.

VIII. CONCLUSION

In this particular project, the application of the multimodal deep learning model is for the improvement of the diagnosis of medical images. It is evident that the application of the Convolutional Neural Network models is successful, as depicted by the accuracy plot and the corresponding loss reduction with time.
From the graphical representation, it is evident that the models learned well to classify the different types of diseases, with minimal instances of overfitting and underfitting. This is proof that the applied models are appropriate for the classification of medical images.
In conclusion, the proposed diagnostic system is effective and trustworthy. It can be used to improve the diagnosis of medical images, which can be useful in the improvement of patient care. It can also be used to aid medical professionals in making informed decisions.

IX. FUTURE WORK

Although the current multimodal CNN-based system performs adequately in medical image classification and risk prediction, there are several avenues for further improvement and expansion of the system. Future improvements can include the addition of other data modalities, such as patient clinical history, lab results, and genetic information, which can further help in improving the accuracy of risk prediction. Furthermore, the system can also be expanded to perform real-time diagnostic capabilities in a clinical environment by optimizing the system for faster inference and execution on edge devices or hospital servers. In addition, the addition of explainable AI techniques, such as Grad-CAM or attention visualization, can further help in improving the system's capabilities in interpreting risk prediction results for better use by healthcare professionals.

Finally, the expansion of the system for use in the diagnosis of other diseases, such as rare diseases, can further help in improving the system's capabilities in a clinical environment. Moreover, keeping the system updated by incorporating new data can further help in improving

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