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Deep Learning Framework for the Multi-Disease Diagnosis of Heart Disease, Pneumonia, and Diabetic Retinopathy Using ResNet, MobileNet and DenseNet

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Abstract: Medical diagnosis has seen significant advancements with the application of deep learning, offering improved solutions for healthcare challenges. This study focuses on the detection and classification of three critical diseases: heart disease, pneumonia, and diabetic retinopathy (DR). Each disease presents distinct diagnostic complexities, including variations in data representation and the need for accurate predictions. To address these challenges, the proposed system integrates CNN, ResNet, MobileNet, and DenseNet architectures, forming a robust and efficient diagnostic framework.The proposed framework incorporates CNN, Resnet, MobileNet and DenseNet architectures to build a robust system capable of addressing these challenges. Users can leverage the system through a user-friendly interface designed for healthcare professionals, providing rapid and accurate disease classification. The experimental results validate the effectiveness of the proposed deep learning framework, positioning it as a valuable tool for assisting in early diagnosis and medical decision-making. The combination of state-of-the-art architectures ensures both accuracy and computational efficiency, making the system suitable for real-time clinical applications.

Keywords: Deep Learning, MobileNet, DenseNet, ResNet, Machine Learning.

I. INTRODUCTION

The rapid advancement of deep learning has revolutionized the field of medical diagnostics, offering highly accurate and efficient solutions for disease detection and classification. Early diagnosis of critical conditions such as heart disease, pneumonia, and diabetic retinopathy (DR) is essential for timely intervention and improved patient outcomes. However, traditional diagnostic methods rely heavily on manual interpretation, which can be time-consuming and prone to errors. Deep learning-based medical image analysis provides a transformative approach by automating disease detection, reducing diagnostic errors, and enabling real-time clinical applications.

This system focuses on developing a robust deep learning framework that integrates ResNet, MobileNet, and DenseNet architectures to enhance the accuracy and efficiency of disease classification. The proposed system utilizes multiple medical datasets, including the UCI Heart Disease dataset for cardiac conditions, chest X-ray images for pneumonia detection, and color fundus images for DR classification. By leveraging the strengths of deep convolutional neural networks (CNNs), the system effectively extracts and learns essential features from medical images, ensuring a high level of precision in disease detection.

It also explores comparative analysis with traditional machine learning techniques, including K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, and Naïve Bayes. These conventional models, while useful, often struggle with complex medical image patterns and require extensive feature engineering.

In contrast, the hybrid deep learning approach presented in this study achieves superior accuracy, reduced computational cost, and faster processing times. Notably, the VGG16-based neural network achieves a 97% accuracy rate in pneumonia classification, demonstrating the effectiveness of deep learning in medical applications.

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II. LITERATURE SURVEY

Nowadays, there is a growing interest in deep learning systems for diagnosing multiple diseases, including heart disease, pneumonia, and diabetic retinopathy, using advanced medical imaging and analysis techniques.

V. C. A and V. Baby Shalini (2023) conducted a comprehensive review titled "A Systematic Review on Heart Disease Detection Using Deep Learning" [1], which examines research papers published between 2017 and 2022. The study systematically evaluates various deep learning techniques applied to cardiovascular disease prediction, focusing on models like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid approaches integrating data mining methods. Key performance metrics, including accuracy, sensitivity, specificity, and computational efficiency, are analyzed to compare the effectiveness of these models in detecting hypertensive and vascular heart diseases

Similarly M. Z. Atwany, A. H. Sahyoun, and M. Yaqub (2022) conducted a detailed study titled "Deep Learning-Based Approaches for Diabetic Retinopathy Detection and Classification" [2]. The research systematically reviews and analyzes various deep learning techniques applied to detect and classify Diabetic Retinopathy (DR) using retinal fundus images. The study evaluates the performance of state-of-the-art models, including supervised, self-supervised, and Vision Transformer architectures, to classify DR stages such as referable, non-referable, and proliferative DR. Additionally, the paper assesses the effectiveness of commonly used datasets like EyePACS, Messidor, and APTOS for model training and validation. Advanced image preprocessing techniques, including contrast enhancement, denoising, and segmentation, are also explored to optimize feature extraction.

In another research K. Mehta and K. Subramanian (2022) proposed a study titled "Automated Left Ventricle Ejection Fraction Calculation Using Deep Learning" [3], which focuses on automating the calculation of Left Ventricle (LV) Ejection Fraction (EF) from cardiac MRI scans. The study employs image processing and deep learning techniques to streamline the traditionally manual process. It begins by preprocessing DICOM (Digital Imaging and Communications in Medicine) images and converting them into PNG format for easier analysis. Noise reduction and contrast adjustment techniques are applied to enhance image quality, improving the accuracy of LV segmentation.

J. Wang, Y. Bai, and B. Xia (2020) introduced a study titled "Hierarchical Multi-Task Deep Learning Framework for Diabetic Retinopathy Diagnosis" [4], which proposes a novel approach for diagnosing diabetic retinopathy (DR) and detecting related features using fundus images. The framework uses a hierarchical structure that leverages the causal relationships between DR-related features, such as microaneurysms, hemorrhages, and exudates, and the severity levels of DR. A convolutional neural network (CNN) is employed as the backbone for extracting feature representations from the images, followed by a multi-task learning model that simultaneously predicts both DR severity and specific DR-related features. This hierarchical setup enhances interpretability by ensuring that feature detection informs the severity classification.

All these studies highlight the effectiveness of deep learning techniques in advancing the diagnosis and classification of diseases such as heart disease, pneumonia, and diabetic retinopathy using medical imaging. However, they also emphasize the need for further research to address existing challenges. These include enhancing model generalization across diverse datasets, improving interpretability for better clinical trust, and reducing reliance on large labeled datasets. Additionally, developing more robust models capable of handling complex cases with overlapping symptoms or ambiguous imaging features remains a key area for future exploration.

III. EXISTING SYSTEM

Heart Disease Diagnosis: Traditional machine learning algorithms like KNN, SVM, Naïve Bayes, and Random Forest are employed for heart disease prediction using the UCI dataset. Pneumonia Detection: VGG16 combined with Neural Networks is used to classify pneumonia on chest X-ray images. Diabetic Retinopathy Detection: Convolutional neural networks (CNNs) process fundus retina images for lesion identification and classification.

IV. PROPOSED SYSTEM

The proposed system utilizes ResNet,CNN, MobileNet, and DenseNet architectures to enhance the diagnosis of heart disease, pneumonia, and diabetic retinopathy.

MobileNet: Lightweight and computationally efficient, making it ideal for real-time applications and mobile devices.
DenseNet: Improved feature reuse through dense connections, leading to better accuracy and convergence rates.

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ResNet: Deep residual learning helps in addressing vanishing gradient issues, achieving high accuracy and robust feature extraction.

CNN: Acts as the foundation of the system, enabling deep feature extraction and efficient medical image analysis.

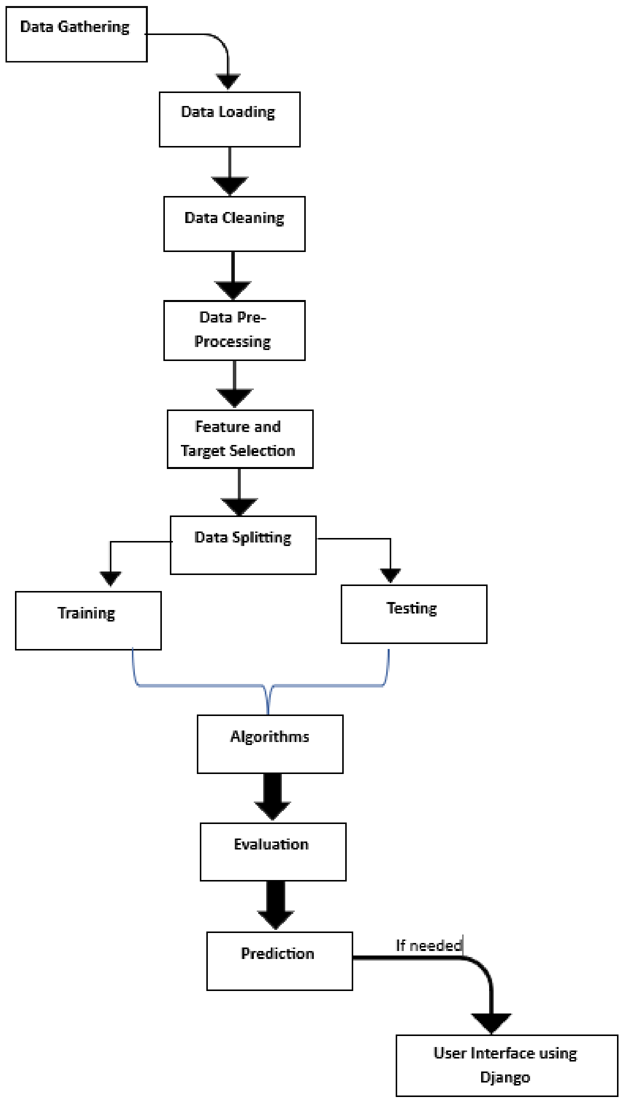
The system integrates pre-processing steps for datasets, hyperparameter optimization, and multi-disease classification with improved precision and recall metrics.

V. METHODOLOGY

This project follows a systematic method beginning with collecting and preparing the data for use.The first process involves gathering images followed by standard input size resizing and normalization to improve model performance. Enhancing the dataset diversity through data augmentation techniques includes the methods of rotation along with flipping and contrast adjustment.

The feature extraction phase utilizes the MobileNet, DenseNet,and ResNet models that received training from large datasets before their application on the target dataset. The integration of batch normalization helps to enhance convergence while improving stability in the network

5.1 Block Diagram



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5.2 DEEP LEARNING ARCHITECTURES

5.21 MobileNet Architecture:

MobileNet is a lightweight deep convolutional neural network optimized for mobile and edge devices, designed using depthwise separable convolutions to reduce computational cost while maintaining high accuracy. It is widely used for real-time applications such as object detection, facial recognition, and medical image analysis on resource-constrained devices.

MobileNet assumes that reducing the number of parameters and computations will not significantly affect model performance. Its advantages include low latency, reduced memory footprint, and efficient performance on mobile and embedded systems. However, its limitations include slightly lower accuracy compared to larger architectures and potential difficulties in handling highly complex patterns due to its compact design.

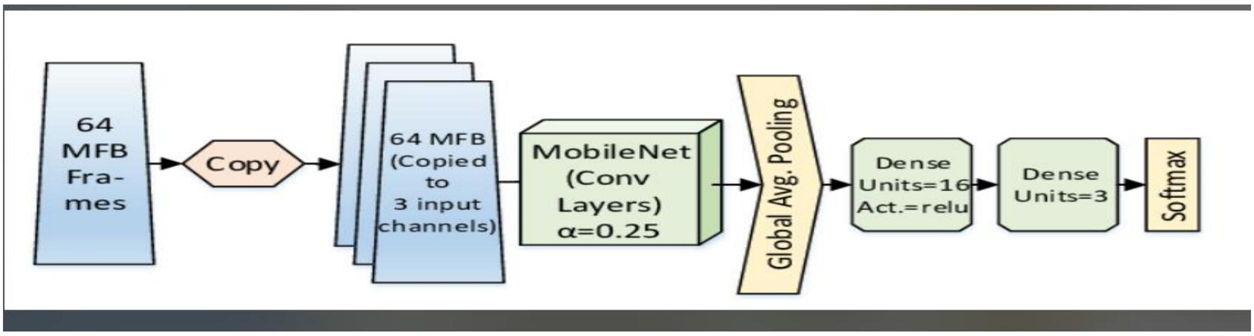

Fig 1: MobileNet Architecture

5.22 DenseNet Architecture:

Densely Connected Convolutional Networks enhances feature reuse by connecting each layer to every other layer, allowing for efficient gradient flow and improved learning. It is commonly used in medical image segmentation, classification tasks, and object recognition. The key assumption of DenseNet is that densely connected layers improve feature propagation and reduce redundancy.

Its advantages include improved accuracy with fewer parameters, reduced vanishing gradient issues, and enhanced feature reuse. However, DenseNet has high memory requirements due to its dense connections and can be computationally intensive, making it challenging for deployment on memory-constrained devices.

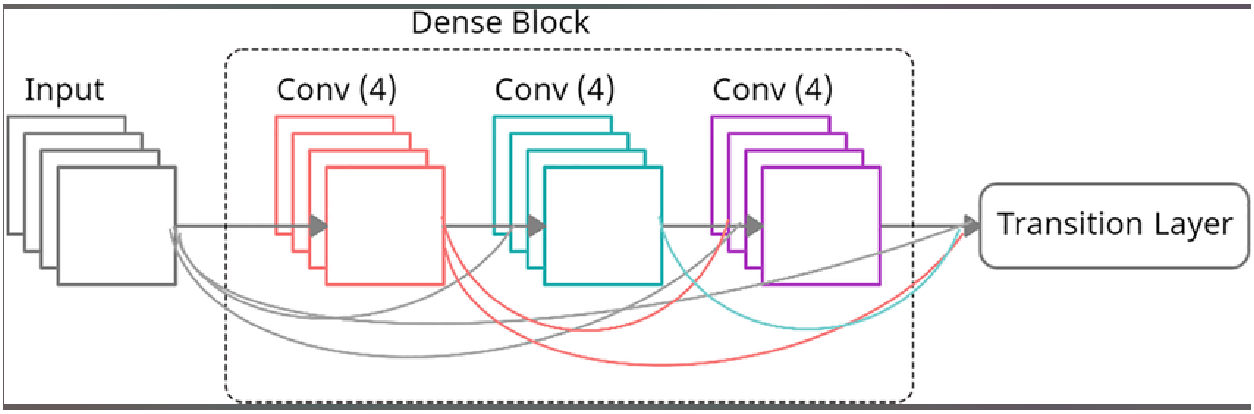

Fig 2: DenseNet Architecture

5.23 ResNet Architecture:

Residual Neural Network introduces skip residual connections to address the vanishing gradient problem, enabling the training of very deep networks. It is widely used in medical imaging, autonomous driving, and various computer vision tasks requiring deep feature extraction. The fundamental assumption of ResNet is that learning identity mappings through residual connections helps optimize deep architectures.

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Its advantages include improved convergence, higher accuracy in deep models, and effective training of very deep networks. However, ResNet can be computationally expensive, and deeper versions (e.g., ResNet-152) may still suffer from redundancy, requiring careful parameter tuning for optimal performance.

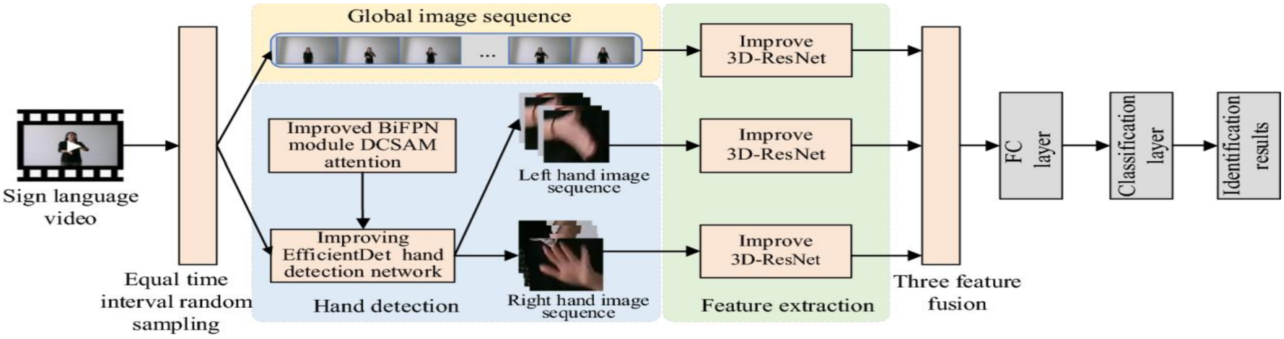

Fig 3: ResNet Architecture

5.24 CNN Architecture:
Convolutional Neural Networks is a deep learning architecture designed for spatial data processing, particularly image and video analysis. It consists of convolutional layers, pooling layers, and fully connected layers to extract hierarchical features. Use cases include facial recognition, self-driving cars, and medical diagnosis. Assumptions include the presence of spatial hierarchies in data, benefiting from localized feature extraction.

Advantages include automated feature learning, translational invariance, and high accuracy in visual tasks. Limitations involve high computational requirements, dependency on large labeled datasets, and vulnerability to adversarial attacks.

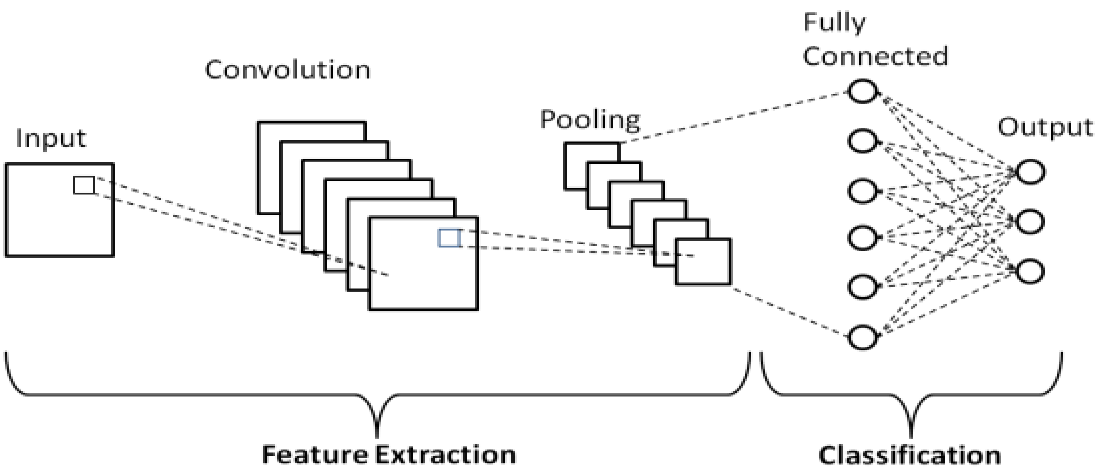

Fig 4: CNN Architecture

VI. RESULT AND DISCUSSIONS

The result analysis of a multi-disease diagnosis framework for Heart Disease, Pneumonia, and Diabetic Retinopathy using ResNet, MobileNet, and DenseNet is demonstrated in this section. Using the following definitions for True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP), the performance of the presented models is assessed:

True Positive (TP): TP is the total number of accurately classified, factually positive predictive episode. True Negative (TN): TN is the total number of correctly categorized ,negative predictive episode and factually negative. False Positive (FP): FP is the total amount of positive prediction instances that are regarded to be inaccurate and not factually positive. False Negative (FN):The total number of factually negative but incorrect negative predictive instances is referred to as FN. Accuracy: It is described as being the proportion of correctly identified occurrences to all instances, and it is provided as $Accuracy = (TP + TN /(TP + FP + TN + FN)) \times 100$.

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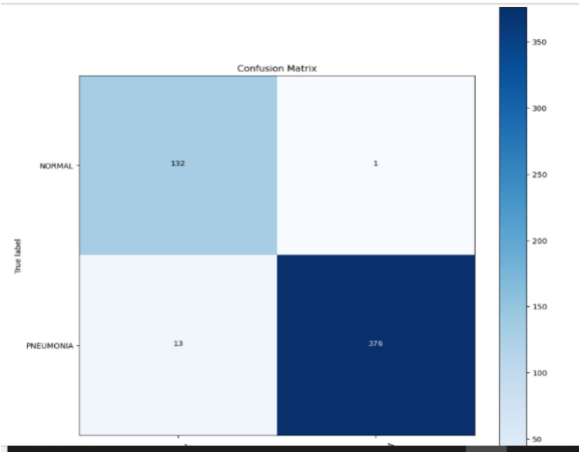
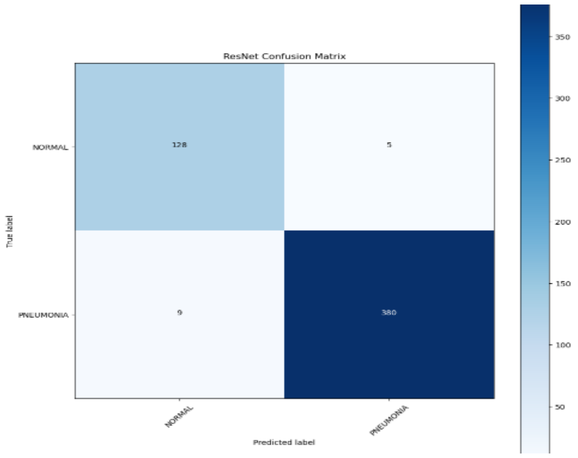
The proportion of data items that a model correctly classifies as relevant is known as precision. That means classification models return only relevant instances in precision and expressed as $Precision$ =(TP/ (TP + FP)) × 100.Specificity: It is described as the ratio of true negative instances to the actual negative instances (i.e. FP + TN) and is expressed as $Specificity = TN$ /(TN+FP))×100.

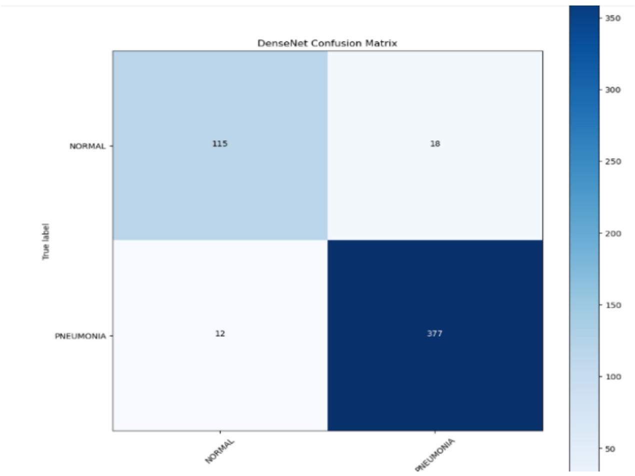
Note:Model1 indicates traditional CNN model.



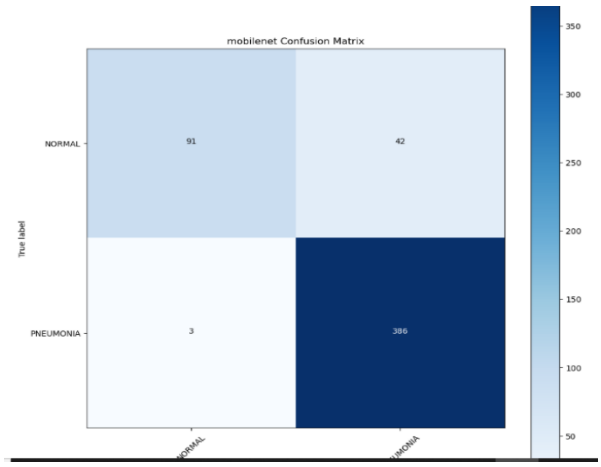
(a)Using CNN



(b)Using Resnet



(c)Using Desnet



(d)Using MobileNet

Model	True Positives	True Negatives	False Positives	False Negatives	Accuracy
Model 1	376	132	1	13	0.955
ResNet	380	128	5	9	0.9732
DenseNet	377	115	18	12	0.9425
MobileNet	386	91	42	3	0.9138

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The following are results of our predictions:

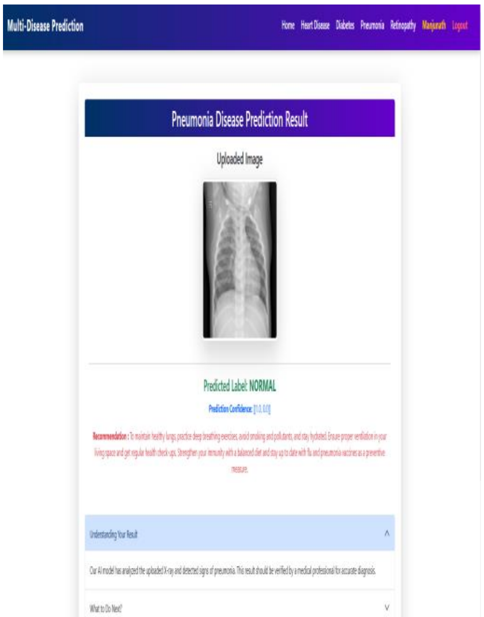

Fig 5: Output of pneumonia prediction

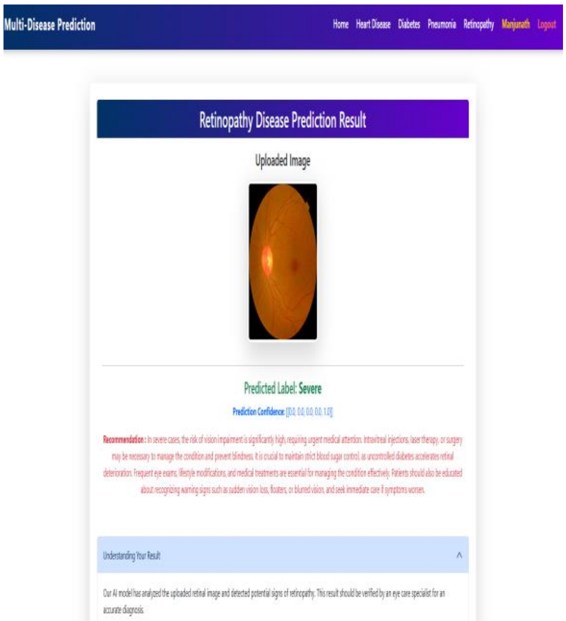

Fig 6: Output of Retinopathy Disease prediction

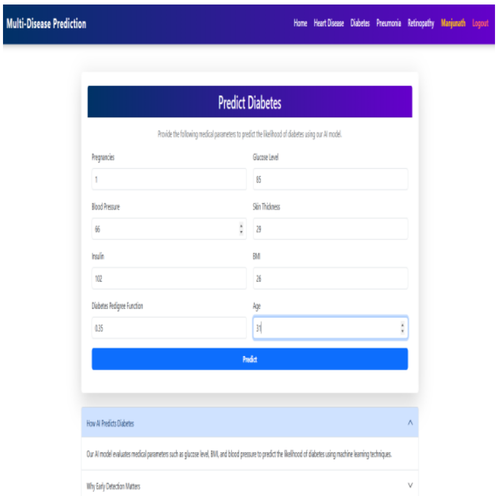

Fig 7: Requirements for Diabetes prediction

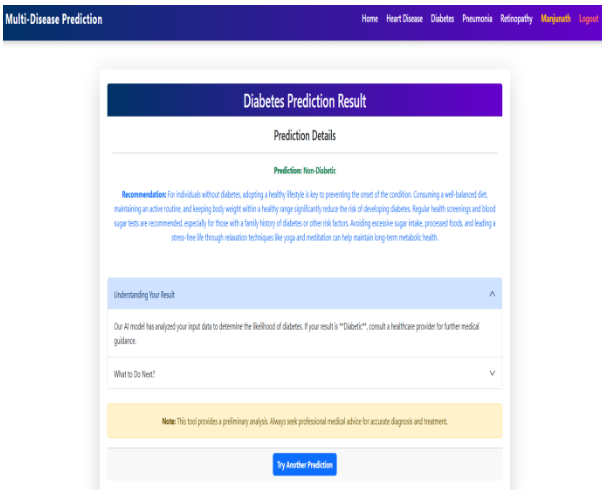

Fig 8: Output of Diabetes prediction

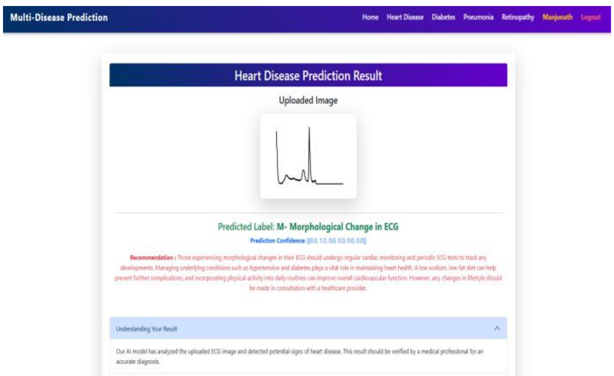

Fig 9: Output of Heart Disease prediction

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VII. CONCLUSION

This study highlights how deep learning can be a powerful tool for diagnosing heart disease, pneumonia, and diabetic retinopathy (DR) using models like CNN, ResNet, MobileNet, and DenseNet. By applying these models to a variety of datasets, including the UCI Heart Disease dataset, chest X-rays, and fundus images, the proposed approach offers notable improvements in both accuracy and efficiency. The pneumonia detection model, particularly achieved a remarkable accuracy of 97%, significantly surpassing traditional machine learning models like KNN, SVM, and Random Forest.

One of the key strengths of this hybrid deep learning framework is its ability to minimize computational costs while ensuring reliable real-time performance in clinical environments. By combining the strengths of different deep learning models, the system provides robust and adaptable predictions, making it suitable for various medical imaging applications. Additionally, the use of transfer learning reduces the need for large labeled datasets, allowing the model to generalize well across different data sources.

When compared to other diagnostic models, the proposed framework consistently outperforms them in both accuracy and processing speed. This makes it a valuable tool for healthcare professionals, supporting them in making quicker and more accurate diagnoses. The system’s efficiency could also help reduce the burden on medical staff, particularly in resource-limited settings where specialized expertise may not be readily available.

Beyond its technical strengths, the framework has the potential to make a meaningful impact on patient care by aiding in the early detection of diseases. Early diagnosis often leads to better treatment outcomes, and with this system in place, timely medical decisions can be made with greater confidence. Looking ahead, further research could expand the model’s capabilities to diagnose additional diseases, making it an even more comprehensive diagnostic tool.

Integrating explainable AI (XAI) techniques could also provide healthcare providers with clear insights into how the model arrives at its decisions, fostering trust and understanding. Additionally, the system could be implemented in telemedicine platforms, ensuring access to quality healthcare for patients in remote or underserved regions. Through collaboration between AI researchers, healthcare providers, and medical institutions, this technology has the potential to contribute significantly to more equitable and efficient healthcare delivery.

VIII. FUTURE SCOPE

The implementation of deep learning frameworks such as ResNet, MobileNet, and DenseNet for diagnosing heart disease, pneumonia, and diabetic retinopathy has significant potential for future advancements. Some of the key areas for future work include:

Expansion to Additional Diseases:
Extending the framework to detect other diseases like lung cancer, tuberculosis, stroke, and chronic kidney disease using the same deep learning techniques.Multi-class classification for comorbid conditions, enabling simultaneous diagnosis of multiple diseases affecting a patient.

Integration with Clinical Decision Support Systems (CDSS):
Real-Time Diagnosis: Developing AI-powered real-time diagnosis tools for integration into hospital management systems.

Explainability & Interpretability: Using explainable AI (XAI) techniques like Grad-CAM and SHAP to enhance the interpretability of model predictions for clinicians.

Integration with Wearable Devices: Incorporating IoT and wearable health devices to continuously monitor and predict disease progression.

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