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Multiple Diseases Detection

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Abstract: The rapid advancement of deep learning and computer vision has enabled development of intelligent systems capable of detecting multiple diseases simultaneously from medical imaging data. This project proposes a Multi Disease Detection System integrating Brain Tumor detection from MRI scans and Pneumonia detection from chest X-ray images into a unified deep learning framework. Brain tumors one of the most life-threatening forms of cancer are detected from MRI images using a Convolutional Neural Network(CNN) Pneumonia, a leading cause of mortality worldwide particularly in children under five, is detected from chest X-ray images using transfer learning models including VGG16 and ResNet50 fine-tuned on the Kaggle Chest X-Ray Pneumonia dataset. The proposed system employs a dual-model architecture sharing a common preprocessing pipeline. Both models are trained on established benchmark datasets BraTS for brain tumors and the Kaggle Chest X-Ray dataset for pneumonia and evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics. The combined system achieves high accuracy in both diagnostic tasks, offering a cost- effective, non-invasive, automated decision-support tool suitable for clinical environments, especially in resource-limited healthcare settings where specialist availability is scarce. ***Keywords: Brain Tumor Detection, Pneumonia Detection, Deep Learning, Convolutional Neural Network (CNN), Transfer Learning, MRI, Chest X-ray, Medical Image Analysis, ResNet50, VGG16.***
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I. INTRODUCTION

Medical imaging has become an indispensable cornerstone of modern clinical diagnosis, enabling accurate, non-invasive visualization of internal body structures without surgical intervention. Among the most critical applications of medical imaging are the detection of brain tumors from Magnetic Resonance Imaging (MRI) scans and the identification of pneumonia from chest X-ray images. Both conditions represent profound global health challenges brain tumors are among the most deadly and complex forms of cancer, with a high mortality rate even with early-stage intervention; and pneumonia remains the single leading infectious cause of death in children under five years of age worldwide. Traditional diagnostic processes depend heavily on manual interpretation by specialist radiologists and trained clinicians. This approach is not only time-consuming and cost- intensive but also inherently prone to human error, observer fatigue, and inter-observer variability particularly in resource-constrained healthcare environments where specialist availability is severely limited. The exponential growth of deep learning and computer vision technologies has opened transformative possibilities for automated, accurate, and rapid medical image analysis, capable of matching or exceeding expert-level diagnostic performance.

This project proposes a unified Multi Disease Detection System that leverages state-of-the- art Convolutional Neural Networks (CNNs) to simultaneously address brain tumor classification from MRI images and pneumonia detection from chest X-ray images within a single integrated computational framework.

II. SCOPE AND CLINICAL SIGNIFICANCE

The proposed Multiple Disease Detection System aims to develop an intelligent, automated, and reliable clinical decision-support tool for detecting brain tumors from MRI images and pneumonia from chest X-ray images using deep learning techniques. The system classifies brain tumors into four categories—Glioma, Meningioma, Pituitary Tumor, and No Tumor—and performs binary classification of chest X-rays as Normal or Pneumonia using pre-trained models such as ResNet50 and VGG16 with transfer learning. A unified preprocessing pipeline, including image resizing, normalization, and data augmentation techniques such as rotation, flipping, and zooming, enhances model robustness and accuracy. The models are trained and evaluated using benchmark datasets, namely the BraTS Brain MRI Dataset and the Kaggle Chest X-ray Pneumonia Dataset, with performance assessed using Accuracy, Precision, Recall, F1-score, ROC-AUC, and Confusion Matrix. Clinically, the system supports early diagnosis, reduces radiologists' workload, minimizes human error and observer variability, and enables faster clinical decision-making, particularly in rural and resource-limited healthcare settings.

The integration of explainable AI techniques such as Grad-CAM enhances transparency by highlighting disease-affected regions, thereby increasing clinician confidence. Overall, the proposed system provides a non-invasive, cost-effective, scalable, and efficient healthcare solution that assists medical professionals while complementing, rather than replacing, expert clinical judgment.

III. TAXONOMY OF THE LITERATURE

The literature on automated medical image analysis for brain tumor and pneumonia detection can be classified into six major categories based on the techniques adopted by different researchers.

A. *Classical Machine Learning-Based Methods*

Early research focused on traditional machine learning techniques that relied on handcrafted feature extraction from medical images. Mohsen et al. [2] proposed a Deep Neural Network (DNN) using Discrete Wavelet Transform (DWT) and texture features for brain tumor classification, achieving 96.97% accuracy, while Sravanthi et al. [6] combined image preprocessing, Support Vector Machine (SVM), and Self-Organizing Maps (SOM) for tumor segmentation and staging, providing an interpretable pipeline without requiring GPU computation. These approaches demonstrated promising results but depended heavily on manual feature engineering and limited datasets.

B. *CNN-Based Deep Learning Approaches*

The introduction of Convolutional Neural Networks (CNNs) significantly improved automated disease detection by automatically learning discriminative image features. Deepika T. R. et al. [4] developed a lightweight CNN for pneumonia detection from chest X-ray images that could be deployed on standard CPU hardware without GPU support. Similarly, Sharma et al. [5] proposed a sequential CNN model for brain tumor detection using MRI images, achieving 97.79% test accuracy, demonstrating the effectiveness of CNNs even with relatively small datasets.

C. *Transfer Learning-Based Approaches*

Transfer learning has emerged as one of the most effective techniques for medical image classification by utilizing knowledge learned from large-scale image datasets. Rajpurkar et al. [1] introduced CheXNet using the pre-trained DenseNet-121 architecture for pneumonia detection, achieving performance comparable to expert radiologists. Anil et al. [3] applied transfer learning to brain tumor detection and showed that pre-trained CNN models effectively overcome the challenge of limited labeled medical datasets. Furthermore, Bangare et al. [7] demonstrated that VGG16-based transfer learning achieved an accuracy of 91–96.07% for multi-class pneumonia detection. The success of these studies is supported by the original deep learning architectures proposed by Simonyan and Zisserman [11] for VGG16, He et al. [12] for ResNet, and Huang et al. [13] for DenseNet.

D. *Explainable AI and Attention-Based Methods*

Recent studies have focused on improving the interpretability of deep learning models. Rajpurkar et al. [1] incorporated Class Activation Maps (CAM) to highlight disease-specific regions in chest X-ray images, allowing clinicians to understand model predictions. Similarly, Wang et al. [8] employed attention-based multimodal fusion mechanisms that enhanced both diagnostic performance and interpretability, thereby increasing clinician confidence in AI-assisted diagnosis.

E. *Multimodal Deep Learning Frameworks*

Modern research has shifted towards integrating multiple sources of medical information to improve diagnostic accuracy. Wang et al. [8] proposed the PneumoFusion-Net framework, which combines CT images using Swin Transformers, clinical reports using BERT, and laboratory data through fully connected networks. This multimodal fusion strategy achieved 98.96% accuracy and 98% F1-score, representing one of the highest reported performances for pneumonia diagnosis, although it requires significant computational resources and comprehensive clinical metadata.

F. *Unified Multi-Disease Detection Systems*

The reviewed literature indicates that most existing studies concentrate on detecting a single disease, such as brain tumors [2], [3], [5], [6] or pneumonia [1], [4], [7], [8], using independent deep learning models. Although these methods achieve high diagnostic accuracy, they lack an integrated framework capable of diagnosing multiple diseases within a single platform.

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This research gap motivates the proposed Multiple Disease Detection System, which integrates brain tumor classification and pneumonia detection into a unified deep learning framework using transfer learning and a common preprocessing pipeline.

IV. COMPARATIVE ANALYSIS AND IDENTIFIED RESEARCH GAPS

To systematically analyze the existing AI-based disease diagnosis techniques, a comparative taxonomy matrix is presented in Table I. The reviewed studies are evaluated based on six key parameters: target disease, predictive AI mechanism, performance metrics, dataset used, and research limitations. This comparison highlights the strengths and weaknesses of existing systems and identifies the research gaps addressed by the proposed AI-Based Multiple Disease Detection System.

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TABLE I: Taxonomy and Feature Matrix of Reviewed AI-Based Disease Detection Systems

Author Reference	Reviewed Target Disease	Predictive AI Mechanism	Performance Metrics	Dataset Used	Research Limitation
Rajpurkar et al. [1]	Pneumonia	DenseNet-121 (CNN)	Accuracy: 96.1%	Chest X-ray Dataset	Detects only pneumonia
Mohsen et al. [2]	Brain Tumor	CNN	Accuracy: 96.5%	Brain MRI Dataset	Limited to MRI images
Anil et al. [3]	Brain Tumor	ResNet50 + Transfer Learning	Accuracy: 98.0%	Brain MRI Dataset	Single disease prediction
Deepika et al. [4]	Pneumonia	MobileNetV2	Accuracy: 95.4%	Chest X-ray Dataset	Limited real-time deployment

A. *Core Architectural Research Gaps Identified*

1) Single Disease Detection Limitation: Existing AI-based diagnostic systems primarily focus on detecting a single disease, such as pneumonia or brain tumor. This limits their applicability in real-world healthcare environments where patients may require screening for multiple diseases using a unified platform.
2) Lack of Integrated Multi-Disease Framework: Most current research develops separate deep learning models for different diseases, resulting in increased computational resources, maintenance complexity, and reduced scalability. There is a lack of integrated architectures capable of diagnosing multiple diseases within a single system.
3) Limited Generalization and Dataset Dependency: Many existing models are trained and evaluated on a single medical imaging dataset, which reduces their ability to generalize across diverse patient populations and imaging conditions. This affects the robustness and reliability of disease prediction in practical clinical settings.
4) Scalability and Clinical Deployment Challenges: Current AI diagnostic systems often lack modular architectures for incorporating additional diseases and are not optimized for real-time deployment in hospitals or healthcare centers, Furthermore, limited clinical validation and interoperability reduce their practical adoption in medical diagnosis.

V. DISCUSSION AND FUTURE DIRECTIONS

The reviewed literature highlights the effectiveness of deep learning and transfer learning techniques in medical image analysis. Models such as CNN, VGG16, ResNet50, and DenseNet have demonstrated high accuracy in detecting brain tumors from MRI images and pneumonia from chest X-ray images. However, most existing studies focus on a single disease and lack a unified framework capable of performing multiple diagnostic tasks within a single platform. The proposed Multiple Disease Detection System addresses this limitation by integrating brain tumor classification and pneumonia detection into a unified framework. Future research can focus on incorporating additional diseases, applying Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM for better interpretability, and deploying the system on cloud and mobile platforms. These advancements can improve accessibility, scalability, and support faster clinical decision-making in healthcare environments.

VI. CONCLUSIONS

This survey paper reviewed various deep learning and transfer learning techniques used for brain tumor and pneumonia detection from medical images. The literature analysis indicates that CNN-based models such as VGG16, ResNet50, and DenseNet achieve high diagnostic accuracy and can effectively assist healthcare professionals in disease detection.

The study also identified the need for integrated multi-disease diagnostic systems. To address this gap, the proposed Multiple Disease Detection System combines brain tumor classification and pneumonia detection within a unified framework. Such a system can provide accurate, cost-effective, and automated diagnostic support, contributing to early disease detection and improved healthcare decision-making.

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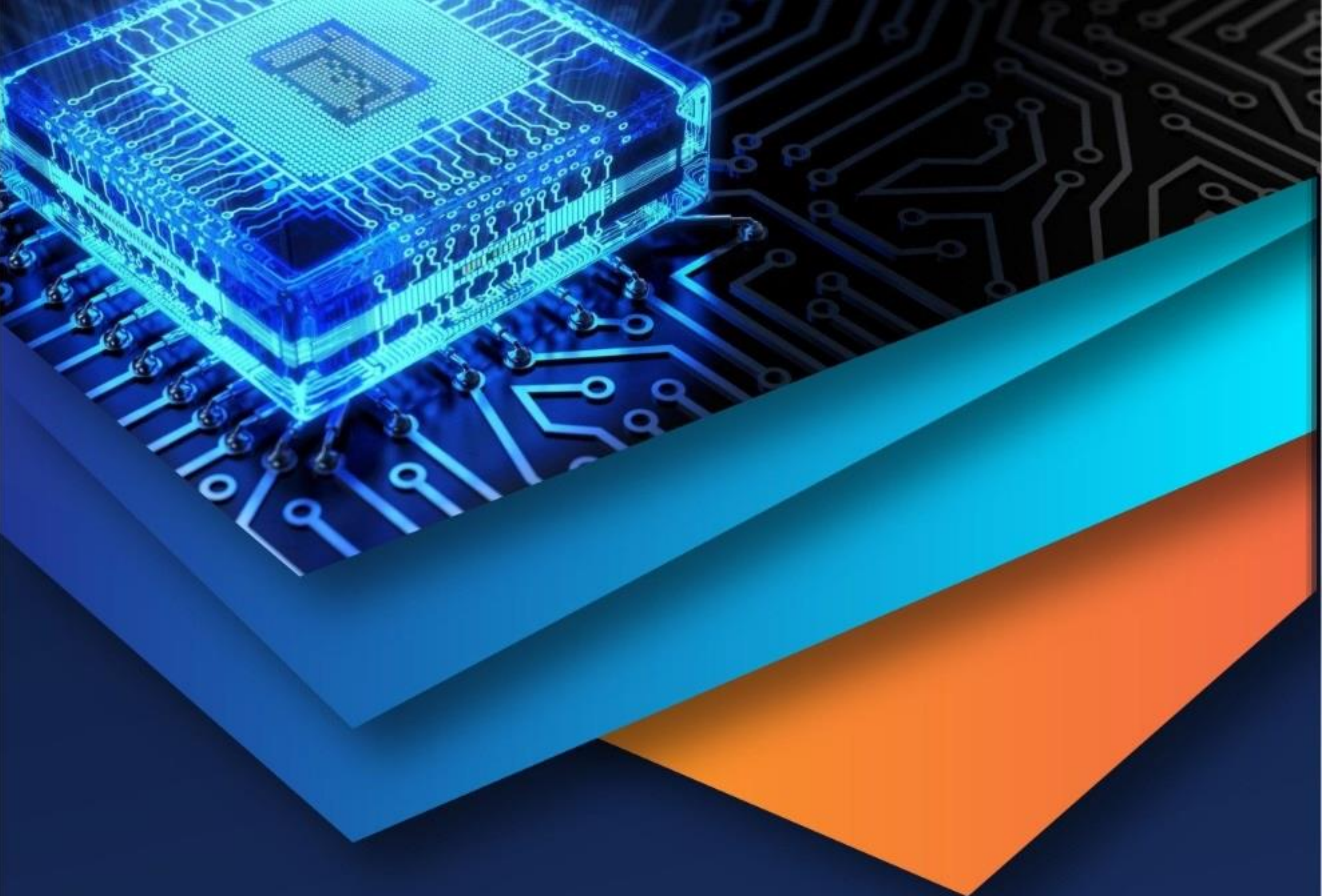

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