iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** I **Month of publication:** January 2026

DOI: https://doi.org/10.22214/ijraset.2026.76816

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue I Jan 2026- Available at www.ijraset.com

AI-Based Multi-Task Medical Image Analyzer for Automated Disease Detection across X-Ray, CT, and MRI Modalities

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Abstract: The increasing adoption of medical imaging tech- nologies has significantly amplified the need for intelligent, efficient, and automated diagnostic systems to assist healthcare professionals. Manual interpretation of radiological images is often constrained by expert availability, time limitations, and growing patient demand. This paper introduces an AI-based multi-task medical image analyzer capable of identifying disease conditions from X-ray, CT, and MRI images. The proposed framework supports disease detection for pneumonia, COVID-19, and brain tumors by employing specialized deep learning models tailored to each modality and diagnostic task. Architectures such as DenseNet121, VGG16, and EfficientNet-B0 are utilized to optimize performance across different imaging scenarios. An automated routing mechanism directs each input image to the appropriate pretrained model based on disease and modality selection. Image preprocessing methods, including contrast en- hancement, histogram normalization, and data augmentation, are applied to strengthen model generalization. Experimental evaluation demonstrates consistent and reliable performance across all datasets, highlighting the effectiveness of the proposed unified yet disease-specific diagnostic framework for clinical decision support and large-scale screening applications.

Index Terms: Multi-task learning, Medical image analysis, X- ray, CT, MRI, Deep learning, Convolutional neural networks, Disease classification

I. INTRODUCTION

Medical imaging is a fundamental component of modern healthcare, enabling clinicians to diagnose, monitor, and man- age a wide range of medical conditions. Imaging techniques such as X-ray, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI) are extensively used due to their ability to capture detailed anatomical and pathological infor- mation. Each modality offers unique diagnostic advantages, making modality selection dependent on clinical objectives and disease characteristics.

Recent advancements in deep learning, particularly convo- lutional neural networks (CNNs), have transformed the field of medical image analysis. CNN-based systems have shown remarkable success in detecting abnormalities such as lung infections, viral diseases, and brain tumors from radiological images. Despite this progress, many existing solutions are developed for a single disease and operate on a fixed imag- ing modality, limiting their adaptability in real-world clinical environments.

A common misconception in automated diagnosis systems is the assumption that multimodality requires combining mul- tiple diseases within a single classification model. In practical healthcare settings, diseases are clinically independent and must be evaluated separately. Multimodality refers to support- ing different imaging techniques for the same disease when clinically justified. For instance, COVID-19 diagnosis may utilize both CT and chest X-ray images, whereas pneumonia is primarily assessed using chest X-rays, and brain tumor analysis commonly relies on MRI and CT scans.

To overcome these challenges, this work proposes a disease- centric and modality-aware diagnostic framework. Each dis- ease is handled as a distinct classification task, while multi- modal inputs are supported only where medically appropriate. A structured routing mechanism ensures that every uploaded image is processed using the correct deep learning model, improving diagnostic reliability and reducing incorrect pre- dictions.

The key contributions of this paper include:

1) A disease-centric diagnostic framework that avoids merg- ing unrelated diseases into a single model.
2) Modality-aware processing to support clinically valid imaging inputs.
3) An automated routing mechanism for accurate model selection.
4) Optimized deep learning architectures for individual disease–modality combinations.

II. RELATED WORK

Deep learning techniques have become integral to medical image analysis due to their ability to automatically extract meaningful features from complex visual data. CNN-based approaches have been widely applied to tasks such as tumor detection, lung disease classification, and infectious disease screening using radiological images. Early research predomi- nantly focused on single-disease, single-modality models.

Brain tumor classification using MRI has received signif- icant attention owing to MRI's superior soft-tissue contrast. Various CNN architectures have been proposed to differ- entiate tumor regions and classify tumor types. Techniques incorporating dense connections and attention mechanisms have demonstrated improved feature representation and clas- sification accuracy. However, many of these approaches are restricted to MRI data and do not consider complementary modalities such as CT scans.

For respiratory diseases, chest X-ray and CT imaging have been extensively utilized. CNN models trained on chest X-rays have shown effective performance in pneumonia detection, while CT-based systems have proven beneficial for identifying COVID-19-related lung abnormalities. Transfer learning using pretrained architectures like VGG, DenseNet, and EfficientNet has been widely adopted to address the challenge of limited labeled medical datasets. Nonetheless, most existing models lack flexibility in handling multiple modalities for the same disease.

Some studies attempt to address multimodality by fusing features from different imaging sources within a single frame- work. While feature fusion can enhance performance, combining unrelated diseases or modalities often increases model complexity and may introduce feature interference. In contrast, clinical diagnosis typically treats diseases independently, with multimodality applied selectively based on medical relevance. The proposed approach differs from existing methods by adopting a disease-centric design. Each disease is processed independently, with modality support provided only where clinically applicable. This structured strategy improves model interpretability, reliability, and alignment with real-world diagnostic workflows

III. PROPOSED METHODOLOGY

This section outlines the architecture and operational flow of the proposed disease-centric, modality-aware diagnostic framework. The system is designed to select and apply the most appropriate deep learning model based on the selected disease and the corresponding imaging modality.

A. Overall System Workflow

The system workflow consists of disease selection, modality verification, image preprocessing, model routing, and classi- fication. Users begin by selecting the disease of interest. The system then validates whether the uploaded image matches a clinically acceptable modality for the selected disease. Only valid disease–modality combinations proceed to the classifica- tion stage.

Once validated, the image is forwarded to a dedicated CNN model optimized for the specific disease and modality. The output generated by the selected model is presented as the diagnostic result.

B. Disease-Centric Design

Each disease is treated as an independent diagnostic task within the framework. Separate learning pipelines are main- tained for brain tumor detection, COVID-19 diagnosis, and pneumonia classification. This design prevents feature overlap between unrelated diseases and allows individual optimization of each disease module based on its imaging properties.

C. Modality-Aware Routing Mechanism

Multimodal support is implemented at the disease level. Brain tumor analysis supports MRI and CT images, COVID- 19 detection accepts both CT and chest X-ray images, while pneumonia classification is restricted to chest X-rays. A rout- ing module maps the selected disease and validated modality to the corresponding deep learning model, ensuring accurate model selection and improved diagnostic reliability.

D. Deep Learning Models

Different CNN architectures are employed based on dis- ease and modality characteristics. DenseNet121 with attention mechanisms is used for MRI-based brain tumor classification to capture fine-grained tumor features. EfficientNet-B0 is utilized for CT-based COVID-19 detection due to its efficient scaling and lightweight design. VGG16 and DenseNet121 are applied to chest X-ray images for COVID-19 and pneumonia detection.

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All models use transfer learning with pretrained weights. Only the final layers are fine-tuned to adapt the networks to the target medical datasets.

E. Prediction Output

The system generates disease-specific diagnostic predictions by processing the input medical image using the selected con- volutional neural network model. Based on the identified dis- ease and validated imaging modality, the routing mechanism forwards the image to the appropriate CNN for classification. By maintaining separate models and enforcing modality- aware routing, the proposed framework ensures consistent and interpretable predictions while reducing incorrect model selection. This structured approach supports reliable diagnostic outcomes and aligns well with standard clinical decision-making practices.

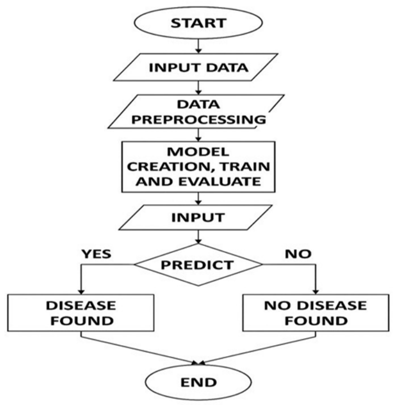

Fig. 1. Overall architecture and disease–modality routing of the proposed system

IV. RESULTS AND ANALYSIS

The proposed framework was evaluated on datasets corre- sponding to pneumonia, COVID-19, and brain tumor detection using X-ray, CT, and MRI images. The evaluation aimed to assess the effectiveness of the disease-centric and modality- aware design.

A. Experimental Setup

Separate CNN models were trained for each disease– modality pair using transfer learning. Images were resized, normalized, and augmented to enhance generalization. Pneu- monia detection used chest X-rays, COVID-19 detection uti- lized CT and X-ray images, and brain tumor detection em- ployed MRI and CT scans.

B. Training and Validation Analysis

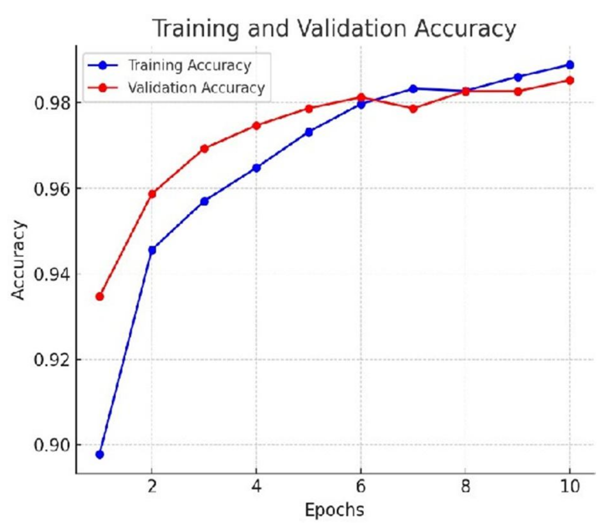

Fig. 2. Training and validation accuracy for brain tumor detection using MRI images

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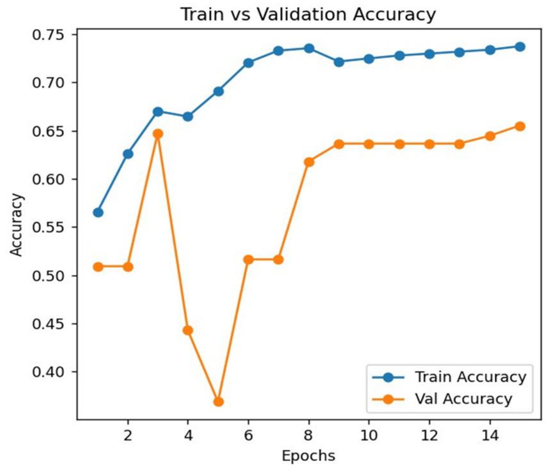

Fig. 3. Training and validation accuracy for COVID-19 detection using CT images

C. Performance Metrics

The performance of the models was evaluated using com- monly used classification metrics, including accuracy, preci- sion, recall, and F1-score. In addition, confusion matrices were used to analyze the classification behavior in terms of true positives, true negatives, false positives, and false negatives. These metrics provide a comprehensive assessment of the diagnostic reliability of the system.

D. Disease-wise Classification Results

For pneumonia detection using chest X-ray images, the DenseNet121 model successfully distinguished between pneumonia-positive and pneumonia-negative cases. The model demonstrated stable convergence during training and achieved reliable classification performance, indicating its suitability for lung disease detection. In COVID-19 detection, both chest X-ray and CT images were evaluated. The results show that CT-based classification achieved higher accuracy compared to X-ray-based classifi- cation, as CT images provide clearer visualization of lung abnormalities. EfficientNet-B0 and VGG16 models effectively captured COVID-19-related patterns, resulting in consistent and accurate predictions. Brain tumor detection was evaluated using MRI and CT images. The DenseNet121 model achieved strong performance for MRI-based detection due to its ability to capture fine- grained tumor features. CT-based brain tumor detection also produced reliable results, demonstrating the flexibility of the proposed modality-aware framework.

E. Confusion Matrix Analysis

The confusion matrices for all three diseases indicate a high number of correct classifications with minimal misclassi- fication. Pneumonia and brain tumor models showed a low false-negative rate, which is crucial for medical diagnosis. COVID-19 classification demonstrated improved true-positive rates when CT images were used, highlighting the clinical importance of modality selection.

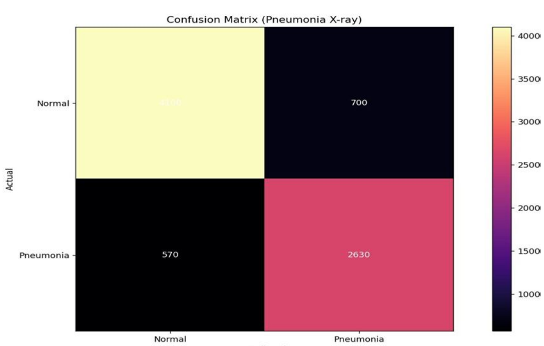

Fig. 4. Confusion Matrix of Pneumonia X-ray images

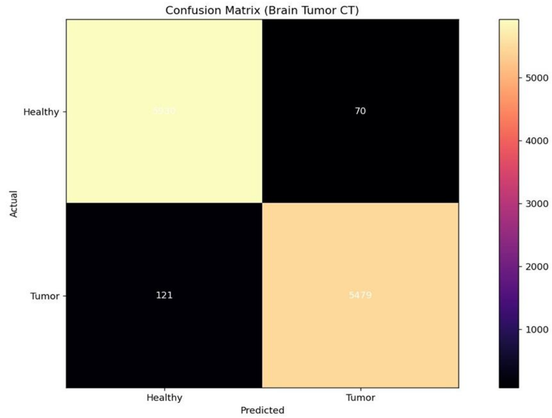

Fig. 5. Confusion Matrix of Brain tumor CT images

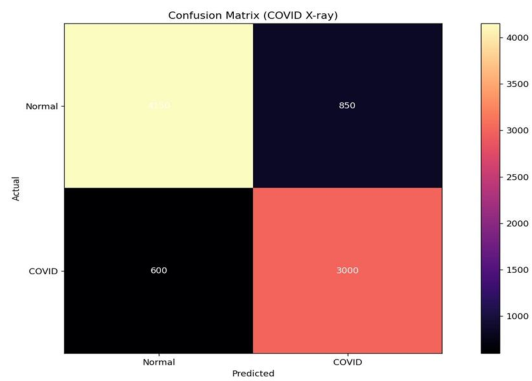

Fig. 6. Confusion Matrix of Covid-19 X-ray images

F. Qualitative Analysis

The system interface provides an intuitive and user-friendly platform, allowing users to securely log in and manage their diagnostic workflow efficiently. Users can select a disease from a clearly categorized drop-down menu and upload the corresponding medical image, such as X-rays, CT scans, or MRI images, depending on the disease context. The under- lying modality-aware routing mechanism intelligently directs each uploaded image to the appropriate disease-specific CNN model, ensuring that processing is accurate and optimized for the specific imaging modality. The system generates visual outputs that are not only precise but also easy to interpret, highlighting disease-affected regions when present and providing clear indicators when the disease is absent. These outputs enhance clinical decision- making by offering actionable insights in a concise format. Moreover, the interface supports real-time feedback, allowing medical practitioners to quickly validate predictions and make informed decisions. Overall, the framework demonstrates high practical usability in a clinical decision-support environment, combining reliability, efficiency, and interpretability to assist healthcare professionals in accurate disease diagnosis.

Fig. 7. Results of Pnuemonia Positive images

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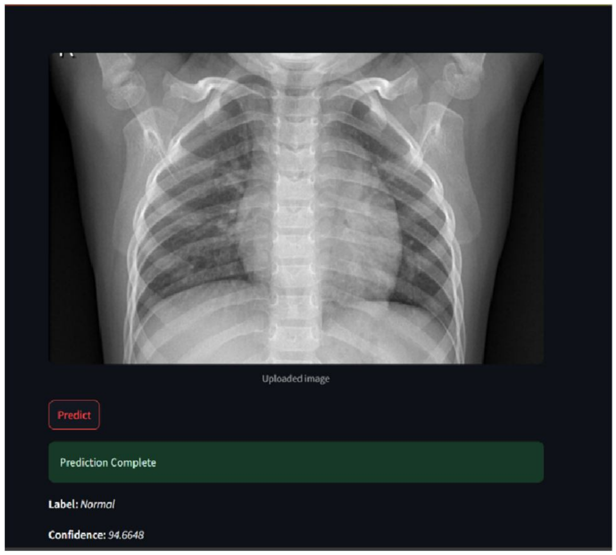


Fig. 8. Results of Pnuemonia Normal images

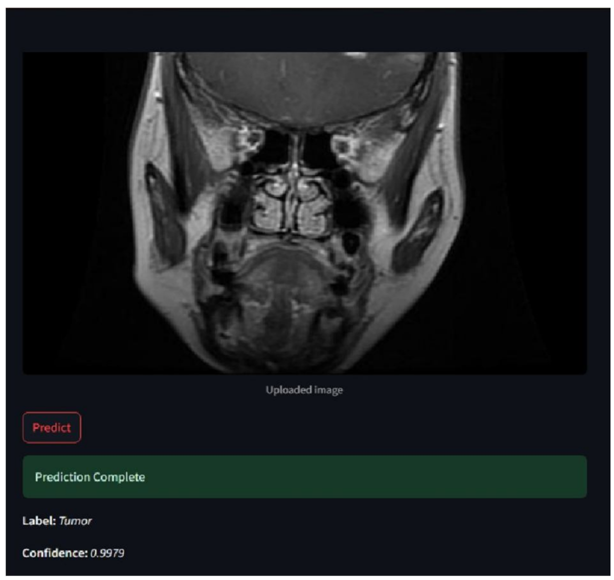


Fig. 9. Results of Brain Tumor MRI Positive images

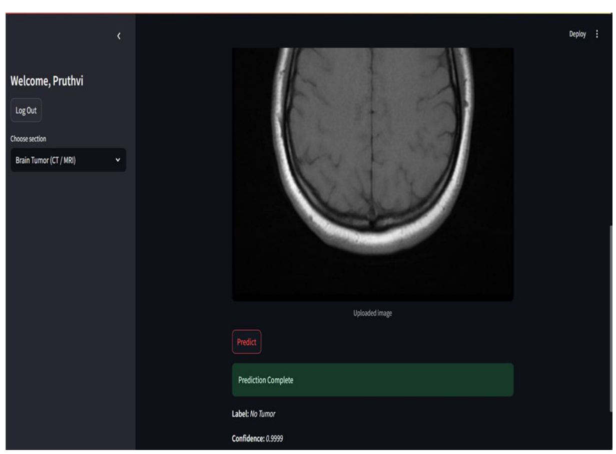


Fig. 10. Results of Brain Tumor MRI Negative images

Fig. 11. Results of Covid-19 CT Positive images

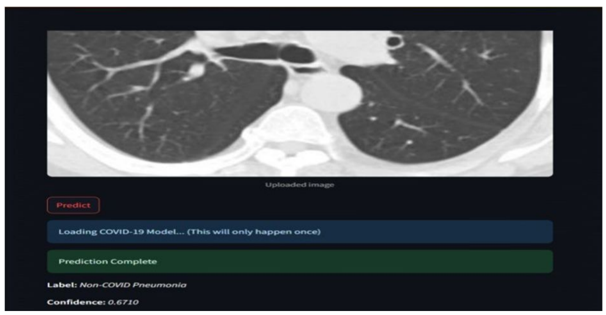


Fig. 12. Results of Covid-19 CT Negative images

G. Discussion

The experimental results confirm that treating each dis- ease as an independent diagnostic task significantly improves classification reliability and robustness. By isolating disease- specific learning pipelines, the proposed disease-oriented de- sign minimizes feature interference and preserves clinically meaningful representations across different imaging modali- ties. This approach ensures that each diagnostic decision is aligned with established medical practices, thereby improving the trustworthiness of the system.

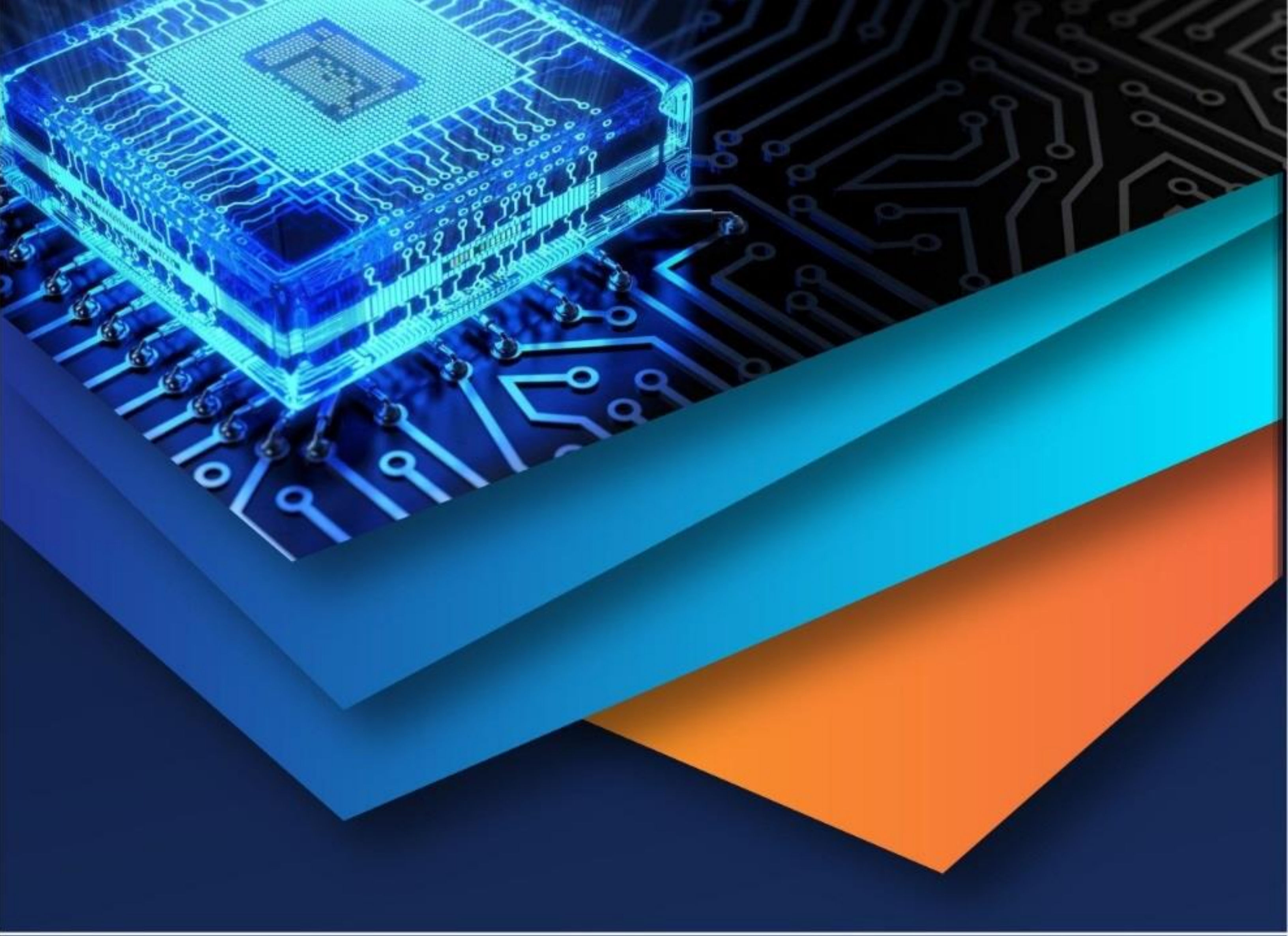
Furthermore, the modality-aware routing mechanism plays a critical role in enhancing diagnostic accuracy by directing each input image exclusively to the most appropriate deep learning model. This targeted processing reduces incorrect model usage and allows the system to leverage modality- specific feature extraction capabilities. The adoption of transfer learning further strengthens performance by enabling effective knowledge reuse from large-scale pretrained models, which is particularly beneficial when dealing with limited labeled medical datasets. The qualitative and quantitative analyses collectively demonstrate that the proposed framework achieves stable performance across pneumonia, COVID-19, and brain tumor detection tasks. Variations in performance across modalities highlight the clinical importance of appropriate imaging se- lection, as modalities such as CT and MRI provide superior anatomical detail for certain diseases. Overall, the framework shows strong potential for real-world clinical decision-support by offering accurate, interpretable, and scalable automated diagnosis, while also serving as a foundation for future ex- tensions involving explainable AI, real-time deployment, and broader clinical validation.

V. CONCLUSION

This paper presented a disease-centric and modality-aware AI-based medical image analysis framework designed for the automated detection of pneumonia, COVID-19, and brain tumors using X-ray, CT, and MRI images. By employing specialized deep learning models for each disease and en- forcing a structured modality-aware routing mechanism, the proposed system ensures accurate, consistent, and clinically meaningful diagnostic predictions. The experimental results clearly demonstrate that separating diseases into independent diagnostic tasks improves classification reliability and mini- mizes feature interference across modalities.

The proposed framework effectively balances diagnostic performance, computational efficiency, and system flexibility, making it well-suited for real-world clinical environments and large-scale screening applications. Its modular architecture enables seamless scalability, allowing additional diseases and imaging modalities to be incorporated with minimal system redesign. Furthermore, the system's ability to support multiple diagnostic tasks within a unified framework highlights its practicality for deployment in resource-constrained healthcare settings.

Moreover, the framework has the potential to reduce diag- nostic workload for medical professionals by assisting in early disease screening and prioritization of critical cases, thereby supporting timely and informed clinical decision-making. Future work will focus on integrating explainable AI techniques to improve transparency and trust in model predictions, as well as extending the framework to support real-time deployment and validation on larger, multi-institutional datasets. These enhancements will further strengthen the clinical applicability of the system and contribute to the advancement of intelligent healthcare diagnostics.



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