



A Review On Image Based Diagnosis Using ResNet-50

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Abstract: The use of advanced computer methods in medical imaging has indeed transformed how we diagnose and plan treatments for diseases. However, despite the progress in using advanced computer methods for medical imaging, there are still notable challenges to overcome in ensuring accurate diagnoses, particularly with complex imaging results. Traditional medical diagnostic methods, which rely on subjective interpretation, often result in diagnostic errors, impacting patient care quality. This study proposes an innovative approach to address the challenges that harnesses deep learning techniques for early image-based diagnosis. By incorporating deep learning techniques into medical imaging analysis, this study represents a crucial step towards overcoming the challenges associated with traditional diagnostic methods, ultimately benefiting both healthcare providers and patients.

Index Terms - Computer methods, deep learning techniques, medical imaging, patients

1. INTRODUCTION

In today's world, the landscape of medical diagnosis is continually evolving, driven by technological innovations that redefine the way healthcare professionals assess and treat patients. The domain of medical science is in a constant pursuit of innovative methodologies to enhance early identification and treatment of various health conditions. Timely identification and intervention play a important role in improving patient outcomes and expediting recovery processes. With this primary objective in mind, our research aims to harness the powerful capabilities of ResNet-50, an advanced Convolutional Neural Network (CNN) architecture, to enable early image-based diagnosis.

In various domains, including medical imaging analysis, deep learning has risen as a powerful tool. Its capacity to automatically learn and extract features from intricate datasets has revolutionized the field, enabling more accurate and efficient diagnosis of diseases. Fig 1. shows the general architecture of deep learning [1]. ResNet-50, in particular, has found widespread applications in image classification tasks, demonstrating superior performance in numerous medical image analyses such as tumour detection, disease classification, and anomaly detection. Its deep architecture enables the extraction of detailed features from medical images, facilitating more reliable identification and prognosis of patient outcomes.

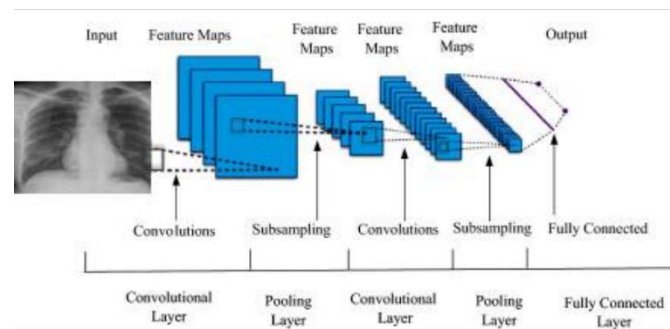


Fig 1. deep learning architecture

ResNet-50 stands out in the world of neural network for its innovative use of residual blocks, which allow it to delve deeper into layers without encountering the usual problems like vanishing gradients. It was introduced by Kaiming He et al. in the year 2015 [2]. By incorporating shortcut connections, ResNet-50 efficiently skips over unnecessary layers during both forward and backward passes, making training smoother and more effective [3]. Fig 2. shows the architecture diagram of ResNet-50 [3]. This architecture's prowess isn't limited to image recognition, it has made significant strides in various fields such as natural language processing, medical imaging, and autonomous vehicles. From improving disease detection in medical scans to enhancing object recognition in self-driving cars, ResNet-50's adaptability and robustness continue to redefine the boundaries of AI application.

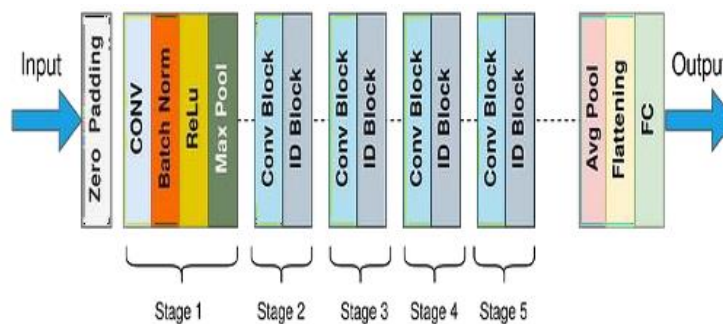


Fig 2. model architecture of ResNet-50

Our specific focus is on the early detection of medical conditions. To meet these challenges, our aim is to intricately tailored to analyze medical imaging modalities relevant to these conditions. To diagnose these conditions, medical professionals employ different imaging modalities tailored to specific needs. These modalities encompass Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-ray, and Electrocardiography (ECG).

- MRI excels at capturing detailed images soft tissues. MRI utilizes radio waves and strong magnetic fields to generate detailed images of internal body structures. It proves especially beneficial for examining soft tissues like the brain, spinal cord, muscles, and joints. MRI is often employed in diagnosing neurological disorders, musculoskeletal injuries, and certain cancers [4]. Fig 3. illustrates various examples of brain tumor MRI images [4].

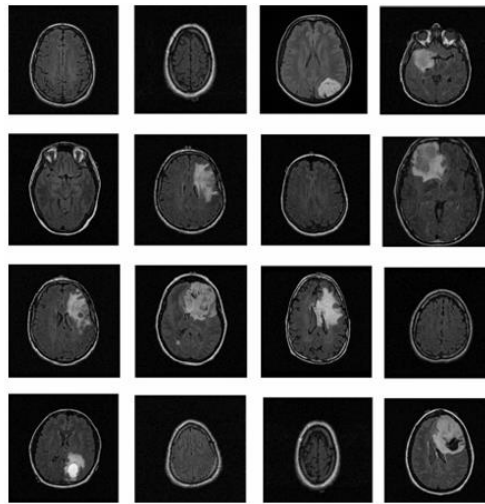


Fig 3: various examples of brain tumor MRI images

- CT provides three-dimensional X-ray images that help visualize internal structures. CT scans combine X-ray images captured from various angles to generate cross-sectional views throughout the body [5]. Fig 4. shows an example of CT scans and X-ray images of a particular person with and without disease [5]. This imaging modality provides detailed views of bones, organs, blood vessels, and tissues. CT scans are commonly used to diagnose conditions such as fractures, tumors, infections, and vascular diseases [6]. Fig 5. shows an example of CT scan of lungs.

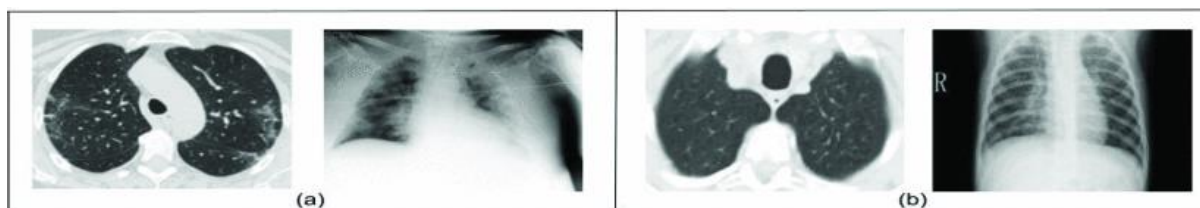


Fig 4 .the sample CT scan and X-Ray of (a) covid and (b) non-covid patients

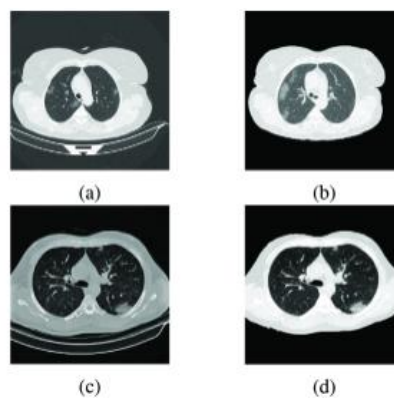


Fig 5. (a), (b): sample slices from COVIDx-CT dataset before and after preprocessing; (c), (d): sample slices from COVID-CT-MD dataset before and after preprocessing

- X-ray is particularly useful for revealing issues related to bones. It holds significant importance in the realm of diagnostic radiology, offering detailed perspectives on the skeletal system. It is particularly instrumental in identifying fractures, joint disorders, and other orthopaedic conditions. X-ray imaging involves passing a small amount of ionizing radiation through the body to produce images of internal structures [7]. An example of X-ray is shown in Fig 6. which shows Normal and Covid-19 detected X-ray images [7].

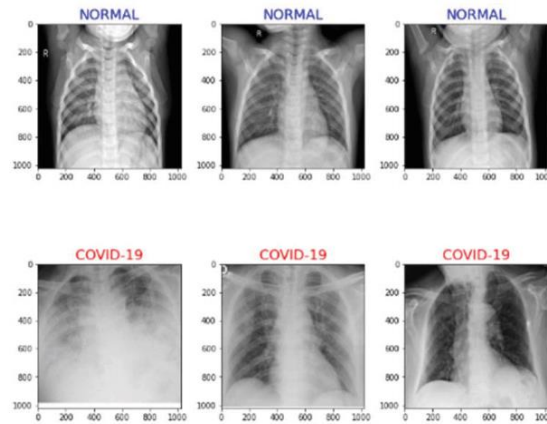


Fig 6. covid-19 and normal (non-covid-19) images

- ECG records the electrical activity of the heart, aiding in the diagnosis of heart conditions. Electrocardiography (ECG), is a fundamental tool in cardiology as it records the electrical activity of the heart, providing essential insights into cardiac health. ECG is crucial in diagnosing different heart conditions, such as arrhythmias, cardiac rhythm disorders, and heart attacks [8]. Fig 7: shows an example of samples of ECG heartbeat of 5 categories [8].

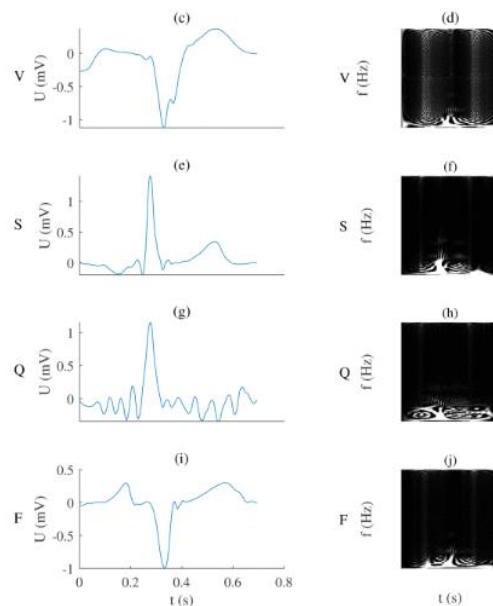


Fig 7: samples of ECG heartbeat of 5 categories of the ANSI/AAMI and their corresponding time-frequency diagrams generating by the HT-WVD method.

Through the integration of advanced deep learning techniques, particularly ResNet-50, into medical imaging analysis, our research strives to improve the precision and effectiveness of medical diagnosis. By automating the process and extracting complex attributes from medical images, our approach has the capability to notably decrease the workload for medical practitioners and improve patient care quality. Ultimately, our aim is to redefine healthcare standards, ushering in a new era of medical excellence characterized by faster and more effective patient recovery.

2. LITERATURE REVIEW

Image-based diagnosis approach is used in many applications like radiology, dermatology, and ophthalmology. With technological advancements, there has been significant progress in the field of medical diagnosis. Several approaches have been developed to diagnose diseases from medical images. An example of such a technique involves utilizing ResNet. ResNet-50, a powerful deep learning architecture, has revolutionized image analysis tasks. Let us consider an example, if a person is suffering from a disease such as brain tumor, ResNet-50 can analyze MRI scans with high accuracy, assisting clinicians in detecting and characterizing tumors in the brain, leading to timely intervention and treatment.

K. Munadi, K. Muchtar, N. Maulina, and B. Pradhan [9] explores the fusion of deep learning (DL) techniques with image enhancement methods for tuberculosis (TB) detection using chest X-ray (CXR) images. TB persists as a substantial global health concern, resulting in millions of deaths reported annually. DL has shown promise across diverse domains, encompassing medical imaging but its application to TB detection is still limited. The authors address this gap by investigating the impact of image enhancement on DL performance, an aspect that has not been extensively studied previously. The study assesses the efficacy of two image enhancement algorithms, namely Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF), on pre-trained DL models, specifically ResNet and EfficientNet. These algorithms aim to improve image quality by highlighting relevant features, particularly in low-contrast CXR images commonly associated with TB diagnosis. Fig 8. Showa the image comparison between original TB CXR, enhanced UM, and enhanced HEF images [9]. The research evaluates the accuracy of classification and the AUC (area under the curve) scores achieved by the DL models trained on enhanced image datasets. The results demonstrate competitive accuracy and AUC scores, indicating the efficacy of integrating image enhancement techniques with DL for TB detection.

Z. -J. Xu, R. -F. Wang, J. Wang, and D. -H. Yu [10] introduces a method for Parkinson's Disease (PD) detection using voiceprints, focusing on augmentation techniques to tackle the scarcity of patient data. They propose a S-DCGAN to generate high-resolution spectrograms, to enhance the quality of image and stability through advanced techniques like feature matching and Spectral Normalization (SN). Fig 9 shows the generation process of spectrogram.[10]. These spectrograms are subsequently employed to enhance the accuracy of voiceprint recognition models. The study evaluates the performance of the model S-DCGAN and ResNet50 classifier, achieving superior recognition accuracy compared to traditional methods. The results demonstrate the effectiveness of augmenting samples in improving PD detection accuracy, offering promising implications for diagnosing medical conditions using voiceprints.

In their study, **N. S. Ismail and C. Sovuthy** [11] address the critical issue of breast cancer detection, particularly prevalent among Malaysian women. They assess the performance of two deep learning models, VGG16 and ResNet50, in distinguishing between normal and abnormal breast tumors using the IRMA dataset. Highlighting the significance of timely identification in reducing mortality rates, the authors underscore the necessity for enhanced screening practices, especially with the increasing number of breast cancer cases due to an aging population. These findings highlight the capability of deep learning techniques in improving breast cancer detection, with potential benefits for enhancing patient outcomes and mitigating mortality rates linked to this widespread disease. The study provides valuable insights into utilizing deep learning for breast cancer detection, illuminating the potential of advanced technology to tackle urgent healthcare challenges. The authors' findings not only emphasize the effectiveness of deep learning models in categorizing breast tumors but also underscore the importance of ongoing research to enhance screening practices and ultimately enhance patient care. With breast cancer continuing to be a major global public health issue, the study emphasizes the significance of employing innovative methods for early detection, with the ultimate goal of preserving lives and enhancing the standard of care for affected individuals.

S. Nayak, S. Kumar, and M. Jangid [12] addresses the significant global health challenge of malaria, which affects approximately 200 million individuals and causes over 400,000 fatalities annually. The paper discusses the role of modern information technology in combating malaria and emphasizes the necessity for enhanced diagnostic techniques to reduce mortality. The focus of the paper is on microscopic malaria detection, and the authors explore the utilization of deep learning for detecting the malaria parasite. Deep learning is highlighted for its speed and accuracy in automating feature extraction from datasets. The research investigates various deep learning models to determine which ones provide better accuracy and faster resolution compared to previously used models. The findings demonstrate that the ResNet 50 model attained the highest accuracy, reaching 0.975504. The paper highlights the potential of deep learning, particularly the ResNet 50 model, to enhance both the efficiency and accuracy of malaria detection, thereby contributing to enhanced diagnostic capabilities for addressing this global health challenge.

In light of the COVID-19 outbreak, **Mohamed Loey et al.** [13] proposed a model for detecting medical face masks in real-life images, with a focus on preventing the spread of COVID-19. The model incorporates two elements: the initial one focuses on feature extraction utilizing the ResNet-50 deep transfer learning model, and the second for detecting medical face masks using YOLO v2. Two medical datasets of face mask were combined for investigation, and the average IoU (Intersection over Union) was used to optimize the process of detection of objects. The proposed model concludes that it has potential applications in public areas to enhance COVID-19 prevention measures.

Swapnil Rajguru et al. [14] investigates automated algorithmic techniques for early-stage lung cancer detection using CT scans images, aiming for enhancing survival rates through prompt diagnosis. Lung cancer, responsible for the highest mortality rates globally, demands accurate and timely detection strategies to mitigate its high fatality rates. Various datasets are analyzed, and the detection process involves image pre-processing, segmentation, feature extraction, and neural system identification. Among the approaches, ResNet-50 transfer learning is notable for its ability to enhance accuracy, leveraging its success in other medical diagnostic systems. The study underscores emphasizing the utilization of sophisticated technology such as deep learning to aid in detecting lung cancer and emphasizes the capability of ResNet-50 in achieving higher accuracy rates, potentially reaching 95%. This research presents a significant step towards improving the identification and prediction of lung cancer, offering promising avenues for early detection and care.

T. A. Youssef et al. [15] introduced ResNetChest, a novel deep learning architecture aimed at automating pneumonia diagnosis through chest X-ray image analysis. Pneumonia remains a significant contributor to global mortality rates, particularly affecting pediatric populations, necessitating efficient and accurate diagnostic tools. Leveraging the ResNet50 model as its backbone, ResNetChest incorporates various layers and techniques such as batch normalization, utilizing convolutional layers, dropout techniques, dense layers, and regularization methods, and offline data augmentation to enhance its diagnostic capabilities. Through rigorous experimentation, ResNetChest achieves an impressive accuracy exceeding 97.65% in classifying chest X-ray images as normal or indicating pneumonia, demonstrating its potential by providing a valuable resource for healthcare professionals in improving timely detection and management of this life-threatening disease.

O. El Ariss and K. Hu [16] proposed a novel approach for Parkinson's Disease (PD) diagnosis, utilizing ResNet50 and converting frequency-domain features from speech recordings into 2-D heat maps. Achieving an impressive accuracy of 93.4% with Tunable Q-Factor Wavelet Transform (TQWT) features, the method surpasses traditional diagnostic techniques, offering a fast, accurate, and non-invasive means of identifying PD patients. This innovative strategy presents a promising avenue for enhancing early detection and management of PD, representing a significant advancement in neurodegenerative disease diagnosis.

While both focused on Parkinson's Disease (PD) detection, employ different methodologies and techniques. Xu et al. [10] utilized S-DCGAN for sample augmentation, enhancing the dataset's size and quality, ultimately improving PD detection accuracy. On the other hand, El Ariss and Hu [16] leverage ResNet50 to process frequency-domain features from speech recordings, converting them into 2-D heat maps for diagnosis. While both methods achieve notable accuracies (Xu et al. achieving superior recognition accuracy compared to traditional methods and El Ariss and Hu achieving an impressive 93.4% accuracy with TQWT features), they differ in their approaches to data augmentation and feature extraction. Xu et al. focus on generating high-resolution spectrograms to enhance the dataset, whereas El Ariss and Hu focus on transforming frequency-domain features into heat maps. These distinct approaches highlight the versatility and effectiveness of different techniques in improving PD detection accuracy and offer complementary insights into advancing medical diagnosis using voiceprints and speech recordings.

These differing methodologies showcase the effectiveness of diverse techniques in improving disease detection rates and ultimately facilitating early intervention, leading to faster recovery rates and improved patient outcomes.

3. COMPARATIVE ANALYSIS

The utilization of deep learning methodologies in medical imaging has revolutionized disease diagnosis and treatment. This comparative study thoroughly examines diverse array of algorithms and techniques employed for the identification and categorization of various medical conditions. From the adoption of convolutional neural networks (CNNs) to innovative approaches like transfer learning and ensemble models, each study provides distinctive perspectives into the intersection of deep learning and healthcare.

S.No	Author	Title	Algorithms and Techniques used	Merits	Demerits
1	S. Jiang, H. Li and Z. Jin [17]	A Visually Interpretable Deep Learning Framework for Histopathological Image-Based Skin Cancer Diagnosis	Deep Residual Attention Network (DRANet), Data Augmentation, CAM (Class Activation Mapping), Filter Response Normalization (FRN), Comparison with baseline models and state-of-the-art image classification models, Evaluation using precision, recall, F1 score, and ROC curves	Achieved competitive accuracy with fewer parameters, Enhanced interpretability	Requires a large dataset for training and testing, Computational complexity may be higher compared to simpler models
2.	P. Ghadekar, A. Khandelwal, P. Roy, A. Gawas and C. Joshi [18]	Histopathological Cancer Detection using Deep Learning	Transfer Learning, Convolutional Neural Networks (CNNs), Classification	Improved accuracy and performance compared to manual histopathological image analysis	Dependency on large, labeled datasets for training, Potential biases in the dataset affecting model performance
3.	S. H. Abboud, H. N. A. Hamed, M. S. M. Rahim, A. Rehman, T. Saba and S. A. Bahaj [19]	Hybrid Retinal Image Enhancement Algorithm for Diabetic Retinopathy Diagnostic Using Deep Learning Model.	Gaussian blur, contrast enhancement, circular crop, ResNet50 deep learning model	Significant improvement in classification accuracy, utilizes both traditional image processing techniques and deep learning models,	Parameter dependency in the enhancement model, Difficulty in detecting certain diabetic retinopathy features,

				Addresses the need for improved image quality in diabetic retinopathy diagnosis	Illumination issues not fully addressed, Limited to grayscale fundus images, Training time for the deep learning model may be lengthy
4.	S. V. Militante, N. V. Dionisio and B. G. Sibbaluca [20]	Pneumonia Detection through Adaptive Deep Learning Models of Convolutional Neural Networks	Deep Convolutional Neural Network Architecture	Flexible and efficient approaches are used, Six CNN models utilized for prediction and recognition, high accuracy rates achieved for some models	Limited information on dataset characteristics, Results may not be reproducible without dataset details
5	M. M. Shukla, B. K. Tripathi, M. Nagle and B. K. Chaurasia [21]	COVID-19 & Lung Disease Detection using Deep Learning	CNN model, ResNet50, VGG 19, Chest X-ray	Proposes a deep learning method for COVID-19 detection using chest X-ray reports, Utilizes CNN models like ResNet50 and VGG 19 for classification, achieves high accuracy (99.3%) in detecting COVID-19 cases, analyses efficacy in terms of accuracy, specificity, sensitivity, and precision.	Limited discussion on the dataset used for training and testing the model, Potential biases or limitations in the dataset may affect the generalizability of the model, Lack of discussion on computational resources required for training the deep learning models.
6.	D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal [22]	Pneumonia Detection Using CNN based Feature Extraction	Deep Learning (Convolutional Neural Networks - CNNs), Transfer Learning, Pre-trained CNN models (AlexNet, VGGNet, Xception, ResNet, DenseNet), Supervised Classifier	Comparative analytical study of pre-trained CNN models, Presentation of models with different classifiers, Evaluation of optimal model with hyperparameter tuning	Lack of patient history in evaluation, Use of only frontal chest X-rays, High computational power required for the model

			Algorithms (Random Forest, Support Vector Machine, Naive Bayes, K-nearest neighbours)		
7.	A. Gupta, M. Padsala and P. Saikia [23]	Detection of Pneumonia from Chest X-Ray Images Using Transfer Learning on Deep CNN	Transfer Learning, Convolutional Neural Networks (CNNs), MobileNet	Proposed method employs transfer learning techniques on CNNs (specifically MobileNet), which demonstrated superior performance compared to traditional methods, Addresses the challenge of accurate pneumonia diagnosis from X-ray images	-
8.	P. Garg, R. Ranjan, K. Upadhyay, M. Agrawal and D. Deepak [24]	Multi-Scale Residual Network for Covid-19 Diagnosis Using Ct-Scans	ResNet50, Ensemble Learning, Data Augmentation, t-SNE, Grad-CAM	Achieves an accuracy of 94.9% and sensitivity of 100%, 89.47%, and 94.55% for Normal, CAP, and COVID-19 patients respectively on the validation set, uses multi-scale feature extraction to detect different dimensions of infection, implements a three-level classifier to enhance robustness.	Some manual pre-processing steps required for cleaning raw images, Complexity may hinder implementation in resource, constrained environments, may require large computational resources for training and inference due to ensemble learning and multi-level training.
9.	D. S, L. Padma Suresh and A. John [25]	A Deep Transfer Learning framework for Multi Class Brain Tumor Classification using MRI	Transfer Learning, Deep Learning, ResNet 50,	Achieved a maximum accuracy of 98.67%, Utilized transfer learning on ResNet 50 for feature	Utilization of pre-trained deep network (ResNet 50) might lead to limitations in fine-tuning for

				extraction and classification	specific dataset characteristics
10.	V. Chetan Reddy, V. Naveen Kumar, Y. Padma Sai, G. Spurthi and A. Mahesh [26]	Multi-Classification of Respiratory Diseases using Deep Learning	Deep Learning, Convolution Neural Net; ResNet50	Achieved 98.45% accuracy in classifying pneumonia, tuberculosis, and COVID-19, Potential to improve diagnostic process, more accurate and efficient treatment options for patients	Limited generalizability
11.	Z. Zheng, H. Zhang, X. Li, S. Liu and Y. Teng [27]	ResNet-Based Model for Cancer Detection	Deep learning, Convolutional Neural Network (CNN), ResNet, Test Time Augmentation	Achieved state-of-the-art performance in metastatic cancer detection, Improved accuracy with Test Time Augmentation	Specific limitations or biases of the ResNet-based model not discussed, Potential computational complexity of deep learning models may be a limitation for deployment in resource, constrained settings
12.	M. Chhabra and R. Kumar [28]	An Efficient ResNet-50 based Intelligent Deep Learning Model to Predict Pneumonia from Medical Images	Deep Learning, Transfer learning, Data Augmentation, Fine-tuning, ResNet-50	Achieved 96.6% accuracy, Better than recent literature work, Screening test for pneumonia diagnosis	-
13.	P. Singh, M. Kumar and A. Bhatia [29]	A Comparative Analysis of Deep Learning Algorithms for Skin Cancer Detection	CNN, RNN, ResNet50, Xception	High accuracy results	Limited comparison between algorithms with real-world application
14	S. Rathore, T. Rana, U. Mittal, T. Gupta, N. Malik and M. S. A S [30]	Brain Tumor Detection by using ResNet-50 and Image Processing Tools	MRI, Image processing, Computational modeling, Transfer learning, Computer architecture, Artificial neural networks,	High Accuracy, Transfer Learning, Efficiency	-

			Brain modeling, CNN		
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4. CONCLUSION

In conclusion, the application of ResNet-50 in image-based diagnosis marks a significant stride in the realm of medical science. By leveraging deep learning techniques, particularly ResNet-50's proficiency in image analysis tasks, this study shows an innovative approach to automate and enhance the accuracy of medical diagnosis. The literature review underscores ResNet-50's pivotal role in various medical imaging applications, ranging from tuberculosis detection to malaria diagnosis. Through rigorous evaluation using diverse datasets, the robustness and precision of ResNet-50 in accurately detecting various medical conditions have been showcased. This study not only adds to the advancement of automated medical diagnosis systems but also holds the potential to alleviate the workload for healthcare professionals while improving patient care quality. By integrating ResNet-50 and deep learning techniques into medical imaging analysis, this study represents a crucial step towards overcoming the challenges associated with traditional diagnostic methods. Moving forward, continued exploration and refinement of ResNet-50's capabilities in medical imaging analysis will further enhance the accuracy and efficiency of diagnostic processes. Ultimately, this research aims to redefine healthcare standards, ushering in a new era of medical excellence characterized by faster and more effective patient recovery.

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