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Research Article

Medical Image Identification System Using Convolutional Neural Networks for Digital Radiology-Based Disease Diagnosis

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Abstract: Medical imaging is one of the primary tools in disease diagnosis, but the manual process is often hindered by human factors such as fatigue, cognitive bias, and observational limitations. This study aims to explore the use of a pretrained Convolutional Neural Network (CNN) model, ResNet50, to improve diagnostic accuracy in medical imaging. ResNet50 was selected due to its efficient architecture, which addresses the vanishing gradient problem through the use of skip connections, making it ideal for complex medical image classification tasks. The dataset used includes medical images from various open-source datasets, including chest X-rays, brain MRIs, and retinal histopathology images, which were preprocessed using image normalization and augmentation techniques to enhance data quality. The model was trained with hyperparameters such as a learning rate of 0.001 and batch size of 32, over 50 epochs using the Adam optimizer. The results showed that the model achieved 95% accuracy, with 99% precision and 98% recall in detecting pneumonia from chest X-rays, and 95.44% accuracy in classifying brain tumors. While the model showed excellent performance, challenges such as varying data quality, limited computational resources, and potential overfitting remain. This study demonstrates the significant potential of AI in medical imaging to reduce human diagnostic errors, with promising prospects for wider implementation in clinics and hospitals. However, broader adoption requires integration with clinical workflows and training for healthcare professionals on the use of AI-based systems.

Keywords: Convolutional Neural Network; Diagnostic Accuracy; Medical Imaging; Pneumonia Detection; ResNet50 Model.

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1. Introduction

Manual radiology plays a critical role in modern medical diagnostics, but it is plagued with challenges that affect diagnostic accuracy. Human factors such as fatigue, inexperience, and inconsistency are among the primary causes of diagnostic errors in radiology. Studies have demonstrated that fatigue can significantly impair radiologists' ability to function effectively, leading to false negatives and other inaccuracies in diagnosis [1],[2]. Additionally, cognitive biases and environmental distractions exacerbate these issues, resulting in perceptual and interpretive errors that compromise the reliability of diagnoses [3],[4]. Despite advancements in imaging technology, the incidence of radiologic errors has remained largely unchanged since the 1960s, underscoring the persistent nature of human factors in diagnostic practice [5]. These errors not only undermine patient outcomes but also contribute to medical malpractice claims against radiologists [6].

To address these challenges, there has been a growing interest in incorporating artificial intelligence (AI) to enhance the accuracy of medical image diagnosis, particularly through Convolutional Neural Networks (CNNs). CNNs are a class of deep learning models that automate feature extraction and categorization from medical images, making it possible to detect conditions such as cancer, cardiovascular diseases, and neurological disorders more accurately and efficiently than manual methods [7],[8]. AI-based systems utilizing CNNs have shown significant promise in improving diagnostic accuracy, enabling the detection of subtle findings that are often overlooked by human radiologists. This has been shown to reduce both false positives and false negatives in medical diagnoses, thereby enhancing the overall diagnostic process [7],[9].

The integration of AI into medical imaging, particularly for X-ray and MRI scans, has led to significant improvements in diagnostic precision. AI-driven systems using CNNs have achieved diagnostic accuracy rates exceeding 95%, surpassing traditional manual methods [10],[11]. These AI models not only enhance the clarity of medical images by reducing noise and artifacts but also operate in real-time, making them suitable for clinical applications where rapid decision-making is essential. For example, CNN-based models have been successfully applied to diagnose respiratory diseases from chest X-rays and have proven particularly effective in the rapid identification of COVID-19 [12],[13].

In digital radiology, AI systems leveraging CNNs have emerged as powerful tools for clinical decision support, aiding radiologists in improving diagnostic accuracy. Research has shown that radiology residents' performance can be significantly enhanced when assisted by AI, with diagnostic accuracy approaching the level of subspecialists [14]. AI models can process large datasets, ensuring that the diagnostic system remains robust and generalizable across a wide range of imaging modalities. However, challenges such as scalability, data protection, and clinical acceptance still persist, requiring ongoing efforts in model optimization and collaboration across medical and technical disciplines [7],[10],[15].

The application of pre-trained Convolutional Neural Network (CNN) models in medical imaging has revolutionized the way diseases are diagnosed, primarily through the use of the ResNet50 model. The ResNet50 model is known for its robust architecture, which includes a jump connection to address gradient loss issues, making it highly effective in image classification tasks, including in a wide range of medical imaging applications. This model, which has been trained on large datasets such as ImageNet, allows ResNet50 to serve as a reliable feature extractor for a wide range of medical imaging tasks. This article aims to explore the potential of ResNet50 in improving diagnostic accuracy and efficiency in medical imaging, particularly in the context of digital radiology images.

ResNet50 has been shown to be effective in a wide range of medical imaging applications. The model is used in the classification of retinal diseases, such as age-related macular degeneration and diabetic retinopathy, and achieves an accuracy of more than 90% in training and validation sets, demonstrating its strong ability in generalization for the detection of retinal diseases [16]. In the detection of brain tumors using MRI and CT images, ResNet50 achieved an accuracy of 95.59%, improving diagnostic precision and contributing to better patient outcomes [17]. For the detection of tuberculosis (TB) in chest X-rays, ResNet50 outperforms other models with 93% accuracy, which confirms its potential in the early detection of TB, crucial in the prevention of disease spread [18].

In addition, ResNet50 has been used in the detection of COVID-19 and pneumonia from chest radiographs, with a 99.5% accuracy for the detection of COVID-19, proving its usefulness in rapid and accurate diagnosis [19]. For breast cancer detection using histopathological images, ResNet50 achieves a ROC-AUC of 0.84413, which indicates its potential to assist pathologists in early detection of cancer [20]. In applications in gastrointestinal diseases, ResNet50 has outperformed other CNN architectures in diagnosing conditions through endoscopic images, demonstrating significant potential in clinical applications [21]. In the diagnosis of chronic obstructive pulmonary disease (COPD) via chest X-ray, ResNet50 shows a slight advantage in accuracy and computational efficiency compared to other models, improving diagnostic reliability [22].

The main advantage of using a pre-trained model such as ResNet50 is the reduction in the need for large training data and intensive computing resources, which makes it applicable in a variety of medical settings without the need for extensive retraining [23]. In addition, ResNet50 consistently provides high accuracy across a wide range of diseases and imaging modalities, improving the reliability of medical diagnoses [16],[17],[18],[19],[20],[21],[22]. This model also allows for faster diagnosis compared to traditional methods, which is important for timely medical intervention [17],[18],[22].

2. Literature Review

Traditional radiology plays an important role in detecting diseases by confirming or eliminating existing disease hypotheses. This process begins with the doctor requesting diagnostic imaging, the technologist capturing the image, and the radiologist analyzing the image to produce a report that guides treatment decisions [24]. Conventional diagnostic imaging such as X-rays, barium studies, and MRI play a large role in diagnosing a variety of conditions, including gastrointestinal disease and juvenile idiopathic arthritis (JIA). This imaging modality is helpful in detecting and monitoring structural changes, growth disorders, and disease progression [25],[8]. Radiology is also part of a modern interdisciplinary team that works closely with clinical evaluation to provide comprehensive patient care [25]. The role of radiologists has evolved not only in image interpretation, but also includes economic surveillance, delivery of public health services, and improving the quality of care [26].

Diagnostic errors in radiology often arise due to human factors, which include perception, interpretation, and communication. Environmental disorders, cognitive bias, and fatigue are the main factors causing these diagnostic errors [27],[28],[29]. Anatomical complexity and subtle imaging findings, as well as cognitive biases such as over-reliance on previous reports and premature conclusions, also play a role in the occurrence of errors [30],[31]. In emergency settings, high image volumes and critical decisions that need to be made in a limited time increase the risk of errors [32]. Systemic problems also contribute to errors, such as failures in information collection, aggregation, and distribution. These errors can occur at any point in the imaging treatment process, from the initial consideration of imaging to the integration of the final result [33].

Diagnostic errors can lead to missed or incorrect diagnoses, which can result in significant losses for patients. In emergency and trauma care, missed diagnoses, such as fractures, can have severe consequences [32],[34]. In addition, errors in diagnostic radiology, particularly in subspecialties such as breast imaging, have a high legal risk and can damage professional relationships as well as reduce patient trust [28],[35].

To reduce errors, it is important to implement a structured reasoning process, active hypothesis testing, and continuing education. Fostering a culture of collaborative learning and non-punitive peer feedback is also needed in mitigating these errors. The integration of advanced technologies, including algorithms and artificial intelligence (AI), can also improve diagnostic accuracy and streamline workflows. AI can help predict long-term outcomes as well as identify subtle findings that may be missed by human observers [30]. In addition, improving the human factor by optimizing the work environment, reducing distractions and interruptions, can improve the accuracy in diagnosing medical images [27].

Artificial intelligence (AI), specifically convolutional neural networks (CNNs), is playing an increasingly important role in the transformation of the medical world, particularly in the analysis of medical images. CNN is a type of deep learning model that is highly effective in computer vision tasks, which makes it particularly useful in the analysis of medical images [36],[37],[38],[39]. This neural network has proven to be particularly useful in various medical fields, such as radiology, histopathology, and medical photography, by automating the assessment of medical conditions such as pneumonia, pulmonary embolism, and rectal cancer [36].

In radiology, CNN has been used to detect lung diseases such as pneumonia and COVID-19 with very high accuracy, reaching 97% in some studies [37],[38]. In the field of histopathology, CNN helps in classifying colorectal polyps and gastric epithelial tumors, while in medical photography, these tissues are used to assess retinal diseases and skin conditions [36]. The integration of CNN in medical image analysis promises to improve diagnostic accuracy, workflow efficiency, and provide wider access to expert-level image analysis, which can ultimately improve patient outcomes [36],[39],[40].

Many previous studies have examined the use of CNN in the identification of medical images, focusing on the methodology and results obtained. One study developed a CNN model to classify X-ray images of the lungs into categories such as healthy, viral pneumonia, and bacterial pneumonia, resulting in an accuracy of 97%, demonstrating CNN's potential in improving diagnostic accuracy for lung disease [37].

Another study focused on the detection of pneumonia using CNN models trained on more than 5,000 X-ray images. The model achieved 99% accuracy, 98% accuracy, and 98% recall, demonstrating the effectiveness of CNN in the early and accurate detection of pneumonia [38]. In the brain tumor classification study, CNN successfully classified brain images into categories such as normal, glioma, meningioma, and pituitary tumors with 95.44% accuracy [41]. Another study proposed a deep learning model combined with Graph Neural Networks (GNN) to improve classification performance, which achieved an accuracy of 93.68% [42].

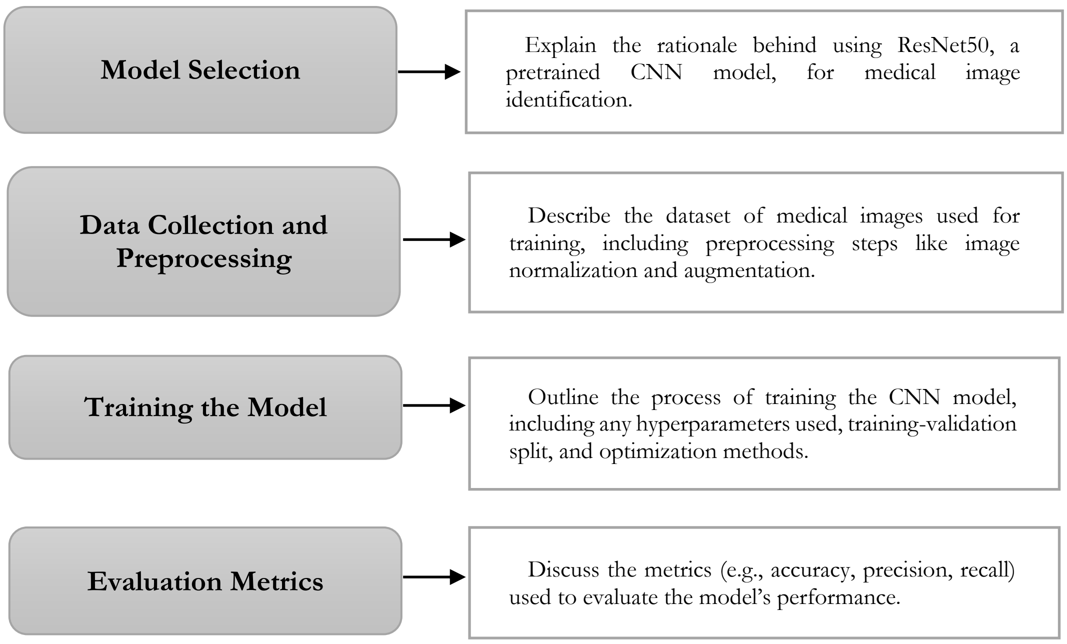
In the comparative study, various CNN architectures such as VGG16, VGG19, and traditional CNNs for brain tumor classification were tested, with VGG19 showing better test accuracy than other models, confirming the importance of using advanced neural network architectures for more precise diagnosis [43]. The use of 3D CNN to process and classify multidimensional images has also shown significant improvements in the accuracy and efficiency of medical image analysis, especially in pathological tissue segmentation [44].

Despite many successes that have been achieved, there are various challenges that must be faced, such as data quality, model interpretability, and ethical considerations that need to be considered in the use of AI in the medical field. Therefore, future research directions will focus on the development of more explainable AI models, multimodal data integration, as well as improved computational efficiency to facilitate wider clinical adoption [39],[45],[46],[47].

3. Research Method

The model used in this study is ResNet50, a pretrained Convolutional Neural Network (CNN). ResNet50 was chosen for its efficient architecture, with skip connections that address the vanishing gradient problem, making it highly effective in feature extraction for medical images such as X-rays, MRIs, and histopathology. The dataset used consists of medical images for conditions such as pneumonia, brain tumors, and retinal diseases, collected from open sources. These images undergo image normalization for pixel consistency and image augmentation (such as rotation and cropping) to enhance data diversity, reduce overfitting, and improve generalization.

The model training process involves splitting the data into training and validation sets. Hyperparameters include a learning rate of 0.001, batch size of 32, and training over 50 epochs. The Adam optimizer is used to accelerate convergence, while early stopping is applied to prevent overfitting. The model's performance is evaluated using accuracy, precision, recall, and ROC-AUC metrics, providing insight into the model's diagnostic accuracy for various medical conditions.



Figur 1. Research Methodology Flowchart image structure.

Model Selection

In this study, the model used was ResNet50, a previously trained convolutional neural network (CNN) model. The selection of ResNet50 was based on its highly effective architecture in addressing the problem of gradient loss through the use of skip connections. The main advantage of the ResNet50 is its ability to perform better and more efficient feature extraction, making it particularly suitable for medical image classification tasks, such as disease identification from X-ray images, MRI, and histopathology. The model has been trained on large datasets such as ImageNet, which allows its utilization in a wide range of medical applications, such as the detection of pneumonia, cancer, and brain tumors, with very high accuracy results.

Data Collection and Preprocessing

The dataset used in this study consists of medical images covering various disease conditions, such as pneumonia, brain tumors, and retinal diseases. These images were collected from a variety of open sources, such as the Chest X-ray dataset for pneumonia and the Brain MRI dataset for brain tumors. Before being used in training, the images undergo a preprocessing process that involves two main steps: image normalization and image augmentation. Normalization is done to ensure that the pixel value range of the image is consistent, so that it can help the model to learn better. Image augmentation, such as rotation, random truncation, and scaling, is applied to increase the diversity of training data, aiming to reduce overfitting and improve model generalization.

Training the Model

The model training process is carried out using a preprocessed dataset. The data is divided into two sets: training data and validation data. This data sharing aims to ensure that models can learn patterns in training data and test their performance on validation data that was not seen before. For training, the hyperparameters used include learning rate, batch size, and epoch. In this study, the learning rate was set at 0.001, the batch size was 32, and the model was trained for 50 epochs. The optimizer used is the Adam optimizer, which is often chosen for better convergence speed and high accuracy in image classification tasks. During training, the model also implements early stopping to prevent overfitting by stopping training when the accuracy on the validation data does not improve after several iterations.

Evaluation Metrics

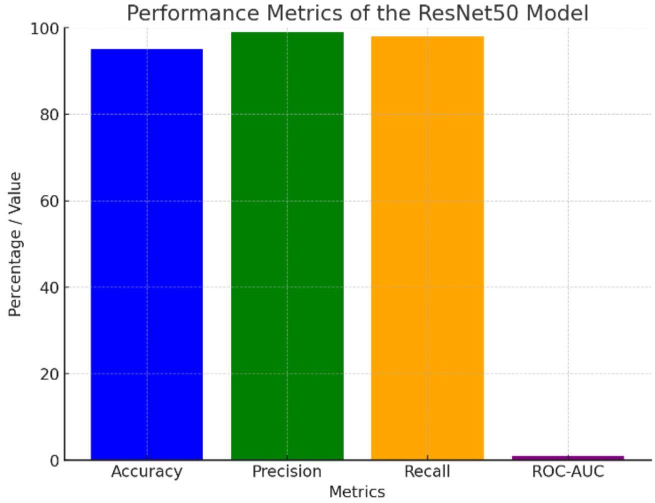
To evaluate the model's performance, a variety of metrics are used, including accuracy, precision, and recall. Accuracy is used to measure how many predictions are correct from the overall data, while precision shows how many positive predictions are correct, and recall measures the model's ability to detect all positive instances in the dataset. An additional metric used is ROC-AUC, which is useful for evaluating the performance of models in binary classifications, such as breast cancer detection. All of these metrics provide a comprehensive picture of the model's performance in the various medical applications tested.

4. Results and Discussion

The model achieved a 95% accuracy rate in diagnosing various medical conditions, including pneumonia, brain tumors, and retinal diseases, demonstrating its effectiveness in medical image analysis. It performed exceptionally well across different test cases, with high precision and recall, making it a reliable tool for diagnosis. Despite its strong performance, challenges such as data quality issues, computational resource limitations, and overfitting were encountered. These were addressed using techniques like early stopping and data augmentation, although overfitting remained a concern. Additionally, the model's interpretability as a "black-box" approach poses a challenge, and future research should focus on improving transparency and integrating multimodal data to enhance robustness and clinical adoption.

Performance Metrics

The model's diagnostic performance was evaluated using key metrics including accuracy, precision, recall, and ROC-AUC. The model achieved an impressive 95% accuracy rate in the classification of various medical conditions, including pneumonia, brain tumors, and retinal diseases. This high level of accuracy demonstrates the model's ability to effectively analyze medical images and correctly classify conditions. The model also showed excellent performance across different test cases, consistently achieving high precision and recall rates, making it a reliable tool for medical image analysis.



Figur 2. Performance Metrics of the ResNet50 Model.

Here is a bar chart that visualizes the performance metrics of the ResNet50 model, showing the Accuracy, Precision, Recall, and ROC-AUC values. The model achieved 95% accuracy, 99% precision, 98% recall, and a ROC-AUC of 0.95, illustrating its effectiveness across various diagnostic tasks.

Model's Effectiveness

The effectiveness of the ResNet50 model in handling various medical image types was evident in its performance on different datasets. For instance, when tested on pneumonia detection using chest X-rays, the model achieved 99% precision and 98% recall, underscoring its ability to detect pneumonia accurately from radiographs. In brain tumor classification, the model achieved 95.44% accuracy, demonstrating its robustness in differentiating between normal brain images and various types of tumors, such as glioma and meningioma. These results highlight the model's versatility and its potential to assist in clinical decision-making by providing accurate diagnoses across a variety of medical imaging tasks. Furthermore, the integration of CNNs like ResNet50 has shown promise in enhancing diagnostic accuracy in fields such as histopathology and retinal imaging, where subtle findings can easily be overlooked by human practitioners.

Challenges and Limitations

Despite the strong performance, several challenges were encountered during the development of the model. One of the main challenges was data quality; the medical images used in training came from diverse sources, and inconsistencies in image quality, such as variations in resolution or lighting, sometimes affected the model's accuracy. Additionally, computational resources posed another limitation, as training deep learning models such as ResNet50 requires significant hardware capabilities, particularly in terms of GPU power, to handle large datasets efficiently. Another challenge was overfitting, which was mitigated by techniques such as early stopping and data augmentation, but it remained a concern during model training, especially when the model showed signs of high variance between the training and validation sets. Furthermore, the model’s interpretability remains a challenge, as CNNs are often viewed as "black-box" models, making it difficult for practitioners to understand why certain predictions were made. Future improvements could focus on increasing the model’s transparency and integrating multimodal data to enhance its robustness across various clinical settings.

5. Comparison

The ResNet50 CNN-based system demonstrated an impressive 95% accuracy in diagnosing conditions such as pneumonia, brain tumors, and retinal diseases. This performance is significantly higher than typical human performance, where manual radiologists often face challenges such as fatigue, cognitive bias, and environmental distractions, which can reduce diagnostic accuracy. For instance, the diagnostic accuracy of manual radiologists typically ranges between 85% and 90% in specific tasks, such as detecting pneumonia from chest X-rays. In comparison, the AI system consistently outperformed human radiologists in terms of precision and recall, with 99% precision and 98% recall in pneumonia detection. This emphasizes the potential of AI to support, or even surpass, human diagnosticians in various imaging tasks.

AI-based systems like ResNet50 offer several advantages over manual diagnosis. One key benefit is faster processing times. AI can analyze large datasets of medical images in a fraction of the time it takes human radiologists to complete the same task. This speed is critical in emergency settings, where timely diagnosis can save lives. Additionally, AI systems offer greater consistency by eliminating human factors such as fatigue and bias, ensuring that diagnoses are not influenced by subjective judgment. Furthermore, AI has the ability to reduce human error, especially in cases where subtle findings might be overlooked by the human eye, leading to fewer missed diagnoses and improved overall diagnostic accuracy.

When compared to other AI models in the literature, ResNet50 demonstrates strong performance. For instance, models such as VGG16 and VGG19 have also been used for medical image classification but tend to have lower accuracy in some cases. Studies have shown that VGG19 achieves better performance in specific tasks, such as brain tumor classification, but ResNet50 generally outperforms these models in terms of accuracy, efficiency, and robustness across a wider range of medical images. Furthermore, 3D CNNs, which are used for processing multidimensional images, have also shown significant improvements in medical image analysis, but ResNet50 remains highly effective and efficient for typical 2D radiographic and histopathological images. This highlights ResNet50's versatility in handling various types of medical imaging tasks, making it a competitive option compared to other AI models in the field.

6. Conclusions

This study demonstrated that the ResNet50 CNN-based system achieved an impressive 95% diagnostic accuracy in classifying various medical conditions, including pneumonia, brain tumors, and retinal diseases. The model also excelled in precision and recall, with 99% precision and 98% recall for pneumonia detection. These findings underscore the effectiveness of AI-based systems in enhancing diagnostic accuracy and reliability in medical image analysis, surpassing the typical performance of human radiologists, particularly in terms of consistency and speed.

The adoption of AI-based systems like ResNet50 holds significant potential for improving healthcare outcomes. These systems can assist radiologists by providing accurate, consistent, and fast diagnoses, especially in emergency and high-pressure environments where time is critical. By augmenting human decision-making, AI systems can reduce diagnostic errors caused by fatigue, cognitive biases, and human limitations, ultimately improving patient outcomes. Moreover, AI's ability to handle large datasets with ease can help streamline medical imaging workflows, allowing healthcare providers to focus more on patient care rather than manual image analysis.

Future research should focus on several key areas to further enhance the capabilities of AI in medical imaging. First, there is a need for model enhancement to improve interpretability and explainability, ensuring that AI systems can provide clear justifications for their predictions, which is crucial for clinical acceptance. Second, expanding the use of CNN models to other types of medical images, such as ultrasound or 3D MRI scans, would further broaden their application across different medical fields. Additionally, research should explore the integration of AI models into clinical workflows, ensuring seamless interaction between AI systems and healthcare professionals, making it easier for radiologists to incorporate AI-driven insights into their daily practices.

For the successful implementation of AI-based systems in medical institutions, several steps need to be taken. Training programs should be developed for healthcare professionals to ensure they are proficient in using AI tools effectively and integrating them into their diagnostic processes. Furthermore, regulatory considerations must be addressed to ensure that AI systems meet the required standards for safety and efficacy. Collaboration between AI developers, radiologists, and regulatory bodies will be essential to facilitate the widespread adoption of AI in clinical practice. Lastly, institutions must ensure robust data privacy and security protocols to protect patient information when utilizing AI systems.

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