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Use Deep Learning for Processing Automation Image DR in Detecting Pneumothorax

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ABSTRACT

Pneumothorax is conditions medical serious thing that happened consequence accumulation air in the pleural cavity, which can cause the collapse lungs and potentially threaten soul if no quick handled. A quick and accurate diagnosis is essential. For determine action proper medical. Digital radiography (DR) is one of the method the most common imaging used in detect pneumothorax. However, the limitations in manual interpretation by manpower medical can cause misdiagnosis or delay in handling. Study This propose approach based on Deep Learning, especially Convolutional Neural Networks (CNN), for automation processing DR image in detect pneumothorax. The model used utilise ResNet-50 and DenseNet-121 architectures with transfer learning techniques for increase accuracy classification. The data used originate from the ChestX-ray14 and SIIM-ACR Pneumothorax Challenge datasets that have been annotated by expert radiology. Research result show that the CNN model was developed reach level accuracy of 92%, with a precision of 90%, a recall of 93%, and an F1-score of 91%. In addition, the technique Grad-CAM visualization is used for increase interpretability of the model with highlight important areas in the image that becomes base decision classification. Implementation of this model No only increase efficiency of pneumothorax diagnosis but can also reduce burden Work power medical as well as increase quality service health. With promising results, research This open opportunity for development more carry on in application of AI in the field radiology.

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1. INTRODUCTION

Pneumothorax is a condition that occurs when air enters the pleural cavity, causing excessive pressure and collapse of the lung. This condition can occur spontaneously or due to trauma, and requires rapid diagnosis to avoid further complications, such as respiratory failure and death. According to the World Health Organization (WHO), the incidence of pneumothorax continues to increase every year, especially among patients with a history of chronic obstructive pulmonary disease (COPD) and heavy smokers.

Chest radiography (CR) is the most commonly used imaging modality in the diagnosis of pneumothorax. However, identification of pneumothorax on CR images is not always easy due to poor contrast and limitations in image resolution. In addition, the diagnosis that relies on manual evaluation by radiologists can lead to variations in interpretation, as well as delays in the medical decision-making process.

With the development of artificial intelligence (AI) technology, especially Deep Learning, medical image analysis has made rapid progress. Deep Learning, especially Convolutional Neural Networks (CNN), has been shown to be able to perform complex tasks in image analysis with high accuracy. According to a recent study by Rajpurkar et al. (2024), a CNN model trained using a large dataset was able to detect lung abnormalities, including pneumothorax, with higher sensitivity and specificity than conventional methods.

Another study by Tang et al. (2024) showed that the integration of Deep Learning in radiology systems can speed up the diagnostic process by up to 50% and reduce the human error rate in DR image interpretation. This study also highlighted that the use of pretrained models such as ResNet-50 and DenseNet can significantly improve the accuracy of pneumothorax detection.

In addition, the implementation of Deep Learning in medical image analysis has a major impact on the world of medicine, especially in increasing the efficiency of medical personnel, reducing the workload of radiologists, and enabling early detection of critical diseases. In recent years, this approach has also been used in various other areas of medical imaging, such as tumor detection in MRI and CT scans. With its capabilities continuing to grow, AI is predicted to become an integral part of the global healthcare system in the coming years.

In addition to the aforementioned studies, a recent study in 2024 also showed that the use of ensemble techniques in CNN models can further improve the accuracy of pneumothorax detection. This technique combines multiple deep learning models to produce more stable and accurate predictions. This approach has been applied in various medical research centers around the world and has been shown to reduce false positives and false negatives in the diagnosis of pneumothorax.

Considering the latest technological developments, the implementation of Deep Learning-based automation in DR image analysis can be a solution to improve efficiency and accuracy in pneumothorax diagnosis. Therefore, this study aims to develop and evaluate the performance of a Deep Learning model in automatically detecting pneumothorax from DR images, as well as exploring its impact on clinical practice in 2024 and beyond.

2. RESEARCH METHODS

This study uses a quantitative experimental method with a Deep Learning-based approach to automate pneumothorax detection from DR images. The data used comes from ChestX-ray14 and the SIIM-ACR Pneumothorax Segmentation Challenge dataset, which consists of thousands of chest radiographic images with annotation labels for pneumothorax classification and segmentation. The data is divided into three main parts, namely the training set (70%) to train the model, the validation set (15%) for parameter tuning, and the testing set (15%) to measure the final performance of the model. Before being used, the data undergoes a preprocessing stage which includes normalization, data augmentation with rotation and flipping techniques, and noise reduction to improve image quality.

The model used in this study is based on Convolutional Neural Networks (CNN) with transfer learning architecture from ResNet-50 and DenseNet-121. This model has several main layers, such as convolutional layers for feature extraction, pooling layers to reduce data dimensions, and fully connected layers that function as the final classification. Model training was carried out using the TensorFlow and PyTorch frameworks with the Adam optimizer, Binary Cross-Entropy loss function, batch size 32, and the number of epochs as many as 50 with an early stopping mechanism to avoid overfitting.

Model evaluation was conducted by measuring accuracy, precision, recall, F1-score, and area under the curve (AUC-ROC) to assess the model's performance in detecting pneumothorax. In addition, model interpretability techniques such as Grad-CAM were used to visualize the areas that the model focused on in detecting pneumothorax. The experimental results showed that the developed CNN model was able to achieve an accuracy level of up to 92%, with significant performance improvements thanks to the use of transfer learning and data augmentation. Based on the results obtained, this study proves that Deep Learning can be an effective solution in automating DR image processing for pneumothorax detection, helping medical personnel in faster and more accurate diagnoses.

3. RESULTS AND DISCUSSION

Deep Learning Model Accuracy

The results showed that the developed CNN model had a pneumothorax detection accuracy rate of 92%, with a precision of 90%, a recall of 93%, and an F1-score of 91%. Models using transfer learning from ResNet-50 and DenseNet-121 performed better than models trained from scratch.

In some recent studies, the use of deeper CNN architectures, such as EfficientNet and Vision Transformer, has also shown increased accuracy in medical image analysis. However, the selection of ResNet-50 and DenseNet-121 in this study was based on a balance between performance and computational efficiency. With a large enough dataset and the augmentation techniques applied, these models can optimally learn patterns in DR images, resulting in more accurate predictions.

According to a study conducted by Wang et al. (2024), the use of CNN for lung disease detection has shown high efficiency in DR image-based diagnosis, with performance comparable to or even superior to human radiologists in some cases. The results of this study support our findings that Deep Learning-based models can be used as accurate and efficient diagnostic tools.

In addition, research conducted by Zhang et al. (2024) shows that increasing the amount of quality training data can significantly improve model accuracy. In this study, a model trained with more than 50,000 DR images was able to achieve an accuracy of up to 95%, indicating that the amount and quality of data greatly affect the performance of the Deep Learning model.

In a clinical context, high-accuracy models can help reduce the workload of radiologists by providing fast and accurate initial analysis results. This system can be used as an early detection tool, allowing doctors to provide faster intervention to critically ill patients. However, even though the model has a high level of accuracy, manual evaluation by doctors is still needed as a confirmation step, especially in cases with a high level of uncertainty.

The success of the model in detecting pneumothorax is also influenced by the quality of the training data annotation. According to a study by Liu et al. (2024), the quality of annotation performed by radiologists has a major impact on the model's ability to generalize lung abnormality patterns. Therefore, in this study, the data used has gone through an annotation validation stage by several radiologists to ensure the accuracy of the labels given.

With the rapid development of AI technology, Deep Learning models for medical image analysis are expected to continue to experience increased accuracy and efficiency. The application of more complex models and the use of better interpretability techniques, such as explainable AI (XAI), are expected to increase user confidence in AI-based clinical decision making.

Grad-CAM Visualization

One of the main challenges in implementing Deep Learning in the medical field is the interpretability of the model. To overcome this challenge, this study uses the Grad-CAM (Gradient-weighted Class Activation Mapping) technique to provide visualization of important areas in the image that are used by the model in making decisions.

Grad-CAM is a method that allows us to understand which parts of the image are considered significant by the model in classifying pneumothorax. With this technique, we can generate activation maps that show the regions with the greatest contribution to the model's decision.

Grad-CAM visualization results show that the model can consistently highlight lung areas with pneumothorax with a good degree of accuracy. In many cases, the model clearly highlights areas with pneumothorax, allowing clinicians to see the correlation between model results and clinical findings.

According to a study conducted by Liu et al. (2024), the use of Grad-CAM in a medical AI system can increase doctors' confidence in the results provided by the model. Their study shows that model interpretability plays an important role in increasing the adoption of AI technology in clinical settings. Similar results were also found in a study by Zhang et al. (2024), where Grad-CAM visualization helped radiologists understand the logic behind AI model decisions, thereby increasing transparency in the use of AI technology in hospitals.

Additionally, Grad-CAM visualization allows for easier identification of model errors. In some cases where the model misclassifies images, Grad-CAM shows that the model’s attention is sometimes drawn to irrelevant or less significant areas. By further analyzing these error patterns, the model can be improved through fine-tuning techniques and additional data augmentation to improve overall performance.

From a clinical perspective, the use of Grad-CAM provides great benefits in improving the accuracy of AI-assisted diagnosis. With this visualization, doctors can quickly review the model's prediction results, confirm or reject the analysis results, and improve the efficiency of medical decision-making. Therefore, the integration of interpretability methods such as Grad-CAM in medical Deep Learning systems is essential to ensure widespread acceptance among medical professionals.

Efficiency and Clinical Impact

The implementation of Deep Learning in pneumothorax detection not only improves the accuracy of diagnosis but also brings significant clinical impact. In a hospital setting, delays in the diagnosis of pneumothorax can increase the risk of life-threatening complications. Therefore, an AI-based system that can automatically detect this condition quickly is very beneficial for medical personnel.

In a study by Smith et al. (2024), the use of a CNN-based model in the emergency department (ED) showed that the time to detect pneumothorax could be reduced by up to 50% compared to conventional methods. This means that patients can receive faster medical intervention, reducing the risk of serious complications.

In addition, the efficiency of the AI system also has an impact on the workload of radiologists. With the increasing number of radiographic examinations each year, the limited number of radiologists often causes a backlog in image analysis. With the help of Deep Learning models, doctors can focus more on more complex cases, while AI handles the initial analysis and provides results that can be reviewed further.

From a cost perspective, research by Wang et al. (2024) showed that hospitals that adopted Deep Learning-based systems experienced a reduction in operational costs of up to 30% due to the reduced need for manual interpretation of simple cases. The use of this technology can also reduce misdiagnosis, which often leads to additional expensive examinations.

In the future, the implementation of AI in the hospital PACS (Picture Archiving and Communication System) system will further increase efficiency in radiology data management. Deep Learning models can automatically flag suspicious images, helping doctors make faster and more accurate decisions. However, although AI provides great benefits, human intervention is still needed to ensure more accurate diagnosis results and consider other clinical factors that may not be recognized by the AI model.

4. CONCLUSION

The results of this study indicate that the use of Deep Learning, especially ResNet-50 and DenseNet-121 based CNN models, significantly improves the accuracy, speed, and efficiency in detecting pneumothorax from DR images. With a high accuracy rate of 92%, this model can be a very valuable tool in clinical diagnosis. The use of the Grad-CAM technique has also helped improve the interpretability of the model, allowing medical personnel to understand the decisions made by the AI system.

In addition to increasing efficiency in diagnosis, Deep Learning-based systems also contribute to reducing the workload of radiologists, accelerating medical decision-making, and lowering hospital operating costs. This efficiency is crucial in the modern medical environment, where the number of radiology examinations continues to increase every year.

However, while Deep Learning shows great potential in supporting medical image analysis, it cannot completely replace the role of doctors. Integration of AI models with PACS systems and hospital workflows must be done carefully to ensure that AI acts as a tool to support clinical decisions, not as a substitute for medical experts.

In the future, further research is needed to improve the robustness and generalization of this model, including the exploration of more complex network architectures and the development of larger, more representative datasets. Implementation of this system on a wider scale also requires further clinical testing to ensure its safety and effectiveness in real medical settings.

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