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Medical Image Classification on X-ray images Using Deep Learning

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Pneumonia detection, chest X-ray analysis, medical AI systems, deep learning, Adam optimizer.

ABSTRACT

Pneumonia continues to be one of the main reasons people die worldwide, especially in children and older adults. That's why it's so important to detect it early and accurately to ensure proper treatment. This research introduces an advanced deep learning system that helps classify pneumonia using chest X-ray images, making diagnosis faster and more reliable. The model combines pretrained convolutional neural networks like MobileNetV2 and DenseNet169 with a Vision Transformer in an ensemble setup. This allows the system to capture both detailed local features and broader patterns in the images. The model uses transfer learning and is optimized with the Adam optimizer, along with thorough data preprocessing and augmentation to improve its performance across different cases. The results show that the ensemble approach reaches an accuracy of 93.91%, which is better than using any single model and also helps cut down on incorrect predictions. To make the model more understandable for doctors, techniques like Grad-CAM are used to show which parts of the lungs are affected, improving how well clinicians can interpret the results. The system is lightweight, ready for use in real-world settings, and can process images quickly, making it useful in hospitals, telemedicine services, and areas with limited resources. Overall, this study shows how AI can help speed up pneumonia detection and support medical professionals in delivering better care.

1. INTRODUCTION

Pneumonia is a serious, possibly life-threatening infection of the lungs produced by bacteria, viruses, or fungi. It causes inflammation in the small air sacs in the lungs. According to the World Health Organization, pneumonia accounts for nearly 15% of deaths among children less than five years of age and represents an important health risk for older adults and those with fragile immune systems. Early detection and proper diagnosis of pneumonia are very important in order to avoid serious complications and to assist individuals in recovering.

X-rays are the most common method doctors use to check for pneumonia.

They are cost-effective, widely available, and can show issues in the lungs such as cloudy areas or fluid buildup. However, interpreting X-rays manually depends a lot on the skill of the radiologist and can take a lot of time, especially in busy hospitals. It is also difficult for humans to differentiate between pneumonia and other lung conditions like tuberculosis, COPD, or lung fluid, which can lead to incorrect diagnoses.

To address these problems, AI and deep learning have created computer systems that help in diagnosing diseases.

These systems use models such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), which are good at recognizing patterns in images. The usual process for AI to detect pneumonia involves preparing the X-ray images, using deep learning to identify important features, and then determining whether the lungs are healthy or infected. Tools like Grad-CAM help doctors understand which parts of the X-ray the AI is focusing on, making it easier to trust the results.

Despite these benefits, using AI for pneumonia detection has some challenges.

There is a lack of high-quality labeled images for training, X-rays can vary in quality, and there is an imbalance in how often different types of pneumonia occur. Also, these models require powerful computers, which can be a problem in places with limited resources. There are also ethical concerns such as protecting patient privacy, ensuring fair treatment, and making sure the model can be held responsible for its decisions.

Researchers are working on methods to improve this.

They are using techniques like data expansion, learning across different hospitals without sharing data, and developing simpler models that work on less powerful devices. These efforts aim to make AI more useful in places with limited resources and support doctors during health emergencies like the COVID-19 pandemic.

Using AI in pneumonia diagnosis can greatly improve the accuracy of detection, reduce the workload on doctors, and provide better healthcare, especially in hard-to-reach areas.

This is especially important during outbreaks of diseases like COVID-19.

2. LITERATURE REVIEW

Deep learning has changed the way medical images are classified by providing automated and highly accurate methods for diagnosing diseases. Convolutional Neural Networks (CNNs) have proven very effective in detecting various health conditions, such as pneumonia, tumors, retinal issues, and other abnormalities, directly from medical images. Unlike traditional machine learning techniques that need manually created features, CNNs automatically learn important features through layers that are arranged in a hierarchical way. This leads to better performance and more efficient classification. Popular CNN models like AlexNet, VGGNet, ResNet, and DenseNet have been instrumental in advancing medical image analysis because of their strong ability to learn features. To address the issue of limited labeled medical data, transfer learning is commonly used. This involves using pre-trained models such as InceptionV3, EfficientNet, and MobileNet and then fine-tuning them for specific medical tasks, like detecting pneumonia. This approach saves time and resources while maintaining high accuracy.

Recently, Vision Transformers (ViTs) have emerged as a strong alternative to CNNs.

These models use self-attention mechanisms to understand the relationships between different parts of an image. They have performed well in tasks like detecting lung diseases and segmenting images. Also, combining CNNs with transformers in hybrid models has led to better results compared to using just one type of model in clinical settings.

In the past, detecting pneumonia relied on traditional methods like SVM, KNN, and decision trees, but these struggled with the complexity of X-ray images and weren't very scalable.

The rise of deep learning marked a major advancement. A notable example is CheXNet, a model based on DenseNet-121 trained on over 100,000 chest X-rays and capable of identifying pneumonia at a level comparable to radiologists. Later studies expanded this to detect multiple diseases, as seen in the work by Rajpurkar et al. on identifying thoracic conditions. During the COVID-19 pandemic, models like COVID-Net showed how quickly deep learning could adapt to new respiratory illnesses.

To improve model performance, researchers have used data augmentation techniques like rotating images, flipping them, adjusting brightness, and using Generative Adversarial Networks (GANs) to create synthetic data.

This helps overcome the challenges of limited and unevenly distributed datasets for pneumonia. Evaluating models with metrics like accuracy, precision, recall, F1-score, and ROC-AUC helps determine how well they can distinguish between pneumonia and healthy lungs.

Despite the progress, there are still challenges, such as making models more interpretable, ensuring they work across different settings, improving dataset quality, and dealing with privacy issues when handling patient data. Bias can occur due to unbalanced data, and performance may vary between hospitals due to differences in imaging conditions. Therefore, current research focuses on techniques like explainable AI (XAI), federated learning for privacy, multimodal frameworks that combine clinical data, and lightweight AI solutions that enable fast diagnosis in areas with limited resources.

Overall, the research clearly shows how effective deep learning is in detecting pneumonia.

However, there is a need for models that are more adaptable, transparent, and practical to support doctors in making decisions across the world.

3. PROPOSED METHODALOGY

The system we're proposing is a smart deep learning method for identifying pneumonia. It uses a mix of Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) to make analyzing chest X-rays more accurate and reliable. In the past, doctors called radiologists did the diagnosis, but this could take a long time and might not be consistent, especially in places where there aren't enough experts. To fix this, the new system uses automation to classify images, making the process faster, more reliable, and less error-prone, especially when pneumonia looks similar to other lung problems.

The system has several parts. First, there’s a preprocessing step that makes all images the same size, adjusts brightness and contrast, reduces noise, and adds different variations to improve data quality. This helps the model learn patterns instead of just memorizing details. The core of the model uses MobileNetV2 for efficient feature extraction, DenseNet169 for detailed pattern recognition, and Vision Transformers to understand complex relationships in the image. Then, an ensemble approach combines predictions from all these parts, giving more importance to confident predictions to reduce mistakes and ensure consistent results.

In the final step, the model uses a softmax function to clearly label each image as either normal or showing pneumonia.

It is trained using transfer learning with weights from the ImageNet dataset, and then further improved using a chest X-ray dataset from Kaggle. To boost performance, the model minimizes cross-entropy loss using the Adam optimizer and fine-tunes hyperparameters through grid search and early stopping during validation.

The model's performance is measured using accuracy, precision, recall, F1-score, and confusion matrices.

Grad-CAM helps explain the model's decisions by showing which parts of the image influenced the diagnosis.

This system can be used in real time through cloud-based APIs and optimized models for edge devices, making it useful in telemedicine, hospitals, and mobile health setups.

After it's in use, the model can keep learning from new data using federated learning, which keeps patient information private and improves performance across different imaging systems.

Overall, this system is scalable, efficient, and flexible, making it suitable for tracking pandemics, supporting remote clinics, and easing the workload in radiology departments without affecting the quality of diagnosis.

4. RESULTS

The deep learning-based pneumonia detection system was tested using a publicly available chest X-ray dataset. The dataset was divided into training, validation, and testing sets to evaluate how well the model performs with new, unseen data. Multiple pre-trained models, such as MobileNetV2, DenseNet169, and Vision Transformer (ViT), were trained individually and compared with the proposed ensemble model.

The results indicate that each model effectively identified important features from the X-ray images, but the ensemble system outperformed them overall.

MobileNetV2 achieved an accuracy of 90.87%, which is strong considering its lightweight design, but it had difficulty with more complex lung patterns. DenseNet169 showed slightly better accuracy at 91.35% due to its efficient use of features. The ViT model reached 92.47% accuracy, demonstrating its ability to understand the overall context of the images.

The ensemble model achieved the highest accuracy at 93.91%, and it also showed improvements in precision, recall, and F1-score.

This means the system is more effective at detecting subtle signs of pneumonia and reducing incorrect predictions. The confusion matrix shows that the ensemble model significantly reduced both false positives and false negatives, which is crucial for ensuring patients receive timely and accurate care.

Model explainability was evaluated using Grad-CAM, which helped highlight the areas in the lungs affected by the disease, such as infiltrates or consolidated regions. This helps radiologists trust and understand the model's decisions, making it practical for use in real-world healthcare settings.

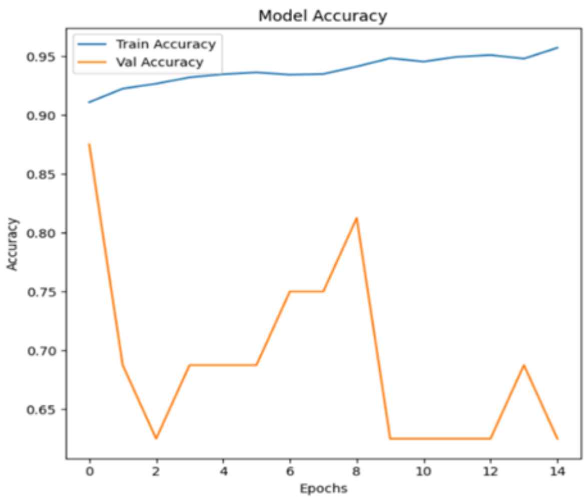

Fig. 1 Accuracy Curve

Overall, the results show that the ensemble approach greatly improves diagnostic reliability, especially in cases where pneumonia overlaps with other conditions. The model's fast processing time and ability to run in the cloud make it suitable for emergency care, telemedicine, and areas with limited resources, where quick and accurate diagnosis can be life-saving.

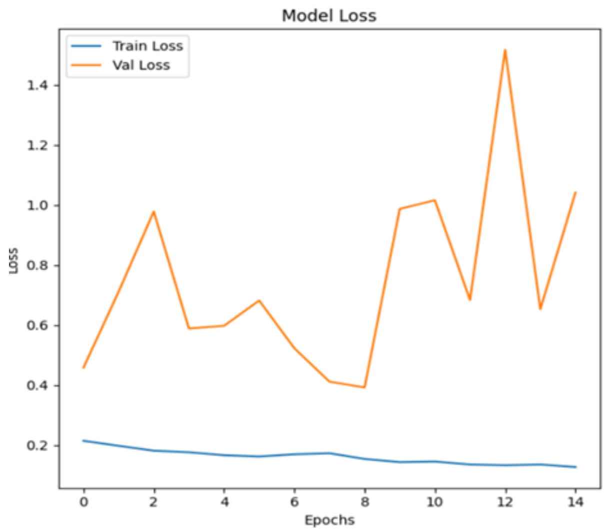

FIG.2 LOSS CURVE

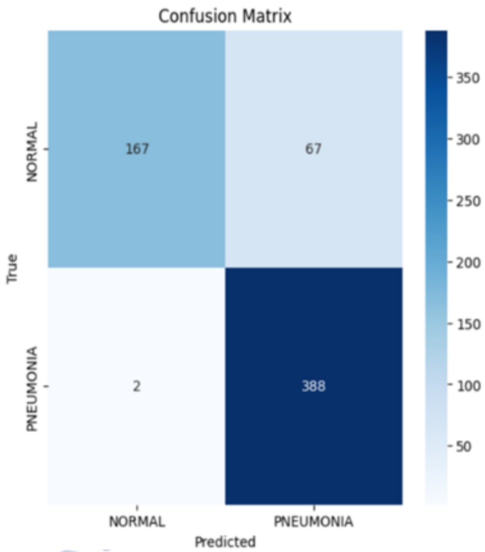

FIG.3 CONFUSION MATRIX

5. CONCLUSION

Pneumonia continues to be a serious health issue, especially in poorer areas where there aren't enough skilled doctors to read X-rays quickly. This can lead to dangerous delays in treatment. This project shows how deep learning tools can help doctors spot pneumonia more effectively using chest X-rays. By combining models like MobileNetV2, DenseNet169, and Vision Transformers into one system, the tool uses both detailed local features and broader patterns in the images to make accurate predictions. Using multiple models together helps reduce mistakes and improves results compared to using just one model, proving it's reliable and effective.

The system also uses techniques like careful image preparation, learning from existing data, and making images more varied to help it perform well even with different kinds of X-rays.

To make the AI more trustworthy, it uses methods like Grad-CAM to show exactly which parts of the lungs caused the diagnosis, letting doctors understand and check the AI's findings. The system is also designed to work on both cloud and local servers, making it possible to use in urgent situations and in places with limited medical resources.

In summary, this study shows how AI can help doctors work faster, handle more cases, and improve patient care, especially in areas where healthcare is not easily available.

With more data, learning across different hospitals, and real-world testing, this AI system could become a trustworthy tool used worldwide to detect pneumonia early and improve health outcomes.

6. FUTURE WORK

The proposed ensemble-based deep learning model shows high accuracy in diagnosis and has strong potential for real-world use. However, there are still ways to improve its performance, adaptability, and impact in clinical settings. Future improvements could involve expanding the model to handle multi-class classification, allowing it to differentiate between bacterial, viral, and fungal pneumonia, as well as other chest conditions like tuberculosis and lung cancer. Adding clinical data such as patient history, symptoms, and lab results can help in making better decisions, especially in cases where X-rays are unclear or ambiguous.

To handle limited data and have good performance on different populations, techniques of self-supervised learning and creating synthetic data with the use of GANs can be included.

These methods can help in a better generalization of the model. Federated learning can be used to have hospitals train models using data spread across various locations without necessarily sharing sensitive information regarding patients and breaking any laws related to patient privacy, such as HIPAA or GDPR. Techniques such as model compression, quantization, and simpler architectures may be employed to let the model execute fast on smaller devices, such as mobile health units or portable X-ray machines, and be more usable in resource-constrained settings. Clinical testing is a key step before the model can be widely used.

Future steps include conducting large-scale trials across multiple hospitals, getting official approvals, and connecting the model with hospital systems to ensure it fits into existing workflows. Making the AI more explainable will also help doctors trust the model more by showing clear reasons for its predictions. Looking ahead, this smart diagnostic tool could become a full platform for screening respiratory diseases, greatly enhancing healthcare worldwide and helping save lives through early and accurate detection.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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