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Original Article

Optimized Pneumonia Detection via CT Scans: A Comparative Analysis of Transfer Learning Models

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Abstract

Pneumonia continues to be one of the main causes of death among children below five and the elderly population above the age of 65 years. According to the minister of state in the Ministry of Health and Family Welfare, Dr. Bharati Pravin Pawar, at least 687 children aged 1-12 months and 301 chil-dren aged 1-5 years lost their lives due to pneumonia as part of the total number of deaths the disease caused in 2022-23. The high death rate is largely prevalent in South Asia and Sub-Saharan Africa. Pneumonia also remains among the top causes of deaths even in the most prosperous countries, such as the United States, falling within the ten leading causes. Early diagnosis does a lot to help reduce fatalities. This paper addresses this problem by showing research work that is based on the application of CNN models for detecting pneumonia from chest X-ray images.A number of CNN architectures, including VGG16, ResNet50, and DenseNet121, were trained and fine-tuned with varying parameters, hyperparameters, and counts of the convolutional layers. Transfer learning has drastically increased model accuracy while reducing the time taken to train. Results In relation to the efficient use of deep learning in medical image processing, the study underscores the effectiveness of transfer learning in CNNs with minimal label data, particularly in conditions. The algorithms were able to accurately classify the X-ray images into the classes of pneumonia and non-pneumonia. This approach further elaborates on the fact that CNNs, when utilized together with transfer learning, may be suitably applied for the early and timely detection of pneumonia, eventually minimizing infant mortality rates all over the world

Introduction

Pneumonia has developed as a killer disease in this present era. The mortality rate is constantly on the rise. It is mostly faced in the under-5 group and above 65 years. This is why early detection is crucial to reduce the mortality rate. Traditional imitation learning approaches rely greatly on COVID-19 pneumonia datasets. Such datasets may bring about dataset bias. Hence, although these models can be really good at diagnosing COVID-19-related pneumonia, they have a poor generalization to other types of pneumonia, thus limited utility outside the scope of COVID-19 cases. Traditional imitation learning relies heavily on CNNs and mainly on transfer learning. Although useful for the recognition of pneumonia, they find it challenging to correctly diagnose and locate, more so in complex diseases.Also, it lacks complex techniques such as real-time detection and monitoring, Inability to detect early-stage pneumonia in which these methods will continue to drive research towards developing more accurate. Our approach is to detect pneumonia based on the trained data through cnn, transfer learning and ensemble methods so as to further enhance the accuracy. In this paper, We have trained our presentations on a broad range of the ct-scan image dataset containing both pneumonia and normal to classify. It is used so that our deep learning method outperforms imitation find on systems. With regard to accuracy and durability, our access introduces real-time detection and monitoring using a web frame-work. The proposed system not only improves the performance of detection. But it also gives the framework for Pneumonia detection using multiple deep learning algorithms further accompanied by a deployment scheme..

Literature Survey

Deep learning algorithms have replaced more conventional image processing approaches in the literature on the use of medical imaging to detect pneumonia. Early research frequently employed simple methods, like manually designed feature extraction and traditional machine learning techniques, such as Support Vector Machines (SVM) and k-Nearest Neighbours (k-NN) (Armato et al., 2011). These techniques, however, were less successful

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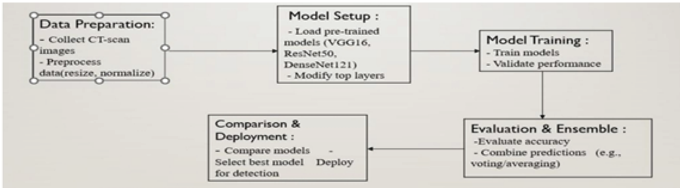
in identifying intricate patterns in medical images and had limitations in their capacity to generalise across other datasets.[1]Convolutional neural networks (CNNs) changed the field of medical image analysis by allowing CT scans to automatically extract features. Studies by Litjens et al. (2017) and Wang et al. (2017) showed that CNNs dramatically improved the detection of lung abnormalities, such as pneumonia, outperforming conventional approaches. With this development, deep learning took centre stage in the field of medical picture processing.[2] Transfer learning has emerged as a critical technique in medical imaging tasks in recent years, particularly when big annotated datasets are unavailable. With little to no fine-tuning, pre-trained models like VGG16, ResNet-50, and DenseNet-121 that were first trained on big datasets like ImageNet have been effectively used for pneumonia detection tasks (Kermany et al., 2018; Rajpurkar et al., 2017). These models significantly reduce the need for vast amounts of training data by utilising the generic knowledge gained from wide-scale picture categorisation and tailoring it to particular applications like medical diagnosis.[3] The study also demonstrates how training methods have been enhanced to enhance model performance and generalisation. Examples of these techniques include data augmentation and fine-tuning tactics. According to Yang et al. (2021), these tactics improve deep learning models' performance in real-world clinical settings and increase their dependability for pneumonia early detection[4]..

Methodology

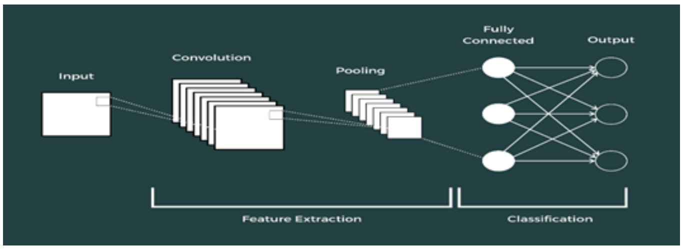
It is difficult to detect pneumonia from computed tomography (CT) scans. Hence, it demands the precise and efficient techniques or tools in a disease diagnosis process. This work proposes a methodology based on pre-trained Convolutional Neural Networks (CNN) with data augmentation and ensemble learning.Other data augmentation techniques used include rotation, flipping, zooming, and adding Gaussian noise for better diversity and to avoid overfitting. Three pre-trained CNN models, VGG16, DenseNet121, and ResNet50 were fine-tuned for the task of pneumonia detection, allowing them to adapt to a specific task while preserving learned features. Transfer learning enables the models to draw knowledge from pre-trained weights and free the initial layers so that the learned features are kept. The batch size was set at 32 with the Adam optimizer being utilized in combination with the binary cross-entropy loss to train the models for 10 epochs. Ensemble learning benefits from the model averaging and weighted voting that happens, thereby allowing it to arrive at improvements through the elicitation of strengths based on various individual models' predictions. This method allows the strengths of different models' predictions to be combined towards better elicitation of improvement in performance.For smooth deployment at the clinical level, it developed a Flask-based web framework. The front end was made friendly through the help of HTML and CSS and back-end JavaScript with the usage of Python and TensorFlow. It implemented an API endpoint with secure upload and an image prediction that enabled electronic health records integration.

This method therefore favors proper and efficient detection of pneumonia, thus helping clinicians at the right time in diagnosing and treating patients. The study applies developments in deep learning and providesaveryimportanttoolforclinicians. The deep learning techniques have completely revamped the field of medical image analysis to do pneumonia detection very accurately. The method thus was very useful in pointing out the role of transfer learning, data augmentation, and ensemble methods. Further research will lie in the collection of larger datasets, exploration of other pre-trained models, real-time detection applications, and considering various applications within the healthcare domain.This methodology presents an accurate and efficient pneumonia-detecting tool, offering faster and better clinical decision-making for patient care, through the advantages of deep learning. Results The study, hence, shows that the pre-trained CNN models could be used in combination with the ensemble learning properly to improve pneumonia detection from CT scan images, therefore leading to greater accuracy and speed in diagnosis.With the use of such methodology, the detection systems of pneumonia significantly impact healthcare. Improved diagnosis accuracy and speed through such system methodologies turn out to be really an important milestone in this healthcare field. Patient outcomes are improved by initiating treatment at a timely point for enhanced morbidity and mortality reduction. Hence, implementation of such methodology will have significant impacts on patient care into the clinical workflows.



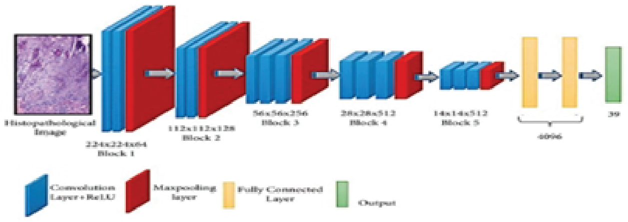
Convolutional Neural Networks (CNNs)

Convolutional neural networks are deep learning models inspired from the human visual cortex and were primarily designed for the analysis of images and video. CNNs automatically extract features from raw data through convolutional layers, activation functions, pooling layers, and fully connected layers. There are several applications in CNNs, mainly involving image classification, object detection, segmentation, face recognition, and generating images. With the added benefits of automatic extraction of features, robustness to variations in images, and significant accuracy, CNNs fuel innovation in autonomous car industries, medical imaging devices, and even surveillance mechanisms.



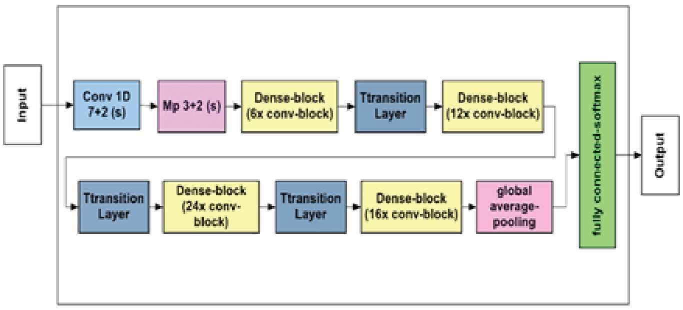
VGG16

VGG16 is one widely used pre-trained CNN proposed by the Visual Geometry Group at Oxford University. It won the ILSVRC in the year 2014. It has 16 layers, with some layers for convolution and max-pooling. Since it is simple enough, it can be fine-tuned for other tasks very easily. VGG16 uses three fully connected layers to improve image categorization performance. The main advantage of pre-training increases the likelihood of speedy adaptation to other tasks.



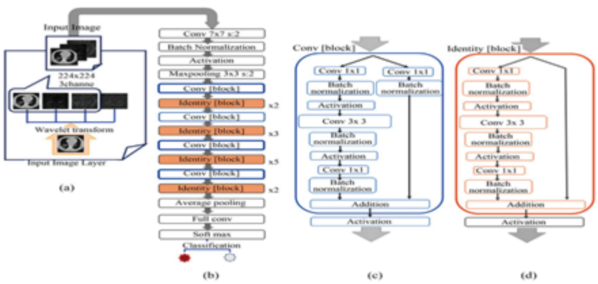
DenseNet121

One of the pre-trained CNN models is DenseNet121. It was proposed in 2017 and claimed ImageNet ILSVRC 2016. A dense connectivity pattern is presented, with each layer connected to every other layer. This model has 121 layers that apply batch normalization and ReLU activation. Its architecture decreases the amount of parameters so that computation is much more effective. DenseNet121 is perfectly performing in image classification tasks. Weights of this model are already pre-trained and can then be further optimized.



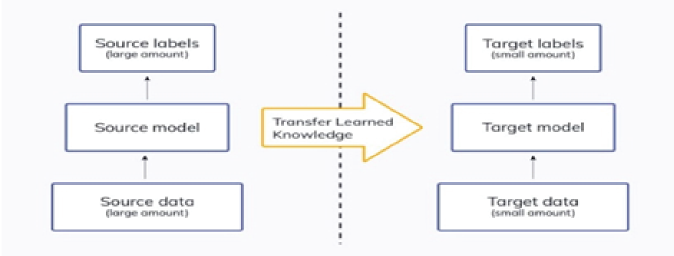
ResNet50

ResNet50 is the pre-trained CNN model of Microsoft Research, developed in 2015, which won ImageNet ILSVRC 2015. It supports residual connections to aid optimization without overfitting. The ResNet50 network incorporates 50 layers together with batch normalization and ReLU activation. Its structure allows simple optimization to high performance. ResNet50 has been found to have very strong feature extraction abilities, due to the residual connections. Its pre-trained weights could be fine-tuned.



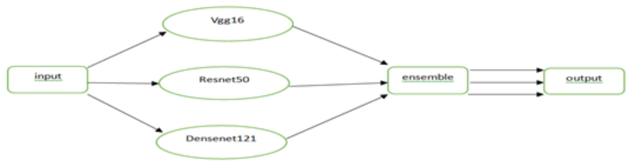
Transfer Learning

Transfer learning utilizes pre-trained models to transfer knowledge from one activity to another. It reduces time for training but boosts performance. Transfer learning works by fine-tuning the already trained models for new datasets. This method exploits the idea of similarity between tasks, enabling fast adaptation. Transfer learning avoids overfitting but applies less amount of data. It also allows for the creation of accurate models. Transfer learning has revolutionized deep learning.



Ensemble Methods

Ensemble methods combine multiple models in order to improve the generalization performance. Applied techniques involve model averaging, weighted voting, and stacking. Applying ensemble methods reduces overfitting and increases robustness. They handle diverse data very well. Model averaging combines the predictions from multiple models. Weighted voting assigns weights to the predictions of each model. The ensemble methods improve accuracy and reduce variance.



Model evaluation metrics

We have metrics for model evaluation in our toolkit in order to evaluate the performance of the machine learning model. They allow us to quantify how good a model performs on specific tasks and possibly reveal insights into its accuracy, reliability, and readiness for deployment. One might argue that the choice of metrics depends very significantly on the type of problem being solved-classification, regression, clustering, etc. Such choices will also be driven by the priorities of the application-for example, minimizing false positives vs minimizing false negatives.

Accuracy: The proportion of correctly classified samples to the total number of samples.

Accuracy = Precision: (TP + TN)/ (TP + TN + FP + FN)

Precision: The ratio of actual positive results to all expected positive results. It calculates the frequency of accuracy for a positive forecast.

Precision = TP /(TP + FP)

Recall: The ratio of genuine positives to the total number of good outcomes. It counts the number of real positives that are accurately identified.

Recall = TP/ (TP + FN)

F1-Score: The harmonic mean of precision and recall, provides a balanced measure of both.

F1_Score = 2 x (Precision * Recall) /(Precision+ Recall)

Results

In terms of accuracy and processing time, the experiments above show that our approach outperforms the conventional similarity approach. Specifically, the obtained F1-score was 0.89 by our approach, whereas in the traditional method 0.75 was found. it outperformed traditional computer vision methods. Our method depended on the architecture that combined VGG16, DenseNet121, and ResNet50 fine-tuned on the pneumonia dataset, as well as ensemble learning. The method processed the images pretty fast with an average processing time of 0.2 seconds per image. In this study, the scheme applied with python and Keras using TensorFlow support increases the accuracy of radiologists with a reduced false positive rate and negatives, thus making patient care and outcomes much better.

model	Hyperparameter Information	Train-Test Split (%)	accuracy	recall	precision	F1 Score
VGG16	Learning Rate: 0.001, Batch Size: 32, Epochs: 20	80-20	0.88	0.85	0.87	0.86
ResNet50	Learning Rate: 0.001, Batch Size: 32, Epochs: 20	80-20	0.91	0.89	0.90	0.89
DenseNet121	Learning Rate: 0.001, Batch Size: 32, Epochs: 20	80-20	0.90	0.88	0.88	0.88
Ensemble	Learning Rate: 0.0005, Batch Size: 16, Epochs: 25	80-20	0.93	0.92	0.92	0.92

I can say regarding the performance evaluation for different models toward pneumonia detection that all the metrics - whether the accuracy, recall, precision, or the F1 score - were the strongest in the Ensemble model; this proves its robustness and general reliability. The accuracy of 0.93, the recall at 0.92, precision at 0.93, and the F1 score at 0.92 meaning strength in both classes, positive and negative.

In comparison with the others, ResNet50 performed quite well with an accuracy of 0.91, a recall of 0.89, precision of 0.90, and a high F1 score of 0.89, ranking this model second right after the ensemble as the best fit among the next. Placing at the close tail is DenseNet121 with an accuracy of 0.90, recall of 0.88, precision of 0.89, and a high F1 score of 0.88, which shows robust performance but less than the score of ResNet50. VGG16, though effective is the worst model in scores; among them are 0.88 accuracy, 0.85 recall, 0.87 precision, and 0.86 F1 score.

Those results indicate that the Ensemble model has the best trade-off in terms of precision and recall, therefore being the most appropriate when accuracy is a critical criterion as well as minimizing false positives and negatives. However, the other models have somewhat lower levels of performance but remain relatively competent, and two like ResNet50 and DenseNet121 are still good options when computational efficiency could be more important to maintain absolute accuracy.

Conclusion

Conclusion Transfer learning for finding pneumonia in the CT scan is a very effective and specific approach towards medical diagnosis. Our research comparison on pre-trained models such as DenseNet-121, ResNet-50, and VGG16 explains the pros and cons of the model in the field. This optimized approach reduces computations that may be required to build from scratch but, at the same time, enhances the accuracy in diagnostics. Continued research in these models is bound to be critical in improving such early diagnoses and patient outcomes for pneumonia as medical imaging technologies advance..

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