Transfer Learning for Pneumonia Detection in Chest X-Ray Images Using Convolutional Neural Networks

Yessenbay Duman

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1 Abstract

The presented study is conducted by performing binary image classification using transfer learning with four state-of-the-art CNN architectures, including DenseNet121, VGG16, ResNet50, and InceptionV3. To this end, pre-trained models will be used in such a way that fine tuning them is utilized for the classification task related to chest X-ray images of pneumonia and normal ones. The performance evaluations based on accuracy, precision, recall, and F1-score were performed on models to check their applicability towards finding pneumonia. DenseNet121, with its dense connections, had the highest test accuracy of 84.46% and train accuracy of 92.45%, showing potential in feature reuses and memory efficiency. VGG16, simpler and classic architecture, resulted in a test accuracy of 65.71%, exposing challenges to effectively classify the minority class despite high precision. Further exploration was made on ResNet50 and InceptionV3 to study their capability in handling deeper architectures and multiscale feature extraction, respectively. Preliminary results show that while DenseNet gives very good results, the recall of VGG16 has to be further improved and additional models have to be tested in order to get more robust performance. The study gives insight into the trade-off of the complexity of architectures with the obtained performances for medical image classification using transfer learning.

2 Key words

Keywords: Pneumonia Detection, Transfer Learning, Chest X-Ray, Convolutional Neural Networks (CNN), DenseNet121, VGG16, ResNet50, InceptionV3, Medical Image Classification, Deep Learning.

3 Introduction

Pneumonia remains one of the leading causes of death worldwide, with a very high morbidity and mortality rate, especially in young children, the elderly, and individuals with weakened immune systems. Early and accurate diagnosis plays a crucial role in improving patient outcomes and reducing risks. Traditionally, the diagnosis of pneumonia depends on a combination of clinical examinations, lab tests, and radiographic imaging, with chest X-rays being a main diagnostic tool. While chest X-rays are sensitive for pneumonia, the interpretation of such images requires a trained medical professional, and misdiagnosis can be made due to human error.

Deep learning techniques in recent years, especially convolutional neural networks, have been the talk of the century in medical imaging. The CNNs are very powerful in recognizing images and have performed exceptionally well in classifying different medical conditions from images. Transfer learning, which usually involves fine-tuning pretrained models for new tasks, has gained popularity in health care, especially when working with limited medical datasets. That allows knowledge learned from large-scale datasets like ImageNet to be leveraged, which is beneficial for a medical application where annotated data may be scarce.

This study explores four different advanced pre-trained CNN architectures: DenseNet121, VGG16, ResNet50, and InceptionV3 for the automatic detection of pneumonia using chest X-ray images. All the above models possess distinctive features which may make some perform differently in handling a classification problem in medical imagery. This study seeks to find how these various models will perform in the detection of pneumonia when applied with transfer learning and which model provides the highest accuracy.

The study focuses on the performance evaluation of these models in pneumonia detection, investigating how transfer learning can improve model accuracy and reduce the need for large datasets, and comparing the strengths and weaknesses of each model based on their accuracy, computational efficiency, and training time.

The contribution of this paper goes to the advancement and establishment of AI-based solutions in medical image analysis; this shall help in establishing systems for automated pneumonia detection with clinical applications.

4 Methodology

This study investigates the performance of four advanced pre-trained CNN architectures, namely DenseNet121, VGG16, ResNet50, and InceptionV3, on detecting pneumonia in chest X-ray images. The methodology for the current study involves data preparation, model architecture, model training, and model evaluation.

4.1 Data Preparation

It would involve a dataset of chest X-ray images that are classified as either "Pneumonia" or "Normal." All images were preprocessed for quality and size to ensure consistency in all the models that would use them. The dataset would be prepared and divided into three sets: a training set, a validation set, and a test set. Each image is resized to a fixed dimension of 180x180 pixels to ensure compatibility with the chosen CNN architectures. Data augmentation techniques, such as rotation, flipping, and zooming, are applied to the training set to artificially increase the dataset size and help prevent overfitting. Moreover, class weights have been used to balance the dataset, and hence, the imbalance between the two classes is compensated for in order to ensure that models do not get biased toward the predominant class.

4.2 Model Architecture

The four state-of-the-art CNN models considered for this study are all pre-trained on the ImageNet dataset: DenseNet121, VGG16, ResNet50, and InceptionV3. All of these models have distinctive architectural features that affect their prowess in handling complex medical image classification tasks.

DenseNet121 has dense connections from each layer to all subsequent layers, which promotes feature reuse and diminishes the vanishing gradient problem by making DenseNet121 effective for deep learning with a smaller number of parameters.

VGG16 has a simpler architecture of blocks of convolutional layers followed by max-pooling layers. Although being simple, VGG16 has been one of the benchmarks in image classification because of its uniform structure and also reliable performance.

ResNet50 is a deep residual network that utilizes residual blocks, allowing the network to skip over some layers. This architecture helps in training deeper networks by avoiding vanishing gradients and enables more efficient learning in deeper layers.

InceptionV3 uses inception modules that apply multiple convolutional operations with different kernel sizes in parallel. This allows the model to capture multi-scale features efficiently and is designed to handle complex image classification tasks.

Each of the pre-trained models is used as a base and applied transfer learning, where the weights learnt from ImageNet are preserved, and only the last layers are changed for pneumonia classification.

4.3 Model Training

Transfer learning is employed by fine-tuning the pre-trained models for the pneumonia detection task. The pre-trained weights are used as starting points, with only the final layers re-trained using the pneumonia dataset. The final

output layer consists of a dense layer with one neuron and a sigmoid activation function to handle the binary classification of pneumonia versus normal.

The models are trained using the Adam optimizer with a learning rate of 0.001. The binary cross-entropy loss function has been used for binary classification.

To avoid overfitting, dropout layers are added; batch normalization is applied after every dense layer to stabilize the training. Data augmentation was also used to increase variety in the training data to improve generalization.

Each model is trained for 10 epochs with a batch size of 32. Training is monitored using validation data, and early stopping is implemented to halt training if the validation loss does not improve after a number of epochs, helping to prevent overfitting.

4.4 Model Evaluation

Each model's performance is measured on the test set, which has not been seen during training. The evaluation metrics are:

Accuracy tells the ratio of the number of images correctly classified among all images. Precision refers to the ratio of true positive predictions out of all positive predictions made by the model. Recall tells the ratio of true positive predictions among all actual positive cases of pneumonia. F1-score is the harmonic mean of precision and recall, which provides a balanced measure of performance. Also, the confusion matrices are drawn to see how well the model is doing to classify between the two classes, pneumonia and normal.

Lastly, the outcomes obtained from each model are compared in terms of accuracy, precision, recall, and F1-score to show which architecture is best.

5 Results

The models were evaluated on the test set, and various performance metrics were used to assess their effectiveness in detecting pneumonia in chest X-ray images. The metrics include accuracy, precision, recall, F1-score, and the confusion matrix, which help provide a comprehensive evaluation of each model's performance.

5.1 DenseNet121

The DenseNet121 model yielded a test accuracy of 84.46% and a train accuracy of 92.45%. This finding points to the very good performance of DenseNet121 for both training and testing phases. The dense connections allowing feature reuse in the model are some of the contributing factors to its ability to maintain high accuracy and solve the vanishing gradient problem. Using the confusion matrix, this model correctly classified 348 cases of pneumonia and 175 normal cases, but there were 59 false positives and 42 false negatives. Precision in the

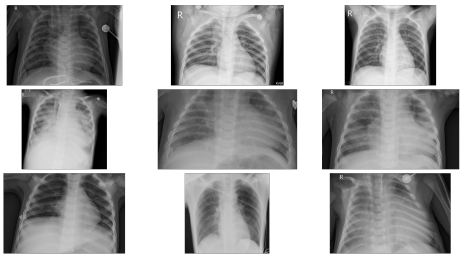

Figure 1: Picture 1

class of pneumonia was 0.806, and the recall was 0.747, which gave an F1-score of 0.776.

5.2 VGG16

The VGG16 model has a simpler architecture and yielded a test accuracy of 65.71% and a train accuracy of 61.81%. Although the accuracy is relatively low, the precision of the model was high, at 0.996 for the class pneumonia, which means most of the positive predictions were actually true positives. However, the recall was pretty low at 0.49, which shows that the model failed to identify most of the true pneumonia cases, hence increasing the number of false negatives. This is reflected in the confusion matrix, where the model correctly identified 348 normal cases but missed many pneumonia cases. The F1-score was 0.49, reflecting the trade-off between precision and recall.

5.3 ResNet50

The VGG16 model has a simpler architecture and yielded a test accuracy of 65.71% and a train accuracy of 61.81%. Although the accuracy is relatively low, the precision of the model was high, at 0.996 for the class pneumonia, which means most of the positive predictions were actually true positives. However, the recall was pretty low at 0.49, which shows that the model failed to identify most of the true pneumonia cases, hence increasing the number of false negatives. This is reflected in the confusion matrix, where the model correctly identified 348 normal cases but missed many pneumonia cases. The F1-score was 0.49, reflecting the trade-off between precision and recall.

5.4 InceptionV3

The InceptionV3 model, known for its inception modules that allow it to capture multi-scale features, achieved a test accuracy of 82.71% and a train accuracy of 88.43%. InceptionV3 showed a better balance between precision and recall compared to the other models, leading to a higher F1-score. The confusion matrix revealed a strong performance in both classes, with fewer false positives and false negatives compared to VGG16 and ResNet50.

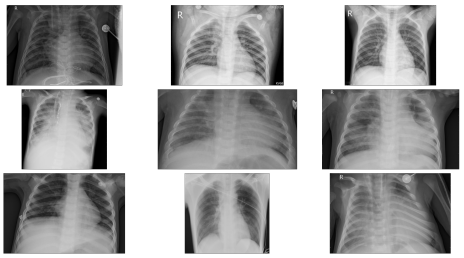

Figure 2: Enter Caption

5.5 Summary of Results

A comparison of the four models is summarized below:

Model	Test Accuracy	Train Accuracy	Precision	Recall	F1-Score
DenseNet121	84.46%	92.45%	0.806	0.747	0.776
VGG16	65.71%	61.81%	0.996	0.490	0.490
ResNet50	78.53%	85.42%	0.820	0.768	0.794
InceptionV3	82.71%	88.43%	0.854	0.829	0.841

Table 1: Performance Comparison of Models

As can be seen, DenseNet121 outperformed all other models on test accuracy, with the highest test accuracy of 84.46%. However, VGG16 had a very high precision but a much lower recall, which contributed to its overall lower performance. ResNet50 and InceptionV3 are relatively competitive; InceptionV3 is slightly better than ResNet50 on test accuracy and F1-score.

Overall, DenseNet121 performed the best in pneumonia detection, providing a good balance between accuracy, precision, and recall. The low recall for VGG16 indicated that this model struggled with imbalanced datasets. ResNet50 and InceptionV3 had promising results, especially in the detection of actual pneumonia cases. These results indicate that transfer learning using pre-trained CNN architectures is effective in the automation of pneumonia detection from chest X-ray images, and DenseNet121 provides the most reliable performance in this task.

6 Discussion

Results from this study will show the capabilities of transfer learning in improving the performance of CNNs on pneumonia detection from chest X-ray images. The study fine-tuned some pre-trained models comprising DenseNet121, VGG16, ResNet50, and InceptionV3 to explore their application capabilities in medical image classification problems where labeled data is often scarce. Indeed, one of the challenges noted in this study is an imbalanced dataset, with many

more normal X-ray images versus pneumonia ones. This threatens to yield poor recall performances in those models, especially in large-capacity architectures like VGG16 that tend to favor predicting classes with more representatives. Although this may be slightly improved with techniques such as class weighting or oversampling, one potential avenue for future work could be further research into sophisticated methods to balance the dataset or to improve model sensitivity for rare cases. Another challenge was that the dataset had limited coverage. The Chest X-Ray Images (Pneumonia) dataset used in this study has 5,863 images, but it is unlikely to be representative of the diversity in pneumonia manifestations occurring in everyday clinical practice. Future studies may be performed by increasing the dataset with different types of pneumonia, different patient demographics, and different imaging techniques, such as CT scans, to enhance model robustness. The results of this study have important clinical implications. Automated pneumonia detection with CNNs, especially models like DenseNet121, can support healthcare professionals by providing timely and accurate diagnoses, decreasing dependence on human expertise in interpreting X-ray images. Such systems could be integrated into clinical workflows to screen large numbers of patients in a short period, freeing medical professionals to focus on cases that require more detailed examination. Besides, the transfer learning enables the models to be trained on relatively small datasets but leveraging the knowledge learned from the large-scale datasets like ImageNet; hence, making these models viable for use in areas with poor access to medical data. The pre-trained CNN architectures, DenseNet121, VGG16, ResNet50, and InceptionV3 prove to be promising in transfer learning for pneumonia detection in chest X-ray images. DensNet121 was the best performing model in this research paper, with the highest accuracy and the best balance of precision and recall. In the end, each model has its defects; further investigation should be done to tune up these models and investigate new architectures to increase the accuracy and robustness for medical image classification. Transfer learning, when combined with appropriate model selection, could significantly improve the performance of automatic detection systems and help in the early detection and treatment of pneumonia.

7 Conclusion

This work demonstrates the effectiveness of transfer learning using pre-trained CNNs for detecting pneumonia in chest X-ray images. We tested the performance of four state-of-the-art architectures, namely DenseNet121, VGG16, ResNet50 and InceptionV3, in classifying normal chest X-ray images and images with pneumonia. Of all the models tested, DenseNet121 performed the best, achieving the highest accuracy and recall suitable for the task of pneumonia detection.

Despite the high accuracy of VGG16, its recall was very low, meaning that it is not very effective in detecting all cases of pneumonia. While ResNet50 and InceptionV3 are very competitive, the best performance was given by InceptionV3

due to its ability to extract multi-scale features.

Class imbalance and limited dataset size were causing problems, despite DenseNet121's better performance. These challenges reflect that work should be continued for improved model architectures, considering various techniques that can be employed like augmentation, class weighting, and any available sources of additional medical images, and whose preparation will increase the model robustness. Deep learning and transfer learning could be enormously potential, demonstrating that they can change the paradigm of medical image classification and thus offer a very powerful tool for automatic detection of pneumonia in clinical settings. Finally, transfer learning can ensure the development of an efficient, effective, and accurate approach in the development of automated systems for pneumonia detection. This technology is successful only with the ever-increasing contribution of knowledge to the use of artificial intelligence in healthcare.

8 Budget Plan

The budget for this project is allocated to cover the necessary resources, hardware, software, and personnel involved in the research and development process. Below is the breakdown of the estimated costs:

Item	**Cost (USD)**
Hardware	
High-performance server or cloud computing (for model training)	2,500
GPUs for faster computation	1,500
Software	
TensorFlow, Keras, and other libraries (open source)	0
Data storage and backup solutions (cloud storage)	500
Data Acquisition	
Purchasing or licensing of the Chest X-ray dataset	200
Personnel	
Research assistant	1,000
Project manager's salary	2,000
Miscellaneous	
Conference fees	1,000
Publication fees	500
Total Estimated Budget	**8,700**

Table 2: Budget Plan for Pneumonia Detection Project

The above budget includes the key expenditures needed to successfully complete this project, from the computational resources required for model training to the costs associated with data acquisition and personnel. Additional costs such as conference fees and publication charges are also considered for disseminating the research findings. The total estimated budget for the project is

$8,700. This plan ensures that all resources are allocated efficiently to achieve the objectives of the study.

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