Pneumonia Detection Using Deep Learning

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Keywords: Pneumonia, Deep Learning, Convolutional Neural Networks (CNNs), VGG16, Chest X-Ray, Web-Based Interface.

Abstract: Pneumonia is a serious lung infection that mainly affects children and the elderly people which requires rapid and accurate diagnosis. There are simple and effective methods for pneumonia detection, including the deep learning techniques, such as the convolutional neural network (CNN). As of now, such techniques have proved potential for medical image classification. In this paper, we present a pneumonia detection model built using the VGG16 pre-trained model of convolutional neural network architecture and trained on a labeled dataset of the chest X-ray images. The proposed system implementation is evaluated for its performance and also compared with the traditional methods, which show the significantly improved accuracy. This paper mostly exhibits the potential of transfer learning and using data augmentation to improve model generalization. This model was trained and tested on a chest X-ray image of a labeled dataset, obtaining the accuracy of around 93%. This system is deployed with a local web-based interface, which allowed the users to upload chest X-ray images for the real-time classification. The results show that deep learning can significantly improve the pneumonia detection, providing a more efficient, accurate, and automated alternative to existing diagnostic techniques.

1 INTRODUCTION

Pneumonia is an inflammatory infection of the lung and a respiratory disease caused by bacterial, viral, or fungal agents that affects millions of people worldwide and has a major impact on the healthcare challenges and mortality. Traditionally chest X-ray interpretations are implemented by human radiologists which is time-consuming, prone to human error, and highly dependent on their experience. In case of any misdiagnosis or delayed diagnosis, it may result in serious complications, so making accurate detection and early diagnosis is crucial.

In recent years, artificial intelligence (AI) and deep learning have developed towards automated diagnostic systems for medical image classification. Convolutional Neural Networks (CNNs) have exhibited strong performance in complex patterns in images and obtaining high accuracy in classification tasks. Transfer learning, which utilizes pre-trained models of CNN on large the datasets, has been particularly effective in medical image analysis.

Traditional methods for pneumonia detection, such as manual interpretation of the chest X-ray images, tend to be highly subjective as they require significant medical experience. Other machine learning methods such as support vector machines (SVMs) and logistic regression have been explored variously in the past but generally require extensive feature engineering and have less effectiveness compared with the complex imaging data. Other deep learning models, such as ResNet and Inception, have also been utilized for medical imaging, however, VGG16 particularly has simple architecture model and is highly effective for feature extraction. We use VGG16 to enhance pneumonia detection accuracy while minimizing the computational complexity.

This research mainly utilized the VGG16 model of CNN architecture for pneumonia detection in chest X-ray images. VGG16 is a pre-trained model which is used in the process of feature extraction, was performed after the additional custom layers for classification. This model was trained on a labeled dataset containing the chest X-ray images of normal and pneumonia-affected to develop an automated detection system. This research evaluates the model's performance, helping to reduce the pressure on radiologists and improving patient outcomes and

Aireddy, S., Sanjana, M., Goud, P. U. K., Sameer, M., Ramakrishna, M. K. and Archana, D.
Pneumonia Detection Using Deep Learning.
DOI: 10.5220/0013908400004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 4*, pages 75-80
ISBN: 978-989-758-777-1

aims to automate the efficient pneumonia diagnosis process.

2 LITERATURE REVIEW

In recent years, a number of research studies have explored deep learning for the pneumonia detection. Rohit Kundu, Ritacheta Das et al. (2021) proposed an ensemble based deep learning methodology for pneumonia detection in Chest radiographs. In this the methodology is included of three CNN architectures namely GoogLeNet, ResNet-18, and DenseNet-121 with a weighted average of ensemble methodology using the precision, recall, F1-score, and AUC. This study evaluated the algorithm using the two publicly available datasets of pneumonia with an accuracy of 98.81% and 86.85% and also a sensitivity value of 98.80% and 87.02%. The proposed method also exceeded the state-of-the art (SOA) methods and this method performs better than the other ensembled techniques. Tawsifur Rahman et al. (2020) analyzed and used four pre-trained CNNs - AlexNet, ResNet18, DenseNet201, and SqueezeNet. They are categorized to identify subtypes of pneumonia (normal vs. pneumonia, bacterial vs. viral, three-class classification also) using transfer learning to classify chest X-ray images. The dataset comprised of 5,247 X-rays and the methods reached the classification accuracy of 98%, 95% and 93.3% respectively. The study also supports using AI potentially to assist with the rapid pneumonia diagnosis and screening.

Ayush Pant, Akshat Jain et al. (2020) by considering the higher mortality rate of pneumonia, this paper presented an automated deep learning approach for the early diagnosis of pneumonia detection by utilizing CNNs. The authors tried to combine two CNN architectures with an ensemble model to be allowed for the improvement of issues with the existing methods. This study provides the improved model with robustness and performance in which it is to develop a diagnostic tool for the health care professionals efficiently. Faiza M Qaimkhani, Md G Hussain et al. (2022) studied the mostly applied deep learning methods, which are specifically ANN, CNN, and also the VGG19 architecture, which helps to improve pneumonia identification accuracy efficiently. The study focuses mainly on the early identification, and special emphasis on the cases that occur mostly in the children, although their aim is to provide and serve a reliable, helpful automated system as an aid to healthcare to mainly identify the pneumonia cases rapidly for early treatment. Shagun Sharma, Kalpna Guleria (2023) created a pneumonia detection model that is mostly based on the deep learning techniques by using the VGG-16 architecture. There is a various feature extraction from the chest X-ray images, which are then classified for pneumonia detection. This study aims to support the healthcare professionals by early diagnosis and precision of pneumonia, by improving the health resource efficiency, and also overall outcomes of the patient. These results show that deep learning is a possible method for identification of pneumonia, but, there is still a need for models that balance the high accuracy with computational efficiency for real-time applications.

3 METHODOLOGY

3.1 Methods

Convolutional Neural Networks: Convolutional neural networks (CNNs), are fundamental components of deep learning-based image classification, including pneumonia detection in chest X-rays. Analysis of medical imaging greatly benefits from CNNs' ability to automatically extract hierarchical features from input images. The architecture is formed of different types of layers, which include pooling layers, convolutional layers, activation functions, and fully linked layers. The convolutional layers use learnable filters to identify key characteristics like edges, textures, and patterns at various levels of abstraction. Activation functions like ReLU (Rectified Linear Unit) introduce non-linearity which enables the model to recognize the complex patterns in medical imaging. Pooling layers, such as max pooling, enhance computational efficiency while maintaining essential information by reducing the spatial dimensions of feature maps. Once these features are extracted and then processed through the fully connected layers, the model classifies the image as either 'Normal' or 'Pneumonia'. As CNNs can learn spatial structures and identify the complex patterns which human radiologists might miss, they perform better in medical imaging than the traditional machine learning techniques. The automatic feature extraction, which reduces the need for manual feature engineering, makes CNNs a resilient and effective method for pneumonia detection in chest X-ray analysis.

Pre-trained Model VGG16: The most commonly used convolutional neural network (CNN) architecture VGG16 was pre-trained model used on the large ImageNet dataset, which includes datasets of having millions of images in hundreds of categories of images. VGG16 is very successful in transfer learning in the field of medical image analysis, because of its ability to learn rich feature representations through pre-training models, including the pneumonia detection. There are 16 layers that form the architecture, which includes convolutional layers, pooling layers, and fully connected layers. Convolutional layers mainly use tiny 3x3 receptive fields to collect the hidden information in photos. Instead of beginning from scratch, we usually take the advantage of VGG16's capacity to extract high-level spatial features and textural information from the chest X-ray images by utilizing it as a basis model. On top of the pre-trained model convolutional layers, more custom layers like the dense and dropout layers are added to improve the model for binary classification which maintains the important hierarchial features. This method in general significantly decreases the training time and improves the model accuracy because VGG16 is already pre-trained on the broad features of images that can be optimized for pneumonia detection. Additionally, by freezing initial layers and training on the top layers of the pneumonia specified data. We ensure the better model generalization which reduce the risk of overfitting, and improve the model's ability to detect pneumonia in real chest X-ray images.

Model Enhancement Techniques: The pneumonia detection model is optimized with various preprocessing, classification, and optimization strategies to improve its performance and generalization. Data augmentation methods such as rescaling, flipping and rotation are mostly utilized in image preprocessing to introduce variations in the training data, avoid overfitting, and enhance model robustness. These modifications optimize the model's ability to generalize to unseen chest X-ray images. This model was developed for binary classification, to classify chest X-ray images as either 'Normal' or 'Pneumonia', where it applies a sigmoid activation function in the output layer, and to optimize strategies which include learning rate scheduling, dropout layers and the Adam optimizer are used to achieve even better performance. When validation loss gradually decreases then the learning rate management supports stable convergence by lowering the rate, at the same time the Adam optimizer automatically optimizes learning rates for improved training performance. To prevent overfitting and improve generalization, dropout layers acts as a regularization method by randomly disabling neurons while training. The combination of these methods results with high accuracy and effective model of deep learning for pneumonia detection. Figure 1 shows the Normal chest X-ray and Figure 2 shows the Pneumonia chest X-ray respectively.

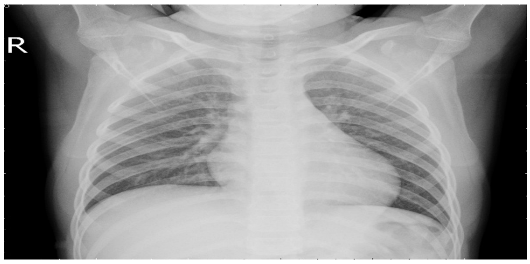


Figure 1: Normal chest X-Ray.

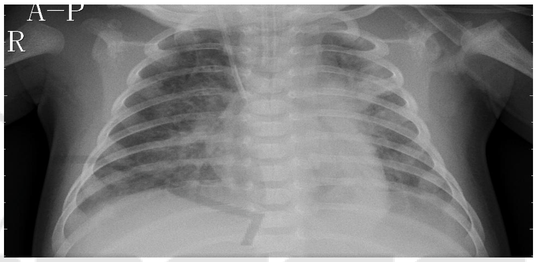


Figure 2: Pneumonia chest X-Ray.

3.2 Working

The methodical process of the pneumonia detection system begins with the dataset preparation, which utilizing a labeled dataset of chest X-ray images. The three subsets of the dataset are the training set, validation set, and test sets. The test set provides an accurate and fair evaluation of the model's performance, the validation set supports hyperparameter optimization and performance tracking, and the training set is used to train the model. This prevents overfitting and provides an effective training process. In the next stage, VGG16 is utilized as the fundamental model to develop the architecture of the model. The custom dense layers with ReLU activation are added to VGG16, a pre-trained model of CNN because to improve non-linearity and learning capacity and also dropout layers are employed to improve model generalization by reducing the risk of overfitting through the random deactivation of neurons during the training period. The final output layer predicts the chest X-ray image which shows whether it is 'Normal' or 'Pneumonia' for binary classification by using the sigmoid activation function. This model is been trained using the augmented data of the image, that goes through stability-improving changes such as rescaling, flipping and rotation. By using the Adam optimizer, the learning rates are continuously adjusted to optimize the convergence speed. The early stopping process is used to prevent overfitting and unwanted computation by finishing the training process when validation loss stabilizes. The continuous learning is maintained by assessing the training process using accuracy metrics and loss curves. Once the training process is completed then the evaluation phase utilizes a various metrics to evaluate the model's performance, including accuracy, precision, recall, and F1-score, which evaluates the model’s effectiveness in data classification on the test dataset. Additionally, the prediction accuracy is analyzed by evaluating true positives, false positives, true negatives, and false negatives using a confusion matrix. During the deployment phase, the trained model is integrated into a Flask-based web interface, providing a real-time communication. The web-based application enables users to upload the chest X-ray images, which are then processed by the model to predict the condition of pneumonia. This interface provides an efficient automated diagnostic system that helps healthcare professionals by making faster and more accurate decisions.

4 RESULT AND ANALYSIS

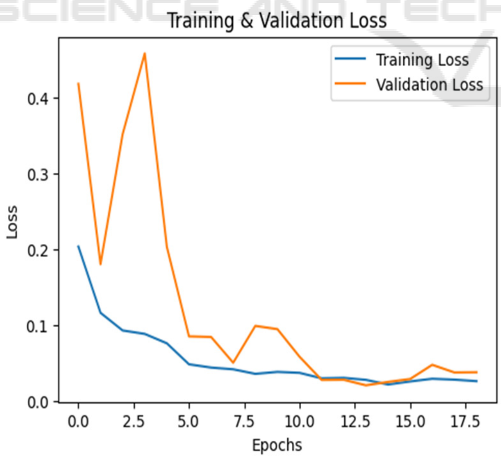


Figure 3: Training & validation loss graph.

The graph in figure 3 shows the training and validation loss during the training period. The blue line which is represented as training loss gradually decreases, showing that the model improves and processes more data. The orange line which represented as validation loss fluctuates in the beginning but afterward, it becomes steady at a low value. This shows that the model generalizes well to new data. The early fluctuations in validation loss indicate slight uncertainty, but there are no major signs of overfitting. The consistently stable downward trend confirms an effective learning.

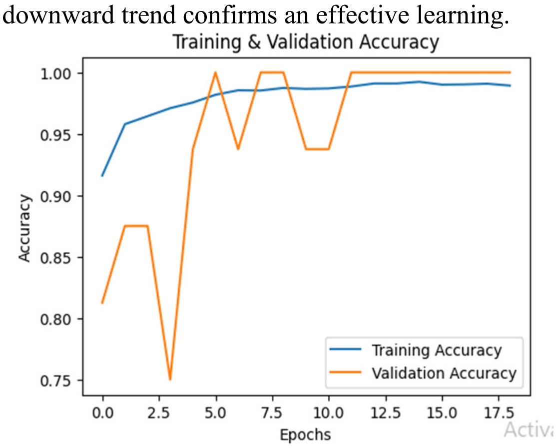


Figure 4: Training & validation accuracy graph.

The graph in figure 4 which mentioned above signifies the training and validation accuracy. The training accuracy line increases easily and attains a high value above 95%. On the other hand, the validation accuracy line fluctuates in the beginning before reaching close to 100%. These fluctuations imply that the model in the early stages had difficulty with validation data but eventually adjusted well. For both the training and new data the final accuracy levels indicate that the model is providing accurate predictions, pointing to have a good generalization.

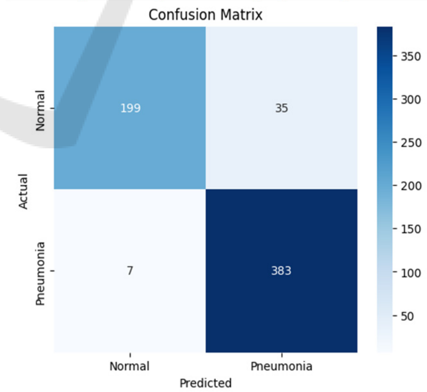
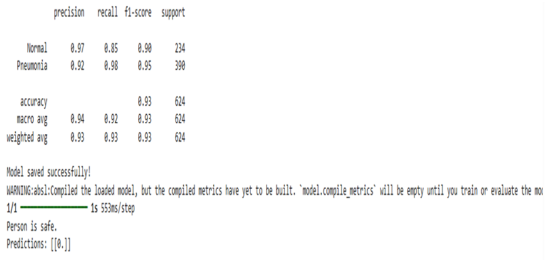


Figure 5: Confusion matrix.

The image in figure 5 shown above is the confusion matrix, which helps us to understand that how accurately the model classifies the chest X-ray images. Among all the normal cases, 199 were correctly detected, yet 35 cases were misclassified as pneumonia. In the case of pneumonia, the model correctly recognized 383, but 7 wrongly identified as normal. The least number of false negatives, the 7 cases only is highly important because this indicates that the model almost never misses actual pneumonia cases, which is important for real-world medical applications. On the other hand, the false positives which are 35 cases that are higher, this is actually better because it reduces the chance of missing pneumonia cases.



```
              precision    recall  f1-score   support

      Normal       0.97      0.85      0.90       234
   Pneumonia       0.92      0.98      0.95       390

    accuracy                           0.93       624
   macro avg       0.94      0.92      0.93       624
weighted avg       0.93      0.93      0.93       624

Model saved successfully!
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the mo
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 553ms/step
Person is safe.
Predictions: [[0.]]
```

Figure 6: Classification report & prediction result.

The above figure 6 is a classification report of the pneumonia detection model that highlights the model's effective performance.

- The precision for the normal cases is 0.97, which means the 97% of predicted normal cases are exactly normal.
- The recall for the normal cases is 0.85, which means the 85% of actual normal cases were correctly identified.
- The precision for the pneumonia cases is 0.92, and recall is 0.98, showing that the model identifies pneumonia cases in a very effective way.
- The model achieves an overall accuracy of 93%, indicating high model performance.
- The macro and weighted averages of precision, recall, and F1-score are approximately 0.93, verifying equal performance for both classes.

At the bottom of the classification report, the note 'Model saved successfully!' shows that the trained model has been saved and can be used later in future. The last part that is the prediction output which says the 'Person is safe' shows that the uploaded image of chest X-ray was correctly classified as normal, with the prediction value [[0.]] likely falls into the normal category in the model's processing system.

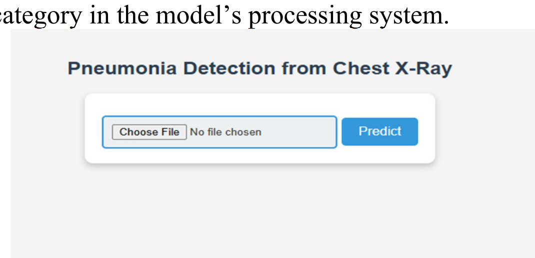


Figure 7: Web interface for pneumonia detection.

This above-mentioned figure 7 is a Flask-based web interface which is simple and user-friendly to enable users to upload the chest X-ray images for pneumonia detection. This interface is running on local host (127.0.0.1:5000) on your computer, this makes that it is only accessible from your own machine during testing locally. By uploading an image through the file upload button, and then pressing the 'Predict' button, users can have the model identify whether it is normal or pneumonia. After the prediction, the application will provide a result such as 'Person is safe' or 'Person is has Pneumonia', ensuring the output is clear and easy to understand. This deployment is an easy access to users, allowing anyone to test the chest X-ray images easily without having the direct interaction with the code, making it an effective tool for quick and real-time diagnosis.

5 CONCLUSIONS

This research used CNN and VGG16 to build a deep learning model for pneumonia detection system. This model achieved high accuracy in classifying the chest X-ray images, demonstrating the capability of deep learning in the field of medical diagnosis. A web-based interface developed to make the system utilized in real-time experience, providing a faster and effective automatic diagnostic system. The future enhancements may include using an extensive dataset for higher accuracy and faster model performance. In summary, this study highlights AI-driven systems that supports in medical field assisting doctors in treating and detecting pneumonia at early stage.

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