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Pneumonia Detection Using Deep Learning Techniques

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Abstract

Background: Pneumonia, a common and possibly fatal respiratory infection, frequently necessitates an early and correct diagnosis in order to be treated effectively. In order to enable quick and accurate diagnosis of pneumonia, we are using deep learning models in this research that have been trained on chest X-ray images.
Objectives: Two different models were created and trained with a dataset of chest X-ray images: ResNet50, a custom Convolutional Neural Network (CNN). The models' remarkable accuracy of 98%, 88%, respectively, showed how well they could differentiate between photos with pneumonia and those without it.
Statistical Analysis: Furthermore, we used the Flask framework to deploy these models as a web application, making this technology easily accessible and user-friendly.
Findings: The resulting website has a simple interface through which people may upload the chest X-ray photos. Once the photo is submitted, the deep learning models that have been implemented quickly analyse them and make predictions about whether the images show pneumonia or normal.
Applications and Improvements: This implementation provides a useful tool for healthcare providers to help diagnose pneumonia in addition to demonstrating the potential of deep learning in medical diagnostics.

Keywords: e Pneumonia detection, Deep learning, Chest X-ray images, ResNet50, Convolutional Neural Network (CNN), Flask framework, Web application.

1. Introduction

The rapid growth and potential complications of pneumonia, a respiratory infection with inflammation in the lung, are still cited as causing significant health problems worldwide. Correct and accurate diagnosis of pneumonia is critical for effective treatment and patient outcomes. Chest radiography is a key diagnostic tool, and it provides sensitivity to lung abnormalities related to pneumonia. It is also incredibly non-invasive and widely available. Due to increasing cases and a smaller number of specialists available to make diagnosis, the screening process become a tough task. Therefore, for a quick and precise diagnosis, clinicians must rely on machine learning algorithms. Several machine learning approaches have already been used for analysing chest X-ray images.
Traditional methods like support vector machine (SVM) have several disadvantages. Over the years, their performance has degraded and is not considered at par with practical standards.

Moreover, their development is very time consuming. Recent advances in deep learning techniques have revolutionized medical image analysis, especially in this field of radiology. Convolutional Neural Networks (CNN) and other deep learning models have demonstrated exceptional skill in extracting complex patterns and features from medical images, resulting in their performance surpassing human capabilities for many tasks. In the detection of pneumonia, these models have shown some promise in automatically analysing chest X-rays to identify signs of infection with high accuracy.

By utilizing deep learning, the aim of this project is to identify pneumonia in chest X-ray images. We trained and evaluated two separate deep learning models: ResNet50 and a custom convolutional neural network (CNN). We used a dataset which consists of 5856 images of chest X-ray and those 5856 are classified into 2 classes' pneumonia and normal consists 4273 and 1583 images respectively, the models were trained to train using these models with care, each image being classified as either representative of pneumonia or normal. Through rigorous training and validation, our models achieved impressive accuracies of 98% and 88%, respectively, demonstrating their ability to effectively discriminate between pneumonia infected and normal chest X-rays.

2. Literature Survey

Without a skilled radiologist, chest x-ray interpretation might be challenging. The goal of many studies are to automate x-ray analysis. A team of academics created a deep learning framework-based system in February 2018 to categorize photos for diabetic retinopathy and macular degeneration. It also categorized typical chest X-ray images and pneumonia. 5,232 paediatric chest X-ray pictures were used to train the model, of which 1,349 showed normal results and 3,883 showed pneumonia. They achieved 92.8% accuracy, 93.2% sensitivity, and 90.1% specificity.

The winning submission for the 2018 RSNA Pneumonia Challenge on Kaggle focused on the detection and localization of pneumonia in chest x-rays by utilizing a fully convolutional network integrated with object detection features. Another study suggested using chest x-rays to classify pneumonia using deep learning architecture.

Convolutional neural networks and residual network architecture were employed by the model to classify the photos. The accuracy of 78.73% was attained, surpassing the 76.8% top-scoring accuracy previously held. Additionally, other researchers have only used pure CNN that is, they have not used transfer learning to classify photos of pneumonia, achieving a validation accuracy of 93.73%. Because pneumonia disease has a vague look, it might overlap with other conditions and mimic other anomalies, making it difficult to diagnose from X-ray pictures.

A CAD method was introduced by Leandro et al. to detect pneumonia in children. A CAD system was proposed by Hiroyuki et al. to diagnose interstitial diseases and locate nodules using chest X-ray images. Five distinct classifiers were used in the CAD system Rafael et al. created to categorize pneumonia and normal chest X-ray pictures. Cross-validation testing is used to test Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes, Multi-Layer Perceptron, and Decision Tree optimized models. KNN has an accuracy of 93%. Deniz et al. concentrated on the biological progression of pneumonia and the accurate classification of pneumonia utilizing pictures from chest radiographs, which had a 78.73% classification rate. In order to classify tuberculosis, Zain et al. used Bayesian based CNN to learn the intricate features from X-ray pictures, and they were able to reach an accuracy of 86.46%.

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3. Existing System

Support Vector Machine

One of the most widely used supervised learning techniques for both classification and regression issues is supporting vector machine, or SVM. But it's mostly applied to machine learning classification challenges. In order to make it simple to classify fresh data points in the future, the SVM method seeks to identify the optimal line or decision boundary that can divide n-dimensional space into classes. We refer to this optimal decision boundary as a hyperplane. SVM selects the extreme vectors and points to aid in the creation of the hyperplane. The algorithm is referred regarded as a Support Vector Machine since these extreme situations are known as support vectors.

Decision Tree

Decision trees are non-parametrical supervised learning algorithms that are used in both classification and regression. A decision tree has a hierarchical tree structure with a root node, branch, internal node and leaf node. In decision tree learning, a greedy search is used to find the optimal partition points within the tree. The process of partitioning is then repeated in the top-down, recursive way until all or most of the records are classified under class labels. Whether or not all the data points are homogeneous sets depends on the complexity of your decision tree. A smaller tree may be able to achieve pure leaf nodes that is, data points within a single class but as the tree grows, it becomes harder to maintain this purity and often results in too much data falling within a subtree. This is called data fragmentation and often results in overfitting.

Random Forest

Random Forest is one of the most widely used supervised learning algorithms. It is used for both Classification as well as Regression problem in ML. Random Forest is based on the idea of ensemble learning, where multiple classifiers are used to solve a complicated problem and improve the model performance. As the name indicates, a random forest is a classifier which consists of several decision trees on different subsets of a given dataset. The average of the decision trees improves the predictive accuracy of the dataset. Instead of relying on a single decision tree, a random forest takes the predictions from each tree and predicts the final output based on the majority of predictions. The more trees in the forest, the higher the accuracy and the problem of overfitting is avoided.

4. Proposed System

A subset of machine learning is called deep learning. Artificial neural networks are used in Deep Learning to process the data. It can figure out intricate linkages and patterns in the data. Layers of connected nodes that process and change data make up neural networks, which are designed to resemble the structure and operation of the human brain.

Dataset

The dataset has subfolders for each image category (Pneumonia/Normal) and is arranged into three folders (train, test, and val). There are two categories (Pneumonia/Normal) and 5,863 X-ray images (JPEG). Anterior-posterior chest X-ray images were chosen from retrospective cohorts of paediatric patients from Guangzhou Women and Children's Medical Center, Guangzhou, aged one to five. Every chest X-ray image was taken as a standard clinical procedure for the patients. All chest radiographs were first screened for quality control by eliminating any low quality or unreadable scans before being subjected to the analysis of chest x-ray pictures. Before the photos' diagnoses could be used to train the AI system, they were evaluated by two board-certified medical professionals. A third expert verified the evaluation set to make sure there were no grading problems.

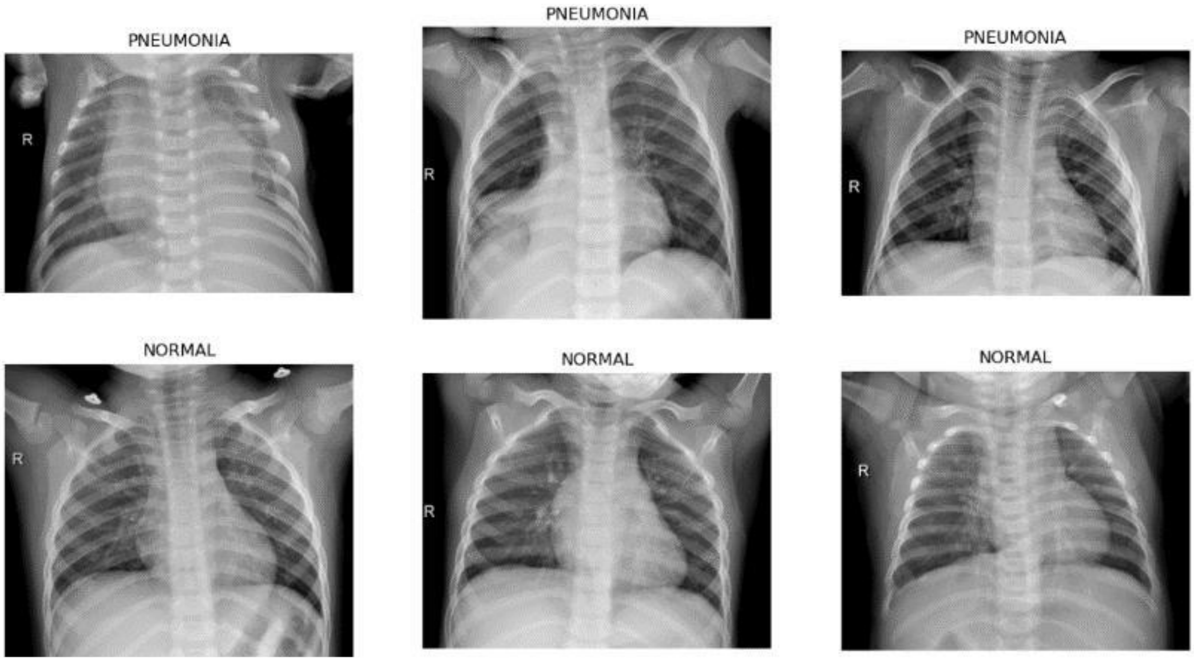

Figure 1. Chest X-ray samples

Preprocessing

Before training the model, preprocessing steps are usually applied to the dataset. These pretreatment stages make that the data reflects the qualities needed by the model architecture and is in a format that is appropriate for training. Move the dataset into memory from its source. You may use data augmentation to artificially expand the dataset and enhance model generalization if it is comparatively small. For image data, random rotations, flips, shifts, zooms, and brightness modifications are common data augmentation methods. Resize the pictures to a predetermined scale that corresponds to the deep learning models' anticipated input size. Since (224, 224) pixels are a typical input size for many image classification models, including ResNet50, we mentioned resizing the photos to that size in our instance. Adjust each image's pixel value to fall inside a defined range. Normalization can enhance model convergence and aid in training process stabilization. The dataset was divided into test and training sets. 4978 photos make up the training set, while 878 images make up the test set, which is used to assess how well the finished model performs with untested data.

ResNet50 model

Microsoft Research created the deep convolutional neural network (CNN) architecture known as ResNet50 in 2015. ResNet50 is one of a variation "Residual Network". The network has 50 layers deep, and the number "50" in the name relates to the number of layers in the network.

ResNet50 is a potent picture classification model that produces cutting-edge outcomes when trained on huge datasets.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 2048)              23587712

 dense (Dense)               (None, 2)                 4098

=================================================================
Total params: 23,591,810
Trainable params: 23,538,690
Non-trainable params: 53,120
_________________________________________________________________
```

Figure 2. Summary of ResNet50

We used Image net weights to the ResNet50 model. Only the densely connected layers of the ResNet50 model were able to learn from the pneumonia dataset since we frozen the convolutional base layers to stop their weights from changing during training. By defining the optimizer, the loss function, and the evaluation metric, we set up the model for training. Lastly, we used the training data to train the model, and we kept an eye on its performance on the validation set to make necessary hyperparameter adjustments and avoid overfitting. By going through this iterative approach, we were able to achieve a high degree of accuracy in the classification task by successfully optimizing the ResNet50 model to detect pneumonia from chest X-ray pictures.

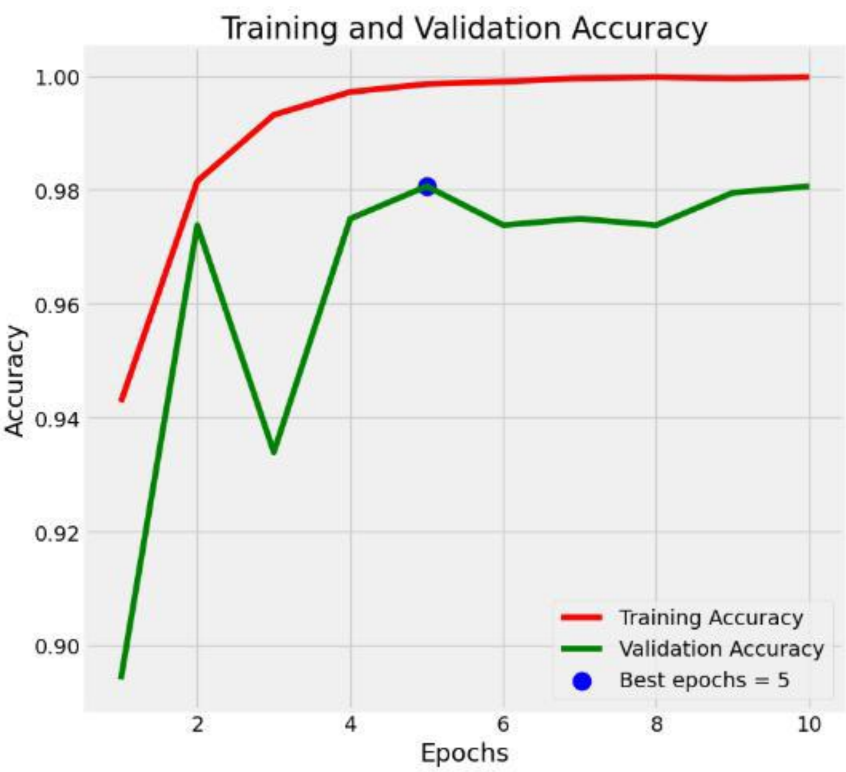

Figure 3. Training and validation accuracy of ResNet50 model

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Convolutional neural network (CNN)

Neural networks are the foundation of deep learning techniques, which are a subset of machine learning. They are made up of node layers, which have an output layer, an input layer, and one or more hidden levels. Every node has a threshold and weight that are connected to one another. If a node's output exceeds a predetermined threshold value, it becomes active and transmits data to the network's next tier. If not, no data is transferred to the network's subsequent tier. Convolutional neural networks function better with picture, speech, or audio signal inputs than other types of neural networks. They consist of three primary types of layers: fully-connected (FC) layer, pooling layer, and convolutional layer.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_1 (Conv2D)           (None, 222, 222, 64)      1792

 max_pooling2d_1 (MaxPooling  (None, 111, 111, 64)     0
 2D)

 conv2d_2 (Conv2D)           (None, 109, 109, 64)      36928

 max_pooling2d_2 (MaxPooling  (None, 54, 54, 64)       0
 2D)

 flatten_1 (Flatten)         (None, 186624)            0

 dense_2 (Dense)             (None, 128)               23888000

 dropout (Dropout)           (None, 128)               0

 dense_3 (Dense)             (None, 64)                8256

 dropout_1 (Dropout)         (None, 64)                0

 dense_4 (Dense)             (None, 2)                 130

=================================================================
Total params: 23,935,106
Trainable params: 23,935,106
Non-trainable params: 0
_________________________________________________________________
```

Figure 4. Summary of CNN

Using the Keras Sequential API, we built the CNN model architecture, which consists of dropout layers for regularization to reduce overfitting and max-pooling layers for spatial down sampling after convolutional layers with ReLU activation functions for feature extraction. To the model for classification, we added fully linked dense layers with ReLU activation functions. For binary classification, we then added a final output layer with a sigmoid activation function. By defining the optimizer, the loss function, and the evaluation metric, we set up the model for training. In order to optimize the CNN model for accurate pneumonia identification from chest X-ray pictures, we lastly trained it using the training data and monitored its performance on the validation set to modify hyperparameters as appropriate and prevent overfitting.

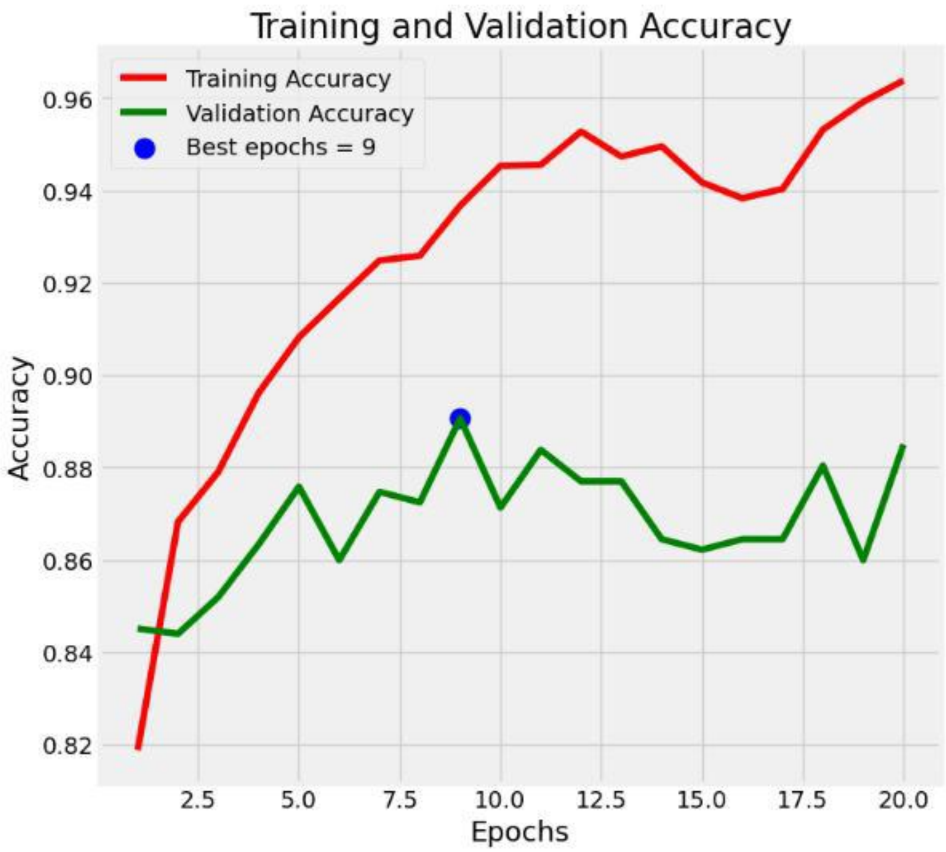

Figure 5. Training and validation accuracy of CNN model

Results

	precision	recall	f1-score	support
NORMAL	0.97	0.96	0.97	227
PNEUMONIA	0.99	0.99	0.99	651
accuracy			0.98	878
macro avg	0.98	0.98	0.98	878
weighted avg	0.98	0.98	0.98	878

Figure 6. Classification report of ResNet50

	precision	recall	f1-score	support
NORMAL	0.81	0.72	0.76	227
PNEUMONIA	0.91	0.94	0.92	651
accuracy			0.88	878
macro avg	0.86	0.83	0.84	878
weighted avg	0.88	0.88	0.88	878

Figure 7. Classification report of CNN

5. Conclusion

The ResNet50 model distinguished pneumonia from chest X-ray pictures with an astounding 98% accuracy rate. This model performed remarkably well in recognizing pneumonia patients because to its deep architecture and pre-trained weights on ImageNet. With an accuracy of 88%, the CNN model demonstrated strong performance in the diagnosis of pneumonia. Although the custom CNN did not perform as well as ResNet50, it was still a dependable model for the purpose. To sum up, this experiment shows how well deep learning models in particular, ResNet50 and the custom CNN work for pneumonia detection. These models' great accuracy makes them an invaluable tool for helping with pneumonia diagnosis. This initiative has the potential to have a significant effect on the healthcare sector and enhance patient outcomes with additional development and implementation.

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