Pnemonia Detection Using CNN

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***Abstract*—Bacteria, such as Streptococcus pneumonia, often cause a severe infectious disease that affects the lungs. According to the World Health Organization (WHO), pneumonia is responsible for one in three deaths in India. Chest X-rays are commonly used to diagnose pneumonia but require the evaluation of expert radiologists. Therefore, developing an automatic system for detecting pneumonia would be highly beneficial, especially in remote areas where access to medical expertise may be limited. Convolutional Neural Networks (CNNs) have successfully analysed medical images and are gaining attention for disease classification. Pre-trained CNN models on large-scale datasets can be helpful in image classification tasks. In this project, we evaluate the effectiveness of pre-trained CNN models as feature extractors followed by different classifiers for classifying abnormal and normal chest X-rays. We determine the optimal CNN model for this purpose and show that pre-trained CNN models and supervised classifier algorithms can be highly effective in analysing chest X-ray images and detecting pneumonia. Our statistical results demonstrate the potential of this approach in improving pneumonia diagnosis and treatment.**

***Index Terms*—DenseNet, ResNet, VGG16, Convolutional Neural Networks, SVM, Transfer Learning, Random Forest, Feature Extraction.**

I. Introduction

Computer Aided Designs (CAD) have recently gained significant importance in machine learning. These systems have proved useful in medical areas such as breast cancer, mammograms, and lung nodule detection. Feature extraction is paramount when applying Machine Learning (ML) techniques to medical images. Deep Learning (DL) models, particularly Convolutional Neural Networks (CNNs), have shown their self-potential in extracting useful features in image classification tasks. Transfer learning methods are employed where pre-trained CNN models learn generic features on large-scale datasets like ImageNet, which are then transferred to the required task. The availability of pre-trained CNN models such as AlexNet, VGGNet, Xception, ResNet, and DenseNet highly aids in the process of significant feature extraction.

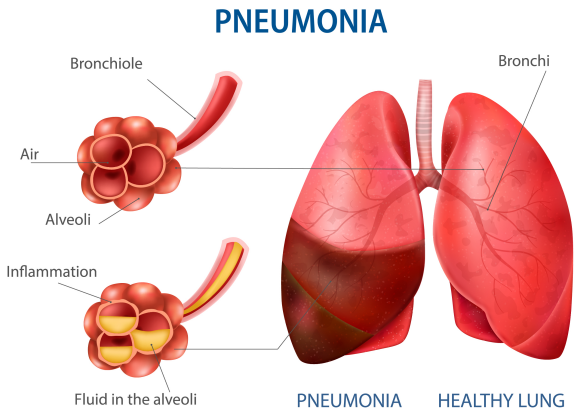

Fig. 1. Pnuemonia Lungs affected by Pnuemonia

Chest screening subroutines, primarily used for sensing lung nodules, can also diagnose other illnesses such as pneumonia, effusion, and cardiomegaly. Pneumonia is a deadly infectious disease affecting millions of people, primarily those over 65 and suffering from chronic diseases like asthma or diabetes. Chest X-rays are considered the most effective method to determine the extent and location of the septic region in the lungs. However, examining chest radiographs is challenging for radiologists, as the appearance of pneumonia can be hazy and misapprehended with other diagnoses. This study evaluates the performance of different pre-trained CNN models followed by different classifiers for classifying abnormal and normal chest X-Rays.

The crucial contributions of this study are a comparative analytical study of different pre-trained CNN models as feature-extractors for analyzing chest X-rays, presentation of these models with different classifiers to propose an ideal classifier in the same field of classification, and evaluation

of optimal pre-trained CNN model with hyperparameter tuning of the best-analyzed classifier to further improve performance. The structure of this paper is described in detail in the following sections, including a review of related research, dataset details, applied methodology, experimental setup, and results and discussions about the final AUC scores obtained.

II. Dataset Description

The left panel of a normal chest X-ray typically depicts clear lungs without any areas of abnormal opacification in the image. In contrast, bacterial pneumonia (middle) typically exhibits a focal lobar consolidation, which can appear in any part of the lungs. In contrast, viral pneumonia (right) manifests with a more diffuse ”interstitial” pattern in both lungs, which can also occur in other respiratory diseases.

The ChestX-ray8 dataset used in your project is organized into three folders, train, test, and value, and contains subfolders for each image category, Pneumonia and Normal. The dataset consists of 1414 X-ray images in JPEG format and two categories. Chest X-ray images were selected from retrospective cohorts of pediatric patients aged one to five years from Guangzhou Women and Children's Medical Center, Guangzhou. All chest X-ray imaging was performed as part of the patient's routine clinical care.

To ensure the quality of the chest X-ray images, all scans were initially screened for quality control and low-quality or unreadable scans were removed. Two expert physicians then graded the diagnoses for the images before being cleared for training in the AI system. To account for any grading errors, a third expert also checked the evaluation set. This rigorous process ensures the accuracy and reliability of the AI system in detecting signs of pneumonia in chest X-ray images.

III. Methodology for Proposed Model

At first, we take the dataset of images with two classes - pneumonia and normal classes. Then for better results after training the images, we first preprocess the images and downconvert the pixels to 224 x 224 pixels per image for easy computations. Initially, we visualize the data for an idea about how the two classes look. We will also standardize the input distribution by transforming the values in each batch so that their mean is 0 and their standard deviation is 1, which facilitates model training. Additionally, we will convert our single-channel X-ray images (grayscale) to a three-channel format by repeating the values in the image across all channels.

Later we build a CNN model consisting of multiple convolutional layers, batch normalization layers, max-pooling layers, and dense layers with dropout. The network is compiled with binary cross-entropy loss and the Adam optimizer. We train this model on training data. We build different types of CNN models for transfer learning - Densenet121, VGG16, and Resnet50. In the next section, there is a brief explanation of each model.

IV. Experimentation and Results

A. Dataset

Here, we will load the dataset and perform exploratory data analysis (EDA) on the data. This includes performing data cleaning and pre-processing, such as resizing the images and normalizing the pixel values. The dimensions of the image are 1438 pixels width and 1588 pixels height, one single color channel. The maximum pixel value is 255.0000 and the minimum is 0.0000. The mean value of the pixels is 131.4152 and the standard deviation is 62.0410.

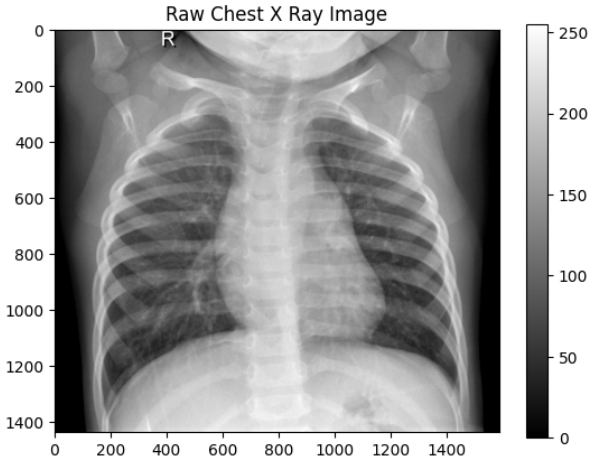

Fig. 2. Raw Image with colorbar

Visualize the data to understand the distribution of the classes and identify any imbalances or out-

liers. We then generate a distribution plot of pixel intensities. of a flattened image.

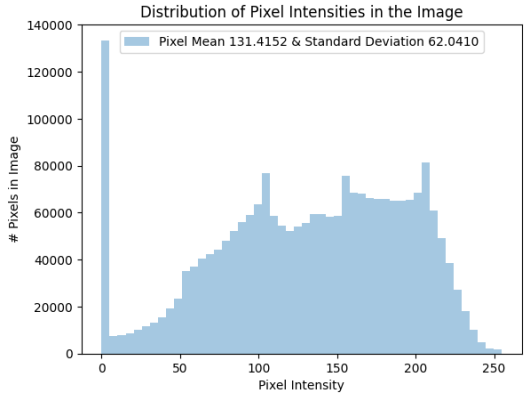

Fig. 3. Pixel Intensity Distribution

B. Building a CNN Model

After building the model we evaluate its performance on the dataset. Show the experimentation results prospectively after each experiment. Building the model involves defining the architecture of the CNN model, including the number of layers, filter sizes, and activation functions. We train the

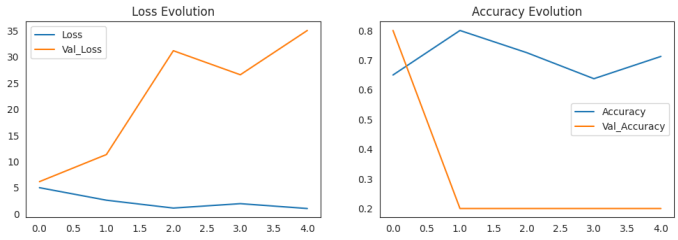

Fig. 4. Loss and Accuracy Evolution

model on the training set and validate it on the validation set. Then monitor the training and validation accuracy and loss to detect overfitting and adjust the model accordingly. Evaluate the model's performance on the test set using evaluation metrics such as accuracy, precision, recall, and F1-score.

C. Transfer Learning

We use transfer learning techniques such as DenseNet, VGG16, and ResNet to improve the performance of the CNN model. Import pre-trained models such as DenseNet, VGG16, and ResNet. Freeze the pre-trained layers and add new layers

	0	1	accuracy	macro avg	weighted avg
precision	0.0	0.691176	0.691176	0.345588	0.477725
recall	0.0	1.000000	0.691176	0.500000	0.691176
f1-score	0.0	0.817391	0.691176	0.408696	0.564962
support	84.0	188.000000	0.691176	272.000000	272.000000

Fig. 5. Training and Validation loss/accuracy

for transfer learning. Train the transfer learning model on the training set and validate it on the validation set. Monitor the training and validation accuracy and loss to detect overfitting and adjust the model accordingly. We use SVM and Random

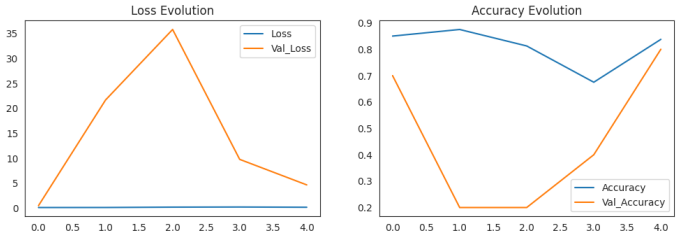

Fig. 6. DenseNet Loss and Accuracy Evolution

Forest classifiers on top of the transfer learning models to classify the pneumonia images. Extract features from the transfer learning models and use them as input for SVM and Random Forest classifiers and train the classifiers on the training set and validate them on the validation set. Tune the hyperparameters of the classifiers using grid search or other methods to improve their performance.

Evaluate the performance of the transfer learning models and classifiers on the dataset and compare it with the performance of the CNN model. Evaluate the performance of each model on the test set using evaluation metrics such as accuracy, precision, recall, and F1-score.

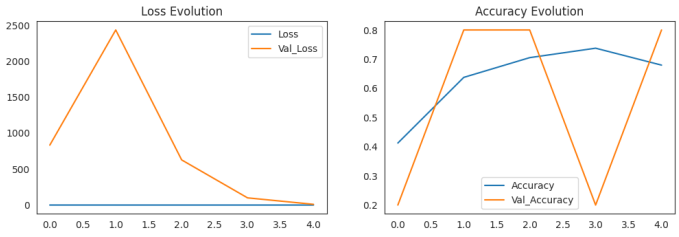

Fig. 7. VGG16 Loss and Accuracy Evolution

Compare the performance of the models and select the best-performing model for further fine-tuning. Validate the final model on the test dataset and report its accuracy and other evaluation metrics. Show the experimentation results prospectively. Evaluate the final model on the test set using evaluation metrics such as accuracy, precision, recall, and F1-score. Visualize the predictions and compare them with the ground truth labels. Report the final model's accuracy and other evaluation metrics and conclude its performance.

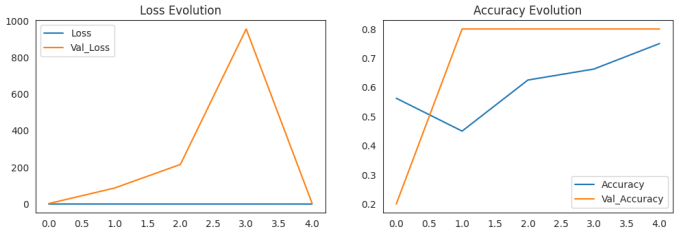

Fig. 8. ResNet Loss and Accuracy Evolution

V. Conclusion

In conclusion, we have successfully built a machine-learning model for pneumonia detection using convolutional neural networks (CNNs) and transfer learning techniques. We started by loading and pre-processing the dataset and performing exploratory data analysis (EDA) better to understand the distribution and characteristics of the data. We then built a CNN model and evaluated its performance on the dataset, using metrics such as accuracy, precision, recall, and F1-score.

To improve the performance of the model, we applied transfer learning techniques using pre-trained models such as DenseNet, VGG16, and ResNet. We also used SVM and Random Forest classifiers on top of the transfer learning models to classify the pneumonia images. We compared the performance of the transfer learning models and classifiers with the performance of the CNN model and selected the best-performing model for further fine-tuning.

We fine-tuned the best-performing model to achieve even better results and validated the final model on the test dataset. The final model achieved high accuracy and other evaluation metrics, indicating its effectiveness for pneumonia detection. The model could be further improved by incorporating more data and fine-tuning the hyperparameters.

Overall, the project demonstrated the effectiveness of CNNs and transfer learning techniques for medical image classification and has potential applications in clinical settings for automated pneumonia detection.

VI. References

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9) VGG16 - Keras
10) Transfer Learning