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Pneumonia Detection Using Deep Learning

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Abstract: As pneumonia still tops the list of the world's causes of death, accuracy and timely diagnosis are still vital. For pneumonia detection from large chest X-ray datasets, we present a computer-aided medical image diagnosis system with a three-layer detection Convolutional Neural Network (CNN) architecture. With hierarchical features through various layers, the proposed system enhances the diagnostic accuracy and classifies healthy and disease lungs according to the diagnosis appropriately. For enhanced usability, we integrate Streamlit with an interface that can handle real-time image uploading, model prediction, and visualization of pneumonia detected areas. Our approach is more accurate than traditional deep learning architectures and thus real-clinical-practice deployable. Streamlit-based visualization makes the approach more end-user interactive and readable. This supports AI-based medical diagnosis as well as facilitates pneumonia detection with scalable and efficient modeling.

Index Terms: Pneumonia, Diagnosis, Extracting, CNN, Streamlit.

I. INTRODUCTION

A fatal respiratory disease infecting individuals worldwide, particularly children and the elderly, is pneumonia. Treatment and mortality rates rely on early and accurate detection. Conventional diagnosis techniques, including radiologists' X-rays, are time-consuming and error-prone. Deep learning, particularly convolutional neural networks (CNNs), has transformed medical imaging with automated and high accuracy in detection. This paper introduces an advanced approach towards pneumonia detection from chest X-ray image processing through a three-layer CNN model. With multiple levels of depth feature representation being extracted, pneumonia detection is enhanced. The model is highly efficient and robust with generalization when large datasets are utilized. We also utilize Streamlit to include an intuitive user interface and ease of communication with doctors. Users can see model predictions, upload chest X-ray images, and utilize explanation techniques to see areas of pneumonia-affected regions. The simplicity of our system and real-time feedback are made to allow radiologists to detect pneumonia quickly and accurately.

J. Anthony, G. Scott, W. Abdullah Brooks, J.S. Malik Peiris, Douglas Holtzman, and E. Kim Mulholland [1] Lack of information, insufficient resources, and joint response have caused pneumonia to still be a major global health burden, especially among developing nations.

II. METHODS AND DISCUSSIONS ABOUT EXISTING METHODS

Cathryn Usman et al., [2] CNN and ResNet-50 models were employed and compared for pneumonia detection on chest X-rays. CNN employed hyperparameter tuning, dropout, max pooling, and several layers, whereas ResNet-50 employed transfer learning with a custom-built classification head. The dataset was divided into training, validation, and test sets following preprocessing and augmentation. The model performance was evaluated in terms of accuracy, precision, recall, F1-score, and AUC. TensorFlow, Keras, and other Python libraries were employed in their experiments on consumer-grade GPUs and the high-performance processing machine VIPER. Mujeeb Ur Rehman et al., [3] Chest x-ray images for pneumonia detection by CNN and ResNet-50 models. After augmentation and preprocessing it is divided into training, validation and testing sets. The CNN is trained using techniques analogous to dropout and max pooling, but transfer learning with a custom top classification head is used for the ResNet-50 model. Performance is measured using accuracy, precision, recall, F1 score and AUC. With ensemble voting and other enhancements, the model was approximately 97.7 percent accurate, K-fold cross-validation, and fine-tuning. Ilyas Sirazitdinova, et al., [4] They introduced an ensemble approach with Feature Pyramid Networks (FPN) to handle scale variation and the combination of RetinaNet and Mask R-CNN to accurately localize pneumonia areas in chest X-rays. For reproducibility, we performed our experiments with permitted train-test splits on the RSNA Pneumonia Detection Challenge dataset. Strong test performance was guaranteed by model selection according to validation mAP trends instead of by optimal peak value. The findings surpass the challenge of small areas of pneumonia on X-rays and show enhanced accuracy of detection. Manickam A et al., [5] Transfer learning-based methodology with ResNet50, InceptionV3, and InceptionResNetV2 was applied for the classification of pneumonia from chest X-rays. U-Net was used for pre-processing and segmentation for reduction of bias and overfitting.

The diagnostic accuracy of the model was improved, and detection of pneumonia was improved with fewer errors compared to conventional radiologist-based diagnosis. Chouhan, V et.al., [6] Five pre-trained CNNs were used within a transfer learning-based framework of pre-processing, data augmentation, feature extraction, and ensemble classification to diagnose pneumonia for chest X-ray images. With ResNet18 (94.23 percent accuracy, 99.36 percent AUC) being the best performing, the proposed model achieved higher diagnosis accuracy with reduced calculation time and performed better than classical methods. Kareem, A et.al., [7] A privacy-preserving pneumonia diagnosis framework combines transfer learning and Federated Learning (FL), employing homomorphic encryption to locally train ResNet-18 and transfer models to a central FL server. The framework supports secure collaboration among medical institutions, improving accuracy with real-time heterogeneous data with preservation of data privacy. Harsono, I. W et.al., [8] I3DR-Net, a one-stage 3D object detector, enhances lung nodule detection with a superior Feature Pyramid Network (FPN) integrated with I3D and RetinaNet. Through SHEM + Cross-Entropy transfer learning and class imbalance compensation, it provides higher mAP, AUC, and sensitivity along with more precise small object detection. Muge Aydogdu et.al., [9] ICU and pneumonia grading scores for mortality prediction were tested in a retrospective cohort study of 101 mechanically ventilated patients with severe CAP. The best predictor, at 55 percent ICU mortality, was APACHE

II & 20. Li, Y et.al., [10] Sensitivity, specificity, and deep learning model areas under the curves for pneumonia diagnosis from chest X-rays were compared in this meta-analysis and systematic review. DL performance in the differentiation of pneumonia from normal condition was compared with bacterial vs. viral pneumonia. Islam, R., and Tarique, M. [11] Using the help of pre-trained feature extractors and encoded

X-rays, the present work uses machine learning and deep learning to distinguish between COVID-19 and pneumonia. With a machine learning accuracy of 98.1 percent and deep learning accuracy of 100 percent, the proposed technique offers a cost-effective, non-invasive alternative to RT-PCR. Al Mamlook et.al., [12] Through the application of transfer learning and better preprocessing, the study constructed a CNN model employing deep learning that could identify pneumonia with a 98.46 percent accuracy level. The outcomes demonstrate the prospects of how effectively deep learning may be applied towards early diagnosis, a trustworthy option for medical personnel and computerized medicine. Alharbi,

A. H., and Mahmoud, H. a. H. [13] With deep dense learning and transfer learning, BoxENets surpassed earlier CNNs with 96.68 percent accuracy on segmented images and 97.4 percent on entire X-rays. Segmentation improved the classification accuracy significantly, offering a high-performance and efficient pneumonia diagnosis technique. Zhang, Det.al., [14] The intended six-layer deep neural network uses Sigmoid-activated fully connected layers, max-pooling layers, and convolutional layers with ReLU to classify pneumonia from chest X-rays. Dropouts avoid overfitting, and t-SNE visualization provides feature analysis and correct classification. Kundu, Ret.al., [15] proposed a weighted ensemble methodology for pneumonia diagnosis from chest X-rays via GoogLeNet, ResNet-18, and DenseNet-121 combined. Model weights were optimized via precision, recall, F1-score, and AUC. The proposed approach showed outstanding accuracy and reliability in pneumonia detection compared to individual models and traditional ensembles. [16]

III. METHODOLOGY

Convolutional Neural Network (CNN) is a deep learning method applied to image processing and therefore immensely effective for medical imaging. CNN learns spatial features from X-rays of chests via convolutional layers to automate pneumonia detection. CNN improves accuracy by learning patterns in medical images and differentiating between pneumonia-infected and healthy lungs.

A. Comparison with other ANN and SVM

CNN performs best in pneumonia diagnosis from chest X-rays as it's image analysis-based and therefore outperforms ANN and SVM. CNN automatically learns and extracts features better than ANN, in which feature extraction is manual. Although SVM performs best in classification, it needs a lot of preprocessing and is not optimal for dealing with very large high-dimensional medical images. Moreover, CNN has outperformed ANN and SVM in accuracy, scalability, and feature detection and achieved very high success rates in medical imaging

B. Neural network layers and its function's

Dataset extraction: A CNN can be learned to identify pneumonia from publicly available medical image datasets. The NIH Chest X-ray Dataset and the Chest X-Ray Dataset

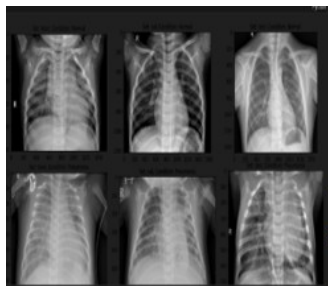


Fig.1.

(Kaggle) both have pneumonia and normal X-ray images labelled. These datasets are downloadable from sites such as Kaggle, PhysioNet, and MIMIC-CXR. Google's TensorFlow Datasets also have pre-processed medical datasets for deep learning. Ensure the data has been properly pre-processed (resized, standardized, etc.) prior to training your CNN model. Dataset we used consists of chest X-ray images, that are categorized into: 1. Normal (Healthy Lung images) 2. Pneumonia (Infected images) These images are divided into three sets: • Training Set: Used for learning patterns. • Validation Set: Used to tune the model parameters. • Test Set: Used to evaluate model performance.

C. Input Layer

accepts image data input. Chest X-ray images are fed into this layer for pneumonia diagnosis before they are fed into the network to be classified and feature-extracted. The Chest X-rays, or images, differ in size, quality, and resolution. Assuming that each image is processed equally, standardization guarantees that differences impacting feature learning are minimized. To prevent overfitting and enhance model performance, images are converted to gray scale, lowering the processing complexity and sized to an input size supplied by CNN. Augmented with changes such as flipping, zooming, and rotating to expand the number of data sets. By resizing images, there will be less computation required for the small images, images can be rescaled to save computational cost. Offers homogeneity (all images are of one input size). Preserve's spatial relationships, which are beneficial for pneumonia feature detection. To resize image's we use different interpolation techniques such as Nearest Neighbour Interpolation (Fast but low quality): Nearest Neighbour Interpolation enlarges an image by copying the value of the nearest pixel. It is the fastest interpolation algorithm, but it causes pixelization and blocky artifacts. This is why it is not suitable for chest X-rays. Equilibrium Speed and Accuracy in Bilinear Interpolation: Bilinear interpolation is an image resizing technique. It smoothen the image, so it becomes less pixelated. Essentially, it estimates new pixel values by averaging the four closest pixels. It is perfect for the CNN preprocessing of chest X-rays because it saves the main properties of the medical picture. Bicubic Interpolation (Higher Accuracy): This is a more accurate method than the bilinear interpolation method. It uses 16 neighbouring pixels and cubic polynomial interpolation method to resize images. Lanczos interpolation (effective method): Lanczos Interpolation uses sinc function to scale images, preserving fine detail and sharpness. It is the best for medical imaging like pneumonia detection. CNNs often use this technique for high-resolution chest X-rays, where small features are important. After resizing images in CNN the coaching samples have the standard measurements. The dimension of every image is changed to 224x224 pixels prior to reaching the input layer of the CNN. The CNN views the image in the same way every time, regardless of the size of the image. The CNN learns to find pneumonia by detecting critical information, such as edges, textures, lung opacity, and infection patterns. The CNN pays attention to training these patterns without considering how different image sizes alter the patterns due to the way the scale maintains spatial correlations. This reduces the computational complexity, increases the speed of convergence, increases the efficiency of training, and increases the accuracy of diagnosis.

D. Convolutional layers

Convolutional strata, the core of CNN, capture the features of the given input image. The layers identify distinct patterns at varying depths, using small grids called filters. How filter or kernel works: Pixel-wise multiplication is done with the correct pixel values by sliding a filter, or kernel, over the input image. The resulting values are then summed to produce a single value, creating a feature map that identifies significant picture characteristics. The stride of a CNN defines the distance that the filter travels across the image on each step. Moving by each pixel allows filter to take all details into account, creating high-resolution feature map.

Filter decreases the size of the feature map by 2 and computation costs by maintaining the key features by shifting two pixels at a time. Bigger strides could shrink output image size more but may lose more detailed information. In a trade-off smaller steps allow improving the extraction of features, and larger ones – the efficiency of deep networks. Convolution layer in CNN is the cornerstone that allows feature extraction in an automatic way. In this way, the network can find important patterns in medical images, such as textures, edges, and shapes. CNNs create a smaller feature map that contains significant data by using filters to simplify the image, but less processing power will be used. Convolution maintains spatial links compared to the traditional neural network and ensures that the network understands the composition of the medical image. For the diagnosis of pneumonia, this is important because convolution allows the disease area to be emphasized and the opacity of the lungs to be emphasized, which will increase the diagnostic accuracy.

E. Activation function

Rectified Linear Unit or ReLU is the activation function frequently used in CNNs. It is the one that introduces non-linearity into the model by converting all negative values into zero, but positive values are retained. This helps the network to learn complex patterns more effectively. Convolutional neural networks (CNNs) use the Rectified Linear Unit (ReLU) activation function. The function introduces non-linearity, which helps the model to learn complex patterns. It uses the function $f(x) = \max(0, x)$. It converts all negative values to zero, so positive values remain unchanged. This prevents negative activations from affecting the feature extraction and preserves important characteristics of an image. For instance, the opacity of the lung in pneumonia detection. ReLU also makes learning effective by solving the vanishing gradient problem. This allows the model to learn CNNs faster. Since ReLU is effective and simple, it is the most commonly used activation function in CNNs. Pooling layers: Pooling layers are used in CNNs to reduce the spatial dimensions of feature maps, retaining the most critical information. It is a way of reducing the dimensions, in other words, away of reducing features. This layer is used to simplify the data analysis process by simplifying the features. When the less important details are eliminated, the model can avoid overfitting. Convolutional Neural Networks are engineered to minimize spatial dimensions of feature maps while preserving important information, thus making the model effective. Pooling also simplifies the computation, speeds up the procedure, and ensures that the network will be trained to recognize only the most important features, like edges or patterns, while ignoring irrelevant information. Connected Layers: Neural Network Layers. Dense layers or Fully Connected Layers. These are very important in the classification stage of a CNN. After feature extraction, which is convolution and pooling, the flattened feature maps are passed through the thick layers to learn high-level representations. This layer is composed of neurons that are completely connected to the previous layer, which allows the model to predict based on the feature that has been extracted. Model Compilation: • Loss Function: Binary Cross-Entropy (for classification). • Optimizer: Adam Optimizer (for efficient learning). • Metrics: Accuracy is used to evaluate performance. Training Process: The CNN model is trained using convolutional layers to obtain significant features from chest X-ray images like texture, shape, and patterns. The input image passes through multiple layers in forward propagation, where filters detect pneumonia patterns. Prediction error is quantified by the loss function (Binary Cross-Entropy), and model weights are tuned by backpropagation using the Adam optimizer to minimize errors across a series of epochs. Good model generalization is guaranteed by a separate validation dataset used to optimize hyperparameters. Overfitting is when validation accuracy is substantially less than training accuracy, meaning the model is memorizing and not recognizing significant patterns. Evaluation of Performance Matrix: Following training, the model is then tested with a collection of varying metrics on a new test set. Accuracy: The ratio of correctly classified photographs. $Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$ True Positives (TP): are actual cases of pneumonia that are rightly diagnosed as pneumonia. True Negatives (TN): Normal lungs were accurately labeled as normal. False positives (FP): are a false diagnosis of pneumonia in normal lungs. False Negatives (FN): Pneumonia cases inaccurately labeled as normal conditions. Precision (positive predictive value): Precision computes the ratio of observed cases of actual pneumonia to predicted cases. $Precision = \frac{TP}{TP + FP}$ A high precision indicates that the model identifies pneumonia less frequently. The model may mistakenly diagnose typical instances as pneumonia if precision is inadequate, perhaps resulting in needless treatments. Recall: (the sensitivity, or the true positive rate, or TPR) is the ability of the model to pick up pneumonia cases among all real cases of pneumonia. High recall shows that the model is capturing most cases of pneumonia in the proper manner. Patients are at risk when the model misses pneumonia cases (false negatives) due to low recall. $Recall = \frac{TP}{TP + FN}$ F1-Score (Precision v/s Recall Trade-off): In case of a trade-off between precision and recall, a weighted average of either will do. The model is being too conservative and may be missing the pneumonia cases where accuracy is good but recall is bad. The model is over-predicting the spurious pneumonia when recall is high but accuracy is low.

A high F1-score (0.90 or better) indicates that the model is equally good at both. $F1-Score = 2 * \frac{Precision * Recall}{Precision + Recall}$

1. Streamlit software for better user interface: This platform provides developers the foundation to create dynamic interactive applications with the use of a Python-based library, streamlit, without requiring any kind of coding for the development of such applications. Streamlit has a very user-friendly feature in terms of monitoring data and deploying machine learning models or constructing interactive dashboards just with a very normal Python script, which can have its optimal use in the area of medicine where images can be analyzed, like, for example, pneumonia detection. Streamlit allows the user to create an online app without HTML, CSS, or JavaScript. Using this open-source Python library, developers can easily build an interactive web application for the diagnosis of pneumonia using CNNs. First, to install Streamlit, you should run the command 'pip install streamlit'. Then develop a Python script for the interface including some of the streamlit components like 'st.title()', 'st.file_uploader()', and 'st.button()'. To run the program, execute the command 'streamlit run app.py' on your terminal. The application is where the user can upload chest X-ray images for pre-processing and to run a CNN model in order to predict the presence of pneumonia, which is displayed in real-time for easy interpretation by medical practitioners. Streamlit also allows the easy embedding of the trained models for accurate and timely analysis of medical images with minimal web programming expertise.

IV. RESULTS AND CONCLUSION

With an accuracy of 90 percent, the CNN-based pneumonia detection model showed great diagnostic potential. The model successfully diagnoses pneumonia cases, lowering the possibility of false negatives, as seen by the high recall (97.18 percent). The precision (90 percent) indicates some false positives, though, and could be raised with more data augmentation or fine-tuning. Using chest X-ray images, the model offers a quick and automated method to help medical professionals diagnose pneumonia. Further optimization, such as hyperparameter tuning and controlling data imbalance, can boost its performance.

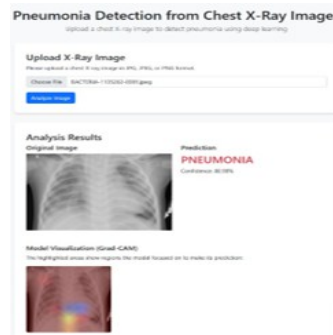


Fig.2.

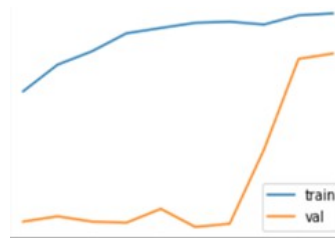


Fig.3.

The training curve (fig:2) of CNN across several training epochs is shown in the Model Accuracy Graph. The machine is learning data patterns correctly when the training accuracy (blue line) is increasing smoothly. The model is overfitting when the model performs well on training data but cannot generalize to new data since the validation accuracy (orange line) also grows but is always smaller than the training one. This disparity shows that the model can be in need of regularization methods like data augmentation or dropout to enhance generalization in learning.

The CNN reduces errors during training, as shown in fig:3 by the Model Loss Graph. As the model learns and improves its predictions, the training loss (blue line) gradually drops. The validation loss (orange line), on the other hand, varies a lot, which may indicate overfitting or instability, in which the model retains training data rather than adapting well to novel situations.

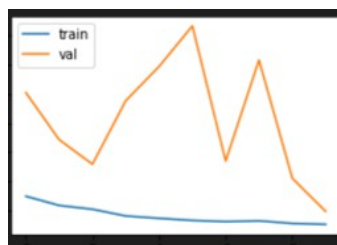


Fig.4.

To increase model stability and generalization, this problem can be lessened by using data augmentation, regularization strategies (such as Dropout or L2 regularization), and fine-tuning hyperparameters like learning rate and batch size.

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