Machine Learning Model for Pneumonia Detection From Chest X-Rays

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Abstract

Pneumonia is a serious respiratory infection that can lead to severe complications if not diagnosed and treated promptly. Chest X-rays are a widely used diagnostic tool to identify pneumonia, but the accurate and timely interpretation of these images is often challenging for healthcare professionals. This research presents a novel approach to automate pneumonia detection from chest X-rays using Convolutional Neural Networks (CNN).

The proposed model leverages the power of CNN, a deep learning architecture specifically designed for image analysis, to automatically learn and extract relevant features from the chest X-ray images. The dataset consists of a large number of annotated chest X-rays collected from diverse patient populations, including both pneumonia-positive and pneumonia-negative cases.

Preprocessing techniques are applied to standardize the images and reduce noise, ensuring the CNN's robustness to variations in image quality and positioning. The CNN model is trained using a transfer learning strategy, utilizing a pre-trained model with weights learned from a large-scale dataset.

During the training process, the CNN learns to differentiate between normal and pneumonia-infected lung patterns, thereby enabling accurate classification of pneumonia cases in unseen chest X-rays. The performance of the model is evaluated using various metrics, such as sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC-ROC).

Experimental results demonstrate the effectiveness of the CNN-based approach in accurately identifying pneumonia cases from chest X-rays, achieving high sensitivity and specificity rates. The proposed model shows promising potential as a reliable and efficient tool for aiding radiologists and healthcare practitioners in pneumonia diagnosis.

Furthermore, this research contributes to the ongoing efforts in developing AI-based medical systems that can assist healthcare professionals in making accurate and timely diagnoses, ultimately improving patient outcomes and reducing healthcare costs. Nonetheless, further validation on larger and more diverse datasets is essential to establish the generalization and scalability of the CNN-based model for pneumonia detection in real-world clinical settings.

Keywords: Pneumonia detection, chest X-rays, Convolutional Neural Networks (CNN), deep learning, medical image analysis, transfer learning, healthcare, diagnostic aid.

1. Introduction

Image processing is a technology that provides fast and accurate results on computer systems [1], [2]. Recently, the model that is often preferred in image processing is the deep learning model. Convolution Neural Network (CNN), which is the sub-branch of deep learning, has a multi-layered structure in contrast to machine learning. Deep learning models have demonstrated their effectiveness in many areas [3]. One of its areas of interest is biomedical engineering. The introduction of deep learning models in the biomedical field has contributed to this area.

From past to present, infectious diseases are one of the most important factors that threaten human health. Pneumonia is one of the leading infectious diseases [4]. It is the inflammation caused by the

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virus and bacteria that microscopically adversely affect the air sacs. Approximately 7% of the world's population is affected by pneumonia every year, and 4 million of the affected patients face fatal risks. So, early diagnosis is important in such diseases. Typical symptoms of pneumonia include chest pain, shortness of breath, cough, etc. are located. The diagnosis of pneumonia in childhood is difficult due to the low sensitivity of microbiological tests and weak clinical finding. Thus, the chest X-ray has become an important diagnostic tool in the diagnosis of pneumonia in children. Diagnostic tools include sputum culture and chest X-rays [5]. It is a time-consuming process in the medical area that physicians look and diagnose chest X-rays. It is an extremely positive development in terms of time and cost to diagnose by utilizing existing technological means and software. The deep learning models have ensured more efficient results compared to traditional methods through Chest X-ray images obtained from pneumonia patients.

Computer-assisted diagnosis (CAD) systems have been proposed to improve accurate diagnostic performance and prevent possible errors in medical applications. In other words, CAD aims to recognize the occurrence of pneumonia cases and to prevent cases that may adversely affect public health. In this issue, deep learning methods have been used to extract the features of the chest X-rays. This study suggests that the proposed CAD system reveal the most efficient features of pneumonia and contribute positively to the classification results.

Advances in deep learning have recently played an effective role in the biomedical field. Deep learning has pronounced its name with the high generalization performances for many difficult problems related to the field. It has yielded remarkable performance results compared to state-art of the models for many diseases. Automatic analysis of chest X-rays images with CNN models has begun to gain further interest. Several procedures such as tuberculosis detection, segmentation, mass detection and classification were performed on X-ray images. In addition, hybrid (combined) CNN models showed better results than CNNs. Detection of pneumonia was performed by selecting specific regions of interest (ROI) on X-ray images. Transferring technique was also used by creating multiple label classes over X-ray images. Chest X-ray and computed tomography images were used for chest segmentation.

2. Literature Survey

Tilve et al. [6] focused on surveying and comparing the detection of lung disease using different computer-aided techniques and suggests a revised model for detecting pneumonia, which will then be implemented as part of future research. In this survey, this work also tried to familiarize ourselves with the different image pre-processing techniques used to convert raw X-ray images into standard formats for analysis and detection, machine learning techniques such as CNN, RESNET, CheXNet, DENSENET, ANN and KNN, which is an important phase in accurate pneumonia detection.

Toğaçar et al. [7] used lung X-ray images that are available for the diagnosis of pneumonia. The convolutional neural network was employed as feature extractor, and some of existing convolutional neural network models that are AlexNet, VGG-16 and VGG-19 were utilized so as to realize this specific task. Then, the number of deep features was reduced from 1000 to 100 by using the minimum redundancy maximum relevance algorithm for each deep model. Accordingly, we achieved 100 deep features from each deep model, and we combined these features so as to provide an efficient feature set consisting of totally 300 deep features. Consequently, the results point out that the deep features provided robust and consistent features for pneumonia detection, and minimum redundancy maximum relevance method was found a beneficial tool to reduce the dimension of the feature set.

Račić et al. [8] described the use of machine learning algorithms to process chest X-ray images in order to support the decision-making process in determining the correct diagnosis. Specifically, the

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research is focused on the use of deep learning algorithm based on convolutional neural network to build a processing model. This model has the task to help with a classification problem that is detecting whether a chest X-ray shows changes consistent with pneumonia or not and classifying the X-ray images in two groups depending on the detection results.

Salvia et al. [9] developed a system based on modern DL methodologies in close collaboration with Fondazione IRCCS Policlinico San Matteo's Emergency Department (ED) of Pavia. Using a reliable dataset comprising ultrasound clips originating from linear and convex probes in 2908 frames from 450 hospitalised patients, this work investigated detecting Covid-19 patterns and ranking them considering two severity scales. This study differed from other research projects by its novel approach involving four and seven classes. Patients admitted to the ED underwent 12 LUS examinations in different chest parts, each evaluated according to standardised severity scales. This work adopted residual convolutional neural networks (CNNs), transfer learning, and data augmentation techniques. Hence, employing methodological hyperparameter tuning, we produced state-of-the-art results meeting F1 score levels, averaged over the number of classes considered, exceeding 98%, and thereby manifesting stable measurements over precision and recall.

Chandra et al. [10] presented a method for automatic detection of pneumonia on segmented lungs using machine learning paradigm. The paper focused on pixels in lungs segmented ROI (Region of Interest) that are more contributing toward pneumonia detection than the surrounding regions, thus the features of lungs segmented ROI confined area is extracted. The proposed method has been examined using five benchmarked classifiers named Multilayer Perceptron, Random Forest, Sequential Minimal Optimization (SMO), Logistic Regression, and Classification via Regression. A dataset of a total of 412 chest X-ray images containing 206 normal and 206 pneumonic cases from the ChestX-ray14 dataset are used in experiments. The performance of the proposed method is compared with the traditional method using benchmarked classifiers.

Rahman et al. [11] aimed to automatically detect bacterial and viral pneumonia using digital x-ray images. It provided a detailed report on advances in accurate detection of pneumonia and then presents the methodology adopted by the authors. Four different pre-trained deep Convolutional Neural Network (CNN): AlexNet, ResNet18, DenseNet201, and Squeeze Net were used for transfer learning. A total of 5247 chest X-ray images consisting of bacterial, viral, and normal chest x-rays images were pre-processed and trained for the transfer learning-based classification task. In this study, the authors have reported three schemes of classifications: normal vs. pneumonia, bacterial vs. viral pneumonia, and normal, bacterial, and viral pneumonia.

Manickam et al. [12] proposed a novel deep learning approach for automatic detection of pneumonia using deep transfer learning to simplify the detection process with improved accuracy. This work was aimed to preprocess the input chest X-ray images to identify the presence of pneumonia using U-Net architecture-based segmentation and classifies the pneumonia as normal and abnormal (Bacteria, viral) using pre-trained on ImageNet dataset models such as ResNet50, InceptionV3, InceptionResNetV2. Besides, to extract the efficient features and improve accuracy of pre-trained models two optimizers, namely, Adam and Stochastic Gradient Descent (SGD) used, and its performances are analyzed with batch sizes of 16 and 32.

Khan et al. [13] presented an overview of the literature on intelligent pneumonia identification from chest X-rays. The usability, goodness factors, and computational complexities of the algorithms employed for intelligent pneumonia identification are analyzed. Additionally, this study discussed the quality, usability, and size of the available chest X-ray datasets and techniques for coping with unbalanced datasets. A detailed comparison of the available studies revealed that most of the applied datasets are highly unbalanced and limited, providing unreliable results and rendering methods that

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are unsuitable for large-scale use. Large-scale balanced datasets can be obtained via smart techniques, such as generative adversarial networks.

Li et al. [14] indicated high accuracy performance in classifying pneumonia from normal CXR radiographs and also in distinguishing bacterial from viral pneumonia. However, major methodological concerns should be addressed in future studies for translating to the clinic.

Mamlook et al. [15] proposed Deep Learning for the classification task, which is trained with changed images, through multiple steps of pre-processing. Experimentally, it showed that the Deep Learning technique for the classification task performs the best, compared to the other seven Machine Learning techniques. In this study, this work successfully classified chest infection in Chest X-ray Images using Deep Learning based on CNN with an overall accuracy of 98.46%. It achieved a more successful result in detecting Pneumonia cases.

3. Proposed System

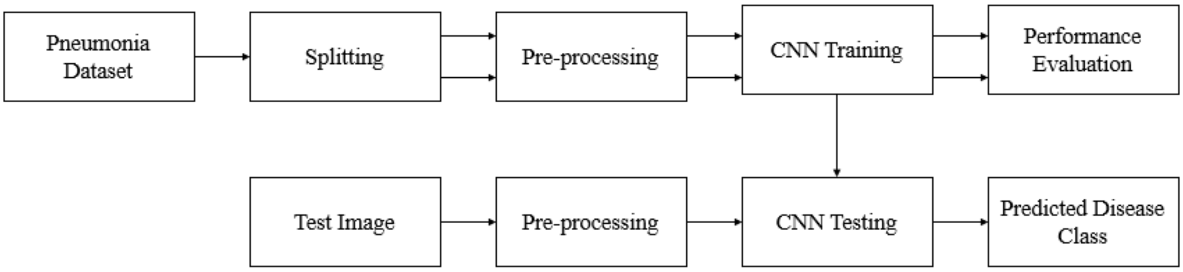

Fig. 1: Block diagram of proposed system.

3.1 Pre-processing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model.

When creating a project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task.

Why do we need Data Pre-processing?

A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set
- Feature scaling

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3.1.1 Splitting the Dataset into the Training set and Test set

In machine learning data pre-processing, we divide our dataset into a training set and test set. This is one of the crucial steps of data pre-processing as by doing this, we can enhance the performance of our machine learning model.

Suppose if we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to understand the correlations between the models.

If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance. So we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets as:

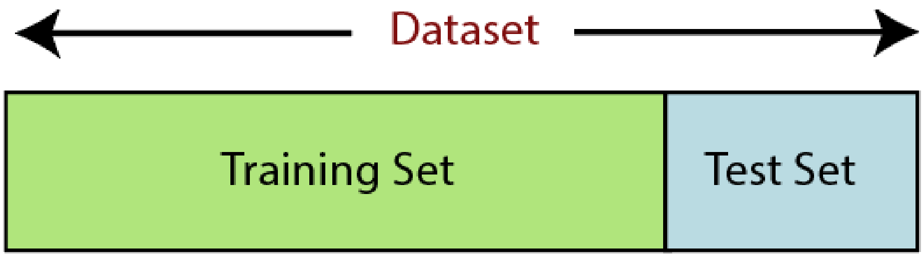

Fig. 2: Dataset splitting.

Training Set: A subset of dataset to train the machine learning model, and we already know the output.

Test set: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output.

3.2 CNN Basics

According to the facts, training and testing of any deep neural network or transfer learning involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F\left(k_x, k_y, d\right)$.

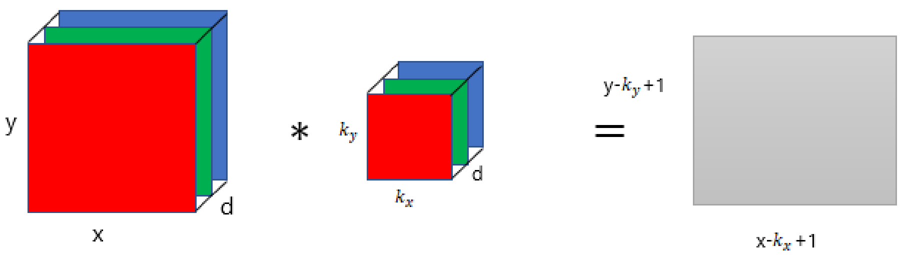

Fig. 3: Representation of convolution layer process.

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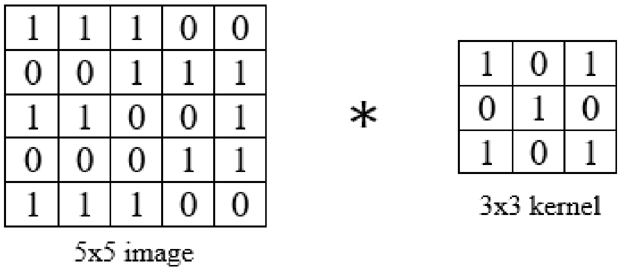
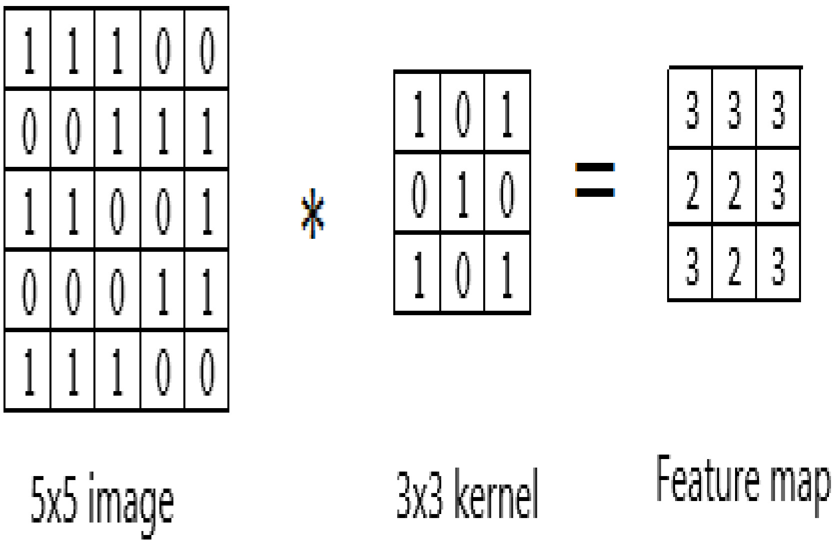
The output obtained from convolution process of input image and filter has a size of $C\left((x-k_x+1),(y-k_y+1),1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.



(a)



(b)

Fig. 4: Example of convolution layer process (a) an image with size $\mathbf{5\times 5}$ is convolving with $\mathbf{3\times 3}$ kernel (b) Convolved feature map.

ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x)=\max\{0,x\}$$

Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

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Softmax classifier

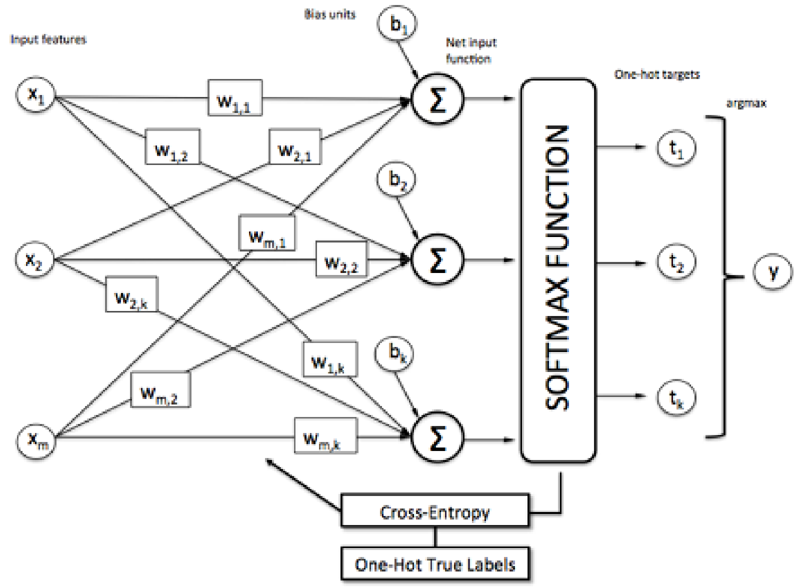

Fig. 5: Vehicle prediction using SoftMax classifier.

Generally, as seen in the above picture softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

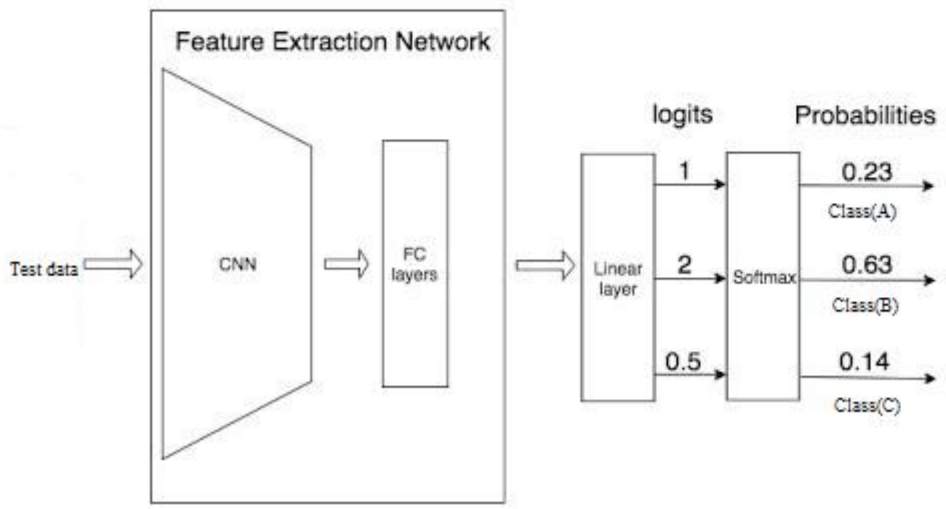

Fig. 6: Example of SoftMax classifier.

In Fig. 6, and we must predict what is the object that is present in the picture. In the normal case, we predict whether the crop is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding

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Technique to calculate the cross-entropy loss and get the max. One-Hot Encoding is the technique that is used to categorize the data. In the previous example, if softmax predicts that the object is class A then the One-Hot Encoding for:

Class A will be [1 0 0]

Class B will be [0 1 0]

Class C will be [0 0 1]

From the diagram, we see that the predictions are occurred. But generally, we don't know the predictions. But the machine must choose the correct predicted object. So, for machine to identify an object correctly, it uses a function called cross-entropy function.

So, we choose more similar value by using the below cross-entropy formula.

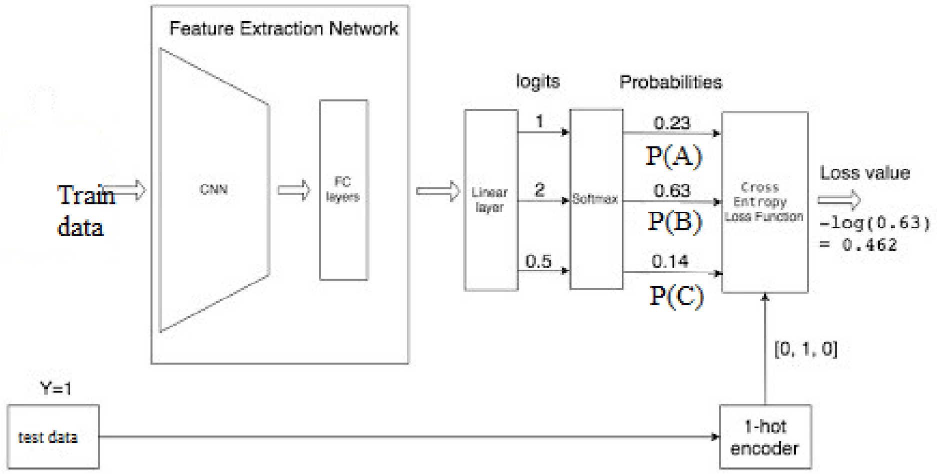
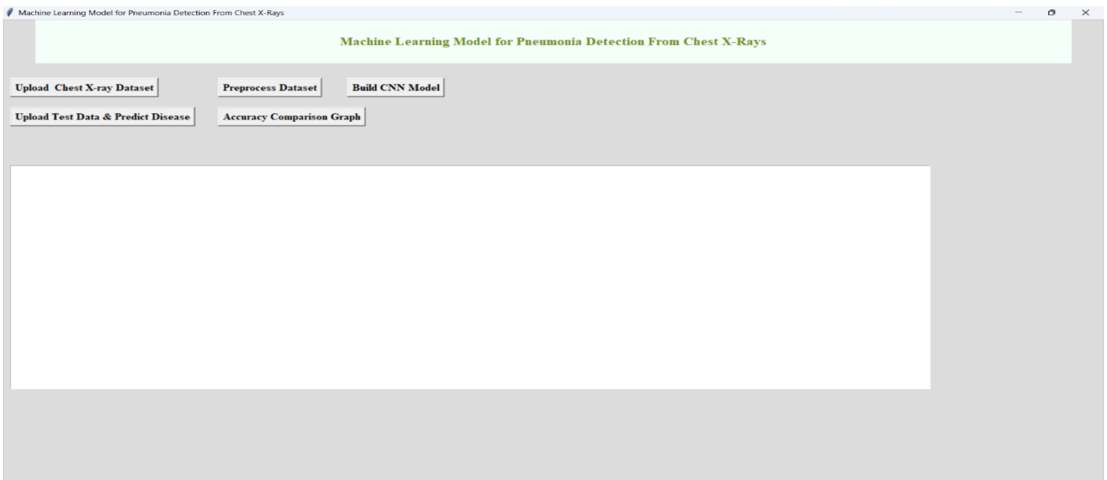


Fig. 7: Example of SoftMax classifier with test data.

In the above example we see that 0.462 is the loss of the function for class specific classifier. In the same way, we find loss for remaining classifiers. The lowest the loss function, the better the prediction is. The mathematical representation for loss function can be represented as: -

$$LOSS = np.sum(-Y * np.log(Y\_pred))$$

4. Results



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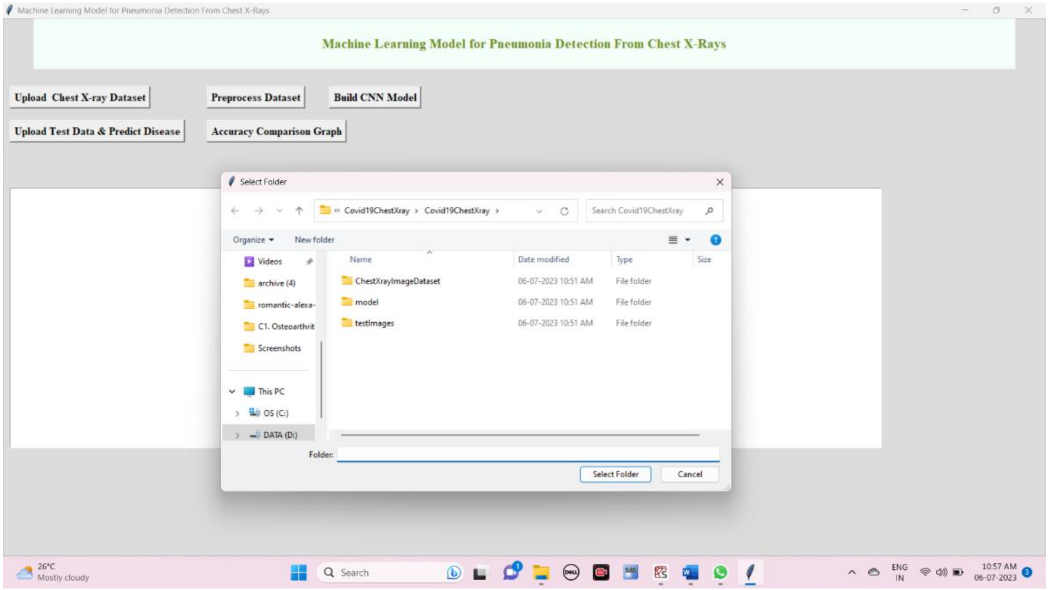

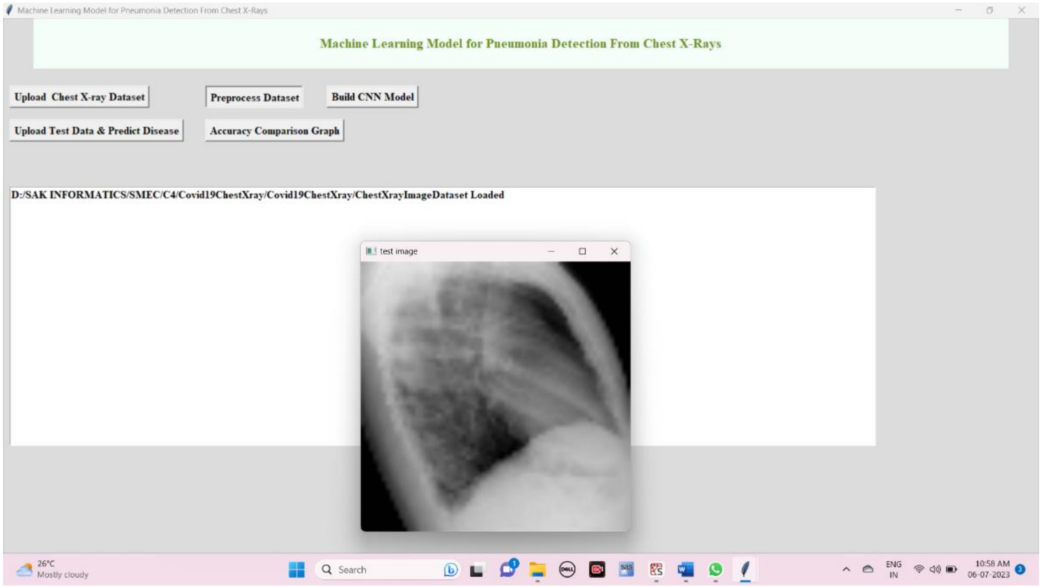

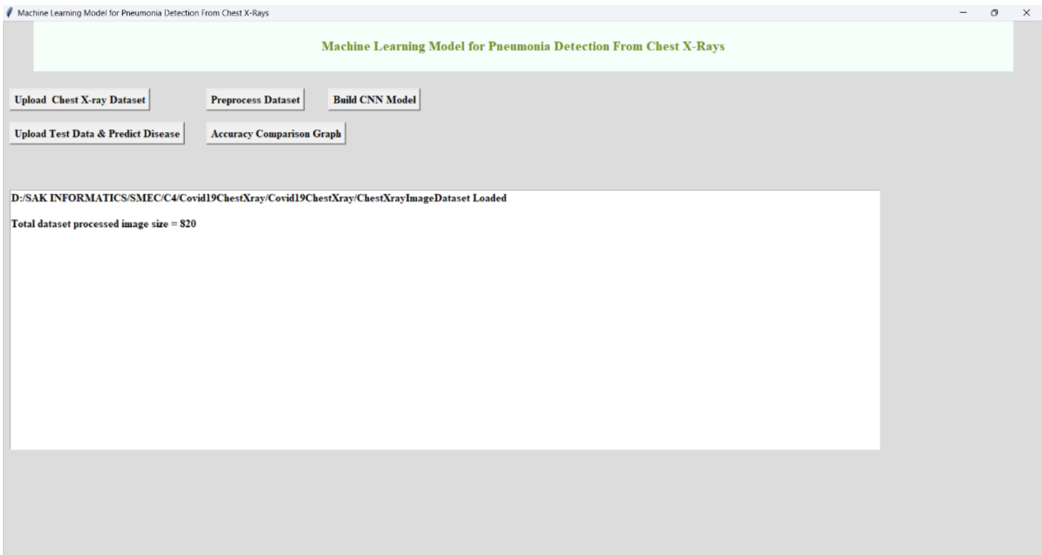

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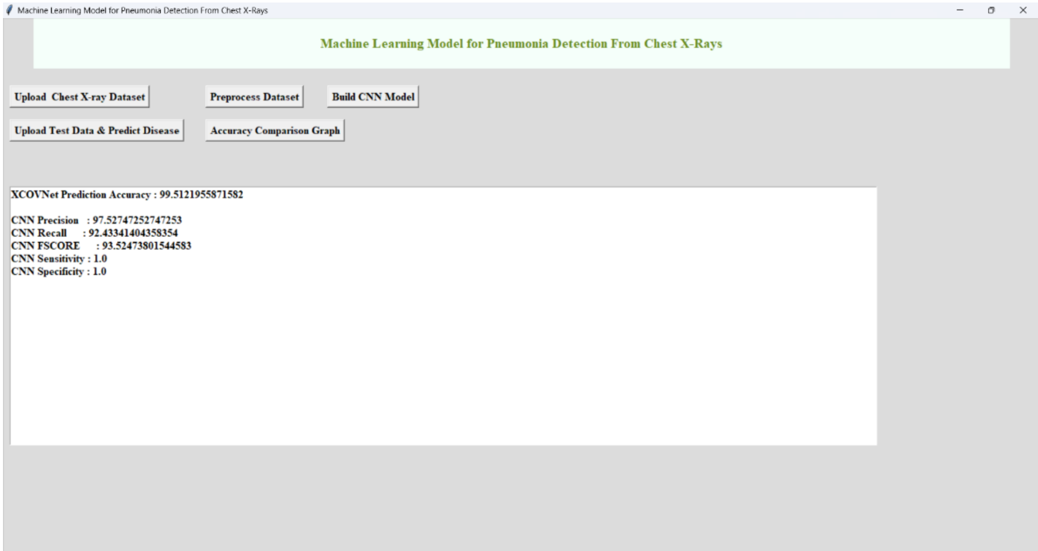

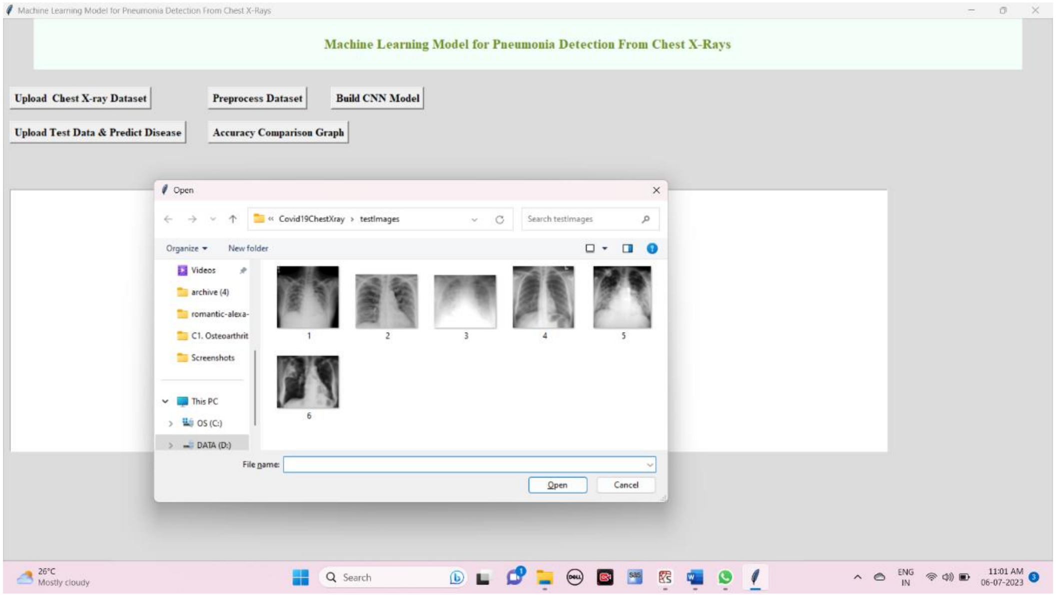

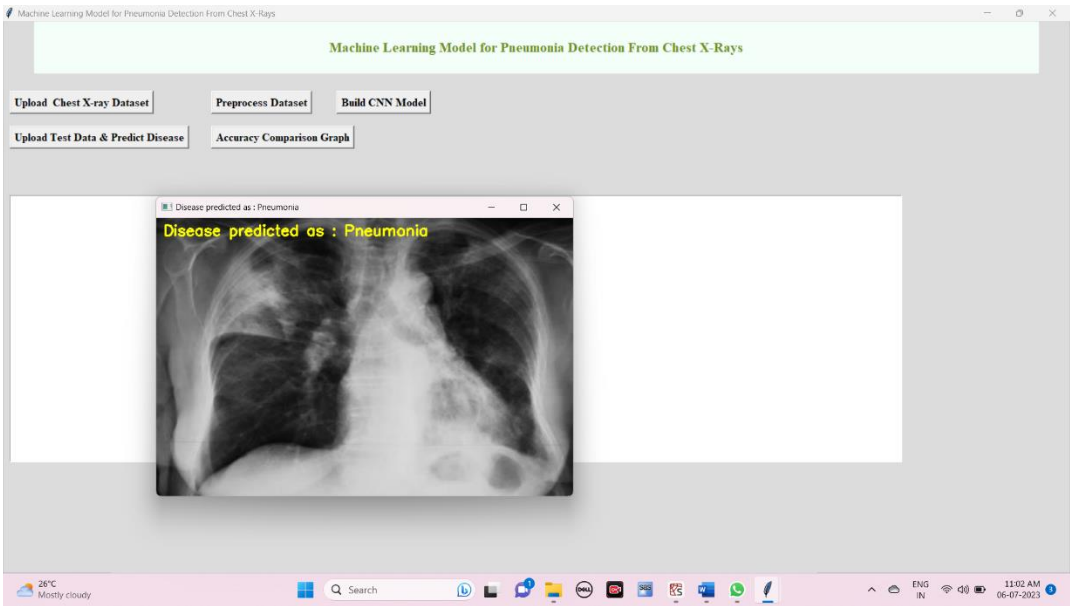

5. Conclusion and Future Scope

This work successfully developed and evaluated a machine learning model for pneumonia detection from chest X-rays using Convolutional Neural Networks (CNN). The results obtained from the experiments demonstrated the model's ability to accurately classify pneumonia cases, showcasing its potential as an effective diagnostic tool in the field of medical image analysis. The CNN-based approach leveraged the power of deep learning to automatically extract relevant features from chest X-ray images, enabling the model to discriminate between normal and pneumonia-infected lung patterns with high sensitivity and specificity. By achieving accurate results, the proposed model has the potential to assist radiologists and healthcare practitioners in making timely and precise pneumonia diagnoses, ultimately leading to improved patient outcomes and better overall healthcare delivery.

Future Scope

The future scope of this research includes expanding the dataset with diverse chest X-ray images and applying data augmentation techniques to enhance the model's generalization capabilities. Incorporating explainable AI methods will provide insights into the model's decisions, increasing trust in medical AI systems. Exploring multi-modal approaches by combining data from various imaging modalities and clinical information can lead to more comprehensive diagnostic solutions. Optimizing the model for real-time processing and fine-tuning it for specific patient populations can improve accuracy and personalized diagnostics. Additionally, ensemble learning techniques, rigorous clinical validation, and privacy-preserving measures are vital aspects to explore for enhancing the overall performance and applicability of the pneumonia detection system in real-world clinical settings.

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