Pneumonia Detection Using Deep Learning

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***Abstract*— Pneumonia is a life-threatening infectious disease that affects one or both of a person's lungs and is usually caused by the bacteria Streptococcus pneumoniae. According to the World Health Organization (WHO), one in three deaths in India is due to pneumonia. Chest X-rays used to diagnose pneumonia require experienced radiologists to evaluate. Thus, the development of an automatic pneumonia detection system would be useful for rapid treatment of the disease, especially in remote areas. Due to the success of deep learning algorithms for medical image analysis, convolutional neural networks (CNNs) have received much attention in disease classification. In addition, features learned on large datasets by pre- trained CNN models are very useful in image classification tasks. In this work, we try to create a pair of models that classify pneumonia and detect pneumonia based on lung X-rays.**

Index Terms*— CNN, FLASK SERVER,IMAGE PROCESSING & PREDICTION,TENSERFLOW, XAMPP.

I. INTRODUCTION

Pneumonia could be a condition where the discuss sacs within the lungs gotten to be aroused due to an disease. This aggravation can cause the sacs to fill with liquid or discharge, driving to indications like hacking with mucus or discharge, fever, chills, and trouble breathing. Different life forms such as microbes, infections, and organisms can cause pneumonia. Therapeutic experts analyze it utilizing methods like chest X-rays, blood tests, and sputum societies. Pneumonia is classified based on its securing, counting community- acquired, hospital-acquired, or healthcare-associated pneumonia. It influences individuals of all ages, with children appearing side effects like fast breathing and fever, whereas grown-ups may involvement hacking, chest torment, and weakness. Avoidance techniques incorporate antibodies, great cleanliness, and convenient treatment custom fitted to the particular cause of pneumonia. Raising mindfulness.

CNN Algorithm

Convolutional Neural Networks (CNNs) are a class of deep neural networks specifically designed for processing structured grid data, such as images. They have proven to be highly effective in computer vision tasks, including image classification, object detection, and image recognition.

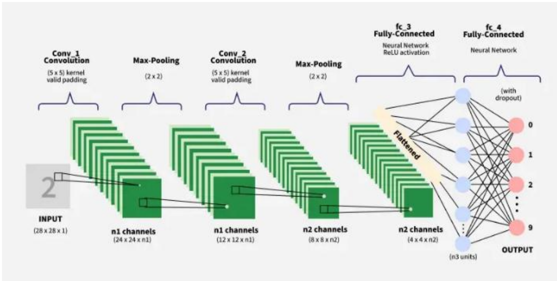


Fig.1.Working of CNN

Proposed system

To overcome these confinements, it is pivotal to actualize an inventive arrangement. Utilizing machine learning (ML) models can enormously progress the exactness of pneumonia discovery by preparing them on labeled lung X-rays, which would empower the distinguishing proof of unpretentious designs. This framework would incorporate functionalities such as recognizing between viral and bacterial pneumonia and joining the ML show with a secure web server for verification and real-time information preparing. This coordinates framework would empower authorized healthcare suppliers to safely transfer X-ray pictures, permitting the ML demonstrate to rapidly analyze and classify pneumonia sorts.

II. DESIGN AND DATAFLOW

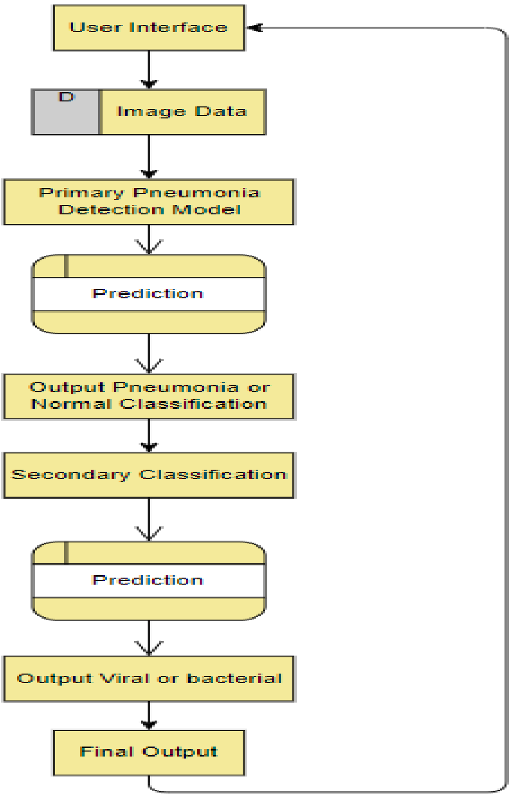


Fig. 2.Data Flow Diagram

Processes:

P1: User uploads chest X-ray image.

P2: Front-end sends image data to Flask server. P3: Flask server preprocesses image (resizing, normalization). P4: Flask server feeds preprocessed image to model 1.

P5: Model 1 predicts presence/absence of pneumonia.

P6: Flask server feeds preprocessed image to model 2 (if pneumonia predicted in P5).

P7: Model 2 predicts viral or bacterial pneumonia (if applicable).

P8: Flask server stores prediction results in database.

P9: Flask server retrieves prediction results from database. P10: Flask server sends prediction results to front-end.

P11: Front-end displays prediction results on user dashboard.

Use Case diagram:

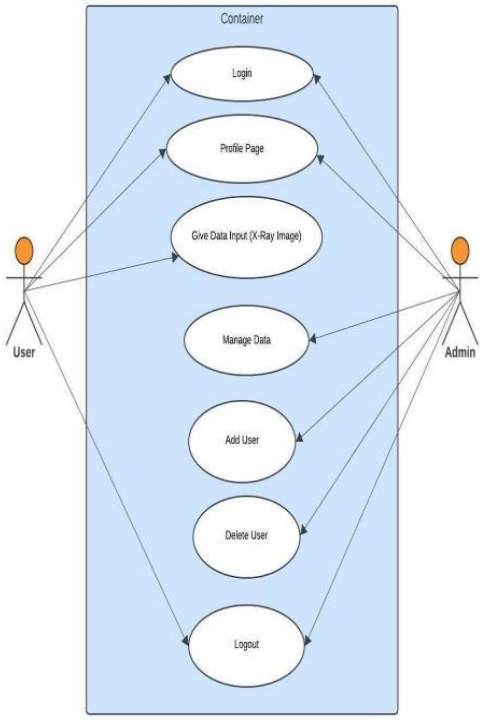


Fig. 3. Use Case Diagram

Use Case Description:
The use case diagram you sent depicts a web application with two main user types: user and admin. Let's break down the functionalities:

- Login: This use case allows a user to log in to the web application.
- Profile Page: This use case allows a user to access their profile page, where they can presumably view their account information.
- Give Data Input (X-Ray Image): This use case allows a user to upload an X-ray image to the container, likely for storage or analysis.
- Manage Data: This use case group is specific to the admin user and allows them to manage data stored within the container. It includes the following functionalities:
- Add User: This use case allows the admin to add a new user to the system.
- Delete User: This use case allows the admin to delete a user from the system.
- Logout: This use case allows a user or admin to log out of the web application.

III. IMPLEMTED DESIGN

Usage is the realization of an application, or execution of a arrange, thought, demonstrate, plan, determination, standard, calculation, or approach. I utilized framework execution and site usage.
Systems implementation is the process of:

1. Defining how the information system should be built.
2. Ensuring that the information system is operational and used.
3. Ensuring that the information system meets quality standards.

For implementation of a website:
The website can be installed on a server.
1. The owners of the website are to be properly trained to use all the features of the website.
2. To show the accuracy of the website and conformance of the owners or users.
3. To show the accuracy of the website and conformance of the owners or users.

IV. METHODOLOGY

This segment diagrams the technique utilized in creating the pneumonia location framework employing a Convolutional Neural Organize (CNN). The design of the demonstrate is partitioned into three stages:

A. *Pre-Processing Stage*:
The input images are resized to 150x150 pixels to reduce computational complexity and speed up processing.

B. *Normalizing and Augmentation Stage:*
Information Preprocessing includes grayscale normalization to moderate brightening contrasts. Information Enlargement methods are utilized to misleadingly grow the dataset and maintain a strategic distance from overfitting. This incorporates irregular revolutions by 30 degrees, zooming by 20%, level and vertical shifts by 10% of the width and tallness, and flat flipping.

C. *Generating and Training the Model Stage:*
The model architecture includes:
- Input Layer: Grayscale image with a resolution of 150x150 pixels.
- Convolutional Layers: Five convolutional layers with varying filter sizes and ReLU activation.
- Batch Normalization: Applied after certain convolutional layers for normalization.
- Max Pooling Layers: Applied after each convolutional layer to reduce spatial dimensions.
- Dropout Layers: Used to reduce overfitting by randomly dropping neurons during training.
- Flatten Layer: Flattens feature maps into a vector.
- Fully Connected Layers: Includes one fully connected layer with 128 units and ReLU activation.
- Output Layer: One unit with sigmoid activation for binary classification.
- Compilation: RMSprop optimizer and binary cross- entropy loss function are used, with accuracy as the evaluation metric.

While training the model with normal and pneumonia images at 12 epochs:

Epoch	Learning Rate	Accuracy
1.	0.0010	0.8482
2.	0.0010	0.9024
3.	0.0010	0.9195
4.	0.0003	0.9475
5.	0.0003	0.9502
6.	0.0003	0.9530
7.	0.0003	0.9557
8.	0.00009	0.9548
9.	0.00009	0.9643
10.	0.00009	0.9649
11.	0.000027	0.9689
12.	0.000027	0.9684

Table 1: Model 1 Epochs

While testing the date with unknown data instead of validation data at each step the actual accuracy of the model is 91.34%. Similarly, while training another model with viral pneumonia and bacterial pneumonia images:

Epoch	Learning Rate	Accuracy
1.	0.0010	0.6317
2.	0.0010	0.6899
3.	0.0010	0.7103
4.	0.0010	0.7172
5.	0.0010	0.7144
6.	0.0010	0.7301
7.	0.0010	0.7262
8.	0.0010	0.7327
9.	0.0010	0.7286
10.	0.0010	0.7242
11.	0.0010	0.7430
12.	0.0010	0.7378
13.	0.0010	0.7450
14.	0.0010	0.7399
15.	0.0010	0.7505
16.	0.0010	0.7463

17.	0.0010	0.7507
18.	0.0010	0.7571
19.	0.0010	0.7533
20.	0.0010	0.7620
21.	0.0010	0.7600
22.	0.0010	0.7600
23.	0.0010	0.7620
24.	0.0010	0.7613

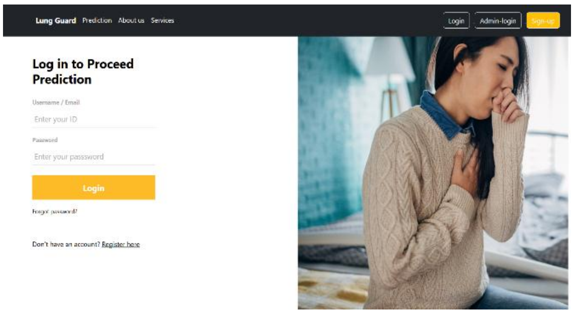
Table 2: Model 2 Epochs

While testing the date with unknown data instead of validation data at each step the actual accuracy of the model is 86.74%.

V. RESULTS AND DISCUSSIONS

The best results achieved with DenseNet169 architecture as feature extractors can be explained due to its capability of accessing feature- maps from all of its preceding layers. Literature studies of DenseNets mentions the information flow from the beginning layer to the end layers and removal of redundant features by transition layers as the primary reasons for the high-features representations.

To our knowledge, no literature was found to perform the studies on the combination of CNN based feature extractions and supervised classifier algorithms for the underlying task. In regard, we have proposed a model architecture for detecting Pneumonia from frontal chest X-ray images with the utilization of Densenet as feature-extractors and SVM as the process of meliorating the model performance, we found that our customized model outperforms the results documented in the recently released work of Benjamin Antin et al. for the same problem of pneumonia detection the process of meliorating the model performance, we found that our customized model outperforms the results documented in the recently released work of Benjamin Antin et al. for the same problem of pneumonia detection.



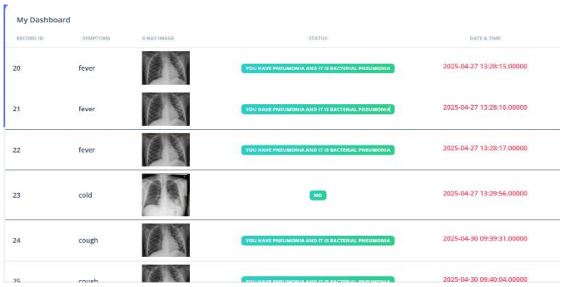


Fig. 4. Prediction of Pneumonia

VI. CONCLUSION

The accessibility of master radiologists is pivotal for precise conclusion of thoracic maladies. This consider points to improve restorative mastery in districts with constrained get to radiologists, especially centering on early determination of Pneumonia to avoid unfavorable results, counting mortality, in farther ranges. There has been restricted earlier work on particularly recognizing Pneumonia from the dataset specified, making the improvement of calculations in this range profoundly useful for progressing healthcare administrations.

This venture centers on creating and preparing machine learning (ML) models utilizing different profound learning methods, especially Convolutional Neural Systems (CNNs), for pneumonia discovery and classification. Utilizing CNNs diminishes time, taken a toll, and complexity compared to conventional strategies, subsequently diminishing the chance of understanding mortality due to deferred pneumonia location. The proposed approach is outlined to be reasonable and open to a wide extend of individuals.

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