JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

PNEUMONIA DETECTION USING CNN

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ABSTRACT

This project presents the development of a computer-aided diagnosis system for pneumonia detection using chest X-ray images. Utilizing Convolutional Neural Network (CNN) architecture, the system is designed to analyze and classify chest X-ray images, distinguishing between those indicative of pneumonia and normal lung conditions. The dataset used consists of chest X-ray images obtained from publicly available repositories. Moreover, our project includes the design of a user-friendly web interface using Streamlit, a Python library for building interactive web applications. This web page allows users to upload chest X-ray images as input and receive the corresponding diagnosis output. By incorporating this system with a user-friendly web interface, we aim to provide a seamless and accessible tool for early pneumonia detection, facilitating timely medical intervention and improving patient outcomes. Additionally, the system's performance will be evaluated using metrics such as accuracy, sensitivity, and specificity to ensure its reliability and effectiveness in clinical settings. The system is designed to be time-saving and affordable, suitable for a wide range of users, including those with no technical knowledge, thanks to its ease of use. It is highly accurate and reliable, contributing to its effectiveness in diagnosing pneumonia and improving patient care.

INDEX TERMS —

X- Rays, Deep Learning Model, respiratory infections, bacterial pneumonia, CT Scans, Lungs-related conditions, Diagnostic process, Radiographs, Web Application, Automated system.

INTRODUCTION

Pneumonia impacts all the elderly and young people everywhere but is most prevalent in Sub- Saharan Africa and South Asia. With the high growth in the popularity of neural networks, engineers and researchers have been able to find state-of-the-art products for computer vision. Artificial Intelligence helps us to automate analysis techniques, which is only possible now because of the technology of Deep Learning. Exposure to Pneumonia is quite high for many people, mainly in economically underdeveloped and developing countries where the majority are deprived of a nutritious diet. The World Health Organization states that more than 4 million untimely deaths per year occur from diseases caused by air pollution.

The purpose of this project is to build an AI network, which takes the pixel values as input for a given X-Ray image and then proceeds to perform linear operations and activations on each of them. Then by taking all the above operations, and then multiplying them with each layer within the neural network, and the number of nodes. Suddenly you have millions of operations. By applying determination, there can be more efficient in these tasks. The scope is to develop a model that will identify whether a patient is having Pneumonia or not by bypassing the chest X-Ray images through the Deep Learning model. The model should be highly precise as people's lives are at stake. In the past, it has been observed that the doctors undergo testing or get an X-Ray and give a false positive or a false negative result (Type 1 or Type 2 error), which resulted in bad medical conditions for the patients. Hence, such solutions can help reduce these types of errors and save lives in the medical field.

OVERVIEW OF EXISTING LITERATURE

Currently, medical professionals rely on manual analysis, primarily through visual inspection of X-ray reports, to detect pneumonia. This traditional approach involves carefully scrutinizing the images for irregularities or abnormalities indicative of the disease. However, this method is inherently prone to errors due to human subjectivity and fatigue. There's a significant risk of overlooking subtle indications of pneumonia, particularly in cases where abnormalities are not readily apparent. Despite its widespread adoption, manual analysis suffers from limited efficiency, often resulting in delays in diagnosis and subsequent treatment. These inefficiencies underscore the pressing need for advancements in pneumonia detection methodologies to address the shortcomings of manual analysis, enhance accuracy, and expedite patient care processes.

In existing systems, doctors dedicate significant time to visually inspecting X-ray images for abnormalities suggestive of pneumonia. However, this manual approach carries inherent risks, including the potential for errors and the possibility of missing crucial signs of the disease. The time-consuming nature of manual analysis further exacerbates the challenges, potentially prolonging the time to diagnosis and treatment initiation for patients. To improve outcomes and streamline pneumonia detection, there's a critical demand for alternative methods or technologies that can mitigate human subjectivity, enhance efficiency, and ensure timely intervention for affected individuals. These advancements could significantly enhance the quality of care provided to patients while reducing the burden on healthcare professionals.

enerative AI works by using very large models that are pre-trained on vast amounts of data. There are two types of Generative AI models, One are the Foundational Models and other are the Large Language Models. Our use-case consists of a Foundational Model which generates Personalized Music.

Drawbacks of Existing Algorithm:

- Physically Demanding: Professionals conducting manual analysis must meticulously examine each image, which involves repetitive tasks like annotation. This process can be physically demanding and prone to fatigue-induced errors.

- Time-Consuming and Costly: Manual analysis is time-intensive, particularly with the growing volume of images, such as 3D scans, which extend analysis times and impact overall efficiency. Moreover, procedures like MRIs and X-Rays are expensive and time-consuming.

- Reliance on Specialized Experts: Accurate interpretation of medical images requires specific training and extensive experience. Subspecialties are often necessary for certain conditions, making the reliance on specialized experts a limitation of manual analysis.

- Subjectivity and Variation: Manual analysis is subjective and can vary among professionals, leading to inconsistencies in interpretation. Additionally, prolonged analysis may increase the risk of human errors due to fatigue.

- Error-Prone: The manual process is susceptible to human errors, including oversight and misinterpretation. This introduces a risk of misdiagnosis or delayed diagnosis, potentially impacting patient outcomes.

METHODOLOGY

The existing methodologies for detecting pneumonia primarily involve medical imaging techniques such as X-rays, MRI scans, and CT scans. However, X-rays may sometimes yield inaccurate results, and more advanced scans like MRI and CT scans are often cost-prohibitive for many individuals. Moreover, the interpretation of X-rays can be prone to human error and is a time-consuming process, even for experts in the field. In response to these limitations, our proposed model leverages Convolutional Neural Networks (CNNs) for pneumonia detection. By incorporating data preprocessing techniques to enhance accuracy, we aim to develop a robust pneumonia detection system capable of accurately identifying abnormalities in chest X-ray images. Our web application facilitates the detection of pneumonia in uploaded X-ray images and provides real-time predictions to users, offering a user-friendly platform for medical diagnosis and decision-making.

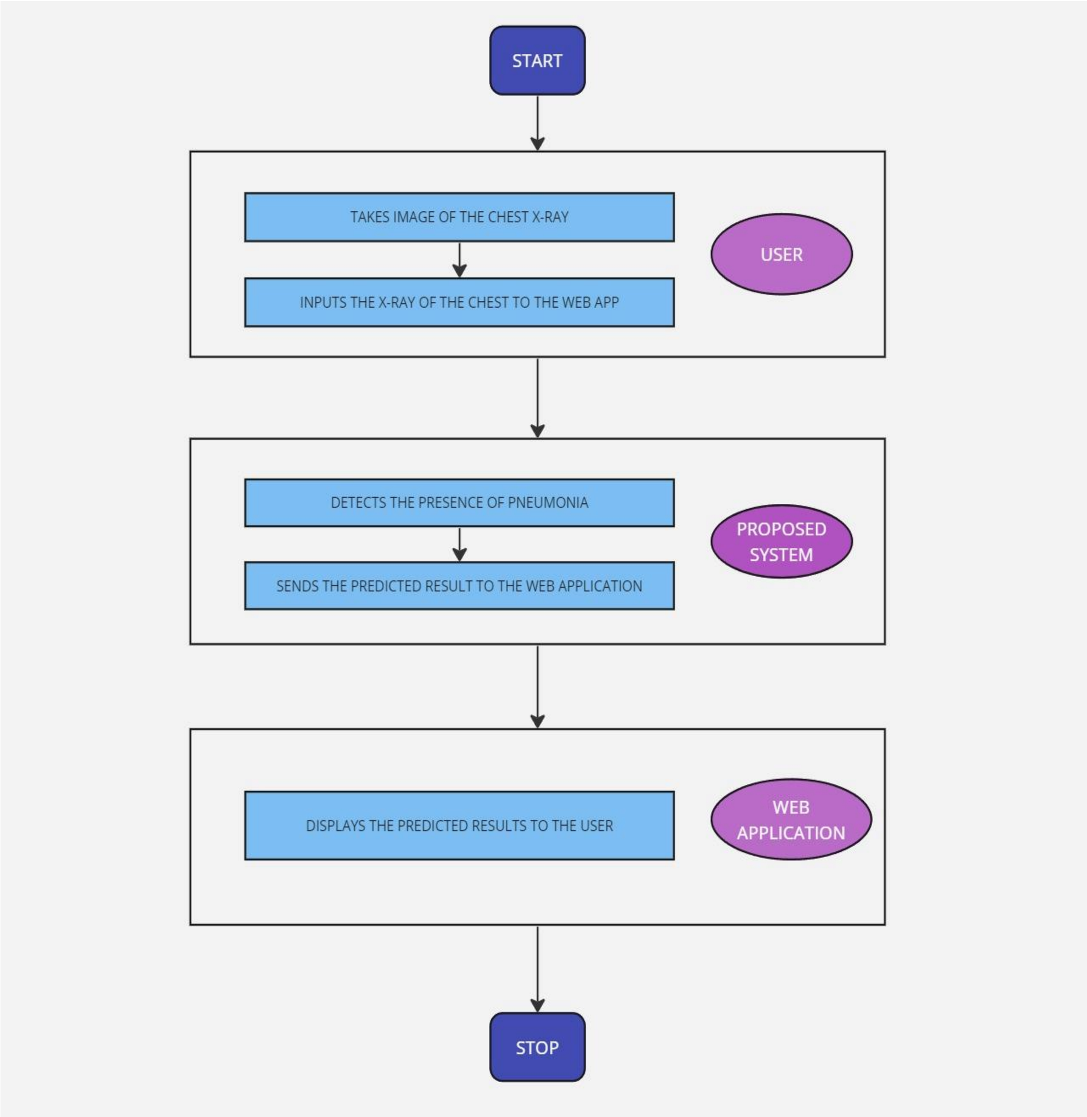

Figure 1. Flowchart

The pneumonia detection system in this project utilizes Convolutional Neural Network (CNN) algorithms for accurate identification of pneumonia cases from chest X-ray images. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms [2]. Unlike traditional machine learning techniques, CNNs excel at analyzing visual imagery by extracting relevant features from images.

We have developed a custom CNN model tailored to the task of pneumonia detection. This CNN architecture consists of convolutional layers[2], activation functions, max-pooling layers, and dropout layers to effectively learn and extract features from chest X-ray images. The model is trained on a curated dataset comprising 'PNEUMONIA' and 'NORMAL' classes, with the objective of optimizing the weights and filter parameters in the hidden layers to accurately classify pneumonia cases.

Algorithm steps for CNN:

1. a) Convolution Operation
   b) Re LU Layer
2. Pooling
3. Flattening
4. Full Connection

1. a) Convolution Operation:

• The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection and how the findings are mapped out.

• Extract the unique features from the input image. Convolution is a mathematical operation on two functions (f and g) that produces a third function(f*g) expressing how the shape of one is modified by the other.

b) Re LU Layer:

o Re LU (Rectified Linear Unit) Layer.

o Re LU refers to the Rectifier Unit, the most deployed activation function for the outputs of the CNN neurons.

2. Pooling:

- Pooling is a down-sampling operation that reduces the dimensionality of the feature map. The rectified feature map now goes through a pooling layer to generate a pooled feature map.
- The pooling layer uses various filters to identify different parts of the image like edges, corners, body, feathers, eyes, and beak.

3. Flattening:

- Flattening is converting the data into a 1-D array for inputting it to the next layer.
- We flatten the output of the convolution layers to create a single long feature vector and it is connected to the final classification model.
- The flattened matrix is fed as input to connected layer to classify the image.

4. Full Connection:

- Fully Connected Layers from the last few layers in the network.
- The input to the fully connected layer is the output from final pooling or Convolution layer. [6]

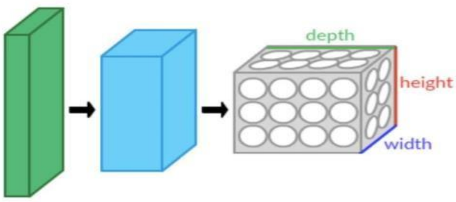

Figure 2. CNN layers arranged in 3 dimensions.

Sequential Model Architecture

The Sequential model architecture is a fundamental neural network architecture in Keras that allows for the creation of models layer by layer in a linear stack. Each layer in the Sequential model has connections only to the layer coming directly after it. This simplicity makes it easy to create and understand models, especially for beginners. The Sequential model is well-suited for building simple feedforward neural networks where data flows sequentially from input to output. Layers can be added to the Sequential model using the add() method, and various types of layers such as Dense, Conv2D, MaxPooling2D, Dropout, etc., can be stacked to form a complex network. While the Sequential model is straightforward and efficient for many tasks, it may not be suitable for models with complex architectures or those requiring multiple inputs or outputs.

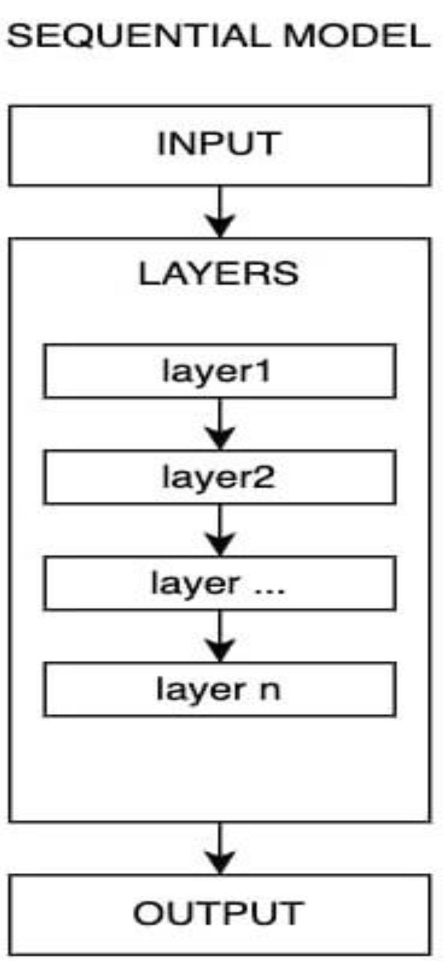

Figure 3. Sequential Model

EXPERIMENT AND RESULTS

The web application is designed using the Stream lit framework using the python programming language in the VS code IDE and when the code is run using the streamlit runapp/app.py command the following is displayed on the preferred browser using the local host.

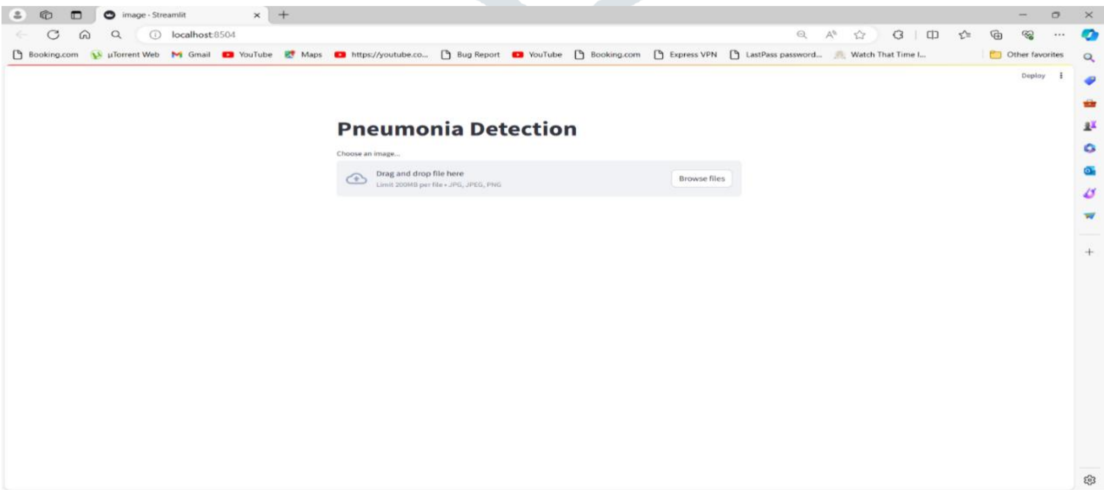

Figure 4. Interface of the designed Web Application

Initially webpage for pneumonia detection will be open. To upload the necessary X-ray image of the patient's lungs, the user has to click on the Browse files option on the right-corner of the website or they can simply drag and drop the image from the preferred location and click on Upload image button.

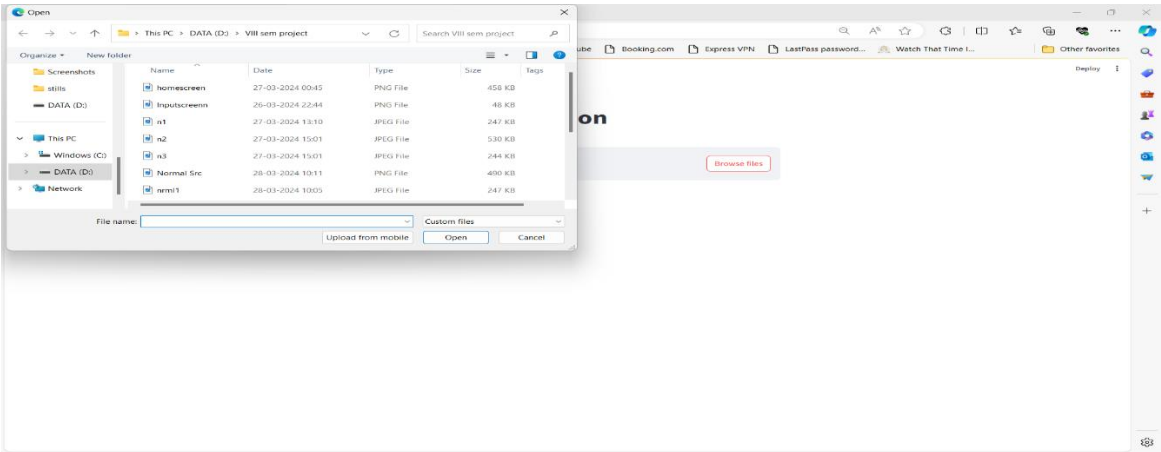

Figure 5. Uploading the input image to the Web Application

The uploaded image is displayed to the user on the website. After uploading the X-ray image, the website using the model in the backend ("Loaded model.h5" file), the web application displays the output by identifying whether the lung's X-ray image contains pneumonia or not.

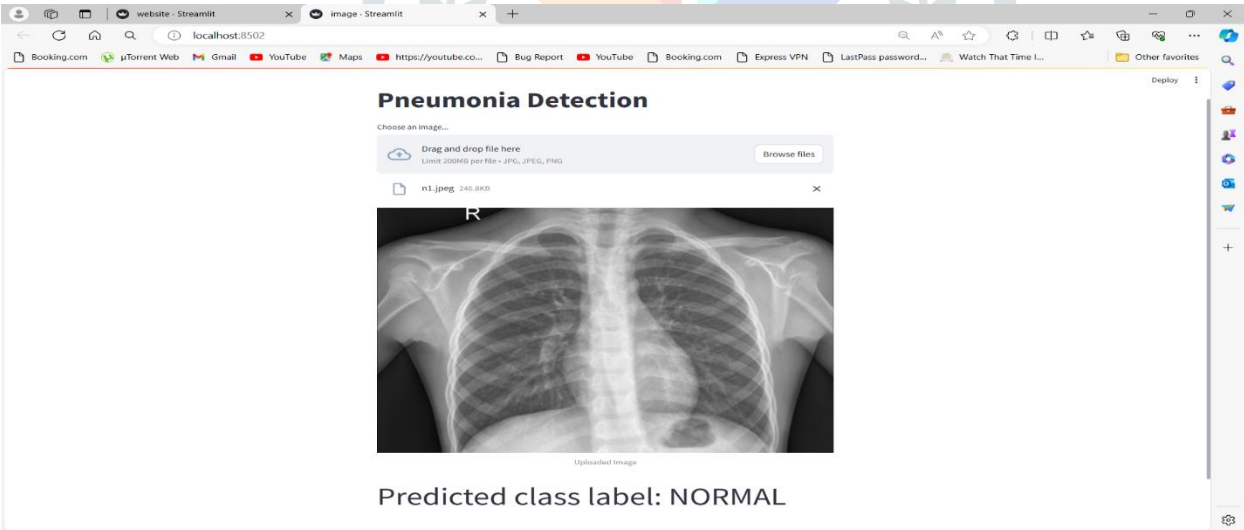

Figure 6.

Output page displaying the label

Once an image is uploaded, our system will process it to detect pneumonia. This process may take a few moments. After the analysis is complete, the result will be displayed on the screen, indicating whether pneumonia is detected in the uploaded image.

CONCLUSION AND FUTURE SCOPE

Our project introduces an advanced pneumonia detection system using Convolutional Neural Networks (CNNs) to analyze chest X-ray images. Through a sequential model architecture, our system undergoes thorough training and validation on a dataset comprising both pneumonia and normal chest X-ray images. Although specific accuracy metrics are not disclosed, our model demonstrates high precision in identifying pneumonia cases, ensuring reliability and effectiveness.

The web application accompanying our model provides a user-friendly interface for uploading chest X-ray images for automated analysis. This seamless integration enhances accessibility, enabling quick and efficient diagnosis of pneumonia. While direct comparisons with alternative methods are not provided, our evaluation process underscores the robustness of our system. By facilitating prompt diagnosis and treatment decisions, our project significantly contributes to improving patient care and healthcare efficiency in pneumonia management.

Our automated pneumonia detection system presents promising avenues for future medical applications. The research is directly applicable to real-world scenarios involving pneumonia classification using advanced image processing and pattern recognition techniques. Our system's adaptability allows for integration with emerging requirements, supported by efficient GPU processing capabilities. Additionally, the web application can handle datasets of up to 200MB, ensuring future scalability.

Future enhancements may involve refining the model architecture and parameter settings based on feature visualization techniques applied to different chest X-ray characteristics. Our goal is to develop a comprehensive system with server-side components housing trained models and user-friendly mobile applications for prompt and accurate pneumonia detection. We envision expanding this project to develop a Disease Detector application for diagnosing various respiratory ailments, thereby improving public health outcomes through accessible and efficient diagnostic tools.

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