International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 07 | July - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Deep-Lung Diagnosis – Deep Learning-Based Lung Disease Classification and Detection Using CNN and ResNet Models

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Abstract - The classification, detection and certainty measurement of lung x-ray image anomalies using advanced sophisticated deep learning techniques such as CNN have witnessed a growth betterment especially to reach a working solution that focus on chest illnesses e.g. asthma, pneumonia, TB,COVID-19, lung cancer. Numerous datasets have been used to test the model to the maximum extend its capability and its accuracy message seems well received. Additionally, a user-friendly graphical interface allows medical practitioners to quickly assess and interpret x-ray images with precise outcomes based on CNN. The aim is to integrate powerful algorithms of deep learning into medical practice so as to establish faster and more reliable diagnostic tools for chest diseases that will enable early intervention, personalized treatment options as well as improved patient outcomes.

Key Words: Deep-Lung Diagnosis, Convolutional neural network, Mask CNN, Lung Disease classification, X-Ray Images.

1.INTRODUCTION

Medical tomography is seeing some exciting new developments with deep-learning algorithms offering opportunities to spot problems and categorize diseases better. This paper explores using deep learning, especially CNN for catching issues and convolutional-neural-networks to classify lung diseases from x-rays. Spotting oddities early when looking at lung x-rays matters a ton for jumping on illnesses faster. To train our proposed detection, we rely on publicly available datasets that help to properly and accurately detect the abnormal regions in lung images. However, another important aspect is the accurate classification of the disease since that greatly affects the treatment. Using CNN's, one of the most effective deep-learning architectures that can learn unique features from image data, we train the model to detect abnormalities using various datasets ranging from pneumonia, tuberculosis, COVID-19, and lung cancer. Our aim is to build a classification model that can categorize lung X-ray images properly into disease groups.

The approach employed involves categorizing various tasks for disease classification and detection. While the CNN model focuses on disease classification and for detection. To meet the requirements of healthcare professionals and clinical processes, we propose a modular framework that is versatile and adjustable, maintaining a distinct division of responsibilities. Throughout the paper, comprehensive testing is conducted on diverse datasets to meticulously assess the effectiveness and precision of the models in both detection and disease classification.

pneumonia is very rigorous, occasionally deadly illnesses that can have an effect on hundreds of thousands of people ecumenical in locations with few resources. Pneumonia is characterized by means of irritation in one or both of the lung's air sacs, often due to the presence of bacteria, viruses, or fungi. Pneumonia is the foremost purpose of sickness and death in older adults and puberty. For the purposes of management and treatment, pneumonia must be properly and quickly diagnosed. Standard diagnostic procedures, in addition to lab testing, clinical examinations, and expert interpretation, can be resource- and time-intensive, even if they are reliable.

Due to their labor-intensive, expensive, and time-consuming nature, these outdated methods provide difficulties in healthcare environments with constrained funding. However, recent advancements in the deep-learning technology which is a subgroup of machine-learning provide encouraging prospects. Applications that forecast diseases benefit greatly from convolutional-neural-networks' (CNN's) .

Creating a dependable algorithm to study a chest X-ray of a affected person and decide if they have pneumonia, is an extraordinarily difficult task. The accuracy of the algorithm is essential as it immediately impacts the lives of individuals. Additionally, this algorithm utilizes advanced deep-learning techniques, especially CNN for health problem classification and for identification, to decorate the processing of lung images. By employing a modular structure, it enables early detection and unique categorization of illnesses with chest disorders. This is achieved by way of setting apart the tasks of detection and illness classification into wonderful components.

2. LITERATURE SURVEY

Shabana Urooj et al. , focused on developing a more efficient tuberculosis detection system. through the proposed method as Stochastic learning with artificial-neural-network model by just taking some random variations using Chest X-ray images. The proposed method incorporates a random function to the neural network, which could be achieved by assigning stochastic transfer functions to the network directly or assigning stochastic weight to the network. The result from the present study is out performed that the proposed method showed better performance than the Ensemble Deep Learning and Automatic Frontal Chest Radiograph Screening System, as shown below in the results. The proposed method shows the improved efficiency with the

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sensitivity rate of 96.12%, the specificity of 98.01%, Accuracy 98.45%, and F-Score 95.88% respectively. [1]

T. Rajasenbagam et al. introduced a research paper by presenting a study on Pneumonia infection detection in the lungs using a Deep-Convolutional-Neural-Network model with Chest X-ray images. The research paper trained the proposed Deep CNN models on the Pneumonia Chest X-ray images dataset. A Content-based image retrieval is used to annotate the images in the dataset. This process retrieves the images from the training dataset based on its visual content, regardless the metadata or textual information about it. They present a Pneumonia infection diagnosis model utilizing VGG19 Net architecture . A GPU system was employed to be trained with our data. The model's performance evaluation through the common metrics accuracy, precision, recall, and F1 score proved that their proposed model performed better than the existing model.[2]

V. Sirish Kaushik and colleagues have published a research paper with their original convolutional neural network model for the accurate detection of pneumonic lungs in chest X-rays. Since it can become a tool for work of specialists in the medical field that helps to diagnose and cure pneumonia with high efficiency, this model is of paramount significance. The proposed model includes four convolutional layers, and the goal is to "develop a model from scratch and to design a CNN model that classifies and detects pneumonia from the chest X-Ray" . With a slightly lower accuracy of 92.31%, the model has managed to reach the recall rate of 98%. It is a highly important part since the high recall assumes a small number of false-negative cases that can put the patient's life at risk .[3].

Khairul Munadi and colleagues introduced a study with the primary aim of comparing and assessing the impacts of two distinct pre-processing methods, namely Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF), on the utilization of pre- trained Convolutional-Neural-Networks (CNN) for tuberculosis (TB) detection. The research integrates deep-learning techniques with UM and HEF image enhancement, and employs EfficientNet-B4, ResNet50, and ResNet-18 models to train TB images in order to enhance detection accuracy. The utilization of an image enhancement system is crucial for pre-processing TB images, enabling the pre-trained network to learn and evolve into a more effective model. The tentative results authorize that the proposed approach achieves highly modest accuracy levels.

L. Priya presented a paper that introduces a unique method for analyzing adult asthma using a Convolutional-Neural-Network (CNN) which is trained on a public asthma dataset. Using neuron-wise and layer wise visualization techniques, the CNN achieves an 83.61% accuracy in diagnosing adult asthma based on respiratory symptoms alone. The study's main objective is to identify factors involving asthma, so that aiding in healing and empowering adults to safeguard against potential triggers.[5]

3. PROPOSED MODEL

The Convolutional-Neural-Network (CNN) is a widely used deep learning neural network with multiple layers, including a max pooling layer. The layers help in automatic picture recognition of X-rays. The Rectified Linear Unit (ReLU) layer improves nonlinearity. It resembles the fixed network of a trial-and-error system. The study seeks to identify patterns in patients and classify them as having Disease or not.

The Fig . 1 block diagram represents the way the system has been designed. The user at first provides an image as input

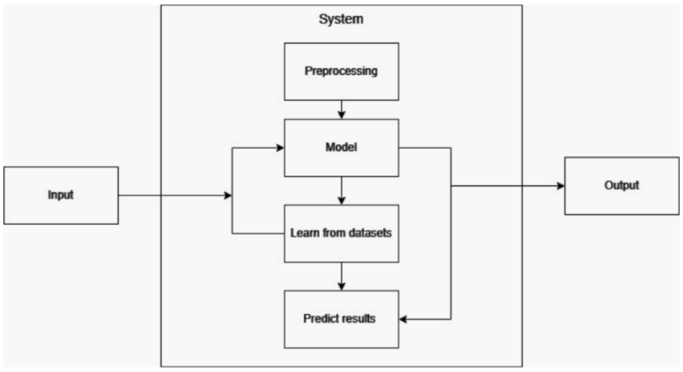

Fig 1 - Model Block Diagram

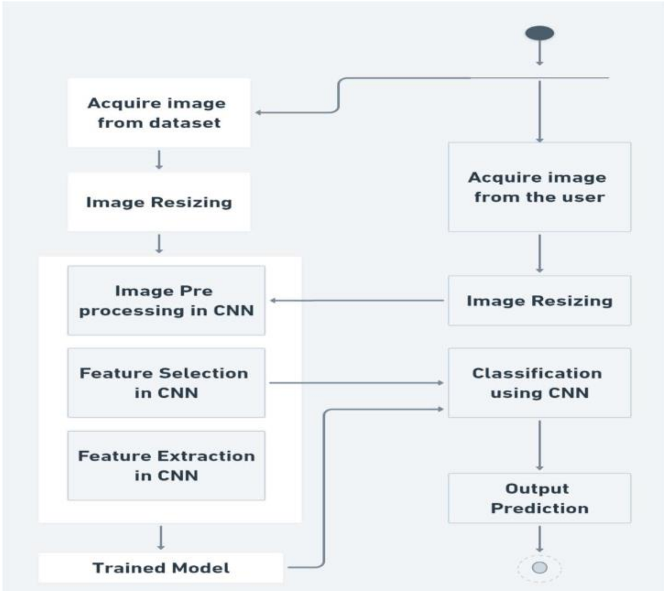

Fig 2 - Process Flow Diagram

which is approved on to the system. The system pre-processes the image and pass it to the model. The model would even now train from the datasets which is used to classify and predict the output of different lung diseases. Once the output is predicted, the predicted output is also shown to the user in the form of text. i.e. to tell if there is any lung disorder or the given image is normal . If any disorder is observed then it would display the type of disease. The Fig 2 represents a process flow diagram of a system for classifying images using a Convolutional-Neural-Network (CNN). The architecture of the CNN model is the technique's first stage. Classification often involves multiple convolutional layers, followed by pooling and fully connected layers. The system can acquire images from either a dataset or the user. Regardless of the source, the image is preprocessed for the CNN. The preprocessed image is fed into the CNN to extract features. These features are then selected for the classification task. The selected features are used to classify the image using a trained CNN model. The final stage is the output prediction, where it classifies to which group does the image belongs to.

A custom Convolutional-Neural-Network architecture for pneumonia examination on chest X-ray images was developed in this work. Several convolutional layers followed by pooling layers and then fully connected layers for feature extraction and classification were trained using Image-Data-Generator and data augmentation along with other hyper-parameter tuning. The training and validation accuracy after 5 epochs of training to assess the progress of the model are satisfactory.

The design of a Convolutional-Neural-Network model using cell pictures, which is integrated into the model layers of convolutional and ReLU activation and followed by max-pooling layers, the fully connected layer utilizing ReLU activation and the output layer incorporating the sigmoid . This model uses the data augmentation strategies during the training, hence, it can perform the unknown data efficiently. The program is able to classify cell pictures are tainted with a parasite to alias parasitized or uninfected.

A. Five Classification

1. Data collection and Preprocessing:
   - Datasets of chest x-ray images are collected through a variety of sources like Kaggle and our databases include public repositories and the photos are classified with five classes: cancer -class A, viral pneumonia -class B, covid-19 -class C , tuberculosis -class D, and normal –class E.
   - Preprocess the data set by scaling the photos into 50×50 pixels and classifying each photo into its classification code . We also do data augmentation through rotation, flipping, and zooming to increase the variety of our training set.
2. Model Architecture:
   - Convolutional-neural-networks (CNN) are used. The model is made up of three convolutional layers, and followed by max-pooling layers for feature extraction. The flattened output goes through two fully linked layers. Dropout regularization is used to prevent overfitting. The output layer contains 5 units that use SoftMax activation for multi-class classification. During training the model is built with a categorical cross-entropy loss and the Adam optimizer. Training is completed in 100 epochs with a batch size of 64.The confusion matrix and classification's report are used to assess model performance. Plots are used to illustrate accuracy, loss, precision, recall, and the F1 score.

B. Pneumonia Detection

1. Data collection and Preprocessing:
   - Chest X-ray images from the Kaggle Chest X-ray Images dataset are used.
   - Images are resized to 128x128 pixels and normalized.
2. Custom CNN Model:
   - A custom CNN architecture is designed for Pneumonia detection.
   - The model comprises convolutional layers, max-pooling layers, and fully connected layers with SoftMax output.

4. RESULTS

A. Experimental result of Five Classification.

- Cancer: Precision = 1.00, Recall = 0.96, F1-score = 0.98
- Viral Pneumonia: Precision = 0.95, Recall = 0.95, F1-score = 0.95
- Covid-19: Precision = 0.95, Recall = 1.00, F1-score = 0.97
- Tuberculosis: Precision = 1.00, Recall = 1.00, F1-score = 1.00
- Normal: Precision = 0.91, Recall = 0.91, F1-score = 0.91

The confusion matrix provides a detailed overview of the model's performance across different classes, as shown in Figure 3.

Figures 4 and 5 illustrate the training and validation accuracy/loss curves, respectively. The model demonstrates convergence without significant overfitting.

B. Detection Result

Overall result indicates the promising performance of the pneumonia detection system utilizing the Custom CNN model achieved accuracy of 95% highlight the system's effectiveness in accurately identifying the disease. These results contribute to the advancement of disease detection technologies and showcase the potential of deep learning models in improving diagnostic capability. Pneumonia Detection:- 95%.

5. DISCUSSION

To sum up, our model was quite successful by analyzing X-ray pictures, the suggested CNN model provides a significant improvement in the detection and classification of chest disorders, such as pneumonia, TB, COVID-19, and lung cancer. This application, which has an intuitive interface, helps doctors detect these illnesses quickly and accurately. Our approach can be deemed flexible and resilient because it was able to diagnose and classify various chest diseases. Nonetheless, a better study and tests would be required to see whether our models are strong and flexible enough for implementing on larger populations and datasets. Also, further work would be required to develop models that can be implemented into clinical workflows and residency and sued in medical trials.

Research concludes by highlighting the revolutionary potential of deep-learning in transforming the diagnosis of illness and the provision of healthcare. Our goal is to use artificial intelligence to enhance health outcomes for people around the world and progress medical technology.

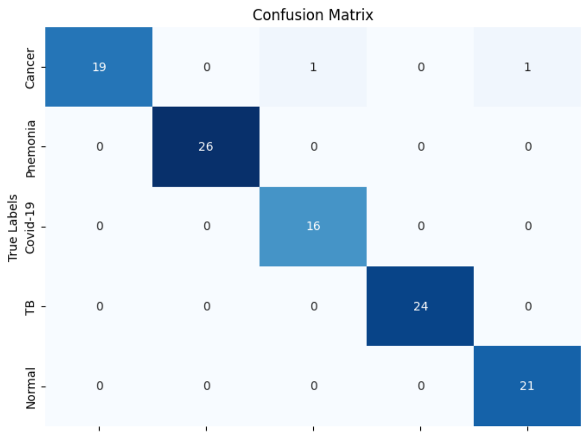

Fig 3 - Confusion Matrix

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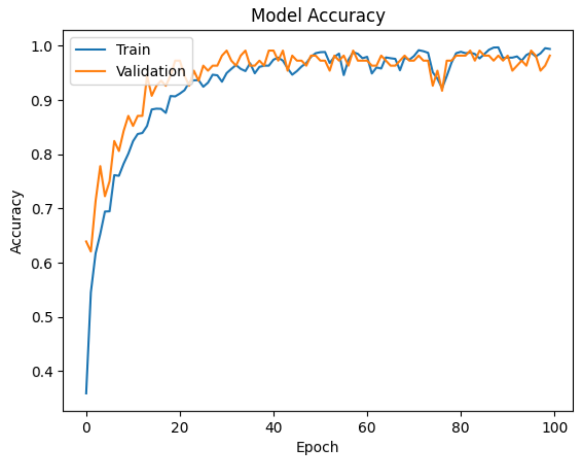

Fig 4 – Model Accuracy graph

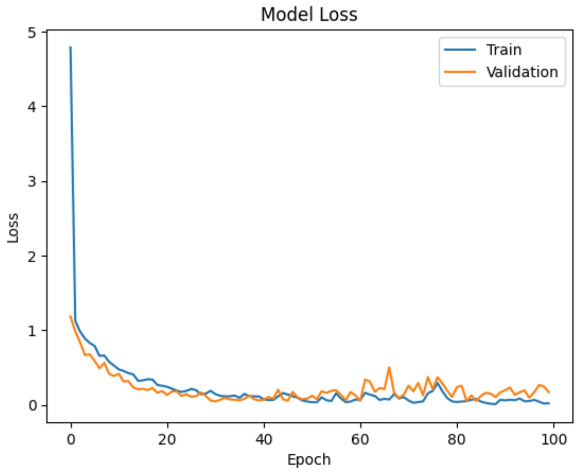

Fig 5 - Model loss graph

6. CONCLUSIONS

It provides a CNN-based method for categorizing lung disease images into five groups: cancer, viral pneumonia, Covid-19, tuberculosis, and normal. The experimental results show that the suggested model can reliably identify different types of lung illnesses from chest X-ray images. Our technique has the potential to help healthcare providers diagnose lung disorders more quickly and accurately, thereby improving patient outcomes.

The creation of deep learning model for detecting pneumonia marks a big step forward in automated illness diagnosis using medical pictures. The customized CNN model for pneumonia detection have demonstrated promising accuracy in recognizing abnormal lung patterns more clearly.

The machine learning algorithms can help healthcare practitioners diagnose diseases fast and effectively by using convolutional neural networks. These models provide useful tools for screening huge numbers of medical pictures, especially in resource-constrained settings where access to qualified medical personnel is limited.

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