Lwcnn:Light Weight Cnn Model To Detect Pneumonia Using Chest X-Ray Images

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Abstract: There is a sustainable worldwide effect, both in terms of disease and death, that is caused by pneumonia, which is a disorder that is easily affects the children and old age people. In recent days, pneumonia has easily affect the people because of pollution, increase in population and unhygienic conditions of living. It is a respiratory infection caused by bacteria and virus that affects the lungs. Many developed and developing nations also affected by pneumonia. Pneumonia can be identified by three different ways like CT scans, US scans and X-ray images. Due to the advancement in image recognition and deep learning technologies, computed vision devices predict infected and uninfected lung images with more accuracy .To make it success in rural areas, we employ a light weighted model to run through low-cost resource constraint devices and achieved remarkable training accuracy of 98.75%. Accuracy analyzed with three different learning rates and also compared with VGG-16, Mask-RCNN, and DenseNet121.

Keywords: Pneumonia, Respiratory infection, Light weight CNN, X-Ray, VGG-16, Mask-RCNN, DenseNet121.

I. INTRODUCTION

Pneumonia is a lung disorder that is easily affected by children, and it is easily spread by pollution and the unhygienic condition of the environment in both developed and developing nations. It is a respiratory infection caused by bacteria or viruses, and it is a global health issue. In many rural areas, pneumonia detection is hard to find; they have gone through many CT scans and X-ray images. We developed a light-weight model to detect pneumonia using chest x-ray images. It is useful for rural healthcare centers to detect pneumonia easily.

To address this challenge, we undertook a project focusing on the development of a highly accurate light-weight pneumonia detection system using a Convolutional Neural Network (CNN) using chest X-ray images to improve the accuracy and performance using the Adam learning rate.

In today's world, there has been growing interest in recent technological innovations, particularly artificial intelligence (AI) and deep learning, to address the challenges associated with pneumonia diagnosis and management. Chest X-ray imaging, a cornerstone in the diagnostic process of pneumonia, offers a non-invasive and widely accessible modality for identifying pulmonary abnormalities.

In designing our model, we are using some activation functions to improve the performance and accuracy of detection. The Rectified Linear Unit (ReLu) activation function is used for input layers, and the sigmoid activation function is used for output layers to detect positive or negative. Conventional 2D, batch normalization, and max-pooling are used to extract relevant features from the input X-ray images improve the accuracy of the detection of pneumonia.

The main goal of this project is to design and evaluate a lightweight model for pneumonia detection that can operate efficiently on low-power devices and improve the accuracy of the detection of pneumonia by using chest X-ray images. Data augmentation is used to avoid overfitting in the model.

We are using a data set consisting of 27500 chest X-ray images in our project. With a large dataset, we can improve our model effectively, improve efficiency, and reduce the overfitting of images in the model. It also improves the model's performance. This can result in higher accuracy.

Our proposed CNN model has established architectures, including VGG-16, Mask-RCNN, and DenseNet121. We aim to assess the efficiency, robustness, and scalability of our approach in detecting pneumonia from chest X-ray images, with a particular focus on its applicability in resource-limited settings

We achieved a training accuracy of 98.75%. We employed the Adam optimizer with carefully chosen learning rates in an optimal combination during the training phase. Ultimately, the successful development and deployment of a pneumonia detection system using chest X-ray images will increase the accuracy of the detection of pneumonia.

We developed an automated detection of pneumonia using chest X-ray images as an input, and it delivered an accurate result for the patient. It will be helpful for rural healthcare centers that do not have proper medications to detect pneumonia. Generic pneumonia is detected by CT scans. Many healthcare centers have X-ray scans, and by using these scans, doctors will easily detect the pneumonia.

II. LITERATURE SURVEY

The literature survey reveals a significant interest in utilizing deep learning methodologies for the automated detection and diagnosis of COVID-19 using chest X-ray images. Several studies have been conducted, each employing different convolutional neural network (CNN) architectures and techniques to achieve accurate results
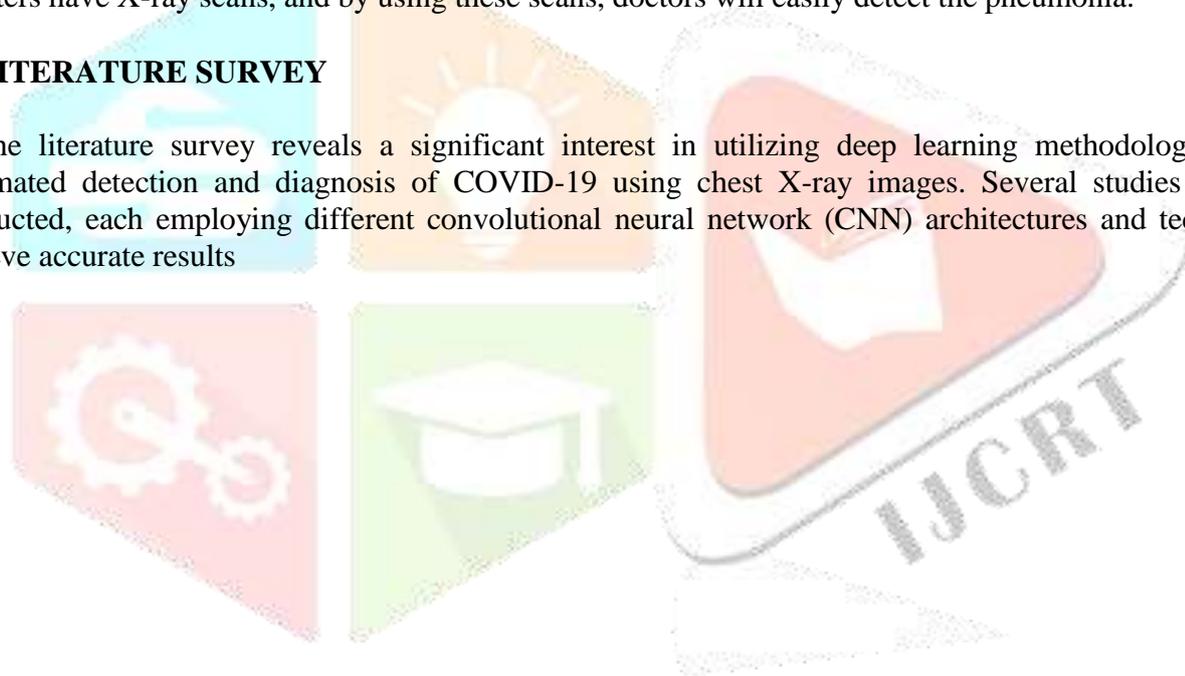
S. No	Title	Methodology	Type of Image	Dataset Used
1	Automated detection of covid-19 cases using deep neural network with X-ray.	DarkNet based CNN model	Chest X-Ray	Normal:500, Infected:127
2	CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images.	CNN model	Chest X-Ray	Normal:1203, Infected:1591
3	COVID-19 pneumonia accurately detected on chest radiographs with artificial intelligence	CNN model	Chest X-Ray	Normal:200, Infected:102
4	Covid-19: Automatic detection from X-ray images utilizing transfer learning with CNN.	ResNet50+ResNet101	Chest X-Ray	Normal:315, Infected:250
5	Explainable Deep Learning for Pulmonary Disease and Coronavirus COVID-19 Detection from X-rays.	VGG-16model	Chest X-Ray	Normal:3520, Infected:250
6	A deep learning approach to detect Covid-19 coronavirus with X-Ray images.	ResNet50+ResNet101	Chest X-Ray	Normal:315, Infected:250

Table 1: Literature Survey

In the study by [1], a DarkNet based CNN model was proposed for automated detection of COVID-19 cases. Their dataset comprised chest X-ray images categorized into normal and infected cases, with an achieved accuracy of 87.02%. Similarly, [2] introduced CoroNet, a CNN model specifically designed for detecting and diagnosing COVID-19 from chest X-ray images. Their approach achieved an accuracy of 89.6% using a dataset consisting of both normal and infected cases.

Furthermore, [3] demonstrated the accuracy of COVID-19 pneumonia detection on chest radiographs using artificial intelligence, achieving an AUROC of 0.96. This study utilized a CNN model trained on a dataset containing normal and infected cases of COVID-19.

Transfer learning was employed in [4], where ResNet50 and ResNet101 architectures were utilized to automatically detect COVID-19 from X-ray images. Their approach achieved an impressive accuracy of 94.72%.

Moreover, [5] employed a VGG-16 model for explainable deep learning in pulmonary disease and COVID-19 detection from X-rays. With a dataset comprising a large number of normal and infected cases, their method achieved a notable accuracy of 97%. Finally, [6] presented a deep learning approach using ResNet50

and ResNet101 architectures, achieving a remarkable accuracy of 97.77% in detecting COVID-19 from chest X-ray images.

III. STATE OF ART MODELS

The current methods for diagnosing respiratory illnesses, particularly pneumonia, face several challenges that hinder their effectiveness in providing accurate and timely diagnoses. Traditional approaches rely heavily on manual examination and interpretation of patient symptoms and medical imaging, such as chest X-rays or CT scans. However, these methods are often subjective, time-consuming, and prone to human error.

Furthermore, existing diagnostic systems may lack the capability to leverage diverse data types effectively. For instance, patient data, including symptoms, demographic information, and clinical history, are typically stored in CSV files. While these files provide a structured format for organizing patient details, they may not fully capture the complexity of respiratory conditions or facilitate comprehensive analysis.

Similarly, datasets such as Cough sound recordings offer valuable insights into respiratory symptoms but may require sophisticated feature extraction techniques and machine learning models to extract meaningful information accurately. The reliance on handcrafted features and conventional machine learning algorithms may limit the ability to capture subtle variations and nuances in cough patterns, potentially impacting diagnostic accuracy.

Moreover, while image processing and machine learning models have shown promise in detecting pneumonia from medical imaging, such as chest X-rays, the current approaches may lack scalability and generalization across diverse patient populations. Additionally, the interpretation of imaging data may vary among healthcare professionals, leading to inconsistencies in diagnosis and treatment decisions.

Furthermore, the existing models, like M3Lung-sys, although incorporating advanced techniques such as slice-level and patient-level classification networks, may still face challenges in achieving optimal performance across different datasets and clinical settings. Variations in imaging protocols, patient demographics, and disease manifestations can introduce complexities that traditional models may struggle to address effectively

IV. PROPOSED LIGHT WEIGHT MODEL

Dataset:

In our study, we focus on utilizing chest imaging for pneumonia prediction, particularly emphasizing X-ray images over CT scans and ultrasound (US) due to cost efficiency and practical considerations in rural healthcare centres. While CT scans and US offer high-resolution imaging and additional diagnostic information, their availability is limited, especially in resource-constrained settings. Therefore, we opt for X-ray imaging as it is more commonly accessible in rural healthcare facilities and provides sufficient diagnostic information for pneumonia detection.

We utilize a comprehensive dataset containing 27,500 chest images for feature extraction. This dataset encompasses a diverse range of cases, including normal and pneumonia-affected individuals. By leveraging this extensive dataset, we aim to extract informative features from the X-ray images, which are essential for developing accurate and reliable predictive models for pneumonia detection.

Our decision to focus on X-ray imaging aligns with the practical realities of healthcare delivery in rural areas, where access to advanced imaging modalities such as CT and US may be limited or unavailable. By leveraging X-ray images and a large-scale dataset, we aim to develop a cost-effective and accessible solution for pneumonia prediction, ultimately improving diagnostic capabilities and patient outcomes in underserved communities.

Preprocessing:

Image processing for pneumonia detection involves several steps: initial acquisition of chest X-ray or CT scan images, followed by preprocessing to reduce noise and enhance image quality. Segmentation isolates the lung area, focusing analysis. Feature extraction captures texture, shape, and intensity patterns indicative of pneumonia, followed by feature selection and dimensionality reduction to refine the dataset. Classification, employing machine learning algorithms, distinguishes between pneumonia and normal conditions. Post-processing refines results, and evaluation assesses performance metrics like sensitivity and specificity. This pipeline enables effective pneumonia detection from medical images, aiding diagnosis and treatment.

Data Augmentation:

For reducing the overfitting and increase the detection of pneumonia data augmentation is used. Data augmentation is used for detection of pneumonia from chest X-rays and improve the accuracy for detection of pneumonia. Chest x-ray images are used for image data augmentation by rotating the image by a different angle. Flipping the chest X-ray images by horizontally or vertically. Scaling is used for zooming the images in or out this increases the accuracy of detection. Data augmentation is used for rotating, flipping, scaling the chest X-ray images for improving the accuracy of detection of pneumonia.

ReLU (Rectified Linear Unit):

ReLU is a linear activation function. When the input value is positive, it will act by immediately outputting the value; when the output value is negative, it will produce zero. We take the input as Relu for activation functions for input layers.

Sigmoid Activation:

Sigmoid is used for producing the output from the hidden layers to a range of 0 and 1 this probability that belongs to input positive class. The output of the sigmoid functions always falls between the range of 0 and 1 as a probability decision.

Adam learning rate:

The Adam optimizer adjusts learning rates for each parameter during training based on past gradients, enhancing convergence speed and model performance in tasks to detection of pneumonia using the chest X-rays for improving the performance of detection. The adam learning rate increase the performance of pneumonia detection.

Learning rate = 1e-5 with a training accuracy of 96.15% and a validation accuracy of 81.25%, so the learning rate can be low for efficient learning. The model appears to have learned training data, but the result is not effectively applied to the validation data because it indicates the potential for overfitting. In this pneumonia detection, the model is closely related to the training images, but it fails to identify the pneumonia's strongest matches in the newly unseen images.

The learning rate of 0.001 is slightly similar to the previous learning rate, but the training accuracy is 97.12% and the validation accuracy is the same as the previous data set. It may also have overfitting, so it does not provide an efficient result for pneumonia detection

Epoch	Training Accuracy	Validation Accuracy
Epoch 1	85.83%	75.00%
Epoch 2	93.54%	62.50%
Epoch 3	96.01%	81.25%
Epoch 4	96.20%	81.25%
Epoch 5	96.66%	87.50%
Epoch 6	96.74%	100.00%
Epoch 7	96.78%	97.80%
Epoch 8	96.73%	98.15%
Epoch 9	97.32%	100.00%
Epoch 10	97.74%	92.40%
Epoch 11	97.58%	93.57%
Epoch 12	97.80%	96.24%
Epoch 13	97.78%	97.24%
Epoch 14	98.18%	98.75%
Epoch 15	98.33%	99.45%
Epoch 16	98.39%	100.00%
Epoch 17	98.50%	100.00%
Epoch 18	98.47%	100.00%
Epoch 19	98.87%	100.00%
Epoch 20	98.75%	100.00%

Table 3: Description of Proposed Learning rates

Finally, the learning rate of 0.0001 produces the best results for pneumonia detection using x-ray images because the training accuracy is 98.75%. This model learned well and provided effective results for hidden data. In this pneumonia detection, the model is well trained, and the learning rate gives successful results that capture the relevant features of pneumonia in chest x-ray images, leading to accurate predictions and efficient results.

A learning rate of 0.0001 consistently yields optimal results for pneumonia detection using chest X-ray images. Through 20 iterations with different datasets, the model achieves a stable training accuracy of 98.75%.

We tested our pneumonia detection model on Kaggle and it did really well. It consistently got 98.75% accuracy, which shows it is good at finding pneumonia in X-ray images. Additionally, it worked great on new images that we had not seen before, so we know it can be trusted in real-life situations.

V.METHODOLOGY:

In our approach, the input layer is configured to accept X-ray images with a resolution (150,150,1)150 - width and 150-breadth channel size 1(grey colour).We incorporate several 2D convolutional layers (Conv2D) the features are extract from the chest X-ray inputs images. Each Convo 2D layers is used for learning the different features and patterns. By specifying various filter sizes and kernel values in these layers, we aim to capture a diverse range of image characteristics relevant to pneumonia detection. Additionally, we introduce dropout layers between Conv2D for preventing the overfitting dropping a input

during the taring of chest X-ray datasets.This approach enhancethe robustness and generalization capability of our model for accuratedetection of pneumonia.

After the convolutional layers, we incorporate a flattening layer. The flattening layer is used to convert a multidimensional input data into a one-dimensional array. we condense the information while preserving the spatial relationships captured during feature extraction. This process prepares the data for input into the dense layers, facilitating further processing and classification. The flattening layer plays a crucial role in the transition from convolutional feature extraction to fully connected layers for final classification tasks, such as pneumonia detection.

The next layer is Dense layer it is a fully connected layer, type of layer in neural network which one layer connected to the previous layer. Dense layers consist of neurons that are connected to every neuron in the preceding layer, allowing for comprehensive information integration and feature combination. In our architecture, these dense layers serve to further process the extracted features from the convolutional layers, enabling higher-level abstraction and learning. By adjusting the number of neurons and incorporating activation functions, such as ReLU in these dense layers, we enhance the model's capacity to capture complex patterns and relationships within the data, ultimately facilitating accurate pneumonia detection.

In the output layer, we typically employ a single neuron for binary classification tasks like pneumonia detection. The output neuron's activation value represents the model's prediction probability for the pneumonia X-ray input image. For binary classification, we commonly use activation functions like sigmoid, which squashes the output values between 0 and 1, indicating the likelihood of pneumonia. This output layer enables the model to make predictions based on the features extracted and learned throughout the network, accurate detection of pneumonia from the input chest X-ray images.

Batch Normalization:

It is a technique used to train (ANN) more quickly and stably. BN works by normalizing the inputs of layers by re-centring and rescaling.Batch normalization is a technique used to improve training stability and increase performance.

Max pooling:

Max pooling is a type of operation used in convolutional neural networks, specifically for images. It reduces the noise in the chest x-ray images. Max pooling layer to reduce the dimensions of the feature maps.

T4 GPUs significantly speeds up training for our model. With parallel processing, we can experiment with larger batches and complex architectures, accelerating development and deployment of our pneumonia detection system.

VI.RESULTS AND DISCUSSION

In this study, we have developed a user-friendly interface integrated with a Convolutional Neural Network (CNN) model for the automated detection of respiratory diseases from chest X-ray images. Our approach involved training the CNN model on a sizable dataset comprising 29,500 chest X-ray images and employing data augmentation techniques to enhance model robustness and prevent overfitting during training.

Through rigorous experimentation and evaluation, our system demonstrated promising results in accurately diagnosing respiratory diseases, with a focus on pneumonia detection. By leveraging deep learning and image analysis techniques, we have provided a reliable and efficient solution for healthcare professionals to aid in the timely and accurate diagnosis of respiratory illnesses.

The integration of data augmentation techniques during training proved crucial in improving the model's performance and generalization capabilities, enabling it to effectively handle variations and complexities in chest X-ray images. Furthermore, the development of a user-friendly interface enhances

accessibility and usability, empowering healthcare professionals to leverage our system as a practical tool for enhancing diagnostic efficiency.

Learning rate = 1e-5 with a training accuracy of 96.15% and a validation accuracy of 81.25%, so the learning rate can be low for efficient learning. The model appears to have learned training data, but the result is not effectively applied to the validation data because it indicates the potential for overfitting. In this pneumonia detection, the model is closely related to the training images, but it fails to identify the pneumonia's strongest matches in the newly unseen images.

The learning rate of 0.001 is slightly similar to the previous learning rate, but the training accuracy is 97.12% and the validation accuracy is the same as the previous data set. It may also have overfitting, so it does not provide an efficient result for pneumonia detection.

The performance proposed model is evaluated using the following formulas:

Accuracy=(TP+TN)/(TP+TL+FP+FN)…….(1)

Sensitivity=TP/(TP+FN)…………………....(2)

F1-score=2TP/(2TP+FP+FN)………………(3)

Finally, the learning rate of 0.0001 produces the best results for pneumonia detection using x-ray images because the training accuracy is 98.75%. This model learned well and provided effective results for hidden data. In this pneumonia detection, the model is well trained, and the learning rate gives successful results that capture the relevant features of pneumonia in chest x-ray images, leading to accurate predictions and efficient results.

We have a dataset consisting of 27500 x-ray images, and we run this dataset in Kaggle while giving input as a ReLU and the output as a sigmoid. This gives results with high training accuracy and low validation accuracy, but it does not give the exact output, and efficiency is low.

In the second time, we run the same dataset in a Kaggle with different perimeters of input as a ReLU and output as a Soft-max, but it gives the same training accuracy for all detecting datasets and also gives constant validation accuracy.

Finally, we use binary classification in deep learning. We take the same dataset to identify pneumonia, with input as a ReLUand output as a sigmoid, which gives the same results for training and validation accuracy. By using Adam's learning rate, we increase the accuracy and decrease the time of execution.

Overall, our project contributes to the advancement of computer-aided diagnosis systems for respiratory diseases, offering a valuable resource for improving patient care and healthcare efficiency. Moving forward, further research and development efforts can focus on expanding the capabilities of our system, optimizing performance, and integrating additional features to support comprehensive respiratory disease diagnosis and management. Through continued innovation and collaboration, we can strive towards better healthcare outcomes and improved quality of life for patients worldwide

Ref. No	Methodology	Accuracy Achieved
[1]	DarkNet based CNN model	87.02%
[2]	CNN Model	89.6%
[3]	CNN Model	92%
[4]	ResNet50+ResNet101	94.72%
[5]	VGG-16model	97%
[6]	ResNet50+ResNet101	97.77%

[7]	**Proposed Light weight CNN model**	**98.75%**

Table 4. Comparison of Accuracy achieved by proposed model with state-of-the-art method

Conclusion:

Now we have developed a website to detect pneumonia using chest X-ray images of the lungs. In the future, we are going to develop a mobile app to detect pneumonia and help people, especially in places with few doctors and rural health care centers. The app quickly spots pneumonia signs in X-ray images, so people can get treatment early. It's important to respect privacy and work with doctors to make sure the app works well ,By listening to feedback and making improvements, the app can keep helping more people stay healthy, especially in areas with limited medical help.

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