UNDER PEER REVIEW

Early Detection of Pneumonia Using Deep Learning on Chest Radiographic Images

Abstract— **Pneumonia is considered to be one of the most important respiratory diseases that affect the human respiratory system and is fatal if it is not diagnosed at an early stage. The most common image processing technique that is used in the detection of pneumonia is the X-ray imaging technique. It is quite difficult and time-consuming for the radiologists to manually process the images of the X-ray images and detect the presence of pneumonia. Therefore, this project is developed with the aim of developing a highly efficient and accurate pneumonia detection system by making use of the deep learning technology. The proposed system is developed by making use of the dense convolutional neural network technique because the technique is highly efficient in the reuse of features. In addition to this, the proposed system is also developed by making use of the image processing techniques such as resizing, normalization, and augmentation. The proposed system is tested and trained by making use of the publicly available dataset for the chest X-ray images. The efficiency of the proposed system is tested and analyzed by making use of the accuracy, precision, recall, F1 score, and AUC values. The proposed system is quite efficient in detecting.**

INTRODUCTION

Pneumonia is considered a critical respiratory disease that causes the air sacs in the lungs to become inflamed. This is considered a life-threatening disease if not detected and treated at the early stages. It is considered one of the most common causes of death worldwide, especially among children, the elderly, and those with low immune systems. According to global health reports, pneumonia has been considered one of the biggest challenges facing the healthcare system globally due to its prevalence and potential complications. Therefore, early diagnosis is critical in reducing the mortality rate.

The most commonly used diagnostic technique in detecting pneumonia is the imaging technique using the patient's chest X-rays. This is because the X-ray imaging technique offers a clear representation of the abnormalities occurring in the patient's lungs. However, the interpretation of the patient's X-ray images is considered a complex process that requires high expertise. This is because the process of manually interpreting the X-ray images is considered tedious and is likely to be affected by human error. This is especially true in rural areas where there is a scarcity of radiologists, which has been considered a challenge in the early diagnosis of pneumonia.To address these challenges, the integration of Artificial Intelligence (AI) in healthcare has gained significant attention, particularly in medical image analysis. Deep learning, a subset of AI, has shown remarkable performance in automatically analyzing complex medical data. Convolutional Neural Networks (CNNs), in particular, have proven to be highly effective in extracting hierarchical features from images and performing accurate classification tasks. Unlike traditional machine learning techniques that rely on handcrafted features, deep learning models can learn relevant patterns directly from raw image data, thereby improving efficiency and accuracy.

In recent times, various models are proposed for the detection of pneumonia using deep learning. Among the models proposed in recent times, it is stated that DenseNet (Densely Connected Convolutional Networks) performs better when compared to the other models. This is because the feature propagation in the DenseNet model is effective. All the layers in the model are connected to all the other layers in the model. This makes the model effective in the feature learning process and in improving the accuracy of the model.

The proposed system is developed based on the DenseNet121 model with the idea of transfer learning in developing the system for the detection of pneumonia. In the proposed system, various preprocessing techniques are used to improve the performance of the model. The techniques used in the proposed system are resizing the image, normalization of the image, and augmentation of the image. This improves the quality of the image. The quality of the image is improved because the image is resized and normalized.

The main objective of carrying out this particular research is to develop an effective, reliable, and automated system which could help healthcare professionals in making quick and accurate diagnoses of pneumonia. The system could be highly effective in reducing the dependency on making the diagnosis by humans and in reducing the chances of any errors that could take place during the process. Therefore, with the development of this particular system, it is possible to further develop AI-based healthcare solutions. Moreover, it could also be highly beneficial in emphasizing the potential of deep learning in the field of healthcare diagnostics.

I. EASE OF USE

A. Simple User Interface

The system has an interface that is easy to use and comprehend, and users can upload their images of the X-ray of the chest without requiring any technical knowledge. The system is designed in such a way that even those in the medical field with little training can use the system.

B. Quick Image Upload and Processing

The system allows users to upload images of X-rays in different formats, such as JPG and PNG. The system also processes the image and performs operations such as normalization and image rescaling, which do not require manual intervention.

C. Real-Time Prediction Results

The system is also capable of providing results in real time, as the predictions take only a few seconds to come up.

D. Clear Output with Confidence Score

The system also displays the results in an easy and understandable format, showing whether the image is Normal or Pneumonia and also showing the percentages and level of severity.

E. Minimal Technical Knowledge Required

The system is also designed in such a way that the user does not have to be technically sound in terms of deep learning and other related subjects, making it easy to use even for rural healthcare workers.

II. PROBLEM STATEMENT

The diagnosis of pneumonia using chest X-ray images is considered to be a crucial but challenging task in the healthcare domain. As the number of patients is increasing, along with the scarcity of skilled professionals, there is a high probability of delaying the diagnosis of pneumonia. Moreover, the interpretation of the images is considered to be a complex task, which is always challenging to accomplish within a specific period of time. Therefore, the limitations of the existing pneumonia diagnosis methods need to be discussed, followed by the need to improve the existing system.

A. Limitations of Manual Diagnosis

The manual diagnosis of pneumonia using chest X-ray images is considered to be a complex task, which is always associated with possible errors due to the limited skills of professionals.

B. Challenges in Healthcare Environments

As the number of skilled professionals is limited in rural areas, along with the scarcity of time, the manual diagnosis of pneumonia using chest X-ray images is considered to be an inefficient process.

C. Limitations of Traditional Methods

The existing machine learning models, which are considered to be shallow models, are not capable of accurately interpreting complex images.

III. LITERATURE SURVEY

Pneumonia is an essential respiratory disease which is a significant health threat to the health of all people in the world, particularly children, old people, and immunocompromised individuals. It is, therefore, of critical importance that pneumonia be diagnosed at its early stages in order to avoid complications. Over the years, several pneumonia diagnosis techniques have been developed, which include traditional techniques as well as techniques that make use of artificial intelligence.

A. Background

Pneumonia is an infectious disease that results in inflammation in the air sac of the lungs. The inflammation in the lungs results in fluid accumulation in the lungs, which in turn results in complications in breathing. Pneumonia, therefore, is a significant danger to human health if it is not diagnosed in its early stages. One of the pneumonia diagnosis techniques is X-ray imaging of the chest, which results in an image of the abnormalities in the lungs, which include opacities and infiltrations. However, there are some complications associated with using X-ray imaging of the chest in diagnosing pneumonia in patients. Some of the complications include that X-ray imaging of the chest is a tedious process that demands the attention of experts in order to avoid human error..

B. Traditional Diagnosis Methods

Generally, the process of diagnosing pneumonia in the patient includes considering the symptoms of the disease in the patient, such as fever, cough, pain in the chest region, tiredness, breathing difficulties, etc. In addition to this, the patient is also subjected to laboratory tests and an X-ray test. The radiologist studies the image of the patient in the X-ray and tries to detect unusual features in the patient's lung area. The process is subjective in nature. In the case of high patient volume, the process of diagnosing pneumonia in the patient is tedious in nature due to the scarcity of skilled professionals. Thus, the conventional process is unreliable in nature and indicates the need for developing new technologies in the medical diagnosis process.

C. Machine Learning Approaches

Before the advent of deep learning techniques, there have been many machine learning techniques implemented in the detection of pneumonia. The machine learning techniques implemented in the detection of pneumonia include SVM, Decision Tree, and Random Forest. However, there were certain disadvantages associated with the implementation of machine learning techniques. The accuracy of the implemented model depends on feature extraction. However, feature extraction is not capable of handling complex features. Therefore, there were certain disadvantages associated with the implementation of machine learning techniques.

D. Deep Learning Approaches

Due to the advancement in the field of artificial intelligence, the deep learning architectures, i.e., Convolutional Neural Networks (CNN), have been able to achieve promising results in the analysis of images. It is also able to automatically learn the features from images, and hence there is no need to make any feature selection in the system. Among all the architectures of Convolutional Neural Networks, DenseNet, also known as Densely Connected Convolutional Network, is gaining significant popularity in the detection of pneumonia in patients. DenseNet-121 is a variant of DenseNet, in which all the layers of the network are connected with all other layers in a feed-forward fashion. This makes it possible to avoid the problems of vanishing gradients and overfitting, which generally occur in deep neural networks. With the help of transfer learning, it is also able to achieve high accuracy even with a limited number of images available in the medical field. It is also effective in detecting the pattern in images of X-rays.

E. Key Findings from Existing Studies

Research studies have proved that deep learning-based models have better performance than traditional machine learning-based models for the detection of pneumonia. In addition, deep learning-based models have high accuracy, sensitivity, and specificity. Therefore, deep learning-based models can be used for the effective detection of pneumonia. In addition, the effectiveness of deep learning-based models for the detection of pneumonia can be improved. This can be achieved by using a technique called transfer learning. In this technique, knowledge from other images, such as ImageNet, can be used. In addition, Gradient Weighted Class Activation Mapping, also known as Grad-CAM, has been proposed for the effective visualization of deep learning-based models. Using visualization techniques, it is possible to understand what part of the X-ray image is being used for making predictions. Therefore, the role of visualization techniques in AI-based models for the detection of pneumonia can be considered significant for bridging the gap between AI-based systems and medical professionals.

F. Research Gaps

Despite the improvements that have been made in the pneumonia detection systems, it has been observed that the systems developed have several drawbacks. For instance, the majority of the systems developed were based on insufficient data sets. This has affected the generalization ability of the developed models. In addition, the majority of the studies were based on simulated scenarios. Thus, it is challenging to assess the viability of the developed models in real-world scenarios. Another drawback of the pneumonia detection systems developed in the past is that they were not integrated with the hospital systems. The majority of the systems developed were standalone systems. Thus, they were not providing adequate support to the healthcare professionals.

IV. PROPOSED METHODOLOGY

The proposed system outlines the process of how pneumonia can be detected with the help of images using various techniques of deep learning. The proposed system can be regarded as an accurate solution for the detection of pneumonia with images, considering the methodologies used in the proposed system. The proposed system can be divided into various phases, such as data collection, data preprocessing, etc.

A. Data Collection

The first step is to collect the images of the chest X-rays that are publicly available and in the hospitals. The dataset is already provided with class labels. The dataset has two classes: Normal and Pneumonia. The dataset represents the various conditions of the lungs and is used to train the deep learning model.

For the proper implementation of the deep learning model, the dataset has to be divided into three sets:

Training Set – This is used to train the deep learning model.

Validation Set – This is used to set the parameters of the deep learning model and avoid overfitting in the deep learning model.

Testing Set – This is used to test the deep learning model.

The dataset is already in balance and has no bias in classifying the data.

B. Data Preprocessing and Feature Engineering

The Data Preprocessing step is one of the most important steps to be taken in order to improve the performance of the model. The images collected for the chest X-rays are subjected to various preprocessing techniques in the following way:

Image Resizing: The collected images are resized to the dimension of 224 * 224 pixels because this dimension is required for the DenseNet-121 model.

Normalization: The pixel values are normalized to the range of 0 and 1 for efficient training of the model.

Data Augmentation: Various transformations are applied to the collected images in order to increase the diversity and prevent overfitting.

This helps the model learn better and improves the generalization ability of the model.

In the context of deep learning models, feature engineering is automatically carried out. The important features are learned by the model from the collected images. The important features that are learned are:

Lung opacities, Infiltration patterns, Abnormal textures and shadows.

These features are very important in order to distinguish the normal and pneumonia-affected lungs

C. Feature Extraction Using DenseNet121

The proposed system is based on the DenseNet121 model, which is a type of deep convolutional neural network. It is recognized for its high efficiency in the reuse of features and the smooth flow of gradients. The DenseNet model connects all the layers with each other, which enhances the use of features.

The advantages of using the DenseNet121 model include:

- Reduces vanishing gradient problem
- Improves feature propagation
- Improves learning efficiency
- Requires fewer parameters compared to conventional CNN

The DenseNet121 model is pre-trained on the ImageNet dataset, which can be fine-tuned for pneumonia detection.

D. Model Development and Training

During this phase, the pre-trained model is used for binary classification. The final layers of the pre-trained model have been modified accordingly in order to classify images into two classes: Normal and Pneumonia.

Components of model training:

Loss Function: The loss function used is the Binary Cross-Entropy Loss Function.

Optimizer: Adam optimizer is used in order to optimize the weight updates in an efficient manner.

Activation Function: The sigmoid function is used in order to perform the binary classification.

Epochs: The number of epochs is generally in the range of 10 to 20 iterations depending upon the system's performance.

For training the model using transfer learning, the initial layers of the pre-trained model DenseNet121 have been frozen, and the final layers have been trained in order to minimize the training time with high accuracy, especially when dealing with small data sets.

E. Prediction and Classification

Once the model is trained, it is possible to make predictions on the class of the new chest X-ray image. The same preprocessing techniques are applied to the input image before prediction.

The system will provide the following outputs:

Prediction Label: Normal or Pneumonia

Confidence Score: Probability of the predicted class

A threshold value is used in the final classification process, for example, 0.5. If the probability is greater than the threshold value, it is considered pneumonia; otherwise, it is considered normal.

F. Decision Support System

The final phase is to display the prediction results to the user through an interface. The system does not only display the classification result but also includes other information such as the confidence level and the level of severity.

This helps healthcare professionals to:

- Make decisions faster
- Reduce the workload of diagnosis
- Increase the accuracy of the diagnosis

The system can be used in the healthcare industry to support doctors in making decisions in the early stages of treatment.

V. RESULT & DISCUSSION

The proposed system of detecting pneumonia employs a structured deep learning method for the efficient processing of the images of the chest X-ray images provided by the user. The proposed system of detecting pneumonia is efficient in the classification of the images and the prediction of the results. The proposed system of detecting pneumonia employs a process, and the process can be identified through the model architecture diagram of the proposed system of detecting pneumonia.

The proposed system of detecting pneumonia employs the input layer, where the user is allowed to provide the images of the chest X-ray. The user is allowed to provide the images of the chest X-ray of any size, quality, and type. Therefore, the user is required to preprocess the images before providing them to the proposed system of detecting pneumonia.

The preprocessing of the images of the proposed system of detecting pneumonia employs a number of operations on the images of the chest X-ray provided by the user. The user is required to resize the images to a specific size, normalize the images, and augment the images before providing them to the proposed system of detecting pneumonia.

After the images are preprocessed, they are passed through the DenseNet-121 feature extraction layer. DenseNet-121 is a deep convolutional neural network where all the layers are connected to all the other layers. This enables the efficient use of all the features as well as the gradients. This helps in the learning of complex features from the chest X-ray images, which include lung opacities, infiltrates, and texture changes, all of which are associated with pneumonia.

The feature maps are then passed through the Global Average Pooling (GAP) layer. This layer compresses all the spatial features of the images into a single feature vector. This reduces the number of parameters, prevents overfitting, and enhances the efficiency of the network.

The feature maps are then passed through the Fully Connected (Dense) layer. This layer is an essential component of the feature combination process.

Finally, the classification is done using a Sigmoid function. The Sigmoid function is used for binary classification. The Sigmoid function provides an output in the form of probability, which ranges from 0 to 1, indicating the probability of the presence of pneumonia in the image.

Finally, in the output layer, the system provides the prediction result in the form of Normal or Pneumonia, along with the confidence level. Such an output will be beneficial for healthcare professionals.

The proposed model is appropriate for real-time use since it is efficient, accurate, and user-friendly.

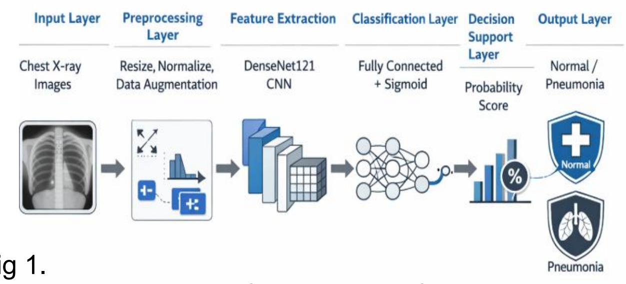

Fig 1.
DenseNet121 Model for the detection of Pneumonia

VI. IMPLEMENTATION

The proposed system of detecting pneumonia is implemented in an efficient manner by using the deep learning frameworks and user interface tools. The proposed system of detecting pneumonia is implemented in real time since all the functions of training models and prediction are implemented in one application.

The implementation of the proposed system of detecting pneumonia is done using Python. The reason behind choosing Python is that it has large libraries that can be used in implementing machine learning and image processing. TensorFlow and Keras were used in implementing the deep learning model. The reason behind choosing TensorFlow and Keras is that it has the ability to be used in implementing deep learning models.

Streamlit is used in implementing the user interface tool. The reason behind choosing Streamlit is that it is a lightweight web application that can be used in implementing machine learning with minimal code. This will be achieved through importing the pre-trained model that has already been fine-tuned for the purpose of being used in the detection of pneumonia. The name of this model is DenseNet-121. This model will be stored in the form of a file, which will have a certain kind of extension. For instance, it could be .h5. The file will be required in the import process. This will ensure that the program is able to make the prediction without having to be trained every time it is run. This will ensure that the program runs in the shortest time possible, thus the system's response time is maximized.

Once this preprocessing step is done, the image is converted into a numerical array and then expanded into a batch format before it is input into the model for prediction. The DenseNet-121 model works on the image and returns a probability score that shows the probability of the presence of pneumonia. This probability value is then used for final classification.

The system displays the prediction results in a user-friendly manner. The probabilities of the presence of pneumonia and that of a normal condition are shown as percentages. A progress bar is also included in the display.In addition to classification, the system provides a **severity indication feature**, which categorizes the result into different levels such as low, moderate, or high severity based on the probability value. This helps healthcare professionals quickly assess the condition of the patient and prioritize further medical actions.

There is also the presence of a feature that gives an indication of the severity of the result. This feature gives a classification of the result to various levels, which could be low, moderate, or high, depending on the value obtained. This is beneficial in that healthcare professionals would be able to get an indication of the condition of the patient.

There is also the presence of real-time prediction in the implementation. This is beneficial in that the results would be obtained in a matter of seconds after the image is uploaded. This reduces the time taken in diagnosing patients. There is also the presence of the ability of the system to handle invalid inputs. This is beneficial in that error messages would be displayed in case of invalid or corrupted images uploaded.

The implementation of the system is beneficial in that it is a reliable system, considering that it utilizes deep learning techniques. The fact that it is an interactive system also makes it beneficial in that it is effective in offering assistance to healthcare professionals in making accurate diagnoses.

VII. CONCLUSION

In this regard, it is worth mentioning that in this research, there has been a successful development and implementation of a deep learning-based system for pneumonia detection with the aid of chest X-ray images. In this regard, it is worth mentioning that the proposed system for pneumonia detection has been developed with the aid of the DenseNet-121 model, along with the application of the transfer learning approach in order to ensure accurate and efficient classification of pneumonia and normal conditions.

The application of deep learning in the proposed system enables the system to automatically learn complex features associated with medical images without any need for manual engineering. The proposed system for pneumonia detection has been developed with the aid of the most significant preprocessing techniques in the development of any image classification system. The application of the DenseNet-121 model in the proposed system enables the system to utilize features and gradients in order to improve accuracy and avoid overfitting.

One of the significant advantages of the proposed system is that it can offer real-time predictions with their corresponding confidence levels as well as severity levels. This would enable healthcare professionals to make decisions in a faster manner. The use of a user-friendly interface using Streamlit would also enable non-technical users to use the proposed system with ease. Thus, the proposed system would be able to reduce the workload of the radiologists to a significant extent, which would in turn reduce the chances of human error in the process of diagnosis.

The proposed system would be highly beneficial in scenarios where there is a shortage of skilled radiologists in rural areas. With the proposed system, there would be a higher possibility of early detection of pneumonia, which would enable the treatment of pneumonia in a timely manner, thus reducing mortality rates.

Despite the effectiveness of the system, there are some limitations, such as the quality of the dataset used in the system, which can be improved in the future by using larger datasets, as well as the requirement for computational resources to train the models used in the system.

To conclude, the proposed pneumonia detection system using deep learning is an effective solution for the detection of pneumonia, which can be used in the field of artificial intelligence to improve healthcare services. The proposed system can be used to improve the accuracy of medical professionals in detecting pneumonia, which can be achieved by incorporating such technologies in healthcare systems.

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VIII. REFERENCES

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