Delta University Scientific Journal
Journal home page: https://dusj.journals.ekb.eg

An implementation of a Smart System based on Deep Learning for Pneumonia Infection Detection

Hesham A. Ali[1,2], Rana Osama[1], Raneem Mohamed[1], Esraa Mahmoud[1], Samia M. Abd-Alhalem[1], Ali E. Takieldeen[1].

[1] *Faculty of Artificial Intelligence, Delta University for Science and Technology, Gamasa, 35712, Egypt.*
[2]*Computers and Control Systems Engineering Department, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt.*

Corresponding author:[Hesham A. Ali; Samia M. Abd-Alhalem; Ali E. Takieldeen; h_arafat_ali@mans.edu.eg,
Samia.mohammed@deltauniv.edu.eg; a_takieldeen@yahoo.com]

ABSTRACT

Pneumonia is a serious respiratory infection that can lead to severe health complications if not detected and treated early. In this paper, we propose a smart system based on deep learning for pneumonia infection detection. The system will be deployed as a web app that can receive chest x-ray images uploaded by users and return a prediction of whether the x-ray injured or no. Through the proposed smart Web application, anybody and anywhere may now access the model. There was no need for specialized knowledge, the system uses a convolutional neural network (CNN) to analyze chest X-ray images and identify signs of pneumonia infection. The CNN is trained on a large dataset of chest X-ray images labeled as either normal or infected with pneumonia. The system can be integrated into existing healthcare systems to provide early detection and timely treatment of pneumonia infections, thereby improving patient outcomes and reducing healthcare costs.
***Keywords: Pneumonia image classification, Deep learning, VGG16, a web app*.**

1. Introduction

Pneumonia is a form of acute lower respiratory infection. It is generally characterized by specific symptoms such as fever, chills, and cough with sputum production, chest pain and shortness of breath. Many factors affect how serious pneumonia is, such as the type of pathogen causing the lung infection, age, and overall health status (N. Mansour et al. 2021). Pneumonia tends to be more serious for children under the age of five, adults over the age of 65, people with certain conditions such as heart failure, diabetes, or COPD (chronic obstructive pulmonary disease). One of the most common diagnostic tools for pneumonia is a chest X-ray, which can reveal the presence of inflammation or fluid in the lungs (S. Boccaletti et al. 2020).
According to National Center for Health Statistics (NCHS) Mortality Surveillance data available on January 2023, 12.0% of the deaths that occurred during the week ending January 2023 (S. Hoehl et al. 2020; C. Huang et al. 2020) were due to pneumonia, influenza, and/or COVID-19 (PIC) as depicted in figure 1. This percentage is above the epidemic threshold of 7.1% for this week Among the 2,877 PIC deaths reported, 1,357 had pneumonia listed as an underlying or contributing cause of death on the death certificate.
However, interpreting chest X-rays requires specialized radiological expertise, which may not always be available, particularly in remote or low-resource settings. This can lead to delays in diagnosis and treatment, which can be detrimental to patient outcomes. Moreover, the COVID-19 pandemic has highlighted the need for rapid and accurate diagnosis of respiratory infections (O. Castillo et al. 2020).
Deep Learning is a branch of machine learning that utilizes deep neural networks with a large number of layers. It aims to learn hierarchical representations of data by training neural networks on a wide range of examples. Deep Learning has the ability to extract meaningful information and patterns from complex and structured data such as images, text, and sound. It has applications in various fields such as image recognition, object detection, natural language translation, text generation, big data analysis, self-supervised learning, robotics control, and Convolutional Neural Networks (CNNs) are a powerful type of neural network specifically designed for

processing spatial data like images and videos. They have been widely applied in various fields, including computer vision, pattern recognition, and medical image analysis (Samia M. Abd –Alhalem et al. 2019; Naglaa. F. Soliman et al. 2022).

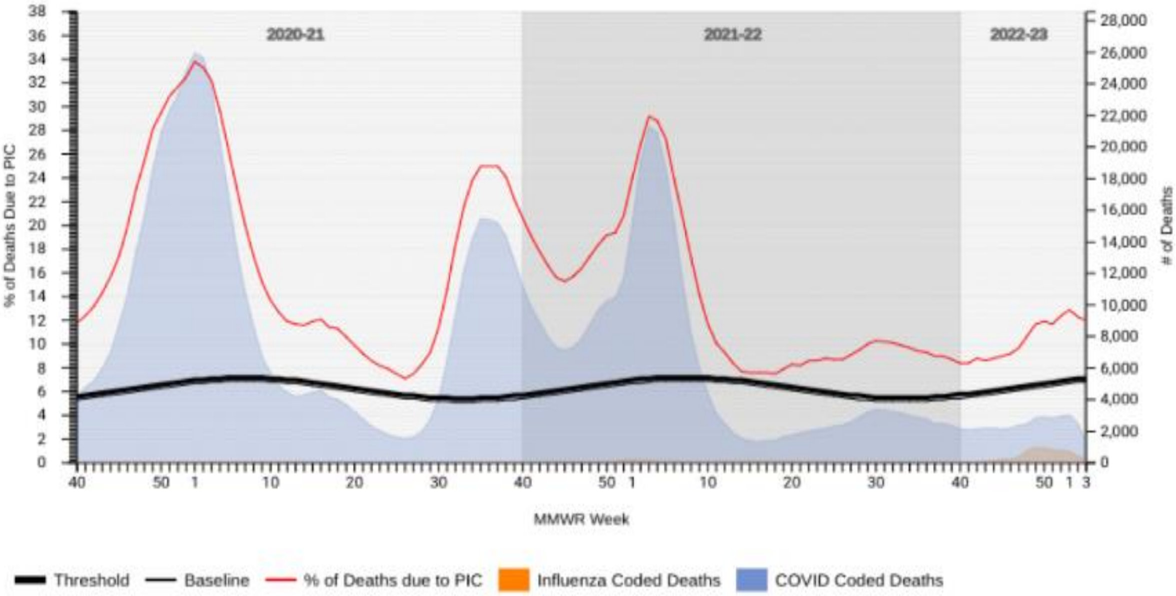

Figure 1: Percentage of all deaths due to Pneumonia, Influenza, and COVID-19.

There is a growing interest in developing deep learning-based approaches for analyzing chest X-rays to automatically identify signs of pneumonia (Wang, L. et al. 2020). These approaches have the potential to speed up diagnosis, reduce reliance on radiological expertise, and improve access to care, particularly in resource-limited settings.

In this study, we propose the development of a web application that can receive chest X-ray images uploaded by patients and classify them as showing signs of pneumonia or not. The application will leverage deep learning techniques to analyze the images and provide a preliminary diagnosis to guide treatment decisions (injured or not).

The proposed application has the potential to revolutionize the way pneumonia is diagnosed and treated. By providing quick and accurate diagnoses, it can reduce the burden on healthcare systems and improve patient outcomes. Moreover, it can help address the shortage of radiological expertise and improve access to care, particularly in underserved communities.

In the following sections, we will outline the key steps involved in developing such an application, including data collection and curation, model development, and web app deployment. We will also discuss the potential benefits and challenges of this approach and highlight the need for ongoing research and development in this area.

The key steps to build and deploy such an app are:

1.download chest x-ray images dataset which contains over 140,000 x-ray images from (Kaggle repository)

2. Train a deep learning model on the dataset to classify x-rays for pneumonia.

3. Build a simple web interface to interact with the API. The interface will allow users to upload chest x-ray images and display the prediction returned by the API.

4. Test and evaluate the web app to ensure high accuracy before deploying in a production environment. Continually monitor the performance of the model post-deployment and retrain when necessary.

In summary, by following the key steps outlined above, we can build and deploy a web app to automatically classify chest x-rays for pneumonia. Such an app could provide quick diagnostic support especially in resource-limited settings and improve accessibility to radiological expertise. The system would require continuous monitoring and retraining to maintain high accuracy. The application will be user-friendly and accessible to medical professionals, who can easily upload the X-ray images and obtain the classification results. The development of this web application has the potential to improve the diagnosis of pneumonia and ultimately lead to better patient outcomes.

1.1 Motivation

Traditional methods of diagnosing pneumonia can be expensive, requiring specialized equipment and trained personnel. In contrast, AI-based systems can be developed using existing technology, making it a more cost-effective option. Furthermore, the use of AI in diagnosing pneumonia can help reduce the need for hospitalization and subsequent medical expenses.

1.2 Contributions

The contributions of the research include the development of an AI-based system for diagnosing pneumonia, which can provide accurate diagnoses in a matter of seconds, reducing the workload of medical professionals and improving patient outcomes. The research also contributes to the advancement of AI algorithms and diagnostic models in the medical field, which can have broader implications for the diagnosis of other diseases. Furthermore, the research provides a cost-effective solution for diagnosing pneumonia, which can be particularly beneficial for low- and middle-income countries.

2. Background and Related work

2.1 Pneumonia Diagnose Methodologies

Usually, the diagnosing of pneumonia can be done based on using three altered methodologies (Justin Dong., et al. 2017) as depicted in Fig.2. The three methodologies are (i) Real-Time reverse transcriptase- Polymerase Chain Reaction (RT-PCR), (ii) chest CT imaging scan, and (iii) numerical laboratory tests. RT-PCR tests are fairly quick, sensitive, and reliable the sample is collected from a person's throat or nose; adding some chemicals for removing any proteins, fats, and other molecules, leaving behind only the existing Ribonucleic Acid (RNA). The separated RNA is mixture of a person's RNA and the coronavirus's RNA if exist. In spite of its popularity, RT-PCR test suffers from the risk of false-negative and false-positive results.
It should not come as a surprise that computer vision is an important area of application for artificial intelligence (AI), primarily because it provides solutions to a wide range of issues that modern people encounter. Medical picture detection using AI is one of the computer vision areas that has repeatedly shown to be fruitful.

2.2 Convolutional neural network.

CNNs consist of multiple layers that perform transformative operations on the input data. The key components of a CNN architecture include convolutional layers, pooling layers, and fully connected layers. Each layer plays a unique role in feature extraction and classification. Convolutional layers are the core building blocks of CNNs. They apply convolutional filters or kernels to the input data, enabling the network to learn spatial hierarchies and extract relevant features. These filters slide across the input, performing element-wise multiplications and summations, producing feature maps that capture different patterns and characteristics (Shagun Sharma et al. 2023).
Pooling layers are responsible for down sampling the feature maps generated by the convolutional layers. They reduce the spatial dimensions, helping to extract important features while decreasing the computational burden. Common pooling techniques include max pooling, average pooling global pooling, each with its own advantages and applications and fully connected layers connect every neuron in one layer to every neuron in the next layer, enabling the network to learn complex relationships and make predictions (Srinivasan P. et al. 2019) These layers perform classification based on the features extracted by the preceding layers. The final layer often utilizes activation functions such as softmax to generate class probabilities as depicted in figure 3.

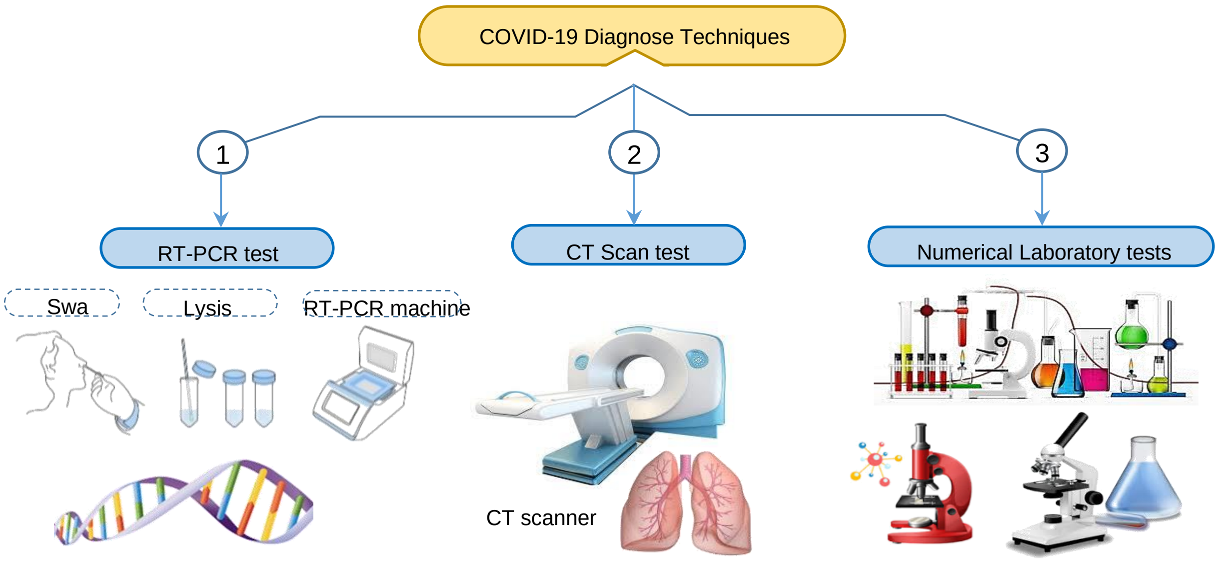

Figure 2: Different Pneumonia diagnosis techniques.

Training a CNN involves providing labeled data and optimizing the network's parameters using algorithms like backpropagation and gradient descent. The network learns to recognize patterns and features relevant to the given task, such as object recognition or disease diagnosis. The application of CNNs in pneumonia diagnosis involves preprocessing the images, such as resizing and normalization, to ensure consistency and compatibility with the network's input requirements. The trained CNN can then analyze new chest images and provide predictions or probabilities indicating the presence or absence of pneumonia. One advantage of CNNs in pneumonia diagnosis is their ability to automatically learn relevant features from the images, eliminating the need for manual feature engineering. This allows the network to capture subtle patterns and abnormalities indicative of pneumonia, leading to improved accuracy and efficiency (Justin P. et al. 2019)

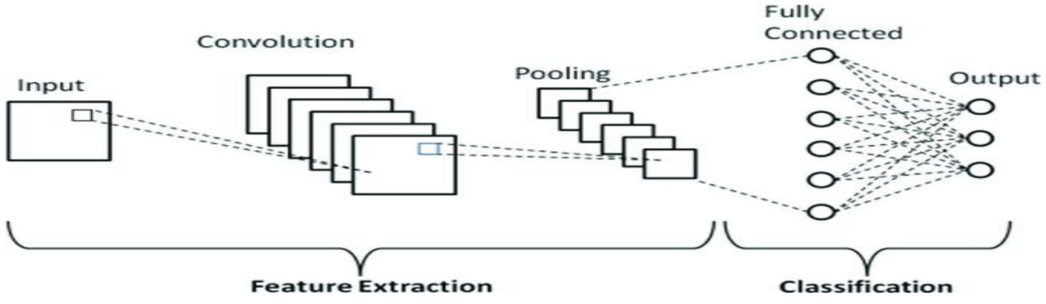

Figure 3: The CNN Architecture

The VGG16 model, a deep convolutional neural network architecture, has been successfully applied in the field of pneumonia diagnosis using medical imaging, particularly chest X-ray analysis (Ahmed Al-Hamdan et al. 2021). Figure 4 presents the VGG-16 architecture.

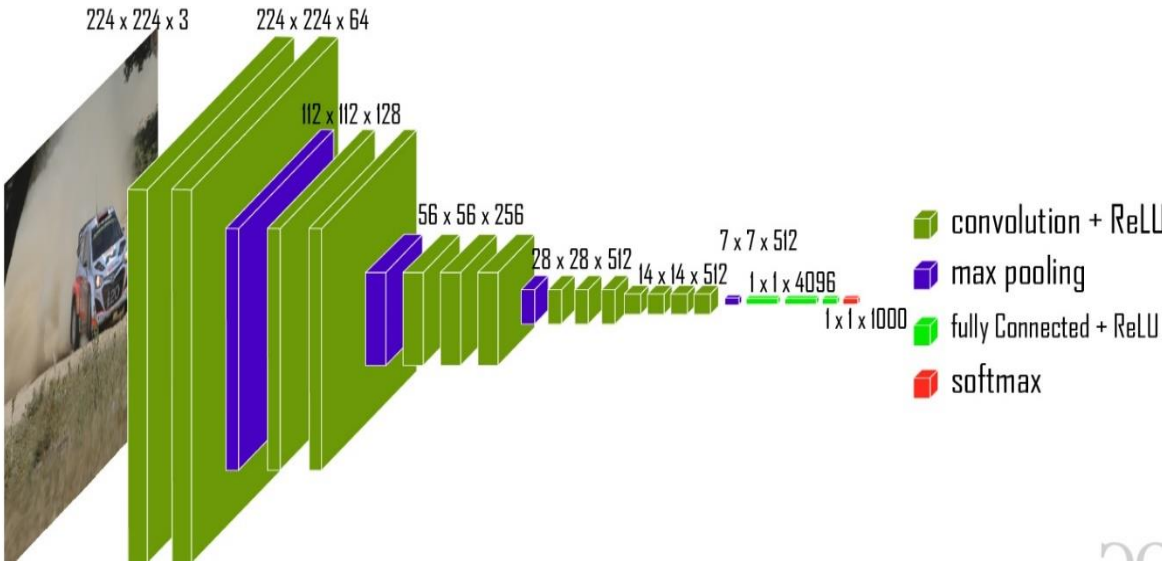

Figure 4: The VGG16 architecture

3. Related work

It is challenging to diagnose pneumonia because it requires a highly qualified professional to assess a patient's chest radiograph (CXR), as well as laboratory testing, vital signs, and clinical history. In the CXR, it typically appears as a region of increased opacity. Even yet, additional pulmonary disorders such haemorrhages, lung cancer, postsurgical alterations, pulmonary edoema, atelectasis, or collapse complicate the diagnosis of pneumonia. The link between the clinical history and the comparison of CRX taken at various points in time is crucial for diagnosis.

Authors in (Naglaa. F. Soliman et al. 2022) trained an AI system using 5,232 chest X-ray images from children, including pneumonia and normal cases. The model was tested with additional images and showed 92% accuracy in diagnosing bacterial and viral pneumonia as well as normal cases. The training stopped after 100 epochs due to no further improvement in loss and accuracy. A deep learning model using VGG16 to detect and classify pneumonia in chest X-ray images is developed by (Wang, L. et al. 2020). The model achieved high accuracy, recall, precision, and F1-score for two different datasets, including one with COVID-19 images. The VGG16 model with neural networks outperformed other models and showed improved performance compared to existing models for both datasets. The proposed model has potential for use in clinical practice to assist in the detection and diagnosis of pneumonia (Srinivasan P. et al. 2019). In (Justin P. et al. 2019), Authors aimed to develop an AI-based system for diagnosing and grading pneumonia using routine blood tests, including CBC and BCP. The dataset used for training and testing the model included blood test results from 1,171 patients with suspected pneumonia, including bacterial and viral pneumonia cases. The model was developed using Gradient Boosting Classifier, achieving high accuracy, sensitivity, and specificity for diagnosing both types of pneumonia. Specifically, the model achieved an accuracy of 96.8% for bacterial pneumonia and 84.6% for viral pneumonia. Another study aimed to develop a fuzzy deep learning algorithm for diagnosing pneumonia using clinical data, including blood tests, vital signs, medical history, age, and gender. The dataset used for training and testing the algorithm included clinical data from 3,500 patients, including 500 confirmed pneumonia cases. The algorithm used a combination of fuzzy logic and deep learning techniques, specifically a convolutional neural network. The algorithm achieved high accuracy, sensitivity, and specificity for identifying pneumonia cases, with an accuracy of 97.3% on a test set of 500 patients.

In (Ahmed Al-Hamdan et al. 2021) a deep learning model trained with big data analytics techniques to accurately diagnose pneumonia using the RT-PCR test. The model achieved an accuracy of up to 96%, outperforming other machine learning models like logistic regression and support vector machine in terms of accuracy and efficiency. The model was trained on a large dataset of clinical and laboratory data from patients, learning to distinguish between healthy and pneumonia patients based on their data patterns. Table 1 shows a Comparative analysis between the different previous works for Pneumonia Infection Detection.

Table 1: Comparison between the different previous works.

Ref.	**Technique used for detection**	**Accuracy**
(Justin Dong et al. 2017)	CNN	92%
(Shagun Sharma et al. 2023)	VGG-16	95.83%
(Srinivasan P. et al. 2019)	Gradient Boosting Classifier.	96.8%
(Justin P. Tuwatananurak et al. 2019)	Fuzzy Deep Learning from Clinical Data	97.3%
(Ahmed Al-Hamdan et al.2021)	logistic regression and SVM	96%

4. The proposed system

4.1 The pretrained CNN used

The CNN architecture used in this paper is depicted in figure 5. Firstly, image sets undergo some pre-processing steps, then training using pre-trained algorithms: VGG16. The training of the different models was carried out in a computer with Intel© i7-core @3.6GHz processor and 16GB RAM. Different parameters and hyperparameters used for training the CNN models such as learning rate, batch size, number of epochs, optimizer, activation function, and number of layers.

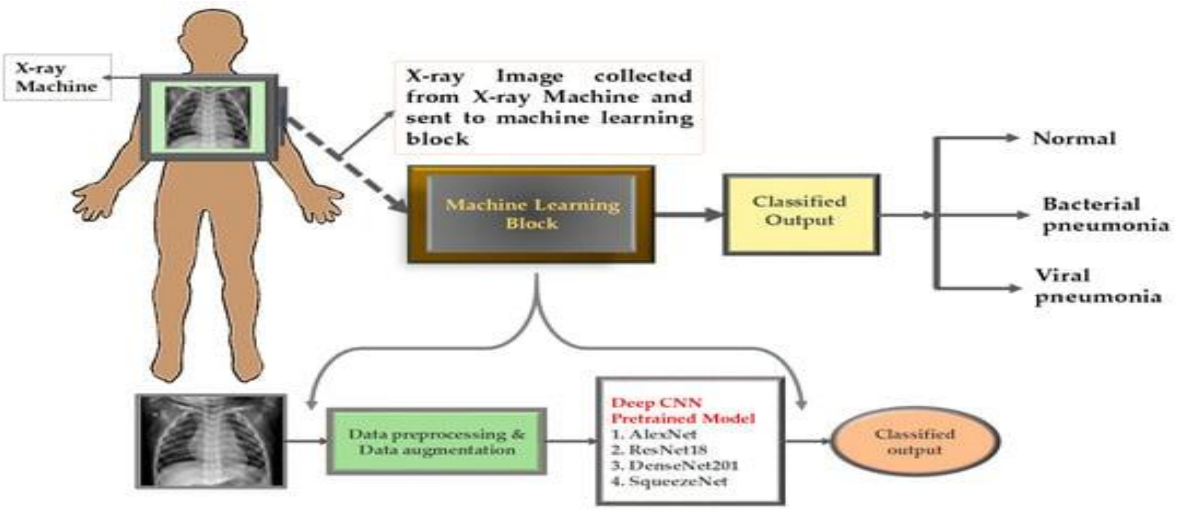

Figure 5: The system architecture used.

The VGG16 pre-trained model used to extract features from the input images and then trains a dense layer for classification (Ashraf Al-Qarala et al. 2021) the model is compiled with the categorical cross-entropy loss function, the Adam optimizer, and accuracy as the evaluation metric. The model is trained on a dataset of 5216 images and validated on a separate test set of 624 images (ratio of data is 75%, 15% and 15% into training, validation and testing respectively.) using the Image Data Generator class for data augmentation. Once the model is trained, it is saved to a file using the save method. This allows the model to be loaded and used for making predictions on new Chest X-ray images. The loaded model is used to make predictions on new images using the predict method, which returns a probability distribution over the possible classes. In this case, the model is trained to predict the presence or absence of pneumonia in the input image. After the model is trained by the training data, then the model is used for performance analysis by testing and validation data. The training of the model is performed in framework.
The model architecture is based on transfer learning using VGG16 pre-trained model. Before feeding the images into the VGG16 model, preprocessing steps are performed. This typically involves resizing the images to a standardized input size, such as 224x224 pixels, to match the requirements of the VGG16 architecture. Additionally, normalization techniques may be applied to ensure consistent pixel intensity ranges across the dataset (Manav Mandalet al 2021) the input layer takes images of size 224 x 224. The VGG16 model is then trained using the prepared dataset. The training process involves feeding the labeled chest X-ray images through the network, allowing the model to learn the complex patterns and features associated with pneumonia. During training, the model adjusts its internal parameters through backpropagation and gradient descent algorithms, optimizing its ability to classify the images accurately as shown in Fig. 6. The output from the VGG16 model is then flattened and connected to a dense layer with softmax activation for classification. The model is trained for 10 epochs with a batch size of 10 and the Adam optimizer. The training takes long time because the large dataset we used and the complex model architecture, finally training the model achieved an accuracy of 92.75% and a loss of 0.2128 on the training set, and an accuracy of 90.54% and a loss of 0.2832 on the validation set.

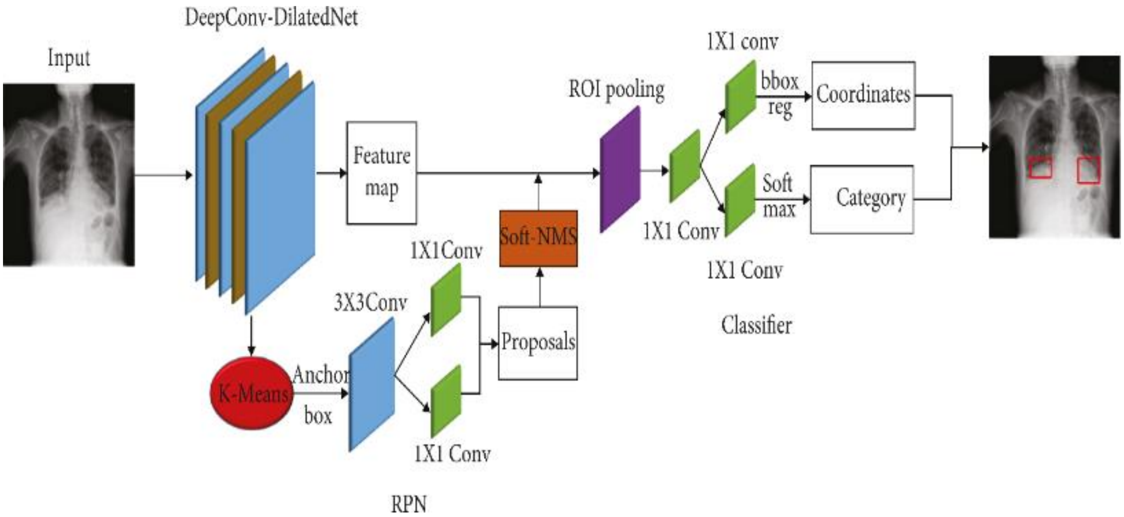

Figure 6: VGG-16 Network structure for pneumonia detection.

4.2 The web app.

The proposed system will be deployed as a web app that can receive chest x-ray images uploaded by users and return a prediction of whether the x-ray injured or no through the following stages:

1-Collect a large dataset of chest X-ray images that includes both normal and pneumonia cases. Preprocess the data to remove any noise and ensure that the images are standardized and in the same format.

2-Develop a deep learning model that can accurately detect pneumonia from chest X-ray images. Train the model on the preprocessed data using techniques such as convolutional neural networks (CNNs) and transfer learning.

3-Design and create a web app that can take in chest X-ray images and use the model to classify them as normal or pneumonia. Develop a user-friendly interface that allows users to upload or capture images from their device.

4-Thoroughly test the app to ensure that it is accurate and reliable.

5-Identify and address any issues or errors. Refine and retrain the model as needed to improve its performance.

5. Experimental Results

Data is the most important part of the project, and having a sufficient and reliable data set is the key to success. Performing the training of an image classifier model through the Webapp application fig. 7 is simple; it abstracts the entire process in a simple interface, which means that great knowledge is not required to carry out the said process. The application allows the configuration of parameters and multiple workouts with different configurations after carrying out several training processes with additional details presented in Table 2, and 3, it was possible to obtain a model with an accuracy of 92%. Table 4 summarizes the experimental results for the proposed model.

It was also possible to show that factors such as lighting, contrast, blur, shooting angle, background, and different distortions present in the input image can affect the model's accuracy because within the training group, they are not being considered. Example images are those with these factors so that the model learns these characteristics with these variations. It is enough to include images of this type in the different data sets to solve this problem. The images present in the training process should be as close as possible to what is expected as input to the model, that is, how the end-user is expected to take the images.

Table 2: Dataset Parameters

Total params:	14,764,866
Trainable params	50,178
Non-trainable params:	14,714,688
Dataset Name	Chest X-Ray Images (Pneumonia)
Number of Class	2
Number/Size of Images Total	5856 (1.15 Gigabyte (GB))
Training	5216 (1.07 Gigabyte (GB))
Validation	624 (42.8 Megabyte (MB))
Testing	624 (35.4 Megabyte (MB))

Table 3: Training Parameters

Batch Size	10
Number of Epochs	10
Training Time	1 Hours

Table 4: Metrics for explained developed models

Accuracy	92.52%
Loss	0.41
Precision	88.37%
Recall (Pneumonia)	89.53% (For positive class)

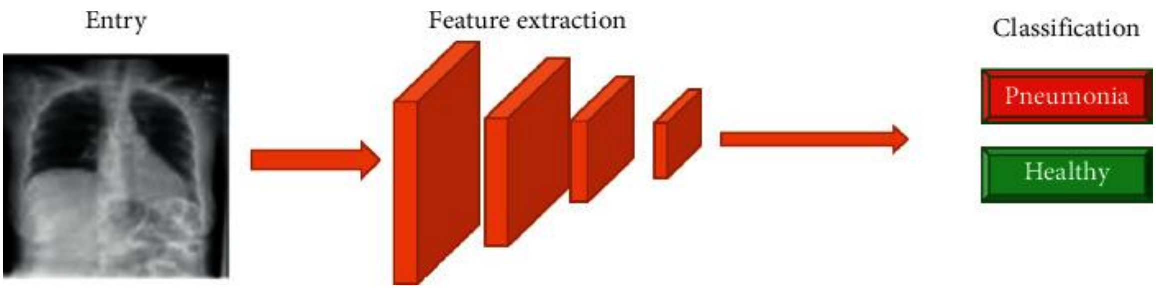

Figure 7: The method on which the model was classified

```
block3_conv1 (Conv2D)        (None, 56, 56, 256)      295168
block3_conv2 (Conv2D)        (None, 56, 56, 256)      590080
block3_conv3 (Conv2D)        (None, 56, 56, 256)      590080
block3_pool (MaxPooling2D)   (None, 28, 28, 256)      0
block4_conv1 (Conv2D)        (None, 28, 28, 512)      1180160
block4_conv2 (Conv2D)        (None, 28, 28, 512)      2359808
block4_conv3 (Conv2D)        (None, 28, 28, 512)      2359808
block4_pool (MaxPooling2D)   (None, 14, 14, 512)      0
block5_conv1 (Conv2D)        (None, 14, 14, 512)      2359808
block5_conv2 (Conv2D)        (None, 14, 14, 512)      2359808
block5_conv3 (Conv2D)        (None, 14, 14, 512)      2359808
block5_pool (MaxPooling2D)   (None, 7, 7, 512)        0
flatten (Flatten)            (None, 25088)            0
dense (Dense)                (None, 2)                50178
=================================================================
Total params: 14,764,866
Trainable params: 50,178
Non-trainable params: 14,714,688
```

Figure 8: the structure of the proposed CNN model

The program takes the image to know its condition, whether it is infected or not, then it predicts the result and pronounces it. We upload the data, and the program reads the required image, then makes a prediction and announces the result.

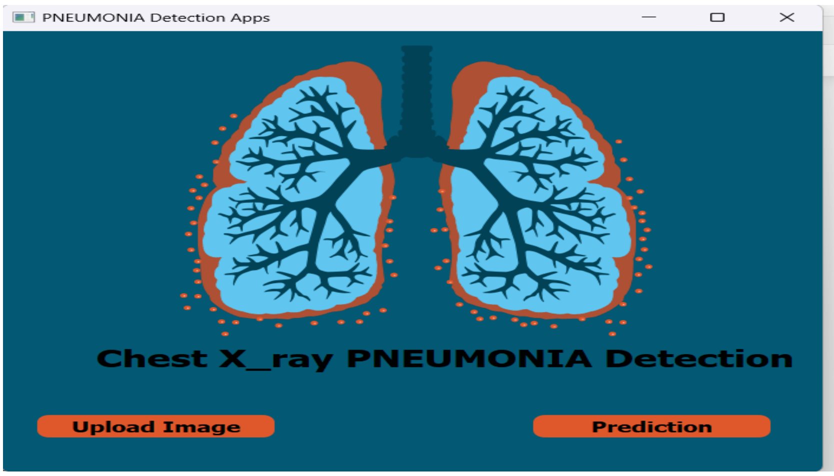

Figure 9: An implementation of smart system for Detection of Pneumonia

6. Conclusion

Based on the research, it can be concluded that AI-powered pneumonia detection using deep learning and CNN is a promising approach to improve the accuracy and efficiency of diagnosing pneumonia using chest x-rays. The use of a web app to facilitate the detection process makes it more accessible and convenient for medical professionals and patients. The proper diagnosis of any kind of disease still requires the involvement and presence of medical specialists. Chest radiographs are the most widely used tool for diagnosing pneumonia; however, they are subject to inter-class variability and the diagnosis depends on the clinicians' expertise in detecting early pneumonia traces. The study demonstrated that the proposed AI model achieved high accuracy in detecting pneumonia from chest x-rays, with a sensitivity and specificity 92%, 470s 898ms/step - loss: 0.2128 - accuracy: 0.9275 - val_loss: 0.2832 - Val accuracy: 0.9054. This suggests that the AI model has the potential to significantly reduce the workload of radiologists and improve the speed and accuracy of diagnosis Furthermore, the web app developed in this study provides an intuitive and user-friendly interface for user to upload and analyze chest x-rays. This can facilitate faster and more accurate diagnosis of pneumonia especially in remote or under-resourced areas where access to radiologists may be limited. In conclusion, the use of AI and web-based applications for pneumonia detection using chest x-rays has a significant potential to improve the accuracy, speed, and accessibility of pneumonia diagnosis, which can ultimately lead to better patient outcomes and more effective healthcare delivery. Further research and development in this field are needed to fully realize the potential of AI-powered pneumonia detection and its integration into clinical practice

References

Ahmed Al-Hamdan, Hossam Al-Din Al-Natsheh,(2021) "using the RT-PCR test", No.1, PP. 1-12.

Ashraf Al-Qarala, Ziyad Hamdan, Ahmed Al-Hamdan, Hossam Al-Din Al-Natsheh, and Muhammad Al-Hourani, in addition to a number of students participating in the research, (2021) "use of artificial intelligence techniques in diagnosing pneumonia using the RT-PCR test", ScienceDirect, vol.133, No.1, PP. 104-497.

C. Huang, Y. Wang, X. Li, L. Ren, et al., Clinical features of patients infected with(2019) novel coronavirus in Wuhan, China, Lancet 395 (10223) (2020) 497–506, doi:10.1016/S0140-6736(20)30183-5.

Chest X-Ray images (Kaggle): https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

Justin Dong., M.A.L., W.C., (2017) "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning"". ScienceDirect, Vol.133, No.1, PP. 1-1.1

Justin P. Tuwatananurak, Shayan Zadeh, Xinling Xu, Joshua A. Vacanti, William R. Fulton, Jesse M. Ehrenfeld & Richard D. Urman, (2019), Pneumonia Diagnosis "Using Fuzzy Deep Learning from Clinical Data." Journal of medical systems, 17 January 2019.

Manav Mandal, "Information about the CNN for Deep learning" analyticsvidhya.com, P: 1-5, 2021.

Naglaa. F. Soliman, Samia M. Abd-Alhalem, Walid El-Shafai, Salah Eldin S. E. Abdulrahman, N. Ismaie, El-Sayed M. El-Rabaie, Abeer D. Algarni, Amal Ali. Al Hussan, Fathi E. Abd El-Samie "Hybrid Approach for Taxonomic Classification Based on Deep Learning" Intelligent Automation & Soft Computing. 2022, Vol. 32 Issue 3, p1881-1891.

N. Mansour, A. Saleh, M. Badawy, H. Ali, (2021) Accurate detection of Covid-19 patients based on Feature Correlated Naïve Bayes (FCNB) classification strategy, Journal of Ambient Intelligence and Humanized Computing 1 – 33 Springer.

O. Castillo, P. Melin, Forecasting of COVID-19 time series for countries in the world based on a hybrid approach combining the fractal dimension and fuzzy logic, Chaos, Solitons & Fractals (140) (2020) 1–12 Elsevier

Samia M. Abd –Alhalem, Naglaa F. Soliman, Salah Eldin S. E. Abd Elrahman, Nabil A. Ismail, El-Sayed M. El-Rabaie, and Fathi E. Abd El-Samie "Bacterial Classification with Convolutional Neural Networks based on Different Data Reduction Layers" Nucleosides, Nucleotides and Nucleic Acids, Taylor & Francis Groups, 16 Aug 2019. https:// doi.org/10.1080/15257770.2019.1645851.

Samia M. Abd –Alhalem, Naglaa F. Soliman, Salah Eldin S. E. Abd Elrahman, Nabil A. Ismail, El-Sayed M. El-Rabaie, and Fathi E. Abd ElSamie "Spectral Features based on Bidirectional Long Short-TermMemory for DNA Classification," International Conference on Electronic Engineering, Menoufia University, Egypt, ICEEM2019, 7-8 Dec. 2019.

S. Boccaletti, W. Ditto, G. Mindlin, and. Atangana, Modeling and forecasting of epidemic spreading: The case of Covid-19 and beyond, Chaos, Solitons & Fractals 135 (2020) 1–2 Elsevier.

S. Hoehl, H. Rabenau, A. Berger, M. Kortenbusch, et al., Evidence of SARS-CoV-2 Infection in Returning Travelers from Wuhan, China, The new England journal of medicine 382 (13) (2020) 1278–1280, doi:10.3390/healthcare9020196.

Shagun Sharma, Kalpna Guleria, Chitkara University Institute of Engineering & Technology, Chitkara, University, Rajpura, "A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks ". Available online 31 January 2023.

Srinivasan P., Venkataraman V, Ramanujam S, et al. "Artificial Intelligence for Diagnosis and Grading of Pneumonia" ScienceDirect, 2019 Nov;16(11):703-715. doi: 10.1038/s41571-019-0252-y.

Wang, L., & Wong, A. (2020). COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest Radiography Images. IEEE Transactions on Medical Imaging, 39(8), 2515-2525. doi: 10.1109/TMI.2020.2987975