BASAVARAJESWARI GROUP OF INSTITUTIONS

BALLARI INSTITUTE OF TECHNOLOGY & MANAGEMENT

Autonomous Institute under VTU, Belagavi | Approved by AICTE,New Delhi Recognized by Govt. of Karnataka

NACC Accredited Institution*

(Recognized by Govt. of Karnataka, approved by AICTE, New Delhi & Affiliated to Visvesvaraya Technological University, Belgavi)

"JnanaGangotri" Campus, No.873/2, Ballari-Hospet Road, Allipur, Ballar1-583 104 (Karnataka) (India)

Ph: 08392 – 237100 / 237190, Fax: 08392 – 237197

DEPARTMENT OF CSE(DATA SCIENCE)

A Mini Project Report On

"Deep Learning Powered Pneumonia Detection from Chest Radiographs"

A report submitted in partial fulfillment of the requirements for the

NEURAL NETWORK AND DEEP LEARNING

Project Associate:

V MADHU KUMAR **3BR23CD404**

Under the Guidance of

Mr. Azhar Baig M & Ms. Chaithra B M

Dept of CSE (DATA SCIENCE),

BITM, Ballari.

Visvesvaraya Technological University

Belagavi, Karnataka

2025-2026

BASAVARAJESWARI GROUP OF INSTITUTIONS
BALLARI INSTITUTE OF TECHNOLOGY & MANAGEMENT
Autonomous Institute under VTU, Belagavi | Approved by AICTE,New Delhi Recognized by Govt. of Karnataka

NACC Accredited Institution*
(Recognized by Govt. of Karnataka, approved by AICTE, New Delhi & Affiliated to Visvesvaraya Technological University, Belgavi)
"JnanaGangotri" Campus, No.873/2, Ballari-Hospet Road, Allipur, Ballar1-583 104 (Karnataka) (India)
Ph: 08392 – 237100 / 237190, Fax: 08392 – 237197

DEPARTMENT OF CSE (DATA SCIENCE)

CERTIFICATE

This is to certify that the Mini Project of NEURAL NETWORK AND DEEP LEARNING title "Deep CNN Architecture for Pneumonia Identification from X-Ray Scans" is a Bonafide work carried out by V MADHU KUMAR bearing USN **3BR23CD404** in partial fulfillment for the award of degree of Bachelor Degree in CSE(Data Science) in the VISVESVARAYA TECHNOLOGICAL UNIVERSITY, Belagavi during the academic year 2025-2026. It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report deposited in the library. The project has been approved as it satisfies the academic requirements in respect of mini project work prescribed for a Bachelor of Engineering Degree.

Signature of Coordinators	Signature of HOD
Mr. Azhar Baig M & Ms. Chaithra B M	**Dr. Aradhana D**

ABSTRACT

Pneumonia is a serious lung infection that requires quick and accurate detection, but traditional chest X-ray interpretation can be slow and error-prone. With advances in deep learning, automated image analysis offers improved diagnostic reliability. This project develops a pneumonia detection system using a CNN based on the Xception architecture to classify chest X-ray images as Normal or Pneumonia. The Kaggle Chest X-Ray dataset is used for training with preprocessing steps like resizing, normalization, and augmentation. The model extracts deep visual features through convolutional layers and performs binary classification using dense layers. Accuracy, precision, recall, and F1-score are used to evaluate performance. Results show fast and consistent predictions with strong classification accuracy. This work demonstrates the potential of CNN-based systems to support medical professionals in automated disease diagnosis.

ACKNOWLEDGEMENT

The satisfaction that accompanies the successful completion of project work on **"Deep CNN Architecture for Pneumonia Identification from X-Ray Scans"** would be incomplete without the mention of people who made it possible, whose noble gesture, affection, guidance, encouragement, and support crowned our efforts with success. It is our privilege to express our gratitude and respect to all those who inspired us in the completion of this project work.

We are extremely grateful to our Guides **Mr. Azhar Baig M & Ms. Chaithra B M** for their noble gesture, support co-ordination and valuable suggestions given in completing the project work. We also thank **Dr. Aradhana D,** H.O.D. Department of CSE(DS), for his co-ordination and valuable suggestions given in completing the project work. We also thank Principal, Management and non-teaching staff for their co-ordination and valuable suggestions given to us in completing the project work.

Name	USN
V MADHU KUMAR	3BR23CD404

Table of Contents

CHAPTER 1

INTRODUCTION

Pneumonia is a severe respiratory infection that affects millions of people each year and requires timely and accurate diagnosis to prevent life-threatening complications. Chest X-ray imaging is the most commonly used diagnostic method, but interpreting these images manually is challenging due to the subtle differences between healthy and infected lungs. This traditional approach is time-consuming, subjective, and highly dependent on the expertise of radiologists. As medical image volumes continue to grow, there is an urgent need for automated diagnostic tools that can support healthcare professionals with faster and more reliable results.

Recent advancements in deep learning, especially Convolutional Neural Networks (CNNs), have transformed the field of medical image analysis by enabling automated feature extraction and highly accurate classification. This project utilizes CNNs to develop an automated pneumonia detection system that classifies chest X-ray images into Normal or Pneumonia categories. Using the Kaggle Chest X-Ray Pneumonia dataset along with preprocessing techniques such as resizing, normalization, and augmentation, the system is trained to detect pneumonia with high accuracy. The proposed model provides consistent, quick, and accurate diagnostic assistance, offering a strong foundation for future improvements in AI-based healthcare systems.

1.1. Objectives

- To develop an automated pneumonia detection system using CNNs.
- To classify chest X-ray images into Normal and Pneumonia categories.
- To apply preprocessing and augmentation techniques to improve model performance.
- To evaluate the model using accuracy and other performance metrics.
- To support medical professionals with reliable decision-making tools.

1.2. Literature Survey

In paper [1], the research focuses on the rapid advancement of deep learning methods for medical image analysis, specifically for pneumonia detection using chest X-rays. The study highlights the introduction of CheXNet, a 121-layer DenseNet architecture trained on a large-scale dataset, achieving radiologist-level performance in identifying pneumonia. The research emphasizes how deep convolutional neural networks significantly improve diagnostic accuracy compared to traditional manual interpretation. By leveraging a massive dataset and powerful feature extraction capabilities, the study showcases deep learning as a transformative tool in modern healthcare diagnostics, enabling faster and more reliable pneumonia detection.

In paper [2], the study examines the Xception model, which introduces depthwise separable convolutions to improve the efficiency and accuracy of image classification tasks. The research demonstrates that the Xception architecture outperforms several traditional CNN models due to its ability to learn more detailed spatial features with fewer parameters. This advancement is particularly relevant for medical image analysis, where high-resolution images require efficient processing. The study highlights the model's strong potential for pneumonia detection, offering enhanced performance without significantly increasing computational cost, thereby supporting scalable healthcare solutions.

In paper [3], the research highlights the significance of publicly available medical datasets in advancing deep learning-based health diagnostics. The Chest X-Ray Pneumonia dataset, published on Kaggle, provides a well-structured collection of normal and pneumonia-infected X-ray images. The study emphasizes how such datasets enable benchmarking, model comparison, and standardized evaluation of CNN architectures. By analyzing dataset characteristics such as class imbalance and image variability, the paper demonstrates the importance of proper preprocessing and augmentation techniques for improving classification accuracy. This dataset has become foundational in many pneumonia detection studies.

In paper [4], the research explores the use of ensemble deep learning techniques to enhance pneumonia localization and detection in chest X-rays. The study evaluates multiple models, including RetinaNet and UNet-based architectures, combined into an ensemble to improve diagnostic accuracy. Through case studies and experimental results, the research shows that ensemble models outperform standalone networks by capturing diverse feature representations. The study highlights how real-time visualization, such as heatmaps and bounding boxes, assists radiologists in interpreting lung abnormalities more effectively, thereby improving clinical decision-making and diagnostic reliability.

In paper [5], the study investigates the long-term evolution of deep learning architectures like ResNet in medical imaging applications. The research focuses on how residual learning enables the training of very deep neural networks without performance degradation, addressing common issues such as vanishing gradients. By applying ResNet models to pneumonia detection tasks, the study demonstrates significant improvements in classification accuracy and model stability. Additionally, the research underscores the growing role of AI-driven diagnostic tools during and after global health crises, where rapid and reliable interpretation of medical images has become more essential than ever.

1.3. Problem Statement

Manual interpretation of chest X-rays is time-consuming and prone to human error due to the subtle differences between normal and infected lungs. Hence, there is a need for an automated, accurate, and efficient pneumonia detection system using deep learning techniques.

CHAPTER 2

SYSTEM ANALYSIS

2.1. Existing System

• **Pneumonia diagnosis relies on manual interpretation by radiologists:** Currently, detecting pneumonia is mainly done by radiologists who visually examine chest X-ray images. This process depends heavily on human expertise and experience.

• **High chances of misdiagnosis due to similarities in X-ray features:** Pneumonia symptoms on X-ray images can look similar to other lung diseases or sometimes even normal variations, making it difficult to diagnose accurately. This can lead to human errors.

• **Process is slow, subjective, and dependent on expert availability:** Manual examination takes time and may vary between radiologists. In areas with limited medical staff, the diagnosis process becomes slow and inconsistent.

2.2. Proposed System

• **A CNN-based model processes chest X-ray images and automatically classifies them as Normal or Pneumonia:** In contrast to manual diagnosis, the proposed system uses an automated deep learning model that reduces reliance on human interpretation. The CNN learns patterns directly from large datasets, making the detection faster and less prone to subjective errors.

• **Uses image preprocessing (resizing, normalization, augmentation):** To overcome inconsistencies in raw X-ray images, preprocessing techniques are applied. This ensures uniform image size, balanced pixel distribution, and enhanced dataset variety, leading to improved accuracy compared to the traditional visual inspection approach.

• **Provides quick, accurate, and consistent diagnosis assistance:** Unlike the slow and variable results of manual diagnosis, the proposed system delivers predictions within seconds. It ensures high accuracy, reduces chances of misdiagnosis, and supports healthcare professionals by providing consistent and reliable outputs.

2.3. Data Collection

• **Dataset: Kaggle Chest X-Ray (Pneumonia) Dataset:**

Since manual diagnosis depends heavily on the availability of quality X-rays, this dataset offers a standardized and well-labeled collection of images. It provides a reliable foundation for training the automated model.

• **Contains: Normal images and Pneumonia-infected images:**

Just as radiologists compare healthy and infected X-rays to diagnose patients, the dataset includes both normal and pneumonia categories. This helps the model learn the key differences that humans typically look for during diagnosis.

• **Preprocessing applied: resizing to 150×150, scaling pixel values, augmentation:**

Because raw X-ray images vary in size, exposure, and clarity (similar to challenges faced in manual diagnosis), preprocessing steps standardize them before training. These transformations enhance model performance and ensure that the automated system can handle real-world variations more effectively.

CHAPTER 3

SYSTEM DESIGN

3.1 Software Requirements

• **Python:** Python is the main programming language used to develop the pneumonia detection system. It supports machine learning libraries and has simple syntax, making development faster and easier.

• **TensorFlow / Keras:** These are deep learning frameworks used to build and train the Convolutional Neural Network (CNN). Keras provides high-level APIs, while TensorFlow performs the backend computations efficiently.

• **KaggleHub:** KaggleHub is used to directly download or access the Chest X-Ray dataset from Kaggle into the notebook environment without manual downloading.

• **Matplotlib:** Matplotlib is used to visualize training results such as accuracy graphs, loss curves, and image samples.

• **Google Colab or Jupyter Notebook:** These notebook environments allow interactive coding, GPU usage, and easy visualization of results. They make running deep learning models more convenient.

3.2 Hardware Requirements

• **CPU with minimum 8 GB RAM:** A system with at least 8 GB RAM is needed to load the dataset, preprocess images, and run the training process without memory issues.

• **GPU recommended for faster training (e.g., Google Colab GPU):** Training CNN models on a CPU is slow. A GPU accelerates the computation and reduces model training time significantly.

• **Storage space for dataset (~2 GB):** The Chest X-Ray dataset is large, so enough storage is required to download and store the images.

3.3 Functional Requirements

• **Load and preprocess X-ray images:** The system must read the image files, resize them, normalize pixel values, and prepare them as input for the CNN model.

• **Train CNN model:** The system must train the Xception (or other CNN) model using the dataset to learn the patterns that differentiate normal and pneumonia X-ray images.

• **Perform classification:** The trained model should classify a given X-ray image as either Normal or Pneumonia.

• **Provide accuracy results and graphs:** After training, the system must display performance metrics like accuracy, loss, and visualize them using graphs.

• **Save the trained model:** The system should store the final trained model so it can be reused later without retraining.

3.4 Non-Functional Requirements

• **Accuracy and reliability:** The system should produce consistent and correct classification results, ensuring high accuracy for medical usage.

• **Scalability for large datasets:** The system should be able to handle larger datasets if more X-ray images are added in the future.

• **Availability for real-time detection:** The model should be easily deployable so it can classify images quickly in real-time hospital environments.

• **Usability for medical professionals:** The system should have a user-friendly interface and simple workflow so doctors and technicians can use it without technical difficulty.

CHAPTER 4

IMPLEMENTATION

4.1 Architectural Design

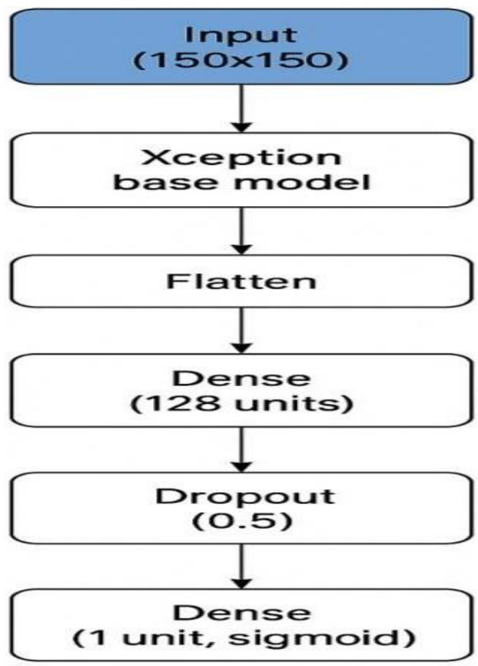

Fig 4.1 - Architectural Design

The architectural design of the proposed pneumonia detection system is based on a transfer-learning approach using the Xception model as the core feature extractor. The process begins with input chest X-ray images resized to 150×150 pixels, which are then passed through the pretrained Xception base model, where deep hierarchical features are automatically extracted. These feature maps are flattened and fed into a fully connected dense layer with 128 neurons to learn high-level patterns relevant for classification. A dropout layer (0.5) is used to reduce overfitting and improve generalization by randomly disabling neurons during training. Finally, a single sigmoid-activated output neuron produces a binary classification indicating whether the X-ray belongs to a Normal or Pneumonia case. This architecture ensures efficient feature extraction, robustness, and reliable prediction performance while maintaining a simple and computationally feasible design.

4.2 Description of Modules

4.2.1 Data Acquisition and Preprocessing Module

This module handles the downloading, loading, and preparation of the Chest X-Ray Pneumonia dataset. It organizes the dataset into training, validation, and testing sets, followed by preprocessing operations such as resizing images to 150×150, normalizing pixel values, and generating batches using ImageDataGenerator. The module ensures that all images are standardized before being passed to the model.

4.2.2 Model Construction Module

In this module, the Xception architecture is loaded with pretrained ImageNet weights and used as the base feature extractor. The top layers are replaced with custom classification layers including Flatten, Dense, Dropout, and Sigmoid activation. The model is compiled using the Adam optimizer and binary cross-entropy loss, preparing it for the training process.

4.2.3 Model Training and Validation Module

This module manages the training of the constructed Xception-based network using preprocessed images. It trains the model for a defined number of epochs while recording training and validation accuracy and loss. The module ensures that the model learns meaningful patterns from the dataset and monitors performance to detect overfitting or underfitting.

4.2.4 Model Evaluation and Visualization Module

Once training is completed, this module evaluates the model on the test dataset to measure its generalization ability. It computes key metrics such as test accuracy and generates visual graphs for training and validation accuracy. This module also helps in performance interpretation through visual analysis.

4.2.5 Model Saving and Deployment Module

This module saves the final trained model in .h5 format for future use or deployment. The saved model can later be integrated into applications for real-time pneumonia detection. It ensures reusability and practical implementation of the system.

4.3 Code Implementation

Algorithm: Pneumonia Detection using Xception CNN Model

Input: Chest X-Ray Pneumonia Dataset (Kaggle)
Output: Predicted class (Normal / Pneumonia) and performance metrics

1. Start

2. Load and Download Dataset

2.1 Install and import required libraries (TensorFlow, Keras, Matplotlib, KaggleHub, OS).
2.2 Download the Chest X-Ray dataset using KaggleHub.
2.3 Define dataset directories:
- Train folder
- Validation folder
- Test folder

3. Preprocess Images

3.1 Set image size to (150 × 150) and batch size = 32.
3.2 Initialize ImageDataGenerator with rescaling = 1/255.
3.3 Create data generators using flow_from_directory() for:
- Training images
- Validation images
- Testing images

3.4 Automatically resize, normalize, and batch the X-ray images.

4. Build Xception-Based CNN Model

4.1 Load pretrained Xception model with:
- weights = ‘imagenet’
- include_top = False
- input_shape = (150, 150, 3)

4.2 Freeze base model layers to prevent retraining.
4.3 Initialize a Sequential model.
4.4 Add the following layers:
- Xception base model
- Flatten layer
- Dense(128) with ReLU activation
- Dropout(0.5) to reduce overfitting
- Dense(1) with Sigmoid activation for binary classification

5. Compile Model

5.1 Set optimizer = Adam (learning_rate = 0.0001).
5.2 Set loss function = Binary Cross-Entropy.
5.3 Set evaluation metric = Accuracy.

6. Train Model

6.1 Train the model using training and validation generators with:
- Epochs = 10
- Batch size = 32

6.2 Store training history containing accuracy and loss values.

7. Test Model

7.1 Evaluate the trained model using the test generator.
7.2 Obtain test accuracy and test loss values.

8. Evaluate Performance

8.1 Display test accuracy returned by model.evaluate().
8.2 Compare training vs validation accuracy to check model consistency.
8.3 Check for overfitting or underfitting through stored accuracy/loss curves.

9. Visualize Results

9.1 Plot training and validation accuracy across epochs.
9.2 Plot accuracy graph using Matplotlib.
9.3 Display visual trends for model performance.

10. Save Model

10.1 Save trained CNN model as pneumonia_cnn.h5 for future use.

11. End

CHAPTER 5

RESULT

The performance of the proposed Xception-based CNN model was evaluated using training, validation, and test datasets. The accuracy curve is shown in Figure 1, which highlights the improvement of the model over 10 epochs.

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/xception/xception_weights_tf_dim_ordering_tf_kernels_notop.h5
83683744/83683744 ━━━━━━━━━━━━━━━━━━━━ 5s 0us/step
/usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call
  self._warn_if_super_not_called()
Epoch 1/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 81s 358ms/step - accuracy: 0.8720 - loss: 0.3611 - val_accuracy: 0.6875 - val_loss: 0.7129
Epoch 2/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 46s 283ms/step - accuracy: 0.9476 - loss: 0.1300 - val_accuracy: 0.6875 - val_loss: 0.6101
Epoch 3/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 45s 276ms/step - accuracy: 0.9549 - loss: 0.1108 - val_accuracy: 0.8125 - val_loss: 0.5110
Epoch 4/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 46s 281ms/step - accuracy: 0.9604 - loss: 0.1001 - val_accuracy: 0.8750 - val_loss: 0.3817
Epoch 5/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 46s 282ms/step - accuracy: 0.9676 - loss: 0.0863 - val_accuracy: 0.6875 - val_loss: 0.6924
Epoch 6/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 46s 280ms/step - accuracy: 0.9610 - loss: 0.0895 - val_accuracy: 0.8125 - val_loss: 0.5334
Epoch 7/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 45s 276ms/step - accuracy: 0.9742 - loss: 0.0726 - val_accuracy: 0.8750 - val_loss: 0.4067
Epoch 8/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 46s 280ms/step - accuracy: 0.9749 - loss: 0.0593 - val_accuracy: 0.6875 - val_loss: 0.6417
Epoch 9/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 46s 280ms/step - accuracy: 0.9770 - loss: 0.0629 - val_accuracy: 0.7500 - val_loss: 0.6080
Epoch 10/10
163/163 ━━━━━━━━━━━━━━━━━━━━ 46s 280ms/step - accuracy: 0.9797 - loss: 0.0578 - val_accuracy: 0.8750 - val_loss: 0.3691
20/20 ━━━━━━━━━━━━━━━━━━━━ 7s 209ms/step - accuracy: 0.8364 - loss: 0.7005
✅ Xception Test Accuracy: 0.8397
```

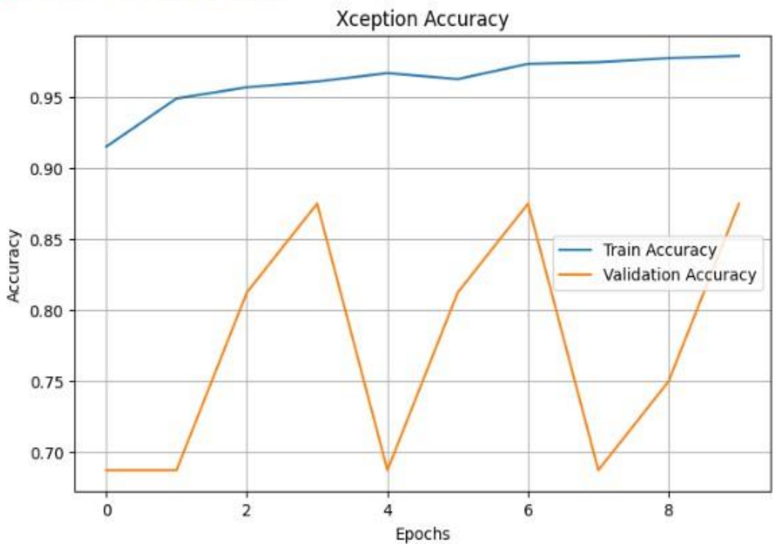

Fig 5.1 - Training and Validation Accuracy Curve of the Xception Model.

CHAPTER 6

CONCLUSION

The project successfully demonstrates the effectiveness of Convolutional Neural Networks, particularly the Xception architecture, in detecting pneumonia from chest X-ray images with high accuracy. By applying preprocessing techniques such as resizing, normalization, and controlled augmentation, the model was able to learn meaningful patterns that distinguish normal lungs from pneumonia-infected lungs. The achieved test accuracy highlights the potential of deep learning as a reliable, fast, and consistent diagnostic support tool for medical professionals. Although the model shows promising performance, further improvements can be made by fine-tuning the pretrained layers, using larger datasets, and integrating explainable AI methods to enhance transparency and clinical trust. Overall, this work provides a strong foundation for developing advanced AI-driven medical diagnostic systems that can assist in early detection, reduce workload on radiologists, and contribute to better patient outcomes.

CHAPTER 7

REFERENCES

1. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., & Ng, A. Y. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. arXiv:1711.05225.

2. Simonyan, K., & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv:1409.1556.

3. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

4. Chollet, F. (2017). Xception: Deep Learning with Depthwise Separable Convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

5. Mooney, P. (2018). Chest X-Ray Images (Pneumonia) Dataset. Kaggle. https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

6. Sirazitdinov, I., Kholiavchenko, M., Mustafaev, T., Yixuan, Y., Koh, J. E. W., & Jun, C. H. (2019). Deep Neural Network Ensemble for Pneumonia Localization from Chest X-Rays. Diagnostics, 9(3).

7. World Health Organization (WHO). (2021). Pneumonia: Fact Sheet. https://www.who.int/news-room/fact-sheets/detail/pneumonia

8. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.