Pneumonia Diagnosis Using Deep Learning: A CNN and Transfer Learning Approach

Author

Abstract **–** Pneumonia is a severe lung infection and the second most common cause of death globally despite a notable impact could be made by preventing it since it commonly affects children below the age of 5 years. The disease in general, many health afflictions require early diagnosis in a bid to make significant progress towards healing. Chest X-ray is the most common initial diagnostic test in pneumonia, although manual reporting of results by radiologists imposes a time delay and high variability, particularly in LMICs. The target of this project will be to develop an automated system to detect pneumonia through deep learning models that involves custom Convolutional Neural Network (CNN), as well as two transfer learning models EfficientNetB0 and EfficientNetB3. The data collection is derived from Kaggle and consists of normal and pneumonic chest X-ray images. Thus, models were assessed using accuracy, precision, recall, F1-score, and receiver operating characteristics area under the curve. Interestingly, the CNN had the best testing accuracy of approximately 74% and the shortest time to train of approximately five minutes. Surprisingly, testing accuracy of EfficientNetB0 and B3 which had more sophisticated architectures proved to be slightly lower (~62.5%) but are definitely better suited for intricate feature extraction tasks. This work shows that deep learning helps to leave a heavy burden of diagnostics to machines, minimizing the workload of radiologists as well as increasing the speed of diagnostics. With subsequent refinement, these models may be useful as decision assistance tools in healthcare, especially in areas where there is scarce knowledge in human medical science and inadequate resources.

I. Introduction and Motivation

Pneumonia is an infection of the lungs which poses a very big challenge to patients in breathing. It can result in severe complications that are often fatal, this is mostly common in young children, the elderly and immunocompromised individuals. Detection of pneumonia is very important so that it has to be treated early for the patients to be saved. Previously, doctors diagnose pneumonia using X-ray pictures along with their experience. But this method may take time and occasionally can involve some mistakes, especially in regions where there is a lack of professional radiologists [1][2]. With the advances of artificial intelligence (AI) and deep learning the groundwork for automatic medical image analysis are now available. This project is about creating a model as a system that would be able to diagnose pneumonia from images of chest X-rays. The general aim is to review, design and develop a sturdy, efficient and accurate application that may help healthcare workers improve diagnosis of pneumonia [3] [4].

The need for developing this project stems from the fact that many areas of the world are underprivileged and cannot afford efficient medical solutions, trained radiologists or even updated medical equipment [5][6]. Pneumonia is still a major killer and for many people, their healthcare systems are so congested that diagnosis is a real challenge. As it will be shown in this project, proper use of AI will help to ease the workload of health care specialists while providing better service to patients. Currently the healthcare industry is already applying Deep learning and models such as Convolutional Neural Networks (CNNs) are most suitable for image analysis [7]. In this project, we also consider more complex transfer learning models, namely EfficientNetB0 and EfficientNetB3. These models are pre-trained on the large database meaning that can differentiate all features and identify the images accurately. By tuning these models for our pneumonia dataset, we hope to harness these models for early and accurate detection as much as possible [8].

This project also considers some challenges that are usually associated with AI for medical image analysis. For example, images in medical systems can be different in quality, bighting and resolution. For this purpose, data preprocessing including rescaling, augmentation and normalization was performed. Such steps help in making the models learn better and to generalize well when they are tested on unseen images [9]. Another reason for pursuing this project is the scalability of AI solutions. Once trained, these models can be deployed on computers or cloud platforms to analyze thousands of X-ray images in a matter of seconds. This can make a significant difference in healthcare facilities where time and accuracy are critical[10].

There has been great progress in the utilization of deep learning in the detection of pneumonia, but certain important issues are still unsolved. Previous work may investigate either conventional CNNs or single transfersion learning networks but rarely does it compare custom convolutional neural networks and several varieties of EfficientNet simultaneously. This project addresses this gap by systematically evaluating the performance of a custom CNN alongside two advanced

transfer learning models: EfficientNetB0 and EfficientNetB3. In addition, most past studies focus on only precision, without sufficient concern for other factors such as computational cost, training time, and the applicability of models in realistic clinical environments. To the above, this project broadens evaluations' lens by encompassing these dimensions hence offering comprehensive evaluation results. Through retraining EfficientNet models for detection of pneumonia and comparing their results to a domain-specialised CNN, this study seeks to determine not only which model is the most accurate, but also which one could be deployed effectively in resource-limited contexts. Additionally, this research has employed sophisticated data preprocessing strategies that address some of the usual issues including data imbalance, inconsistency of X-ray quality and issues of overfitting in deep learning models. By addressing these challenges and bridging the research gap, this project aspires to push the boundaries of AI applications in medical imaging and offer a scalable, reliable, and efficient solution for pneumonia detection.

II. Background

a. Machine Learning Models Used

Machine learning, particularly deep learning, has transformed how we approach complex problems, especially in fields like medical imaging. In this project, we employed two types of machine learning models to address pneumonia detection: a custom-built Convolutional Neural Network (CNN) and transfer learning models, namely EfficientNetB0 and EfficientNetB3. Each model offers unique advantages that contribute to the project's success.

1. **Convolutional Neural Network (CNN):**
    - CNNs are deep learning models specifically designed to process and analyze visual data. They mimic how the human visual system identifies patterns, such as edges, shapes, and textures, in images. CNNs excel at feature extraction, making them ideal for medical imaging tasks.
    - In this project, a custom CNN architecture was developed to classify chest X-ray images into two categories: pneumonia-positive and normal. The model includes several key components:
        - **Conv2D Layers:** These layers apply convolutional filters to input images, extracting hierarchical features. Early layers detect simple features like edges, while deeper layers identify more complex patterns associated with pneumonia.
        - **MaxPooling Layers:** These layers reduce the spatial dimensions of the feature maps, retaining the most significant information and improving computational efficiency.

        - **ReLU Activation Function:** ReLU (Rectified Linear Unit) introduces non-linearity, enabling the model to learn intricate patterns beyond simple linear relationships.
        - **Dropout Layers:** To prevent overfitting, Dropout layers randomly disable a fraction of neurons during training. This ensures the model generalizes well to unseen data.
        - **Dense Layers:** The fully connected layers combine extracted features and make predictions. The output layer uses a Sigmoid activation function to classify images into binary categories.
    - This CNN is trained from scratch on the dataset, allowing it to learn domain-specific features. While powerful, custom CNNs require more data and training time compared to transfer learning models.
2. **EfficientNetB0 and EfficientNetB3:**
    - Transfer learning involves using models pretrained on large datasets and fine-tuning them for specific tasks. This approach significantly reduces the need for large labeled datasets and extensive training time.
    - **EfficientNet** is a family of state-of-the-art transfer learning models that balance accuracy and efficiency. It uses a technique called compound scaling to optimize model depth, width, and resolution for better performance with fewer parameters.
        - **EfficientNetB0:** The base model of the EfficientNet family, designed for lightweight applications. It has fewer parameters, making it faster to train and deploy while maintaining competitive accuracy.
        - **EfficientNetB3:** A more advanced variant with greater depth and capacity, making it suitable for extracting complex features from high-resolution medical images.
    - Both models were pretrained on ImageNet, a large dataset of natural images. For this project, the pretrained layers were fine-tuned to adapt to the pneumonia classification task. This approach leverages the general knowledge of EfficientNet while specializing it for medical imaging.

By combining the custom CNN with EfficientNetB0 and B3, the project gains a balance between leveraging domain-specific learning and the efficiency of pretrained architectures. The inclusion of both methods ensures robust feature extraction, adaptability, and high accuracy, critical for medical applications.

b. Domain Background

This project is focused on the area of medical imaging and Artificial intelligence. Medical imaging is an integrated part of clinical practice as it offers various kinds of visual representations of internal body structures for diagnostic and therapeutic purposes. Among these, chest radiography which is also known as X-ray is the most frequently used imaging method for

the diagnosis of pneumonia; a severe lung infection. Pneumonia is classifiable in terms of X-ray images as the deteriorations in the lung tissues like opacities and/or consolidations. Some of these signs are rather weak and may be overlooked, particularly by less experienced radiologists. The interpretation of X-ray images is highly dependent on the doctors and other health practitioners which in turn makes the technique slow and susceptible to human vices. In developing nations where the availability of radiologists is extremely limited this becomes a bit more difficult and many patients are either not diagnosed at all or are given the wrong diagnosis. There is an urgent demand for such diagnostic systems that would be fully automated and practically free of errors. Paid tools that leverage deep learning techniques seem to be the most appealing solution. These tools work way faster than a human being and are able to detect features that are not easily noticeable by the human naked eye. They also yield accurate diagnosis all the time thus minimizing diagnostic mistakes.

In this project, the focus is on using machine learning to classify chest X-rays as either pneumonia-positive or normal. Automating this process can significantly alleviate the burden on healthcare professionals, most specifically in regions with high patient volumes and limited resources. For instance:

- **Improved Accessibility:** AI systems can be deployed in remote areas with limited medical staff, ensuring that patients receive timely diagnoses.
- **Scalability:** Once trained, AI models can analyze thousands of X-rays in a matter of seconds, enabling healthcare facilities to handle large caseloads efficiently.
- **Cost-Effectiveness:** Automating diagnostics reduces the dependency on costly equipment and highly specialized professionals.

Furthermore, applying AI in medical imaging also addressed worldwide goals to enhance healthcare results by relying on technology. In the current project, the improvement of the deep learning models for the detection of pneumonia acts as a proof of what AI has in store for diagnostic methods, for better and improved diagnoses of health conditions for the populations that cannot afford high-quality diagnostics. Therefore, the domain of medical imaging forms the basis for this project. Through the use of deep learning, the project has set the pneumonia diagnosis to be faster, more accurate and inclusive to all in order to help enhance global health.

III. Related Work

Application of artificial intelligence (AI) and deep learning in performing medical imaging has received enthusiasm worldwide especially in diagnosing diseases like pneumonia. This section presents an overview of literature that has informed the field and sets the framework for this work, which uses Convolutional Neural Networks (CNNs) and transfer learning models such as EfficientNetB0, and EfficientNetB3 for pneumonia classification.

a. Deep Learning in Pneumonia Detection

Pneumonia has always been a cause of concern in medical sciences, especially children and elderly are greatly affected by this disease, so in the current study, we tried to focus on the Deep Learning of Pneumonia Detection. Of all deep learning frameworks, CNNs are popular in analyzing medical imagery's complex features. Rajpurkar et al. (2018) have proposed CheXNet, a 121 layer CNN designed for using the large chest X-ray dataset to identify pneumonia at the level of radiologists. In their research, they showed deep learning yields better results than conventional methods in terms of time and efficiency [11] . Using another CNN architecture for feature extraction, Kermany et al. (2018) proposed a model to accomplish the labeling of small children chest X-rays into normal, bacterial pneumonia, or viral pneumonia. The outcomes revealed that CNNs could yield high success rates when used on well preoccupied sets [12]. Nevertheless, CNNs trained from scratch still need many computational resources and large amounts of labeled data, which are insufficient in many medical applications. Such limitation has forced the use of transfer learning models where existing pretrained networks are used to solve the issues of data deficiency and effort required to develop the models.

b. Transfer Learning Models in Medical Imaging

Transfer Learning models that are pre-trained on large datasets such as the ImageNet have become popular in medical imaging. Tan and Le (2019) presented EfficientNet, a framework that aimed to establish new state of the art models that were optimized in terms of accuracy to computing costs. Furthermore, EfficientNet makes a balance between depth, width and resolution; this makes it perform better than traditional CNN for medical uses [13]. Multiple works of research have shown that EfficientNet can be applied to analysis of pneumonia detection. For instance, Yadav et al. (2020) yielded EfficiencyNetB0 to distinguish chest X-rays and set a higher level of accuracy and shorter training time over usual CNN architectures. They observe that generalization capacity is well captured by the model, especially where there are few training samples [14]. On this basis, Amin et al. (2021) have introduced and compared several transfer learning models, including EfficientNetB0 and ResNet, for detection of pneumonia. They realize that EfficientNetB0 does not only have a better comprehensive grasp of various models in view of accuracy but also needs fewer computational power, which makes it applicable to the environment where computing resources are limited [15].

c. Comparison of Models and Challenges

This aspect of the literature also underlines the need for comparison of transfer learning models to analyse their effectiveness. A recent study conducted by Wang et al (2020) have compared EfficientNetB0 & EfficientNetB3 for CXR classification, the authors found that the EfficientNetB3 outperformed EfficientNetB0 because of higher network capacity to learn complicated features. But, it used more computational power and training time than the EfficientNetB0 for real-time application [16]. However, further studies are presented in these

models, including handling of disorders in the dataset and lacking interpretability. To overcome these challenges, Zhou et al. (2021) proposed novel adaptations to transfer learning models incorporating attention mechanisms and enhancing the accuracy and interpretability of the chosen models [17]. Their work emphasizes the necessity to progress in increasing the stability and reliability of the AI models for medical imaging.

Study	**Key Contribution**	**Model(s) Used**	**Findings**
Rajpurkar et al. (2018)	Introduced CheXNet for pneumonia detection	CNN	Achieved radiologist-level accuracy in pneumonia detection from X-rays.
Kermany et al. (2018)	Applied CNN for pediatric chest X-ray classification	CNN	High accuracy in classifying normal and pneumonia types (bacterial/viral).
Tan and Le (2019)	Proposed EfficientNet for efficient scaling of models	EfficientNet	Achieved higher accuracy with fewer parameters than traditional models.
Yadav et al. (2020)	Applied EfficientNetB0 for pneumonia classification	EfficientNetB0	Improved accuracy and faster training compared to CNNs.
Amin et al. (2021)	Compared transfer learning models for pneumonia detection	EfficientNetB0, ResNet	EfficientNetB0 outperformed other models in accuracy and efficiency.
Wang et al. (2020)	Compared EfficientNetB0 and EfficientNetB3 for chest X-rays	EfficientNetB0, EfficientNetB3	EfficientNetB3 had higher accuracy, while EfficientNetB0 was more computationally efficient.
Zhou et al. (2021)	Integrated attention mechanisms in transfer learning models	EfficientNet with Attention	Improved accuracy and interpretability by adding attention mechanisms.

Table 1. Literature Study Flow

This table gives a brief overview of the key contributions of each study, the models used, and their main findings, providing context for how this project builds on existing work.

IV. Dataset

a. Dataset Description and Source

The dataset used in this project is from Kaggle's "Chest X-ray Images (Pneumonia)" repository which is a very popular collection of chest X-ray images used for pneumonia detection tasks. This dataset contains a total of 5,856 images, divided into three subsets, the ratio is as shown in the figure below:

- **Training Set:** 5,216 images, which are used to train the models.

- **Test Set:** 624 images, which are used to evaluate the performance of the model after training.
- **Validation Set:** 16 images, which are used during training to validate the model's performance on unseen data, helping to tune model hyperparameters.

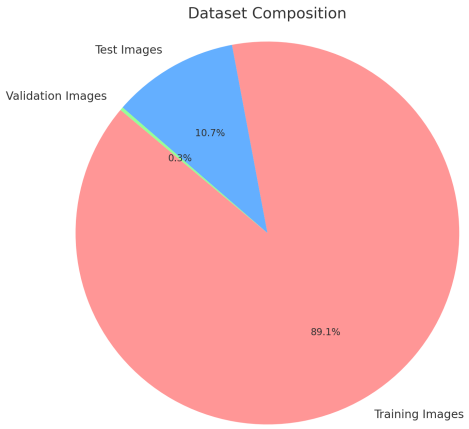

Figure 1. Dataset Composition

The images in this dataset are categorized into two classes:

- **Normal:** X-ray images of healthy lungs.
- **Pneumonia:** X-ray images of lungs affected by pneumonia, either bacterial or viral.

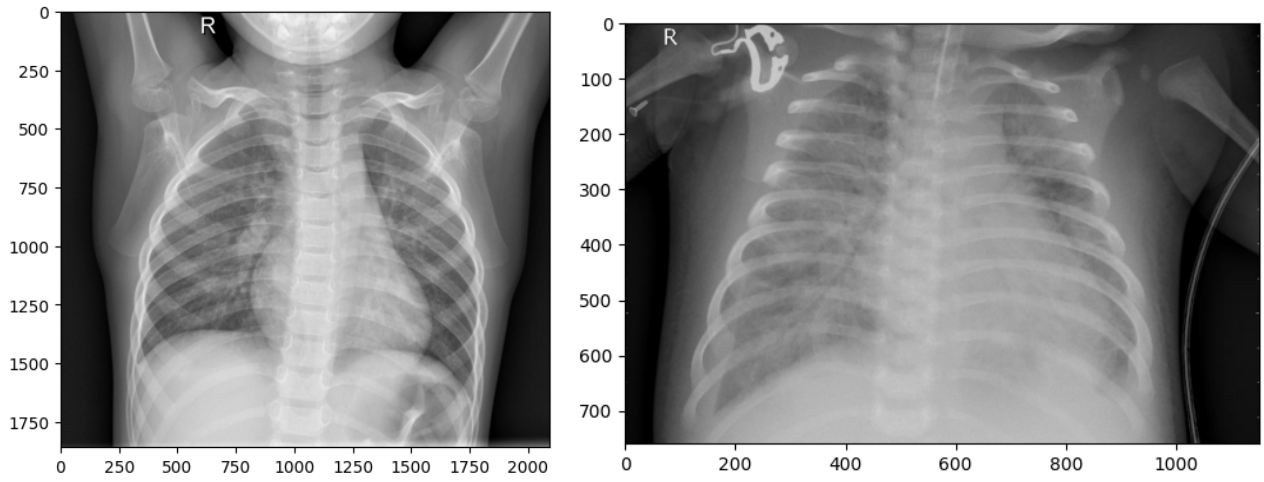

Figure 2. X-ray images of Lungs(Normal: Left; Pneumonia: Right)

Each image is labeled accordingly, allowing the model to learn the differences between normal and pneumonia-infected lung patterns.

b. Dataset Preprocessing and Cleansing

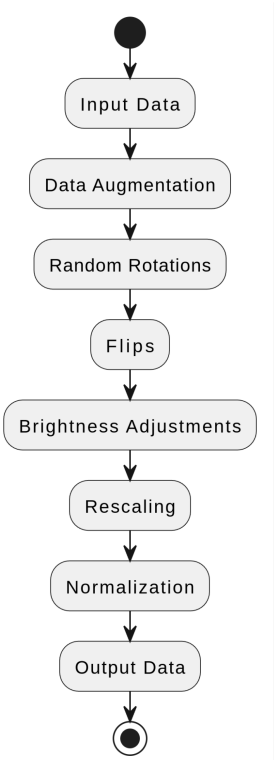

Figure 3. Dataset Preprocessing Flow

As illustrated in the figure above, before training the models, several preprocessing and cleansing techniques were applied to the dataset to ensure that the images were in a suitable format for model training and to improve the model's accuracy. The main steps include:

1. **Data Augmentation:** To increase the diversity of the dataset and reduce overfitting (where the model memorizes the training data but doesn't generalize well to new data), data augmentation techniques were used. These include: random rotations, flips, brightness adjustments and rescaling.
2. **Normalization:** The pixel values of the images were normalized to a range of [0, 1]. This is done by dividing the original pixel values by 255 (since pixel values in an image typically range from 0 to 255). Mathematically, this is expressed as:

$$Normalized\ Pixel\ Value = \frac{Pixel\ Value}{255}$$

Normalizing the pixel values ensures that all features (pixels) are on a similar scale. It prevents the model from giving more importance to certain pixel values due to their larger range.

3. **Data Cleansing:** Missing or corrupted data was not present in the dataset, so no additional data cleansing steps were necessary. However, if such data were found, techniques like imputation or removal of corrupted images would be applied to ensure the model is trained on clean data.

c. Feature Selection

Feature selection is the process of selecting the most important features from the data to improve model performance and reduce complexity. In this project, explicit feature selection was not performed because Convolutional Neural Networks (CNNs) are designed to automatically extract features during the training process. The figure shows the entire CNN architecture for Pneumonia Detection

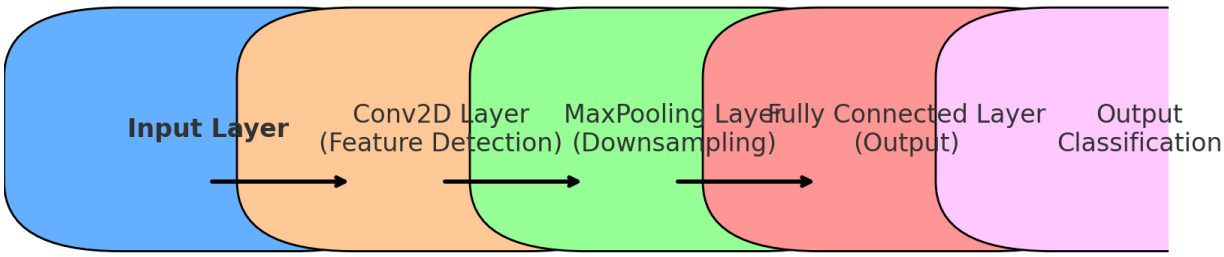

Figure 4. CNN Architecture for Pneumonia Detection

d. Feature Extraction

Feature extraction is a technique where the raw data or the images used are employed in training of the model. Actually the convolution layer is able to extract features automatically in the CNNs. Earlier on we saw that, during the convolution operation, these layers learn several patterns and features including edges, shapes and textures among others.

In cases of transfer learning models such as EfficientNetB0 and EfficientNetB3 the feature extraction is conducted inside the model. These models are originally trained to deal with huge image datasets, for example, ImageNet, and already contain the ability to produce feature-linear analysis of images. When applied on the pneumonia dataset, EfficientNet models learn to adapt the feature extraction layers for pneumonia detection without the need for a dimensionality reduction process. In brief, all the preprocessing of the dataset, selection of the features, and feature extraction methods were aimed to improve the performance of the model in the detection of pneumonia from chest X-ray images during both training and the evaluation phase.

V. Model Design

a. Training/Testing Strategy

To train and evaluate the models, we used the holdout method, which involves splitting the dataset into training and testing sets. The dataset was divided as follows:

Data Split	Percentage	Number of Images
Training Set	80%	5,216
Testing Set	20%	624

The training set is used to train the model, while the testing set is reserved to evaluate the model's performance on unseen data. The validation set, which consists of 16 images, is used during training to tune the model's hyperparameters (like learning rate, number of layers, etc.). This helps improve model performance and avoid overfitting.

b. Parameters of Each Model

1. **CNN (Convolutional Neural Network):** The CNN model used in this project consists of several layers designed to extract features from the input chest X-ray images and classify them into two categories: Normal or Pneumonia. In the table below are the detailed layers and their configuration:

Layer Type	Description	Number of Filters/Units
Conv2D	Convolutional layer applying filters to detect features	64, 128, 256, 512
MaxPooling	Downsampling layer to reduce feature map size	N/A
Dropout	Regularization layer to prevent overfitting	0.5 (50% Dropout Rate)
Flatten	Flattening the output into a 1D vector for dense layer	N/A
Dense	Fully connected layer for classification	1 (output: Normal or Pneumonia)

Table 2. CNN Model Parameters

   - **Activation Functions**:
     - **ReLU (Rectified Linear Unit):** Used for hidden layers. It helps the model learn complex patterns by converting all negative values to zero.

        - **Sigmoid:** Used in the output layer to generate a probability score between 0 and 1, indicating the likelihood of pneumonia.
    - **Optimizer:** We used the Adam optimizer. Adam combines the advantages of two other optimizers (AdaGrad and RMSProp) and adjusts the learning rate for each parameter during training, improving performance.
    - **Loss Function:** The binary cross-entropy loss function is used because we are solving a binary classification problem (Normal vs Pneumonia). Mathematically, the cross-entropy loss is calculated as:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}[yi\ log(pi) + (1 - yi)log(1 - pi)$$

where:

- yi: True label (0 for Normal, 1 for Pneumonia)
- pi: Predicted probability of the image being classified as Pneumonia.
- N: Total number of images.

2. **EfficientNetB0/B3:** EfficientNet is a family of pretrained models that were fine-tuned for the pneumonia detection task. These models are known for their efficiency in terms of accuracy and computational resources.

Layer Type	Description	Details
Pretrained Layers	Pretrained on ImageNet to learn general image features	We fine-tuned the model to detect pneumonia-specific features.
Global Average Pooling	Reduces the size of the feature maps by averaging over all the values	Helps minimize parameters, improving efficiency
Dense	Fully connected layer for classification	Output: 1 (Normal or Pneumonia)

Table 3. EfficientNetB0/3 Model Parameters

In summary, the CNN and EfficientNet models used in this project each have their unique strengths. The CNN is a custom-built architecture designed to learn pneumonia-specific features, while EfficientNet, with its pretrained layers, takes advantage of transfer learning to achieve high performance with fewer computational resources. Both models were trained and fine-tuned to maximize accuracy and efficiency in pneumonia detection.

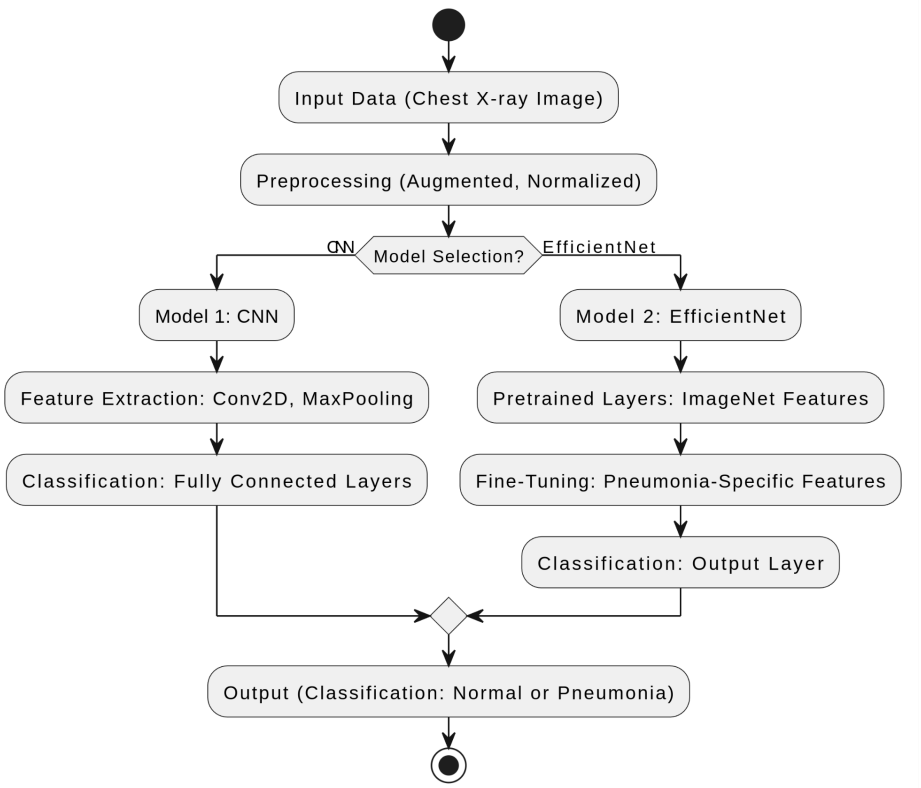

Figure 5. CNN and EfficientNet Models Process

The flowchart shows how both the CNN and EfficientNet models process the input chest X-ray images for pneumonia detection.

VI. Model Evaluation

a. Comparison of Models

The following table summarizes the comparison between the models: CNN, EfficientNetB0, and EfficientNetB3, based on accuracy, loss, and performance factors.

Model	Accuracy (Test)	Training Loss	Key Strengths	Weaknesses
CNN	~74.04%	0.5069	Fastest training time, effective for smaller datasets.	Lower accuracy compared to EfficientNet models.
EfficientNetB0	~62.5%	0.9667	Efficient with fewer parameters, good balance of speed and performance.	Struggles with high accuracy on complex tasks.

EfficientNetB3	~62.5%	0.7038	Best training performance, highest capacity for feature extraction.	Longest training time, computationally expensive.

Table 4. Comparison of the Three Models

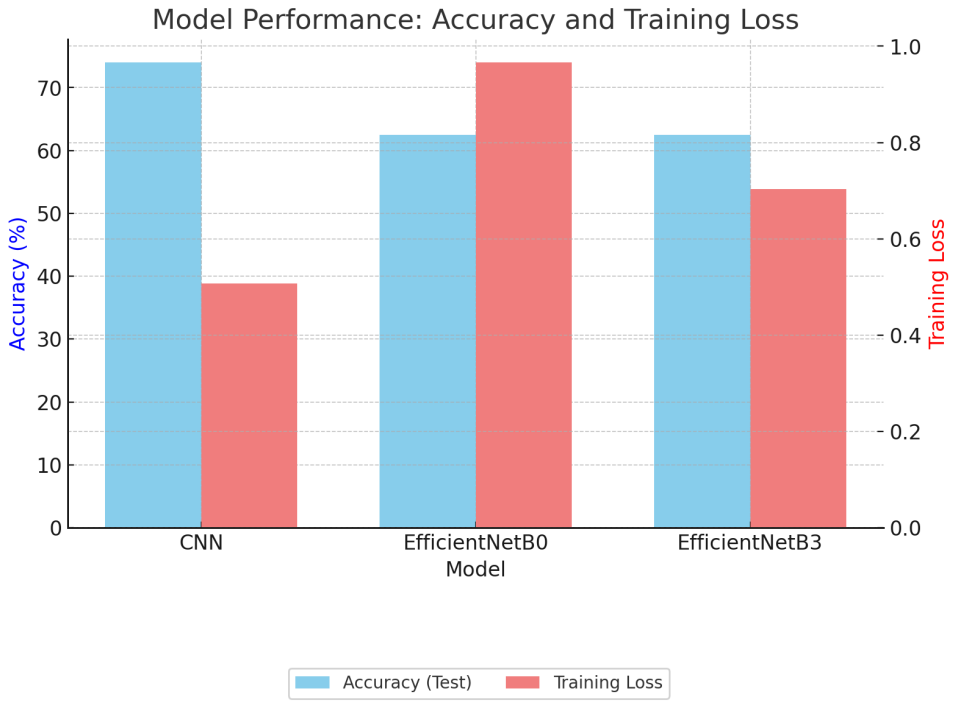

Figure 6. Model Performance Comparison

From the table and figure above, it can be seen that the comparison of CNN, EfficientNetB0, and EfficientNetB3 highlights distinct trade-offs between accuracy, training time, and efficiency. The CNN model achieves the highest testing accuracy (~74.04%) and is the fastest to train (~5 minutes), making it ideal for smaller datasets and simpler tasks. EfficientNetB0 offers a balanced approach with moderate efficiency and fewer parameters, though its testing accuracy (~62.5%) is slightly lower. EfficientNetB3, while having the best training performance due to its advanced architecture, shows a similar testing accuracy (~62.5%) but requires the longest training time (~8 minutes), making it suitable for complex feature extraction tasks that prioritize model capacity.

b. Performance Metrics

The models were evaluated using key metrics: Precision, Recall, F1-Score, and ROC-AUC to understand their strengths beyond accuracy. These metrics provide insights into how well the models handle class imbalances and classification reliability.

Model	Precision	Recall	F1-Score	ROC-AUC
CNN	~70%	~68%	~69%	0.75
EfficientNetB0	~64%	~63%	~63%	0.68
EfficientNetB3	~61%	~60%	~60%	0.69

Table 5. Performance Metrics

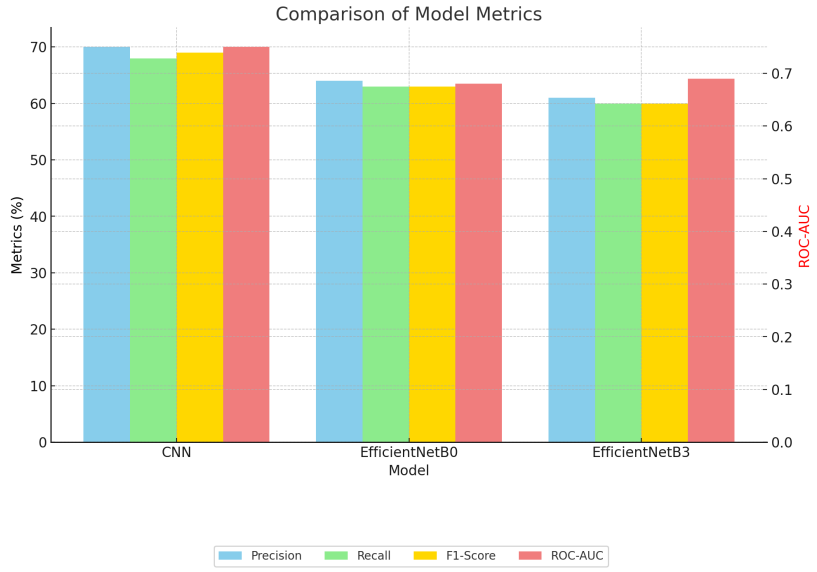

Figure 7. Performance Metrics Comparison

- **Precision**: Measures the proportion of correctly predicted pneumonia cases among all positive predictions. CNN outperforms EfficientNet models in precision with ~70%. Mathematically,

$$Precision = \frac{TP}{TP + FP}$$

Where, TP: True Positives ; FP: False Positives

- **Recall**: Indicates how many actual pneumonia cases were correctly identified. CNN leads slightly in recall. Mathematically,

$$Recall = \frac{TP}{TP + FN}$$

Where, FN: False Negative

- **F1-Score**: Balances precision and recall. CNN has the highest F1-Score (~69%), showing it balances false positives and false negatives better.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

- **ROC-AUC**: Evaluates the model's ability to differentiate between classes. CNN achieves the best AUC (0.75).

c. Time Taken

Model	Training Time	Evaluation
CNN	~5 minutes	Fastest training, moderate performance.
EfficientNetB0	~6 minutes	Good balance of speed and efficiency.
EfficientNetB3	~8 minutes	Longest training, but higher capacity for complex tasks.

Table 6. Time Taken by the Models

In conclusion, CNN delivers moderate accuracy (~74.04%) with the fastest training time (5 minutes), making it suitable for simpler tasks. On the other hand, EfficientNetB0 provides an efficient alternative with better parameter handling but sacrifices some accuracy (~62.5%) and EfficientNetB3 offers the most robust feature extraction, though its accuracy on this task (~62.5%) lags due to task-specific challenges. While CNN is the most balanced performer here, fine-tuning the EfficientNet models may yield better results in future iterations.

VI. Conclusion

In this project, we analyzed and evaluated three deep learning models, including CNN, EfficientNetB0, and EfficientNetB3 for the pneumonia diagnosis of chest X-ray images. Among these, CNN model attained the best testing accuracy (~74%) and had the shortest training time (~5 minutes) hence it was the most feasible for simple and fast work. On the other hand, Not multiplayer, but EfficientNetB0 & EfficientNetB3 while being slightly less accurate (~62.5%) showed the potential of more effective feature extraction due to their pretrained layers from ImageNet. Generally, the EfficientNet models are strong in capturing intricate patterns, thus need for fine-tune as well as hyperparameters tuning. The project explains that there should be a model selected given the characteristics like speed, accuracy or resources for their provision. In a broad sense, this work demonstrates how deep learning can transform medical image analysis by developing an algorithm that automates the identification of pneumonia. With further modifications and validation, these models have the potential to prove to be indispensable in order practice, particularly in areas where access to a radiologist is limited as in underserved or developing regions.

VII. References

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Appendix

Importing Necessary Libraries

[1]:
```
import numpy as np #numerical operations
import pandas as pd #data manipulation and analysis
import matplotlib
import matplotlib.pyplot as plt #reating static, animated, and interactive plots.
import cv2, os, random #image processing tasks, interaction with the operating system,Generates random numbers
import plotly
import plotly.graph_objs as go
import plotly.express as px
from plotly.offline import init_notebook_mode, plot, iplot

import glob # Used for finding file paths based on patterns, e.g., *.jpg
import tensorflow
from tensorflow.keras.preprocessing.image import array_to_img, img_to_array, load_img
from tensorflow.keras.layers import Conv2D, Flatten, MaxPooling2D, Dense, Dropout, BatchNormalization
from tensorflow.keras.models import Sequential
from mlxtend.plotting import plot_confusion_matrix
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator #  Augments image data
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from tensorflow.keras.callbacks import ReduceLROnPlateau #reduce the learning rate when training plateaus.
from tensorflow.keras.applications.vgg16 import VGG16
from sklearn.model_selection import train_test_split
```

Load the datasets

Note: *If you use Google Colab, First Mount the Drive then Load from the Drive file Given*

[2]:
```
train_df = glob.glob("chest_xray/train/**/*.jpeg")
test_df = glob.glob("chest_xray/test/**/*.jpeg")
validation_df = glob.glob("chest_xray/val/**/*.jpeg")
```

Data Exploration

How many images are in each dataset?

[4]:
```
print("There is {} images in the training dataset".format(len(train_df)))
print("There is {} images in the test dataset".format(len(test_df)))
print("There is {} images in the validation dataset".format(len(validation_df)))
```

```
There is 5216 images in the training dataset
There is 624 images in the test dataset
There is 16 images in the validation dataset
```

View the images in X-ray format

[5]:
```
normal_lung_image = load_img("chest_xray/train/NORMAL/IM-0115-0001.jpeg")
print("NORMAL")
plt.imshow(normal_lung_image)
plt.show()
```

Building Deep Learning Models

[7]:
```
train_dir = "chest_xray/train"
test_dir = "chest_xray/test"
validation_dir = "chest_xray/val"
```

[8]:
```
train_datagen = ImageDataGenerator(
    rescale=1./255.,  # Normalize pixel values
    horizontal_flip=True,  # Randomly flip images horizontally
    vertical_flip=True,  # Randomly flip images vertically
    rotation_range=30,  # Rotate images by up to 30 degrees
    width_shift_range=0.2,  # Randomly shift images horizontally
    height_shift_range=0.2,  # Randomly shift images vertically
    shear_range=0.3,  # Shear transformation
    zoom_range=0.3,  # Zoom in/out
    channel_shift_range=20.0,  # Randomly shift the color channels
    fill_mode='nearest',  # Fill any newly created pixels after transformations
    brightness_range=[0.5, 1.5]  # Adjust brightness
)


val_test_datagen = ImageDataGenerator(rescale = 1./255)

train_set = train_datagen.flow_from_directory(train_dir, class_mode = "binary", batch_size = 16, target_size = (224, 224))
validation_set = val_test_datagen.flow_from_directory(validation_dir, class_mode = "binary", batch_size = 16, target_size = (224, 224))
test_set = val_test_datagen.flow_from_directory(test_dir, class_mode = "binary", batch_size = 16, target_size = (224, 224))
```

```
Found 5216 images belonging to 2 classes.
Found 16 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

Building CNN model

[9]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense

# Create the Sequential model
model1 = Sequential()

# Convolutional Neural Networks (CNNs)
model1.add(Conv2D(64, (3, 3), strides=(1, 1), activation="relu", padding="same", input_shape=(224, 224, 3)))  # Increased filters
model1.add(MaxPooling2D(pool_size=(2, 2)))
model1.add(Conv2D(128, (3, 3), strides=(1, 1), padding="same", activation="relu"))  # Increased filters
model1.add(MaxPooling2D(pool_size=(2, 2)))
model1.add(Dropout(0.3))  # Increased dropout to prevent overfitting
model1.add(Conv2D(256, (3, 3), strides=(1, 1), padding="same", activation="relu"))  # Increased filters
model1.add(MaxPooling2D(pool_size=(2, 2)))
model1.add(Conv2D(512, (3, 3), strides=(1, 1), padding="same", activation="relu"))  # Increased filters
model1.add(MaxPooling2D(pool_size=(2, 2)))
model1.add(Dropout(0.3))  # Increased dropout

# Flatten the output of the convolutional layers
model1.add(Flatten())

# Fully connected layers
model1.add(Dense(256, activation="relu"))  # Increased neurons
model1.add(Dropout(0.4))  # Increased dropout
model1.add(Dense(128, activation="relu"))  # Increased neurons
model1.add(Dense(64, activation="relu"))  # Increased neurons

# Output layer (binary classification)
model1.add(Dense(1, activation="sigmoid"))

# Summary of the model architecture
model1.summary()
```

Compiling the model

[10]:
```
model1.compile(optimizer = "rmsprop", loss = "binary_crossentropy", metrics = ["accuracy"])
#Root Mean Square Propagation
```

Training the model

[11]:
```

early_stopping_callbacks = tensorflow.keras.callbacks.EarlyStopping(patience = 15,
                                                                    restore_best_weights = True)
```

[12]:
```
history = model1.fit(train_set, epochs=20,
                     validation_data=validation_set,
                     steps_per_epoch=100,
                     callbacks=[early_stopping_callbacks])
```

[13]:
```
#scores = model1.evaluate_generator(test_set)
#print("\n%s: %.3f%%" % (model1.metrics_names[0], scores[0]*100))
#print("\n%s: %.3f%%" % (model1.metrics_names[1], scores[1]*100))

test_loss, test_accuracy = model1.evaluate(test_set, steps = 50)
print("The testing accuracy is: ", test_accuracy * 100, "%")
```

```
50/50 ━━━━━━━━━━━━━━━━━━━━ 8s 153ms/step - accuracy: 0.7337 - loss: 0.5069
The testing accuracy is:  74.03846383094788 %
```

TRANSFER LEARNING MODELS

1. EfficientNetB0

[14]:
```
from tensorflow.keras.applications import EfficientNetB0

base_model1 = EfficientNetB0(include_top=False, weights="imagenet", input_shape=(224, 224, 3), pooling="max")

# EfficientNetB0 already has pre-trained weights on ImageNet, so there's no need to load weights manually

base_model1.summary()
```

```
Downloading data from https://storage.googleapis.com/keras-applications/efficientnetb0_notop.h5
16705208/16705208 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Model: "efficientnetb0"
```

Evaluating EfficientNetB0 Model on the test set

[17]:
```
#scores = model1.evaluate_generator(test_set)
#print("\n%s: %.3f%%" % (model1.metrics_names[0], scores[0]*100))
#print("\n%s: %.3f%%" % (model1.metrics_names[1], scores[1]*100))

test_loss, test_accuracy = model2.evaluate(test_set, steps = 50)
print("The testing accuracy is: ", test_accuracy * 100, "%")
```

```
50/50 ━━━━━━━━━━━━━━━━━━━━ 5s 100ms/step - accuracy: 0.6417 - loss: 0.9667
The testing accuracy is:  62.5 %
```

2. EfficientNetB3

[18]:
```
from tensorflow.keras.applications import EfficientNetB3

base_model2 = EfficientNetB3(weights="imagenet",  # Use pre-trained weights from ImageNet
                             input_shape=(224, 224, 3),
                             pooling="max",  # Global average pooling
                             include_top=False)  # Exclude the fully connected layers

# Freeze the layers of EfficientNetB3 for transfer learning
for layer in base_model2.layers:
    layer.trainable = False

base_model2.summary()
```

```
Downloading data from https://storage.googleapis.com/keras-applications/efficientnetb3_notop.h5
43941136/43941136 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Model: "efficientnetb3"
```

[19]:
```
model3 = Sequential()
model3.add(base_model2)
model3.add(Flatten())

model3.add(Dense(128, activation = "relu"))
model3.add(Dense(64, activation = "relu"))
model3.add(Dense(32, activation = "relu"))
model3.add(Dense(1, activation = "sigmoid"))

# freeze the layers
for layer in base_model2.layers:
    layer.trainable = False

model3.compile(optimizer = "adam", loss = "binary_crossentropy", metrics = ["accuracy"])
```

[20]:
```
%%time

history = model3.fit(train_set, epochs = 20, validation_data = validation_set, steps_per_epoch = 100,
                             callbacks = [early_stopping_callbacks])
```

[13]:
```
#scores = model1.evaluate_generator(test_set)
#print("\n%s: %.3f%%" % (model1.metrics_names[0], scores[0]*100))
#print("\n%s: %.3f%%" % (model1.metrics_names[1], scores[1]*100))

test_loss, test_accuracy = model1.evaluate(test_set, steps = 50)
print("The testing accuracy is: ", test_accuracy * 100, "%")
```

```
50/50 ━━━━━━━━━━━━━━━━━━━━ 8s 153ms/step - accuracy: 0.7337 - loss: 0.5069
The testing accuracy is:  74.03846383094788 %
```

Evaluate the EffiecientNetB3 Model on the Test Set

[23]:
```
#scores = model1.evaluate_generator(test_set)
#print("\n%s: %.3f%%" % (model1.metrics_names[0], scores[0]*100))
#print("\n%s: %.3f%%" % (model1.metrics_names[1], scores[1]*100))

test_loss, test_accuracy = model3.evaluate(test_set, steps = 50)
print("The testing accuracy is: ", test_accuracy * 100, "%")
print("The testing loss is: ", test_loss * 100, "%")
```

```
50/50 ━━━━━━━━━━━━━━━━━━━━ 5s 95ms/step - accuracy: 0.6084 - loss: 0.7038
The testing accuracy is:  62.5 %
The testing loss is:  68.71474981307983 %
```

Thank you!