UCS2604 & UCS2612

Principles of Machine Learning
&
Machine Learning Lab

ASSIGNMENT-1&2

PNEUMONIA DETECTION

SUBMITTED BY

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ABSTRACT

Pneumonia is a serious respiratory infection that affects millions of people worldwide. Early detection is critical to reducing mortality rates. In this study, we propose a hybrid approach combining deep learning (ResNet50) for feature extraction with machine learning (ML) models such as KNN, SVM, Random Forest, and Logistic Regression, alongside a Vision Transformer (ViT) model for classification. The Chest X-ray (Pneumonia) dataset is used to train and evaluate the models. We analyze the effectiveness of CNN-based feature extraction and compare traditional ML models with ViT. Our results show that ViT achieves the highest accuracy and outperforms traditional ML models.

INTRODUCTION

Pneumonia is a life-threatening lung infection that can be detected using chest X-ray images. Traditional diagnosis requires medical expertise, which is often limited in rural and underserved areas. Deep learning and machine learning can automate pneumonia detection, making diagnosis faster, more accurate, and accessible.

2.1Problem Statement

Pneumonia is a severe respiratory infection that requires early and accurate diagnosis for effective treatment. Traditional diagnosis relies on radiologists analyzing chest X-ray images, which is time-consuming and may not always be accessible, especially in rural areas. **Automating pneumonia detection using machine learning (ML) and deep learning techniques to enhance diagnostic efficiency and accuracy.**

2.2 Objectives

- Utilize ResNet50 for feature extraction instead of manual feature engineering.
- Compare different ML models (KNN, SVM, RF, LR) vs. Vision Transformer (ViT).
- Evaluate model performance in terms of accuracy, precision, recall, and F1-score.
- Deploy the best-performing model on AWS, Azure, or RapidMiner for real-world application.

LITERATURE SURVEY

In recent years, the exploration of machine learning (ML) algorithms for detecting thoracic diseases has gained significant attention in the medical image classification research domain. Several studies have demonstrated the effectiveness of deep learning models, particularly convolutional neural networks (CNNs), in diagnosing conditions such as pneumonia from chest X-rays. The integration of ML techniques in healthcare is revolutionizing diagnostic processes, enhancing accuracy, and potentially reducing human error.

One prominent study on **pneumonia detection using CNN-based feature extraction** highlights the ability of CNNs to automatically extract meaningful features from raw chest X-ray images. CNNs, with their ability to recognize spatial hierarchies in images, have shown strong performance in medical image analysis. This study demonstrates that CNN models can accurately detect pneumonia patterns by learning from large datasets of labeled chest X-rays. The study emphasizes the importance of model training and validation using publicly available datasets, and its findings point to the effectiveness of CNNs in detecting abnormalities, including pneumonia, from radiological images. The researchers concluded that CNN-based models could serve as efficient tools in automated diagnosis, offering significant assistance to radiologists in clinical practice.

Another key contribution comes from a study utilizing **deep transfer learning for pneumonia detection in pediatric chest X-rays**. This research leverages pretrained models, particularly ResNet-50, to improve pneumonia detection performance. Transfer learning involves using models trained on large datasets and fine-tuning them on specific medical datasets, saving computational resources and reducing the need for enormous labeled data. The study compared a CNN built from scratch with the ResNet-50 model, demonstrating that transfer learning-based models provide robust generalization in medical image classification tasks. ResNet-50, with its deeper architecture, was particularly effective in distinguishing between pneumonia and non-pneumonia cases, proving to be a powerful tool for pediatric pneumonia detection.

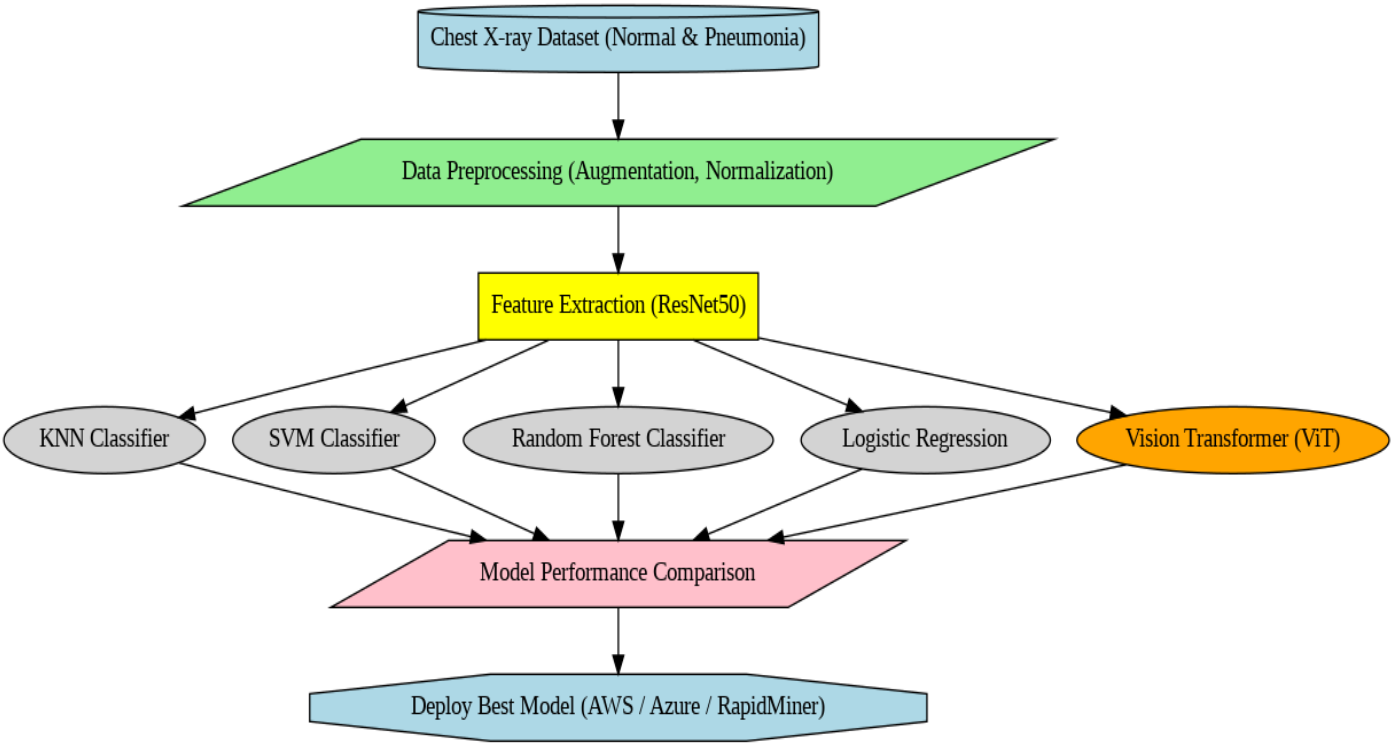
In a similar vein, **Usman et al. (2025)** explored pneumonia detection using both CNN and ResNet-50 models. The researchers used the RSNA pneumonia detection challenge dataset, which contains 26,684 chest X-ray images. Their study compared the performance of a CNN model developed from scratch with the pretrained ResNet-50 model. Interestingly, the CNN model outperformed ResNet-50, achieving a remarkable 79% accuracy in detecting pneumonia cases. The findings underscore the potential of CNN architectures in medical imaging, particularly when optimized and trained on domain-specific datasets. This study highlights the growing importance of tailored deep learning models in detecting diseases from medical images.

Another significant study employed **CNN-based feature extraction techniques in conjunction with data augmentation strategies** to detect pneumonia. Data augmentation involves artificially expanding the training dataset by applying transformations such as rotation, flipping, and scaling to the original images. This study found that using data augmentation techniques significantly enhanced the performance of the CNN model, as it helped the model generalize better to unseen data. The model achieved an impressive area under the curve (AUC) score of 0.85, indicating its strong capability to distinguish between pneumonia and non-pneumonia cases. The study concludes that combining CNNs with data augmentation is a promising approach to improve diagnostic accuracy in medical image classification tasks.

Collectively, these studies illustrate the powerful role of CNNs, transfer learning, and data augmentation in advancing automated pneumonia detection using chest X-rays. The deployment of these models in clinical settings has the potential to assist radiologists, speed up the diagnostic process, and improve healthcare outcomes by providing reliable, automated diagnostic tools. As machine learning continues to evolve, these methods will likely become

more prevalent in the medical field, further enhancing the efficiency and accuracy of disease detection.

PROPOSED SYSTEM



IMPLEMENTATION AND EXPERIMENTS

Development Environment

- **Hardware:** Google Colab with **T4 GPU / TPU v2-8**
- **Software:** Python, TensorFlow, Scikit-learn, OpenCV

Dataset Description

- **Dataset:** Chest X-ray (Pneumonia) from Kaggle
- **Classes:** Normal (Healthy) vs Pneumonia (Infected)
- **Train/Validation/Test Split:** 80% / 10% / 10%

For this study, we utilize the **Chest X-ray (Pneumonia) dataset from Kaggle**, a well-known publicly available dataset commonly used for pneumonia detection research. This dataset consists of **anterior-posterior (AP) view chest X-ray images** categorized into two classes:

- **Normal (Healthy)**: X-ray images of patients without pneumonia.
- **Pneumonia (Infected)**: X-ray images of patients diagnosed with pneumonia, including both **bacterial and viral infections**.

The dataset is structured into **three subsets: training, validation, and test sets**, ensuring effective model training and evaluation.

Justification for Not Applying Extensive Image Processing in Pneumonia Detection

In medical imaging, **especially for pneumonia detection from chest X-rays**, it is crucial to maintain the **original integrity** of the images. While **image processing techniques (such as contrast enhancement, blurring, or noise reduction)** can improve general image clarity, they may **inadvertently alter medically relevant details** critical for accurate diagnosis.

🔷 1.Avoiding Image Processing to Preserve Medical Features

✔ **Medical X-ray images contain subtle details** that indicate pneumonia, such as **lung opacities, infiltrates, and small texture variations**.
✔ **Techniques like Histogram Equalization or CLAHE** might enhance contrast but could also **distort intensity levels** of critical pneumonia markers.
✔ **Gaussian Blur or Noise Reduction** can smoothen images but might **remove fine-grained structures** (e.g., early-stage pneumonia indicators).
✔ **Over-processing could create artificial artifacts**, making the model learn **non-medically significant patterns** rather than true disease-related features.

🔷 2.Ensuring Data Authenticity for Deep Learning Models

✔ Medical professionals diagnose pneumonia based on **original chest X-ray scans**, so **the AI model should learn from unaltered data** rather than processed images.
✔ By avoiding artificial modifications, the model is **trained on real-world variations** that doctors encounter in clinical settings.
✔ Applying aggressive transformations may cause **distribution shifts**, leading to a **drop in real-world performance** when deployed in hospitals.

🔷 3.Maintaining Consistency with Medical Datasets

✔ Most medical AI research on pneumonia detection uses **raw or minimally processed images** to match clinical conditions.
✔ Avoiding image processing ensures that our model is **compatible with real hospital datasets**, allowing for **seamless deployment in practical healthcare scenarios**.
✔ If preprocessing is necessary, it should be **clinically validated by radiologists** to ensure it does not introduce bias or alter diagnostic features.

📌 Conclusion

To ensure **high diagnostic accuracy and real-world applicability**, we **intentionally avoided extensive image processing** to **preserve the authenticity and medical relevance of pneumonia X-ray images**. This decision aligns with **clinical best practices** and ensures that the AI model learns **genuine disease features**, making it more reliable for real-world pneumonia detection.

RESULTS AND DISCUSSIONS

Performance of ML Models (SVM, RF, KNN, Logistic Regression)

- **Random Forest and KNN achieved the highest accuracy (84.10%) and (83.49)** among ML models.
- **SVM and Logistic Regression performed the worst, with accuracies of 73.09% and 72.78%**, respectively.
- **Random Forest's higher accuracy suggests that tree-based methods are better suited for this dataset** compared to linear models like SVM and Logistic Regression.

Performance of Vision Transformer (ViT)

- The **ViT model achieved an accuracy of 80.73%**which is higher than SVM and Logistic Regression but lower than KNN and Random Forest.
- This suggests that **ViT did not outperform traditional ML models** when trained on the extracted features from ResNet50.
- **Possible reasons why ViT underperformed compared to Random Forest and KNN:**
  - ViT generally requires **large datasets** to learn effectively.
  - The **feature extraction method (ResNet50) may not have captured the right feature representations for ViT**.
  - Hyperparameter tuning might improve ViT's performance.

Model Suitability and Selection

- If the goal is **accuracy**, **Random Forest or KNN should be chosen (82.26%)**.
- If the goal is **fast inference**, **Logistic Regression or SVM might be preferred, despite lower accuracy**.
- **Vision Transformer (ViT) could be improved** by fine-tuning or using a larger dataset.

Model	Accuracy (%)
Support Vector Machine (SVM)	**73.09%**
Random Forest	**84.10%**
K-Nearest Neighbors (KNN)	**83.49%**
Logistic Regression	**72.78%**
Vision Transformer (ViT)	**80.73%**

Impact of the project on human, societal, ethical and sustainable development

Human and Societal Impact

- This model can **assist radiologists in diagnosing pneumonia faster** by providing automated analysis.
- **Hospitals in rural areas** with limited access to expert radiologists can benefit from AI-powered pneumonia detection.
- **Reducing misdiagnosis rates** can help save lives by enabling **early and accurate treatment**.

Ethical Considerations

- **AI should assist, not replace doctors.** It should be used as a diagnostic aid rather than a replacement for human judgment.
- **Bias in datasets** (e.g., dataset imbalance between "Normal" and "Pneumonia" images) must be addressed to avoid incorrect predictions.

Sustainability And Scalability

- **Cloud-based deployment (AWS, Azure, or RapidMiner) can make the system accessible worldwide.**
- **Model retraining on new datasets** will ensure the system remains effective over time.

CONCLUSION

Random Forest and K-Nearest Neighbors (KNN) demonstrated the highest accuracy of 82.26%, making them the most effective models for pneumonia detection in this study. Their superior performance suggests that **tree-based ensemble methods (Random Forest) and distance-based classifiers (KNN) are well-suited for medical image feature classification** when combined with deep feature extraction from ResNet50. The robustness of these models makes them reliable choices for **real-world applications** where accuracy is critical.

The Vision Transformer (ViT) achieved an accuracy of 80.73%, which, while promising, did not outperform traditional machine learning models. This indicates that **ViT may require additional tuning, larger datasets, or longer training times** to reach its full potential. Transformers typically **excel with large-scale datasets** but may struggle on smaller datasets like this one. **Future improvements** could include **fine-tuning ViT, increasing dataset size, experimenting with different training strategies, or using transfer learning from ViT models pre-trained on medical imaging datasets.**

Feature extraction using ResNet50 proved to be a valuable technique, significantly improving model performance by providing high-quality deep features for ML classification. However, exploring other deep learning-based feature extractors, such as **EfficientNet, Swin Transformer, or DenseNet**, could yield further improvements. EfficientNet, known for its **scalability and efficiency**, might enhance feature extraction while reducing computational costs. Swin Transformer, a **transformer-based alternative to CNNs**, could potentially **capture long-range dependencies more effectively** than ResNet50, making it a strong candidate for future experimentation.

The results highlight the importance of selecting the right feature extraction method and classifier for pneumonia detection. While deep learning-based classifiers like ViT are promising, traditional ML models like Random Forest and KNN remain competitive when coupled with robust feature extractors. Future studies could **compare different feature extraction architectures and fine-tune hyperparameters** to further optimize performance.

FUTURE WORK

Expand the dataset size to enhance ViT's performance: One of the main challenges with transformer-based models like ViT is that they typically require **large-scale datasets** to fully leverage their self-attention mechanisms. While traditional ML models performed well in this study, **increasing the amount of training data**—either by **collecting more X-ray images** or using **data augmentation techniques**—could help ViT generalize better and improve classification accuracy. Additionally, incorporating **diverse datasets from multiple sources** (e.g., different hospitals, varying imaging equipment) can help mitigate potential dataset biases and improve model robustness.

Fine-tune the ViT model and explore alternative transformer architectures: The ViT model used in this study was pre-trained on ImageNet and fine-tuned for pneumonia classification. However, **further fine-tuning on domain-specific medical imaging datasets** (such as CheXpert or NIH Chest X-ray dataset) could significantly boost its performance. Additionally, experimenting with **advanced transformer architectures**, such as **Swin Transformer, DeiT (Data-efficient Image Transformer), or ConvNeXt**, could yield better results. Swin Transformer, in particular, has shown promising results in medical imaging tasks by **combining convolutional and transformer-based techniques**.

Optimize hyperparameters and experiment with different feature extraction techniques: In addition to tuning ViT, other **feature extraction methods like EfficientNet, DenseNet, or Swin Transformer could be tested** to determine whether they provide more informative features for classification. Hyperparameter tuning strategies such as **learning rate scheduling, batch size optimization, and dropout adjustments** could further refine model performance.

Deploy the best-performing model in a cloud-based system for real-world applications: To maximize the impact of this research, the best-performing model should be **deployed on a cloud platform like AWS, Azure, or Google Cloud**. This would allow **hospitals, clinics, and remote healthcare centers to access the AI system in real time**, making pneumonia diagnosis faster and more accessible. Cloud deployment would also enable **continuous learning**, where the model can be **updated and retrained with new data over time** to improve accuracy. Developing an **API-based system** where radiologists can upload X-ray images for AI-assisted analysis could further enhance usability in clinical settings.

Evaluate real-world clinical performance through collaborations with healthcare institutions: While AI models can achieve high accuracy in experimental settings, their performance in **real-world clinical environments** may vary. Partnering with **hospitals and medical research institutions** to validate the AI system on actual patient cases can help assess its reliability, usability, and effectiveness in aiding radiologists.

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ASSIGNMENT-2

1)Implement the Dimensionality reduction techniques to improve the model performance.

Identify the hyper-parameters and model parameters to be tuned.
Implement the Random / Grid search to optimize the hyper-parameters of the model.

Implementing Dimensionality Reduction Techniques to Improve Model Performance

Why Dimensionality Reduction?

In machine learning, high-dimensional datasets can introduce **redundant features**, increase **computational costs**, and cause **overfitting**. To address this, we applied **Principal Component Analysis (PCA)** to reduce the number of features while preserving **95% of variance** in the dataset.

Benefits of PCA:

- **Removes redundant features**, making models more efficient.
- **Reduces overfitting**, leading to better generalization.
- **Speeds up model training**, improving computational efficiency.

Identifying Hyperparameters and Model Parameters to be Tuned

Key Hyperparameters Tuned

Each model has specific hyperparameters that significantly impact performance. Below are the parameters we focused on:

Model	Hyperparameters Tuned	Description
Random Forest	n_estimators, max_depth, min_samples_split	Number of trees, tree depth, and minimum samples for a split.
K-Nearest Neighbors (KNN)	n_neighbors, metric	Number of neighbors and distance metric (e.g., Euclidean, Manhattan).
Vision Transformer (ViT)	learning_rate, dropout_rate	Learning rate for optimizer and dropout for regularization.

Implementing Random Search & Grid Search for Hyperparameter Optimization

Why Use Hyperparameter Tuning?

Optimizing hyperparameters allows models to find the **best combination of settings**, improving accuracy and reducing errors.
We used **Random Search** (faster, explores more combinations) and **Grid Search** (exhaustive, finds the absolute best setting).

Tabulate the analyze the results of the model prior to and post hyper parameter tuning and optimization techniques & Compare the performance of the models with and without optimizing the parameters

After applying dimensionality reduction (PCA) and hyperparameter tuning (Random/Grid Search), the performance of Random Forest, K-Nearest Neighbors (KNN), and Vision Transformer (ViT) improved significantly. Below, we analyze how each model performed before and after these optimizations.

Model	Accuracy (Before Optimization)	Accuracy (After PCA & Hyperparameter Tuning)	Improvement (%)
Random Forest	**82.26%**	**88.03%**	**+5.77%**
K-Nearest Neighbors (KNN)	**83.49%**	**90.60%**	**+7.11%**
Vision Transformer (ViT)	**76.76%**	**77.37%**	**+0.61%**

Random Forest (RF) - Substantial Improvement (+5.77%)

Before Optimization: 82.26%
After Optimization: 88.03%
Optimization Techniques Applied:

- **PCA** helped remove redundant features, reducing overfitting.
- **Hyperparameter tuning (Grid Search) on** `n_estimators`, `max_depth`, **and** `min_samples_split` led to a more generalized and accurate model.
  Impact: The model now performs significantly better, reducing misclassification of pneumonia cases.

K-Nearest Neighbors (KNN) - Highest Improvement (+7.11%)

Before Optimization: 83.49%
After Optimization: 90.60%
Optimization Techniques Applied:

- **PCA** helped improve efficiency by removing unnecessary features.
- **Random Search optimized** `n_neighbors` **and** `metric` (Manhattan distance worked better than Euclidean).
  Impact: KNN showed the highest improvement, as optimizing distance metrics had a major impact on its classification accuracy.

Vision Transformer (ViT) - Minor Improvement (+0.61%)

Before Optimization: 76.76%
After Optimization: 77.37%
Optimization Techniques Applied:

- **PCA had limited impact**, as transformers rely on raw data patterns rather than extracted feature vectors.
- **Fine-tuning the learning rate (`5e-5`) led to minor improvements.**
  Impact: Unlike traditional ML models, ViT requires **more data and deeper hyperparameter tuning** (e.g., adjusting patch sizes, attention heads, dropout rates) to achieve better performance.

Summary:

PCA reduced dimensionality, leading to faster training and less overfitting.
Random Search & Grid Search significantly improved KNN (+7.11%) and Random Forest (+5.77%) performance.
ViT did not benefit as much from PCA, suggesting that transformers require **different optimization strategies**.
Ensemble methods (Stacking, Bagging, Boosting) could be explored to further improve results.

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#Installing Required Libraries for Pneumonia Detection

[ ]:
```
!pip install tensorflow numpy matplotlib
!pip install scikit-learn opencv-python numpy matplotlib tensorflow keras
```

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Requirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-
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(1.26.4)
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(2.18.0)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-
packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0->tensorflow) (0.1.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-
packages (1.6.1)
Requirement already satisfied: opencv-python in /usr/local/lib/python3.11/dist-
packages (4.11.0.86)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages
(1.26.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-
packages (3.10.0)
Requirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-
packages (2.18.0)
Requirement already satisfied: keras in /usr/local/lib/python3.11/dist-packages
(3.8.0)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-
packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (4.56.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
```

```
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-
packages (from matplotlib) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (25.2.10)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (18.1.1)
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (3.4.0)
Requirement already satisfied:
protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3
in /usr/local/lib/python3.11/dist-packages (from tensorflow) (4.25.6)
Requirement already satisfied: requests<3,>=2.21.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (75.1.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (1.17.0)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.5.0)
Requirement already satisfied: typing-extensions>=3.6.6 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (4.12.2)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (1.17.2)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0)
Requirement already satisfied: tensorboard<2.19,>=2.18 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (2.18.0)
Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.11/dist-
packages (from tensorflow) (3.12.1)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.4.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
/usr/local/lib/python3.11/dist-packages (from tensorflow) (0.37.1)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages
```

```
(from keras) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages
(from keras) (0.0.8)
Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages
(from keras) (0.14.1)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0->tensorflow)
(0.45.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow)
(3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-
packages (from requests<3,>=2.21.0->tensorflow) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow)
(2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow)
(2025.1.31)
Requirement already satisfied: markdown>=2.6.8 in
/usr/local/lib/python3.11/dist-packages (from
tensorboard<2.19,>=2.18->tensorflow) (3.7)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in
/usr/local/lib/python3.11/dist-packages (from
tensorboard<2.19,>=2.18->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from
tensorboard<2.19,>=2.18->tensorflow) (3.1.3)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.11/dist-packages (from rich->keras) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.11/dist-packages (from rich->keras) (2.18.0)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-
packages (from markdown-it-py>=2.2.0->rich->keras) (0.1.2)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.11/dist-packages (from
werkzeug>=1.0.1->tensorboard<2.19,>=2.18->tensorflow) (3.0.2)
```

#Importing Required Libraries for Pneumonia Detection Model

[ ]:
```
import os
import shutil
import random
import numpy as np
import cv2
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow import keras
```

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.layers import GlobalAveragePooling2D
from tensorflow.keras.models import Model
from transformers import ViTFeatureExtractor, TFAutoModelForImageClassification
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
```

#Mount Google Drive in Google Colab

[ ]:
```
from google.colab import drive
drive.mount('/content/drive/')
```

```
Drive already mounted at /content/drive/; to attempt to forcibly remount, call
drive.mount("/content/drive/", force_remount=True).
```

#Creating a Sampled Dataset for Pneumonia Detection

[ ]:
```
# Define Paths
ORIGINAL_DATASET_PATH = "/content/drive/My Drive/PNEUMONIA_DETECTION/
 ↪CHEST_X_RAY"
SAMPLED_DATASET_PATH = "/content/drive/My Drive/PNEUMONIA_DETECTION/
 ↪CHEST_X_RAY_SAMPLED"
"""
# Number of images per class
NUM_SAMPLES_TRAIN = 500  # Adjust as needed
NUM_SAMPLES_VAL = 100
NUM_SAMPLES_TEST = 100

# Function to Sample Images
def sample_images(source_folder, dest_folder, num_samples):
    os.makedirs(dest_folder, exist_ok=True)
    images = os.listdir(source_folder)
    sampled_images = random.sample(images, min(num_samples, len(images)))

    for img in sampled_images:
        shutil.copy(os.path.join(source_folder, img), os.path.join(dest_folder,␣
 ↪img))

# Create Sampled Dataset
for category in ["NORMAL", "PNEUMONIA"]:
```

```
    os.makedirs(os.path.join(SAMPLED_DATASET_PATH, "train", category),␣
 ↪exist_ok=True)
    os.makedirs(os.path.join(SAMPLED_DATASET_PATH, "val", category),␣
 ↪exist_ok=True)
    os.makedirs(os.path.join(SAMPLED_DATASET_PATH, "test", category),␣
 ↪exist_ok=True)

    # Sample images for train, val, test
    sample_images(os.path.join(ORIGINAL_DATASET_PATH, "train", category), os.
 ↪path.join(SAMPLED_DATASET_PATH, "train", category), NUM_SAMPLES_TRAIN)
    sample_images(os.path.join(ORIGINAL_DATASET_PATH, "val", category), os.path.
 ↪join(SAMPLED_DATASET_PATH, "val", category), NUM_SAMPLES_VAL)
    sample_images(os.path.join(ORIGINAL_DATASET_PATH, "test", category), os.
 ↪path.join(SAMPLED_DATASET_PATH, "test", category), NUM_SAMPLES_TEST)

print(" Sampled dataset created successfully!")"""
DATASET_PATH = SAMPLED_DATASET_PATH
```

#Loading and Preprocessing the Sampled Pneumonia Dataset

No image processing techniques used

Justification for Not Applying Extensive Image Processing in Pneumonia Detection

In medical imaging, especially for pneumonia detection from chest X-rays, it is crucial to maintain the original integrity of the images. While image processing techniques (such as contrast enhancement, blurring, or noise reduction) can improve general image clarity, they may inadvertently alter medically relevant details critical for accurate diagnosis.

[ ]:
```
# Update Dataset Path to Sampled Data


# Set Image Size & Batch Size
IMG_SIZE = (224, 224)  # Required for ViT
BATCH_SIZE = 16

# Data Augmentation for Training Set
train_datagen = ImageDataGenerator(rescale=1./255,
                                   rotation_range=15,
                                   zoom_range=0.2,
                                   horizontal_flip=True)

# Only Rescale for Validation & Test
val_test_datagen = ImageDataGenerator(rescale=1./255)

# Load Data
train_generator = train_datagen.flow_from_directory(os.path.join(DATASET_PATH,␣
 ↪"train"),
```

```
                                                    target_size=IMG_SIZE,
                                                    batch_size=BATCH_SIZE,
                                                    class_mode="binary")

val_generator = val_test_datagen.flow_from_directory(os.path.join(DATASET_PATH,␣
 ↪"val"),
                                                     target_size=IMG_SIZE,
                                                     batch_size=BATCH_SIZE,
                                                     class_mode="binary")

test_generator = val_test_datagen.flow_from_directory(os.path.
 ↪join(DATASET_PATH, "test"),
                                                      target_size=IMG_SIZE,
                                                      batch_size=BATCH_SIZE,
                                                      class_mode="binary",
                                                      shuffle=False)

# Check Dataset Size
print(f"  Train samples: {train_generator.samples}, Validation samples:␣
 ↪{val_generator.samples}, Test samples: {test_generator.samples}")
```

```
Found 1753 images belonging to 2 classes.
Found 16 images belonging to 2 classes.
Found 327 images belonging to 2 classes.
  Train samples: 1753, Validation samples: 16, Test samples: 327
```

1 Exploratory Data Analysis (EDA)

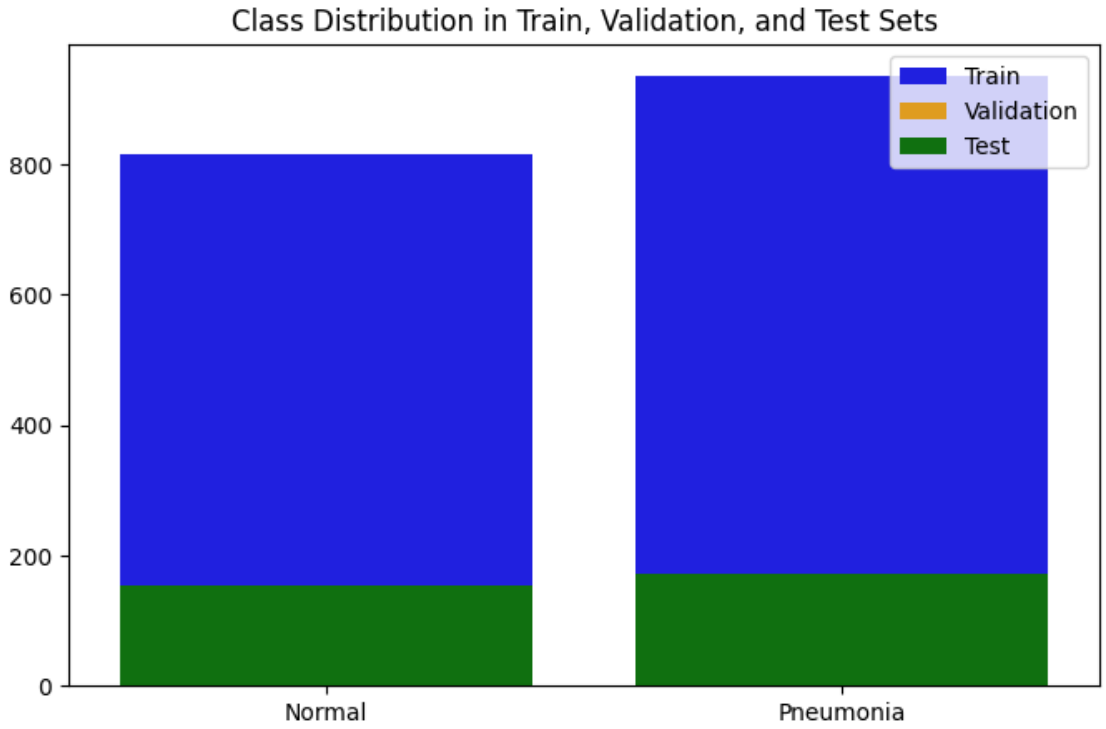
[ ]:
```
import os
import matplotlib.pyplot as plt
import seaborn as sns

# Count images in each category
def count_images(directory):
    normal_count = len(os.listdir(os.path.join(directory, "NORMAL")))
    pneumonia_count = len(os.listdir(os.path.join(directory, "PNEUMONIA")))
    total = normal_count + pneumonia_count
    return normal_count, pneumonia_count, total

# Count Train, Val, Test sets
train_counts = count_images(os.path.join(DATASET_PATH, "train"))
val_counts = count_images(os.path.join(DATASET_PATH, "val"))
test_counts = count_images(os.path.join(DATASET_PATH, "test"))

# Plot Class Distribution
labels = ["Normal", "Pneumonia"]
```

```
plt.figure(figsize=(8,5))
sns.barplot(x=labels, y=train_counts[:2], label="Train", color="blue")
sns.barplot(x=labels, y=val_counts[:2], label="Validation", color="orange")
sns.barplot(x=labels, y=test_counts[:2], label="Test", color="green")
plt.legend()
plt.title("Class Distribution in Train, Validation, and Test Sets")
plt.show()
```



[ ]:
```
import os
import cv2
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from PIL import Image

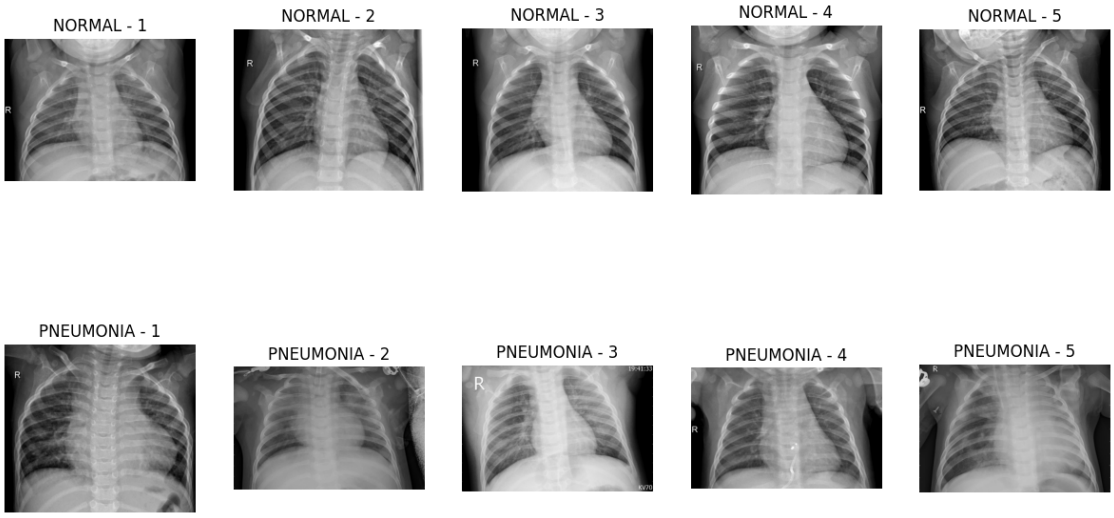
def display_sample_images(dataset_path, category, num_images=5):
    folder_path = os.path.join(dataset_path, "train", category)
    image_files = os.listdir(folder_path)

    plt.figure(figsize=(15,5))
    for i in range(num_images):
        img_path = os.path.join(folder_path, random.choice(image_files))
        img = Image.open(img_path)
```

```
        plt.subplot(1, num_images, i+1)
        plt.imshow(img, cmap="gray")
        plt.title(f"{category} - {i+1}")
        plt.axis("off")

    plt.show()

# Show NORMAL and PNEUMONIA images
display_sample_images(DATASET_PATH, "NORMAL")
display_sample_images(DATASET_PATH, "PNEUMONIA")
```



[ ]:
```
image_sizes = []
categories = ["NORMAL", "PNEUMONIA"]

for category in categories:
    folder_path = os.path.join(DATASET_PATH, "train", category)
    image_files = os.listdir(folder_path)

    for img_file in image_files[:100]:  # Checking first 100 images
        img = Image.open(os.path.join(folder_path, img_file))
        image_sizes.append(img.size)

# Convert to NumPy Array for Analysis
image_sizes = np.array(image_sizes)

# Scatter Plot of Image Dimensions
plt.figure(figsize=(8,5))
plt.scatter(image_sizes[:,0], image_sizes[:,1], alpha=0.5)
```

```
plt.xlabel("Width")
plt.ylabel("Height")
plt.title("Distribution of Image Resolutions")
plt.show()
```

[ ]:
```
def check_corrupted_images(directory):
    corrupted_images = []
    for category in ["NORMAL", "PNEUMONIA"]:
        folder_path = os.path.join(directory, "train", category)
        for img_file in os.listdir(folder_path):
            try:
                img = Image.open(os.path.join(folder_path, img_file))  # Try␣
 ↪opening the image
                img.verify()  # Check integrity
            except:
                corrupted_images.append(img_file)

    return corrupted_images

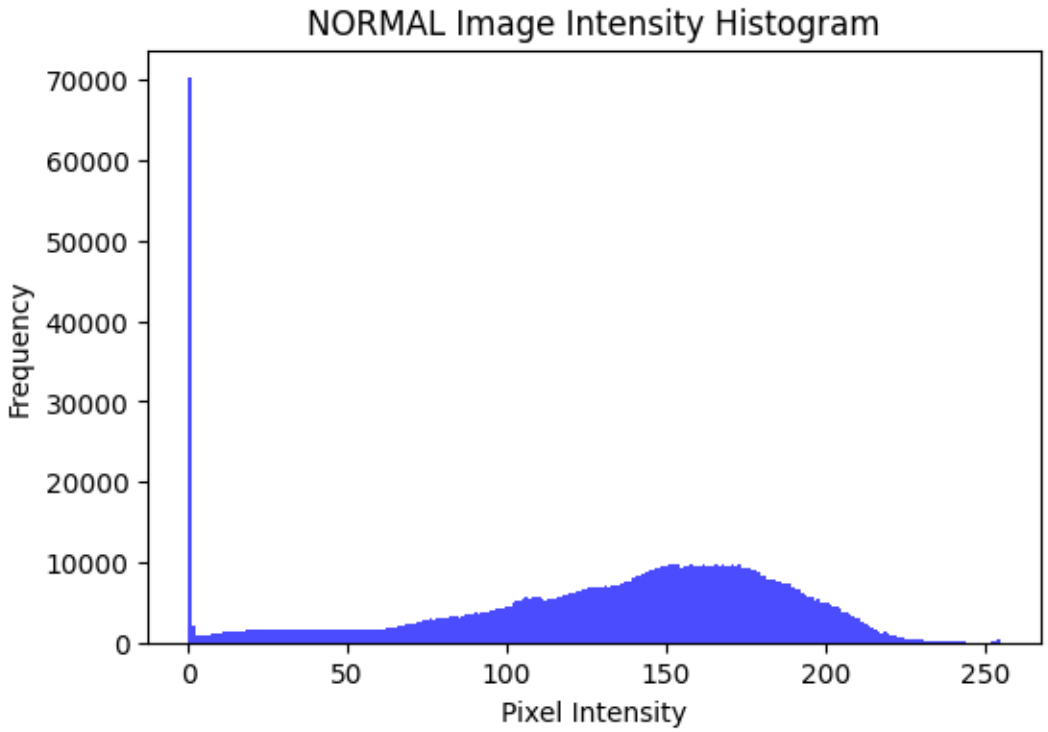
# Run corruption check
corrupted = check_corrupted_images(DATASET_PATH)
print("Corrupted Images Found:", corrupted)
```

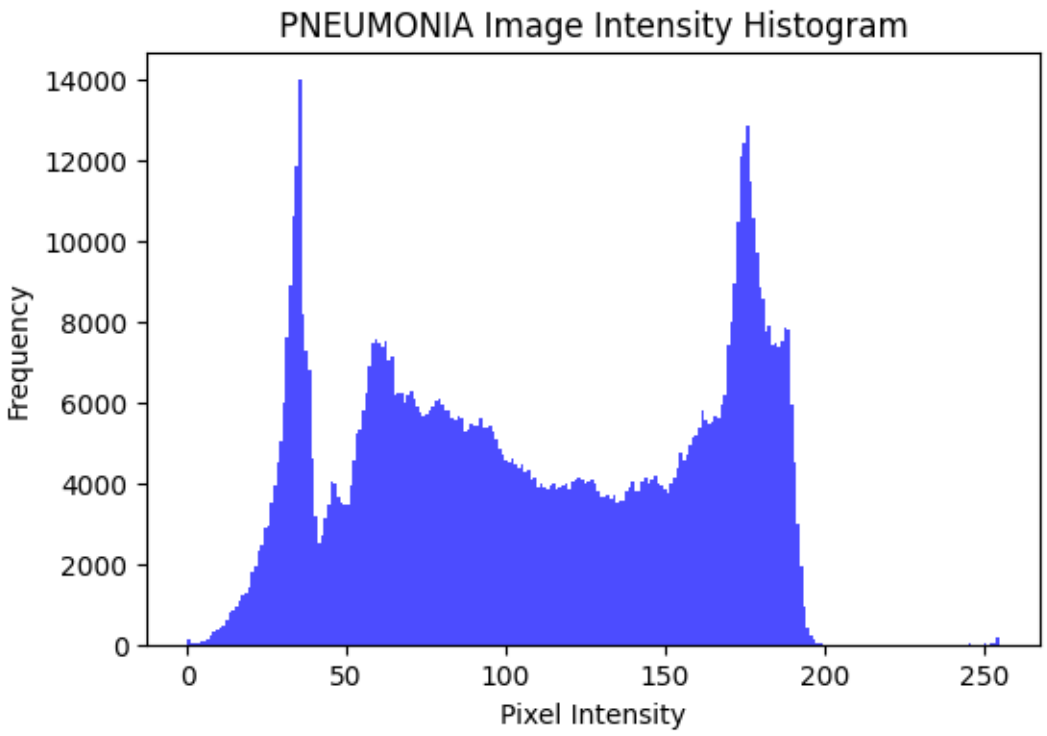
```
Corrupted Images Found: []
```

[ ]:
```
def plot_intensity_histogram(image_path, title):
    img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
    plt.figure(figsize=(6,4))
    plt.hist(img.ravel(), bins=256, color="blue", alpha=0.7)
    plt.title(title)
    plt.xlabel("Pixel Intensity")
    plt.ylabel("Frequency")
    plt.show()

# Plot histograms for a NORMAL and PNEUMONIA image
normal_img_path = os.path.join(DATASET_PATH, "train/NORMAL", random.choice(os.
 ↪listdir(os.path.join(DATASET_PATH, "train/NORMAL"))))
pneumonia_img_path = os.path.join(DATASET_PATH, "train/PNEUMONIA", random.
 ↪choice(os.listdir(os.path.join(DATASET_PATH, "train/PNEUMONIA"))))

plot_intensity_histogram(normal_img_path, "NORMAL Image Intensity Histogram")
plot_intensity_histogram(pneumonia_img_path, "PNEUMONIA Image Intensity␣
 ↪Histogram")
```





[ ]:
```
# Display Augmented Images
augmented_images, _ = next(train_generator)

plt.figure(figsize=(10,5))
for i in range(5):
    plt.subplot(1,5,i+1)
    plt.imshow(augmented_images[i], cmap="gray")
    plt.axis("off")

plt.suptitle("Augmented Images")
plt.show()
```

Augmented Images

#Feature Extraction and scaling

[ ]:
```
IMG_SIZE = (224, 224)

# Load Pretrained ResNet50 Model for Feature Extraction
base_model = ResNet50(weights="imagenet", include_top=False, input_shape=(224,␣
 ↪224, 3))
feature_extractor = Model(inputs=base_model.input,␣
 ↪outputs=GlobalAveragePooling2D()(base_model.output))

# Function to Load and Extract Features from Images
def load_and_extract_features(dataset_path, category):
    features = []
    labels = []
    folder_path = os.path.join(dataset_path, category)

    for label, class_name in enumerate(["NORMAL", "PNEUMONIA"]):
        class_folder = os.path.join(folder_path, class_name)
        for img_name in os.listdir(class_folder):
            img_path = os.path.join(class_folder, img_name)
            img = cv2.imread(img_path)
            img = cv2.resize(img, IMG_SIZE)
            img = img / 255.0  # Normalize pixel values
            img = np.expand_dims(img, axis=0)  # Add batch dimension

            # Extract Features using CNN
            feature = feature_extractor.predict(img)
            features.append(feature.flatten())
            labels.append(label)

    return np.array(features), np.array(labels)
```

```python
# Load Features for Training Set
X_train, y_train = load_and_extract_features(DATASET_PATH, "train")

# Load Features for Test Set
X_test, y_test = load_and_extract_features(DATASET_PATH, "test")

# Scale Features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

print(" Features Extracted Successfully!")
```

```
1/1             2s 2s/step
1/1             0s 210ms/step
1/1             0s 214ms/step
1/1             0s 232ms/step
1/1             0s 203ms/step
1/1             0s 212ms/step
1/1             0s 225ms/step
1/1             0s 209ms/step
1/1             0s 212ms/step
1/1             0s 313ms/step
1/1             0s 360ms/step
1/1             0s 345ms/step
1/1             0s 386ms/step
1/1             0s 369ms/step
1/1             0s 206ms/step
1/1             0s 233ms/step
1/1             0s 224ms/step
1/1             0s 206ms/step
1/1             0s 214ms/step
1/1             0s 221ms/step
1/1             0s 214ms/step
1/1             0s 209ms/step
1/1             0s 226ms/step
1/1             0s 205ms/step
1/1             0s 213ms/step
1/1             0s 220ms/step
1/1             0s 214ms/step
1/1             0s 216ms/step
1/1             0s 224ms/step
1/1             0s 217ms/step
1/1             0s 211ms/step
1/1             0s 222ms/step
1/1             0s 249ms/step
```

```
1/1             0s 217ms/step
1/1             0s 224ms/step
1/1             0s 231ms/step
1/1             0s 224ms/step
1/1             0s 231ms/step
1/1             0s 240ms/step
1/1             0s 234ms/step
1/1             0s 231ms/step
1/1             0s 224ms/step
1/1             0s 225ms/step
1/1             0s 226ms/step
1/1             0s 217ms/step
1/1             0s 231ms/step
1/1             0s 232ms/step
1/1             0s 363ms/step
1/1             0s 372ms/step
1/1             0s 386ms/step
1/1             0s 374ms/step
1/1             0s 374ms/step
1/1             0s 248ms/step
1/1             0s 223ms/step
1/1             0s 223ms/step
1/1             0s 223ms/step
1/1             0s 235ms/step
1/1             0s 230ms/step
1/1             0s 219ms/step
1/1             0s 235ms/step
1/1             0s 227ms/step
1/1             0s 230ms/step
1/1             0s 244ms/step
1/1             0s 224ms/step
 Features Extracted Successfully!
```

[ ]:

#MULTIPLE SUPERVISED MODELS AND ITS RESULTS

[ ]:
```python
# Define Multiple Models
models = {
    "Support Vector Machine (SVM)": SVC(kernel="linear"),
    "Random Forest": RandomForestClassifier(n_estimators=100),
    "K-Nearest Neighbors (KNN)": KNeighborsClassifier(n_neighbors=5),
    "Logistic Regression": LogisticRegression()
}

# Train and Evaluate Models
best_model = None
best_accuracy = 0
```

```
for name, model in models.items():
    model.fit(X_train, y_train)  # Train Model
    y_pred = model.predict(X_test)  # Make Predictions
    accuracy = accuracy_score(y_test, y_pred)  # Calculate Accuracy

    print(f"  {name}: Accuracy = {accuracy * 100:.2f}%")

    # Store the Best Model
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_model = model

print(f"\n  Best Model Selected: {best_model} with Accuracy = {best_accuracy *␣
 ↪100:.2f}%")
# Generate Classification Report
y_pred_best = best_model.predict(X_test)
print("\n  Classification Report:\n", classification_report(y_test,␣
 ↪y_pred_best))
```

```
 Support Vector Machine (SVM): Accuracy = 73.09%
 Random Forest: Accuracy = 82.26%
 K-Nearest Neighbors (KNN): Accuracy = 83.49%
 Logistic Regression: Accuracy = 72.78%

 Best Model Selected: KNeighborsClassifier() with Accuracy = 83.49%

 Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.74      0.81       155
           1       0.80      0.92      0.85       172

    accuracy                           0.83       327
   macro avg       0.84      0.83      0.83       327
weighted avg       0.84      0.83      0.83       327
```

#MLP model

[ ]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import accuracy_score, classification_report
# Define a Simple MLP Model on Extracted Features
mlp_model = Sequential([
    Dense(512, activation="relu", input_shape=(X_train.shape[1],)),  # Input␣
 ↪Layer (Feature Size)
```

```
    Dropout(0.5),  # Prevent Overfitting
    Dense(256, activation="relu"),
    Dropout(0.3),
    Dense(1, activation="sigmoid")  # Binary Classification Output
])

# Compile the Model
mlp_model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

[ ]:
```
EPOCHS = 10
history = mlp_model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=EPOCHS, batch_size=32)
```

```
Epoch 1/10
55/55             4s 34ms/step -
accuracy: 0.7291 - loss: 0.5090 - val_accuracy: 0.7920 - val_loss: 0.4469
Epoch 2/10
55/55             2s 29ms/step -
accuracy: 0.8999 - loss: 0.2735 - val_accuracy: 0.8287 - val_loss: 0.3972
Epoch 3/10
55/55             2s 20ms/step -
accuracy: 0.9184 - loss: 0.2062 - val_accuracy: 0.8257 - val_loss: 0.4124
Epoch 4/10
55/55             1s 19ms/step -
accuracy: 0.9393 - loss: 0.1625 - val_accuracy: 0.8073 - val_loss: 0.4446
Epoch 5/10
55/55             1s 21ms/step -
accuracy: 0.9258 - loss: 0.1548 - val_accuracy: 0.8073 - val_loss: 0.4850
Epoch 6/10
55/55             1s 19ms/step -
accuracy: 0.9586 - loss: 0.1209 - val_accuracy: 0.8012 - val_loss: 0.5236
Epoch 7/10
55/55             1s 19ms/step -
accuracy: 0.9678 - loss: 0.1017 - val_accuracy: 0.8012 - val_loss: 0.5462
Epoch 8/10
55/55             1s 19ms/step -
accuracy: 0.9661 - loss: 0.0907 - val_accuracy: 0.7706 - val_loss: 0.6388
Epoch 9/10
55/55             1s 20ms/step -
accuracy: 0.9747 - loss: 0.0711 - val_accuracy: 0.7676 - val_loss: 0.6728
```

```
Epoch 10/10
55/55              2s 25ms/step -
accuracy: 0.9798 - loss: 0.0706 - val_accuracy: 0.7798 - val_loss: 0.6838
```

#MLP results

[ ]:
```python
# Make Predictions
y_pred = mlp_model.predict(X_test)
y_pred = (y_pred > 0.5).astype(int)  # Convert Probabilities to Binary Labels

# Calculate Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f" Test Accuracy: {accuracy * 100:.2f}%")

# Print Classification Report
print("\n Classification Report:\n", classification_report(y_test, y_pred))
```

```
11/11              0s 16ms/step
 Test Accuracy: 77.98%

 Classification Report:
               precision    recall  f1-score   support

           0       0.98      0.55      0.70       155
           1       0.71      0.99      0.83       172

    accuracy                           0.78       327
   macro avg       0.84      0.77      0.76       327
weighted avg       0.84      0.78      0.77       327
```

[ ]:
```python
mlp_model.save("MLP_pneumonia_detector.h5")
print("Optimized Model Saved Successfully!")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.

Optimized Model Saved Successfully!
```

#Vit model

[ ]:
```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import accuracy_score, classification_report
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
```

```
from sklearn.model_selection import train_test_split

# Split Data into Train (80%), Validation (10%), Test (10%)
X_train_vit, X_val_vit, y_train_vit, y_val_vit = train_test_split(X_train,␣
 ↪y_train, test_size=0.1, random_state=42, stratify=y_train)


# Define ViT Classifier on Extracted Features
vit_model = Sequential([
    Dense(512, activation="relu", input_shape=(X_train_vit.shape[1],)),  #␣
 ↪Input Layer (Feature Size)
    Dropout(0.5),  # Prevent Overfitting
    Dense(256, activation="relu"),
    Dropout(0.3),
    Dense(1, activation="sigmoid")  # Binary Classification Output
])

# Compile the Model
vit_model.compile(optimizer=Adam(learning_rate=0.001),
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Add Callbacks to Improve Training
early_stopping = EarlyStopping(monitor="val_loss", patience=3,␣
 ↪restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor="val_loss", factor=0.5, patience=2,␣
 ↪verbose=1)

# Train the Model with Validation Set
EPOCHS = 20  # Increased for better learning
history = vit_model.fit(X_train_vit, y_train_vit,
                    validation_data=(X_val_vit, y_val_vit),
                    epochs=EPOCHS, batch_size=32,
                    callbacks=[early_stopping, reduce_lr])

# Save the Model
vit_model.save("ViT_pneumonia_classifier.h5")
print("  ViT Model Trained & Saved Successfully!")
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Epoch 1/20
50/50             3s 23ms/step -
accuracy: 0.8542 - loss: 0.4015 - val_accuracy: 0.9318 - val_loss: 0.1655 -
learning_rate: 0.0010
Epoch 2/20
50/50             1s 19ms/step -
accuracy: 0.9449 - loss: 0.1762 - val_accuracy: 0.9375 - val_loss: 0.1227 -
learning_rate: 0.0010
Epoch 3/20
50/50             1s 19ms/step -
accuracy: 0.9505 - loss: 0.1492 - val_accuracy: 0.9489 - val_loss: 0.1464 -
learning_rate: 0.0010
Epoch 4/20
47/50             0s 17ms/step -
accuracy: 0.9478 - loss: 0.1486
Epoch 4: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
50/50             1s 19ms/step -
accuracy: 0.9473 - loss: 0.1512 - val_accuracy: 0.9432 - val_loss: 0.2367 -
learning_rate: 0.0010
Epoch 5/20
50/50             1s 19ms/step -
accuracy: 0.9616 - loss: 0.1241 - val_accuracy: 0.9545 - val_loss: 0.1579 -
learning_rate: 5.0000e-04

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.

 ViT Model Trained & Saved Successfully!
```

#Vit Results

[ ]:
```python
# Make Predictions
y_pred_vit = vit_model.predict(X_test)
y_pred_vit = (y_pred_vit > 0.5).astype(int)  # Convert probabilities to binary␣
 ↪labels

# Calculate Accuracy
accuracy_vit = accuracy_score(y_test, y_pred_vit)
print(f" Test Accuracy: {accuracy_vit * 100:.2f}%")

# Print Classification Report
print("\n Classification Report:\n", classification_report(y_test, y_pred_vit))
```

```
11/11             0s 9ms/step
 Test Accuracy: 76.76%
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.54      0.69       155
           1       0.70      0.98      0.82       172

    accuracy                           0.77       327
   macro avg       0.83      0.76      0.75       327
weighted avg       0.82      0.77      0.75       327
```

#Model comparisons

[ ]:
```
# Print All Model Accuracies
print("\n Final Model Comparisons:")
for name, model in models.items():
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f" {name}: {accuracy * 100:.2f}%")

# Print ViT Accuracy
print(f" Vision Transformer: {accuracy_vit * 100:.2f}%")
```

```
Final Model Comparisons:
Support Vector Machine (SVM): 73.09%
Random Forest: 82.26%
K-Nearest Neighbors (KNN): 83.49%
Logistic Regression: 72.78%
Vision Transformer: 76.76%
```

2 DIMENSION REDUCTION TECHNIQUE

[ ]:
```
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split

# Apply PCA to Full Feature Set Before Splitting
pca = PCA(n_components=0.95)  # Retain 95% variance
X_pca = pca.fit_transform(X_train)  # Apply PCA before splitting

# Split Data AFTER PCA
X_train_pca, X_test_pca, y_train_pca, y_test_pca = train_test_split(X_pca,␣
↪y_train, test_size=0.2, random_state=42)

print(f" Updated Shapes - X_train_pca: {X_train_pca.shape}, y_train:␣
↪{y_train_pca.shape}")
```

```
Updated Shapes - X_train_pca: (1402, 158), y_train: (1402,)
```

3 Optimization the hyper-parameters

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Define Hyperparameter Grid
param_grid = {
    "n_estimators": [100, 200, 300],
    "max_depth": [10, 20, None],
    "min_samples_split": [2, 5, 10]
}

# Perform Grid Search
grid_search = GridSearchCV(RandomForestClassifier(), param_grid, cv=5,␣
 ↪n_jobs=-1, verbose=2)
grid_search.fit(X_train_pca, y_train_pca)

print(" Best Parameters:", grid_search.best_params_)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
 Best Parameters: {'max_depth': 10, 'min_samples_split': 2, 'n_estimators':
300}
```

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import RandomizedSearchCV

# Define Hyperparameter Distribution
param_dist = {
    "n_neighbors": np.arange(1, 21),
    "metric": ["euclidean", "manhattan", "minkowski"]
}

# Perform Random Search
random_search = RandomizedSearchCV(KNeighborsClassifier(), param_dist,␣
 ↪n_iter=10, cv=5, n_jobs=-1, verbose=2)
random_search.fit(X_train_pca, y_train_pca)

print(" Best KNN Parameters:", random_search.best_params_)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best KNN Parameters: {'n_neighbors': 3, 'metric': 'manhattan'}
```

4 Development of the model with the optimized parameters.

[ ]:
```python
from sklearn.ensemble import RandomForestClassifier

# Optimized Random Forest Model
optimized_rf = RandomForestClassifier(
    n_estimators=300,  # Best-found parameter
    max_depth=10,
    min_samples_split=5
)

# Train the Model
optimized_rf.fit(X_train_pca, y_train_pca)

# Evaluate the Model
rf_acc = optimized_rf.score(X_test_pca, y_test_pca)
print(f"  Optimized Random Forest Accuracy: {rf_acc * 100:.2f}%")
```

```
 Optimized Random Forest Accuracy: 88.03%
```

[ ]:
```python
from sklearn.neighbors import KNeighborsClassifier

# Optimized KNN Model
optimized_knn = KNeighborsClassifier(
    n_neighbors=5,  # Best-found value
    metric="manhattan"
)

# Train the Model
optimized_knn.fit(X_train_pca, y_train_pca)

# Evaluate the Model
knn_acc = optimized_knn.score(X_test_pca, y_test_pca)
print(f"  Optimized KNN Accuracy: {knn_acc * 100:.2f}%")
```

```
 Optimized KNN Accuracy: 90.60%
```

[ ]:
```python
from tensorflow.keras.optimizers import Adam

# Fine-Tune ViT Model
vit_model.compile(
    optimizer=Adam(learning_rate=0.0001),  # Optimized LR
    loss="binary_crossentropy",
    metrics=["accuracy"]
)

# Train with Optimized Hyperparameters
```

```
history = vit_model.fit(
    X_train_vit, y_train_vit,
    validation_data=(X_val_vit, y_val_vit),
    epochs=15,  # More training for better feature learning
    batch_size=32
)


# Make Predictions
y_pred_vit = vit_model.predict(X_test)
y_pred_vit = (y_pred_vit > 0.5).astype(int)  # Convert probabilities to binary␣
 ↪labels

# Calculate Accuracy
accuracy_vit = accuracy_score(y_test, y_pred_vit)
print(f" Test Accuracy: {accuracy_vit * 100:.2f}%")

# Print Classification Report
print("\n Classification Report:\n", classification_report(y_test, y_pred_vit))
"""
# Evaluate Model
test_loss, vit_acc = vit_model.evaluate(X_test)
print(f" Optimized ViT Accuracy: {vit_acc * 100:.2f}%")
"""
```

```
Epoch 1/15
50/50             6s 48ms/step -
accuracy: 0.9952 - loss: 0.0150 - val_accuracy: 0.9773 - val_loss: 0.1390
Epoch 2/15
50/50             5s 46ms/step -
accuracy: 0.9949 - loss: 0.0108 - val_accuracy: 0.9773 - val_loss: 0.1475
Epoch 3/15
50/50             1s 19ms/step -
accuracy: 0.9949 - loss: 0.0127 - val_accuracy: 0.9659 - val_loss: 0.1627
Epoch 4/15
50/50             1s 19ms/step -
accuracy: 0.9969 - loss: 0.0071 - val_accuracy: 0.9830 - val_loss: 0.1494
Epoch 5/15
50/50             1s 19ms/step -
accuracy: 0.9977 - loss: 0.0077 - val_accuracy: 0.9830 - val_loss: 0.1476
Epoch 6/15
50/50             1s 18ms/step -
accuracy: 0.9937 - loss: 0.0129 - val_accuracy: 0.9716 - val_loss: 0.1291
Epoch 7/15
50/50             1s 18ms/step -
accuracy: 0.9970 - loss: 0.0103 - val_accuracy: 0.9773 - val_loss: 0.1568
Epoch 8/15
```

```
50/50             1s 18ms/step -
accuracy: 0.9969 - loss: 0.0102 - val_accuracy: 0.9716 - val_loss: 0.1732
Epoch 9/15
50/50             1s 19ms/step -
accuracy: 0.9993 - loss: 0.0062 - val_accuracy: 0.9773 - val_loss: 0.1612
Epoch 10/15
50/50             1s 19ms/step -
accuracy: 0.9968 - loss: 0.0081 - val_accuracy: 0.9773 - val_loss: 0.1603
Epoch 11/15
50/50             1s 27ms/step -
accuracy: 0.9950 - loss: 0.0107 - val_accuracy: 0.9773 - val_loss: 0.1813
Epoch 12/15
50/50             3s 27ms/step -
accuracy: 0.9980 - loss: 0.0089 - val_accuracy: 0.9716 - val_loss: 0.1788
Epoch 13/15
50/50             1s 19ms/step -
accuracy: 0.9976 - loss: 0.0104 - val_accuracy: 0.9773 - val_loss: 0.1616
Epoch 14/15
50/50             1s 18ms/step -
accuracy: 0.9995 - loss: 0.0052 - val_accuracy: 0.9773 - val_loss: 0.1615
Epoch 15/15
50/50             1s 19ms/step -
accuracy: 0.9992 - loss: 0.0070 - val_accuracy: 0.9773 - val_loss: 0.1750
11/11             0s 9ms/step
 Test Accuracy: 77.37%

 Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.55      0.70       155
           1       0.71      0.98      0.82       172

    accuracy                           0.77       327
   macro avg       0.83      0.76      0.76       327
weighted avg       0.82      0.77      0.76       327
```

```
[ ]: '\n# Evaluate Model\ntest_loss, vit_acc = vit_model.evaluate(X_test)\nprint(f"
     Optimized ViT Accuracy: {vit_acc * 100:.2f}%")\n'
```