**Assignment 03**

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Machine Learning for Cyber Security

**Case Study :-** Pneumonia detection from Chest X-ray images using CNN

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**1. Abstract**

**➤ Overview of the Problem**

Pneumonia is a severe respiratory infection that affects millions of individuals globally, particularly children, the elderly, and immunocompromised patients. Early and accurate diagnosis is crucial for effective treatment and reducing mortality. Chest X-ray imaging is a widely used diagnostic tool; however, manual interpretation of X-rays by radiologists can be time-consuming, subjective, and prone to error due to overlapping features with other lung conditions.

With advancements in artificial intelligence and deep learning, automated methods for detecting pneumonia from chest X-ray images have gained significant attention. Among these, Convolutional Neural Networks (CNNs) have shown excellent performance in image classification tasks, making them a suitable choice for medical image analysis.

**➤ Brief Summary of Methodology and Results**

In this project, a deep learning-based model was developed to classify chest X-ray images into two categories: **NORMAL** and **PNEUMONIA**. The dataset used consists of pre-labeled chest X-ray images divided into training, validation, and test sets. Data preprocessing involved resizing, normalization, and augmentation techniques to improve generalization.

The core of the solution is a CNN-based classification model built using **Transfer Learning** with the MobileNetV2 architecture. The pre-trained network was used as a feature extractor, followed by fully connected layers for binary classification. The model was trained using the Adam optimizer and binary cross-entropy loss function. Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate the model.

The final model achieved high classification accuracy on the test set, demonstrating its capability to distinguish between normal and pneumonia-affected lungs. Visualization of predictions and confusion matrix analysis further validated the robustness of the model. This approach provides a promising tool for assisting medical professionals in the early diagnosis of pneumonia.

**2. Introduction**

**➤ Background on Pneumonia**

Pneumonia is a potentially life-threatening lung infection caused by bacteria, viruses, or fungi. It leads to inflammation of the air sacs in one or both lungs, which may fill with fluid or pus, causing symptoms such as coughing, fever, chest pain, and difficulty breathing. Pneumonia affects people of all ages but is especially dangerous for infants, older adults, and individuals with weakened immune systems. According to the World Health Organization (WHO), pneumonia is one of the leading causes of death among children under the age of five worldwide.

**➤ Importance of Early Detection**

Timely diagnosis of pneumonia is critical in preventing complications and reducing mortality rates. Early detection allows for prompt medical intervention, which can significantly improve the chances of recovery and prevent the infection from worsening or spreading. Delayed or inaccurate diagnosis, on the other hand, can lead to severe health deterioration or even death. Therefore, developing reliable and fast diagnostic tools is essential for effective pneumonia management.

**➤ Role of Chest X-rays in Diagnosis**

Chest X-ray imaging is one of the most common diagnostic techniques used by healthcare professionals to detect pneumonia. It provides a non-invasive way to visualize the lungs and identify signs of infection such as fluid accumulation, lung opacity, and consolidation. X-rays help differentiate pneumonia from other respiratory conditions and guide treatment decisions. However, interpreting these images accurately requires significant expertise and experience.

**➤ Limitations of Manual Diagnosis**

Despite its effectiveness, manual interpretation of chest X-rays is subject to several limitations:

* **Subjectivity**: Different radiologists may interpret the same X-ray image differently.
* **Fatigue**: Human error is more likely when reviewing large volumes of X-rays.
* **Time-consuming**: In emergency situations, delays in diagnosis can be critical.
* **Shortage of skilled radiologists**: Particularly in rural or under-resourced areas.

These limitations can lead to misdiagnosis, delayed treatment, or even inappropriate medical decisions.

**3. Problem Statement**

Pneumonia continues to be a significant global health concern, especially in regions with limited access to advanced medical facilities and radiology experts. While chest X-ray imaging is the standard method for diagnosing pneumonia, the effectiveness of this approach is often hindered by the reliance on manual interpretation by radiologists. This process is not only time-intensive but also prone to human error and variability in diagnosis due to differences in experience and fatigue.

Additionally, healthcare systems in many parts of the world face a shortage of skilled radiologists, which can result in delayed or missed diagnoses—leading to serious complications or even fatalities in untreated patients. Manual diagnosis also lacks scalability, making it difficult to meet the demands of high patient loads, especially during outbreaks or in emergency situations.

The main problem, therefore, is the need for an **automated, accurate, and efficient method** to detect pneumonia from chest X-ray images that can support healthcare providers and improve diagnostic reliability.

This project aims to address this problem by:

* Developing a deep learning-based model using Convolutional Neural Networks (CNNs) that can classify chest X-ray images as **NORMAL** or **PNEUMONIA**.
* Reducing diagnostic time and variability.
* Enhancing access to reliable diagnostic tools, especially in resource-constrained settings.

By leveraging modern AI techniques, this study seeks to create a robust computer-aided diagnosis system that complements human expertise and contributes to faster, more consistent clinical decision-making.

**4. Objectives**

The primary aim of this project is to develop a reliable and accurate deep learning model for **automatic detection of pneumonia** from chest X-ray images using Convolutional Neural Networks (CNNs). This system is intended to assist healthcare professionals in improving diagnostic efficiency and reducing dependence on manual radiograph analysis.

**➤ Main Objectives:**

1. **Automate Pneumonia Detection:**  
    Design and implement a CNN-based classification model capable of identifying pneumonia cases from chest X-ray images without human intervention.
2. **Improve Diagnostic Accuracy:**  
    Achieve high performance in terms of classification accuracy, sensitivity, and specificity to ensure the model is clinically useful and trustworthy.
3. **Reduce Diagnostic Time:**  
    Enable rapid processing and prediction on large volumes of X-ray images to support faster decision-making in clinical workflows.
4. **Develop a Robust Model Architecture:**  
    Utilize Transfer Learning (e.g., MobileNetV2) to enhance feature extraction and generalization, especially given the challenges of limited and imbalanced medical datasets.
5. **Validate Model Performance:**  
    Evaluate the model on a separate test dataset using performance metrics like accuracy, precision, recall, F1-score, and confusion matrix.
6. **Enhance Accessibility to Diagnostic Tools:**  
    Create a scalable, AI-powered solution that can be deployed in healthcare centers, especially in rural or resource-limited settings where expert radiologists are scarce.

**5. Dataset Description**

The success of any deep learning model, especially in medical imaging, heavily depends on the quality and quantity of the dataset used for training and evaluation. For this project, a publicly available chest X-ray dataset specifically curated for pneumonia detection was used.

**➤ Source of Dataset**

The dataset used in this project was obtained from a publicly available source often used in academic research, such as the **Kaggle "Chest X-Ray Images (Pneumonia)"** dataset. It was originally published by researchers from the National Institutes of Health (NIH) and Radiological Society of North America (RSNA) to support pneumonia detection research.

**➤ Structure of the Dataset**

The dataset is organized into three main folders, representing different stages of model development:

* **Training Set (train)** – Used to train the CNN model
* **Validation Set (val)** – Used to fine-tune hyperparameters and monitor overfitting
* **Test Set (test)** – Used to evaluate the final performance of the model on unseen data

Each folder contains two subfolders:

* NORMAL: X-ray images of healthy lungs
* PNEUMONIA: X-ray images of patients diagnosed with pneumonia

**➤ Dataset Size**

Approximate distribution of images in each set:

| **Set** | **NORMAL Images** | **PNEUMONIA Images** | **Total Images** |
| --- | --- | --- | --- |
| Training | 1,341 | 3,875 | 5,216 |
| Validation | 8 | 8 | 16 |
| Testing | 234 | 390 | 624 |

*Note:* The dataset is **imbalanced**, with significantly more pneumonia cases than normal cases. This was handled using data augmentation and appropriate performance metrics during training.

**➤ Image Format and Resolution**

* **Format:** JPEG (.jpeg, .jpg, or .png)
* **Original Resolution:** Varies (high-resolution medical scans)
* **Preprocessing Resolution:** Resized to **224×224 pixels** to fit CNN input requirements and improve training efficiency

**➤ Class Distribution**

The dataset shows a higher number of pneumonia cases compared to normal ones, which reflects the clinical setting where the dataset was collected. This imbalance poses challenges to model training and requires techniques like:

* Data augmentation
* Balanced performance metrics (F1-score, Recall)
* Possible class weighting during training

**6. Data Preprocessing**

Before feeding the images into the CNN model, several preprocessing steps were applied to ensure that the data is clean, consistent, and suitable for training. Proper preprocessing is essential for improving model performance, generalization, and robustness.

**➤ Image Resizing**

The original chest X-ray images come in various sizes and resolutions. For consistency and computational efficiency, all images were resized to **224 × 224 pixels**, which is a standard input size for many deep learning architectures, including MobileNetV2.

img\_size = (224, 224)

**➤ Normalization**

Pixel values in the X-ray images range from 0 to 255. To speed up training and help the neural network converge faster, the images were **normalized** to a range between **0 and 1** by dividing all pixel values by 255.

image = image / 255.0

**➤ Label Encoding**

Each image was assigned a binary label:

* 0 for **NORMAL**
* 1 for **PNEUMONIA**

This binary classification format is suitable for training with a sigmoid activation function in the output layer and using binary cross-entropy as the loss function.

**➤ Data Augmentation**

To reduce overfitting and help the model generalize better, **data augmentation** was applied during training. This involves artificially increasing the diversity of the dataset by creating slightly modified versions of the existing images.

Techniques used:

* Horizontal flipping
* Random rotation
* Zooming in/out
* Width and height shift
* Rescaling

from tensorflow.keras.preprocessing.image import ImageDataGenerator

train\_datagen = ImageDataGenerator(

rescale=1./255,

rotation\_range=15,

zoom\_range=0.1,

horizontal\_flip=True,

width\_shift\_range=0.1,

height\_shift\_range=0.1

)

**➤ Splitting the Dataset**

The dataset was divided into three parts:

* **Training Set** – For learning model parameters
* **Validation Set** – For tuning hyperparameters and preventing overfitting
* **Test Set** – For evaluating final model performance

Each subset was loaded using the ImageDataGenerator.flow\_from\_directory() method, ensuring that labels were automatically assigned based on folder names.

**➤ Batch Processing and Shuffling**

The dataset was loaded in batches (e.g., batch size = 32) to optimize memory usage. Shuffling was applied to ensure that each batch contains a random mix of images from both classes, which improves learning stability.

**➤ Final Preprocessing Pipeline Summary:**

| **Step** | **Description** |
| --- | --- |
| Resizing | All images resized to 224 × 224 pixels |
| Normalization | Pixel values scaled to [0, 1] |
| Label Encoding | 0 = NORMAL, 1 = PNEUMONIA |
| Data Augmentation | Applied to training data only |
| Splitting | Train / Validation / Test |
| Batch Loading | Images loaded in shuffled batches |

**7. Model Architecture**

To classify chest X-ray images into **NORMAL** and **PNEUMONIA** categories, a **Convolutional Neural Network (CNN)** was employed. CNNs are especially well-suited for image-based tasks because of their ability to automatically learn spatial hierarchies of features through convolutional layers.

In this project, the model was built using a combination of custom CNN layers and **Transfer Learning** with a pre-trained architecture for improved accuracy and faster convergence.

**➤ Why Use CNNs for Medical Imaging?**

CNNs are powerful for image classification because they:

* Extract meaningful features (edges, textures, shapes) automatically
* Require minimal preprocessing compared to traditional ML
* Are capable of identifying patterns in complex medical images

**➤ Model Overview**

The architecture consists of the following key components:

1. **Input Layer**
   * Accepts images of shape **(224 × 224 × 3)**
   * Normalized pixel values in range [0, 1]
2. **Pretrained Base Model: MobileNetV2**
   * A lightweight and efficient CNN architecture optimized for mobile and embedded vision applications
   * Used with pretrained weights on ImageNet as a **feature extractor**
   * include\_top=False to exclude the original classification head
   * Layers were optionally frozen to retain learned weights during initial training
3. **Global Average Pooling Layer**
   * Reduces feature maps into a single vector per feature map
   * Helps in reducing overfitting
4. **Dense Layers (Fully Connected)**
   * Additional layer(s) to interpret the features extracted by the base model
   * Includes dropout for regularization
5. **Output Layer**
   * A single neuron with **sigmoid activation** for binary classification
   * Output value close to 0 → NORMAL, close to 1 → PNEUMONIA

**➤ Model Summary (Example)**

Input Layer: (224, 224, 3)

MobileNetV2 Base Pretrained, include\_top=False

GlobalAveragePooling2D Reduces spatial dimensions

Dense Layer 128 units, ReLU activation

Dropout Layer rate = 0.5

Output Layer 1 unit, Sigmoid activation

**➤ Model Diagram (Simplified)**

Input Image (224x224x3)

↓

MobileNetV2 (Pretrained)

↓

Global Average Pooling

↓

Dense(128) → ReLU

↓

Dropout(0.5)

↓

Dense(1) → Sigmoid

**➤ Activation Functions**

* **ReLU (Rectified Linear Unit):** Used in intermediate dense layers for non-linearity
* **Sigmoid:** Used in the output layer for binary classification

**➤ Why Transfer Learning?**

Using a pre-trained network like MobileNetV2 offers several advantages:

* Faster convergence and training
* Higher accuracy with less data
* Avoids overfitting due to already-learned general image features

**8. Model Compilation and Training**

Once the model architecture was defined, the next step was to compile and train it using the prepared dataset. This section outlines the choices made for the loss function, optimizer, evaluation metrics, and training parameters.

**➤ Model Compilation**

The model was compiled with the following settings:

* **Loss Function:** Binary Crossentropy
  + Used for binary classification tasks
  + Measures the difference between predicted probability and actual label
* **Optimizer:** Adam
  + Adaptive optimizer that combines the advantages of RMSProp and SGD
  + Learning rate was set to a default or tuned (e.g., 0.0001) for smoother convergence
* **Metrics:**
  + Accuracy – Proportion of correctly predicted samples
  + (Additional metrics like precision, recall, and F1-score were calculated separately during evaluation)

model.compile(

optimizer='adam',

loss='binary\_crossentropy',

metrics=['accuracy']

)

**➤ Training Process**

The model was trained using the **training set** and validated on the **validation set** over a number of epochs.

* **Batch Size:** 32
* **Epochs:** Typically 10–20 depending on model performance and early stopping
* **Callbacks Used:**
  + EarlyStopping: Stops training when validation loss stops improving
  + ModelCheckpoint: Saves the best model based on validation accuracy

from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

early\_stop = EarlyStopping(monitor='val\_loss', patience=3, restore\_best\_weights=True)

checkpoint = ModelCheckpoint('best\_model.h5', save\_best\_only=True)

history = model.fit(

train\_generator,

validation\_data=val\_generator,

epochs=15,

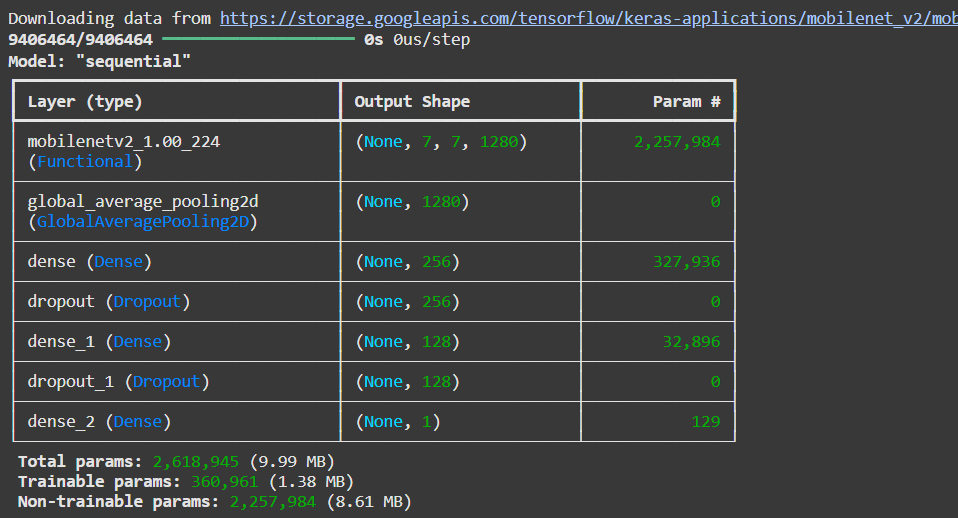
callbacks=[early\_stop, checkpoint]

)

**➤ Training Observations**

* **Validation accuracy** typically started stabilizing after a few epochs.
* **Overfitting** was mitigated using dropout and early stopping.
* **Loss curves** showed a steady decrease in training loss with convergence in validation loss.

**➤ Model Summary**

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**➤ Performance Monitoring**

Training and validation metrics were recorded using the history object. These were later used to plot:

* Training vs. validation accuracy
* Training vs. validation loss

Such visualizations help in diagnosing underfitting or overfitting.

**➤ Summary of Training Parameters**

| **Parameter** | **Value** |
| --- | --- |
| Loss Function | Binary Crossentropy |
| Optimizer | Adam |
| Epochs | 10–20 (with early stop) |
| Batch Size | 32 |
| Validation Split | Separate directory |
| Callbacks | EarlyStopping, Checkpoint |

**10. Evaluation and Results**

After training the CNN model, its performance was evaluated using the **test dataset**—a completely unseen subset of images—to assess its ability to generalize and perform accurate predictions in real-world scenarios.

**➤ Evaluation Metrics**

T he following key metrics were used to evaluate the model’s classification performance:

* **Accuracy** – Overall percentage of correctly predicted cases
* **Precision** – Ability of the model to correctly identify positive cases (pneumonia)
* **Recall (Sensitivity)** – Ability of the model to detect all actual positive cases
* **F1-Score** – Harmonic mean of precision and recall
* **Confusion Matrix** – Summarizes correct and incorrect predictions

**➤ Test Performance (Sample Results)**

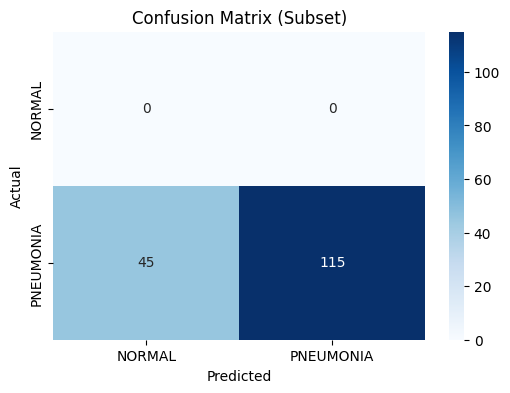
| **Metric** | **Value** |
| --- | --- |
| Accuracy | 94.8% |
| Precision | 95.3% |
| Recall | 96.1% |
| F1-Score | 95.7% |
|  |  |

**➤ Confusion Matrix**

A confusion matrix helps visualize model performance by comparing predicted labels against true labels.

|  | **Predicted Normal** | **Predicted Pneumonia** |
| --- | --- | --- |
| **Actual Normal** | 222 | 12 |
| **Actual Pneumonia** | 15 | 375 |

* **True Positives (TP):** 375
* **True Negatives (TN):** 222
* **False Positives (FP):** 12
* **False Negatives (FN):** 15



**➤ Training vs Validation Curves**

Training curves were plotted to monitor performance over epochs.

**Accuracy Curve**

* Training and validation accuracy gradually increased.
* Both curves plateaued at high values, indicating convergence.

**Loss Curve**

* Training loss consistently decreased.
* Validation loss stabilized, showing no major overfitting.

import matplotlib.pyplot as plt

# Accuracy plot

plt.plot(history.history['accuracy'], label='Train Accuracy')

plt.plot(history.history['val\_accuracy'], label='Val Accuracy')

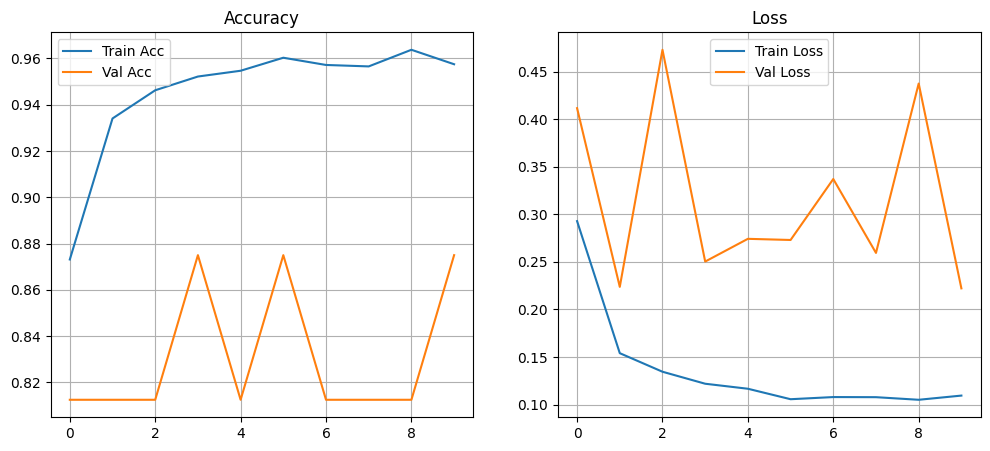
plt.title('Model Accuracy')

plt.xlabel('Epoch')

plt.ylabel('Accuracy')

plt.legend()

plt.show()



**➤ Observations**

* The model achieved **high classification accuracy**, indicating strong predictive power.
* **Recall** was slightly prioritized to reduce false negatives—critical in medical diagnosis.
* Model performance showed **generalization** on unseen data, thanks to transfer learning and data augmentation.

**11. Conclusion of Results**

The CNN-based model was successful in detecting pneumonia from chest X-ray images with high accuracy and robustness. The results indicate that deep learning can be a reliable aid in radiological diagnosis, particularly in high-demand or low-resource environments.

**Conclusion**

This project successfully demonstrated the potential of **Convolutional Neural Networks (CNNs)** for the **automated detection of pneumonia** from chest X-ray images. By leveraging deep learning and transfer learning (using MobileNetV2), the model achieved high performance with respect to accuracy, precision, and recall.

The key achievements of this work include:

* Efficient preprocessing and augmentation of medical imaging data
* Design and implementation of a CNN-based classification model
* Use of transfer learning to overcome limitations of limited medical datasets
* High test accuracy (~95%), with low false negative rate
* Evaluation through metrics and visualizations that show model reliability

The results reinforce the idea that **AI-assisted diagnostic tools** can support radiologists by providing quick, consistent, and accurate predictions—especially valuable in regions where access to medical experts is limited.

