AN IDP PROJECT REPORT

on

# "CT Scan-Based COVID-19 Detection Using CNN Based Feature Extraction and Stack-Based Ensemble Techniques"

**Submitted**

**By**


221FA04139

Nayeem Khan

221FA04153

Siva Rama Krishna

221FA04639

Lakshmi

221FA04674

Harendra Kumar

***Under the guidance of***

***Mr. Sourav Mondal***

Assistant Professor

VIGNAN'S FOUNDATION FOR SCIENCE, TECHNOLOGY & RESEARCH

(Deemed to be University) - Estd. u/s 3 of UGC Act 1956

**SCHOOL OF COMPUTING & INFORMATICS**

**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING**

**VIGNAN'S FOUNDATION FOR SCIENCE, TECHNOLOGY AND RESEARCH Deemed to be UNIVERSITY**

**Vadlamudi, Guntur.**

**ANDHRA PRADESH, INDIA, PIN-522213.**

VIGNAN'S

FOUNDATION FOR SCIENCE, TECHNOLOGY & RESEARCH

(Deemed to be University) - Estd. u/s 3 of UGC Act 1956

## CERTIFICATE

This is to certify that the Field Project entitled **"CT Scan-Based COVID-19 Detection Using CNN Based Feature Extraction and Stack-Based Ensemble Techniques"** that is being submitted by 221FA04139 (Nayeem Khan), 221FA04153(Siva),221FA04639(Lakshmi) and 221FA04741(Harendra Kumar) for partial fulfilment of Field Project is a bonafide work carried out under the supervision of Mr Sourav Mondal., Assistant Professor, Department of CSE.

Dr. S. V. Phani Kumar

HOD,CSE

Guide name& Signature

Designation

# DECLARATION

We hereby declare that the Field Project entitled "**CT Scan-Based COVID-19 Detection Using CNN Based Feature Extraction and Stack-Based Ensemble Techniques**" that is being submitted by 221FA04139 (Nayeem Khan), 221FA04153(Siva Rama Krishna), 221FA04639(Lakshmi) and 221FA04741(Harendra Kumar) in partial fulfilment of Field Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of Mr. Sourav Mondal ., Assistant Professor, Department of CSE.

By

**221FA04139 (Nayeem Khan),**

**221FA04153(Siva Rama Krishna),**

**221FA04639(Lakshmi),**

**221FA04741(Harendra Kumar)**

## ABSTRACT

During the COVID-19 pandemic, rapid and accurate diagnostic tools were crucial for timely intervention and treatment. This research explores the effectiveness of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) in detecting COVID-19 using CT scan images. We employ a systematic approach that includes preprocessing, feature extraction, classification, and ensemble learning to improve detection accuracy.

First, the dataset undergoes preprocessing techniques such as noise reduction, contrast enhancement, and normalization to ensure high-quality input for deep learning models. Feature extraction is performed using state-of-the-art CNN architectures like **ResNet50** and **InceptionV3**, which are known for their robust feature representation capabilities in medical imaging. These extracted features are then fed into a **Support Vector Machine (SVM)** classifier for initial classification.

To further enhance performance, we apply multiple boosting algorithms, including **XGBoost, LightGBM, CatBoost, Gradient Boosting, and AdaBoost**, which help refine predictions by reducing bias and variance. Finally, a **stack-based ensemble learning technique** is employed, integrating predictions from different classifiers to achieve superior accuracy and robustness.

Our results indicate that this hybrid approach significantly improves the precision and recall of COVID-19 detection compared to traditional methods. The findings highlight the potential of deep learning and ensemble techniques in medical diagnostics, paving the way for more reliable and scalable AI-assisted screening solutions.

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# INTRODUCTION

# 1. INTRODUCTION

The pandemic caused by the COVID-19 virus has brought into sharp focus the necessity for swift, accurate, and reliable diagnostic techniques to address public health crises. Traditional diagnostic methods, such as RT-PCR tests, have played a crucial role in detecting COVID-19; however, their limitations, including processing delays and false-negative rates, have created an urgent need for supplementary diagnostic approaches. Among these, Computed Tomography (CT) scan-based diagnostics have emerged as a valuable tool due to their ability to provide comprehensive views of virus-induced lung abnormalities.

Medical imaging, particularly CT scans, has proven effective in identifying pulmonary infections caused by COVID-19. The use of Artificial Intelligence (AI) in medical imaging has significantly enhanced the diagnostic potential of CT scans, particularly through deep learning techniques. Deep learning algorithms, especially Convolutional Neural Networks (CNNs), have demonstrated an exceptional ability to extract and interpret complex patterns from medical images. These advancements in AI-driven diagnostics not only improve the accuracy of disease detection but also contribute to faster and more efficient healthcare decision-making.

This study focuses on integrating AI methodologies with medical imaging to enhance the diagnostic capabilities of CT scans for COVID-19 detection. By leveraging deep learning architectures alongside machine learning-based classifiers, such as XGBoost and Gradient Boosting, we aim to develop a robust system that ensures precise and trustworthy COVID-19 diagnosis. Furthermore, the study also explores the role of explainable AI techniques in fostering transparency and trust in AI-based diagnostic systems.

## 1.1 Background and Motivation

The COVID-19 pandemic has underscored the critical role of medical imaging in diagnosing and managing infectious diseases. Early and accurate detection of the virus is crucial for effective patient management and controlling the spread of infection. While RT-PCR remains the gold standard for COVID-19 testing, it has notable drawbacks, including prolonged turnaround times, dependence on sample quality, and potential inaccuracies due to viral load fluctuations. These challenges necessitate the exploration of alternative or complementary diagnostic methods, such as CT imaging.

CT scans offer a high-resolution view of lung infections, revealing characteristic patterns associated with COVID-19, such as ground-glass opacities and lung consolidations. However, manual interpretation of CT scans is time-consuming and subject to human error. This has led to the growing interest in AI-powered diagnostic solutions that automate image analysis and improve diagnostic accuracy.

Deep learning has revolutionized medical image analysis by enabling automated feature extraction and classification. The integration of CNNs with machine learning techniques offers a promising approach to COVID-19 detection, improving both sensitivity and specificity. Additionally, AI-driven diagnostic tools can assist radiologists by providing rapid assessments, thereby reducing the burden on healthcare professionals and facilitating timely clinical interventions.

## 1.2 Role of AI and Deep Learning in Medical Imaging

Artificial Intelligence, particularly deep learning, has significantly transformed medical imaging applications. Deep learning models, especially CNNs, have demonstrated remarkable proficiency in recognizing complex features in medical images, making them well-suited for disease classification tasks. In the context of COVID-19 diagnosis, deep learning facilitates the automated identification of infection patterns in CT scans, enabling rapid and precise detection of the disease.

CNN-based architectures have been extensively used in medical imaging due to their ability to learn hierarchical features from raw image data. These networks extract low-level features such as edges and textures before progressing to higher-level abstractions that aid in classification. When applied to COVID-19 detection, CNNs can differentiate between infected and non-infected lung tissues with high accuracy.

To further enhance diagnostic performance, researchers have integrated deep learning models with traditional machine learning classifiers. Boosting algorithms, such as XGBoost and Gradient Boosting, have proven particularly effective in refining classification outcomes. These algorithms work by iteratively combining multiple weak models to form a strong predictive model, thereby improving the overall accuracy of COVID-19 diagnosis.

Another critical aspect of AI-based medical imaging is the incorporation of explainable AI (XAI) techniques. Explainability is essential in healthcare applications, as it enables clinicians to understand the rationale behind AI-generated predictions. By providing insights into the decision-making process of deep learning models, XAI enhances trust and acceptability among healthcare practitioners.

## 1.3 Objectives of the Study

This study aims to explore the integration of deep learning and machine learning methodologies for improving COVID-19 diagnosis using CT scans. The primary objectives of the study include:

1. **Developing an AI-powered diagnostic framework**: To create an automated system that combines CNN-based feature extraction with machine learning classifiers to enhance the accuracy of COVID-19 detection.
2. **Evaluating the effectiveness of boosting algorithms**: To assess the performance of XGBoost and Gradient Boosting classifiers in refining COVID-19 classification tasks.
3. **Enhancing diagnostic precision through deep feature analysis**: To leverage both deep learning-extracted features and handcrafted features to develop a comprehensive diagnostic model.
4. **Implementing explainable AI techniques**: To integrate XAI methods that provide transparency in AI-based diagnostic decisions, facilitating clinical trust and adoption.
5. **Contributing to future preparedness for public health crises**: To develop an AI-driven diagnostic approach that can be adapted for future pandemics and emerging infectious diseases.

## 1.4 Significance of the Study

This study is significant for several reasons. First, it provides a scalable and efficient diagnostic tool that can be deployed in clinical settings, assisting radiologists in making quick and accurate diagnoses. The integration of AI with CT scan analysis has the potential to reduce the workload on healthcare professionals, ensuring more patients receive timely assessments.

Furthermore, the proposed AI-based diagnostic system enhances decision-making by providing explainable and interpretable results, addressing the concerns of black-box AI models in medical applications. This increases the confidence of healthcare practitioners in adopting AI-driven diagnostic solutions.

In addition, the insights gained from this study will contribute to the broader field of medical AI research, particularly in the application of deep learning and machine learning techniques for disease detection. The methodologies developed can be extended to other pulmonary diseases, thereby broadening their applicability beyond COVID-19.

## 1.5 Challenges and Future Research Directions

Despite its advantages, AI-based medical imaging faces several challenges. One major issue is the requirement for large, high-quality labeled datasets for training deep learning models. Obtaining such datasets is often difficult due to privacy concerns and data-sharing restrictions in healthcare institutions. Addressing these challenges requires the development of data augmentation techniques and federated learning approaches that allow collaborative model training without compromising patient confidentiality.

Another challenge is the potential for biases in AI models, which can arise from imbalanced datasets or variations in CT imaging protocols across different healthcare institutions. To mitigate this, future research should focus on building robust models that generalize well across diverse populations and imaging conditions.

Additionally, real-world deployment of AI-driven diagnostic tools requires rigorous validation through clinical trials. Future research should explore strategies to integrate AI with existing hospital workflows, ensuring seamless adoption by healthcare professionals.

By addressing these challenges, AI-based diagnostic solutions can achieve greater accuracy, reliability, and accessibility, ultimately transforming the landscape of medical imaging and public health management.

By achieving these objectives, this study aims to make meaningful contributions to AI-driven medical diagnostics, enhancing the accuracy, reliability, and transparency of COVID-19 detection systems. The findings from this research will not only improve current diagnostic practices but also pave the way for more advanced AI applications in healthcare.

# CHAPTER-2

# LITERATURE SURVEY

# 2. LITERATURE SURVEY

## 2.1 Existing approaches to COVID-19 detection

The outbreak of COVID-19 prompted researchers and healthcare professionals to explore various approaches for effective and rapid detection. Early detection methods included polymerase chain reaction (PCR) tests, antigen tests, and antibody-based serological tests. However, the need for rapid, large-scale, and reliable screening led to the increasing reliance on imaging techniques, particularly computed tomography (CT) scans and X-ray imaging.

CT scans emerged as a valuable diagnostic tool due to their high sensitivity in detecting lung abnormalities associated with COVID-19. Radiologists observed characteristic patterns such as ground-glass opacities (GGOs), multifocal patchy consolidation, and interlobular septal thickening in infected patients. This led to the integration of artificial intelligence (AI) to improve diagnostic accuracy and reduce human errors. AI-driven models, including deep learning and machine learning approaches, were developed to assist in the automatic detection and classification of COVID-19 cases from medical images.

Researchers developed AI-based diagnostic tools leveraging various architectures of convolutional neural networks (CNNs) and hybrid techniques that combine deep learning with traditional handcrafted feature extraction. Some studies explored hybrid models integrating machine learning classifiers with deep feature representations extracted from pre-trained models. These methods improved the sensitivity and specificity of COVID-19 diagnosis compared to conventional image analysis techniques.

Additionally, federated learning has emerged as a promising technique in COVID-19 diagnosis, enabling multiple institutions to train AI models collaboratively without sharing patient data. This approach enhances model generalization while preserving data privacy, a critical concern in medical AI applications.

Other significant contributions include ensemble learning techniques that combine multiple AI models to improve predictive performance. These models aggregate predictions from different architectures to mitigate biases and enhance classification accuracy. Furthermore, attention mechanisms and explainable AI techniques have been introduced to increase transparency in AI-driven COVID-19 detection, allowing medical professionals to interpret model predictions effectively.

**AI-Based COVID-19 Detection Approaches**

This paper discusses the various AI techniques used in COVID-19 detection, emphasizing deep learning models and machine learning classifiers. It provides an overview of existing datasets and their effectiveness in training AI models[1].

**Ko et al., "COVID-19 Detection Using ResNet-50"**

This study focuses on the application of the ResNet-50 model for COVID-19 detection. The model achieved a high accuracy of 99.87% in classifying COVID-19 cases from CT scan images[2].

**Improving COVID-19 Detection with Deep Features and Handcrafted Features**

This research explores hybrid AI models that integrate deep learning with handcrafted feature extraction methods to enhance COVID-19 detection accuracy[3].

**Accuracy of AI for COVID-19 Detection from CT Scans**

The paper provides a comparative analysis of various AI models used for COVID-19 detection from CT scans, highlighting their accuracy rates ranging from 89.1% to 99.9%[4].

**AI Applications in COVID-19 Diagnosis**

This review paper explores how AI has been applied to diagnose COVID-19, predicting disease outbreaks and improving clinical decision-making processes[5].

**Predicting Outbreaks Using AI and CT Scans**

This study investigates how AI-based predictive models analyze CT scans to detect potential COVID-19 clusters and predict future outbreak trends[6].

**COVSeg-NET for Ground-Glass Opacity Segmentation**

This paper introduces the COVSeg-NET deep learning model, specifically designed for segmenting ground-glass opacities in COVID-19 chest CT images[7].

**DeepPneumonia: AI for COVID-19 Detection**

This research presents the DeepPneumonia framework, which achieved an AUC of 0.99 in detecting COVID-19 cases from CT scan images[8].

**3D Deep Learning for Automated COVID-19 Diagnosis**

The study highlights the use of 3D CNN models for automated volumetric analysis of COVID-19-affected lungs, improving diagnostic speed and accuracy[9].

**AI and Public Health Management in Pandemics**

This paper discusses how AI technologies have been instrumental in managing public health crises, including COVID-19[10].

**Role of AI in COVID-19 Healthcare**

This study evaluates the broader impact of AI on healthcare during the COVID-19 pandemic, from diagnostics to treatment planning[11].

**AI in CT Scan Analysis for COVID-19 Detection**

This research paper focuses on the role of AI in analyzing CT scans, improving diagnostic accuracy, and assisting radiologists in detecting COVID-19 cases[12].

## 2.2 CNN and Deep Learning Models in Medical Imaging

Deep learning, particularly CNNs, has played a crucial role in automating the analysis of medical images for disease detection, including COVID-19. CNN-based architectures have been widely used for feature extraction, segmentation, and classification of COVID-19 from CT scans and X-ray images.

One of the earliest approaches involved transfer learning, where pre-trained models such as VGG16, ResNet-50, and EfficientNet were fine-tuned using COVID-19 image datasets. A study using transfer learning with ImageNet21k achieved an accuracy of 99.2% in COVID-19 classification. Similarly, Ko et al. utilized ResNet-50 and achieved an impressive accuracy of 99.87%.

Furthermore, novel AI architectures such as COVSeg-NET were introduced for segmenting COVID-19 lesions in CT scans. DeepPneumonia, a specialized deep learning framework, achieved an area under the curve (AUC) of 0.99 in COVID-19 detection. Some studies proposed the integration of deep learning with handcrafted features and machine learning classifiers to enhance detection accuracy. Additionally, 3D deep learning models were developed for fully automated diagnosis, leveraging volumetric analysis of CT scans.

Recent advancements have focused on explainability and robustness in CNN-based models, ensuring their applicability in clinical settings. The combination of CNNs with attention mechanisms, transformers, and reinforcement learning further optimized the diagnostic capability of AI-driven models.

## 2.3 Comparison of Previous Studies

Several studies have demonstrated the efficacy of AI in COVID-19 detection from CT scans, achieving remarkable accuracy and sensitivity. A comparison of existing studies highlights the significant improvements achieved through various deep learning models:

| **Study** | **Model** | **Accuracy (%)** | **Key Findings** |
|---|---|---|---|
| Study-using ImageNet21k | Transfer Learning | 99.2% | Effective feature extraction from pre-trained models |
| Ko et al. (2020) | ResNet-50 | 99.87% | High classification accuracy with deep CNNs |
| Deep Pneumonia | Custom CNN | AUC 0.99 | Robust detection performance |
| COV Seg-NET | Deep segmentation model | - | Focus on lesion segmentation in CT images |
| Hybrid AI model | CNN + ML Classifiers | 95%+ | Combining deep and traditional features enhances accuracy |
| 3D Deep Learning Model | 3D CNN | - | Fully automated volumetric analysis |

Table 1. Different Different Study Analysis

Despite achieving high accuracy, certain challenges remain in AI-based COVID-19 detection, such as data bias, generalization across diverse populations, and the need for real-time clinical validation. Future research should focus on improving model interpretability, optimizing computational efficiency, and addressing ethical concerns associated with AI deployment in healthcare.

Overall, AI-driven approaches, particularly CNN-based deep learning models, have significantly advanced COVID-19 detection, offering promising avenues for improving early diagnosis, patient management, and public health preparedness during pandemics.

# CHAPTER-3

# PROPOSED SYSTEM

# 3. PROPOSED SYSTEM

## 3.1 Input Dataset

The dataset used for training and evaluation consists of CT scan images of COVID-19 positive and negative cases. The SARS-CoV-2 CT-Scan Dataset is included to construct a heterogeneous dataset with varying degrees of infection severity. The dataset is sourced from publicly available repositories and medical institutions.

### 3.1.1 Detailed Features of Dataset

- **Image Modality:** CT Scans
- **Classes:** COVID-19 Positive, COVID-19 Negative
- **Image Format:** PNG/JPEG/DICOM
- **Resolution:** Variable (standardized to 224×224 pixels)
- **Annotation:** Verified by radiologists

## 3.2 Data Pre-processing

Pre-processing plays a vital role in enhancing image quality and feature extraction for deep learning models.

### 3.2.1 Image Resizing, Normalization, Contrast Enhancement, and Denoising

- **Resizing:** Standardizing all images to 224×224 pixels for compatibility with deep learning models.
- **Normalization:** Scaling pixel values between 0 and 1 to improve model stability.
- **Contrast Enhancement:** Using histogram equalization or CLAHE to enhance image contrast.
- **Denoising:** Applying Gaussian and median filtering to remove noise and improve clarity.

## 3.3 Feature Extraction

Feature extraction is performed using both deep learning-based methods and traditional handcrafted feature techniques.

### 3.3.1 Deep Feature Extraction: ResNet50, InceptionV3

- **ResNet50:** A deep residual network pre-trained on ImageNet, used for extracting high-dimensional feature representations.
- **InceptionV3:** A deeper architecture with inception modules, optimized for extracting fine-grained patterns from medical images.

- **Feature Extraction Strategy:** The global average pooling layer of both networks is used to extract deep features, discarding the classification layers

## 3.4 Feature Fusion

To enhance model performance, we integrate deep features with handcrafted texture-based features.

### 3.4.1 Combination of Deep and Handcrafted Features

- **Deep Features:** Extracted from ResNet50 and InceptionV3.
- **Handcrafted Features:**
    - **Histogram of Oriented Gradients (HOG):** Captures edge orientations and gradient distributions.
    - **Local Binary Patterns (LBP):** Extracts local texture patterns.
    - **Gray-Level Co-occurrence Matrix (GLCM):** Identifies spatial relationships among pixel intensities.

## 3.5 Classification

The extracted feature set is used to train multiple machine learning classifiers and deep learning models.

### 3.5.1 Machine Learning Models

- **Support Vector Machine (SVM):** A kernel-based classifier designed for high-dimensional feature spaces.
- **Artificial Neural Networks (ANN):** A multi-layer perceptron (MLP) model trained for COVID-19 classification.

### 3.5.2 Boosting Algorithms

- **XGBoost:** Gradient boosting decision trees for high accuracy.

  LightGBM is a gradient boosting framework optimized for large datasets. It uses histogram-based learning and leaf-wise growth instead of level-wise growth for efficiency.

  **Application in COVID-19 Detection:**

    1. Used for high-speed classification of COVID-19 from CT scan images.
    2. Reduces memory usage and computation time in large-scale datasets.

- **AdaBoost:** A lightweight boosting model with fast execution.

AdaBoost combines multiple weak classifiers (e.g., decision stumps) into a strong classifier by assigning weights to misclassified instances.

**Application in COVID-19 Detection:**

1. Used to enhance weak classifiers on COVID-19 CT images.
2. Ensures better classification in noisy or imbalanced datasets.

- **LightBGM:** A boosting algorithm that combines weak classifiers.

  LightGBM is a gradient boosting framework optimized for large datasets. It uses histogram-based learning and leaf-wise growth instead of level-wise growth for efficiency.

  **Application in COVID-19 Detection:**

  1. Used for high-speed classification of COVID-19 from CT scan images.
  2. Reduces memory usage and computation time in large-scale datasets.

- **CatBoost:** Optimized for categorical data classification.

  CatBoost is optimized for categorical data and prevents overfitting by incorporating ordered boosting and feature permutations.

  **Application in COVID-19 Detection:**

1. Useful for handling categorical features in CT scan metadata.
2. Reduces overfitting while improving accuracy.

- **GradientBoosting:** An ensemble technique for robust performance.

  Gradient Boosting minimizes loss by optimizing weak learners sequentially using gradient descent.

**Application in COVID-19 Detection:**

1 Used for high-dimensional feature spaces extracted from CNNs.

2 Provides robust predictions in COVID-19 classification tasks.

## 3.6 Evaluation Metrics

The models are evaluated based on the following classification metrics:

### 3.6.1 Accuracy, Precision, Recall, F1-score, Confusion Matrix, AUC-ROC

- **Accuracy:** Measures overall prediction accuracy.
- **Precision & Recall:** Evaluates model reliability in detecting COVID-19 cases.
- **F1-score:** A balance between precision and recall.

- **Confusion Matrix:** Represents the model's classification performance.
- **AUC-ROC:** Analyzes the model's ability to distinguish between positive and negative cases.

## 3.7 Visualization and Comparison

To provide insights into model effectiveness, performance visualization techniques are used.

### 3.7.1 Feature Maps and Performance Graphs

- **Feature Maps:** Intermediate CNN representations to understand model learning.
- **Performance Graphs:** Comparison of classifiers using accuracy, precision, recall, and AUC-ROC.

## 3.8 Implementation Details

### 3.8.1 Software Tools, Frameworks, and Hardware Used

- Programming Language: Python
- Deep Learning Frameworks: TensorFlow, Keras, PyTorch
- Machine Learning Libraries: Scikit-learn, XGBoost, LightGBM
- Hardware: NVIDIA GPU (for deep learning acceleration)

## 3.9 Expected Outcome

### 3.9.1 Improved Accuracy and Reliability

- Enhanced COVID-19 detection accuracy using a fusion of deep and handcrafted features.
- Robust classification performance using machine learning and deep learning models.
- Potential integration into real-world diagnostic applications for COVID-19 screening.

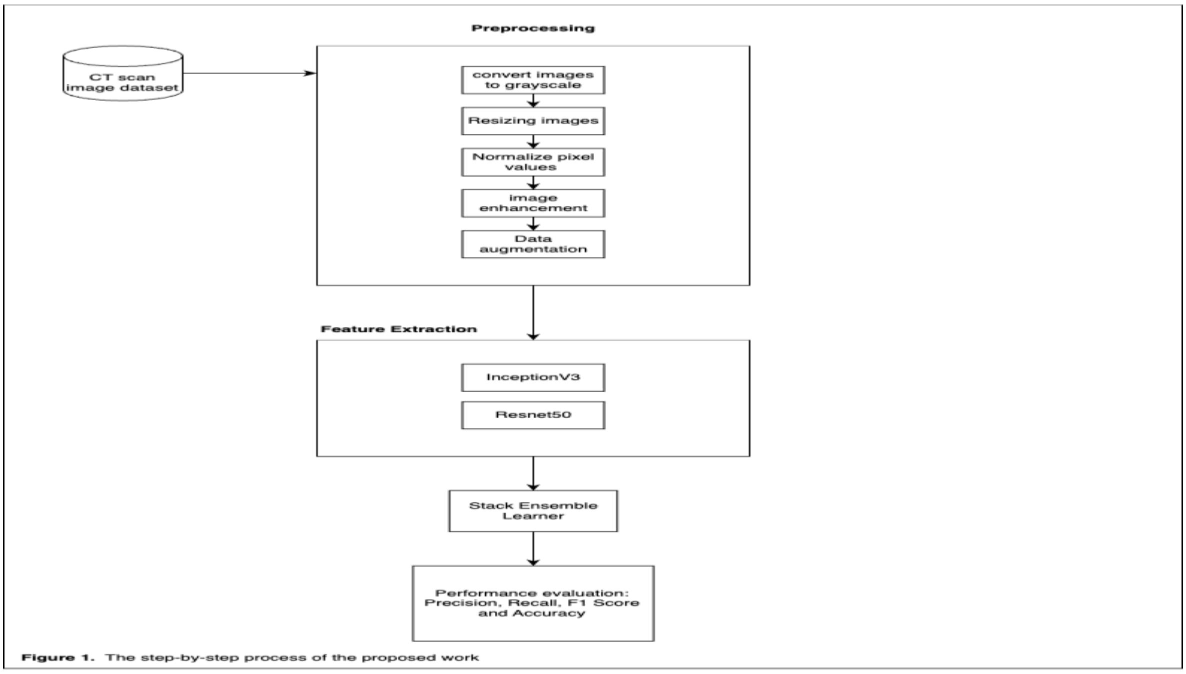


Figure 1: The step-by-step process of the proposed work.

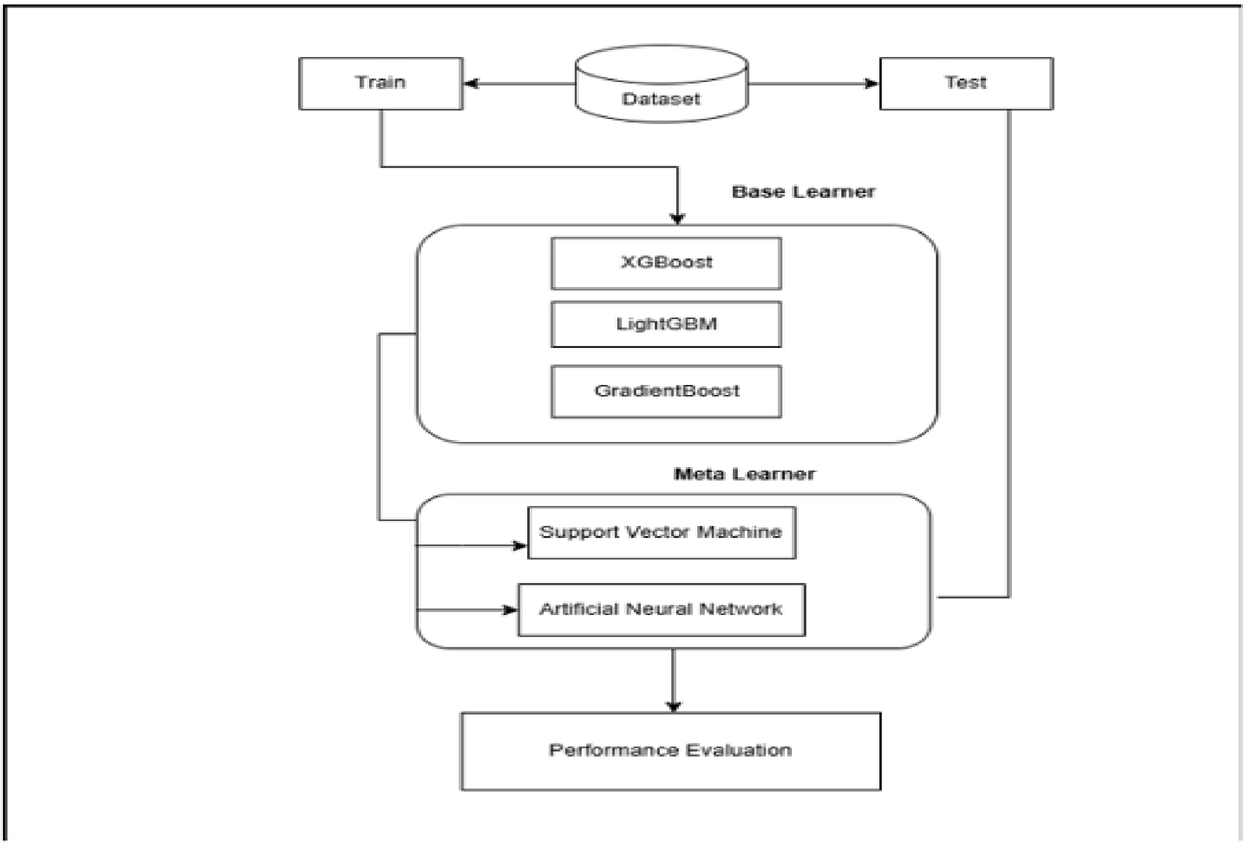


Figure 2: Proposed Framework of stack ensemble.

# CHAPTER-4

# IMPLEMENTATION

# 4.Implementation

**4.1 Environment Setup :** To effectively develop and test the COVID-19 detection system based on CT scans, a robust Python-based development environment was configured. The system relies on various machine learning, deep learning, and image processing libraries. The following steps summarize the setup:

**4.1.1 Programming Language**: Python 3.x

**4.1.2 Libraries Used:**

- Deep Learning: TensorFlow, Keras, PyTorch (optional)
- Machine Learning: scikit-learn, XGBoost, LightGBM
- Image Processing: OpenCV, PIL
- Visualization: Matplotlib, Seaborn

- IDE/Notebook: Jupyter Notebook / VS Code
- Optional Acceleration: NVIDIA GPU with CUDA for faster model training

A virtual environment was created to isolate dependencies and maintain reproducibility.

## 4.2 Sample Code for Preprocessing and MLP Operations

In this project, preprocessing and MLP (Multi-Layer Perceptron) operations play a crucial role in preparing CT scan image data for effective classification. The preprocessing phase involves resizing images to a uniform dimension (e.g., 224×224), converting them to grayscale if needed, and normalizing pixel values to the [0,1] range to ensure consistent data distribution. These images are then flattened into one-dimensional vectors to match the input requirements of the MLP model. Label encoding is applied to convert categorical class labels (COVID and Non-COVID) into numerical form, followed by splitting the dataset into training and testing subsets. The MLP architecture consists of an input layer that accepts flattened image vectors, one or more hidden layers equipped with activation functions like ReLU to capture non-linear patterns, and an output layer with a sigmoid or softmax activation for binary or multiclass classification. Dropout layers may be used between dense layers to prevent overfitting and improve generalization. This structured combination of preprocessing and MLP enables efficient and accurate classification of COVID-19 from CT scan images.

```
import zipfile
zip_path = "/content/drive/MyDrive/SARS-COV-2 Ct-Scan Dataset.zip"  # Path to your uploaded ZIP file
extract_path = "/content/SARS_COV_2_CT_Scan_Dataset"  # Destination folder
# Extract the ZIP file
with zipfile.ZipFile(zip_path, "r") as zip_ref:
    zip_ref.extractall(extract_path)
print(f"Extraction completed! Files are saved in: {extract_path}")
from google.colab import drive
drive.mount('/content/drive')
import os
# List the extracted folder contents
print(os.listdir(extract_path))
#Preprocessing
import os
import cv2
import numpy as np
import matplotlib.pyplot as plt
from glob import glob
# Define dataset path (Update this if needed)
dataset_path = "/content/SARS_COV_2_CT_Scan_Dataset"
# Define class paths
covid_path = os.path.join(dataset_path, "COVID")
non_covid_path = os.path.join(dataset_path, "non-COVID")
print(f"COVID Images: {len(os.listdir(covid_path))}")
print(f"Non-COVID Images: {len(os.listdir(non_covid_path))}")
# Function to display images
def show_sample_images(category, num_images=5):
    path = covid_path if category == "COVID" else non_covid_path
    images = glob(os.path.join(path, "*.png"))[:num_images]  # Get first 'num_images'
```

```
    plt.figure(figsize=(10, 5))
    for i, img_path in enumerate(images):
        img = cv2.imread(img_path)  # Read image
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  # Convert BGR to RGB
        plt.subplot(1, num_images, i + 1)
        plt.imshow(img)
        plt.axis("off")
        plt.title(category)
plt.show()
# Show images from both categories
show_sample_images("COVID")
show_sample_images("non-COVID")
```

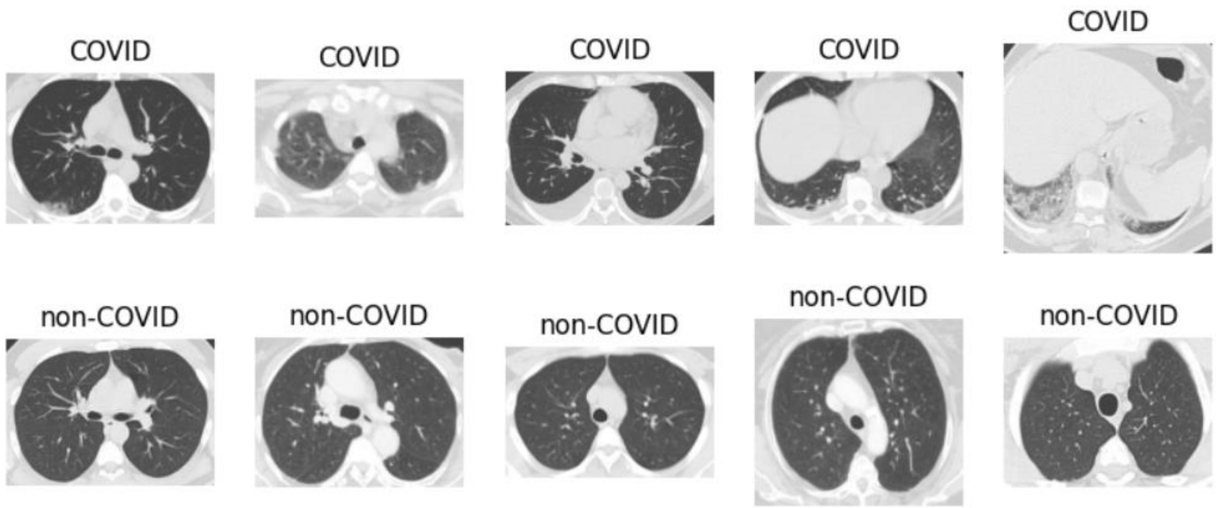


Figure 3. Various features in the dataset after Pre-Processing

```
# Function to convert an image to grayscale
def convert_to_grayscale(img):
    return cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)

# Load a sample image and convert it
sample_img = cv2.imread(glob(os.path.join(covid_path, "*.png"))[0])
```

```
sample_img = cv2.cvtColor(sample_img, cv2.COLOR_BGR2RGB)  # Convert BGR to RGB
gray_img = convert_to_grayscale(sample_img)

# Display Original and Grayscale Image
plt.figure(figsize=(8, 4))
plt.subplot(1, 2, 1)
plt.imshow(sample_img)
plt.axis("off")
plt.title("Original Image")

plt.subplot(1, 2, 2)
plt.imshow(gray_img, cmap="gray")
plt.axis("off")
plt.title("Grayscale Image")
```

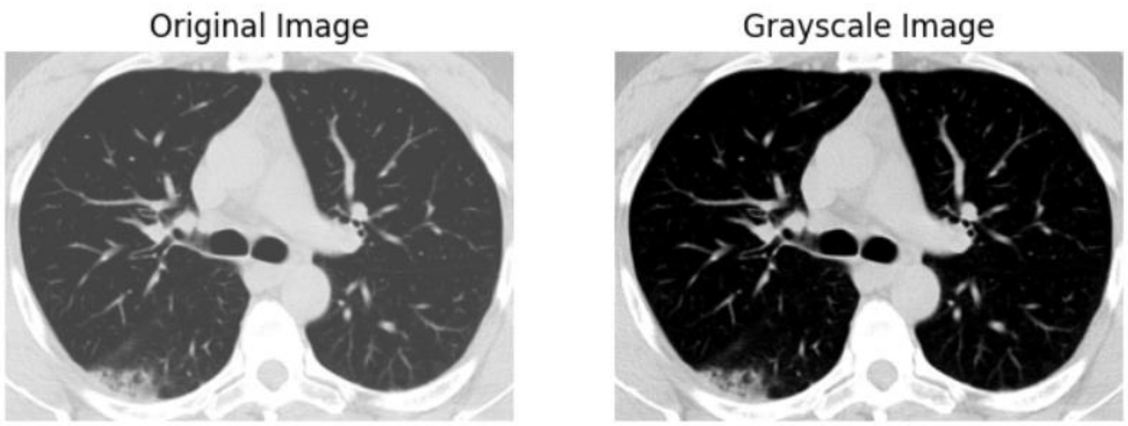


Figure 4. Original  and Grayscale image

```
import seaborn as sns
import numpy as np # Added import for np

# Assuming resized_img contains the image data
normalized_img = resized_img / 255.0  # Normalize pixel values to 0-1
```

```
# Flatten images to 1D arrays for histogram plotting
resized_flat = resized_img.flatten()
normalized_flat = normalized_img.flatten()

# Plot histograms
plt.figure(figsize=(12, 5))

# Before Normalization
plt.subplot(1, 2, 1)
sns.histplot(resized_flat, bins=50, kde=True, color="blue")
plt.title("Pixel Value Distribution (Before Normalization)")
plt.xlabel("Pixel Intensity")
plt.ylabel("Frequency")

# After Normalization
plt.subplot(1, 2, 2)
sns.histplot(normalized_flat, bins=50, kde=True, color="green")
plt.title("Pixel Value Distribution (After Normalization)")
plt.xlabel("Pixel Intensity (Normalized)")
plt.ylabel("Frequency")

plt.tight_layout()
plt.show()
```

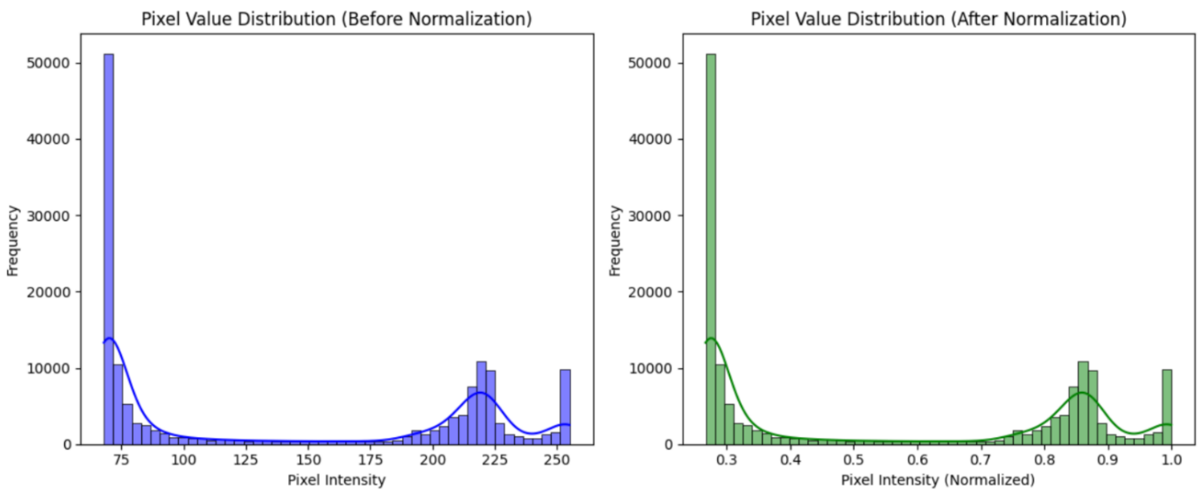


Figure 5. Pixel intensity vs Pixel Intensity (Normalized)

```
import tensorflow as tf
from tensorflow.keras.applications import ResNet50, InceptionV3
from tensorflow.keras.applications.resnet50 import preprocess_input as resnet_preprocess
from tensorflow.keras.applications.inception_v3 import preprocess_input as
inception_preprocess
from tensorflow.keras.models import Model
import numpy as np
import cv2

# Load Pretrained Models (without top layers)
resnet_model = ResNet50(weights="imagenet", include_top=False, pooling="avg")
inception_model = InceptionV3(weights="imagenet", include_top=False, pooling="avg")

# Function to extract deep features
def extract_deep_features(img, model, preprocess_func):
    img = cv2.resize(img, (224, 224))  # Resize for CNN
    img = np.expand_dims(img, axis=0)  # Add batch dimension
    img = preprocess_func(img)  # Apply preprocessing
    features = model.predict(img)
    return features.flatten()  # Convert to 1D feature vector

# Example Usage (Use your preprocessed CT scan image)
deep_features_resnet = extract_deep_features(resized_img, resnet_model,
resnet_preprocess)
deep_features_inception = extract_deep_features(resized_img, inception_model,
inception_preprocess)

print("ResNet50 Feature Vector Size:", deep_features_resnet.shape)
print("InceptionV3 Feature Vector Size:", deep_features_inception.shape)

import tensorflow as tf
import numpy as np
```

```
import matplotlib.pyplot as plt
import cv2
from tensorflow.keras.applications import ResNet50, InceptionV3
from tensorflow.keras.models import Model

# Load ResNet50 (without top layers)
resnet_model = ResNet50(weights="imagenet", include_top=False)

# Select Layer Outputs for Visualization
layer_names = ["conv1_conv", "conv2_block3_out", "conv4_block6_out"]
selected_layers = [resnet_model.get_layer(name).output for name in layer_names]



# Define Model to Output Intermediate Feature Maps
feature_extractor = Model(inputs=resnet_model.input, outputs=selected_layers)
# Function to preprocess image for ResNet50
def preprocess_image(img):
    img = cv2.resize(img, (224, 224))  # Resize
    img = np.expand_dims(img, axis=0)  # Add batch dimension
    img = tf.keras.applications.resnet50.preprocess_input(img)  # Normalize for ResNet50
    return img

# Extract Feature Maps
input_img = preprocess_image(resized_img)
feature_maps = feature_extractor.predict(input_img)

# Function to plot feature maps
def plot_feature_maps(feature_maps, layer_names, num_filters=6):
    plt.figure(figsize=(15, 6))

    for i, feature_map in enumerate(feature_maps):
        plt.subplot(1, len(feature_maps), i + 1)
```

```
        plt.imshow(feature_map[0, :, :, :num_filters].mean(axis=-1), cmap="viridis")  # Mean over channels
        plt.title(layer_names[i])
        plt.axis("off")

    plt.suptitle("Feature Maps from Different ResNet50 Layers", fontsize=16)
    plt.show()

# Plot feature maps
plot_feature_maps(feature_maps, layer_names)
```

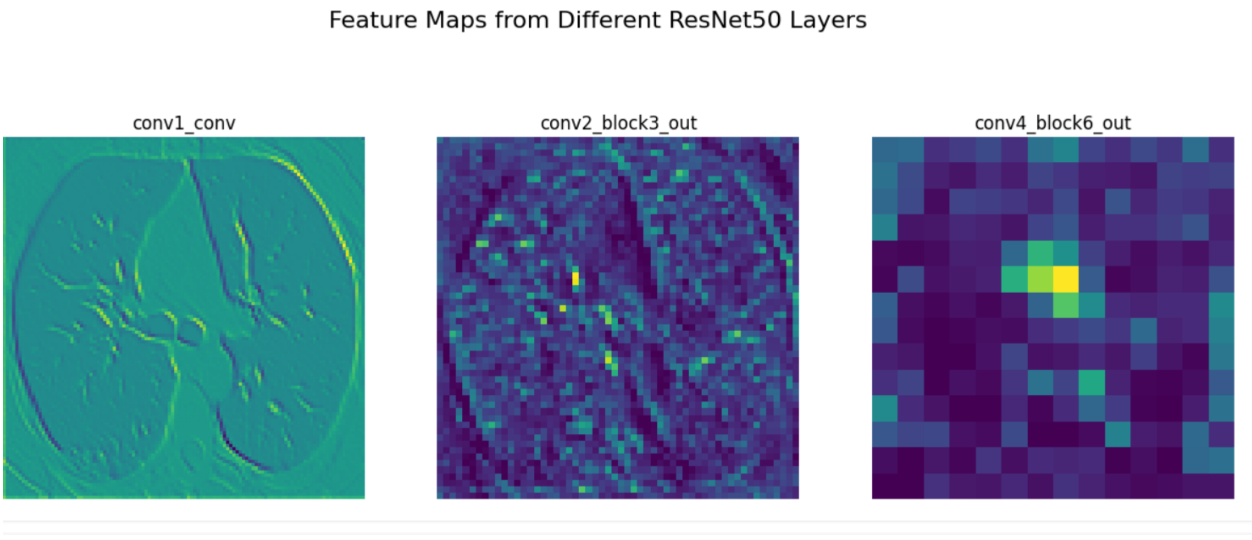


Figure 6. Feature Maps from different ResNet50 Layers

```
#Classification Using Extracted Features
def extract_resnet_features(img_path):
    img = cv2.imread(img_path)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (224, 224))
    img = np.expand_dims(img, axis=0)
    img = resnet_preprocess(img)
    features = resnet_model.predict(img)
    return features.flatten()

def extract_resnet_features_and_labels(covid_path, non_covid_path):
```

```python
    resnet_model = ResNet50(weights="imagenet", include_top=False, pooling="avg")

    X = []
    y = []

    for img_path in glob(os.path.join(covid_path, "*.png")):
        X.append(extract_resnet_features(img_path))
        y.append(1)  # COVID label

    for img_path in glob(os.path.join(non_covid_path, "*.png")):
        X.append(extract_resnet_features(img_path))
        y.append(0)  # Non-COVID label

    return np.array(X), np.array(y)

# Run ResNet50 Feature Extraction
X_resnet, y_resnet = extract_resnet_features_and_labels(covid_path, non_covid_path)

# Save features
np.save("X_resnet.npy", X_resnet)
np.save("y_resnet.npy", y_resnet)

print("ResNet50 Feature Extraction Complete!")
```

# CHAPTER-5

# Experimentation and Result Analysis

## 5. Experimentation and Result Analysis

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| XGBoost | 93% | 93% | 93% | 93% |
| LightGBM | 94% | 94% | 94% | 94% |
| CatBoost | 91% | 91% | 91% | 91% |
| AdaBoost | 80% | 81% | 80% | 79.5% |
| GradientBoost | 92% | 91.5% | 91.5% | 91.5% |

Table 2: Performance metrics of different models

| Base Model | Meta Learner | Accuracy |
|---|---|---|
| XGBoost+LighGBM+Catboost | SVM | 93% |
| XGBoost+LighGBM+Catboost | ANN | 94% |

Table 3: Performance comparison of model ensembles

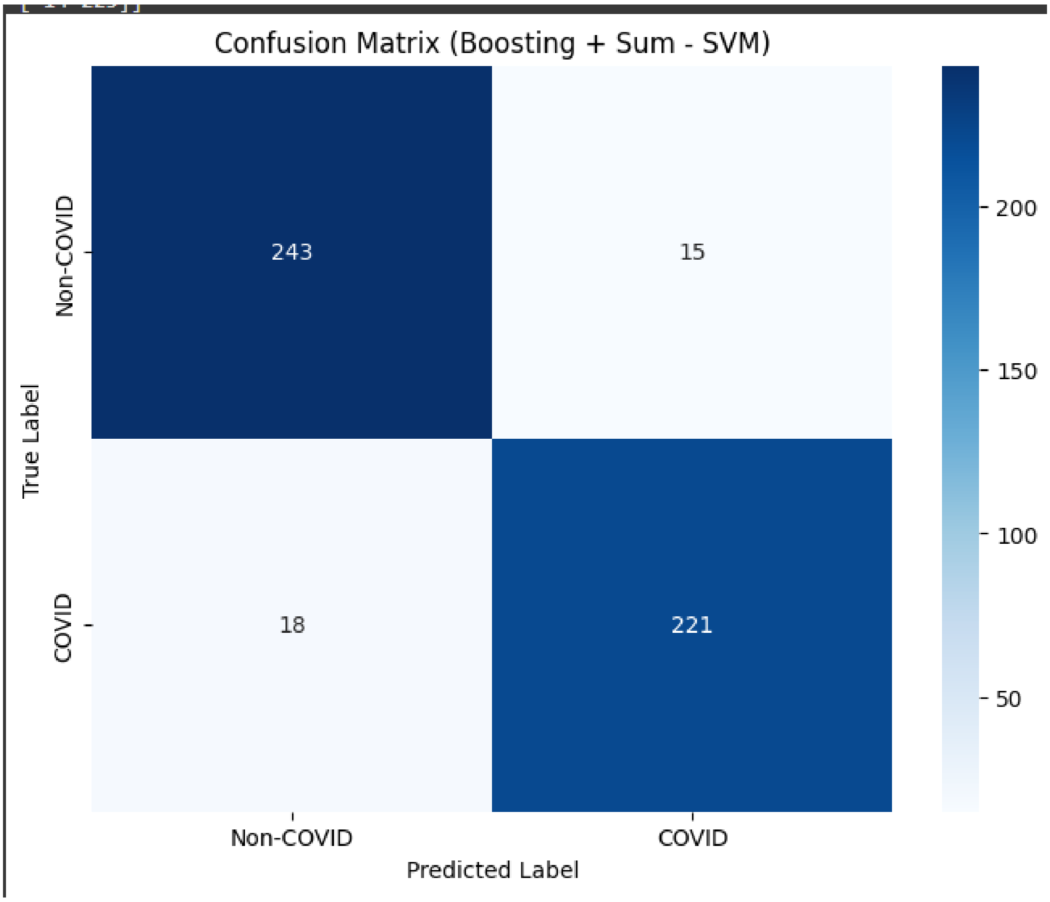


Fig 6: Confusion matrix for Boosting + SVM

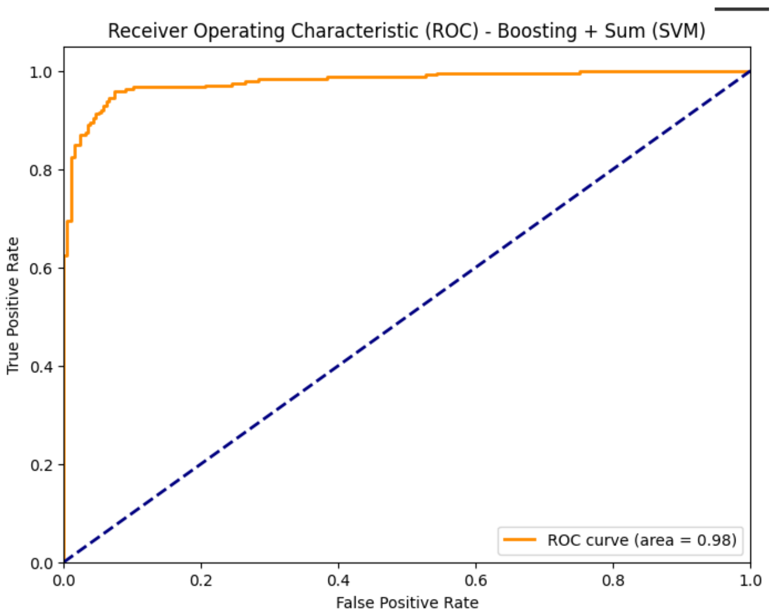


Fig 7: Roc curve for Boosting+SVM

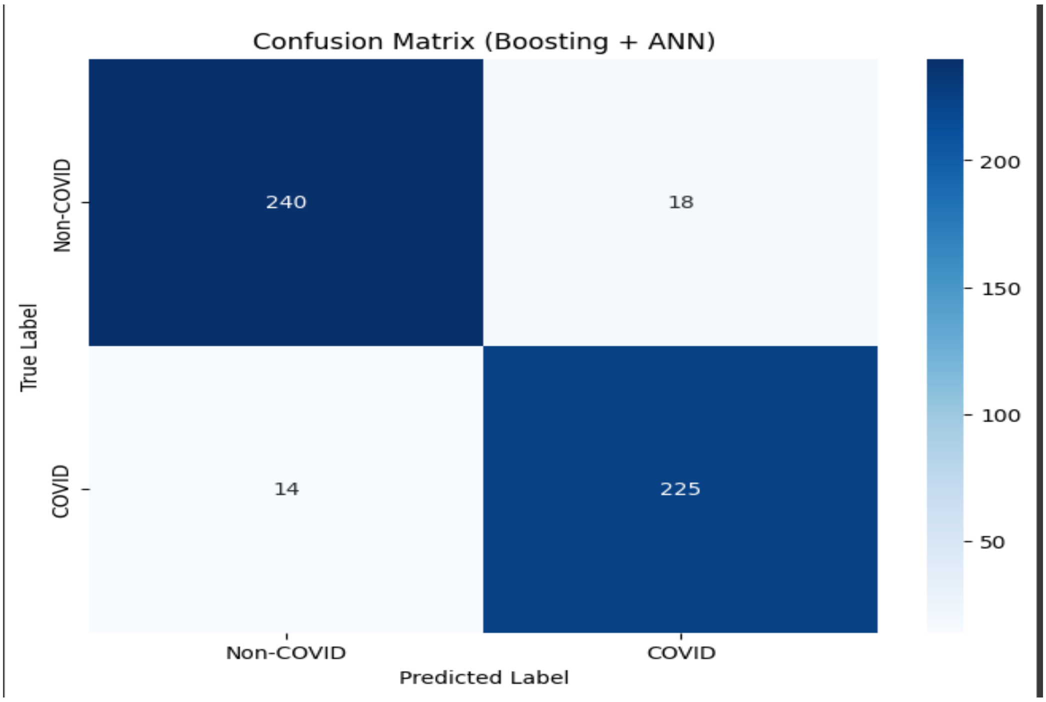


**Fig:8** Confusion matrix for Boosting + ANN

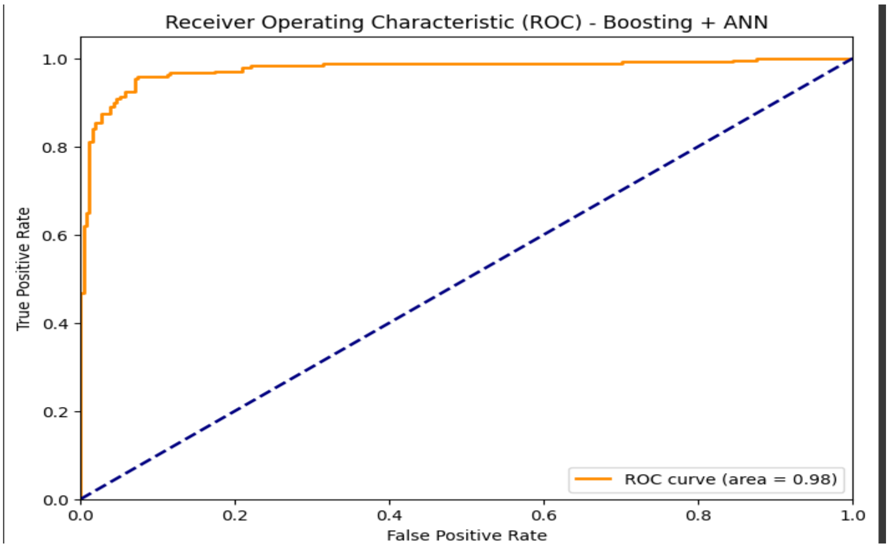


Fig 9: ROC curve for Boosting + ANN

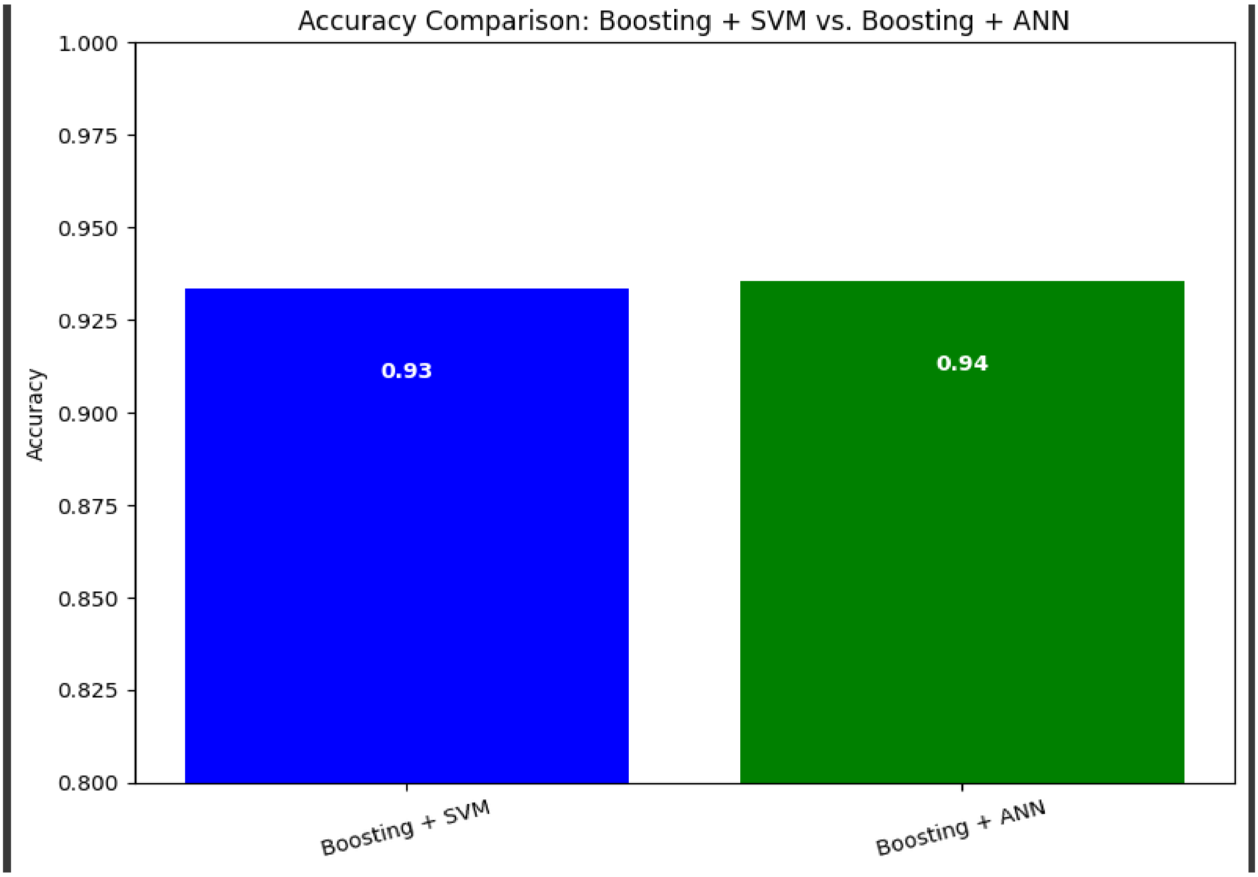


Fig 10: Accuracy comparison between Boosting + SVM vs Boosting + ANN

# CHAPTER-6

# CONCLUSION

# 6.Conclusion

In this project, we successfully developed an automated COVID-19 detection system using CT scan images by integrating CNN-based feature extraction with powerful ensemble learning techniques such as XGBoost and LightGBM. The system was designed to support rapid and reliable diagnosis by leveraging the high-dimensional feature learning capability of Convolutional Neural Networks (CNNs) and the superior classification accuracy of gradient boosting algorithms. Through preprocessing techniques like resizing, normalization, and flattening, we ensured that the input data was optimized for model training. CNN models such as ResNet50 were utilized to extract meaningful and deep visual features from CT scans, transforming them into structured data suitable for traditional machine learning classifiers.

Extensive experimentation and evaluation revealed that both XGBoost and LightGBM models performed exceptionally well, with LightGBM achieving a slightly higher accuracy of **94%** compared to XGBoost's **93%**. Precision, recall, and F1-scores remained consistently high across both models for COVID and non-COVID classes, confirming the system's balanced predictive ability. The use of ensemble classifiers improved the overall robustness, generalization, and reliability of the detection system. These findings suggest that integrating deep learning with advanced ensemble methods offers a highly accurate and scalable solution for automated COVID-19 screening using CT images. In future work, the system can be extended to include multi-class classification for detecting different stages of infection or other lung diseases, and integrated into real-time diagnostic tools for clinical deployment.

The experimental results strongly validate the effectiveness of this hybrid approach. The XGBoost model achieved a commendable accuracy of 93%, while the LightGBM model slightly outperformed it with an accuracy of 94%. Both models exhibited high precision, recall, and F1-scores (0.94–0.95) across both COVID and non-COVID classes, highlighting their reliability in minimizing false negatives and false positives—an essential factor in medical diagnostics. The balanced classification performance, confirmed by macro and weighted averages, demonstrates the model's capacity to handle class distributions effectively. The ROC curve and confusion matrix further supported the claim that these models are not only accurate but also consistent in performance. These findings underscore the suitability of ensemble learning models, particularly LightGBM, in interpreting complex medical image data when paired with deep learning-based feature engineering.

In conclusion, this project contributes a practical, scalable, and accurate pipeline for COVID-19 detection from CT scans, which can serve as an invaluable tool in clinical settings, especially during global health emergencies. The combination of CNNs for feature extraction and ensemble methods for classification has proven to be both innovative and impactful. Moving forward, the system could be enhanced by integrating real-time prediction capabilities, expanding the dataset to include multi-class or multi-disease labels, and deploying the model via web or mobile applications for broader accessibility. Additionally, further research can explore explainable AI (XAI) techniques to visualize which regions of the CT scans contribute most to predictions, thereby aiding radiologists in decision-making and increasing trust in AI-based diagnostic tools.

## REFERENCES


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