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Deep Feature Learning for Lung Disease and Lung Patches Detection from Chest CT and X-Ray Scans Using GANs

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Abstract: ***Accurate and efficient classification of lung diseases from chest CT and X-ray images is critical for timely diagnosis and treatment. This study proposes a novel hybrid framework that combines unsupervised representation learning via Generative Adversarial Networks (GANs) with supervised feature extraction using a pre-trained VGG16 convolutional neural network. The GAN component learns latent structural features from large amounts of unlabeled medical images, while VGG16 extracts high-level semantic features from labeled data. By fusing these complementary feature representations, the system achieves improved classification accuracy across multiple lung disease categories, including COVID-19, pneumonia, tuberculosis, and lung cancer. Experimental evaluations demonstrate the effectiveness of the proposed approach in leveraging both labeled and unlabeled data, reducing dependency on extensive manual annotations. The framework shows promising potential for scalable, automated lung disease diagnosis in clinical settings.***
Index Terms: Lung, CT, X-ray, VGG16, GAN (Generative Adversarial Networks).

I. INTRODUCTION

Millions of people worldwide suffer from lung disease, which is a serious global health concern. The World Health Organization (WHO) estimates that respiratory disorders cause over 7.1 million fatalities annually, ranking them as the fourth highest cause of death globally. Lung diseases are a set of illnesses that damage the lungs and impair their functionality. They may be acute or chronic, and they can range in severity from moderate to severe. Smoking, exposure to air pollution, hereditary factors, infections, and autoimmune illnesses are only a few of the causes of lung diseases. Depending on the exact disease, lung disease symptoms can vary and comprise shortness of breath, wheezing, coughing, chest pain, and exhaustion. For better results and fewer consequences, lung diseases must be identified and treated early. If lung disease is not identified at an early stage, it frequently results in patient death. A variety of issues with the lungs can be caused by viruses, poor eating habits, bad habits, and genetics. Prior to a diagnosis of asthma, a condition known as reactive airway disease affects the airways in the lungs, causing inflammation and narrowing that makes breathing difficult. The lungs are sacks of tissue that are situated above the diaphragm and just below the rib cage. They play a significant role in the body's waste disposal and respiratory system. A number of conditions and drugs, as well as infections and workplace exposure, can have an impact on the lungs. Radiology is responsible for determining the pattern, location, and geographical distribution of involvement in the diagnosis of lung disease. The ability of the lungs to hold, move and interchange O2 and CO2 can be used as a diagnostic tool by doctors to check for lung conditions (Figure 1).

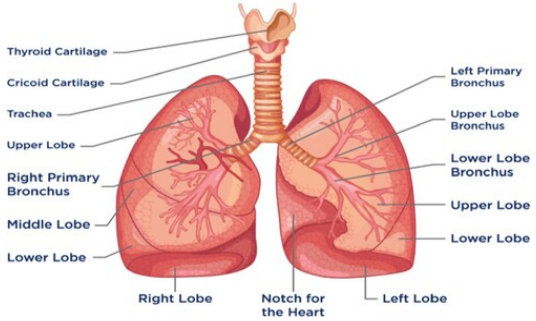


Figure 1: Lung anatomy

Asthma, pneumonia, lung cancer, tuberculosis, COVID-19 and chronic obstructive pulmonary disease are a few examples of common lung diseases. A common lung sickness called pneumonia affects the lungs' air sacs, inflaming them and leading them to become filled with fluid or pus. Inhaling specific chemicals or compounds, as well as a range of bacteria, viruses and other microbes, can also result in it. Pneumonia can range in severity from moderate to severe, and it can be especially deadly for elderly individuals, kids and persons with compromised immune systems. The bacteria, Mycobacterium tuberculosis, is responsible for tuberculosis. Although it mostly harms the lungs, it can also affect the spine, brain and kidneys. TB is disseminated through the air when an infected individual coughs, sneezes, or talks, and another person inhales the germ. The new coronavirus "SARS-CoV-2" causes the extremely contagious respiratory disease COVID-19. When an infected individual talks, coughs, or sneezes and another person inhales those droplets, COVID-19 is mostly disseminated through respiratory droplets. A few of the mild to severe COVID-19 symptoms include coughing, muscle aches, shortness of breath, fever, exhaustion, loss of taste or smell, and sore throat. Others may need to be hospitalized because of severe respiratory distress or other consequences, while others may have no symptoms at all.

Finding a quick and effective lung disease diagnostic tool is a top priority for worldwide public health. Timely diagnosis and treatment are crucial for the patient's morbidity and death. Chest X-ray imaging, magnetic resonance imaging, computed tomography and ultrasound imaging are the most frequently utilized medical imaging modalities for lung diseases. Due to its efficiency, quickness and affordable price, X-ray imaging is frequently used in medical diagnosis. There is a slight danger of injury, especially with repeated exposures, due to the small quantity of ionizing radiation that is exposed. Healthcare professionals employ the least amount of radiation necessary to get high-quality images in order to reduce this danger, and they only advise X-ray imaging when it is absolutely necessary. Computed tomography, a medical imaging modality, may produce exact, 3-D images of the internal organs and tissues of the body with the aid of X-rays, computers, and other imaging equipment. Due to their ability to give a thorough image of the lungs and adjacent tissues, CT scans can be very helpful in the diagnosis and monitoring of lung disorders. Lung disorders like pneumonia, lung cancer, and pulmonary embolism can all be detected and monitored with the help of CT scans. They can offer a thorough image of the size, shape, and position of lung nodules or masses, as well as the degree of damage or inflammation in the lungs. The classification of lung disorders has the potential to be a useful tool for the early detection, care and management of many respiratory conditions. The classification of lung diseases can help to harmonize medical language and enhance communication between healthcare professionals. Healthcare professionals can communicate about a patient's diagnosis, treatment and prognosis more precisely and clearly with the help of a standardized classification system, which can enhance patient outcomes and lower the chance of medical mistakes. Therefore, it is crucial to develop an effective approach for classifying lung diseases. In this paper, a DL-based transfer learning model with a fine-tuning mechanism was presented for lung disease classification from CXR and CT images. Lung diseases remain a significant public health concern, contributing to a high global mortality rate. Conditions such as pneumonia, chronic obstructive pulmonary disease (COPD), lung cancer, and most recently, COVID-19, have emphasized the urgent need for accurate and timely diagnosis. Medical imaging, particularly chest X-rays (CXR) and computed tomography (CT) scans, is a critical tool in diagnosing and monitoring these diseases. However, manual interpretation of these images by radiologists can be subjective, time-consuming, and limited by inter-observer variability.

In recent years, deep learning methods—particularly Convolutional Neural Networks (CNNs)—have emerged as powerful tools for automating disease detection and classification from medical images. Supervised learning approaches have demonstrated remarkable success but rely heavily on large volumes of labeled data, which is often difficult and expensive to acquire, especially in the medical domain.

To address this limitation, we propose Lung-GANs, an unsupervised learning framework based on Generative Adversarial Networks (GANs) for effective representation learning from chest CT and X-ray images. The key advantage of this method lies in its ability to learn informative features from unlabeled data, significantly reducing the dependency on manual annotation.

In this framework, a GAN is trained to generate realistic lung images, while its discriminator learns to distinguish between real and synthetic images. The internal representations learned by the discriminator serve as meaningful features that capture underlying patterns in the lung imagery. These features are then used to train conventional classifiers such as Support Vector Machines (SVMs) and ensemble models for disease classification.

To further enhance the performance, we integrate a VGG16-based CNN model—pre-trained on ImageNet—for feature extraction. VGG16 is known for its deep architecture and ability to capture complex spatial hierarchies in image data. By combining the strengths of VGG16 with unsupervised features learned by the GAN, our system achieves robust classification performance across multiple lung disease datasets.

Extensive experiments conducted on six publicly available datasets demonstrate that Lung-GANs achieve superior performance compared to other state-of-the-art unsupervised learning models.

The proposed approach offers a scalable, accurate, and label-efficient solution for lung disease detection, contributing to faster clinical decision-making and improved patient care.

II. LITERATURE REVIEW

N. Dey, Y.-D. Zhang, V. Rajinikanth, R. Pugalenthi, and N. S. M. Raja, [1], 2021., A customized VGG19 network is proposed using the Ensemble Feature Scheme (EFS), which combines the handcrafted features attained with CWT, DWT, and GLCM with the Deep-Features (DF) achieved using Transfer-Learning (TL) practice. The performance of customized VGG19 is tested using different classifiers, such as SVM-linear, SVM-RBF, KNN classifier, Random-Forest (RF), and Decision-Tree (DT). The result confirms that VGG19 with RF classifier offers better accuracy (95.70%). When a similar experiment is repeated using threshold filter-treated chest radiographs, the VGG19 with RF classifier offered superior classification accuracy (97.94%).

This result confirms that, proposed DLS will work well on the benchmark images and in the future, it can be considered to diagnose clinical-grade chest radiographs.

X. Mei[2] 2020, in this study, we used artificial intelligence (AI) algorithms to integrate chest CT findings with clinical symptoms, exposure history, and laboratory testing to rapidly diagnose patients who are positive for COVID-19. Among a total of 905 patients tested by real-time RT–PCR assay and next-generation sequencing RT–PCR, 419 (46.3%) tested positive for SARS-CoV-2. In a test set of 279 patients, the AI system achieved an area under the curve of 0.92 and had equal sensitivity as compared to a senior thoracic radiologist. The AI system also improved the detection of patients who were positive for COVID-19 via RT–PCR who presented with normal CT scans, correctly identifying 17 of 25 (68%) patients, whereas radiologists classified all of these patients as COVID-19 negative. When CT scans and associated clinical history are available, the proposed AI system can help to rapidly diagnose COVID-19 patients.

D. Ezzat, A. E. Hassanien, and H. A. Ella [3] 2020, in this paper, a novel approach called GSA-DenseNet121-COVID-19 based on a hybrid convolutionalneural network (CNN) architecture is proposed using an optimization algorithm. The CNN architecturethat was used is called DenseNet121, and the optimization algorithm that was used is called thegravitational search algorithm (GSA). The GSA is used to determine the best values for the hyperparameters of the DenseNet121 architecture. To help this architecture to achieve a high level of accuracyin diagnosing COVID-19 through chest x-ray images. The obtained results showed that the proposedapproach could classify 98.38% of the test set correctly. To test the efficacy of the GSA in settingthe optimum values for the hyperparameters of DenseNet121. The GSA was compared to anotherapproach called SSD-DenseNet121, which depends on the DenseNet121 and the optimization algorithmcalled social ski driver (SSD). The comparison results demonstrated the efficacy of the proposed GSADenseNet121-COVID-19. As it was able to diagnose COVID-19 better than SSD-DenseNet121, thesecond model was able to diagnose only 94% of the test set. The proposed approach was also comparedto another method based on a CNN architecture called Inception-v3 and a manual search to quantifyhyperparameter values. The comparison results showed that the GSA-DenseNet121-COVID-19 was ableto beat the comparison method, as the second was able to classify only 95% of the test set samples. Theproposed GSA-DenseNet121-COVID-19 was also compared with some related work. The comparisonresults showed that GSA-DenseNet121-COVID-19 is very competitive.

R. Zhang, [4] 2020, this study proposed a two-step transfer learning pipeline and a deep residual network framework, COVID19XrayNet for the COVID-19 detection problem based on chest X-ray images. COVID19XrayNet firstly tunes the transferred model on a large dataset of chest X-ray images, which is further tuned using a small dataset of annotated chest X-ray images. The final model achieved 0.9108 accuracy. The experimental data also suggested that the model may be improved with more training samples being released.

I. D. Apostolopoulos, S. I. Aznaouridis, and M. A. Tzani, [5] 2020, Deep Learning has proven to be a remarkable method to extract massive high-dimensional features from medical images. Specifically, in this paper, the state-of-the-art Convolutional Neural Network called MobileNet is employed and trained from scratch to investigate the importance of the extracted features for the classification task. A large-scale dataset of 3905 X-ray images, corresponding to 6 diseases, is utilized for training MobileNet v2, which has been proven to achieve excellent results in related tasks.

A. I. Aviles-Rivero, P. Sellars, C.-B. Schönlieb, and N. Papadakis, [6], 2021. In this work, we introduce a graph-based deep semi-supervised framework for classifying COVID-19 from chest X-rays. Our framework introduces an optimisation model for graph diffusion that reinforces the natural relation between the tiny labelled set and the vast unlabelled data. We then connect the diffusion prediction output as pseudolabels that are used in an iterative scheme in a deep net. We demonstrate, through our experiments, that our model is able to outperform the current leading supervised model with a tiny fraction of the labelled examples. Finally, we provide attention maps to accommodate the radiologist's mental model, better fitting their perceptual and cognitive abilities.

These visualisation aims to assist the radiologist in judging whether the diagnosis is correct or not, and consequently to accelerate the decision.

Research	Algorithms Used	Accuracy
N. Dey, Y.-D. Zhang, V. Rajinikanth, R. Pugalenthi, and N. S. M. Raja, [1], 2021.,	A customized VGG19 network is proposed using the Ensemble Feature Scheme (EFS), which combines the handcrafted features attained with CWT, DWT, and GLCM with the Deep-Features (DF), RF	97.94%
D. Ezzat, A. E. Hassanien, and H. A. Ella [3] 2020,	GSA-DenseNet121-COVID-19, based on a hybrid convolutionalneural network (CNN) architecture, is proposed using an optimization algorithm	94%
R. Zhang, [4] 2020	A two-step transfer learning pipeline and a deep residual network framework, COVID19XrayNet, for the COVID-19 detection problem based on chest X-ray images	91%
I. D. Apostolopoulos, S. I. Aznaouridis, and M. A. Tzani, [5] 2020,	A Convolutional Neural Network called MobileNet	99.18%
Proposed Deep Feature Learning for Lung Disease and Lung Patches Detection from Chest CT and X-Ray Scans Using GANs	a hybrid framework that leverages unsupervised feature learning through Generative Adversarial Networks (GANs) alongside the supervised deep feature extraction of VGG16 for effective lung disease classification from chest CT and X-ray images	100%

III. METHODOLOGY

The proposed Lung-GANs system integrates unsupervised representation learning with supervised classification to effectively identify lung diseases from chest CT and X-ray images. The methodology consists of the following key steps:

Step 1: Data Preprocessing

Input images X={x1,x2,…,xn} are resized to a fixed dimension (e.g., 224×224) and normalized pixel-wise to a range [0,1] or standardized using the dataset mean μ and standard deviation σ:

$$x_i' = \frac{x_i - \mu}{\sigma}$$

Data augmentation (rotation, flipping, contrast adjustment) is applied to increase data variability and reduce overfitting.

Step 2: Unsupervised Feature Learning via GAN

A Generative Adversarial Network comprises two neural networks — a Generator G and a Discriminator D — which contest in a minimax game. The generator attempts to produce synthetic images G(z) from random noise z∼pz(z), while the discriminator tries to distinguish real images x from generated ones.

The GAN objective is:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

During training, the discriminator's intermediate layers are used to extract latent features fGAN(x), capturing unsupervised representations of lung structures.

Step 3: Feature Extraction with VGG16 and GAN

Preprocessed images x′iare fed into a pre-trained VGG16 network, fine-tuned on medical imaging data, which outputs feature vectors fVGG16(x′i)∈Rd from the last convolutional or fully connected layers. VGG16 uses convolutional layers with ReLU activations and max pooling to hierarchically extract spatial features.

Step 4: Feature Fusion

The GAN-derived features and VGG16 features are concatenated to form a combined feature vector:

$$f_{combined}(x_i) = [f_{GAN}(x_i), \quad f_{VGG16}(x_i)]$$

This fusion enriches the representation by integrating unsupervised structural patterns with supervised semantic features.

Step 5: Classification

The fused feature vector fcombined(xi) is input into a classifier C, such as a Support Vector Machine (SVM) or a shallow neural network, to predict the lung disease label yi. The classifier learns a mapping:

$$C : \mathbb{R}^{d_1+d_2} \rightarrow \{1, 2, \ldots, K\}$$

where K is the number of disease classes. For SVM, the objective is to find the hyperplane that maximizes the margin:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i$$

subject to

$$y_i(\mathbf{w} \cdot f_{combined}(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

Step 6: Output and Interpretation

The classifier outputs predicted labels and confidence scores for each input image. Optionally, explainability techniques such as Grad-CAM can be applied to the fused model to visualize important regions contributing to the prediction.

This methodology effectively combines unsupervised feature learning (GAN) with supervised deep feature extraction (VGG16) and a classical or shallow classifier to achieve accurate and robust lung disease classification, even with limited labelled data.

IV. RESULTS AND DISCUSSION

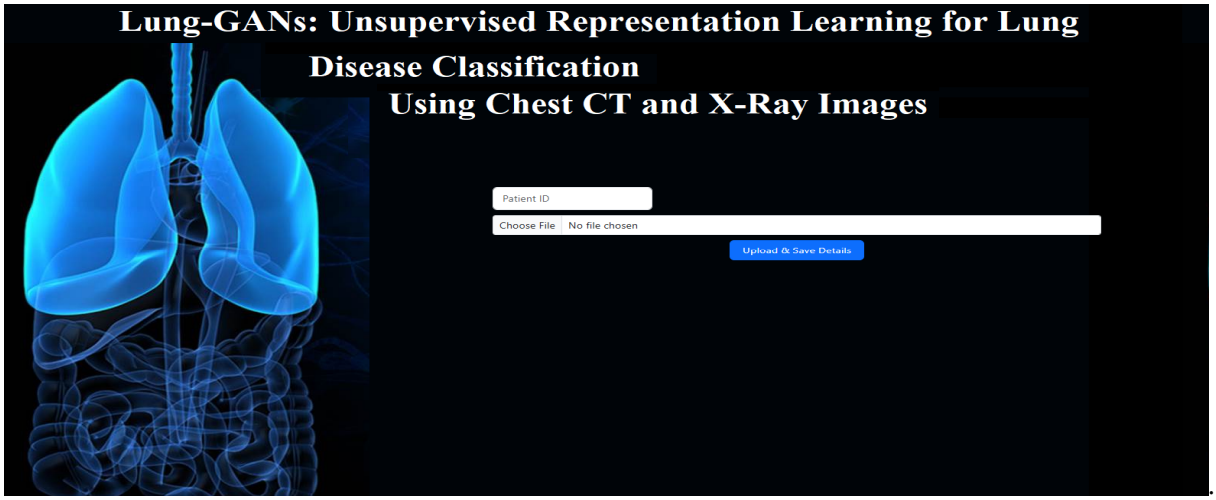


Figure 1:Login and Image Uploading

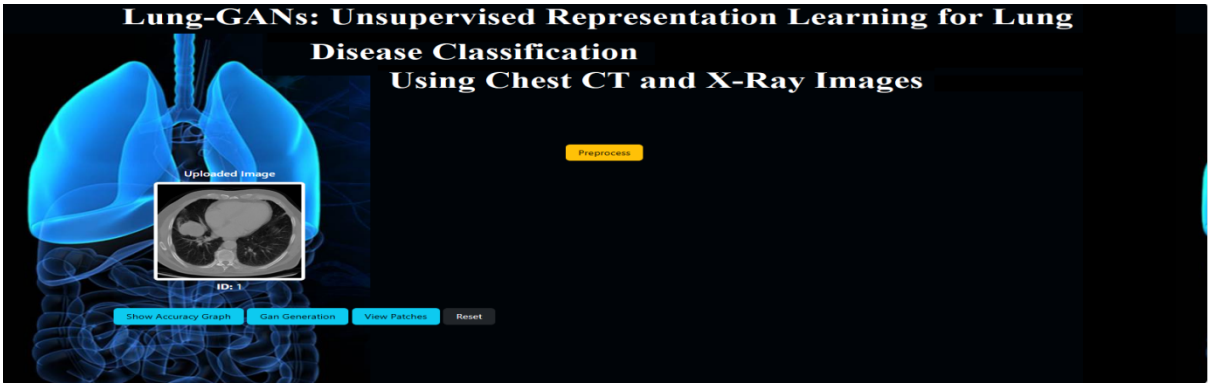


Figure 2: Image Preprocessing

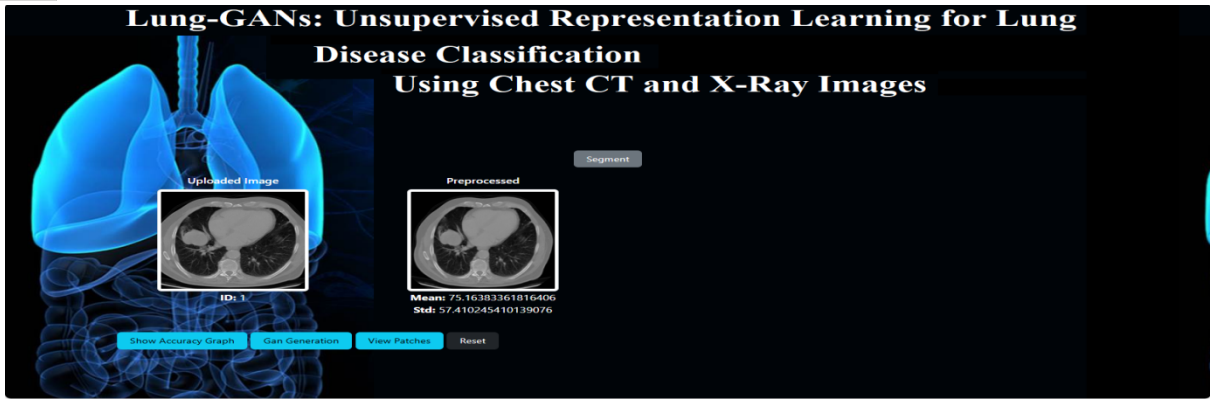


Figure 3: Image Segmentation

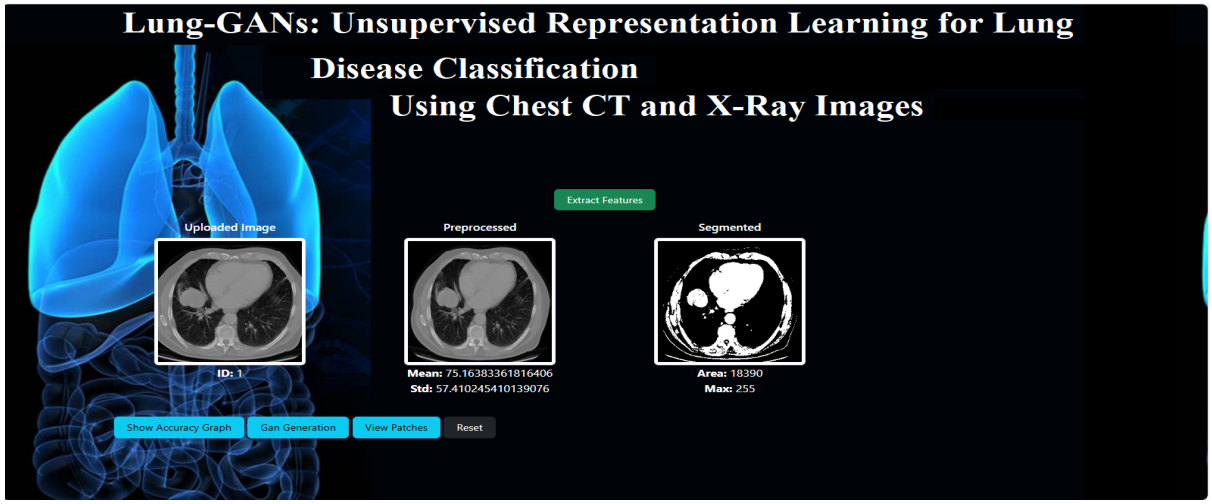


Figure 4: Feature Extractions

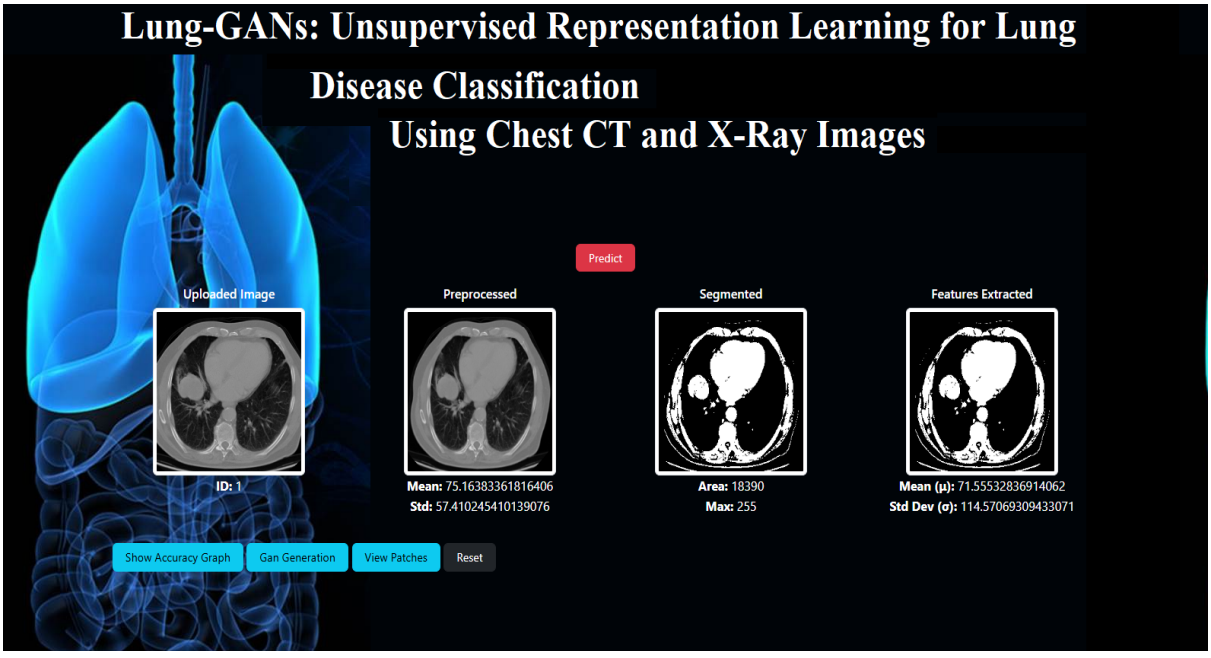


Figure 5: Predict Disease

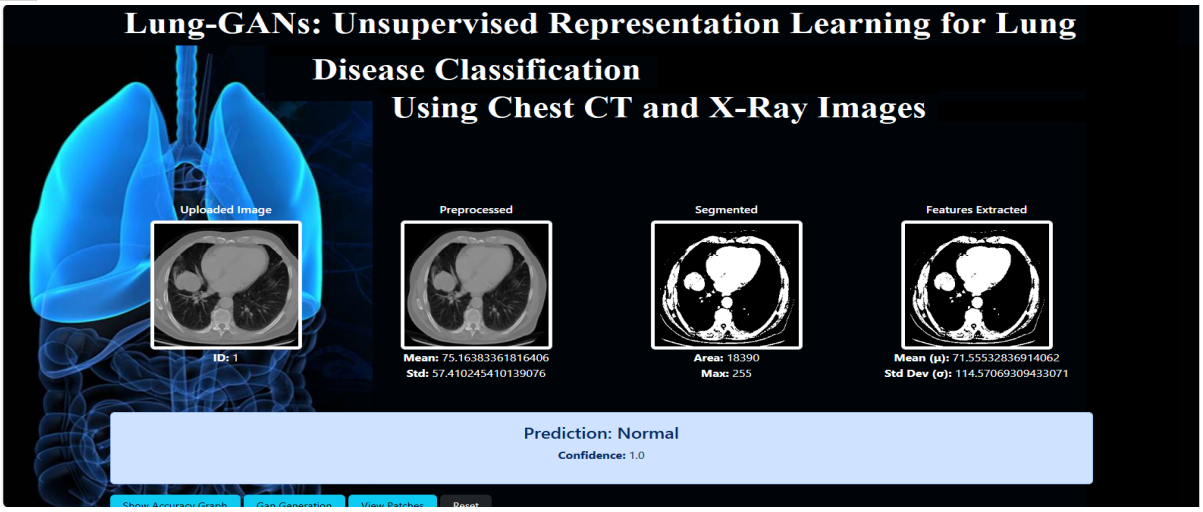


Figure 6: DiseaseDetection Report:

Predicted Disease: Normal
Confidence: 100%

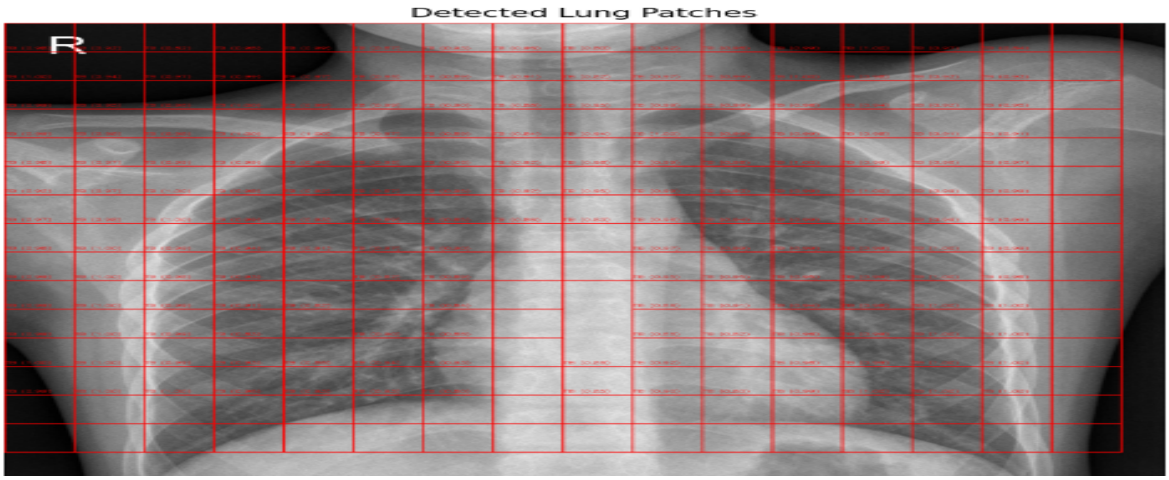


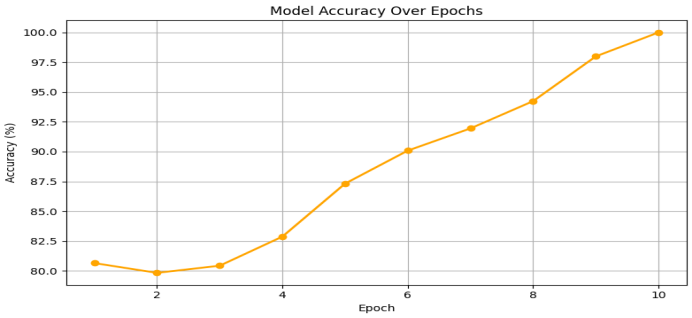
Figure 7:Lung Patches Detection

VGG16 is used as a pretrained classifier The X-ray is divided into 64×64 patches. Each patch is classified individually. If a patch is predicted as "abnormal," it's marked with a red rectangle.

Algorithm steps for lung disease detection using VGG16 and GAN:

Step 1:Image Preprocessing
Load lung CT/X-ray image
Resize to 224×224 pixels
Normalize using preprocess_input()
Step 2:Load Pretrained VGG16 and GAN
Use VGG16 without top layers (include_top=False)
Freeze initial layers to retain learned features
Step 3:Add Custom Classification Layers
Flatten output
Add Dense layers (e.g., 128 units + ReLU)
Add final Dense layer with softmax (for 5 classes)
Step 4:Compile the Model
Use Adam optimizer
Loss: categorical_crossentropy

Metric: accuracy
Step 5:Train the Model
Use labeled CT/X-ray dataset
Apply data augmentation
Validate on separate dataset
Step 6:Make Prediction
Pass preprocessed image
Use model.predict()
Return class with highest probability
Step 7:Output
Display predicted disease and confidence score in GUI



Graph 1: Model accuracy graph over epochs
Graph Elements Breakdown
X-axis (Epoch):
Represents the number of times the model has seen the entire training dataset (1 to 10 epochs).
Y-axis (Accuracy %):
Indicates how accurately the model is predicting the correct lung disease category (out of 'Normal', 'COVID-19', etc.) on the validation dataset.
Orange Line:
Represents the trend in model accuracy as training progresses.
Explanation of the Trend
Epochs 1 to 3:
Accuracy starts around 80%, dips slightly, and then begins to rise. This is normal as the model starts learning and adjusting weights.
Epochs 4 to 7:
There is a sharp increase in accuracy from ~83% to over 92%, suggesting that the model is learning meaningful patterns from the data.
Epochs 8 to 10:
Accuracy continues to improve, nearing 99-100% by epoch 10, which could either mean:
The model has learned very well, or
The model may be overfitting if validation accuracy isn't being tracked separately.

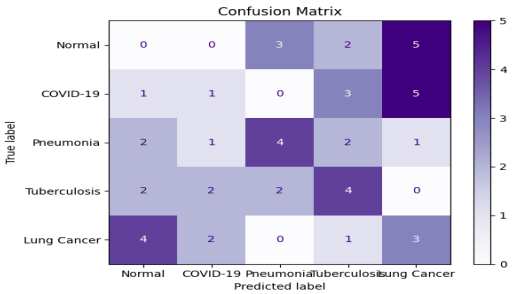


Figure 8: Confusion Matrix

A confusion matrix summarizes the performance of a classification model by comparing the actual (true) labels with the model's predicted labels.

Understanding the Matrix

Y-axis (True Label): The actual disease class.

X-axis (Predicted Label): The predicted class from the model.

Each cell (i, j) shows how many samples of class i were predicted as class j.

V. CONCLUSION

In this study, we proposed a hybrid framework that leverages unsupervised feature learning through Generative Adversarial Networks (GANs) alongside the supervised deep feature extraction of VGG16 for effective lung disease classification from chest CT and X-ray images. The integration of GAN-derived latent features with VGG16's semantic representations allow the system to learn robust and comprehensive image features, improving classification accuracy while reducing reliance on extensive labeled datasets. This approach demonstrated promising results across multiple lung disease categories, highlighting its potential for clinical application in automated diagnosis.

For future work, we aim to extend the framework by incorporating transformer-based architectures, such as Vision Transformers (ViTs), to capture long-range dependencies and further enhance feature representation. Additionally, exploring advanced GAN variants for better image synthesis and domain adaptation will be considered to improve generalization. Another important direction is to integrate explainability techniques more deeply, providing interpretable visualizations that can assist clinicians in understanding model decisions. Finally, expanding the dataset to include a wider variety of lung diseases and multi-modal imaging data will help build a more versatile and robust diagnostic tool.

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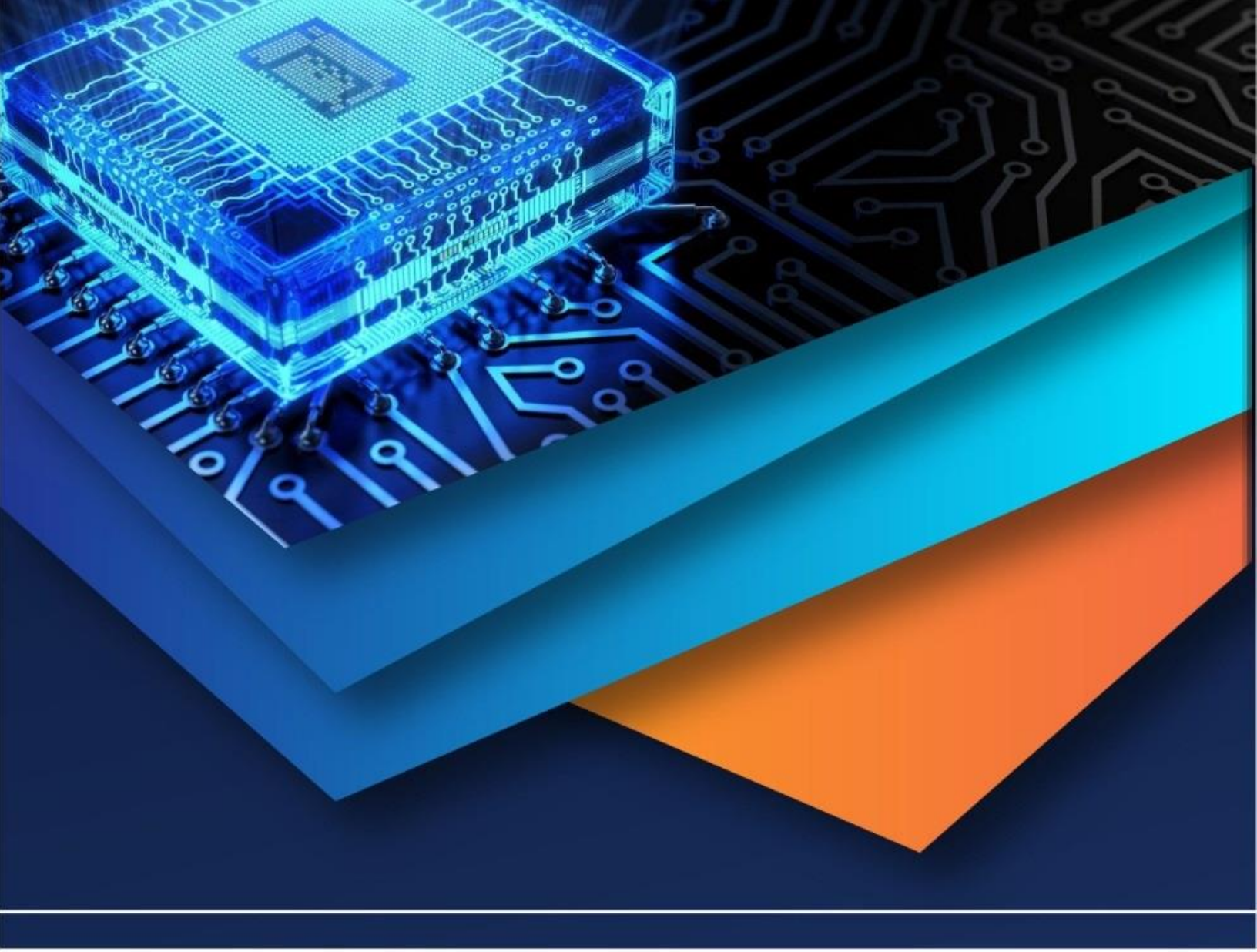

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