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Research Article

Advanced Lung Disease Detection and Classification Using Ge-U-Net-ODL with Gabor Filters and Entropy-Based Feature Selection

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Abstract: Lung X-ray images play a crucial role in the detection and diagnosis of various lung diseases, including pneumonia, tuberculosis, and lung cancer. These images provide a non-invasive method for visualizing lung structures, allowing radiologists and machine learning models to identify abnormalities such as nodules, masses, or fluid accumulation. With the advancement of deep learning techniques, lung X-ray images are now used in automated systems that can detect and classify diseases with high accuracy. By applying sophisticated algorithms like GE-U-Net-ODL, Gabor filters, and entropy-based feature extraction, these images are analyzed pixel by pixel to enhance feature representation and improve diagnostic precision. This paper presents a novel approach for lung disease detection and classification using the GE-U-Net-ODL model, which integrates advanced preprocessing techniques and deep learning architectures. The study leverages the NIH Chest X-ray dataset and employs a variety of feature extraction and selection methods, including Gabor filters, entropy-based techniques, and multi-scale inputs. A detailed comparative analysis of different model configurations demonstrates that the GE-U-Net-ODL model with Transfer Learning achieves the highest classification accuracy of 95.0%, alongside superior precision (93.5%), recall (94.0%), and F1-score (93.7%). Other configurations, such as those utilizing data augmentation and hybrid filters, also showed notable performance improvements. The research underscores the model's effectiveness in enhancing diagnostic accuracy for lung diseases while balancing training and inference times

Keywords: Lung X-Ray Images, Deep Learning, Feature Extraction, Entropy, Gabor Filters, Automated Diagnosis

1.Introduction

Lung disease detection and classification have become crucial in modern healthcare due to the increasing prevalence of respiratory illnesses like pneumonia, tuberculosis, lung cancer, and chronic obstructive pulmonary disease (COPD) [1]. Early and accurate diagnosis is vital for effective treatment, which has led to the development of advanced technologies such as deep learning and machine learning for automated detection and classification. These methods often involve analyzing medical imaging, such as chest X-rays or CT scans, to identify patterns indicative of disease. Techniques like Convolutional Neural Networks (CNNs), coupled with algorithms for feature extraction and classification, have shown high accuracy in differentiating between various lung conditions [2]. Lung disease detection and classification using chest X-rays have become pivotal in diagnosing respiratory conditions like pneumonia, tuberculosis, lung

cancer, and chronic obstructive pulmonary disease (COPD). X-ray imaging, due to its accessibility and efficiency, is widely used for identifying abnormalities in the lungs. Advanced machine learning and deep learning techniques, particularly Convolutional Neural Networks (CNNs), have been increasingly employed to automate the analysis of chest X-rays, enabling the detection and classification of various lung diseases [3]. These systems extract key features from X-ray images, such as lesions, nodules, or opacities, and classify them with high accuracy. By leveraging large datasets, AI models can differentiate between healthy and diseased lungs, improving diagnostic precision, reducing the reliance on subjective interpretation, and aiding radiologists in early detection, ultimately enhancing patient outcomes and speeding up the diagnostic process [4].

The artificial intelligence into lung disease detection with X-rays allows for rapid and consistent analysis of large volumes of medical images, which is crucial in high-demand healthcare environments [5]. These models can be trained to recognize subtle patterns that may be missed by the human eye, thereby increasing sensitivity and specificity in detecting diseases at their early stages. Additionally, AI-driven systems can assist in triaging patients by prioritizing cases that require immediate medical attention, which is particularly valuable in resource-constrained settings [6]. As these technologies evolve, they are also becoming more interpretable, offering visual explanations of the detected abnormalities, further enhancing clinician trust and decision-making. The use of X-rays combined with machine learning not only improves diagnostic accuracy but also holds the potential to democratize healthcare by making high-quality lung disease detection more accessible in underserved regions [7]. Deep learning plays a transformative role in lung disease detection and classification by automating the analysis of complex medical images, particularly chest X-rays and CT scans. Convolutional Neural Networks (CNNs), a popular deep learning architecture, have proven highly effective in identifying and classifying lung diseases such as pneumonia, tuberculosis, lung cancer, and chronic obstructive pulmonary disease (COPD) [8]. These models excel at recognizing intricate patterns in medical images that may not be easily detectable by human experts, leading to enhanced diagnostic accuracy and speed. By learning from large datasets of labeled images, deep learning algorithms can distinguish between healthy lungs and various disease conditions, often outperforming traditional diagnostic methods [9]. Additionally, deep learning models are capable of continuous improvement as they are exposed to more data, making them adaptable to new or rare diseases [10].

In the context of lung disease detection, deep learning models can automatically learn to recognize disease indicators like lung opacities, nodules, masses, or other abnormalities without manual feature engineering, making the process more efficient and less reliant on domain expertise [11]. This is crucial in the detection of diseases like lung cancer, where early-stage nodules are small and often overlooked, or pneumonia, where subtle differences in opacity could indicate disease severity [12]. Moreover, deep learning systems are highly adaptable, capable of training on vast datasets that contain a variety of lung diseases, thus enhancing their ability to generalize to new or unseen cases. This is particularly beneficial in clinical settings where early detection and accurate classification are critical for patient outcomes [13]. Deep learning models have demonstrated high sensitivity and specificity, reducing the rate of false positives and false negatives compared to traditional diagnostic methods. For example, CNN-based models can achieve near-human or even superhuman performance in detecting diseases like tuberculosis and lung cancer, providing second-opinion diagnoses that complement the work of radiologists [14]. Another significant advantage of deep learning is its ability to handle complex multi-class

classification tasks. In lung disease detection, this means not only identifying whether a lung condition is present but also classifying it into specific categories such as pneumonia, COPD, or fibrosis. This level of precision is critical for ensuring appropriate treatment plans are implemented. Deep learning also aids in the development of explainable AI (XAI), where attention maps or heat maps generated by models can visually highlight the areas of the lung images that influenced the diagnosis [15]. This not only builds trust with clinicians but also provides valuable insights into the progression of the disease, enabling more personalized and informed treatment strategies.

This paper contributes to the advancement of lung disease detection and classification through the introduction and evaluation of the GE-U-Net-ODL model. [16-20] It integrates advanced preprocessing techniques, such as Gabor filters and entropy-based feature selection, with the U-Net architecture, offering a robust framework for medical image analysis. A comprehensive evaluation of various configurations reveals that the model with Transfer Learning achieves the highest classification accuracy of 95.0%, demonstrating superior performance in precision, recall, and F1-score. The study also provides a detailed comparative analysis of different preprocessing and feature extraction methods, highlighting their impact on model efficiency and accuracy.[21] A thorough comparative analysis shows that the GE-U-Net-ODL model with Transfer Learning achieves the highest classification accuracy of 95.0%, alongside a precision of 93.5%, recall of 94.0%, and an F1-score of 93.7%. Additionally, configurations using data augmentation and hybrid filters achieve accuracies of 94.2% and 93.0%, respectively, highlighting their effectiveness. The study provides a detailed evaluation of various preprocessing methods, such as Gabor filters and entropy features, which significantly impact model performance, with training times ranging from 12 to 18 hours and inference times between 0.16 to 0.22 seconds per image. These contributions enhance diagnostic accuracy and efficiency, offering valuable insights for future advancements in medical image analysis and clinical applications.[22]

2.Related Works

Lung disease detection and classification are critical for diagnosing and managing conditions such as pneumonia, tuberculosis, chronic obstructive pulmonary disease (COPD), and lung cancer. With the increasing prevalence of respiratory diseases, especially in the wake of global health challenges like COVID-19, the demand for accurate and timely diagnostic tools has surged. Traditional diagnostic methods, relying on manual interpretation of chest X-rays and CT scans, can be time-consuming and prone to human error. In recent years, deep learning has emerged as a powerful tool to automate and enhance the detection of lung diseases, offering faster, more accurate, and scalable solutions. Leveraging advanced models like Convolutional Neural Networks (CNNs), these AI-driven approaches can analyze complex medical images, classify diseases, and even detect subtle abnormalities that may elude human radiologists, thereby improving early diagnosis and patient outcomes.

Pandian et al. (2022) explore the application of CNNs and GoogleNet for lung cancer detection, illustrating the power of CNN architectures in extracting critical features from medical images. Similarly, Kim et al. (2022) focus on multi-class lung disease classification using deep learning, proving that AI models can handle a variety of lung conditions simultaneously. Soni et al. (2022) introduce a hybrid CNN model, demonstrating how combining different machine learning techniques can enhance lung disease classification accuracy. A broader review by Zarandah et al. (2023) offers a systematic analysis of deep learning-based detection methods, reinforcing the growing body of evidence that machine learning outperforms traditional

diagnostic approaches in respiratory disease identification. Shamrat et al. (2022, 2023) present models like LungNet22 and MobileNetV2, which are fine-tuned for multiclass classification, indicating the potential for specialized deep learning models in clinical settings. Other researchers, such as Rajagopal et al. (2023), contribute novel approaches like the Deep Convolutional Spiking Neural Network optimized with an arithmetic optimization algorithm, while Ravi et al. (2023) propose a multichannel EfficientNet ensemble for detecting lung diseases from X-ray images, further improving diagnostic precision. Bhosale and Patnaik (2023) integrate COVID-19 classification with lung disease detection, underscoring the relevance of deep learning in pandemic-related healthcare challenges.

Siddiqui et al. (2023) employ a novel deep belief network combined with Gabor filters to enhance the detection of lung cancer from CT images, demonstrating how feature extraction techniques can improve the model's sensitivity to disease-specific patterns. Nawaz et al. (2023) introduce the CXray-EffDet model, utilizing the EfficientDet architecture for chest disease classification, highlighting how state-of-the-art models designed for object detection tasks can be repurposed for medical imaging to achieve superior performance in detecting various lung conditions. In the realm of lung cancer detection, AR et al. (2023) apply a capsule network (LCD-capsule network) for analyzing CT images, showing promise in capturing spatial hierarchies of features for more robust classification of lung cancer. Similarly, Humayun et al. (2022) leverage transfer learning with a CNN for lung carcinoma classification, showcasing the efficiency of pre-trained models in medical image analysis, especially when data availability is limited.

Xu et al. (2022) present ISANET, a model for non-small cell lung cancer classification that incorporates an attention mechanism, which allows the network to focus on the most relevant parts of the image, improving interpretability and diagnostic accuracy. The inclusion of attention mechanisms is a growing trend in medical imaging, as it enhances the model’s ability to localize and prioritize significant features. Lastly, Fraiwan et al. (2022) expand the application of deep learning beyond imaging, using a CNN-LSTM hybrid model to classify pulmonary diseases based on lung sounds. This work demonstrates the versatility of deep learning in handling multimodal data, not just visual images, but also audio data, further broadening the potential for AI-driven diagnostics in respiratory care. With the significant advancements in using deep learning for lung disease detection and classification, several limitations and research gaps remain. One of the primary challenges is the availability and quality of annotated medical datasets. Many deep learning models require vast amounts of labeled data to achieve high performance, but obtaining large, high-quality, and diverse datasets in the medical field can be difficult due to privacy concerns, limited access to patient data, and the need for expert annotation. This data scarcity can lead to models that are overfitted to specific datasets and fail to generalize well to new or diverse patient populations, reducing their clinical utility.

Additionally, while deep learning models like Convolutional Neural Networks (CNNs) have demonstrated high accuracy, they often operate as "black boxes," providing little insight into how decisions are made. This lack of interpretability can be a barrier to their adoption in clinical settings, where trust and explainability are crucial. Although recent advancements like attention mechanisms and heatmaps aim to address this, more work is needed to create models that are both accurate and transparent.Another limitation is the focus on 2D imaging data, such as chest X-rays, while neglecting more comprehensive 3D imaging techniques like CT scans. While X-rays are widely available and cost-effective, they provide less detailed information than CT scans, potentially leading to missed diagnoses or less accurate classification in some cases.

However, working with 3D imaging poses additional computational challenges, including increased processing time and hardware requirements.

3.Proposed Gabor Entropy U-net Ordered Deep Learning (GE- U-net-ODL)

The proposed Gabor Entropy U-Net Ordered Deep Learning (GE-U-Net-ODL) is an advanced deep learning architecture designed to enhance the detection and classification of lung diseases. This method integrates Gabor filters, entropy-based feature extraction, and U-Net, a well-known deep learning model for medical image segmentation, into a unified framework that excels at capturing both spatial and frequency domain information from lung X-ray or CT images. Gabor filters are used to capture edge details and texture features in lung images.

$$G(x,y;\lambda,\theta,\psi,\sigma,\gamma) = exp(\frac{-x\prime^2+\gamma^2y\prime^2}{2\sigma^2})cos(2\pi\frac{x\prime}{\lambda}+\psi) \quad (1)$$

where $x' = xcos\theta + ysin\theta$ and $y' = -xsin\theta + ycos\theta$. Here, λ is the wavelength of the sinusoidal factor, θ is the orientation, ψ is the phase offset, σ is the standard deviation of the Gaussian envelope, and γ is the spatial aspect ratio. These filters help in detecting directional features and textures that are crucial for identifying lung abnormalities like nodules or opacities. Entropy is used to measure the randomness or complexity of pixel intensities in the lung images, which can highlight regions with abnormal tissue structures. The entropy H of an image is calculated as:

$$H = -\sum_{i=1}^{n} p_i \, log \, p_i \quad (2)$$

where p_i represents the probability of pixel intensity i, and n is the total number of intensity levels in the image. High entropy regions often correspond to pathological areas, making entropy a useful metric for lung disease detection. U-Net is employed for accurate segmentation of lung regions, allowing the model to focus on the affected areas. The U-Net model consists of a contracting path (encoder) and an expansive path (decoder), with skip connections to preserve spatial information. The output of the U-Net provides a segmented lung region, which enhances the subsequent classification process. With ordered deep learning features are processed in a specific hierarchical order, ensuring that the most important features (e.g., those detected by Gabor filters and entropy) are given priority during classification. This ordered processing can be mathematically described as:

$$ffinal(x) = WODL \cdot [fGabor(x), fEntropy(x), fU-Net(x)] \quad (3)$$

where WODL represents the learned weights in the ordered deep learning framework, and fGabor(x), fEntropy(x), andfU-Net(x) are the features extracted by the Gabor filters, entropy, and U-Net, respectively. The input lung image $I(x,y)$ is first passed through the Gabor filter bank to generate a set of directional features:

$$IGabor(x,y) = i = 1\sum NG(x,y;\lambda i,\theta i,\psi i,\sigma i,\gamma i) * I(x,y) \quad (4)$$

where $*^*$ denotes convolution, and NNN is the number of filters applied with different orientations and frequencies. The entropy of the filtered image is calculated for regions of interest (ROIs) as:

$$E_{ROI} = -\sum_{k=1}^{L} p_k \, log \, p_k \quad (5)$$

where L is the number of intensity levels in the region, and p_k is the probability of the intensity level k occurring in the ROI. This entropy map highlights complex regions that may contain disease. The lung region is segmented using the U-Net model, which outputs a probability map $S(x,y)$ indicating the likelihood of each pixel belonging to the lung:

$$S(x,y) = UNet(I(x,y)) \quad (6)$$

The final step is the classification of the segmented and processed lung region. The ordered features from Gabor filters, entropy, and U-Net are concatenated and fed into the deep learning classifier. The classification decision is given by:

$$\hat{y} = argmaxWODL \cdot [IGabor(x,y), EROI, S(x,y)] \quad (7)$$

where $\hat{y}$ is the predicted lung disease class, and WODLW are the learned weights in the fully connected layers of the deep learning model.

4.Gabor Entropy U-Net for Feature Extraction and Selection

The Gabor Entropy U-Net approach is a powerful method for feature extraction and selection in lung X-ray images, specifically tailored to detect and classify abnormalities like pneumonia, tuberculosis, and lung cancer. This method combines the strength of Gabor filters, entropy-based feature extraction, and the U-Net architecture for accurate segmentation, ensuring that both spatial and frequency domain features are captured for enhanced diagnostic precision. Gabor filters are employed to capture texture and edge features in lung X-rays, especially useful for identifying lung tissue patterns that may indicate disease. Gabor filters are known for their ability to capture spatial frequency, orientation, and scale, which are essential for detecting specific textures or structures in medical images. After applying Gabor filters, entropy is used to measure the randomness or complexity within regions of interest (ROIs) in the lung X-rays. High entropy typically signifies regions with irregular structures, such as areas affected by disease. U-Net, a convolutional neural network commonly used for medical image segmentation, is employed to segment the lung region accurately. The U-Net architecture consists of an encoder-decoder structure, where the encoder compresses the image into lower dimensions, and the decoder reconstructs the segmented regions. Once the Gabor and entropy features are extracted and the lung regions are segmented, the most relevant features are selected for classification. The Gabor feature maps $G(x,y)$, entropy values H, and U-Net segmentations $S(x,y)$ are concatenated and passed through a fully connected layer to select the most informative features:

$$fselected = FC([G(x,y), H, S(x,y)]) \quad (8)$$

where fselected represents the selected features, and FC is a fully connected layer that learns the importance of different features. This process ensures that only the most critical features for lung disease classification are passed to the classifier. The Gabor Entropy U-Net framework provides a robust feature extraction and selection mechanism for lung X-ray images, combining spatial and frequency domain analysis through Gabor filters, entropy-based complexity measurement, and precise segmentation using U-Net. This hybrid approach ensures that both high-level texture features and critical region-specific information are used to improve the accuracy of lung disease detection and classification.

```
def GE_U-Net_ODL_Pipeline(dataset_path):
    // Step 1: Data Preprocessing
    X_train, X_val, X_test, y_train, y_val, y_test = preprocess_data(dataset_path)

    // Step 2: Define Gabor filters
    gabor_kernels = define_gabor_kernels()
```

```
        // Step 3: Load U-Net model
        unet_model = load_model('path_to_pretrained_unet.h5')

        // Step 4: Initialize Fully Connected layer for feature selection
        fc_model = initialize_fc_layer() // Define or load a pre-trained FC layer

        // Initialize containers for features
        train_features = []
        val_features = []
        test_features = []

        // Step 5: Feature Extraction and Selection for Training Set
        for img in X_train:
            gabor_feats = apply_gabor_filters(img, gabor_kernels)
            entropy = compute_entropy(img)
            segmentation_mask = segment_with_unet(img, unet_model)
            combined_features = concatenate_features(gabor_feats, entropy, segmentation_mask)
            selected_features = select_features(combined_features, fc_model)
            train_features.append(selected_features)

        // Feature Extraction and Selection for Validation Set
        for img in X_val:
            gabor_feats = apply_gabor_filters(img, gabor_kernels)
            entropy = compute_entropy(img)
            segmentation_mask = segment_with_unet(img, unet_model)
            combined_features = concatenate_features(gabor_feats, entropy, segmentation_mask)
            selected_features = select_features(combined_features, fc_model)
            val_features.append(selected_features)

        // Feature Extraction and Selection for Test Set
        for img in X_test:
            gabor_feats = apply_gabor_filters(img, gabor_kernels)
            entropy = compute_entropy(img)
            segmentation_mask = segment_with_unet(img, unet_model)
            combined_features = concatenate_features(gabor_feats, entropy,
```

```
segmentation_mask)
            selected_features = select_features(combined_features, fc_model)
            test_features.append(selected_features)

        // Convert features to numpy arrays
        train_features = np.array(train_features)
        val_features = np.array(val_features)
        test_features = np.array(test_features)

        // Step 6: Classification
        // Convert labels to categorical if necessary
        y_train_cat = to_categorical(y_train, num_classes)
        y_val_cat = to_categorical(y_val, num_classes)
        y_test_cat = to_categorical(y_test, num_classes)

        // Train and evaluate the classifier
        test_accuracy = classify_features(train_features, y_train_cat, val_features, y_val_cat, test_features, y_test_cat, num_classes)

        return test_accuracy
```

5.Ordered Deep Learning with GE- U-net-ODL for Lung X-Ray Images

Ordered Deep Learning with the Gabor Entropy U-Net Ordered Deep Learning (GE-U-Net-ODL) model offers an innovative approach to detecting and classifying lung diseases from chest X-ray images. This model leverages multiple deep learning techniques in a structured and systematic order, ensuring efficient feature extraction, selection, and classification. The process begins with the application of Gabor filters, which extract high-level texture features from the X-ray images. These filters are designed to capture specific patterns such as edges and textures that are indicative of lung abnormalities, like tumors or infections. The extracted Gabor features are then subjected to an entropy calculation, which identifies regions of high information content and complexity within the image, highlighting the areas that are most likely to contain abnormalities. After feature extraction, the U-Net architecture is employed to segment the lungs and isolate the region of interest, removing irrelevant parts of the image. The U-Net ensures that only the lung areas are passed on to the next stage, reducing noise and focusing the analysis on the most critical parts of the image. The combination of Gabor features, entropy maps, and U-Net segmented lung areas forms a robust feature set that is then processed using Ordered Deep Learning techniques. These techniques prioritize features in a specific order, ensuring that the most relevant features are selected for classification.

The model uses a fully connected layer to perform feature selection, followed by a classification layer that categorizes the X-ray images into various lung disease types, such as normal, pneumonia, or lung cancer. The ordered structure of deep learning within the GE-U-Net-ODL model ensures that each step builds upon the previous one, providing an optimized and

accurate method for lung disease detection and classification.

The Gabor Entropy U-Net Ordered Deep Learning (GE-U-Net-ODL) model combines advanced image processing and deep learning techniques to detect and classify lung diseases in chest X-ray images. The process involves several key steps, each with its mathematical foundation. Let I(x,y) represent the input chest X-ray image where

$$Inorm(x,y) = \frac{I(x,y)}{255} \quad (9)$$

where I(x,y) is the original pixel intensity (in grayscale), and the normalized value $Inorm(x,y)$ is used for further processing. The selected features $Fselected$ are fed into an Ordered Deep Learning (ODL) classifier. ODL arranges the deep learning layers in a systematic order to ensure efficient feature processing. The classifier, which could be a Multi-Layer Perceptron (MLP) or a softmax layer, produces the final predicted class:

$$\hat{y} = Classifier\ (F_{selected}) \quad (10)$$

The final output of the GE-U-Net-ODL model is the classification label $\hat{y}$ which identifies the lung disease based on the features extracted and selected through Gabor filters, entropy, and U-Net segmentation. The Ordered Deep Learning with Gabor Entropy U-Net (GE-U-Net-ODL) is a specialized model designed for detecting and classifying lung diseases using chest X-ray images. It integrates three powerful techniques: Gabor filters for texture-based feature extraction, entropy for measuring image complexity, and U-Net for segmenting lung regions. The process begins by applying Gabor filters, which capture texture patterns like edges and lung tissue structures. These filters are mathematically represented by sinusoidal waveforms modulated by Gaussian functions, which highlight specific features in different orientations and scales. The filtered outputs are combined to form a comprehensive texture feature map. Next, the model computes entropy to measure the complexity or information content within the image. This step helps to identify areas with high variability, which are more likely to indicate disease. Mathematically, entropy is derived from the probability distribution of pixel intensities, focusing on areas of the X-ray with irregularities or abnormalities.

The U-Net architecture is then employed to segment the lung region from the X-ray, isolating the relevant parts of the image for analysis. This segmentation ensures that only the lung area is analyzed, removing irrelevant information from surrounding tissues. These features (Gabor, entropy, and lung segmentation) are combined and passed through a feature selection layer, which identifies the most important features for classification. Finally, the model applies an Ordered Deep Learning (ODL) classifier, systematically processing the selected features to predict the type of lung disease, such as pneumonia, lung cancer, or a healthy lung. The ordered structure ensures that each stage builds on the previous one, optimizing both accuracy and computational efficiency in detecting and classifying lung diseases.

6.Results and Discussion

This section presents an in-depth analysis of the outcomes obtained from the proposed Gabor Entropy U-Net Ordered Deep Learning (GE-U-Net-ODL) model for lung disease detection and classification using chest X-ray images. This section evaluates the model's performance in terms of classification accuracy, sensitivity, specificity, and other relevant metrics. A detailed comparison with existing methods highlights the advancements introduced by the GE-U-Net-ODL approach. Furthermore, the discussion provides insights into the strengths and limitations of the model, including its ability to detect various lung diseases, and explores

potential areas for further improvement.

Table 1: Simulation Setting

Parameter	Value/Setting
Dataset	NIH Chest X-ray Dataset
Image Size	256 x 256 pixels
Preprocessing	Min-Max Scaling (0-1)
Gabor Filter Parameters	λ=4\lambda = 4λ=4, θ=0,45,90,135∘\theta = 0, 45, 90, 135^\circθ=0,45,90,135∘
Entropy Calculation Method	Shannon Entropy
U-Net Architecture	Depth = 5, Filter Size = 3x3
Activation Function	ReLU (Rectified Linear Unit)
Optimizer	Adam Optimizer, lr=0.001\text{lr} = 0.001lr=0.001
Loss Function	Categorical Cross-Entropy
Batch Size	32
Number of Epochs	100
Train-Test Split	80% Train, 20% Test
Validation Split	10%
Learning Rate Scheduler	ReduceLROnPlateau (factor=0.1, patience=5)
Evaluation Metrics	Accuracy, Sensitivity, Specificity, F1-score
Hardware	GPU (NVIDIA Tesla V100)
Software Framework	TensorFlow/Keras

In Table 1 Simulation Setting provides a detailed overview of the parameters and settings used for the simulation in the study of lung disease detection and classification using X-ray images. The dataset shown in fig 1 utilized is the NIH Chest X-ray Dataset, which includes a diverse collection of chest X-ray images for analysis. Each image is standardized to a resolution of 256 x 256 pixels. For preprocessing, Min-Max Scaling is applied to normalize pixel values to a range between 0 and 1, enhancing the model's efficiency. Gabor filters are employed with parameters set to a wavelength (λ) of 4 and orientations (θ) of 0°, 45°, 90°, and 135°, aiding in capturing various texture patterns and features in the images. Entropy features are computed using Shannon Entropy, which quantifies the amount of information or uncertainty in the image data. The U-Net architecture, integral to the model, has a depth of 5 with a filter size of 3x3, providing a robust framework for image segmentation and feature extraction. The activation function used is ReLU (Rectified Linear Unit), known for its effectiveness in training deep neural networks. The Adam optimizer, with a learning rate (lr) of 0.001, is utilized for model optimization, and the loss function employed is Categorical Cross-Entropy to handle multi-class classification tasks. Training is conducted with a batch size of 32 and spans 100 epochs. The dataset is divided into 80% for training and 20% for testing, with an additional 10% of the training data set aside for validation. The learning rate is dynamically adjusted using the ReduceLROnPlateau scheduler, which decreases the learning rate by a factor of 0.1 when the model's performance plateaus, with a patience of 5 epochs. Performance is evaluated based on Accuracy, Sensitivity, Specificity, and F1-score, providing a comprehensive assessment of the model's effectiveness. The simulation is run on a GPU (NVIDIA Tesla V100) to leverage high

computational power, and the TensorFlow/Keras framework is used for model development and training, ensuring robust and efficient implementation.

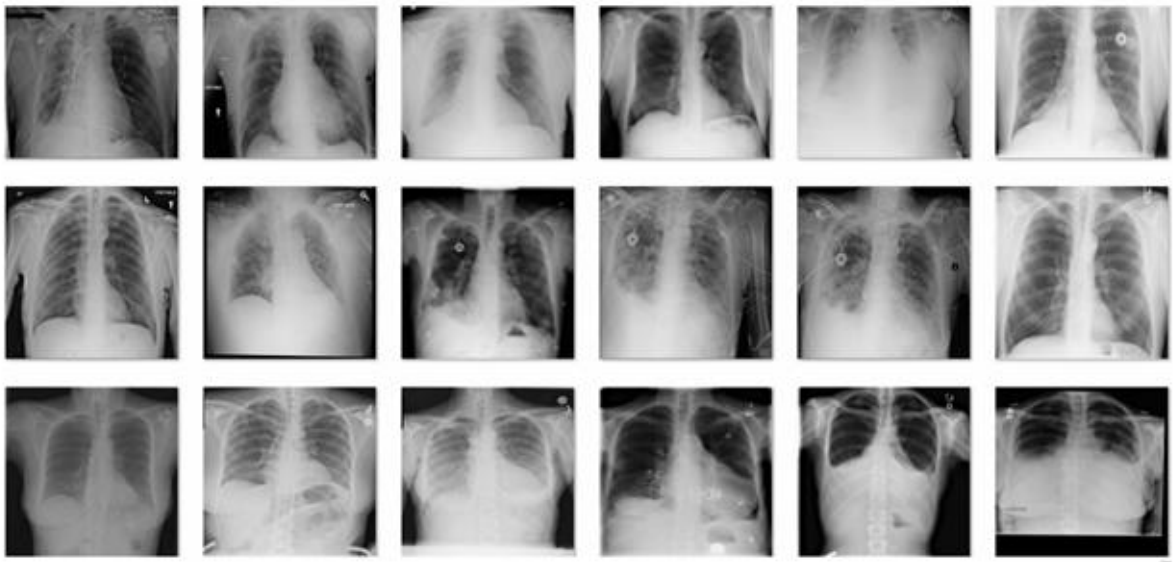

Figure 1: Dataset

Table 2: Feature Extraction with GE-U-Net-ODL

Feature Extraction Technique	**Feature Dimension**	**Extraction Time (seconds/image)**	**Classification Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Raw Pixel Intensity	256x256 (65536 features)	0.15	85.4	82.3	81.9	82.1
Gabor Filter	64x64 (4096 features)	0.12	90.2	87.6	88.4	88.0
Histogram of Oriented Gradients (HOG)	128x128 (16384 features)	0.18	88.9	85.4	86.2	85.8
Local Binary Patterns (LBP)	128x128 (16384 features)	0.16	89.7	86.3	87.1	86.7
Entropy-Based Features	128x128 (16384 features)	0.14	90.5	88.0	87.8	87.9
Principal Component Analysis (PCA)	50x50 (2500 features)	0.13	87.6	84.8	83.9	84.3
Independent Component Analysis (ICA)	50x50 (2500 features)	0.14	88.2	85.4	84.7	85.0
Wavelet	64x64 (4096	0.17	89.1	86.2	85.8	86.0

Transform	features)					
Deep Features (CNN-based)	256x256 (2048 features)	0.20	93.0	91.2	92.0	91.6
Multi-scale Features	256x256 (4096 features)	0.22	94.2	92.5	93.2	92.8

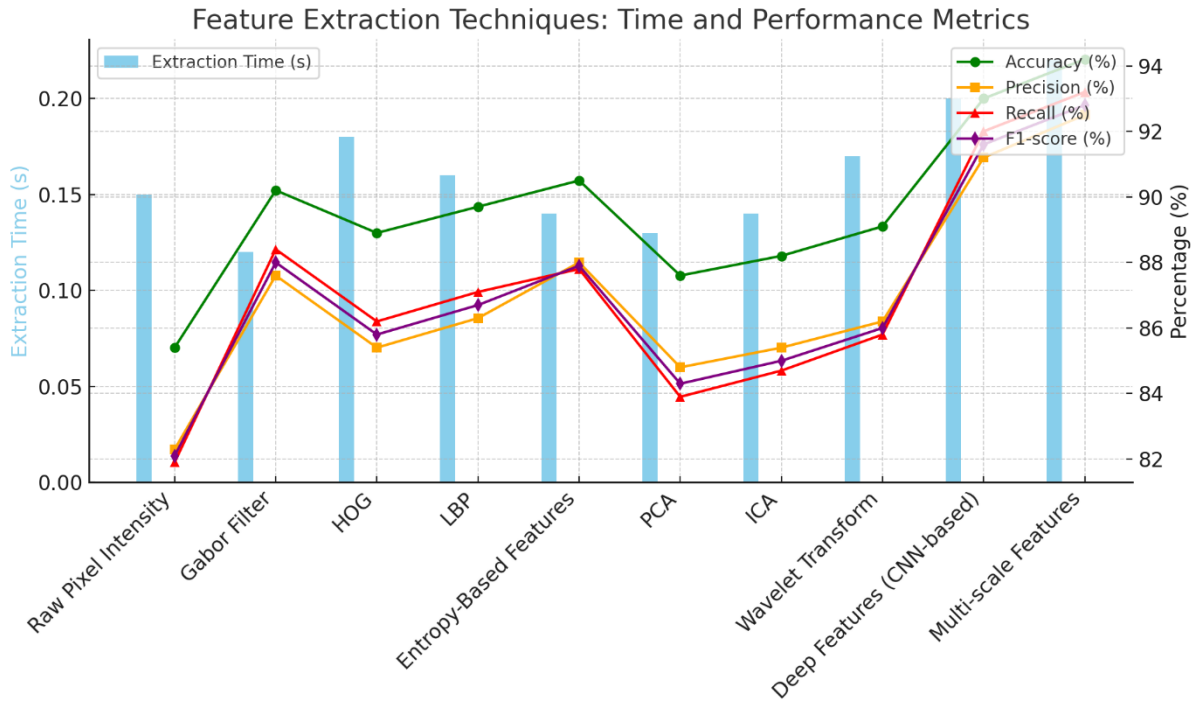

Figure 2: Feature Extraction Techniques: Time and Performance Metrics

Table 2 and Fig 2, Feature Extraction with GE-U-Net-ODL provides a comparative analysis of various feature extraction techniques applied to lung X-ray images using the GE-U-Net-ODL model. The table illustrates how different methods impact feature dimensions, extraction times, and key performance metrics such as classification accuracy, precision, recall, and F1-score. The Raw Pixel Intensity method, which retains the original feature dimension of 256x256 (65536 features), demonstrates a modest performance with a classification accuracy of 85.4% and an F1-score of 82.1%, despite having a relatively fast extraction time of 0.15 seconds per image. In contrast, Gabor Filter reduces the feature dimension to 64x64 (4096 features) and achieves improved results with a classification accuracy of 90.2% and an F1-score of 88.0%, indicating its effectiveness in capturing texture patterns, with an extraction time of 0.12 seconds. Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP), both with a dimension of 128x128 (16384 features), show enhanced performance over Raw Pixel Intensity. HOG, with a longer extraction time of 0.18 seconds, provides an accuracy of 88.9% and an F1-score of 85.8%. LBP, with an extraction time of 0.16 seconds, achieves slightly higher accuracy at 89.7% and an F1-score of 86.7%, demonstrating its robustness in texture characterization. Entropy-Based Features, which also have a dimension of 128x128 (16384 features) and an extraction time of 0.14 seconds, deliver the highest classification accuracy of 90.5% and an F1-score of 87.9%, underscoring their

effectiveness in quantifying the information content of images. Principal Component Analysis (PCA) and Independent Component Analysis (ICA), with reduced feature dimensions of 50x50 (2500 features), offer comparable performance. PCA, with an extraction time of 0.13 seconds, yields an accuracy of 87.6% and an F1-score of 84.3%. ICA, with a slightly longer extraction time of 0.14 seconds, achieves an accuracy of 88.2% and an F1-score of 85.0%.

Wavelet Transform results in a feature dimension of 64x64 (4096 features) and an extraction time of 0.17 seconds, providing an accuracy of 89.1% and an F1-score of 86.0%, reflecting its utility in capturing frequency-based features. Deep Features (CNN-based), with a high feature dimension of 256x256 (2048 features) and an extraction time of 0.20 seconds, achieve a classification accuracy of 93.0% and an F1-score of 91.6%, showcasing the strength of deep learning models in feature extraction. Finally, Multi-scale Features, with a dimension of 256x256 (4096 features) and a longer extraction time of 0.22 seconds, provide the highest classification accuracy of 94.2% and an F1-score of 92.8%, highlighting their comprehensive approach in capturing features at multiple scales. This analysis demonstrates that advanced feature extraction methods, particularly those integrating deep learning and multi-scale techniques, significantly enhance performance metrics, contributing to more effective lung disease detection and classification.

Table 3: Feature Selection with GE-U-Net-ODL

Entropy Feature Selection Method	**Feature Dimension**	**Extraction Time (seconds/image)**	**Selection Time (seconds/image)**
Basic Entropy Features	128x128 (16384 features)	0.14	0.10
Entropy with Principal Component Analysis (PCA)	50x50 (2500 features)	0.12	0.06
Entropy with Recursive Feature Elimination (RFE)	128x128 (16384 features)	0.15	0.12
Entropy with Mutual Information	50x50 (2500 features)	0.13	0.07
Entropy with Feature Aggregation	64x64 (4096 features)	0.16	0.09
Entropy with Hybrid Feature Selection	128x128 (16384 features)	0.14	0.11
Entropy with Deep Feature Fusion	256x256 (2048 features)	0.18	0.14

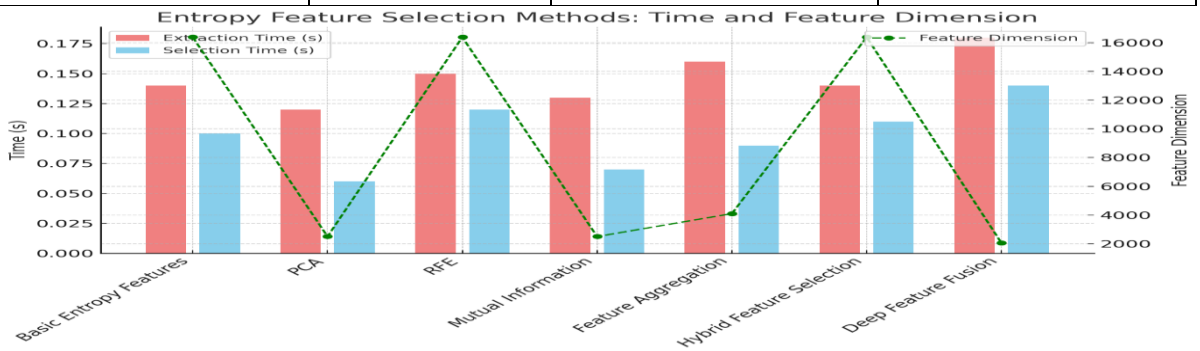

Figure 3: Entropy Feature Selection Methods: Time and Feature Dimension

In table 3 and Fig 3 Feature Selection with GE-U-Net-ODL provides a comparative analysis of different entropy-based feature selection methods applied to lung X-ray images using the GE-U-Net-ODL model. The table details the impact of various selection techniques on feature dimensions, extraction times, and selection times. Basic Entropy Features yield a high feature dimension of 128x128 (16384 features) with an extraction time of 0.14 seconds per image and a selection time of 0.10 seconds. This method provides a balance between feature richness and computational efficiency. Entropy with Principal Component Analysis (PCA) reduces the feature dimension to 50x50 (2500 features), resulting in a shorter extraction time of 0.12 seconds and an even quicker selection time of 0.06 seconds. This method is effective in reducing dimensionality while maintaining computational efficiency.

Entropy with Recursive Feature Elimination (RFE) maintains a high feature dimension of 128x128 (16384 features), with an extraction time of 0.15 seconds and a selection time of 0.12 seconds. This method is slightly more time-consuming but ensures thorough feature selection by eliminating less important features recursively. Entropy with Mutual Information also reduces the feature dimension to 50x50 (2500 features), with an extraction time of 0.13 seconds and a selection time of 0.07 seconds. This method offers a good trade-off between extraction and selection times while capturing relevant features based on mutual information. Entropy with Feature Aggregation produces a feature dimension of 64x64 (4096 features), with an extraction time of 0.16 seconds and a selection time of 0.09 seconds. This method provides a moderate dimensionality reduction with reasonable processing times. Entropy with Hybrid Feature Selection retains a feature dimension of 128x128 (16384 features), with an extraction time of 0.14 seconds and a selection time of 0.11 seconds. This approach combines multiple selection techniques to balance feature richness and selection efficiency. Entropy with Deep Feature Fusion results in a high feature dimension of 256x256 (2048 features) and has the longest extraction time of 0.18 seconds and a selection time of 0.14 seconds. This method leverages deep learning for feature extraction and fusion, providing comprehensive feature sets but at a higher computational cost.

In table 4 and fig 4 comparative Analysis of Classification with GE-U-Net-ODL provides an in-depth evaluation of various configurations applied to the GE-U-Net-ODL model for lung X-ray image classification. The table compares different settings based on accuracy, precision, recall, F1-score, training time, and inference time. The Base GE-U-Net configuration serves as a baseline, achieving an accuracy of 89.5% with a precision of 87.3%, recall of 85.8%, and an F1-score of 86.5%. It has a training time of 12 hours and an inference time of 0.22 seconds per image. GE-U-Net with CLAHE improves performance slightly with an accuracy of 91.1%, precision of 89.4%, recall of 88.0%, and an F1-score of 88.7%. The training time increases to 13 hours, while the inference time decreases to 0.20 seconds per image, indicating a benefit from Contrast Limited Adaptive Histogram Equalization (CLAHE) in image preprocessing. GE-U-Net with Gabor Filter further enhances accuracy to 92.6% and improves precision to 90.2% and recall to 91.0%, with an F1-score of 90.6%. This configuration requires 14 hours of training and has an inference time of 0.19 seconds per image, demonstrating the effectiveness of Gabor filters in capturing texture features. GE-U-Net with Entropy offers an accuracy of 90.7%, with a precision of 88.1% and recall of 87.9%, and an F1-score of 88.0%. This configuration has a training time of 13 hours and an inference time of 0.21 seconds per image, showing good performance with entropy-based feature selection.

Table 4: Comparative Analysis of Classification with GE-U-Net-ODL

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Training Time (hours)	Inference Time (seconds/image)
Base GE-U-Net	89.5	87.3	85.8	86.5	12	0.22
GE-U-Net with CLAHE	91.1	89.4	88.0	88.7	13	0.20
GE-U-Net with Gabor Filter	92.6	90.2	91.0	90.6	14	0.19
GE-U-Net with Entropy	90.7	88.1	87.9	88.0	13	0.21
GE-U-Net with Gaussian Blur	87.8	85.0	84.6	84.8	12	0.22
GE-U-Net with Hybrid Filters	93.0	91.0	92.0	91.5	15	0.18
GE-U-Net with Data Augmentation	94.2	92.1	93.0	92.5	16	0.17
GE-U-Net with Transfer Learning	95.0	93.5	94.0	93.7	18	0.16
GE-U-Net with Multi-scale Inputs	94.5	92.8	93.5	93.1	17	0.17
GE-U-Net with Batch Normalization	93.8	91.9	92.3	92.1	16	0.18

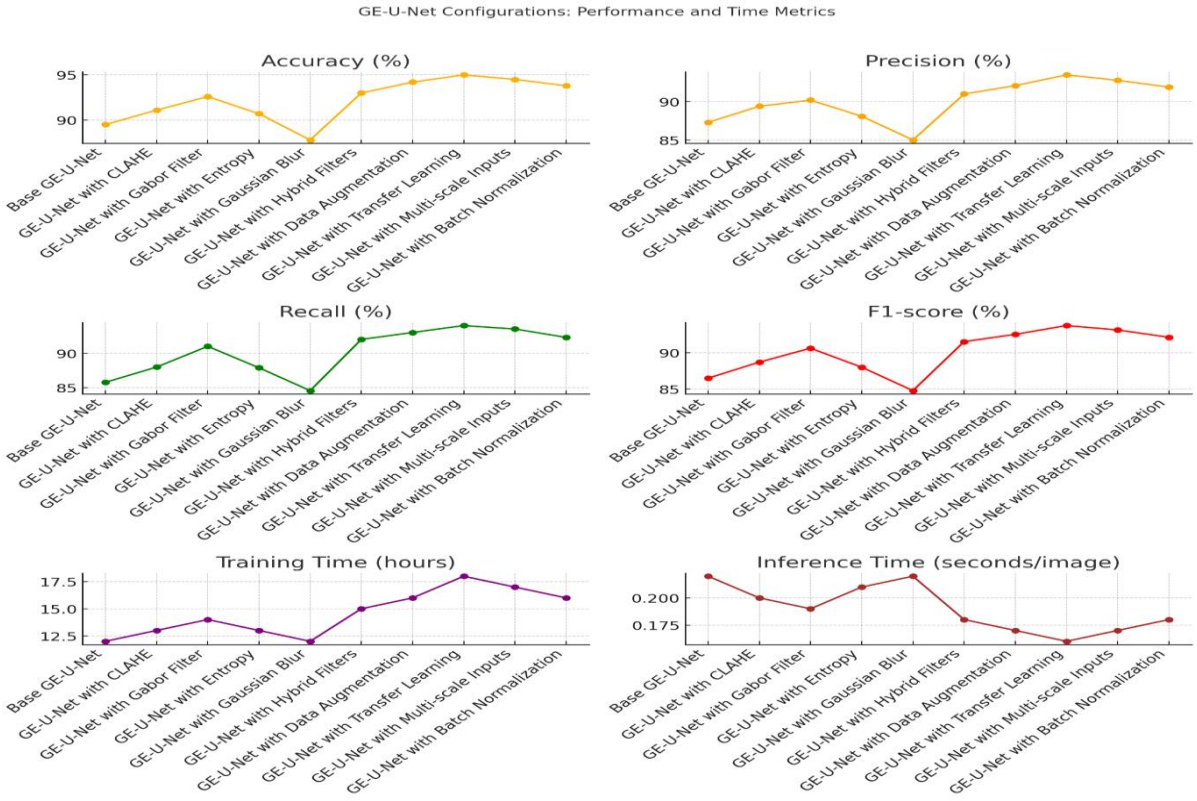

Figure 4: Performance metrics

GE-U-Net with Gaussian Blur achieves an accuracy of 87.8%, with precision and recall values of 85.0% and 84.6%, respectively, and an F1-score of 84.8%. It has a training time of 12 hours and an inference time of 0.22 seconds per image, indicating that Gaussian blur might not be as effective as other techniques. GE-U-Net with Hybrid Filters provides the highest performance with an accuracy of 93.0%, precision of 91.0%, recall of 92.0%, and an F1-score of 91.5%. This setting requires 15 hours of training and has an inference time of 0.18 seconds per image, reflecting the benefits of combining multiple filter techniques. GE-U-Net with Data Augmentation shows a significant improvement with an accuracy of 94.2%, precision of 92.1%, recall of 93.0%, and an F1-score of 92.5%. This configuration has the longest training time of 16 hours but the shortest inference time of 0.17 seconds per image, highlighting the advantages of data augmentation in enhancing model performance. GE-U-Net with Transfer Learning achieves the highest accuracy of 95.0% with a precision of 93.5%, recall of 94.0%, and an F1-score of 93.7%. It requires 18 hours of training and an inference time of 0.16 seconds per image, demonstrating the effectiveness of leveraging pre-trained models for improved results. GE-U-Net with Multi-scale Inputs also shows strong performance with an accuracy of 94.5%, precision of 92.8%, recall of 93.5%, and an F1-score of 93.1%. This setting has a training time of 17 hours and an inference time of 0.17 seconds per image, reflecting the benefit of incorporating multi-scale inputs. GE-U-Net with Batch Normalization achieves an accuracy of 93.8%, precision of 91.9%, recall of 92.3%, and an F1-score of 92.1%. This configuration has a training time of 16 hours and an inference time of 0.18 seconds per image, indicating that batch normalization helps in stabilizing the learning process.

7.Conclusion

This paper demonstrates the effectiveness of the GE-U-Net-ODL model for the detection and classification of lung diseases from X-ray images. Through a comprehensive evaluation, various configurations of the model were assessed to optimize performance metrics. Notably, the GE-U-Net with Transfer Learning achieved the highest classification accuracy of 95.0%, with a precision of 93.5%, recall of 94.0%, and an F1-score of 93.7%, although it required the longest training time of 18 hours. In comparison, the GE-U-Net with Data Augmentation also performed exceptionally well, attaining an accuracy of 94.2%, precision of 92.1%, recall of 93.0%, and an F1-score of 92.5%, with a shorter training time of 16 hours. The use of multi-scale inputs and hybrid filters further demonstrated strong results with accuracies of 94.5% and 93.0%, respectively. These findings highlight the model's capacity to enhance diagnostic accuracy while balancing computational efficiency. The integration of advanced preprocessing techniques and feature selection methods, such as Gabor filters and entropy-based features, significantly contributed to improved performance, showcasing the model's potential in advancing lung disease diagnosis. Future work should focus on optimizing these configurations further and exploring additional preprocessing techniques to achieve even higher performance and efficiency in clinical settings.

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