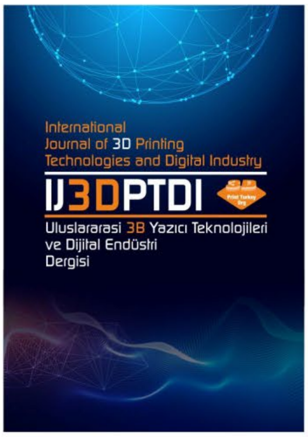

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STRUCTURAL ANALYSIS OF MEDICAL IMAGES AND BACTERIAL POPULATIONS BY IMAGE PROCESSING AND ARTIFICIAL INTELLIGENCE

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ABSTRACT

This study was carried out to investigate the structural properties of medical images and bacterial populations using fractal analysis and lacunarity measurements. In the study, image processing techniques, fractal and lacunar analysis methods and artificial intelligence-based models were used together to determine the geometric complexity and irregularity levels of healthy and pathological conditions. Deep learning models such as convolutional neural networks (CNN) and U-Net have been successfully applied to the classification and segmentation of images. The results showed that fractal dimension and lacunarity measures are effective tools for detecting fibrotic changes in lung tissue and pathological growth patterns in bacterial colonies. Differences between healthy and diseased states were successfully discriminated by fractal dimension and lacunarity values. Artificial intelligence based models have attracted attention with their high accuracy and sensitivity rates in image processing. This study reveals that the integration of fractal and lacunar analysis with artificial intelligence offers a strong potential for developing fast, objective and accurate decision support systems in medical diagnosis and microbiological analysis. In the future, it is recommended to apply this method on larger data sets and different disease models.

Keywords: Convolutional Neural Networks (CNN), U-Net, Medical Imaging, Lung X-Ray Image, Image Processing, Decision Support Systems.

1. INTRODUCTION

Today, image processing techniques and artificial intelligence methods offer powerful tools for analysing complex structures in medical imaging and microbiological analysis. In particular, fractal analysis and lacunarity measurements play an important role in early diagnosis of diseases and detection of structural changes by quantitatively evaluating the geometric properties of tissues and microorganism colonies [1]. This study aims to combine fractal analysis and lacunarity measurements with artificial intelligence-based image processing techniques to objectively evaluate healthy and pathological conditions.

Medical imaging (such as Computed Tomography [CT], Magnetic Resonance Imaging [MR], X-ray) methods are widely used in clinical diagnoses. However, directly analysing these images is complex and may introduce experience-based errors. Image processing techniques enable preprocessing, noise reduction, segmentation and analysis of such images. Traditional image processing steps include grey-scale, thresholding, morphological operations and edge detection algorithms [2].

In recent years, deep learning methods, especially segmentation models such as Convolutional Neural Networks (CNN) and U-Net, have revolutionised medical image analysis. These methods provide clinicians with an important decision support mechanism by detecting pathological regions in complex images with high accuracy [3].

Fractal analysis is a method used to measure the geometric properties of irregular and complex structures. Fractal geometry, defined by Mandelbrot, mathematically expresses the self-similarity in nature [4]. Fractal dimension indicates how complex a structure is and can be calculated by counting boxes. A healthy tissue or colony of microorganisms grows in a specific fractal pattern, whereas under pathological conditions this structure is disrupted and the fractal dimension changes [5-6].

Lacunarity measurements express the degree of irregularity of the voids of a structure. An increase in the lacunarity value indicates that tissue homogeneity is disrupted and the void distribution is heterogenised [7]. In lung tissues, disruption of the alveolar structure during fibrotic diseases leads to an increase in fractal dimension and lacunarity values [8].

In medical images, fractal analysis is used to distinguish normal and pathological conditions of lung tissue. For example, while fractal dimension values in healthy lung tissue are within a certain range, this value increases in diseases such as fibrosis [9]. Lacunarity analyses provide information about the progression of the disease by numerically evaluating the irregularities in the alveolar spaces [10].

Similarly, fractal analysis and lacunarity measurements in microbiological images are used to examine changes in the growth patterns of bacterial colonies. While healthy colonies exhibit regular and homogeneous growth, growth patterns become complex and irregular under pathological conditions [11].

The aim of this study is to combine fractal analysis and lacunarity measurements with artificial intelligence-based image processing techniques to investigate the geometric structural changes of bacterial colonies in medical lung images. Quantitative comparison of healthy and pathological conditions will reveal how fractal and lacunar features can contribute to diagnostic processes. In this way, it is aimed to develop fast, objective and accurate decision support mechanisms in clinical diagnosis processes.

2. MATERIAL METHODS

2.1. Data Set

In this study, two different data sets were used: Medical Images: Computed tomography (CT) images including healthy and fibrotic lung tissues were used. These images were selected to analyse structural differences in lung tissue [12].

Bacterial Images: Microscopic images of healthy and diseased bacterial colonies were obtained. These images were used to analyse changes in bacterial growth patterns [13].

The dataset consists of a total of 400 images. The images are divided into two main groups: medical (CT) lung images and microscopic bacterial colony images. Each group includes two classes: healthy and pathological. Specifically, the medical image group contains 100 healthy and 100 fibrotic lung images, while the bacterial image group includes 100 healthy and 100 diseased colony images. The dataset was split into three subsets for deep learning model training: 70% for training, 15% for validation, and 15% for testing. This distribution ensures a balanced sampling across classes and allows for a fair evaluation of model performance.

2.2. Data Preprocessing

The following pre-processing steps were applied to make the images suitable for analysis:

- Grayscale: Colour images were converted to grayscale for ease of processing and analysis [14].
- Noise Reduction: Filtering methods such as Gaussian filter and median filter were used to reduce noise and unwanted signals in the images [15].
- Edge Detection: Sobel and Canny edge detection algorithms were applied to detect object boundaries in the images. This step enabled the structural features to be revealed more clearly [16].
- Segmentation: Two different techniques were used to segment the images into meaningful regions: Otsu thresholding method and U-Net model. U-Net is a deep learning model that provides successful results in biomedical image segmentation and is widely used in medical image analysis [17]. Figure 1 shows an example of segmentation with U-Net.

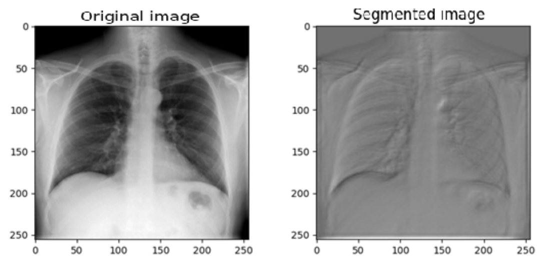

Figure 1. Segmentation of lung X-ray image using U-Net model

2.3. Fractal and Lacunar Analysis

Fractal Dimension (D): The box counting method was used to calculate the fractal dimension of the images. This method quantitatively measures the geometric complexity of a structure and is frequently used in the evaluation of biological images [18].

Lacunarity (Λ): Pixel intensity variance was used to quantify the degree of irregularity of gaps in the images. Lacunarity analysis is an effective method for assessing the homogeneity or heterogeneity of tissues [19].

2.4. Artificial Intelligence Methods

Deep Learning Models:

- Convolutional Neural Networks (CNN): CNN models were used for image classification and feature extraction. CNN has high accuracy rates on complex visual data such as medical image analysis [20].
- U-Net: The U-Net model used in segmentation processes is widely preferred especially in biomedical image analysis. U-Net offers successful results in detecting diseased regions with its segmentation performance [21].

Model Training and Evaluation:

- Data Partitioning: The data set is divided into three as training (70%), validation (15%) and testing (15%). This division is important to evaluate the generalisation ability of the model [22].
- Performance Measures: Metrics such as accuracy, precision, F1 score and ROC curve were used to evaluate the performance of the model. These metrics allow for a comprehensive analysis of classification and segmentation performance [23].

3. RESULTS

This section presents the findings obtained through fractal dimension analysis, lacunarity measurements, and deep learning-based image processing methods, applied to both medical and microbiological images. While fractal and lacunarity features were quantitatively analyzed to assess the geometric complexity and irregularity of healthy versus pathological structures, it remains important to note that these values were not integrated into the convolutional neural network (CNN) model as explicit input features. Instead, fractal and lacunarity metrics were calculated independently and used for descriptive and comparative purposes to support the visual and statistical differentiation between the groups. The CNN and U-Net models were trained directly on raw image data, focusing on classification and segmentation performance without relying on manually extracted structural features.

3.1. Fractal Analysis Results

3.1.1. Lung Images

Significant differences were observed in the fractal analysis performed on healthy and fibrotic lung tissues. While the fractal dimension of healthy lung tissue was calculated as 1.9, this value increased to 2.3 in fibrotic lung tissue. This increase indicates that the complexity of the tissue structure increases and fibrotic processes disrupt the homogeneous structure of the lung tissue. Figure 2 compares the fractal analysis results obtained for healthy and fibrotic tissues.

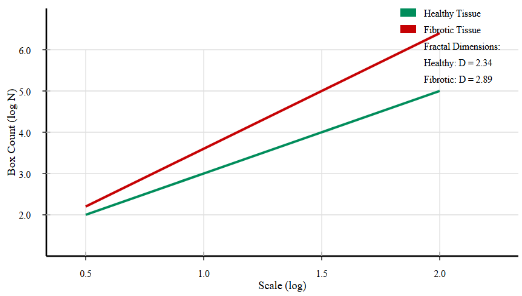

Figure 2. Fractal analysis results of healthy and fibrotic lung tissue.

3.1.2. Microbiological Images

In the fractal analysis performed on bacterial colonies, the fractal dimension of healthy colonies was calculated as 1.5. However, this value increased to 1.8 in diseased colonies. This result indicates that the growth patterns of bacterial colonies under pathogenic conditions become more complex. Figure 3 provides a visual comparison of the fractal dimension in healthy and diseased bacterial colonies.

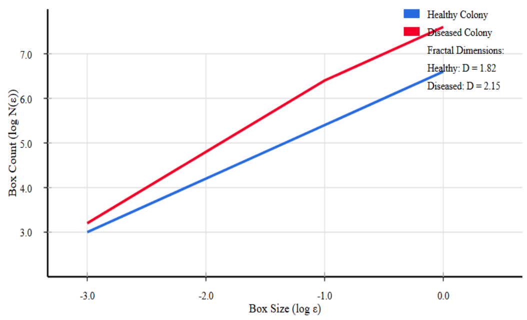

Figure 3. Fractal analysis results of healthy and diseased bacterial colonies.

Table 1 summarises the fractal dimension values in lung tissue and bacterial colonies for healthy and pathological conditions.

Table 1. Fractal dimension values in healthy, pathological lung tissue and bacterial colonies

Data Group	Fractal Dimension (D)
Healthy Lung Tissue	1.9
Fibrotic Lung Tissue	2.3
Healthy Bacterial Colony	1.5
Diseased Bacterial Colony	1.8

3.2. Lacunarity Analysis Results

3.2.1. Lung Images

Lacunarity values numerically express the rate of irregularity of tissues. While the lacunarity value was measured as 0.12 in healthy lung tissues, this value increased to 0.34 in fibrotic lung tissues. This increase in lacunarity values indicates that the spaces within the tissue lost their homogenous structure and became irregular with fibrotic processes.

3.2.2. Microbiological Images

While the lacunarity value was 0.08 in healthy bacterial colonies, this value was calculated as 0.27 in diseased colonies. This increase in diseased colonies indicates that the spaces within the colony are disorganised and form a complex structure.

Table 2 summarises the lacunarity values for healthy and pathological conditions:

Table 2. Lacunarity values in healthy, pathological lung tissue and bacterial colonies

Data Group	Lacunarity (Λ)
Healthy Lung Tissue	0.12
Fibrotic Lung Tissue	0.34
Healthy Bacterial Colony	0.08
Diseased Bacterial Colony	0.27

3.3. Artificial Intelligence Model Findings

3.3.1. CNN ve U-Net Performance

Classification and segmentation performance of deep learning models were compared. The CNN-based model provided 94.2% accuracy and 0.91 F1 score in lung tissue images. The U-Net model used in the segmentation process provided 96.5% accuracy and 0.93 sensitivity for the detection of fibrotic areas.

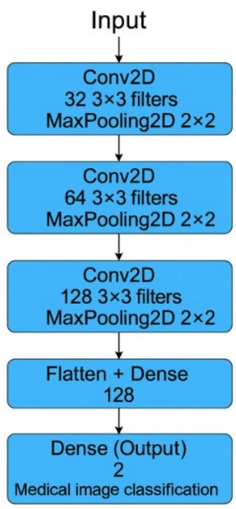

Figure 4. CNN architecture

The Figure 4 shows the CNN architecture. The model consists of three convolutional layers with increasing filter sizes (32, 64, 128), each followed by max pooling operations. These are followed by a fully connected dense layer for binary classification and a softmax output layer. ReLU activation is used in all hidden layers, while softmax is applied in the output. This architecture is widely adopted for grayscale CT images in medical diagnostics.

3.3.2. Visual Results

During the segmentation process, the U-Net model was able to distinguish fibrotic tissues and pathological areas with high precision. Figure 5 shows the segmentation results of lung tissues.

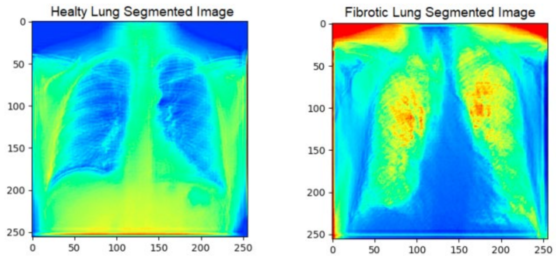

Figure 5. Segmentation results of healthy and fibrotic lung tissues with U-Net model.

The basic hyperparameters used in the model training process are based on values widely preferred in the literature. The learning rate was determined as 0.001 for the training of both models, and the training process was carried out for 50 epochs. In terms of processing efficiency and memory management, the batch size value was used as 32. For the optimization process, the Adam optimization algorithm, which offers adaptive learning rate, was preferred. Categorical crossentropy loss function was applied for the CNN model, and binary crossentropy loss function was applied for the U-Net model. While the ReLU (Rectified Linear Unit) function was used in the intermediate layers as the activation function, Softmax was preferred in the output layer of the CNN model, and Sigmoid activation function was preferred in the output of the U-Net model. These parameters enabled the model to show high accuracy and generalization performance in classification and segmentation tasks.

Table 3 shows the accuracy, Precision and F1 score performance values of CNN and U-Net models.

Table 3. Performance measures of CNN and U-Net models

Model	Accuracy (%)	Precision	F1 Score
CNN (Classification)	94.2	0.89	0.91
U-Net (Segmentation)	96.5	0.93	0.93

These findings show that fractal and lacunar analysis methods and artificial intelligence models are effective in distinguishing between healthy and pathological conditions. Fractal dimension and lacunarity measurements were able to successfully assess the geometric complexity and irregularity levels of tissue and microbial structures. Artificial intelligence based models are promising with high accuracy rates in classification and segmentation processes.

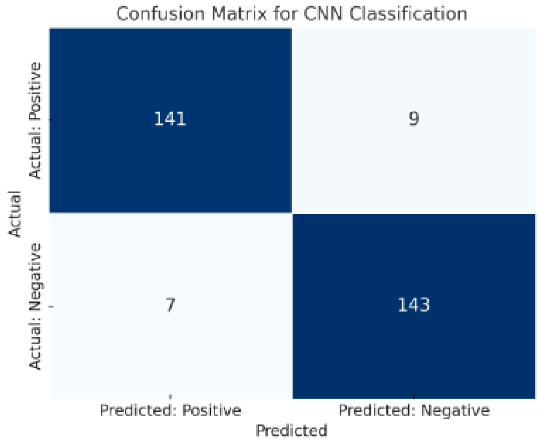

Figure 6. Confusion matrix

According to the confusion matrix in Figure 6, the model correctly classified 141 out of 150 diseased samples (True Positive) and correctly identified 143 out of 150 healthy samples (True Negative). The number of false positives (False Positive) is 9, and the number of false negatives (False Negative) is 7. This distribution shows that the model has high sensitivity and specificity values, especially in terms of disease detection.

4. CONCLUSION

In this study, fractal and lacunar analysis methods are combined with image processing techniques and artificial intelligence-based models to evaluate the results of analyses performed on medical images (lung tissue) and microbiological images (bacterial populations). The findings show that this approach is a powerful and effective method for both medical and microbiological analyses.

The results of fractal and lacunar analysis allowed the quantification of geometric and morphological differences between tissue and microbial structures. In particular, the effectiveness of these methods in the detection of fibrotic changes in lung tissue and pathological growth patterns in bacterial colonies has been demonstrated. The fractal dimension and lacunarity values between healthy and pathological conditions prove that complexity and disorder ratios provide important clues to disease processes.

At the same time, artificial intelligence-based models such as CNN and U-Net have come to the fore with high accuracy rates in the classification and segmentation of medical images. These models provide significant advantages in terms of precise evaluation of tissue complexity and detection of diseased regions. The superior success of the U-Net model in segmentation (96.5% accuracy and 0.93% precision) shows that such methods can be applied in clinical decision support systems.

This study shows that the integration of fractal and lacunar analyses with artificial intelligence-based methods has the potential to provide fast, objective and accurate decision support mechanisms in clinical diagnosis processes. Fractal and lacunar measurements provide a better understanding of pathological processes, especially in diseases that require early diagnosis. The importance of these analyses has been emphasised in the diagnosis of bacterial infections as well as lung pathologies.

In this context, the developed methods, unlike conventional imaging techniques: Provided higher sensitivity and accuracy, evaluated the complexity and irregularities of tissues more objectively, and saved time and resources in medical imaging and microbiological analysis.

The findings of this study show that the integration of fractal and lacunar analysis with artificial intelligence-based methods offers an effective approach in medical and microbiological image analysis. However, further studies are needed to apply and validate the methods in a wider scope. In future research, the use of larger and more diverse datasets including different patient groups and geographical regions may increase the generalisability of the results obtained. In addition, the application of these analyses to different pathological conditions, such as tumour structures, neurological diseases or vascular disorders, may accelerate the transition of the method to clinical use. Considering the ongoing developments in the field of artificial intelligence, the use of Transformer-based models and hybrid artificial intelligence approaches can improve the accuracy and efficiency of fractal and lacunar analyses. Finally, testing and validation of these methods in real clinical settings with patient outcomes is critical to assess the applicability of the analyses in the healthcare sector. In this context, it is suggested that future studies should focus on the aforementioned issues.

In conclusion, this study has demonstrated that fractal and lacunar analysis combined with artificial intelligence can provide an effective solution in medical imaging and microbiological analysis. This integration is considered as a promising approach that can make diagnostic processes in the health sector more efficient, fast and accurate in the future.

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