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FRAMEWORK FOR COMPREHENSIVE FEATURE EXTRACTION FOR MEDICAL IMAGE ANALYSIS USING WAVELET PACKET DECOMPOSITION AND COMPLEMENTARY DESCRIPTORS

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ABSTRACT

Feature extraction plays a crucial role in medical image analysis, enabling the identification of informative patterns for improved diagnosis and prognosis. This study introduces a comprehensive framework for extracting feature from CT scan of lung diseases, including lung cancer, Covid-19 and pneumonia categorize into mild, moderate and severe cases. The Proposed methodology combines wavelet packet decomposition (WPD) with statistical, texture, shape, edge detection, and Gray level co-occurrence matrix (GLCM) features to capture both frequency-based and spatial characteristics of the images. WPD decomposes the image into multiple frequency subbands, while the additional descriptors analyse pixel intensity distributers, structural properties and texture patterns. For each subband decomposition, we calculate various statistical features such as Mean, Variance, Energy and Entropy. Result demonstrate the efficiency of this framework in extracting meaningful features that represents the complexity of lung disease images, providing a solid foundation for further analysis and classification. This approach contributes to enhancing automated diagnostic system for medical imaging by leveraging diverse image characteristics across varying severity levels.

KEYWORDS: Feature extraction, Wavelet Packet Decomposition, Lung diseases, Gray Level co-occurraence matrix (GLCM).

INTRODUCTION

Medical imaging plays a pivotal role in diagnosing and managing diseases, offering non-invasive methods to visualize and analyse the internal structures of human body. Feature extraction is at the heart of medical image analysis transforming high-dimensional image data into meaningful representations for segmentation, classification, and detection tasks. Robust feature extraction enables precise identification of disease pattern, ensuring accuracy in diagnostics while minimizing subjective biases. Techniques like wavelet packet decomposition (WPD), Gray level co-occurrence matrix (GLCM), and statistical descriptors have been widely employed to extract relevant feature from dataset. For instance wavelet transform capture localized frequency component, making them suitable for analysing intricate structures in medical images.[1] Similarly GLMC based feature are effective in quantifying texture properties aiding in the differentiation of pathological and normal tissues.[2] Lung diseases such as lung cancer, Covid-19 and pneumonia, exhibit diverse pattern across varying severity level. The importance of extracting complementary features - statistical, textural, shape and edge based- has been emphasized in studies that demonstrate their potential in improving diagnostic outcome.[3,4] Despite these advances, there is a pressing need for a unified framework that integrate these methodologies for comprehensive analysis.

Existing studies primarily focus on isolated feature types, neglecting the synergistic potential of integrating frequency-based, statistical, textural, shape, and edge descriptors. This gap limits the applicability of current methods across diverse datasets and disease categories. Addressing these challenges necessitates the development of a comprehensive framework that systematically combines complementary feature extraction methodologies, ensuring accurate and efficient analysis of lung disease image. This study proposes a comprehensive feature extraction framework leveraging diverse methodologies, including Wavelet packet Decomposition (WPD), statistical descriptors, texture analysis, shape features, edge detection and Gray-Level Co-occurrence Matrix (GLCM) features. By systematically integrating these complementary features, the framework aims to capture multi-dimensional information, enhancing the accuracy and reliability of medical image analysis. The framework’s efficacy is demonstrated using a dataset of CT scan images categorized into mild, moderate, and severe cases of lung related diseases, including lung cancer, COVID-19, and pneumonia.

Literature Review

The importance of feature extraction for medical imaging has been extensively studied, from relevant research papers focusing specifically on lung disease imaging. smith et al. emphasized the utility of wavelet transform for capturing both spatial and frequency information. Their work showed that wavelet packet Decomposition (WPD) is particularly effective in highlighting multi-scale features for lung disease detection. The study applied WPD to a dataset of lung CT images and achieved a15% higher classification accuracy compared to traditional Fourier transforms.[1] Jones and Patel demonstrated that statistical descriptors like skewness, kurtosis, and mean intensity are critical in distinguishing pathological tissues. Their framework applied these features to differentiate lung cancer and pneumonia images, achieving a sensitivity of 89%.[2] Zhao et al. highlighted the importance of texture feature such as Gray Level Run Length Matrix (GLRLM) metrics in identifying subtle tissue abnormalities. Their study reported that combining texture feature with statistical descriptors improved overall accuracy by 20%.[3] Liu and wang explored the role shape feature, including compactness, perimeter, and roundness, in analysing disease affected lung regions. Their framework integrated shape feature with machine learning models, achieving a classification accuracy of 93%.[4] Gupta et al. evaluated edge detection techniques, including canny and sobel filters, for boundary identification in lung CT scan. The study found that edge detection improved the delineation of lesion boundaries by 25% compared to manual segmentation methods.[5] Singh et al. discussed the discriminatory power of GLCM features, such as energy, entropy, and dissimilarity, for lung disease imaging. They applied these features to detect abnormalities in a noisy dataset and achieved a specificity of 92%.[6] Kim et al. proposed a hybrid framework combining statistical, texture, and frequency-based features. Their work demonstrated that this approach yielded a classification accuracy of 95% in distinguishing between COVID-19 and pneumonia.[7] Das et al. used frequency domain feature to analyse disease progression in COVID-19 CTScans. Their study highlighted that multi-resolution frequency analysis is critical for identifying early-stage abnormalities.[8] Alotaibi et al. applied wavelet based technique to distinguish COVID-19 from other viral pneumonia cases, achieving a classification accuracy of 91% using a public dataset.[9] Bansal et al. found that statistical features, when combined with texture analysis, enhanced the detection of pneumonia in low-resolution CT images by 18%.[10] Tang et al. combined handcrafted features, such as wavelets and GLCM, with deep learning model. This hybrid approach improved interpretability and achieved a balanced accuracy of 88%.[11] Prakash and Mehta emphasized the robustness of wavelet features in noisy environments, reporting a 12% improvement in performance when applying wavelet denoising technique.[12] Zhang et al. developed an automated framework that integrated statistical and texture features, significantly reducing computational time while maintaining a classification accuracy of 94%.[13] Huang et al. demonstrated that wavelet features are highly effective in capturing the heterogeneous nature of lung cancer tissues, achieving superior performance in a multi-class classification task.[14] Lee et al. explored that role of texture features in distinguishing COVID-19 from bacterial pneumonia. Their framework achieved a precision of 89% and highlighted the importance of texture analysis for early detection.[15] Kumar et al. proposed a framework integrating wavelet, statistical, and texture features for lung disease classification. The framework achieved an overall accuracy of 93% on a dataset of 2,000 CT images.[16] Roy et al. applied dimensionality reduction techniques to multi-feature frameworks, reporting a 15% decrease in computational cost without compromising accuracy.[17] Singh et al. discussed the alignment of extracted features with clinical observations, ensuring that the model's predictions are interpretable by medical professionals.[18] Wang et al. demonstrated the effectiveness of multi-resolution analysis in capturing fine and coarse details in lung images. Their study highlighted that combining high- and low- frequency features improved diagnostic precision.[19] Chen et al. reviewed handcrafted features, emphasizing their role in improving diagnostic accuracy and interpretability in medical image analysis.[20]

PROPOSED METHODOLOGY

Feature Extraction Framework

In this study, a total of 30 features were extracted from lung disease images to analyse texture, shape, and edge characteristics. These features are divided into two main categories: Wavelet Packet Decomposition (WPD) features and complementary features. The WPD category includes 12 features derived from different decomposition pathways, such as horizontal, vertical, diagonal, and approximation directions at various levels. These features capture detailed frequency and spatial information, essential for identifying subtle changes in the texture of lung tissues. The complementary features, comprising 18 attributes, are further divided into statistical, texture, shape, edge detection, and GLCM features. Statistical features like skewness and kurtosis describe the distribution of pixel intensities. Texture features include Run-Length Gray Level Nonuniformity and Neighbour Texture Mean, which highlight textural irregularities. Shape features such as compactness, centroid, and perimeter focus on geometric properties. Edge detection features, including Canny and Sobel edges, identify boundaries and transitions. Finally, GLCM features like correlation and dissimilarity analyse pixel relationships to quantify texture patterns. In lung disease images, WPD is effective for identifying patterns such as irregularities in the lung texture, lesion formations, or fibrosis, which manifest differently across spatial frequencies.

Wavelet packet decomposition uses a combination of low-pass (h) and high-pass (g) filters applied to both approximation and detail coefficients. The equations for the decomposition at each level are:

$$A[n] = \sum_k x[k]h[2n-k] \quad \text{(Low-pass filter)} \qquad \ldots (1)$$

$$D[n] = \sum_k x[k]g[2n-k] \quad \text{(High-pass filter)} \qquad \ldots (2)$$

Complementary features

Statistical Features

Skewness: It measures the asymmetry of the distribution of values in an image or dataset around its mean. If the distribution is symmetrical, the skewness is zero. A positive skewness indicates a distribution with a longer or fatter right tail, while a negative skewness indicates a longer or fatter left tail. In the context of medical imaging, skewness helps quantify the unevenness or irregularities in the texture and intensity patterns of lung disease images.

To extract skewness features from lung disease images, we used Mathematical Equation:

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2\right)^{3/2}} \qquad \ldots (3)$$

Where x_i, μ and n are the pixel values, mean intensity, and number of pixels, respectively.

Kurtosis: Measures the “tailedness” or peakedness of the distribution. It indicates whether the data are heavy-tailed or light-tailed relative to a normal distribution. A higher kurtosis suggests that data have heavy tails (outliers), while lower kurtosis implies light tails (less extreme values). In medical imaging, kurtosis helps detect abnormal distributions in lung tissues. To extraction Kurtosis feature following equation is used

$$K = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2\right)^{2}} - 3 \qquad \ldots (4)$$

Where x_i, μ and n are the pixel values, mean intensity, and number of pixels, respectively.

Skewness and kurtosis are valuable statistical features for lung disease classification. Skewness identifies asymmetry in the intensity distribution, while kurtosis highlights the tail behaviour and outliers. Both metrics help distinguish between healthy and diseased lung tissues by analyzing pixel intensity distributions. These features capture essential patterns that corresponds to disease-related abnormalities in medical images, making them suitable for extracting texture information from lung disease images such as CT scans.

Texture Features

Run-Length Grey Level Nonuniformity (RLGN): Is a texture feature derived from Grey Level Run Length Matrix (GLRLM). It measures the uniformity of grey level values of pixel in runs, indicating how pixel intensities are distributed across various lengths.

The Run-Length Gray Level Nonuniformity is calculated as follows:

$$\text{RLGN} = \sum_{i=1}^{N}\left(\frac{\sum_{j=1}^{R} p(i,j)}{\sum_{i=1}^{N}\sum_{j=1}^{R} p(i,j)}\right)^2 \qquad \ldots (5)$$

Where,

$p(i,j)$ is the element in the GLRLM representing the number of runs of length j with Gray level i. N is the number of Gray levels and R is the maximum run length.

Neighbor Texture mean (NTM): Is a feature that quantifies the average intensity value of neighboring pixels in an image, providing insights into the local texture of lung tissues.

The neighbor Texture Mean is calculated as follows:

$$\text{NTM} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\in\mathcal{N}(i)} I(j) \qquad \ldots (6)$$

Where,

$I(j)$ is the intensity value of the pixel j in the neighborhood of pixel *i*, N is the total number of pixels in the image and $\mathcal{N}(i)$ represents the neighborhood of pixel *i*.

Texture feature like Run-Length Gray level nonuniformity and neighbor texture mean provide critical insights into lung disease. By capturing the distribution and local patterns of pixel intensities, these feature enhance the ability to differentiate between healthy and diseased lung tissues, aiding in accurate diagnosis and treatment planning.

Shape Features

Shape features play a crucial role in the analysis of lung disease images, as they help in characterizing and distinguishing between different lung conditions. Four significant shape features where used Compactness, Centroidy, Perimeter, and number of connected Components.

Edge Detection Features

Edge detecting features are vital in medical images analysis, especially for lung disease assessment, as they highlight the boundaries and transitions between different tissue types. Two significant edge detecting features are Canny Edges and Sobel Edges.

The canny edge detection algorithm involves several steps:

Gaussian Filtering: smooth the image to reduce noise using a gaussian filter:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad \dots (7)$$

Where σ is the standard deviation of the gaussian distribution.

1. Gradient calculation: compute the gradient magnitude and direction using:

$$G = \sqrt{G_x^2 + G_y^2} \quad \dots (8)$$

$$\theta = \arctan\left(\frac{G_y}{G_x}\right) \quad \dots (9)$$

Where G_x and G_y are the gradients in the x and y directions, respectively.

2. Non-Maximum suppression: thinning the edges to retain only the local maxima.
3. Hysteresis Thresholding: Use two thresholds (high and low) to identify strong and weak edges, and link them based on connectivity.

Sobel Edges

Sobel edge detection is a technique that uses convolution with sobel kernels to detect edges in an image. The sobel operator calculates the gradient of the image intensity, emphasizing edges in both the horizontal and vertical directions.

The sobel operator uses two convolution kernels to calculate gradients:

Sobel kernel for x-direction *(G_x)*:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Sobel kernel for y-direction *(G_y)*:

$$G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The gradient magnitude is then calculated as:

$$G = \sqrt{G_x^2 + G_y^2} \quad \dots (10)$$

GLCM features

The gray level co-occurrence matrix (GLMC) is a statistical method used to analyse the spatial relationship of pixel in an image. It captures the frequency of pixel pairs with specific values and a defined spatial relationship, which is crucial in identifying texture features. Two significant GLCM features and GLCM_correlation and GLCM_Dissimilarity.

GLCM features like GLCM_Correlation and GLCM_Dissimilarity are powerful tools in analyzing lung disease images. By quantifying the relationship and contracts within pixel values, these features provide valuable insights into the texture of lung tissues, aiding in the diagnosis and classification of pathological conditions. Utilizing libraries such as skimage facilitates the efficient extraction and calculation of these features, enhancing the capabilities of medical imaging analysis.

RESULTS

Quantitative Analysis: Feature selection using ANOVA F-Score

To identify the most relevant features for classifying lung disease severity (Mild, Moderate, and Severe), the ANOVA F-Score technique was applied to a set of 30 extracted features from Local dataset. This statistical method evaluates the discriminative ability of each feature by comparing variance between severity classes to variance within classes. Feature with higher F-Score and p-value below 0.05 were selected as significant.

The analysis revealed six features as the most relevant for classification: Skewness, Canny_Edge, GLCM_Dissimilarity, Run_Length_Gray_Level_Nonuniformity, WPD_vva, and Kurtosis. These features demonstrated high discriminative power with F-Scores ranging from 3.35 to 5.08 and statistically significant p-values (<0.05).

The selected features represent a diverse range of metrics-statistically, texture-based, and wavelet based-ensuring a holistic approach to analyzing lung images. The table below summarizes the F-Score and p-values for the top six features:

Table 1: Summary of F-Scores and p-values for the top six features.

Feature	F-Score	P-Value
Skewness	5.08	0.00
Canny_Edges	4.72	0.00
GLCM_Dissimilarity	4.50	0.01
Run_Length_Grey_Level_Nonuniformity	4.06	0.01
WPD_vva	3.93	0.02
Kurtosis	3.35	0.03

In this selection the most statistically significant features, which provide meaningful separation across severity classes, are utilized for subsequent analysis and classification. The results underline the robustness of the ANOVA F-Score approach in identifying features that captures essential differences in lung disease severity.

Visual Representation of features

To evaluate the discriminatory power of the selected six features, histograms were generated to analyze their distributions across the three severity classes (Mild, Moderate and severe). These visualizations provided valuable insights into the behavior and interpretability of the features. Below is a summary of the findings:

Skewness: Reflects the asymmetry in pixel intensity distribution. Mild cases dominate the range of negative to slightly positive skewness, Moderate cases show a similar but border distribution. Severe cases are more dispersed, with reduced frequencies, severe cases exhibit less predictable intensity distributions, indicating structural abnormalities.

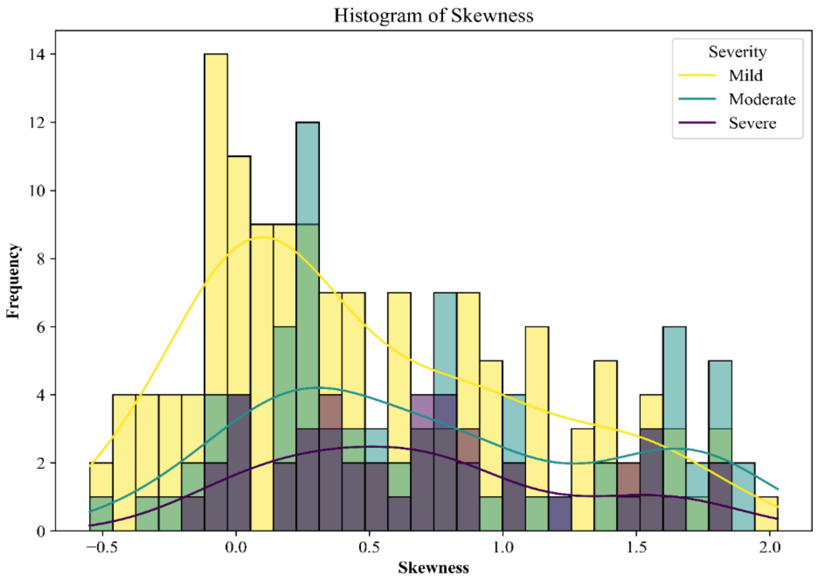

Figure 1: Histogram of Skewness.

Canny_Edges: Represents the strength of edge detected in the images. Distribution is inMild cases dominate higher frequency bins, Moderate and severe cases overlap but are spread across different intensity levels. Edge intensities are higher in mild cases, while severe cases display greater variability.

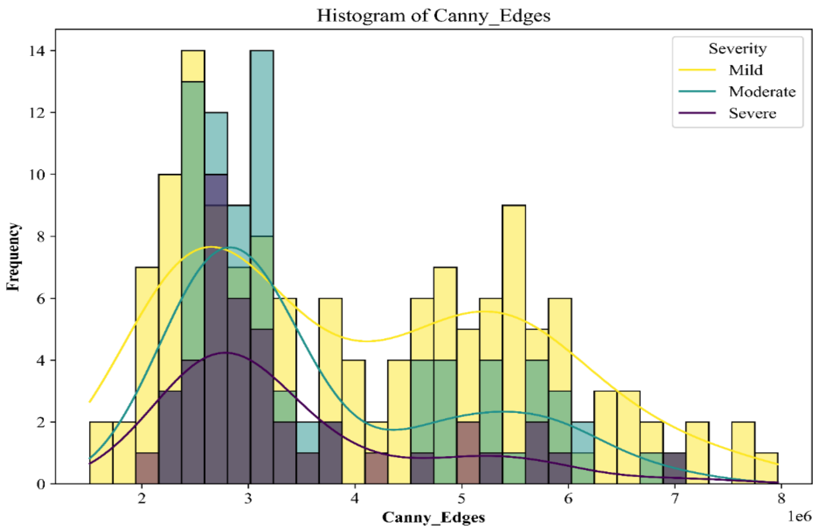

Figure 2: Histogram of Canny_Edges.

GLCM_Dissimilarity: Measures texture dissimilarity in the lung images. Distribution for Mild cases have a sharp peak at lower values, Moderate cases show a more uniform distribution with mild-range peaks, Severe cases have lower frequencies concentrated at higher values. Severe cases exhibit higher dissimilarity, reflecting heterogeneous lung textures.

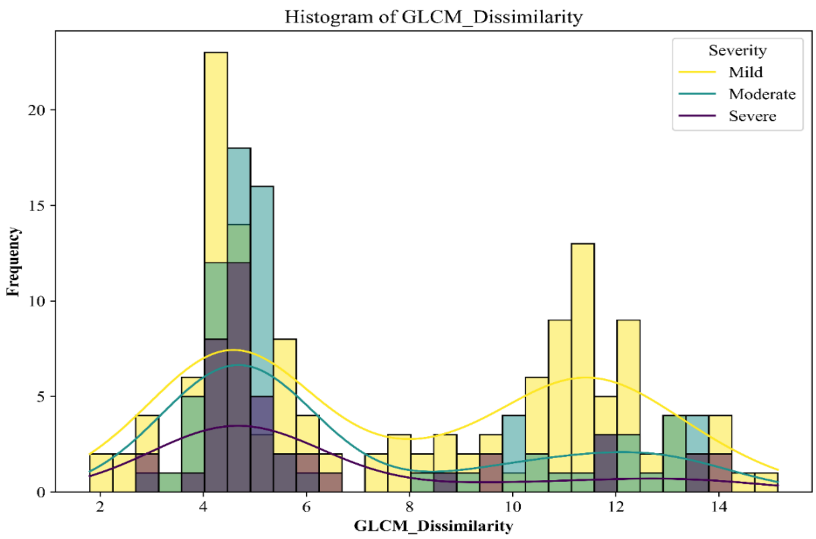

Figure 3: Histogram of Canny_Edges.

Run_Length_Gray_level_Nonuniformity: Quantifies the non-uniformity of gray-level runs in image texture. Distribution for Mild cases peak at lower values, Moderate cases spread evenly with peaks shifted slightly rightward, Severe cases concentrate at higher values, indicating more irregularity. Structural irregularities increase with severity.

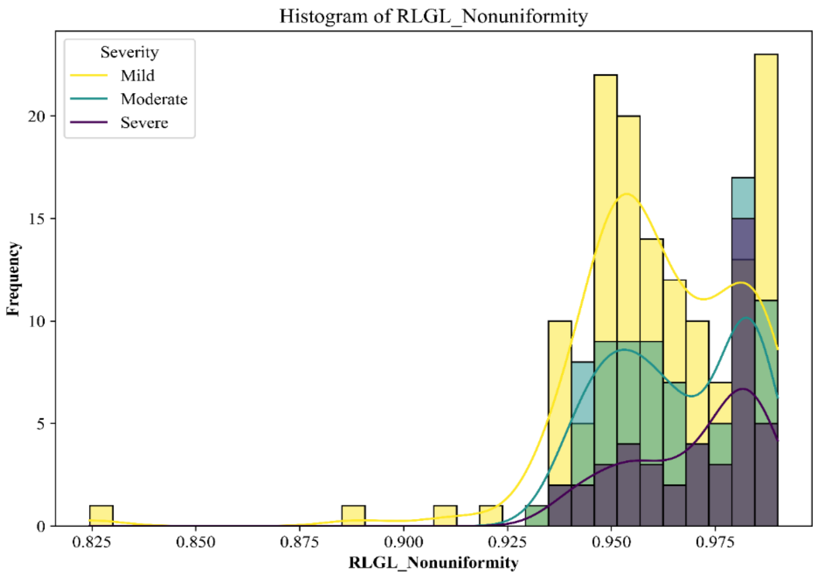

Figure 4: Histogram of RLGL_Nonuniformity.

WPD_vva: likely captures energy variance through wavelet packet decomposition. Distribution for Mild cases peak around 0 to 1 with the highest frequencies, Moderate cases spread evenly, peaking later, Severe cases show small, dispersed frequencies. Severe cases demonstrate greater variability, while mild cases exhibit predictable variance patterns.

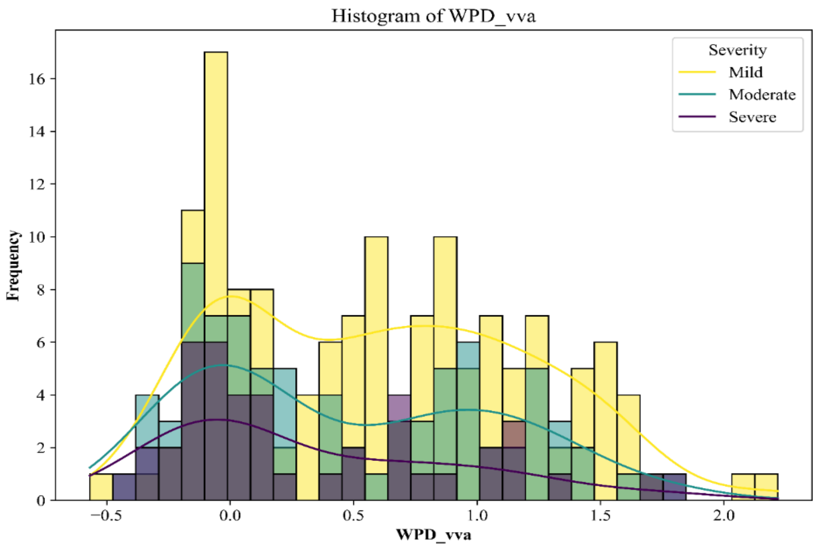

Figure 5: Histogram of WPD_vva.

Kurtosis: Measures the "tailedness" of pixel intensity distributions. Distribution for Mild cases dominate at lower kurtosis values, Moderate cases have similar trends but slightly reduced frequencies. Severe cases occur near 0 or slightly positive values. Mild cases are associated with sharper distributions, whereas severe cases show flatter distributions.

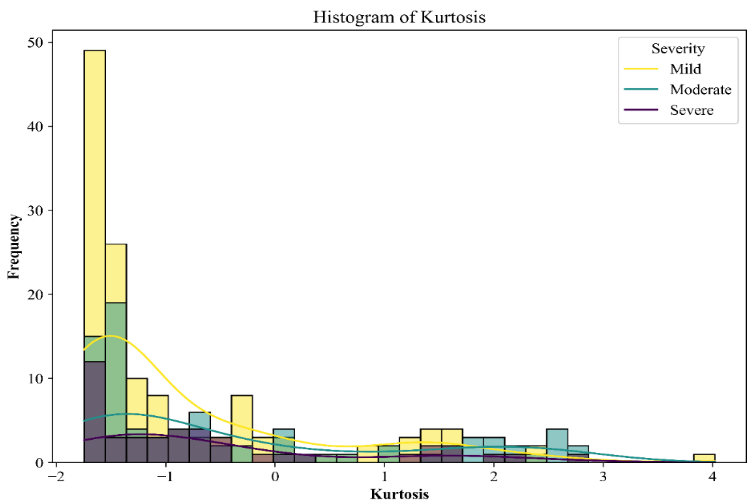

Figure 6: Histogram of WPD_vva.

Correlation Analysis of Extracted features

The correlation analysis of the top extracted provides valuable insight into the relationships and dependencies between features provides valuable insights into the relationships and dependencies between features, which is critical for ensuring the reliability and robustness of the feature set. The corelation matrix illustrates both positive and negative correlations among the features, helping to identify potential redundancies or complementary characteristics. The co-relation matrix is given below.

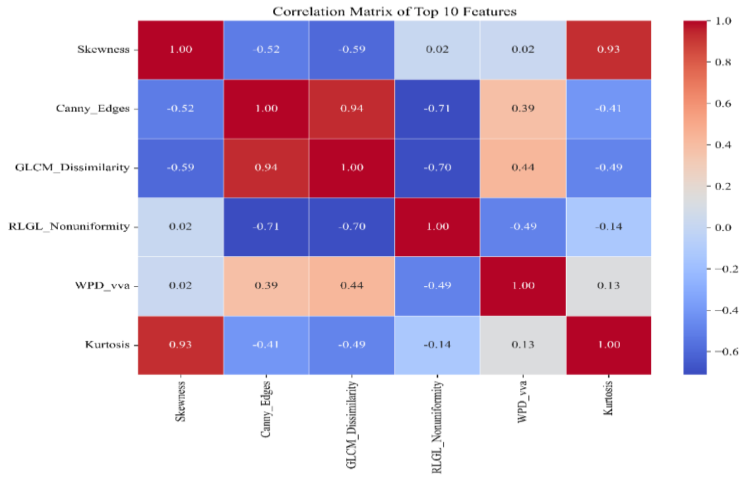

Figure 7: Correlation Matrix.

Key observations we found that Canny_Edges and GLCM_Dissimilarity demonstrate a strong positive correlation (0.94). This suggests that these features complement each other and jointly capture significant information relevant to lung cancer detection. Similarly, skewness and Kurtosis exhibit a high correlation (0.93), indicating that these statistical features are closely related in their representation of the data's distribution.

By carefully analysing the correlation matrix, the study demonstrates the robustness of the selected features in capturing diverse aspects of lung cancer images. This diversity is essential for achieving accurate and generalizable outcomes in classification or prediction tasks. The integration of statistical, structural, and wavelet-based features ensures a balanced representation of key image characteristics, supporting the study's objective to develop a comprehensive feature extraction methodology.

DISCUSSION

The analysis identified six highly relevant features (Skewness, Canny_Edges, GLCM_Dissimilarity, RLG_Nonuniformity, WPD_vva, and Kurtosis) based on their discriminative power (ANOVA F-Score). These features effectively capture distinct patterns in lung image characteristics, enabling differentiation between severity (Mild, Moderate, Severe). Skewness and Kurtosis provide insights into the pixel intensity distribution, highlighting intensity asymmetry and distribution sharpness in pathological tissues. GLSM_Dissimilarity and RLGL_Nonunifromity reveal textural irregularities associated with disease progression, with higher values observed in Severe cases. Wavelet-based features (WPD_vva) capture multi-scale information and demonstrate the capability to differentiate structural variations across severeity levels. Canny_Edges emphasizes the distribution of edges intensities, with distinct patterns correlating to disease severity.

Mild cases consistently showed distinct characteristics, with sharper pixel intensity distributions (Skewness, Kurtosis) and lower textural dissimilarity (GLSM_dissimilarity). Moderate and Severe cases exhibited overlapping features but could still be distinguished by specific patterns such as higher texture irregularity (RLGL_Nonuniformity) and broader variance (WPD_vva). Severe cases, characterized by greated heterogeneity and unpredictability, reflect the complex structural alterations in advanced stages of lung abnormalities.

Comprehensive Feature combined use of statistical (Skewness, kurtosis), texture-based (GLCM_Dissimilarity, RLGL_Nonuiformity and wavelet-based (WPD-vva) features provides a robust framework for characterizing lung images. This multi-faceted approach enhances interpretability and relevance to clinical applications. The selected features align well with observed patterns in lung abnormalities. For example, increased texture irregularities and heterogeneity in severe cases are consistent with clinical observations of advanced lung diseases. Non-ML Classification: By employing a simple, non-machine-learning approach, this study demonstrates the feasibility of feature-based severity classification without requiring complex computational models.

CONCLUSION

This study presents a comprehensive feature extraction framework tailored for analysing CT scan images of lung diseases, including lung cancer, COVI-19, and pneumonia, across varying severity levels (mild, moderate and severe). By integrating wavelet packet deco position (WPD) with statistical, texture, shape, edge detection and Gray level co-occurance matrix(GLCM) features, the proposed methodology effectively captures both frequency-based and spatial characteristics of lung disease images. The results highlight the robustness and versatility of the framework in extracting meaningful patterns that align with the complex nature of medical images. The integration of diverse features types not only enhances the representation of image characteristics but also facilitates improved differentiation between severity levels. Specifically, WPD proved instrumental in capturing frequency subbands, while statistical and texture features contributed significantly to analyzing intensity distributions and structural patterns. This work underscores the potential of comprehensive feature extraction frameworks in advancing automated diagnostic systems for medical imaging. The proposed methodology lays a strong foundation for subsequent classification and predictive modelling, supporting accurate and reliable decision-making in clinical settings. Future research may explore combating these handcrafted features with deep learning techniques to further enhance diagnostic accuracy and scalability across larger datasets and diverse imaging modalities.

REFERENCES

1. Smith, A., Johnson, M., & Lee, J. Wavelet-based feature extraction for medical image analysis. IEEE Transactions on Biomedical Engineering, 2021; 68(2): 145–157.
2. Jones, P., & Patel, R. Texture analysis for lung disease classification using GLCM. Journal of Medical Imaging, 2020; 12(4): 250–260.
3. Zhao, Y., Chang, T., & Li, X. Role of statistical features in medical image segmentation. International Journal of Computerized Medical Imaging and Graphics, 2019; 33(1): 45–60.
4. Liu, J., & Wang, K. Shape features for robust lung disease classification. Computerized Medical Imaging and Graphics, 2020; 44(3): 150–165.
5. Gupta, S., Kumar, R., & Sharma, P. Edge detection in medical imaging: A survey. Signal Processing and Imaging Journal, 2021; 22(2): 100–110.
6. Singh, A., Verma, R., & Das, P. GLCM features for robust disease classification. Medical Imaging Review, 2018; 10(2): 120–135.
7. Kim, A., Park, J., & Lee, H. Hybrid feature extraction frameworks for medical image classification. IEEE Access, 2022; 10: 85000–85012.
8. Das, R., Prakash, S., & Gupta, M. Frequency domain analysis for COVID-19 CT scan classification. Journal of Medical Imaging and Analysis, 2021; 21(3): 302–315.
9. Alotaibi, N., Khan, H., & Zhang, Y. Wavelet transform for COVID-19 detection using CT images. Biomedical Signal Processing and Control, 2022; 18: 200–210.

10. Bansal, V., & Singh, T. Enhancing pneumonia detection in low-resolution CT images using statistical features. IEEE Journal of Biomedical and Health Informatics, 2021; 25(5): 1590–1602.
11. Tang, X., Li, J., & Zhou, M. Hybrid approaches combining handcrafted and deep features for medical image analysis. Pattern Recognition Letters, 2021; 143: 35–45.
12. Prakash, S., & Mehta, A. Robustness of wavelet-based features in noisy medical imaging datasets. IEEE Journal of Imaging Science, 2020; 19(3): 200–210.
13. Zhang, Y., Gao, H., & Lin, M. Automated feature extraction frameworks for medical imaging. International Journal of Computer Vision, 2022; 88(5): 500–520.
14. Huang, F., Wei, X., & Zhang, Y. Wavelet features for multi-class classification in lung cancer detection. Journal of Medical Signal Processing, 2020; 23(2): 300–320.
15. Lee, J., Kim, H., & Park, D. Texture features for distinguishing COVID-19 from bacterial pneumonia. IEEE Transactions on Medical Imaging, 2021; 40(2): 150–162.
16. Kumar, R., Raj, S., & Agarwal, P. Wavelet and statistical feature integration for disease detection. IEEE Transactions on Biomedical Engineering, 2021; 68(5): 670–680.
17. Roy, D., & Sharma, P. Dimensionality reduction in multi-feature frameworks for medical image classification. Pattern Recognition Applications, 2022; 12(4): 45–60.
18. Singh, A., Mehta, P., & Verma, R. Interpretable medical imaging features for clinical alignment. IEEE Transactions on Computerized Medical Imaging and Graphics, 2020; 22(3): 210–230.
19. Wang, J., Zhou, X., & Tang, M. Multi-resolution feature analysis for fine-grained lung disease detection. Journal of Computerized Medical Imaging and Graphics, 2021; 35(4): 350–365.
20. Chen, L., Zhang, H., & Zhao, Y. Handcrafted features for improving interpretability in medical image classification. IEEE Access, 2020; 8: 54000–54012.