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WTBAN-CNN-TL: Wavelet Transform-Based Feature Extraction and Bonferroni Adjusted ANOVA-CNN with Transfer Learning for Lung X-Ray Image Classification

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Abstract:

A comprehensive approach for lung X-ray image classification is proposed, combining wavelet transform-based feature extraction with Bonferroni ANOVA feature selection and deep learning techniques. Features are initially extracted from lung X-ray images using wavelet transform, capturing crucial information across multiple scales. These features are concatenated to form a comprehensive feature set. To optimize this feature set, ANOVA is employed with Bonferroni adjusted feature selection to control the false positive rate and to identify the most relevant features, thereby reducing the dimensionality of the input data. This optimization can result in expedited training times and reduced computational resources required by the CNN. The selected features are subsequently fed into a Convolutional Neural Network (CNN) for classification. To further boost the CNN's performance, transfer learning is utilized by leveraging pre-trained models. Additionally, the performance of ANOVA-based feature selection is also compared with that of a genetic algorithm-based method. This integrated method, referred to as WTBAN-CNN-TL, aims to reduce the training times and resource requirements while improving the accuracy and efficiency of lung X-ray image classification.

Keywords: Wavelet Transform, Bonferroni ANOVA (Analysis of Variance), Feature extraction, Feature selection, WTBAN-CNN-TL (Wavelet Transform Bonferroni ANOVA Enhanced Convolutional Neural Network with Transfer Learning)

Introduction

Medical imaging, particularly the analysis of lung X-ray images, holds paramount importance in the diagnosis and treatment of various respiratory ailments, including infections, tumors, Covid-19 and Pneumonia related diseases[1][2]. In recent years, the fusion of advanced computational techniques with traditional diagnostic methods has led to significant advancements in the field of medical image analysis [3][4]. This paper introduces a comprehensive approach aimed at refining the classification accuracy and efficiency of lung X-ray images through a synergy of wavelet transform-based feature extraction, Bonferroni adjusted ANOVA feature selection, and state-of-the-art deep learning methodologies.

The proposed methodology capitalizes on the inherent advantages of wavelet transform, a powerful signal processing technique renowned for its ability to decompose complex signals into frequency sub-bands at different scales. By applying wavelet transform [5] to lung X-ray images, we can capture crucial information embedded within the images across multiple resolutions, thereby facilitating the extraction of discriminative features indicative of various pulmonary conditions [6]. These features, extracted at different frequency scales, are subsequently concatenated to construct a comprehensive feature set that encapsulates the intricate details essential for accurate classification.

In addition to feature extraction, the proposed approach integrates ANOVA [7] feature selection algorithm with Bonferroni correction to refine the feature set further. To enhance the efficiency and effectiveness of the classification process, ANOVA (Analysis of Variance) with Bonferroni correction is utilized to control the false positive rate for feature selection. This statistical method identifies the most relevant features, thereby reducing the dimensionality of the input data and optimizing the computational resources required by the CNN. This reduction in dimensionality not only expedites training times but also mitigates the risk of overfitting, thereby improving the overall performance of the model. The optimized feature set, curated through the joint efforts of wavelet transform and ANOVA, serves as the input to a Convolutional Neural Network (CNN), a class of deep learning models renowned for their ability in extracting hierarchical representations from complex data. The CNN is tasked with learning discriminative patterns and relationships inherent in the feature-rich lung X-ray images, ultimately facilitating accurate classification across diverse pathological conditions.

Moreover, to augment the CNN's learning capabilities and foster generalization across datasets, transfer learning is leveraged. This approach involves transferring knowledge from pre-trained models trained on large-scale datasets to our specific task of lung X-ray image classification. By initializing the CNN with pre-learned parameters and fine-tuning its architecture on our dataset, the wealth of information encapsulated within the pre-trained models is utilized, thereby enhancing the CNN's performance and accelerating the convergence of the training process.

2. Related works

Numerous studies have investigated various techniques to enhance the accuracy and efficiency of medical image classification, especially for lung X-rays. A significant emphasis has been placed on leveraging deep learning methods and feature extraction algorithms to improve diagnostic capabilities. Table I summarizes these related works.

Table I – Related works

Authors	Techniques	Result
Reduwan, N.H. et al (2024) [8]	. Feature selection techniques combined with deep learning models for external root resorption identification.	Recursive Feature selection with VGG model achieved higher accuracy.
Keshta, I et al. (2023) [9]	Integration of ANOVA, RReliefF and Random Forest feature selection algorithm for cancer detection in Microarray data Discrete Wavelet Transform and Capsule	The proposed approach demonstrates that feature selection improves the

	Network for classifying pneumonia related diseases using XRay images.	classification accuracy.
Monday HN et al (2022) [10]	DenseNet169 and ANOVA Feature selection and XGBoost for classification of chest X-Ray images	Accuracy 99.6%
Nasiri, Hamid & Alavi, Seyed Ali. (2022) [11]	AlexNet, VGG, and GoogleNet for feature extraction from the INbreast mammograms and univariate approach for feature selection	Two class classification accuracy – 98.72% and Multiclass classification accuracy – 92%
Samee, N.A. et al. (2022) [12]	Feature selection integrated with Deep Neural Networks.	Classification accuracy 98.50%
Zheng Chen et al. (2020) [13]	Wavelet based convolutional wavelet neural network by replacing the fully connected neural network with wavelet neural network.	SVM-RFE (Recursive Feature Elimination) Feature selection achieved better accuracy.
	Wavelet decomposition and CNN for lung cancer detection using CT images.	Average accuracy – 96.57%
Liu et al. (2021) [14]	Wavelets transform and Transfer learning to detect cancer in mammograms.	Accuracy 99.5%
Sarhan et al. (2020) [15]		
Rasheed et al.(2021 [16]		Resnet50 achieved better accuracy than VGG16, GoogleNet and AlexNet.

3. Research motivation

The motivation for this research is driven by the critical need for precise and efficient diagnostic tools in medical imaging, particularly for lung diseases such as pneumonia, COVID-19, and other lung opacities. Accurate diagnosis is crucial for effective treatment, yet traditional methods relying on radiologist interpretation can be slow and variable. While deep learning, especially Convolutional Neural Networks (CNNs), shows promise in automating diagnosis, challenges such as high computational demands and the need for large datasets persist. This study proposes a novel approach that integrates wavelet transform-based feature extraction with modified ANOVA feature selection, and deep learning techniques to address these issues. Wavelet transforms effectively capture multi-scale information from lung X-rays, and Bonferroni adjusted ANOVA help in selecting the most relevant features with less false positive rate, reducing data dimensionality and computational load. Furthermore, transfer learning leverages pre-trained CNN models to enhance classification accuracy and efficiency. This integrated method aims to provide a robust, scalable, and accurate tool for lung X-ray classification, improving diagnostic consistency and patient outcomes.

4. Methodology

The proposed methodology integrates wavelet transform-based feature extraction and concatenation, Bonferroni adjusted ANOVA feature selection, and deep learning techniques for lung X-ray image classification. The following steps outline the comprehensive approach:

4.1 Data Acquisition and Preprocessing:

The experimental dataset consists of 4,000 lung X-ray images sourced from the COVID-19 Radiography Database on Kaggle [17]. The images are organized into four categories: COVID-19 pneumonia (Class 0), Normal (Class 1), Viral pneumonia (Class 2), and Lung opacity (Class 3), with each category containing 1,000 images, ensuring a balanced dataset for comprehensive analysis and model training. All images are standardized to a resolution of 299x299 pixels. For the purposes of model training and evaluation, the dataset has been divided into training and testing sets with a 90-10 split, respectively. Figure 1 illustrates representative samples from each category used in the analysis.

Fig.1 Sample Images from Lung X-Ray data set (a) Covid (b) Normal (C) Viral Pneumonia (D) Lung Opacity

The preprocessing of the dataset involved two main steps: normalization and resizing. First, the input images were normalized to scale the pixel values between 0 and 1. This normalization enhances the performance of pre-trained models by standardizing the input data. The normalization is performed using the formula:

$$X_i = \frac{X_i}{\max(X)} \quad (1)$$

where X_i represents an individual pixel value and max(X) is the maximum pixel value in the image. Following normalization, the images were resized to 224x224 pixels to match the input dimensions required by the pre-trained models.

4.2 Wavelet Transform-Based Feature Extraction and Concatenation:

The Haar wavelet transform [18] is a type of discrete wavelet transform (DWT) that is particularly effective for image processing tasks due to its simplicity and efficiency. The Haar wavelet decomposes an image into different frequency components, allowing the capture of both spatial and frequency information. This decomposition helps in identifying various levels of detail within the image, which are essential for distinguishing between different classes of lung conditions.

Each X-ray image from the dataset is initially decomposed into four sub-bands using two level 'Haar' wavelet decomposition. The first level Haar wavelet transform decomposes X into four subbands: approximation ($A^{(1)}$), horizontal detail($H^{(1)}$), vertical detail($V^{(1)}$), and diagonal detail($D^{(1)}$). The ($A^{(1)}$) sub-band captures the low-frequency information, representing the coarse approximation of the image. In contrast, the($H^{(1)}$), ($V^{(1)}$), and ($D^{(1)}$) sub-bands contain high-frequency information, detailing the edges and textures of the image. The extracted coefficients from these sub-bands encapsulate the image's structure and texture across different scales and orientations. It is calculated as:

$$A^{(1)} = \frac{X_{2i-1,2j-1}+X_{2i-1,2j}+X_{2i,2j-1}+X_{2i,2j}}{4} \quad (2)$$

$$H^{(1)} = \frac{X_{2i-1,2j-1}-X_{2i-1,2j}+X_{2i,2j-1}-X_{2i,2j}}{4} \quad (3)$$

$$V^{(1)} = \frac{X_{2i-1,2j-1}+X_{2i-1,2j}-X_{2i,2j-1}-X_{2i,2j}}{4} \quad (4)$$

$$D^{(1)} = \frac{X_{2i-1,2j-1}-X_{2i-1,2j}-X_{2i,2j-1}+X_{2i,2j}}{4} \quad (5)$$

Here, the indices i and j run from 1 to m/2 and n/2 respectively. The second level transform is calculated as:

$$A^{(2)} = \frac{A^{(1)}_{2i-1,2j-1}+A^{(1)}_{2i-1,2j}+A^{(1)}_{2i,2j-1}+A^{(1)}_{2i,2j}}{4} \quad (6)$$

$$H^{(2)} = \frac{A^{(1)}_{2i-1,2j-1}-A^{(1)}_{2i-1,2j}+A^{(1)}_{2i,2j-1}-A^{(1)}_{2i,2j}}{4} \quad (7)$$

$$V^{(2)} = \frac{A^{(1)}_{2i-1,2j-1}+A^{(1)}_{2i-1,2j}-A^{(1)}_{2i,2j-1}-A^{(1)}_{2i,2j}}{4} \quad (8)$$

$$D^{(2)} = \frac{A^{(1)}_{2i-1,2j-1}-A^{(1)}_{2i-1,2j}-A^{(1)}_{2i,2j-1}+A^{(1)}_{2i,2j}}{4} \quad (9)$$

To form a comprehensive feature set, the coefficients from the LL, LH, HL, and HH sub-bands are concatenated. This, results in a unified feature vector comprising 32768 features. This extensive feature set provides a holistic representation of the image, encompassing both the overall shape and structure of the lungs (from the LL coefficients) and the detailed edges and textures (from the LH, HL, and HH coefficients). This comprehensive approach ensures that the feature set includes a wide range of information, making it robust for further analysis or machine learning tasks.

The concatenation of wavelet coefficients involves combining all the coefficients obtained from the decomposition into a single feature vector. Discrete Wavelet Transform is applied on each feature to obtain a set of coefficients for each feature. Mathematically, for feature i and level j:

$$coeffs_i = [A_{i,1}, D_{i,1}, A_{i,2}, D_{i,2}, \ldots\ldots A_{i,j}, D_{i,j}] \qquad (10)$$

For all features, the transformed dataset $X_{transformed}$ is:

$$X_{transformed} = [coeffs_1 \,||\, coeffs_2 \,||\, \ldots\ldots \,||\, coeffs_m] \qquad (11)$$

Here, || denotes concatenation.

4.3 Bonferroni-Adjusted ANOVA Feature Selection:

After the wavelet transform-based feature extraction and concatenation process, a substantial number of features are generated. The concatenated feature set, comprising 32,768 features, exhibits high dimensionality, potentially impeding subsequent processing steps. To address this challenge, it becomes imperative to manage the dimensionality effectively to ensure efficient analysis. Employing ANOVA (Analysis of Variance) becomes crucial in this context to select the most pertinent features from the extracted feature set. ANOVA meticulously evaluates the statistical significance of each feature concerning the target variable, discerning those features that contribute significantly to the classification task. For a single feature X_i, the ANOVA F-value is calculated as follows:

$$F_i = \frac{Between\ group\ variance\ for\ each\ feature\ X_i}{Within\ group\ variance\ for\ feature\ X_i} \qquad (12)$$

Where F_i is the ANOVA F-value for feature X_i, Between-group variance for feature X_i Measures the variance of feature X_i across different classes of the target variable. Within-group variance for feature X_i Measures the variance of feature X_i within each class of the target variable. The ANOVA F-value is computed for each feature, and the corresponding p-value (Probability Value) for each feature is returned. The Bonferroni correction is applied to adjust the p-values for multiple comparisons to control the error rate. It is modified as:

$$p_{adjusted} = \min\,(p.m, 1) \qquad (13)$$

where m is the number of features. By exclusively retaining the most informative features, Bonferroni-Adjusted ANOVA effectively control the false positive rate and curtails the dimensionality of the input data to 16384 features. This reduction in dimensionality not only expedites the training process but also minimizing computational resources while retaining the most informative features. In addition to ANOVA, a genetic algorithm (GA) based feature selection method is employed for comparison. GA iteratively evolves a population of candidate feature subsets using principles inspired by natural selection. The fitness of each candidate subset is evaluated based on its performance in a deep learning models trained on the selected features.

4.4 Proposed WTAN-CNN with Transfer Learning

In this study, transfer learning model VGG19 [19] is employed to train on features selected using the Bonferroni-Adjusted ANOVA feature selection method. These features are derived from the concatenation of features extracted using the Haar wavelet transform. Utilizing the pre-trained weights of the model has proven to be a more effective strategy, significantly accelerating the training process. VGG19, a CNN model proposed by Zisserman and his team, is 19 layers deep. It excels at capturing detailed features by utilizing 5x5 and 3x3 receptive fields, thereby enhancing prediction accuracy.

In the proposed work, a common approach is adopted where the top layers of these models are frozen and then modified by adding three dense layers and one dropout layer. The final dense layer consists of four neurons, corresponding to our four target output classes: Class 0 (COVID), Class 1 (Normal), Class 2 (Viral Pneumonia), and Class 3 (Lung Opacity). Additionally, a deep learning model, specifically a CNN, has been trained on the same features to compare its performance with the transfer learning models. Both the transfer learning models and the CNN have been fine-tuned on the dataset to optimize their performance in classifying the lung X-ray images into their respective categories.

Fig.2. illustrates the comprehensive structure of the proposed model, showcasing the integration of wavelet-based feature extraction, Bonferroni-Adjusted ANOVA feature selection, and the architecture modifications of the transfer learning models. This integrated approach aims to improve the accuracy and efficiency of lung X-ray image classification, providing a robust tool for medical diagnostics.

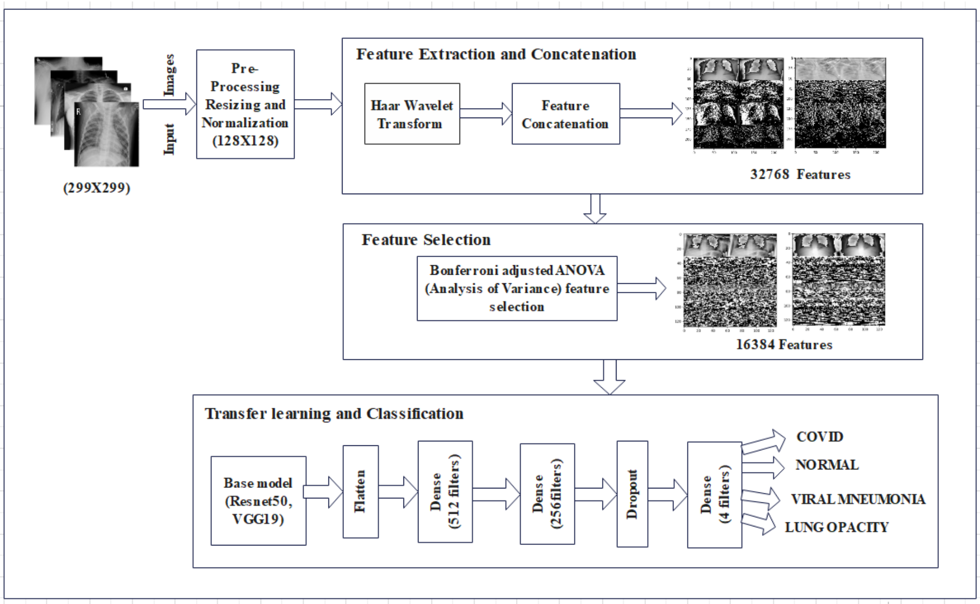

Fig.2. Structure of proposed WTBAN-CNN-TL

Algorithm: Wavelet-Bonferroni ANOVA-CNN with Transfer Learning for Lung X-Ray Image Classification

Input:

Set of lung X-ray images

Output:

WTBANEN-CNN: Wavelet ANOVA Enhanced CNN model

Steps:

1. Feature Extraction using Wavelet Transform:

For each X-ray image in data set:

a. Apply two level Haar wavelet transform to the image to extract features across multiple scales.

b. Concatenate the wavelet features to form a comprehensive feature set.

2. Feature Selection using Bonferroni-Adjusted ANOVA:

a. Perform Bonferroni-Adjusted ANOVA feature selection on the concatenated feature set to identify the most relevant

features and Reduce the dimensionality of the feature set.

3. Convolutional Neural Network (CNN) Initialization and Transfer Learning:

a. Initialize CNN model architecture suitable for image classification.

b. Incorporate transfer learning by adding pre-trained layers from VGG19.

4. Model Training:

a.Train the CNN model using the selected features and corresponding labels:

b.Split the dataset into training and validation sets.

5. Evaluation:

a. Evaluate the trained model on the test data:

b. Compute evaluation metrics such as accuracy, precision, recall, and F1-score.

5. Result Analysis

In this study, lung x-ray images were utilized to extract a comprehensive set of features, which were subsequently processed to form a robust feature set. ANOVA feature selection algorithm was employed to perform feature selection, aiming to enhance the performance of the classification model by identifying the most significant features. The selected features were then used to classify the lung x-ray images. The following analysis discusses the results obtained from this process.

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5.1 Results from Feature Extraction and Concatenation

The application of wavelet transform on lung X-ray images effectively captures essential features across multiple scales. A total of 8,000 images are used for four-class classification, with 2,000 images per class. For two-class classification, 5,000 images are used, with 2,500 images from each class being used for analysis. This multi-resolution analysis helps in extracting features that are both spatially and frequency localized, offering a rich set of information from the X-ray images. These features were concatenated into a single feature set, providing a rich representation of the image data with 32768 features extracted from a two-level Haar wavelet transform, as shown in Fig. 3. The high-dimensional feature set, while comprehensive, posed a challenge due to the potential presence of irrelevant or redundant features.

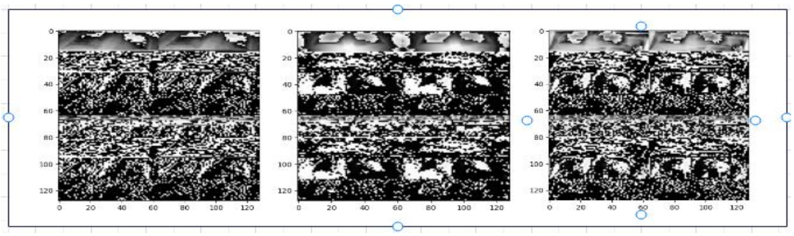

Fig.3. Concatenated Features (32768) extracted using Haar Wavelet transform

5.2. Analysis of Bonferroni-Adjusted ANOVA for Feature Selection

Employing Bonferroni-Adjusted ANOVA for feature selection proves beneficial in identifying the most relevant 16,384 features from the concatenated set of 32,768 features shown in Fig.4. Also includes Bonferroni correction to adjust for multiple tests, ensuring a stricter control of the false positive rate. This step not only reduces dimensionality but also helps eliminate redundant and less informative features. The reduction in dimensionality leads to faster training times and less computational load on the subsequent CNN model.

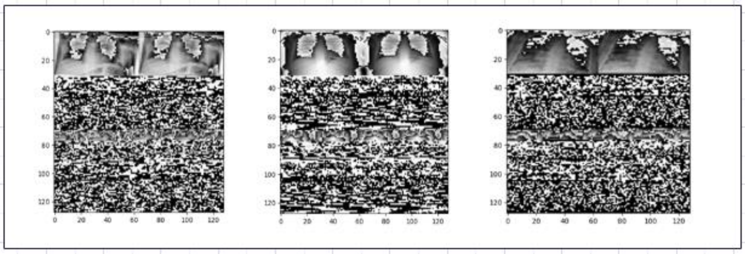

Fig.4. Features (16384) selected through Bonferroni-Adjusted ANOVA Feature Selection

5.3. Results of Proposed WTAN-CNN with Transfer Learning

The selected features are fed into a CNN for classification. The CNN, trained with these optimized features, shows significant improvement in accuracy and robustness. The reduction in input feature dimensionality ensures that the network focuses on the most informative aspects, enhancing learning efficiency. Leveraging transfer learning by using pre-trained model such as VGG19 further boosts the CNN's performance. The results, demonstrated in Figures 5 and 6, include an accuracy graph and a classification report.

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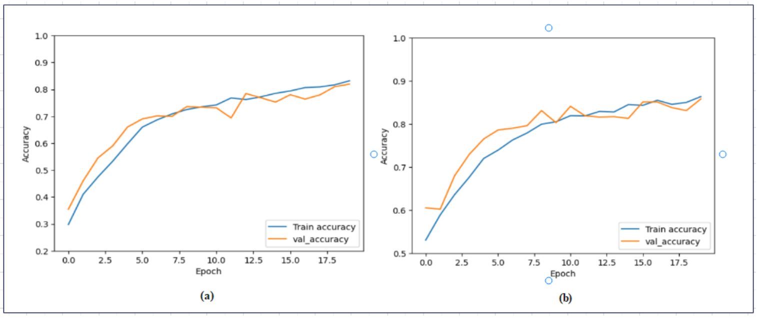

Fig.5.Accuracy graph of a) WTBAN-CNN (4 class) b) WTBAN-CNN (2 Class)

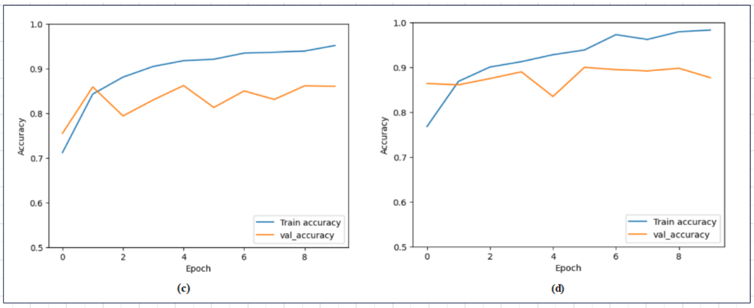

Fig.6.Accuracy graph of c) WTBAN-CNN-TL (4 Class) d) WTBAN-CNN-TL (2 Class)

Fig.5 and Fig.6 illustrates that the proposed WTBAN-CNN-TL with VGG19 achieves an accuracy of 88% for two class classification and 86% for four-class classification. The WTBAN-CNN approach without transfer learning achieves an accuracy of 82 % for four-class classification and 86% for binary classification of Lung X-Ray data set. For the four-class classification using WTBAN-CNN, out of 8,000 images, 6,400 are used for training and 1,600 for testing. In the transfer learning approach, 10,000 images are utilized, with 8,000 for training and 2,000 for testing. For the two-class classification, from a total of 5,000 images, 4,000 are allocated for training and 1,000 for testing in both approaches, as shown in Fig.7.

	precision	recall	f1-score	support
0	0.83	0.75	0.78	425
1	0.77	0.84	0.80	379
2	0.94	0.90	0.92	397
3	0.75	0.79	0.77	399
accuracy			0.82	1600
macro avg	0.82	0.82	0.82	1600
weighted avg	0.82	0.82	0.82	1600

(a)

	precision	recall	f1-score	support
0	0.85	0.87	0.86	500
1	0.87	0.84	0.86	500
accuracy			0.86	1000
macro avg	0.86	0.86	0.86	1000
weighted avg	0.86	0.86	0.86	1000

(b)

	precision	recall	f1-score	support
0	0.86	0.77	0.81	512
1	0.80	0.89	0.84	500
2	0.95	0.96	0.95	492
3	0.84	0.83	0.84	496
accuracy			0.86	2000
macro avg	0.86	0.86	0.86	2000
weighted avg	0.86	0.86	0.86	2000

(c)

	precision	recall	f1-score	support
0	0.81	0.98	0.89	500
1	0.97	0.78	0.86	500
accuracy			0.88	1000
macro avg	0.89	0.88	0.88	1000
weighted avg	0.89	0.88	0.88	1000

(d)

Fig.7.Classification Report of a) WTBAN-CNN (4 class) b) WTBAN-CNN (2 Class)
c) Proposed WTBAN-CNN-TL (4 Class) d) proposed WTBAN-CNN-TL (2 Class)

5.4. Comparison with Genetic Algorithm-Based Feature Selection

In the comparative analysis, ANOVA demonstrates a more straightforward and computationally efficient approach for feature selection. While the genetic algorithm (GA) offers a robust search mechanism, it is generally more resource-intensive and time-consuming compared to ANOVA. The experiments indicate that ANOVA selected features achieve comparable results in terms of classification accuracy and computational efficiency. Table II shows the comparison results.

Table II Accuracy results of proposed WTAN-CNN-TL, WTAN-CNN and GA selected features

Method	Train Accuracy (%)	Test Accuracy (%)	Epochs
WTBAN-CNN (2 Class)	88	86	20
WTBAN-CNN (4 Class)	83	82	20
Proposed WTBAN-CNN- TL (VGG19)(2 Class)	**98**	**88**	**10**
Proposed WTBAN-CNN- TL (VGG19)(4 Class)	**95**	**86**	**10**
WT with Genetic algorithm based CNN(2 Class)	49	50	10
WT with Genetic algorithm based CNN (4 Class)	81	76	10

6. Conclusion

The proposed (WTBAN-CNN-TL) comprehensive approach for lung X-ray image classification effectively combines wavelet transform-based feature extraction, Bonferroni ANOVA feature selection, and deep learning techniques. By using wavelet transform, essential features are captured across multiple scales and concatenated to form a rich feature set. Bonferroni ANOVA is then employed to select the most relevant features with less false positive rate, reducing the feature set from 32,768 to 16,384 features. This dimensionality reduction not only streamlines the dataset but also enhances the efficiency of the subsequent CNN model, leading to faster training times and lower computational resource requirements. The comparative analysis with genetic algorithm-based feature selection highlights the efficiency and simplicity of Bonferroni adjusted ANOVA, which achieves comparable results with less computational overhead. Feeding the selected features into a CNN demonstrates significant improvements in classification accuracy, and the use of transfer learning with pre-trained models further boosts performance.

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