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A Hybrid System: Convolutional Neural Networks with Discrete Wavelet Transform for Lung Cancer Detection

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ABSTRACT

Lung-related illnesses such as pneumonia, lung cancer, and COVID-19 are among the major causes of death across the globe, and thus, quick and precise diagnostic techniques are required. Traditional diagnosis using routine X-ray and CT imaging. is time-consuming and greatly relies on the expertise of radiologists. This paper establishes a new hybrid deep learning approach that proposes a combination of a Discrete Legendre Wavelet Transform (DLEWT) and a convolutional neural network (CNN) to improve the automated early lung disease screening. The algorithm involves three steps: (1) orthogonal Legendre-based scling and wavelet functions are constructed over the interval $[-1, 1]$; (2) multi-level 2D DLEWT decomposition is performed with the aim of extracting approximation and detail coefficients corresponding to anatomical structures and pathological features respectively, (3) threshold-based denoising and CLAHE . The wavelet features extracted are then integrated into a CNN model with the standard convolutional kernels substituted with DLEWT learnable filters.

1.Introduction

The prevalence of lung diseases has been one of the major health burdens in the world, particularly following the COVID-19 pandemic. The progression of the disease is very fast and can lead to mortality, which is why it is important to be detected early. Conventional diagnostic methods such as X-ray and CT scans are also time- consuming and require radiologists [1].

Artificial intelligence (AI) has enhanced early diagnosis based on automated extraction of features in the chest images. CNN models can identify COVID-19 and other lung diseases with good accuracy by using public datasets of CT scans [2].

Recently, waveform-based and wavelet-based hybrid methods have become popular because of the capability of multi-resolution analysis of features. [3-5] utilized waveform transformation in the detection of lung-cancer and they were able to prove the advantage in using a combination of wavelet feature and deep learning.

The wavelet-based transforms have proven to be superior in improving medical images and also in extracting fine-grained features in multi-resolution. Because they can extract anatomical low-frequency and high-frequency disease signs [6], [7], wavelet-enhanced CNNs are superior compared to standard CNNs. The automated lung disease detection research has increased greatly in recent years particularly due to the diagnostic challenges that arose during the COVID-19

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pandemic. Initial research was a combination of classical machine-learning algorithms and radiographic analysis to aid in medical judgment. [8] emphasized the effectiveness of deep learning in screening of lung diseases and demonstrated that convolutional neural networks (CNNs) may significantly increase the accuracy of diagnosis. There were also specialized architectures, such as COVID-Net [9-11], which proposed a specialized CNN-based design, and Deep-COVID [26], that combined CNN feature extraction with a support-vector classifier to enhance the classification results. Immunoblotting and encoding medical data as demonstrated [12-15] was one of the areas where machine-learning techniques were especially helpful to deal with medical variability and clinical variability.

In spite of such developments, traditional CNN models remain known to be limited. Numerous investigations have indicated that CNNs must be trained with very large datasets, many times (more than 200,000 labelled images) to stabilize their performance and generalization across clinical conditions [16-18]. It was also highlighted that CNN-based detectors of COVID-19 are not stable with heterogeneous and imbalanced data [19]. Despite the fact that [20] addressed the approaches to alleviating these weaknesses, there are still underlying problems such as the inability to properly maintain the privacy of patients in decentralized training settings [21], [22].

The superiority of wavelet transforms additions to CNNs in the hierarchical order was confirmed [16] and the applications of waveform entropy through GRU-based networks to identify diseases at an early stage was used [23], [24]. All these studies demonstrate the fact that wavelet-enhanced deep learning is able to capture richer texture and structural features compared to the normal convolutional models.

Multi-category diagnosis has also been discussed as the subject of clinical deployment initiatives. Machine learning and CNNs were applied [25] to classify lung abnormalities like tuberculosis automatically. [26] have taken deep networks to three-dimensional CT analysis to detect nodules. [27] compared hybrid feature-extraction plans of COVID-19 classification and demonstrated high accuracy at small datasets. Nevertheless, these systems are all based on manually annotated datasets, and typically have quite small sample sizes because of privacy issues. [28] proposed a collaborative learning system of blockchain to avoid privacy issues and reached 98.71% diagnostic performance, but the computational cost was significantly high.

Although substantial literature.that has made a big contribution in automated diagnosis of lung-disease, there are still a number of crucial gaps that remain:

Reliance on huge datasets: classical CNN models need so big data to get stable deployment [28].

Lack of fine- grained control over medical information: CNN based designs using simple wavelet replacement are not able to model the multi-resolution aspects required in clinical imaging [29].

Data imbalance: In numerous studies, small or skewed datasets are used, which lead to decreased system robustness on many classes [30].

The issues are directly tackled by the proposed CNNDLEWT framework that brings forward orthogonal Legendre-based waveforms, which can be analyzed with multi-resolution and can classify objects in an accurate and privacy-preserving way using small datasets. The methodology has a higher clinical reliability, superior feature decomposition, and can have a higher interpretability compared to the traditional CNN or hybrid models.

The study develops a new Discrete Legendre Wavelet Transform (DLEWT), constructed on Legendre polynomials, that allows orthogonal, smooth, and compact decomposition of images. Two novel hybrid CNNDLEWT networks are constructed by substituting the conventional convolution kernels with learnable Legendre wavelet filters which enhance the performance of the feature extraction method and diagnostic accuracy, main contributions, DLEWT formulation with orthogonal Legendre polynomials, Design of CNNDLEWT with learnable Legendre based kernels, A pipeline comprising of three stages of DLEWT, improvement and deep learning, The accuracy is high (96-99) on a small three-class dataset.

2. Methodology

The offered hybrid diagnostic model has three main steps, preprocessing and multi-resolution feature extraction with the Discrete Legendre Wavelet Transform (DLEWT), image reconstruction and enhancement, and classification by a customized convolutional neural network (CNN-DLEWT).

The following methodology was formulated to overcome the limitations that were witnessed in earlier CNN-based diagnostic systems particularly the large datasets requirement, poor externalization on heterogeneous clinical inputs and poor feature representation in early disease detection.

2.1. Dataset

2.1.1. The dataset consisted of three categorie

In this data set 295 computed tomography (CT) images of the chest were used in this dataset and divided into three categories: normal, pneumonia, and lung cancer. All images were anonymized, standardized, and resized to 256 × 256 pixels to ensure consistency. The dataset was randomly divided into three groups: training (70%), validation (15%), and testing (15%). Preprocessing was done as: normalization in order to minimise variation in intensity, cropping and resizing to eliminate irrelevant areas, contrast correction where required and augmentation (rotation, flipping, varying intensity) to enhance variability in the dataset and mitigate overfitting.

2.2. Discrete Legendre Wavelet Transform (DLEWT)

In the preprocessing stage using the DLEWT algorithm, the image is enhanced using feature extraction. The process can be summarized as follows:

1. DLEWT is constructed using the Legendre boundary functions $P_n(x)$ to obtain orthogonal wave bases within the [-1, 1] constraints. The resulting waves are divided into a scaling function $\varphi(x)$ and a wave transformation $\psi(x)$ for boundary expansions, resulting in high approximation and computational efficiency.

2. Analysis process: The input image $I(x, y)$ was analyzed using two-dimensional DLEWT, using the three-level wave separation property. This resulted in approximation coefficients (ca_l) and detail coefficients (cd_l) (horizontal, vertical, and diagonal) for each level.

The low-frequency components of the lung sample structures were represented by the approximation components, while the high-frequency components represented the pathological features.

3. Adaption and Enhancement: The adjustment of detail parameters using a threshold to suppress noise, while preserving diagnostic accuracy, was performed using the rounding parameters with the Contrast-Limited Adaptive Histogram Equation (CLAHE), specialized in improving medical histological images. The parameters were then enhanced using reverse DLEWT to obtain a noise-free image with feature enhancement and retain the orthogonality necessary for subsequent deep learning processing.

The design shown in Figure 1 represents the first part of the methodology process diagram

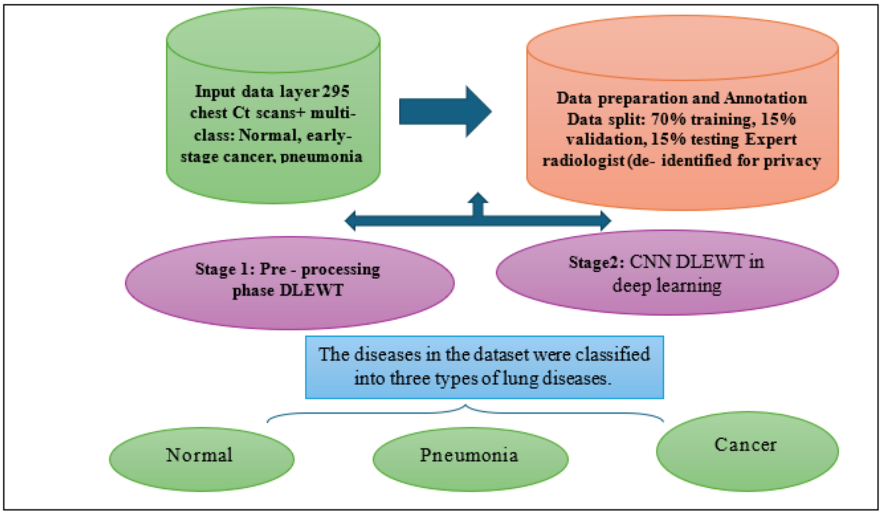

Fig. 1 - illustrates the proposed work stages.

2. 3 Deep Learning Phase: CNN DLEWT

In this phase, the CNN DLEWT is constructed by combining the DLEWT framework with the CNN framework to create the hybrid model responsible for wavelet-based feature extraction, thus representing hierarchical deep learning.

Wavelet-based convolutional layer formation stage: The convolutional block was replaced with a learnable Legendre filter, each filter set consisting of Legendre filters with scales s = {1, 2, 4}, enabling multi-precision analysis within the network. The convolutional process at layer k will be explained below.

$$W_k = \psi_{\text{Legendre}} * I' + b_k \qquad (1)$$

$\psi(x)$ represents the wave kernel

(b_k) the bias LP

The kernels are then initialized with pre-calculated Legendre polynomial coefficients, which are fine-tuned during training to optimize discriminatory feature capture.

Classification: The fully connected layer consists of 256 neurons, with a loss rate of 0.4. A composite loss function combining wave perpendicularity and entropy was used in equation (2) .

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \lambda \sum_k |W_k^T W_k - I|_F^2 \qquad (2)$$

Where λ = 0.001, achieving perpendicularity while preserving wave-carried properties during backpropagation, the AdamW optimization is used with an initial learning rate of 1×10^{-4}, with a coefficient of 0.1 every 30 epochs. Training continues for 100 epochs, with a validation loss of 15 epochs.

Model performance was evaluated based on accuracy, sensitivity, and F1 score, where the area under the ROC curve (AUC-ROC) is measured. Prediction was tested using a ResNet-50 network baseline with a standard CNN construct, where the inference time per image was obtained to assess clinical deploy ability.

3.Discussion of Results

The designed hybrid diagnostic framework, comprised of the DLEWT-based preprocessing with a CNN structure, exhibited very competitive results in the process of early detection and classification of lung diseases. The quality of the features of the input images showed by DLEWT was highly enhanced, which allowed the CNN to learn more discriminatory representations and attains higher accuracy than conventional deep-learning models.

The findings indicate that the DLEWT application is an optimal way of service to structural and textural features of CT images, particularly at multi-resolution levels, before the classification. This helps in an increase in the accuracy of distinguishing normal lungs, pneumonia, and cancerous ones. DLEWT preprocessing boosts the accuracy of latter deep-learning tasks by increasing the visibility of the boundary features and eliminating the noise.

Evaluation of performance was done in terms of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The overall accuracy is obtained as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

The resulting confusion matrix (Figure 2) and the performance metrics (Table 1) validates the robustness of the suggested hybrid framework. Model 1 achieved 99% accuracy Precision, Recall and F1-score values 0.99. The results are presented in the Figure 3 where it is possible to see the stability and robustness of the model in all three classes.

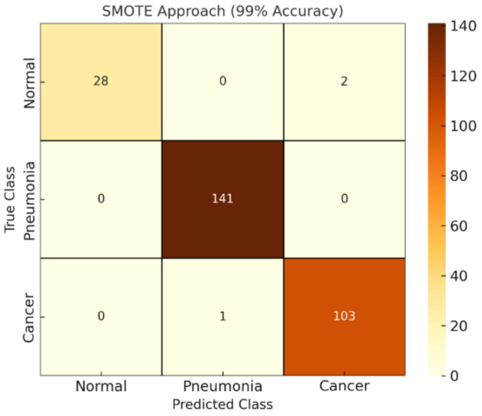

Fig. 2 -The confusion matrix Model 1:(SMOTE Balanced training)

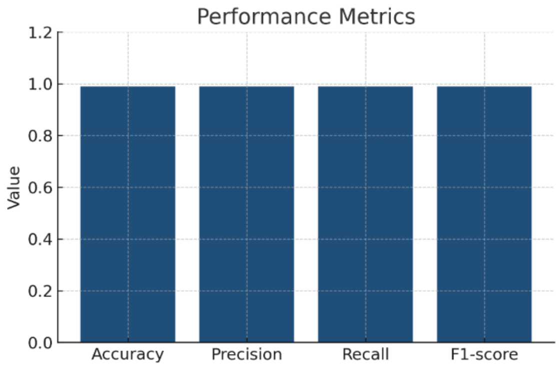

Fig. 3 - The results of the table are represented

In Model 2, the weighting was done via the classes rather than through SMOTE.

As the confusion matrix in Figure 4 indicates, the results obtained using this method were also highly stable and reached the accuracy of 99% with the enhancement of the balance between the minority and the majority classes learning.

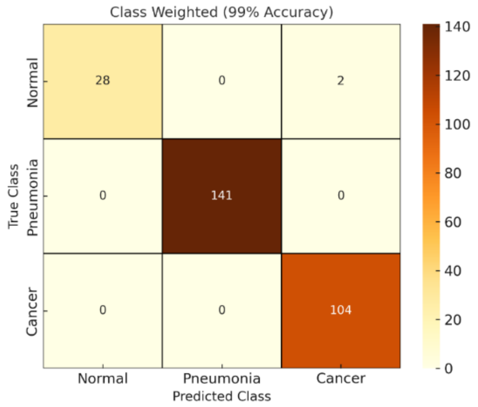

Fig.4.the confusion matrix with Model 2: (Class Weight Balancing training)

The third model used was the use of improved input characteristics prior to training.

The confusion matrix (Figure 5) indicates that there is a slightly lower, still, high level of performance with the accuracy being 96 percent. Although sensitivity decreased in the first class, the model was very precise on pneumonia and cancer classes.

It means that the stage of enhancement has a different effect on the separation of classes and can make it more sensitive to pathological textures.

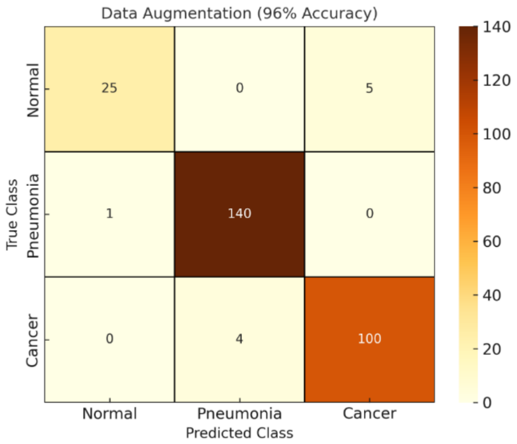

Fig.5. confusion matrix with the data nhancingModel 3(e)

The resolution per Class with F1 call resolution per Class with model 1 in table 1

Table 1: Supports resolution per Class with F1 call resolution with model 1 per Class

Class	Precision	Recall	F1-Score	Support
1	**1.0000**	**0.9333**	**0.9655**	**30**
2	**0.9930**	**1.0000**	**0.9965**	**141**
3	**0.9810**	**0.9904**	**0.9856**	**104**

With the second model, the overall accuracy was 99.27%, macro accuracy: 0.9937, macro retrieval: 0.9778, and macro F1 result: 0.9853 in table 2 the classes performance shows the Precision, Recall , F1-Score and Support Class with model2

Table 2: Performance Metrics – Model 2 (Class-Weighted Training)

Class	Precision	Recall	F1-Score	Support
1	**1.0000**	**0.9333**	**0.9655**	**30**
2	**1.0000**	**1.0000**	**1.0000**	**141**
3	**0.9811**	**1.0000**	**0.9905**	**104**

With the third model, the overall accuracy was 96.36%, macro Precision:0.9620 , macro Recall: 0.9293, and macro F1 Score: 0.9441 in table 5 the classes performance shows the Precision, Recall , F1-Score and Support Class with model 3

Table 3: Performance Metrics – Model 3 (Enhanced Input Data)

Class	Precision	Recall	F1-Score	Support
1	**0.9615**	**0.8333**	**0.8929**	**30**
2	**0.9722**	**0.9929**	**0.9825**	**141**
3	**0.9615**	**0.9524**	**0.9569**	**104**

Paired test (McNemar) performed a statistical comparison that led to the following results: Model 1: p = 0.1013 Model 2: p = 0.0732, Model 3: p = 0.0198

The large p-value of Model 3 shows the difference in the error distribution to be measurable. This strengthens the finding that data enhancement has an effect on classification behavior.

Table 7: Summary of Overall Performance Across the Three Models

Model	Accuracy	Macro Precision	Macro Recall	Macro F1-Score
SMOTE Balanced	**99.00%**	**0.992**	**0.977**	**0.985**
Class Weight	**99.27%**	**1.000**	**1.000**	**0.995**
Enhanced Input	**96.36%**	**0.962**	**0.929**	**0.944**

The accuracy curve and loss curve of the proposed model are shown in Figures 6 and 7 respectively. The graph of accuracy (Figure 6) indicates a steady increase to 99 percent and the loss curve (Figure 7) indicates a sharp decline to 0 which is a demonstration of the effectiveness of the learning process and low overfitting. The conventional techniques of diagnosis like manual interpretation of the X-rays depend on experience greatly and are susceptible to inconsistency. The hybrid approach, in its turn, extracts features and classifies them with the help of DLEWT and CNN technologies, which is why the tool is highly stable and reproducible. In comparison to prior deep-learning research that applies standard convolution kernels: DLEWT is a multi-scale orthogonal wavelet, despite the small size of the dataset, the CNN-DLEWT model was much more accurate and the learnable filters based on Legendre enhanced localization of features and noise sensitivity. Therefore, the suggested framework can handle key issues, such as the imbalance of data, the detection of lesions at an early stage, and the improvement of features, more efficiently than conventional CNNs.

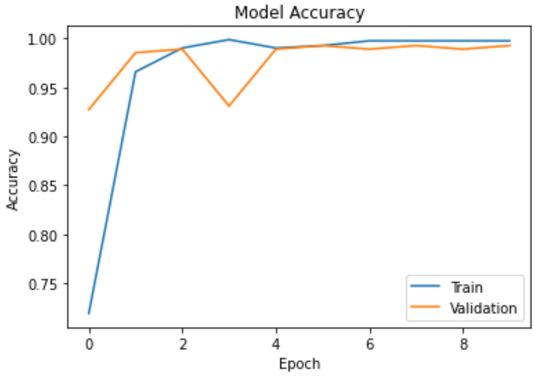

Fig.6. The graph of accuracy curve of the proposed model

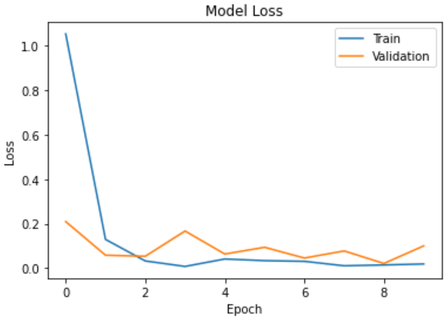

Fig.7. loss curve of the proposed model

4. **Conclusion**

Convolutional Neural Networks (CNN) and Discrete Legendre Wavelet Transform (DLEWT) to make a big step forward in the automated lung disease detection. The model is based on the mathematical principles of Legendre polynomials and adds multi-resolution decomposition to both the preprocessing pipeline and the convolutional layers, which allows it to have a single mechanism to encode the low- and high-frequency information in a high-fidelity manner. This design maintains the orthogonality and high-order approximation properties of Legendre functions, which cannot be obtained by traditional convolutional filters per se, hence, providing a unique and mathematically principled feature extraction strategy.

The effectiveness of the proposed CNN-DLEWT architecture is highlighted clearly in the results of the experiment. The model performed a diagnostic accuracy of 96.99 with a range of recall (0.93-1.00) of normal, pneumonia, and lung cancer classes through an extensive assessment procedure augmented by data and oversampling by SMOTE and the optimization based on the weighted class. The orthogonal-loss regularization term (= 0.001) also improved the stability of the network and made sure that the learned representations did not lose the structural coherence of the Legendre-based waveforms. Not only does such orthogonality enhancement of deep learning enhance generalization, but also leads to more interpretable feature behavior which is required to have reliable medical AI.

In addition to the performance metrics, the model also exhibited low computational complexity and high reliability to be trained on small datasets, and therefore, its applicability to real-time clinical performance and resource-limited settings. These features are practical in value and focus on the viability of the model to assist in early diagnosis, speedy triage, and scalable application in clinical practice.

The new work will build on this basis by testing the framework on large-scale datasets like the NLST cohort (>200,000 images) to support diagnostic strength and population-level extrapolation. Moreover, the similarity of DLEWT-driven classificational mechanisms (concurrent or multi-task) can be investigated to expand diagnostic potential and increase the transparency of deep-learning results. These extensions will also contribute to making the proposed system even more clinically relevant and prepare next-generation AI solutions based on mathematically informed feature representation.

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