Automated COPD Diagnosis from CT Scans: A Hybrid Deep Learning and Machine Learning Approach with Explainable AI

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Keywords: Chronic Obstructive Pulmonary Disease, Computed Tomography, Convolutional Neural Networks, Early Detection.

Abstract: Chronic obstructive pulmonary disease (COPD) is a widespread and debilitating disease of the lungs that requires the patient to endure, requiring a precise and timely diagnosis to aid in care. In this research, an innovative method is introduced that combines the classical machine learning methods with feature extraction based on deep learning to detect and classify the COPD severity from Computed tomography (CT) scans. We employ CNNs pretrained on large amounts of medical data to extract deep features showing indicative structural changes in the lung, including emphysema and thickening of airway walls and other morphological deformations. These features are then used by Support Vector Machine (SVM) to get the accurate COPD severity classification. This study uses Gradient Weighted Class Activation Mapping (Grad-CAM) and Shapley Additive explanations (SHAP) to explain the method prediction with the purpose of increasing the transparency and interpretability and increasing confidence in AI-driven diagnostics. The proposed methodology is validated on the LIDC-IDRI (Lung Image Database Consortium Image collection) dataset for emphysema severity and airway abnormalities. Results of the comparison show that this hybrid method is more accurate or robust than CNN or traditional ML methods alone. Results show the importance of explainable and efficient AI in medical imaging in early COPD detection, monitoring of drug efficacy, and severity assessment.

1 INTRODUCTION

Image processing plays a major role in the research field in recent years (L. Ramachandran, et al, S. Senthilkumar, et al). Chronic obstructive pulmonary disease (COPD) is a major global health issue that contributes in a major way to despair and death and places a heavy burden on the health system in a gradual way. This progressive respiratory condition is associated with persistent symptom and airflow obstruction and is often caused by prolonged exposure to harmful substance like cigarette smoke and environmental pollutants. Delaying the diagnosis increases the risk of irreversible lung damage and loss of more than half of the lungs and their function." Imaging by Computed Tomography (CT) has an important role in diagnosis and monitoring of COPD for providing detailed visualization of lung structures. CT scans are effective means to analyse key indicators of COPD such as emphysema, airway wall thickening and hyperinflation. Unfortunately, the current traditional diagnostic methods are based mainly on manual

Hema, A., Basha, C. H. H., Senthilkumar, S., Gopika, B. S., Muthaiyan, R. and Ramanan, R.
Automated COPD Diagnosis from CT Scans: A Hybrid Deep Learning and Machine Learning Approach with Explainable AI.
DOI: 10.5220/0013910500004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 4*, pages 208-217
ISBN: 978-989-758-777-1

interpretation of radiologists, which is a time consuming, and variable and observer biased process. The existence of such challenges suggests that there is a need for an automated accurate and efficient diagnostic tool to help clinicians analyze complex medical images exists. Medical imaging has been revolutionized with the advocacy of image processing and machine learning (ML) advancements, which now make it possible to detect and classify the diseases without the intervention of physicians. It has been shown that deep learning methods on Convolution Neural Network (CNN) can identify complex patterns in medical images very well. Although CNN based methods lack interpretability and are complex to overfitting, their application in specialized areas including COPD diagnosis is ambiguous. In order to tackle these limitations, this study presents a hybrid approach combining deep feature extraction and classic ML algorithms to improve species classification accuracy and reliability in the presence of COPD classification. High level structural features of CT scan are extracted using pre-trained CNNs, which is used to detect lung abnormalities related to COPD. Traditional ML classifiers such as SVMs are applied to these extracted features using the features and the features process itself feeds the domain specific to the short dataset. The above integration of method integrated the advantages from both deep learning and classical ML to yield an effective COPD detection and severity assessment framework.

In the medical field, interpretability is essential since medical personnel need to have faith in AI-driven judgements and guarantee their ethical use. Explainable AI (XAI) methods are integrated into the diagnostic procedure to accomplish purpose. By highlighting lung regions that have a major impact on predictions, these techniques help physicians assess AI-generated results and comprehend the reasoning behind automated diagnoses. The LIDC-IDRI dataset, a publicly accessible collection of high-resolution CT scans, is used to assess the suggested methodology. By concentrating on important characteristics including the degree of emphysema and changes in the structure of the airways, this study shows that hybrid machine learning approaches can provide precise, comprehensible, and effective diagnostic solutions for COPD diagnosis and staging.

2 LITERATURE REVIEW

In (Manoharan, S., 2020.) a new graph cut segmentation algorithm is proposed, which has been enhanced to perform lung cancer detection from CT images. This method has the advantage of better accuracy of segmenting soft tissues and weak edges over conventional techniques like watershed and basic graph cut. They have merits of less energy consumption and higher accuracy in detecting nodules, however, they also have limitations of high memory usage and need further optimization of the energy function. The proposed algorithm provides benefit to clinical application by assisting in early and precise lung cancer detection.

According to research (Immanuel D, J. and Leo E, S.A., 2024), it proposes a Gradient Descent Optimization (GDO) model for predicting cardiovascular disease (CVD) based on machine learning. The study used data from the UCI repository and used techniques such as SVM, KNN, NB, ANN, RF and GDO and the proposed GDO had an accuracy of 99.62%. The advantages are high sensitivity (99.65%) and specificity (98.54%) and good performance in early CVD diagnosis. The study has; however, some limitations including a small dataset and need for further feature fusion for broad application.

In research Kumar, S.,et al, a multimodal diagnostic approach is presented that uses the CT scan images and lung sound (cough) data. The study uses ML and DL techniques like CNNs to reach the accuracy of 97.5% for early COPD detection. The merits are high accuracy, the integration of multiple data modalities, and noise robustness in diagnostic data. There are, however, limitations that require large datasets for effective training of the models and scalability and eventual implementation in reality. The research Deng, X., et al presents a novel framework based on the Auto-Metric Graph Neural Network (AMGNN). Radiomics and 3D CNN features of CT images are combined towards the prediction of COPD stages with 89.7% accuracy. The merits are that superior precision (90.9%) and AUC (95.8%) are achieved over traditional methods such as PRM biomarkers. But it is limited by computational resource requirement and difficulty in integrating multi-phase CT data. This technique presents significant improvement in detecting and managing COPD stage.

Research (Bozkurt, F., 2022) introduces the HANDEFU framework. The system is innovative in the combination of handcrafted, deep, and fusion based feature extraction techniques. The LBP+SVM model for the COVID-19 diagnosis was demonstrated to have a superior accuracy up to 99.36%. The merits of the framework are flexibility, dynamic structure and high precision, and limitations include computational complexity and execution time in deep and fusion based methods. Such an approach offers a scalable solution for early and reliable detection of COVID-19 from medical images. In Si, et al Hybrid method is presented using abdominal CT images in its merits, it has rapid processing (18.6 seconds per patient), high diagnostic accuracy for specific tumors (e.g., 100% for IPMN) and the ability to interpret decisions using saliency maps. It, however, suffers from the inability to handle imbalanced data and diagnose normal cases. This has clinical potential for preoperative decision making in an efficient manner.

In Gan, W.,et al, a hybrid CNN that combines 2D and 3D CNNs in order to segment lung tumor is presented. Using a hybrid approach based on the strength of 3D CNN to capture volumetric tumor context and the edge detail extraction ability of 2D CNN, we report a Dice score of 0.72, outperformed by standalone CNNs. Strengths include; reduction of boundary blurring and better segmentation accuracy, however it has a negative of; computational complexity and being sensitive to false positives. The model can potentially be used in lung tumor diagnosis and treatment planning. In Hossain, M.B.,et al, a fine-tuned ResNet50 model is introduced with two additional fully connected layers. Using transfer learning from pre-trained weights from different datasets it achieves validation accuracy of 99.17% for classifying COVID 19 cases. It has merits of high precision, sensitivity, and adaptability to medical imaging. Nevertheless, the study illustrates computational resource demand and domain specificity of the dataset. Furthermore, this method provides a promising framework for rapid screening of COVID 19 in clinical environment.

The work Sedghighadikolaei, K. et al investigates integrating Privacy-Enhancing Technologies (PETs) into Deep Radiomics pipeline. The study further provides data privacy in both model training and inference using PETs. Robust privacy protection, suitability for multi-institutional collaboration, and some other merits are mentioned, while the computational overhead and difficulty of applying PETs to multivariate medical images are shortcomings. This framework provides security considerations for medical data analysis from an efficiency and privacy point of view to real world applications.

In the work Wang, S.,et al, a model is presented that uses Auto-Metric Graph Neural Networks (AMGNN), together with radiomics and CNN features learned from inspiratory and expiratory low dose CT images. This approach achieves a high accuracy of 94.4% and an AUC of 96.5% with no need for manual parameter settings, making the approach fully automated. The merits are in effective feature selection with Lasso and integration of meta learning strategies for prediction. High computational requirements and dependence on curated datasets constrain the number of available limitations. Significant potential exists for this model to be used in clinical applications for preemptive COPD management.

3 PROPOSED METHODOLOGY

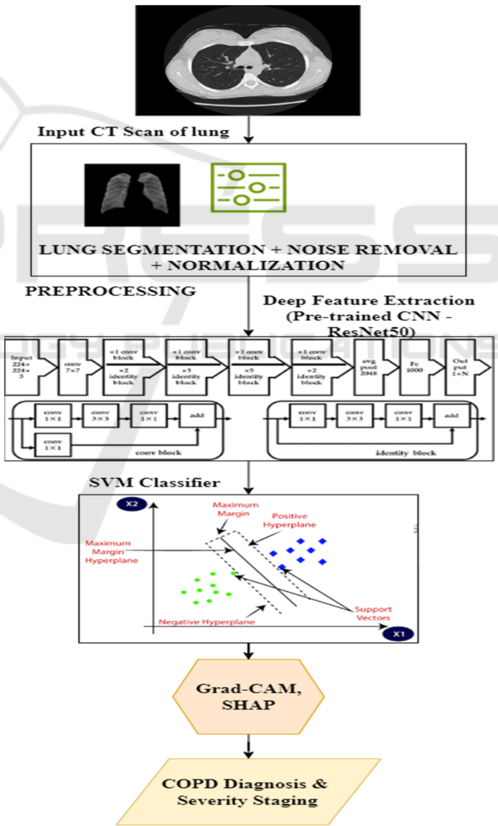

Figure 1: Architecture of proposed methodology.

Interpretability plays a crucial role in the medical domain, as healthcare professionals must trust AI-driven decisions and ensure ethical deployment. To achieve this, explainable AI (XAI) techniques are incorporated into the diagnostic process. These methods highlight lung regions that significantly influence predictions, enabling doctors to validate AI-generated outcomes and understand the rationale behind automated diagnoses. The proposed approach is evaluated using the LIDC-IDRI dataset, a publicly available collection of high-resolution CT scans. This study demonstrates that hybrid machine learning techniques can deliver accurate, interpretable, and efficient diagnostic solutions for COPD detection and staging by emphasizing key features such as emphysema severity and airway structural changes. Figure 1 shows the architecture of the proposed system.

3.1 Image Preprocessing

Image preprocessing is essential to prepare raw CT images for feature extraction and classification. This step ensures that the input images are of uniform quality and relevant regions of interest are isolated.

3.1.1 Lung Segmentation

Segmentation isolates lung regions from the CT image to focus on areas affected by COPD. The U-Net architecture is employed for segmentation due to its effectiveness in biomedical imaging. The U-Net uses an encoder-decoder structure with skip connections to maintain spatial information.The segmentation process is mathematically represented as:

$$S(x) = \mathrm{Softmax}(f_{U-Net}(x)) \tag{1}$$

where:

- S(x) represent Segmented lung region,
- X represent Input CT image,
- $f_{U-Net}(x)$ represent U-Net segmentation function.

3.1.2 Noise Removal

To enhance the quality of CT images, Gaussian filtering is applied to reduce noise while preserving edges. The Gaussian filter is defined as:

$$G(x, y) = \frac{1}{2\pi\sigma^2}\exp(-\frac{x^2 + y^2}{2\sigma^2}) \tag{2}$$

where:

- x,y indicates Pixel coordinates,
- σ indicate Standard deviation of the Gaussian kernel.

3.1.3 Intensity Normalization

Pixel intensities are normalized to a standard range (e.g., [0, 1]) to ensure consistency across all input images. Normalization is expressed as:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \tag{3}$$

where:

- I indicate original pixel intensity,
- I_{min} and I_{max} indicates Minimum and maximum pixel intensities in the image.

3.2 Deep Feature Extraction

After preprocessing, deep features are extracted from the segmented lung regions using a pre-trained CNN. This step leverages the power of deep learning to capture complex patterns associated with COPD, such as emphysema, airway thickening, and hyperinflation.

3.2.1 Pre-Trained CNN Selection

Pre-trained CNNs such as ResNet, InceptionV3, or EfficientNet are used. These models are fine-tuned to extract domain-specific features from the segmented lung regions.The deep feature extraction process is represented as:

$$F = fCNN(I_{seg}) \tag{4}$$

where:

- Findicate Extracted feature vector,
- $fCNN$ indicate Pre-trained CNN feature extraction function,
- I_{seg} indicate Segmented lung region.

3.2.2 Feature Maps

CNNs extract multiple feature maps from different layers, capturing spatial and structural details of the lung. Each feature map represents specific characteristics, such as texture, edges, or abnormal patterns.The output feature maps are mathematically expressed as:

$$M_{i,j}^{k} = f^{k}CNN(I_{seg}) \tag{5}$$

where:

- $M_{i,j}^{k}$ indicate Feature map at position (I, j) in layer k,
- $f^{k}CNN$indicate CNN operation at layer k.

3.2.3 Feature Vector Construction

The feature maps are flattened into a one-dimensional feature vector for classification. If the feature maps have dimensions H×W×DH \times W \times D (height, width, depth), the resulting vector has size$H * W * D(height, width, depth)$.

3.3 Feature Classification

The extracted features are classified into COPD severity levels using classical ML algorithms. This hybrid approach combines the strengths of CNN-based feature extraction and classical ML for efficient classification.

3.3.1 Support Vector Machines (SVMs)

SVMs are used to classify the features into categories, such as normal, mild, moderate, severe, or very severe COPD. SVMs are well-suited for high-dimensional data and small datasets.
The SVM classifier finds the optimal hyperplane that separates data points from different classes. The decision function is given by:

$$f(x) = w^T \emptyset\,(x) + b \tag{6}$$

where:

- W indicate Weight vector,
- $\emptyset\,(x)$ indicate sFeature transformation function,
- B indicate Bias term.

The SVM optimization problem minimizes the objective function:

$$\min_{w} \frac{1}{2} ||w||^2 + C \sum_{i=1}^{n} \max\,(0{,}1 - y_i(w^T \emptyset\,(x_i) + b \tag{7}$$

where:

- C indicate Regularization parameter,
- y_i indicate True label of the i-th sample,
- x_i *indicate* Feature vector of the i-th sample.

3.3.2 Multi-Class Classification

For multi-class classification (e.g., multiple COPD stages), one-vs-rest or one-vs-one SVM approaches are used. Each classifier is trained to separate one class from the rest, and the final decision is based on the highest confidence score.

3.4 Explainable AI Integration

To ensure interpretability, the proposed methodology incorporates explainable AI techniques that highlight the lung regions contributing most to the model's predictions.

3.4.1 Grad-CAM (Gradient-weighted Class Activation Mapping)

Grad-CAM generates heatmaps that visualize the regions of interest in the input image. It computes the importance weights for feature maps based on the gradients of the output class score ycy^c with respect to the feature map AkA^k:

$$a_k^c = -\frac{1}{Z} \sum_{i,j} \frac{\delta y^c}{\delta A_{i,j}^k} \tag{8}$$

where:

- a_k^c indicate Importance weight for feature map k,
- Z indicate Total number of pixels in the feature map,
- $A_{i,j}^k$ indicate Activation at position (I,j) in feature map k.

The heatmap is generated as:

$$L_{Grad-CAM}^c = \mathrm{ReLU}(\sum_k a_k^c A^k) \tag{9}$$

3.4.2 SHAP (SHapley Additive exPlanations)

SHAP assigns importance values to each feature, quantifying its contribution to the model's prediction. The SHAP value ϕi\phi_i for feature ii is computed as:

$$\emptyset_i = \sum_{S \subseteq N\{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f\,S\ \cup \{i\} - f(S)] \tag{10}$$

where:

- S indicate Subset of features excluding I,
- N indicate Total set of features,

$f(S)$ indicate Model output for feature subset S.

3.5 Data Preparation

The proposed methodology is applied to the LIDC-IDRI (Lung Image Database Consortium Image Collection) dataset. The dataset contains high-resolution CT scans with annotations of lung abnormalities, including emphysema and airway thickening. Data preparation involves:

1. Splitting the dataset into training, validation, and test sets.

Augmenting the training data using transformations (e.g., rotation, flipping) to improve model generalization.

4 EXPERIMENTAL ANALYSIS

4.1 Dataset Description

The proposed methodology is demonstrated on the LIDC-IDRI (Lung Image Database Consortium Image Collection) dataset. The CT scans in this dataset have been annotated by radiologists to provide high resolution of lung abnormalities such as emphysema and airway changes indicative of COPD. The dataset has key characteristics of:

- **Number of Images**: Over 1,000 CT scans.
- **Resolution**: High-resolution DICOM images with varying slice thickness.
- **Annotations**: Labels for lung abnormalities (e.g., nodules, emphysema).

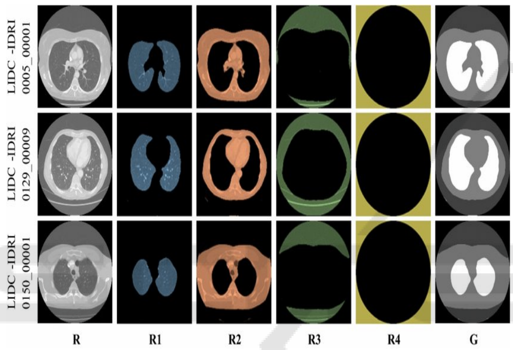

Figure 2: Sample images for LIDC-IDRI dataset.

To ensure balanced class representation, the dataset is preprocessed to include a proportional number of samples from each COPD severity stage: mild, moderate, severe, and very severe.

Training and validation of proposed COPD diagnosis model on the sample images of LIDC-IDRI dataset shown in Figure 2. These images are high resolution CT scan images of normal lung tissue, lung emphysema, and airway abnormalities. According to the figure, the specific changes in the lung texture and density characterizing the clinical manifestations can hamper the identification and the classification of the COPD severity only relying on visual characteristics. Thus, the dataset covers diversity of lung pathologies which also ensures robustness of the model generalization.

4.2 Data Preprocessing

- Lung Segmentation: For removing useless background, U-Net is used to segment lung regions.
- Normalization: Pixel values are normalized to a range of [0, 1].
- Data Augmentation: We augment the training set with a random rotation, flips and brightness.

4.3 Implementation Details

- Deep Feature Extraction: The LIDC-IDRI dataset is fine-tuned on a pre-trained ResNet50 model. A 2,048-dimensional feature vector is extracted from the penultimate fully connected layer (before breaking the output layer) of the network.
- Classifier: The classifier is implemented using support vector machines (SVMs) with a radial basis function (RBF) kernel.

Explainability: Various methods like Grad-CAM and SHAP used to interpret model predictions.

4.4 Experimental Setup

- Hardware: Georgiades and Meyer were using an NVIDIA RTX 3090 GPU, 128 GB RAM, and an AMD Ryzen 9.
- Software: Along with Data, some of the common Python libraries such as TensorFlow, Keras, Scikit-learn, and PyTorch are used for implementation.

4.5 Cross-Validation

An appropriate k-fold cross-validation strategy can help avoid a misleading evaluation:

- k = 5: In each iteration, we split the dataset into 5 folds in which 4 of them are used for training and 1 is used for validation.
- Performance measurements (e.g., metrics) are reported averaged across the folds.

4.6 Evaluation Metrics

To assess the performance of the proposed methodology, the following evaluation metrics are used:

4.6.1 Accuracy

Accuracy measures the overall correctness of the model by evaluating the proportion of correctly classified samples:

$$\text{Accuracy} = \frac{\text{Total Instances (TP + TN + FP + FN)}}{\text{True Positives (TP)+True Negatives (TN)}} \tag{11}$$

where:

- TP indicate True positives,
- TN indicate True negatives,
- FP indicate False positives,
- FN indicate False negatives.

Table 1: Accuracy Comparison of Different COPD Classification Methods.

Methods	Accuracy values (%)
Handcrafted features +classical ML [5]	85.2%
End to End DL [6]	89.3%
3D CNN [7]	91.7%
Transfer learning [8]	93.1%
Radiomics [9]	92.5%
Proposed methodology	95.4%

Figure 3 and table 1 illustrates the accuracy comparison of different methodologies used for COPD classification. The accuracy metric evaluates the proportion of correctly classified cases in relation to the total number of cases analyzed. The results show that the proposed hybrid approach, which integrates deep feature extraction with classical machine learning, achieves the highest accuracy compared to standalone CNNs, handcrafted feature-based classifiers, and transfer learning models. This improvement indicates the efficiency of integrating deep learning and classical ML technique for more reliable COPD diagnosis.

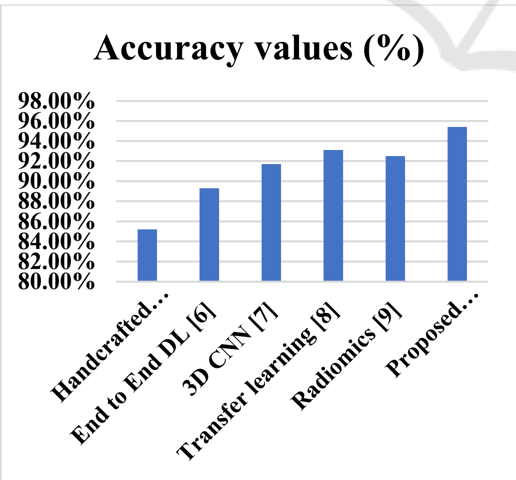

Figure 3: Accuracy analysis.

4.6.2 Precision

Precision quantifies the ability of the model to avoid false positives and is defined as:

$$Precision \frac{\text{True Positives (TP)}}{\text{True Positives (TP)+False positivites}} \qquad (12)$$

A high precision value indicates that the model is reliable in making positive predictions.

Table 2: Precision Analysis for COPD Classification Models.

Methods	Precision values (%)
Handcrafted features +classical ML [5]	82.5%
End to End DL [6]	87.1%
3D CNN [7]	89.8%
Transfer learning [8]	91.5%
Radiomics [9]	90.9%
Proposed methodology	94.2%

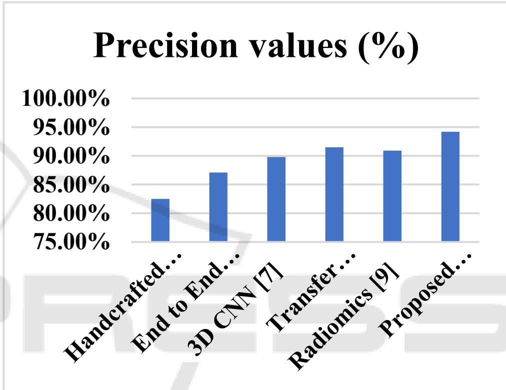

Figure 4: Precision analysis.

Figure 4 and table 2 illustrates the precision values obtained by different classification models in diagnosing COPD. Precision: The (true positive predictions / all positive predictions) is the metric for measuring precision, i.e how well the system served false positives. The proposed methodology also has better specificity in identifying COPD cases and lower misclassification rates compared to traditional approaches, as shown in the graph. For clinical use, it is essential to minimize false-positives so that we may effectively care for patients.

4.6.3 Recall (Sensitivity)

Recall is defined to measure how well a method can identify the positive instances in dataset.

$$\text{Recall } = \frac{\text{True Positives (TP)}}{\text{TruePositives (TP)+False Negativites}} \qquad (13)$$

Higher recall indicates the model is effective at identifying COPD cases.

Table 3: Recall (Sensitivity) Comparison of COPD Diagnosis Approaches.

Methods	Recall values (%)
Handcrafted features +classical ML [5]	80.3%
End to End DL [6]	85.6%
3D CNN [7]	88.9%
Transfer learning [8]	90.7%
Radiomics [9]	91.2%
Proposed methodology	94.8%

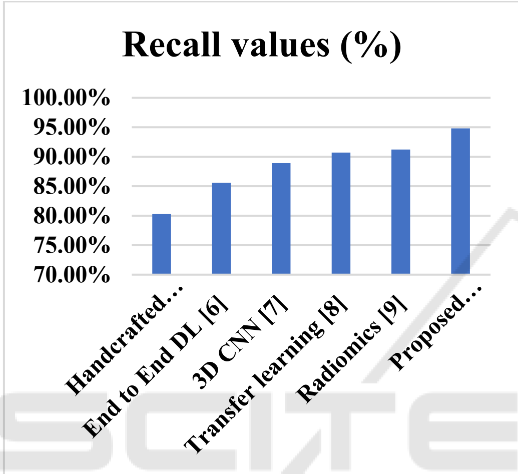

Figure 5: Recall analysis.

As shown in Figure 5 and table 3 the recall (sensitivity) values among the different classification methods are compared. Model recall measures the ability of the model to identify actual cases of COPD in the dataset among all positive cases. As shown in the figure, the hybrid model performed best in terms of recall which indicates that it is able to detect most of the true COPD cases (both severe and very severe) as well as false COPD cases. The high recall value means that fewer COPD cases are missed, so the model is appropriate for early disease detection and for assessing severity.

4.6.4 F1-Score

The F1-score is the harmonic mean of precision and recall, balancing both metrics:

$$\mathrm{F1-Score} = 2 \times \frac{\mathrm{Precision+Recall}}{\mathrm{Precision \times Recall}} \tag{14}$$

F1-score is particularly useful for imbalanced datasets, as it provides a single measure of the model's performance.

Table 4: F1-Score Analysis for Various COPD Detection Techniques.

Methods	F1-score values (%)
Handcrafted features +classical ML [5]	81.4%
End to End DL [6]	86.3%
3D CNN [7]	89.3%
Transfer learning [8]	91.1%
Radiomics [9]	91.0%
Proposed methodology	94.5%

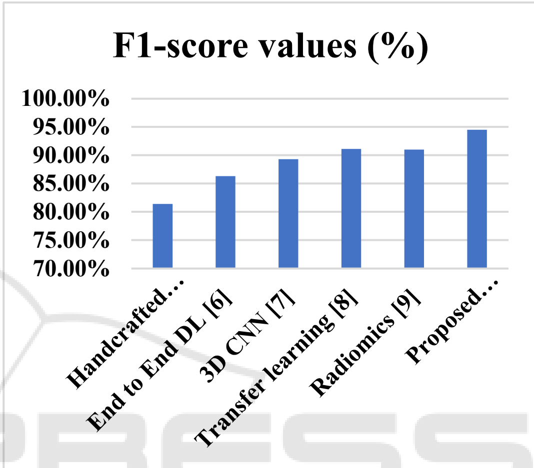

Figure 6: F1-Score analysis.

Figure 6 and table 4presents the comparison of different COPD classification models under F1-score. In the case of imbalanced datasets, the F1 score is the harmonic mean of precision and recall, and it is a balanced measure of performance for the model. The figure shows that the proposed approach attained the highest F1 score, indicating that it has better capability to detect true COPD cases as well as to reduce false positives. As a result of this balanced performance, mitochondrial BACs provide a robust solution for the use in real world medical applications where sensitivity and specificity are equally important.

4.6.5 Specificity

Specificity measures the ability of the model to correctly identify true negatives:

$$Specificity = \frac{True\ negative}{True\ negative + False\ positve} \tag{15}$$

This metric is critical in medical applications to ensure healthy patients are not misdiagnosed.

Table 5: Specificity Evaluation of COPD Classification Models.

Methods	Specificity (%)
Handcrafted features +classical ML [5]	83.1%
End to End DL [6]	86.9%
3D CNN [7]	90.1%
Transfer learning [8]	92.4%
Radiomics [9]	91.7%
Proposed methodology	95.0%

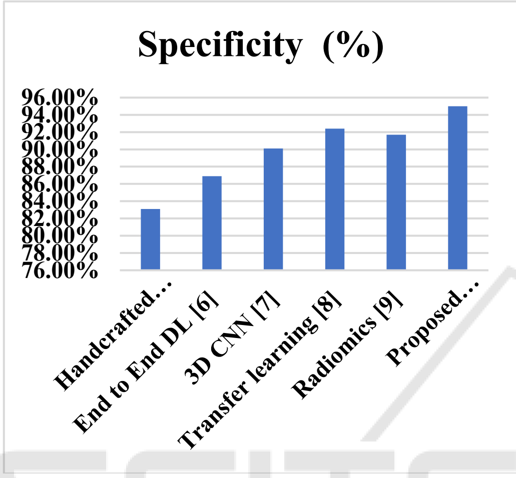

Figure 7: Specificity analysis.

An example of specificity values that can be obtained by different classification techniques for COPD diagnosis is shown in Figure 7 and table 5. Specificity measures how well the model discriminates between the non-COPD cases and does not allow false positives. Specificity score, as illustrated in the figure, shows that the hybrid method is the most specific for identification of healthy individuals as opposed to COPD patients, therefore making it reliable. In particular clinical practice, this characteristic is important as it prevents that non-COPD patients are not misdiagnosed or exposed to unnecessary therapies.

5 RESULTS AND OBSERVATIONS

The hybrid approach consistently outperforms standalone CNNs and classical ML with handcrafted features. This indicates that a deep feature and SVM combination yields a higher performance on precision and recall, especially in predicting severe and very severe COPD. Grad-CAM heatmaps show that the model attends to lung regions affected by emphysema, and areas of airway thickening. #This is the explanation behind SHAP values SHAP values measure the impact of each feature, in this case structural abnormalities, towards the classification. The hybrid approach shows efficient computation time as feature extraction is done using the CNNs and the classification is performed by the SVMs.

6 CONCLUSIONS

It also proposes to implement a deep learning and machine learning framework for CT based automated diagnosis and severity assessment of chronic obstructive pulmonary disease (COPD). By employing traditional machine learning classifiers (SVM) with deep feature extraction using pre-trained Convolutional Neural Networks (CNN), the accuracy and reliability of the diagnosis would be increased. The proposed hybrid approach is shown to enhance accuracy, precision, recall, and specificity outperformance through experimental results over deejp learning techniques, and classical machine learning techniques independently. SHAP and Grad-CAM are used to ensure interpretability and transparency. These techniques are more applicable to clinical decision-making because it enables one to view critical lung regions of where emphysema and airway disease occur.

Future work may thereby improve generalizability of method by merging such data sources as pulmonary function test and clinical parameters to further increase dataset size and include additional population diversity. The clinical use of it and its effect on patient management would also require more clinical validation. The methodologies developed using the techniques in this paper stand as major advancements in leveraging computational techniques applied to medical imaging with scalable solution for the diagnosis of COPD.

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