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Lung Cancer Detection and Classification from Chest CT Images Using an Ensemble Deep Learning Approach

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***Abstract*—Nowadays, Cancer's devastating impact is growing, taking thousands of lives prematurely each day. Lung cancer stands at the forefront of this grim reality. Timely and accurate cancer diagnosis is crucial, as it directly correlates with effective treatment and improved patient outcomes. In this paper, we proposed an ensemble deep-learning method for detecting and classifying lung cancers that greatly impact the Computer Aided Diagnosis (CAD) system. Initially, three deep convolutional neural networks (CNN) Transfer Learning Approaches, MobileNetV2, VGG19, and Resnet50, were used individually to perform classification. Then, these models are combined to perform better in lung cancer diagnosis using the fusion of chest CT and PET-CT images. This approach leverages the strengths of MobileNetV2, VGG19, and ResNet50's pretrained weights for feature extraction, and then the extracted features are concatenated and used for classification through the weighted average ensemble technique. After an extensive experimental analysis, the proposed ensemble model achieved a test accuracy of 98.93%, which is better than the individual model performance (98.67% in MobileNetV2, 98.20% in VGG19, and 97.67% in ResNet50). It can be an efficient diagnostic tool for lung cancer detection, as the prediction results of the proposed deep learning model outperform the recent Transfer Learning approaches.**

***Index Terms*—Lung cancer, Deep learning, VGG19, MobileNetV2, ResNet50, Ensemble method**

I. INTRODUCTION

Lung cancer, identified as one of the leading causes of mortality among cancer patients, has reached alarming proportions. According to the World Health Organization(WHO), it ranked as the second most fatal cancer worldwide in 2014 [1]. There is a grim projection that mortality attributed to lung cancer is expected to escalate, reaching nearly 17 million worldwide by the year 2030. These figures underscore the urgent need for comprehensive strategies in prevention, early detection and treatment to address the escalating impact of lung cancer on a global scale [2].

Screening for lung cancer involves various methods such as computed tomography (CT) scans, Positron Emission Tomography (PET), X-rays, Magnetic Resonance Imaging (MRI), molecular diagnosis, or ultrasound, etc. Among these we used the combination of PET- CT scans that is the most enduring method for lung cancer detection. Fluoro-deoxyglucose Positron Emission Tomography (PET) imaging holds diagnostic and prognostic significance in the initial staging, restaging, and surveillance processes. The PET/CT imaging procedure, encompassing the entire body, has seen growing utilization for assessing lung cancer (LC) patients. PET/CT significantly improves nodal and metastatic staging accuracy and therapy response evaluation in lung cancer. This highlights the evolving landscape of imaging techniques, contributing to a more comprehensive understanding of lung cancer and its diverse manifestations [3].

In aiding physicians with cancer diagnosis, computer aided detection (CAD) systems play an authentic role. CAD systems are primarily built on machine learning methods with a particular emphasis on the dominance of deep learning (DL). One significant disadvantage of traditional machine learning techniques is the requirement for a feature extraction procedure, a step omitted when employing deep learning techniques [1].

In this context, we proposed a weighted average ensemble model with the help of three distinct deep learning architectures: MobileNetV2, VGG19 and ResNet50 for classifying lung cancer as either Adenocarcinoma (ADC), Large Cell Carcinoma (LCC), Small-Cell Carcinoma (SCC), Squamous Cell Carcinoma (SqCC), or Normal. The main contributions of this work are as follows:

- Developing a large balanced chest CT dataset and then training and testing three DL models: MobileNetV2, VGG19, and ResNet50 individually using this dataset through transfer learning concept.
- Creating a weighted average ensemble model using the above three models and tuning this proposed model for better performance on the detection and classification of lung cancers.
- Finally, providing a comparative study with recent related works.

Here, section 2 deals with recent developments in this domain, section 3 holds the materials and methods, experiments and result analysis are discussed in section 4 and the paper concludes with section 5, summarizing key insights and outline prospects for future work in the field.

II. RELATED WORKS

In this section, we analyzed some related works that focused on deep-learning techniques and algorithms for lung cancer classification. Saleh et al. [1] proposed a hybrid CNN-SVM algorithm that classified lung images with an accuracy of 97.91% using a dataset of 5103 CT images. In article [4], Naseer et al. presented LungNet-SVM, an automatic technique for detecting nodules as benign or malignant in CT images using a modified version of the AlexNet architecture and the Support Vector Machine (SVM) algorithm, with 97.64% accuracy. Kareem et al. [5] used the IQ-OTH/NCCD lung cancer dataset containing over 1100 CT-scan images. It suggests an automated system for identifying lung cancer that makes use of SVM classification and image-processing methods and obtains 89.8876% accuracy.

Articles [2], [6] to [9] represent some transfer learning methods for classifying lung cancer and comparing their performance. Ashhar et al. [2] used LIDC-IDRI datasets that investigate how well five CNN architectures (GoogleNet, SqueezeNet, DenseNet, ShuffleNet, and MobileNetV2) classify lung tumors as benign or malignant and GoogleNet is the best-performing CNN architecture with an accuracy of 94.53%. A dual-state transfer learning strategy has been proposed in [6]; they used deep CNNs to effectively identify and classify different forms of lung cancer from chest CT scan images. With the use of pre-trained models such as ResNet50, DCNN, VGG16, and Inceptionv3, the ResNet50 model attained a testing accuracy of 96.12%. Pal et al. [7] diagnosed lung cancer from CT scan images with 82% accuracy for VGG16, 87% accuracy for InceptionV3, and a high accuracy of 95% for ResNet50, which accurately identifies lung cancer nodules and categorizes cancer types (adenocarcinoma, large cell carcinoma, or squamous cell carcinoma). Raza et al. [8] developed EfficientNet architecture with additional top layers in the classification head. Using several data augmentation techniques, the Lung-EffNet model was evaluated on the "IQ-OTH/NCCD" dataset, achieving 99.10% accuracy. Rajasekar et.al [9] used six different deep learning algorithms— CNN, CNN Gradient Descent (CNN GD), VGG16, VGG19, InceptionV3, and ResNet50 to identify lymph node involvement in histopathological slides to address early lung cancer diagnosis and got the highest accuracy in CNN GD (97.86%) and VGG16 (96.52%).

A few researchers [10] to [13] proposed the ensemble models through the transfer learning approaches. Omar et al. [10] presented an effective ensemble transfer learning model for quick diagnosis of colon and lung cancer, which achieves individual accuracies of 98.32%, 98%, and 96.93% by utilizing MobileNetV1, InceptionV3, and VGG16 respectively. Accuracy is increased to 99.44% by the ensemble model. Tandon et al. [11] presented VCNet, a hybrid model that combines features from CapsNet and VGG-16. While CapsNet tackles convolutional neural networks' inadequacies concerning image rotation and aberrant orientations, VGG-16 manages object recognition. Tested on the LIDC dataset, VC-Net outperforms MobileNet, Xception, and VGG-16 (whose testing accuracies are 98%, 97.97%, and 96.95%, respectively), where VCNet achieves a testing accuracy of 99.49% using LIDC-IDRI dataset. Nigudgi et al. [12] approached a hybrid model that combines GoogleNet, VGG, and AlexNet for transfer learning, and then multi-class support vector machine (SVM) classification. The model attains 97% accuracy after being trained on the IQ-OTH/NCCD dataset, which comprises 1190 images classified as normal, benign, and malignant. Shah et al. [13] used Deep Ensemble 2D CNN to detect a Lung Nodule from LUNA 16 dataset and attain 95% accuracy.

After reviewing the pertinent papers, it can be concluded that deep transfer learning methods can be a workable way to diagnose lung diseases using PET-CT scan imaging. However, current DL methods have the problems of high percentages of incorrect forecasts and an unbalanced, small dataset. Therefore, there is a chance to improve the model's resilience and forecast precision. In this work, we proposed a weighted average ensemble model using separate pre-trained MobileNetV2, VGG19, and ResNet50.

III. MATERIALS AND METHODS

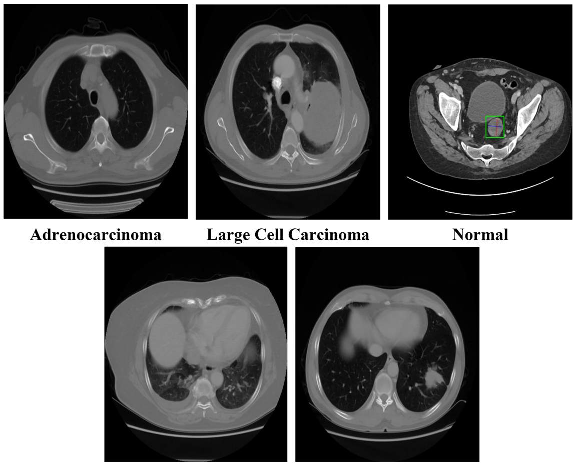
A. Dataset Description

Deep learning approaches have substantially contributed to different domains in recent years, enabling remarkable breakthroughs in image classification and feature learning [11], [14]. The wealth of well-annotated data is one factor contributing to deep learning's success. In the context of lung cancer detection, image quality, proper labelling, sufficient amount of images in each class plays an very important role for proper detection and classification.

Firstly, a Large-Scale CT and PET/CT Dataset of Lung Cancer consisting DICOM images derived from both CT and PET-CT scans of individuals diagnosed with lung cancer has been collected from an open-source repository [15]. Bounding boxes are used to define the locations of tumors in the XML Annotation files that are included with the dataset. These images are retrospectively obtained from patients who underwent lung biopsy and PET/CT examinations due to suspected lung cancer with categorization based on histopathological diagnoses. Patients with Names/IDs containing 'A' are associated with Adenocarcinoma, 'B' with Small Cell Carcinoma, 'E' with Large Cell Carcinoma, and 'G' with Squamous Cell Carcinoma.

Secondly, another Chest CT scan Image dataset contains 3 chest cancer types which are Adenocarcinoma, Large cell carcinoma, Squamous cell carcinoma, and normal images. This is also an open dataset that was collected from the Kaggle repository [16]. Some sample images of different classes are presented in Fig. 1.

In this study, we used two datasets that are comprised of 5 classes. The Chest CT scan Image datasets are already in jpeg format. On the other hand, the records of the first dataset are in DICOM format. In the dataset from Kaggle there are 215, 338, 187, and 260 records in total respectively in normal,



Adrenocarcinoma **Large Cell Carcinoma** **Normal**

Small Cell Carcinoma **Squamous Cell Carcinoma**

Fig. 1. CT and PET-CT images of different classes: Adenocarcinoma, Large Cell Carcinoma, Normal, Small Cell Carcinoma, and Squamous Cell Carcinoma.

Adenocarcinoma (ADC), Large Cell Carcinoma (LCC), and Squamous Cell Carcinoma (SqCC) classes.

In the PET-CT dataset, there are 184300, 808, 48916, and 17106 records for ADC, LCC, SqCC, and SCC respectively. We converted all Dicom format records into jpeg format for ease of our processing. Combining all images, we selected 3000 images randomly from the PET-CT dataset for each three classes including ADC, SqCC, and SCC. For Normal and LCC classes we mixed the two datasets and augmented them to balance the number of images of all classes. For testing, 10% data has been used, where 80% was used to train and 10% for validation resulting in 12000, 1500, and 1500 images for train, validation, and test respectively.

In computer vision, augmenting visual data is crucial for reducing over-fitting and class imbalancing which may lead to bias. This method involves applying various transformations to the pictures in the training dataset. In our dataset, we have very few images in the Normal and LCC classes. To balance the dataset augmentation is applied for these two classes. We applied the ImageDataGenerator function from the Tensorflow library. Random rotations up to 40 degrees, and horizontal and vertical shifts up to 20% of image dimensions are applied to the image for variations in object shape. Random zooming, horizontal flipping for scene generalization, and a nearest fill mode to maintain augmented pixel values close to the original ones are some of the controlled transformations applied while generating images. Fig. 2 shows the difference between the original image and the augmented image with the augmentation pipeline.

B. Deep Learning Models

1) ResNet-50: The Residual Network (ResNet) architecture improves the training speed and accuracy by letting inputs escape specific convolutional layers and minimizing duplicate feature relearning. According to several researches [6], [7], [17], ResNet-50 is successful in CT image classification, demonstrating its capacity to handle vanishing gradient issues. Within the ResNet architecture, this powerful model, developed from scratch without pretrained weights, exhibits its brilliance in picture classification tasks. ResNet-50 has an initial convolutional layer, three convolutional layers in the residual blocks, a shortcut connection, downsampling layers, and global average pooling for parameter reduction. ResNet-50 is empowered by the combination of skip connections and identity mappings, establishing it as a cornerstone in computer vision, and excelling in image classification, object recognition, and image segmentation applications.

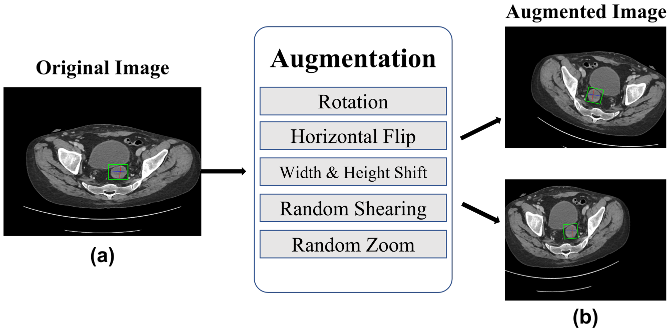


Fig. 2. Image augmentation pipeline: **(a)** original image and **(b)** augmented image.

2) VGG19: An expansion of the VGG16 architecture, the VGG19 is well-known for its 19 layers, which include 3 fully linked layers and 16 convolutional layers [12]. With five of its convolutional blocks and sporadic max-pooling layers for spatial downsampling, VGG19 is a powerful image recognition model. A classifier is implemented in the next fully connected layers, culminating in an output layer with 1000 units for ImageNet classification [6]. VGG19 is well-known for its ease of use, steady filter sizes, and growing depth; these qualities make it useful in a range of computer vision applications. VGG19 is frequently used with pretrained weights for transfer learning in a variety of computer vision applications due to its increased depth and parameter count.

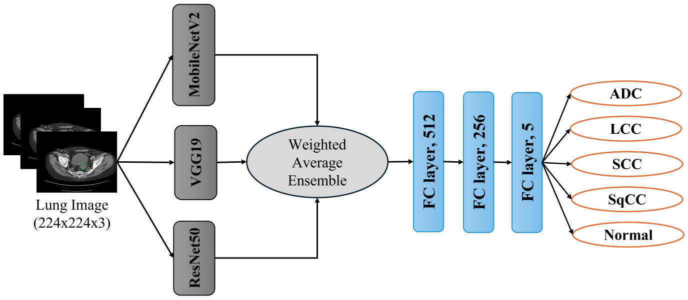


Fig. 3. Proposed ensemble approach with weighted average of MobileNetV2, VGG19 & ResNet50.

3) MobileNetV2: The very effective MobileNet technique, which uses depth-wise separable convolutions to handle each color channel separately, is introduced in the publications marked in [2] and [7]. By applying a different filter to each input channel using depth-wise convolutions, this method avoids combining channels into a single convolution. It uses a depthwise convolution to integrate the features retrieved for each channel, then a deep separable filter and pointwise convolution. With an inverted residual structure, depthwise convolution for low-dimensional input compression and filtering, a shortcut at the bottleneck layer, and a linear convolution to return the feature to its original dimension, Google's MobileNetV2 improves this. The MobileNet family is perfect for real-time applications because of its lightweight architecture and widespread usage of depthwise separable convolutions, which are features tailored for devices with limited resources.

C. Proposed Model

In this paper, we proposed a Weighted Average Ensemble model combining MobileNetV2, VGG19, and ResNet50. In this approach, the last layers of trained MobileNetV2, VGG19, and ReaNet50 models are concatenated and put them in the FC or dense layer. In the final fully connected layers there are 5 filters for classifying the 5 classes with softmax activation function. After training the ensemble model, the weights are saved and these weights are loaded to predict on test images. The proposed model architecture is displayed in Fig. 3. The proposed ensemble approach can be deducted as such-

$$W = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

Where, *W* represents the weighted average, n denotes the number of terms to be averaged which in our case is 3. w_i is the weights applied to the x values and X_i is the data value that needs to be averaged.

D. Performance Evaluation Metrics

The suggested technique is evaluated using the widely used assessment metrics for DL classification models. Measuring true and false prediction values, the metrics include accuracy, recall, mean squared error (MSE), and area under curve score (AUC) of the receiver operating characteristic curve (ROC). This study uses a variety of assessment methods since accuracy measurements alone are unable to demonstrate the effectiveness of deep learning models for classification. To evaluate performance, in addition to these metrics measurements, the accuracy and loss curves with the number of epochs, confusion matrix, and ROC curve have also been examined. The aforementioned metrics' mathematical equations are provided below in eq. (2) to (5).

Here, TP = True Positive, TN = True Negative, FP = False Positive , FN = False Negative,

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

$$recall(sensitivity) = \frac{TP}{TP + FN} \tag{3}$$

$$specificity = \frac{TN}{TN + FP} \tag{4}$$

$$precision = \frac{TP}{TP + FP} \tag{5}$$

IV. EXPERIMENTS AND RESULTS

For the transfer learning in the trials, we employed the pre-trained VGGNet, MobileNet, and ResNet architectures that were trained using the 2012 ImageNet. The criteria utilized to assess the effectiveness of the various categorization techniques were accuracy, recall, MSE, and AUC-ROC. We used 80% data to train, 10% for validation, and 10% for testing.

A. Experimental Setup

In our experiments, we used the Windows operating system and the Anaconda editor to create a Python environment. Tensorflow and Opencv were mainly used in deep learning training and image processing. In the hardware part, the processing device consists of Intel Core i9 processor, with 64 GB random access memory (RAM), 3 TB of solid-state drive (SSD), and 12GB graphics processing unit from NVIDIA.

B. Hyperparameters

Using an Adam optimizer with categorical cross-entropy as the loss function and a learning rate of 0.0001, a batch size of 4 and 50 epochs were chosen. An early halting mechanism that assessed the model's performance on the test set every five epochs was put in place to prevent overfitting. The training process was stopped because the accuracy on the test set plateaued during three consecutive epochs. The learning rate has been reduced gradually to get better performance based on the validation loss.

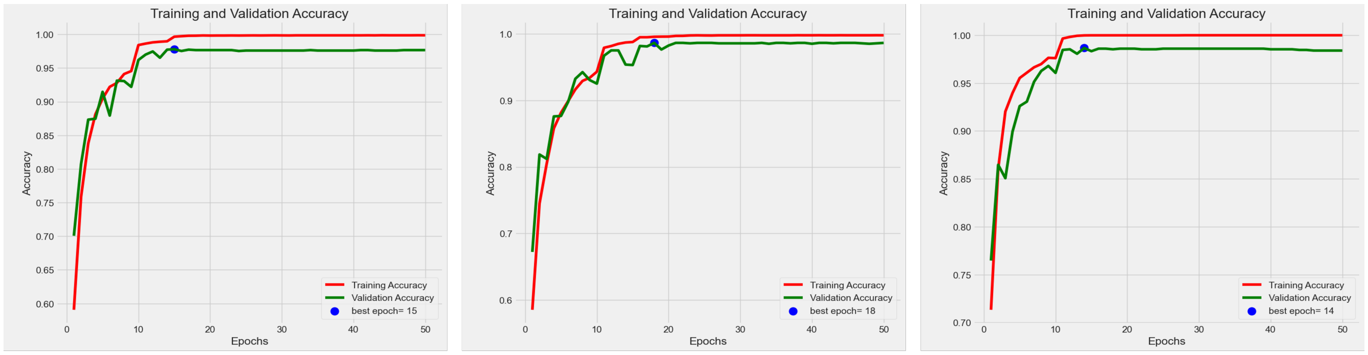
C. Results Analysis

In this experiment, we worked on lung cancer classification. There were 5 classes: Normal, Adenocarcinoma, Small Cell Carcinoma, Squamous Cell Carcinoma, and Large Cell Carcinoma. Several experiments were performed using different state-of-the-art models for image classification. All the image input shapes were (224, 224, 3), and all the models were run with the same parameters and same epoch numbers. From Table I, we can see the performances of different models individually and also the ensemble model for the test dataset.

TABLE I
PERFORMANCE RESULTS OF ALL EXPERIMENTS

Models	***MSE***	***Recall***	***Accuracy***	***AUC***
ResNet50	0.0080	97.60%	97.67%	99.52%
VGG19	0.0052	98.20%	98.20%	99.78%
MobileNet	0.0045	98.67%	98.67%	99.58%
Proposed Ensemble Model	**0.0036**	**98.93%**	**98.93%**	**99.74%**

We ran multiple experiments to compare how our proposed method is better than MobileNetV2, ResNet50, and VGG19. Table I clearly compares how our proposed ensemble approach outperforms the other three experimented transfer learning approaches. The training accuracy of the ensemble model has reached 98.93%. The AUC score, MSE, and sensitivity of proposed method are 99.74%, 0.0036 and 0.9893 respectively. Fig. 4 shows the train and validation accuracy curves for 50 epochs of three transfer learning approaches, whereas Fig. 5



(a)

(b)

(c)

Fig. 4. Accuracy curve on 50 epochs on train and validation for (a) ResNet50, (b) VGG19, (c) MobileNetV2.

Fig. 5. Accuracy curve on 50 epochs on train and validation for proposed ensemble approach.

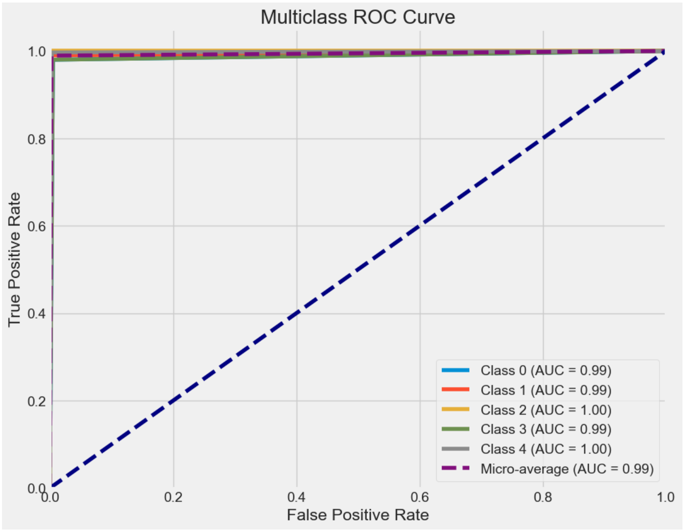


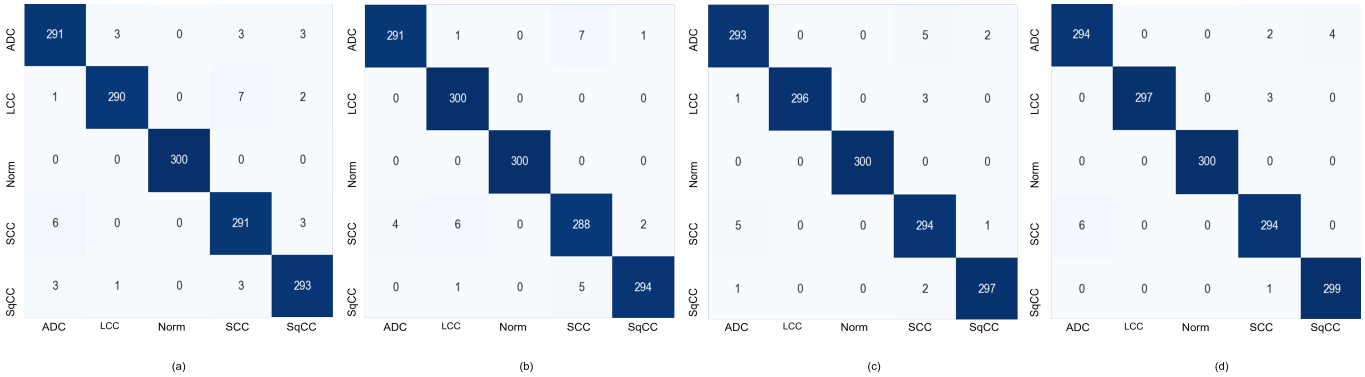
Fig. 6. ROC curve of proposed approach for each class on test dataset and their AUC scores.

shows the accuracy curves of our proposed model. It is visible that the proposed model has reached its culmination point of accuracy at an early stage with respect to the individual transfer learning approaches of Fig. 4. The AUC-ROC curve for proposed model has been shown in Fig. 6 We can see the ROC curve and AUC score for each class. All classes have AUC scores of nearly 100%. It indicates that this model can classify diseases in a very accurate manner. Fig. 7 represents the confusion matrix of all 4 experimented methods. We can see that the false prediction for Resnet50, VGG19, ResNet, and the proposed ensemble method have values of 35, 27, 21, and 16 respectively. Hence it is clear from the confusion matrix that the proposed model can predict lung cancer types with a very high rate of true positive and low rate of false prediction.

In our research, we have conducted a comprehensive comparison with all recent related works and state-of-the-art approaches for lung cancer classification. We have taken into account the fact that the performances of DL models depend on the size and type of the datasets and have selected papers that used almost the same type and size of datasets for a proper comparison. The results, as shown in Table II, clearly demonstrate that our approach outperforms other state-of-the-art approaches, instilling confidence in the effectiveness of our research.

V. CONCLUSION

In this work, lung CT scans are classified as either Adenocarcinoma, Large Cell Carcinoma, Small Cell Carcinoma, Normal, or Squamous Cell Carcinoma using weighted average ensemble learning by using MobileNetV2, ResNet50, and VGG19. These models were also tested individually for lung cancer detection and classification. A large balanced dataset has been developed by the fusion of two different datasets. Utilizing the PET-CT dataset and the Chest CT image dataset, a total of 15,000 image data were retrieved using this approach. After extensive experimental analysis, we



(a)

	ADC	LCC	Norm	SCC	SqCC
ADC	291	3	0	3	3
LCC	1	290	0	7	2
Norm	0	0	300	0	0
SCC	6	0	0	291	3
SqCC	3	1	0	3	293

(b)

	ADC	LCC	Norm	SCC	SqCC
ADC	291	1	0	7	1
LCC	0	300	0	0	0
Norm	0	0	300	0	0
SCC	4	6	0	288	2
SqCC	0	1	0	5	294

(c)

	ADC	LCC	Norm	SCC	SqCC
ADC	293	0	0	5	2
LCC	1	296	0	3	0
Norm	0	0	300	0	0
SCC	5	0	0	294	1
SqCC	1	0	0	2	297

(d)

	ADC	LCC	Norm	SCC	SqCC
ADC	294	0	0	2	4
LCC	0	297	0	3	0
Norm	0	0	300	0	0
SCC	6	0	0	294	0
SqCC	0	0	0	1	299

Fig. 7. Confusion Matrix on test set: **(a)** ResNet50; **(b)** VGG19; **(c)** MobileNetV2; **(d)** Proposed ensemble approach.

TABLE II
COMPARATIVE ANALYSIS WITH RECENT RELATED APPROACHES

Authors	*Method*	*Accuracy*
Saleh et al. [1]	Hybrid CNN-SVM	97.91%
Ashhar et al. [2]	GoogleNet	94.53%
Kareen et al. [5]	SVM	89.88%
Atiya et al. [6]	ResNet50	96.12%
Pal et al. [7]	ResNet50	95.00%
Rajasekar et al. [9]	CNN GD	97.86%
Nigudgi et al. [12]	Ensemble of Alexnet VGG and Googlenet	97.00%
Shah et al. [13]	Deep Ensemble 2D CNN	95.00%
Proposed Approach	**Ensemble of MobilenetV2, ResNet50, and VGG19**	**98.93%**

have found our proposed technique yielded an accuracy of 98.93%, which outperforms its individual model counterparts. The comparative analysis shows that the proposed model can perform comparatively better than the recent existing methods and can be an efficient way of diagnosing lung cancer from chest CT images. Due to limited computation resources, we used a limited dataset with samples of 15000, where 3000 samples are in all 5 classes. In the future work, we are going to train and validate the model with a new large and diverse dataset to make the model robust and enhance the capability of generalization.

ACKNOWLEDGEMENT

All data generated or analyzed during this study are included in this published article. The datasets used in this research are publicly available at [15], [16].
Use of ChatGPT or LLM: Not applicable

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