The Effect of Fully Connected Layers in Different CNN Architectures for Lung Cancer Analysis

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Abstract— **Improving patient outcomes requires early and precise lung cancer classification. Deep learning has been shown to be successful in the interpretation of medical pictures, particularly when convolutional neural networks (CNNs) are used. In this paper, we proposed a deep modified CNN network using three pre-trained models (Densenet169, MobileNetV2, and Resnet50V2) to improve lung cancer classification performance based on the IQ-OTH/NCCD Lung Cancer dataset. The experimental results show that our modified Densenet169 based strategy outperformed existing methods, earning the highest accuracy rates for lung cancer classification. Early identification of lung cancer can enhance patient prognosis and treatment options dramatically. This report outlines future research and advancement opportunities in this vital topic.**

Keywords— Deep learning, Lung cancer, CNN networks, Classification, Transfer learning.

I. INTRODUCTION

Lung cancer, also known as lung carcinoma, is a type of cancer that is characterised by the excessive and uncontrolled proliferation of cells inside the lung tissues. [1]. It is critical to treat this disease in order to avoid metastases from spreading and causing the cancer to spread to other places of the body. [2-5Long-term secondhand smoking exposure is responsible for nearly 90% of lung cancer occurrences [6]. Smokers have a 15% reduced risk of acquiring lung cancer than nonsmokers [7]. Airborne and workplace contaminants consist of substances such as asbestos, nickel, uranium, and radon. Radon is a colorless and odorless gas that is produced through the natural decay of uranium in water, soil, and aged construction materials [8].

There has been significant advancement in the field of computer vision in recent years, leading to its widespread acceptance across a variety of industries. Medical diagnosis is one area where computer vision is gaining popularity. Specifically, the use of computer vision in the diagnosis of lung cancer has grown in popularity and importance for research purposes, leading to earlier identification. It can also assist clinicians improve their decision-making abilities with less time, effort, and money and more accurate judgment rates [9Biomedical images portray the human body at various scales and are created using various imaging methods. These photographs are used to measure and record specific physical characteristics of the human body [10].

Numerous studies have demonstrated that DL methods outperform traditional techniques in terms of precision, error reduction, and noise resistance.. In this context, many researchers have used these techniques for the diagnosis of lung cancer. T. Chandrasekar et al. in [11] introduced MRRXGBDC technique and SOA to enhance lung cancer prediction, achieving 10% accuracy improvement, 50% reduced false positives, and 11% faster prediction time. The authors in [12] proposed a novel deep hybrid learning approach for early lung cancer detection. Evaluating lightweight DNNs, including 2D CNN, SqueezeNet, and MobileNet, achieves 85.21% accuracy, mitigating challenges in lung nodule recognition and classification. Besides, N. Cheng et al. in [13] used gene expression data from 226 patients for tumor metastasis. Through LASSO analysis, 31 transcripts were selected as features for a deep neural network (DNN), resulting in higher precision than other methods. Incorporating 7 vital lung cancer genes further improved model performance with increased AUC and AUPR. Moreover, S. Tripathi et al. in [14] provided a methodology to predict gene mutations in NSCLC patients (EGFR, KRAS, ALK). Integrating clinical, genomics, and PET/CT data via a novel pipeline, a fusion of Convolutional and Dense Neural Networks, including EfficientNets, SENet, and ResNeXt WSL, achieved a high 94% AUC score for mutation prediction. Whereas, A. B. Pawar et al. in [15] applied IoT with on-the-fly training for early lung cancer detection. Image processing and machine learning aid in identifying malignant growth. Subtle symptoms become apparent in advanced stages, including hoarseness, weight gain, and chest pain. The proposed ECNN+ approach enhances accuracy and temporal complexity for early identification. In [16], the authors employed a Computer-Aided Diagnosis (CAD) System that aims to improve lung cancer detection. Histopathological images from biopsies were processed for dataset creation. Training involved Convolutional Neural Networks such as Inception-V3 and ResNet50. The ensemble learning techniques were employed to enhance accuracy and reduce variance on unseen data. Furthermore, M. S. Pethuraj et al. in [17] proposed a Pervasive Data Analytical Framework (PDAF) for lung cancer recurrence prediction using wearable sensors and clinical assessments. PDAF employs processes such as data segregation, feature correlation via optimization, and autoencoder prediction. The framework yields notable improvements, with up to 9.22% accuracy, 9.29% detection, and 7.96% recommendation enhancements. Eventually, Z. Shen et al. in [18] introduced WS-LungNet, a weakly-supervised lung cancer detection and diagnosis network. It addresses label scarcity and inconsistency using semi-supervised computer-aided detection (Semi-CADe) for nodule segmentation and cross-nodule attention computer-aided diagnosis (CNA-CADx) for malignancy assessment. Evaluation shows WS-LungNet achieves 82.99% CPM for nodule detection and 88.63% AUC for lung cancer diagnosis, highlighting its effectiveness in enhancing detection and diagnosis.

In this paper, we introduced a novel method for classifying lung cancer using modified CNN networks based on three distinct pre-trained models. By employing this approach, we achieved superior results compared to using each pre-trained model individually. The key contributions of this research are as follows:

- We investigated the usage of three different pre-trained models, namely DenseNet169, MobileNetV2, and Resnet50V2.
- We applied a deep modified transfer learning approach to each model, augmenting them with new fully connected layers tailored to our dataset.
- The experimental outcomes clearly demonstrated that deep modified transfer learning effectively enhances the performance of pre-trained models.

The remaining of this study is structured as follows: In Section 2, a comprehensive overview of the proposed system, including the dataset and methods employed, is presented. Section 3 focuses on the experimental outcomes, their analyses, and a comparison between our system and state-of-the-art techniques. Lastly, Section 4 concludes the paper.

II. PROPOSED SYSTEM

In this study, we suggest a deep modified CNN network-based lung cancer classification method. The system incorporates pre-trained models (Densenet169, Resnet50V2, and MobileNetV2) and makes use of the IQ-OTHNCCD lung cancer dataset. In order to determine the sturdy architecture underlying these models that is appropriate for the purpose of lung cancer classification, the architecture of each of these implemented pre-trained Networks has been altered by the addition of new fully connected layers. This section discusses the theoretical underpinnings of various strategies. Fig. 1 condenses the proposed method's general overview.

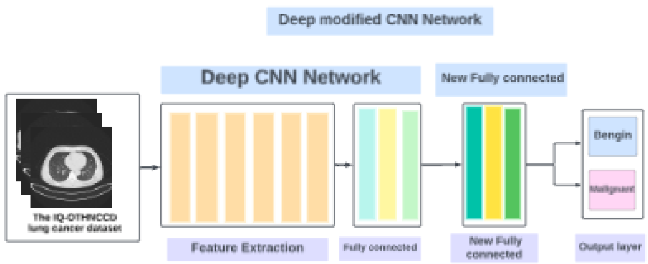
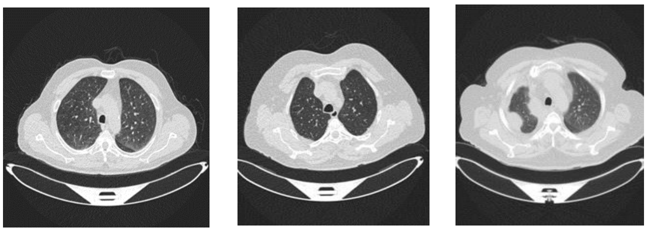


Figure 1: The proposed system's architecture for the lung cancer classification.

2.1.Dataset description

The publicly accessible IQOTH/NCCD lung cancer dataset contains 1,097 CT scans from 110 patients. This dataset was gathered over a three-month period in 2019 at the Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases. It includes photographs of people with lung cancer at various stages as well as healthy people from various age groups, genders, socioeconomic backgrounds, and geographic areas.The images were categorized by the collecting center's oncologists and radiologists into three categories: benign, malignant, and normal. Among the 110 patients, 15 were categorized as benign (containing 120 images), 40 as malignant (containing 416 images), and 55 as normal or healthy (containing 561 images). The images were first saved in DICOM format before being converted to JPG files having 512 by 512 pixel size. These pictures were acquired with a SOMATOM Siemens scanner set to 120kV, a 1 mm slice thickness, and particular window width (350 to 1200 HU) and window center (50 to 600) ranges. In this work, the dataset was split into training and testing set with 80% and 20%, respectively to classify lung cancer data samples as benign or malignant.



Normal Bengin Malignant

Figure 2: Some samples of various classes for the IQ-OH/NCCD dataset.

2.2.DEEP CNN NETWORKS

Deep CNN networks are a strong deep learning technology that is commonly used in computer vision problems. Because of its capacity to learn hierarchical features from raw image data, Convolutional Neural Networks (CNNs) have demonstrated extraordinary performance in image recognition, object detection, and segmentation. Transfer learning, a prominent strategy in CNNs, uses pre-trained models to efficiently tackle new jobs. To benefit from their learned representations, we used three pretrained models in our study: Densenet169, MobileNetV2, and ResNet50V2. When compared to building these deep networks from scratch, our transfer learning technique allowed us to obtain higher outcomes with less training time and data.

2.2.1. ResNet50V2

ResNet50V2 [20] is a 50-layer pretrained CNN model that tackles the vanishing gradient problem using residual and skip connections. It improves accuracy by allowing for the learning of detailed details. The model is appropriate for picture classification, object identification, and image segmentation.

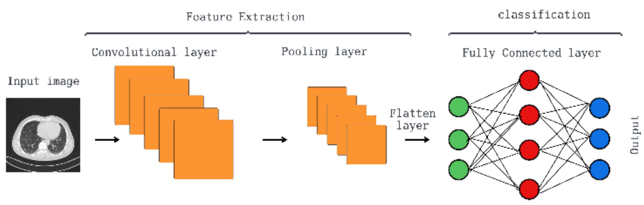


Figure 3: The ResNet50V2's architecture

2.2.2. MobileNetV2

Sandler et al. [21] introduced MobileNetV2, an enhancement over MobileNetV1 [22]. MobileNetV2 is a pretrained CNN model that is optimized for mobile and embedded vision applications. To minimize computing complexity while retaining accuracy, it employs depthwise separable convolutions, inverted residuals, and linear bottlenecks. Its tiny architecture allows it to be employed on resourceconstrained devices for image classification, object identification, and picture segmentation.

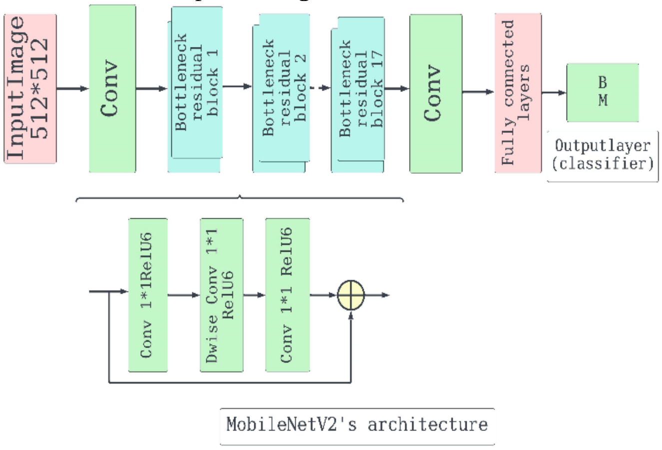


Figure 4: The MobileNetv2's architecture

2.2.3. Densenet169

DenseNet-169 [23] is a pretrained convolutional neural network (CNN) model that incorporates dense connections between layers to handle vanishing gradients. These links provide for efficient information flow, allowing for feature reuse and discriminative representation learning. The model is made up of highly coupled layers inside blocks that are controlled by transition layers. DenseNet-169, which has been trained on ImageNet, is beneficial for computer vision workloads, providing deep representation learning and increased performance.

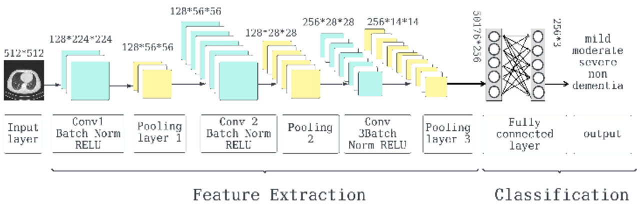


Figure 5: The Densenet169's architecture

III. Results and Discussion

This section provides an in-depth evaluation of the proposed deep modified CNN networks, concentrating on commonly used evaluation criteria applied to the testing data subset. To demonstrate our method's efficacy in comparison to existing state-of-the-art methodologies, we evaluated its performance with many popular deep modified CNN networks described in section (2.2). The dataset was separated into training and testing sets, comprising 80% (333 classified as malignant / 96 classified as benign) and 20% (83 classified as malignant / 24 classified as benign) of the total data, respectively.

3.1. Evaluation Metrices

The suggested method's performance has been assessed using a variety of measures. These metrics are calculated using the confusion matrix, a useful technique for getting a quick overview of the model's prediction outcomes in classification tasks [24, 25]. The confusion matrix reflects the four probable prediction possibilities.

Accuracy (Acc):

$$\frac{(TP+TN)}{(TP+TN+FP+FN)} * 100\% \qquad [1]$$

Sensitivity (Sens) :

$$\frac{TP}{(TP+FN)} * 100\% \qquad [2]$$

Specificity (Spec) :

$$\frac{TN}{(TN+FP)} * 100\% \qquad [3]$$

Precision (Pre) :

$$\frac{TP}{(TP+FN)} * 100\% \qquad [4]$$

TP (True Positive): Correctly predicted positive instances.
TN (True Negative): Correctly predicted negative instances.
FP (False Positive): Incorrectly predicted positive instances.
FN (False Negative): Incorrectly predicted negative instances.

3.2.Performance of Deep CNN networks

To obtain successful lung cancer classification, we performed a thorough study of the deep CNN networks used, namely Densenet169, MobilenetV2, and Resnet50V2. The purpose of this study was to evaluate and compare the performance of various algorithms. We attempted to improve the model's prediction skills by altering important parameters. Several tests were carried out, and the findings, as well as the associated parameter values, are shown in table 1.

Table 1: Performance assessment of various transfer learning models for the IQ-OTHNCCD lung cancer dataset.

Models	Batch	Learning	Results (%)				
			Acc	Sens	Spec	Prec	F1-sc
Resnet50V2	16	0.001	92.64	96.36	94.64	83.33	95.49
		0.0001	83.82	86.29	95.53	29.16	90.67
		0.00001	82.35	86.06	93.75	29.16	89.74
	32	0.001	93.38	93.27	99.10	66.66	96.10
		0.0001	86.02	85.49	100.00	20.83	92.18
		0.00001	79.41	81.81	96.42	00.00	88.52
MobileNetV2	16	0.001	97.79	97.39	100.00	87.50	98.67
		0.0001	85.29	84.84	100.00	16.66	91.80
		0.00001	83.08	86.77	93.75	33.33	90.12
	32	0.001	97.79	97.39	100.00	87.50	98.67
		0.0001	75.73	81.10	91.96	00.00	86.19
		0.00001	49.26	82.08	49.10	50.00	61.45
Densenet169	16	**0.001**	**97.79**	**97.39**	**100.00**	**87.50**	**98.67**
		0.0001	83.82	0.8358	100.00	08.33	91.05
		0.00001	81.61	0.8222	99.10	00.00	89.87
	32	0.001	96.32	0 .9572	100.00	79.16	97.81
		0.0001	77.94	0 .8153	94.64	00.00	87.60

		0.00001	83.08	85.03	96.42	20.83	91.37

Table 2: The Impact of Fully Connected Layers in Different CNN Architectures on Performance Assessment for Lung Cancer Analysis Using the IQ-OTHNCCD Dataset

Models	Batch	Learning	Results (%)				
			Acc	Sens	Spec	Prec	F1-sc
Resnet50V2	16	0.001	98.52	98.24	100.0	91.66	99.11
		0.0001	91.17	90.32	100.0	50.00	94.95
		0.00001	86.76	87.30	98.21	33.33	92.43
	32	0.001	95.58	94.91	100.0	75.00	97.37
		0.0001	87.50	88.00	98.21	37.50	92.82
		0.00001	76.47	82.78	90.17	12.50	86.32
MobileNetV2	16	0.001	99.26	99.11	100.0	95.83	99.55
		0.0001	88.97	88.18	100.0	37.50	93.72
		0.00001	86.02	85.49	100.0	20.23	92.18
	32	0.001	95.58	94.91	100.0	75.00	97.39
		0.0001	86.76	87.33	98.21	33.33	92.43
		0.00001	82.35	82.35	100.0	33.00	90.32
Densenet169	**16**	**0.001**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
		0.0001	88.23	87.50	100.0	33.33	93.33
		0.00001	82.35	82.35	100.0	17.59	90.32
	32	0.001	99.26	100.0	99.10	100.0	99.55
		0.0001	83.08	82.96	100.0	04.16	90.68
		0.00001	82.35	82.35	100.0	08.00	90.32

3.3.Performance comparison

A comparison study was carried out to evaluate the performance of the pre-trained models outlined in the preceding section. Figure 3 depicts the outcomes of this comparison, which evaluated the models using numerous criteria. Notably, the Densenet169 network beat its peers, attaining a phenomenal accuracy of 100.0%. The other networks, MobilenetV2 and Resnet50V2, performed well as well, with accuracies of 99.26% and 98.52%, respectively. Because of its excellent performance, the Densenet169 architecture will be the exclusive focus of the remainder of this study.

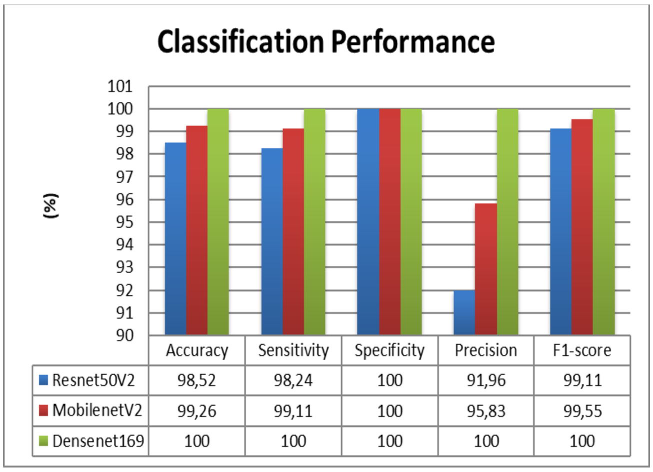


Figure 6: Performance comparison of the three pre-trained models based on various evaluation criteria.

Figure 4 illustrates the accuracy behavior for the best model (Desnenet169), with the blue line depicting the training phase and the orange line representing the testing phase. Notably, both phases achieved the highest accuracy of 100%.

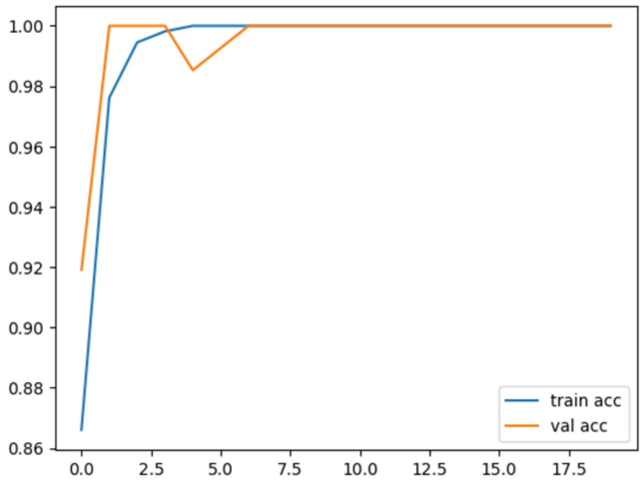


Figure 7: The accuracy behavior during the training and the testing phases.

3.3.Comparison with the state of the art

Using The IQ-OTHNCCD lung cancer dataset and multiple pre-trained models (Densenet169, Resnet50V2, and MobileNetV2), we tested our lung cancer classification methods. As indicated in Table 3, we compared our findings to other research that employed the same dataset and performance indicators as us. The comparison revealed that our strategy outperformed other studies that followed the same path and employed the same performance measures.

Table 2: Comparison of the proposed system with state of the art in terms of accuracy.

Authors	**Method**	**Used database**	**Accuracy (%)**
[26] Rajaguru, H, et al	NLR-GMM	Lung cancer data	92.88
[27] Swaroop, et al	CNN	LUNA16	97.10
[28] Swain, Anil Kumar, et al	CNN	TCIA-PET/CT	97.88

[29] Bębas, Ewelina, et al	Inception v3	155 magnetic resonance	99.60
[30] Abe, Ayomide Adeyemi, et al	DeepNodule-Detect	IQ-OTH/NCCD	98.17
[31] Bishnoi, Vidhi, and Nidhi Goel	CD-CNN	LC25000.	99.20
		TCGA	97.30
		CPTAC	98.80
Proposed Method	Deep modified CNN network (Densenet169)	IQ-OTH/NCCD	100.0

4.Conclusions

In conclusion, our study addresses the critical requirement for early and precise lung cancer categorization by utilizing deep learning approaches, namely convolutional neural networks (CNNs). We use the IQ-OTH/NCCD Lung Cancer Dataset and three pre-trained models (Densenet169, MobileNetV2, and Resnet50V2) to improve lung cancer classification performance by introducing a unique approach, deep modified CNN networks. Through further research, we want to use these powerful CNN models for lung cancer categorization. Our modified Densenet169 stands out among the three pre-trained models, exhibiting improved accuracy rates in lung cancer classification. Our experimental results unambiguously prove our approach's superiority over existing approaches.The tremendous impact of early lung cancer identification on patient outcomes highlights the importance of our study. Furthermore, our finding paves the way for future research and developments in this critical subject.

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