International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 11
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 November 2023*

Comparative Analysis of ResNet, MobileNet, and EfficientNet Models for Lung Nodule Detection and Classification

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***Abstract*:** Cancer is one of the most lethal diseases in the world. In a country as large as India, cancer has significantly burdened the medical infrastructure and the professionals. However, it has been proven that many forms of cancer could be treated, and the survival rate would be considerably higher if the diagnostics were performed accurately and at an earlier stage. In addition to the efforts of physicians and medical professionals, computer scientists have long contributed to the medical field by creating Computer Aided Diagnostics tools. In light of the recent strides made in the realm of Deep Learning, an international cohort of researchers has contributed to the development of a diverse array of neural models and architectures. These endeavors reflect the dynamic landscape of innovation within the field. Several aspects contribute to the effectiveness of Deep Learning computer-assisted diagnostics models; nonetheless, feature extraction plays a crucial part in defining the model's effectiveness. This research investigates the capacity of deep convolutional neural networks (DCNNs) to categorise lung cancer into three distinct groups. In this study, three cutting-edge computer vision architectures, namely ResNet50, MobileNet, and Google's EfficientNet, underwent fine-tuning for the task of classifying CT scans within the LIDC-IDRI dataset. This extensive dataset encompasses 244,527 CT scans categorized into groups denoting "nodule > or =3 mm," "nodule 3 mm," and "non-nodule > or =3 mm." The primary objective was to evaluate the efficiency of the EfficientNet model family, distinguished by substantial reductions in parameters and FLOPS, within the domain of lung nodule classification. This evaluation involved a comparative analysis against the ResNet50 and MobileNet architectures. The results distinctly demonstrated that the EfficientNet model, despite its economy in parameters, outperformed both the ResNet50 and MobileNet models. Notably, the EfficientNet model exhibited notably higher ROC AUC values across all classification categories, excelling in average AUC values for the comprehensive classification task, attaining scores of 0.922 (Micro AUC) and 0.956 (Macro AUC). These findings underscore the superior performance of EfficientNet in this critical medical imaging application.

Keywords: *ResNet50, MobileNet, EfficientNet, Deep Learning, Cancer, Classification*

1. INTRODUCTION

Today, we live in a technologically advanced era, in which Computer-Aided Diagnostics (CAD) has become an integral tool for physicians and other medical professionals around the globe. Medical Imaging and Radiology is one of the fields in medicine that heavily rely on computer scientists to make the process simpler and more reliable by helping the physician make a decision with confidence rather than looking up to another expert, in many cases one may not be accessible or in the worst case may not even exist. One of the most common causes of lung cancer is the use of tobacco, but there are other factors that largely influence a person from diagnosed with lung cancer or not, such as pollution level, place of work, exposure to substances such as asbestos, and family history of lung cancer is also an influencing factor. Contemporary advancements in computer science, particularly in the domains of image processing using deep learning, have significantly permeated the realm of medical image processing [1]. Simultaneously, healthcare experts worldwide concur that the integration of technologically-driven decision support systems has the potential to expedite diagnostic procedures and facilitate the delivery of precise treatments. To realize this vision, the imperative is to develop a highly scalable, dataset-agnostic, and computationally efficient model that can reliably attain the requisite levels of diagnostic accuracy.

Artificial intelligence and deep learning approaches have demonstrated their ability to solve complex challenges in the past. With the use of big datasets, these approaches have attained outcomes equivalent to those of people and in many cases, superior to those of humans. Moreover, the utilization of deep learning algorithms within the domain of medical imaging has witnessed a notable surge. These algorithms serve as instrumental tools for physicians and clinicians by facilitating diverse tasks such as detection, classification, and segmentation. A noteworthy attribute of deep convolutional neural networks (DCNNs) lies in their ability to obviate the necessity for explicit feature engineering. Multiple convolutional layers enable DCNNs to extract features from pictures without the assistance of a human expert [2]. As the depth of the network increases, finer details are recovered. Finally, layers with complete connectivity are employed for the categorization job. Transfer learning is a commonly utilised approach in deep learning for accelerating the training process and achieving better precision.

Pretrained networks, having acquired profound knowledge represented by millions of parameters on distinct datasets, undergo fine-tuning to adapt to specific dataset attributes. This research undertakes a comprehensive examination of the capabilities exhibited by three distinct deep learning architectures within the domain of multi-class classification. The specific focus of this investigation pertains to their performance when applied to the complex task presented by the LIDC-IDRI dataset, a valuable and intricate resource in the field of medical imaging. Specifically, we evaluate the ResNet50 [3] and MobileNet [4] architectures, widely applied in image classification, alongside the relatively novel EfficientNet [5] architecture, a product of Google's innovative scaling approach. Subsequently, this report unfolds as follows: Section 2 provides an overview of prior research in the field; Section 3 elucidates the comprehensive methodology employed in this study, and Section 4 encapsulates the key research findings. A thorough discourse is presented in Section 5, while Section 6 culminates the research endeavor.

2. LITERATURE REVIEW

Before this current research, in earlier studies involving lung nodule classification using both traditional Machine Learning (ML) and advanced Deep Learning (DL) techniques, a common approach was to convert the input data or images into specific features tailored for the task. These carefully curated features were then fed into dedicated classifiers responsible for carrying out the nodule classification.

Khan et al. [6] proposed a comprehensive framework encompassing a series of methodical stages. This framework entails initial steps such as image contrast enhancement, precise segmentation, and meticulous feature extraction. Subsequently, these extracted features are harnessed for both the training and testing phases within a meticulously selected Support Vector Machine (SVM)-based classifier.

In a manner congruent with these developments, Abbas et al. [7] undertook tumor classification endeavors through the extraction of color-texture attributes and the introduction of the AdaBoostMC method, an adaptive boosting multi-label approach. Nevertheless, the advent of augmented computational capabilities and the inundation of extensive datasets instigated a paradigm shift toward the adoption of deep learning techniques. This paradigm shift empowered neural networks to autonomously discern the salient features essential for the classification process. Deep learning methods that leverage convolutional neural networks have shown remarkable success in computer vision and image processing. Krizhevsky et al. [8] trained a deep convolutional network to excel at classifying a vast ImageNet dataset containing 1.3 million high-resolution images spread across 1000 different categories. This achievement was a turning point in the field of computer vision, showcasing the potential of deep learning.

In 2019, Zhang et al. [9] introduced a deep convolutional neural network-based framework with ensemble-based learning and proved that SVM in conjunction with Gradient Boosting Regression Trees and Random Forests provides the highest performance. In the year 2018, Haenssle et al. [10] conducted a significant investigation. In their study, they took Google's Inception v4 architecture and trained it using dermatoscopic images. Then, they did a thorough evaluation of how well this model could make diagnoses, comparing its performance to assessments made by 58 board-certified dermatologists. This research helps us understand how artificial intelligence can be a valuable tool in the field of dermatology, potentially assisting dermatologists in making accurate diagnoses. The study outcomes unveiled a noteworthy trend wherein the CNN model, in the majority of

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cases, exhibited superior diagnostic capabilities in contrast to human experts. This investigation thus reaffirmed the potential of leveraging computational models to augment the proficiency of medical image classification. Performance metrics, including sensitivity, specificity, and the area under the receiver operating characteristics curve (AUC-ROC), served as essential benchmarks for the evaluation [11]. Tran et al. [12] employed a distinctive 15-layer 2D deep convolutional neural network architecture. Their primary objective was to automate the process of feature extraction and categorization of pulmonary candidates, classifying them as either nodules or non-nodules. Their work was a significant contribution to the field of deep learning with the overarching aim of improving the accuracy and precision of lung nodule classification, which holds great significance in medical imaging and diagnosis. The focal loss function is then added to the training procedure to improve the model's classification accuracy.

This research primarily aims to explore how well EfficientNets, which are a family of models introduced by Google in 2019, can be applied to the challenging task of lung nodule classification. We're essentially investigating if these EfficientNets, known for their efficiency and accuracy, can be a game-changer in the field of medical imaging and help improve the classification of lung nodules, which is crucial for early disease detection. This study contributes to the ongoing efforts to make medical image analysis more effective and accurate, potentially benefiting patients by aiding in early diagnosis. This assessment involves a comparative analysis of EfficientNets against the ResNet50 and MobileNet architectures, which are established as fundamental components in computer vision tasks. Notably, this research endeavors to contribute novel insights, as there exists no prior investigation into the applicability of EfficientNets for lung nodule detection within CT image collections. While the ICML study aptly demonstrated the transferability of EfficientNets across five well-known datasets, it's imperative to emphasize that none of these datasets pertained to the domain of medical image processing.

3. METHODOLOGY

3.1. LIDC-IDRI Dataset

In our research, we made use of a very carefully put-together dataset called the Lung Image Database Consortium Image Collection (LIDC-IDRI) [13]. This dataset contains a wide range of CT images of the chest area, which are typically used by doctors for diagnosis and lung cancer screening. What makes it special is that each image has been very thoroughly examined and marked to identify different kinds of irregularities or lesions. It's like a global library of these images that has been designed meticulously. The main purpose of this collection is to help develop and test computer-assisted diagnostic methods, which are all about improving the accuracy of detecting and diagnosing lung cancer. It's a significant resource in the field of medical imaging and diagnosis.

This dataset is a collaborative effort involving seven distinguished academic institutions and eight prominent medical imaging companies. Each case encompasses clinical thoracic CT scans complemented by XML files.

The XML files hold valuable information derived from a thorough two-phase image annotation process. Four skilled thoracic radiologists meticulously analyzed each image in two steps to ensure the most accurate and detailed outcomes.

During the initial blinded reading phase, these radiologists conducted an individual analysis of each CT scan. Subsequently, they categorized identified lesions into one of three distinct groups: "nodule ≥3 mm," "nodule <3 mm," and "non-nodule ≥3 mm." Following this initial phase, an unblinded reading took place, wherein each radiologist independently reviewed their own assessments alongside the anonymized assessments of the other three radiologists. The primary aim of this approach was to detect as many lung nodules as possible within each CT scan, without necessitating unanimous consensus among the radiologists. This strategy was diligently implemented to ensure comprehensive nodule identification.

3.2. Background

This study is motivated by the objective of assessing the classification performance of the EfficientNet architecture concerning lung nodules within the context of the LIDC-IDRI dataset. It undertakes a comparative evaluation, juxtaposing EfficientNet with two widely renowned Convolutional Neural Network (ConvNet) models, namely ResNet50 and MobileNet. Notably, EfficientNet has garnered prominence for its remarkable achievements on the ImageNet dataset, demonstrating efficiency through quicker training and reduced parameterization. This study builds upon prior evidence showcasing the proficiency of the EfficientNet model in distinct contexts, including the ImageNet [14] and COCO [15] datasets. Therefore, the investigation herein extends to encompass the evaluation of ResNet50, MobileNet, and EfficientNet concerning their performance on the challenging LIDC-IDRI dataset, offering valuable insights into their applicability for lung nodule classification.

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3.2.1. ResNet Model

Residual networks, or ResNets for short, are a popular choice in computer vision. They're known for their ability to effectively train very deep neural networks, even those with over 150 layers. They overcome the vanishing gradient problem by using clever techniques like 'skip connections' or 'identity shortcut connections.' To give you a visual, you can think of ResNet50, as shown in Figure 1, as a powerful architecture with nearly 23 million parameters.

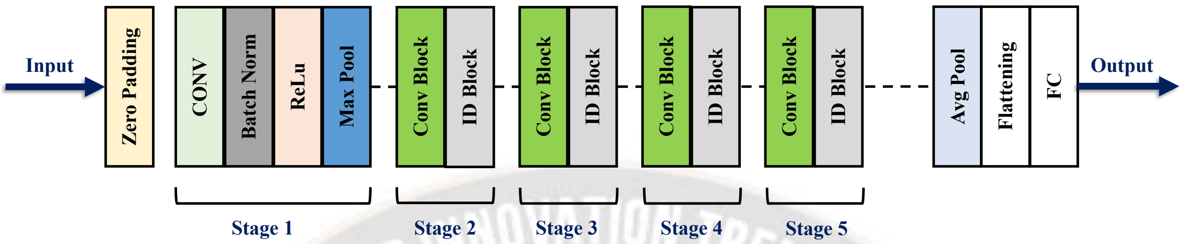


Figure 1 ResNet50 Architecture

3.2.2. MobileNet Model

MobileNet is a CNN architecture optimised for smartphones and other devices with limited resources. It is a lightweight model that use depth-wise separable convolutions to decrease the computation needed for conventional convolutions. This enables the model to be smaller and run quicker while keeping a high degree of precision. In addition, MobileNet employs a technique known as "width multiplier" to modify the number of filters in the network, hence reducing computation while preserving accuracy. These strategies allow MobileNet to be a model that runs efficiently on a broad variety of devices with minimal computing resources [16].

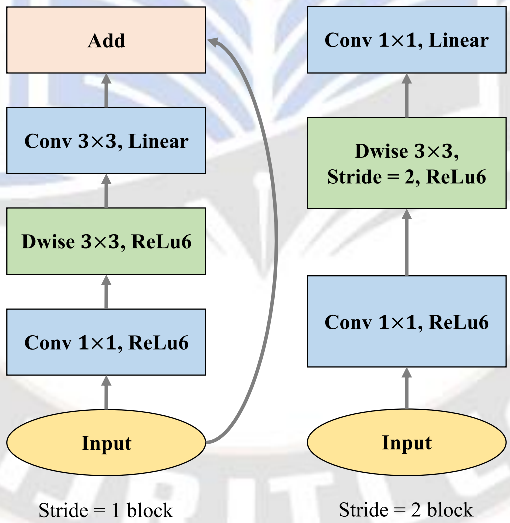


Figure 2 MobileNetV2 Architecture

3.2.3. The EffectiveNet Architecture

In a well-regarded 2019 ICML paper titled 'EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,' Google introduced a family of models known as EfficientNets. Their research outlines a systematic approach to scaling models, a key technique for improving the performance of Convolutional Neural Networks (CNNs). This paper is widely recognized for its valuable insights into optimizing CNNs through appropriate scaling, and it has made a notable impact in the field of deep learning and model development [17]. Traditionally, the quest for enhanced model precision has often involved arbitrary adjustments to dimensions. In a departure from this convention, this research takes a more systematic approach to model scaling. It uniformly scales each dimension using constant scaling coefficients, an approach meticulously tailored to achieve increased precision and efficiency. Moreover, recognizing that network efficiency hinges not only on scaling but also on the foundational architecture, the study introduces a novel baseline network. This baseline network is strategically designed to optimize both accuracy and computational efficiency, as measured by FLOPS. The resultant architectural design leverages a subtly expanded version of the mobile inverted bottleneck convolution (MBConv), a pivotal component that serves as the foundation for the family of EfficientNet models. The study's approach harnesses the demonstrated efficacy of EfficientNet, known for its superior performance on the ImageNet dataset. The primary objective herein is to investigate the transferability of this architectural innovation to the domain of lung nodule classification within the context of the challenging LIDC-IDRI dataset. Notably, EfficientNet stands out with its lean parameterization, containing fewer than 5 million parameters, representing a substantial reduction by a factor of 4.9 compared to counterparts like ResNet50 and MobileNet. This reduction also extends to computational requirements, with a notable decrease of 11 orders of magnitude in FLOPS. As a result, EfficientNet emerges as an expedited and computationally efficient alternative relative to ResNet50 and MobileNet.

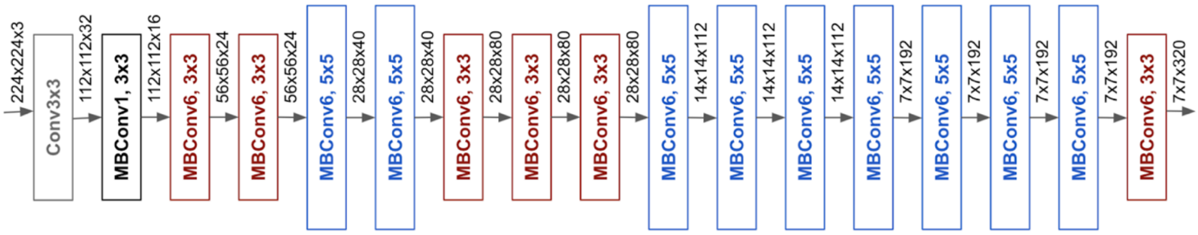


Figure 3 EfficientNet Architecture

3.3. Experimental Setup

The initial step of the project consists of extracting all photos from the Cancer Imaging Archive using the NBIA data retriever programme, then converting them to PNG files [18]. To make the photos compatible with the ResNet50 architecture, their original dimensions were reduced to the standard size of 224 224. In the second step of the experiment, the photos are preprocessed to eliminate any noise that may be present [19]. The dataset's images underwent preprocessing, involving rescaling and adjustments to rotation range, width shift range, and height shift range. For the purpose of this classification challenge, the final layer of the models was substituted with a three-class softmax activation layer, facilitating multiclass categorization of lung nodules.

To ensure methodological consistency and equitable evaluation, all three models were subjected to identical training configurations. The training process involved batch learning with 64 images per batch conducted over 50 iterations. An initial learning rate of 0.001 was utilized. Fine-tuning of the learning rate was executed via Keras's callback function—ReduceLROnPlateau. Here, the 'factor' parameter was set at 0.2, and the 'patience' parameter at 5.

To assess and compare the three models' performance effectively, the dataset was partitioned into distinct subsets: 70% for training, 15% for validation, and another 15% for testing.

4. RESULTS

In order to evaluate the models ResNet50, MobileNet and EfficientNet, in this research work we use the following parameters:

$$\mathrm{PPV} = \frac{TP}{TP + FP}$$

$$\mathrm{TPR} = \frac{TP}{TP + FN}$$

$$\mathrm{F1\ Score} = \frac{TP}{TP + 0.5(FP + FN)}$$

In the context of this analysis:

- Precision (PPV) signifies the ability to correctly label positive cases.
- Recall (TPR) denotes the capability to accurately identify positive cases.
- True Positives (TP) represent the count of correctly labeled positive cases.
- False Positives (FP) correspond to the number of erroneously labeled positive cases.
- False Negatives (FN) indicate the count of negative cases inaccurately labeled as positive.

The F1 Score, a fundamental metric, serves as a statistic that harmoniously combines accuracy and recall. Its application proves essential, particularly in scenarios marked by dataset imbalance. To better understand how sensitivity and specificity interact, we often use a visual aid known as the Receiver Operating Characteristic (ROC) curve. This curve, along with its Area Under the Curve (AUC) values, helps us assess the model's performance comprehensively [20]. Additionally, we examine both the training and validation scores to ensure our models aren't suffering from overfitting or underfitting problems. It's like finding the sweet spot where the model performs its best.

Figure 4 and Figure 5 depict the Received Operation Characteristics (ROC) Area Under the Curve (AUC) and Learning curve plot of all the three models. Table 1 provides a comprehensive overview of the study's findings, encompassing average accuracy scores, F1-scores, and ROC AUC values. Precision is vital; it indicates the ratio of correct positive identifications. When the F1-score approaches 1, it signifies a level of accuracy that is commendable. The outcomes presented in this analysis distinctly demonstrate that EfficientNet surpassed the performance of both ResNet50 and MobileNet. Overall, the EfficientNet model demonstrated greater performance than ResNet50 and MobileNet.

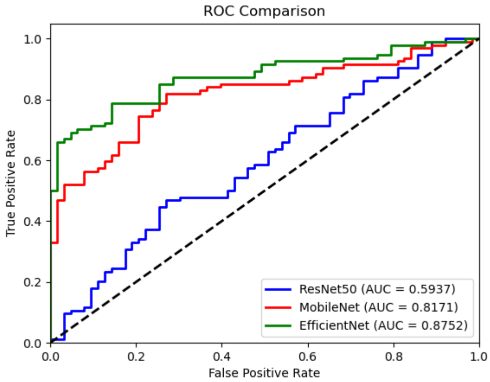
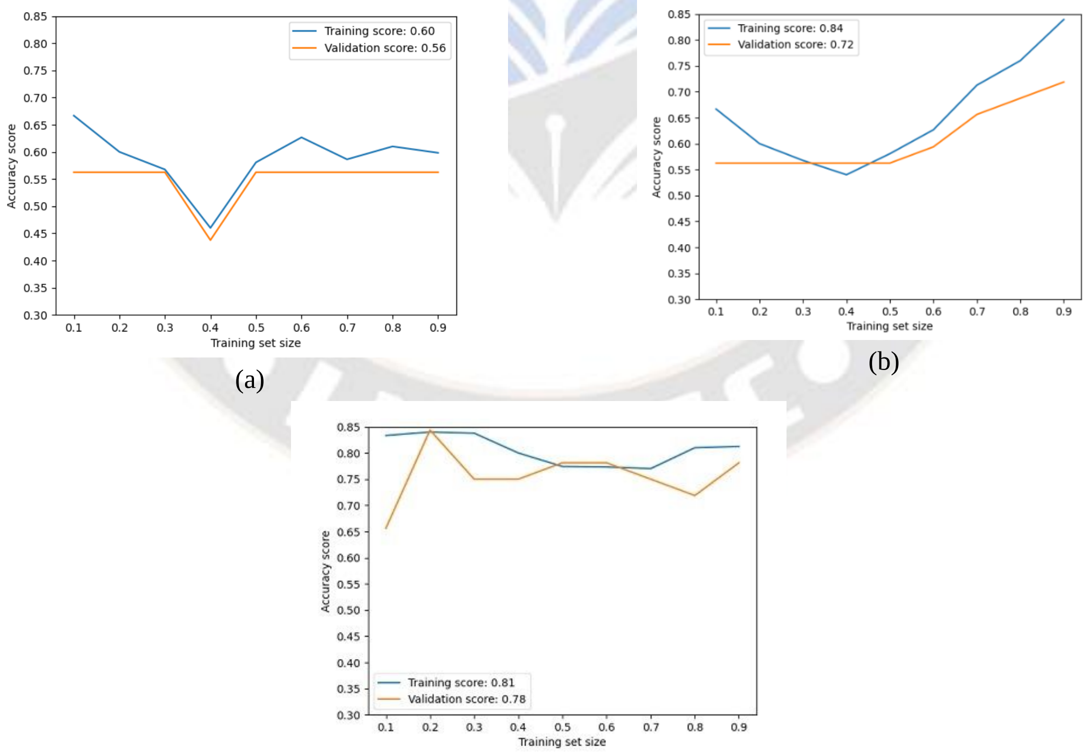


Figure 4 Received Operation Characteristics (ROC) Comparison



(a) (b) (c)

Figure 5 Learning Curves - a. ResNet50, b. MobileNet, c. EfficientNet

Table 1 Performance Comparison

	ResNet50	MobileNet	EfficientNet
Accuracy	0.55	0.69	0.81
F1-Score	0.61	0.66	0.85
Sensitivity	0.57	0.50	0.87
Specificity	0.52	0.97	0.71
ROC AUC	0.59	0.82	0.88

5. DISCUSSION

In the Indian context, lung cancer stands as the predominant contributor to cancer-linked mortality, with tobacco smoking emerging as a prominent risk factor. Alarming statistics from the World Health Organization reveal an annual toll of over 900,000 lives within India succumbing to tobacco-associated afflictions, prominently including lung cancer. Through early identification and prevention, lung cancer incidence and death in India can be drastically reduced. It is crucial to highlight that the effectiveness of lung cancer therapy depends on several aspects, including the disease's stage, the patient's general health, and the patient's reaction to treatment. As was previously noted, the categorization process can be aided by the incorporation of intelligent systems into the conventional techniques of examination by physicians and radiologists. There has been an increase in the employment of artificially intelligent systems to support healthcare workers and physicians. DCNNs have been demonstrated to be effective in a variety of medical imaging applications, including the detection of cardiovascular irregularities, the detection of fractures, and the identification of neurological illnesses, among others. Deep learning was used to examine the efficacy of three distinct DCNN architectures to classify lung nodules. Using particular measures, each of the three designs was analysed. In addition, insight was gathered into how EfficientNet transmits data for the LIDC-IRDI dataset. EfficientNet had superior ROC AUC values for all classes, while in a few instances ResNet50 outperformed EfficientNet somewhat or the results were comparable. With fewer parameters and FLOPS, EfficientNet surpasses ResNet50 and MobileNet in classification accuracy. EfficientNets demonstrate a remarkable capacity to achieve superior accuracy with substantially fewer parameters and reduced CPU resources. This characteristic positions them as a leading choice in the realm of computer vision architecture. Our research findings underscore that Deep Convolutional Neural Networks (DCNNs) can attain classification accuracy on par with human experts, showcasing the remarkable potential of these networks.

6. CONCLUSION

It is not surprising that convolutional networks can aid in the healthcare industry, given the widespread success of deep convolutional neural networks in other fields. This research illustrates the application of deep learning techniques for the fine-tuning of pre-trained convolutional neural networks, enabling the extraction of highly discriminative features from medical images. These features enhance the classification of lung nodules with a level of accuracy surpassing that of human experts. Such advancements hold profound implications for the medical community, as they facilitate rapid and life-saving diagnoses for patients who might otherwise face delays in accessing essential care. Timely and precise diagnosis, as evidenced in this study, significantly impacts patient survival rates. Furthermore, this work sheds light on the latest advancements in deep convolutional neural networks, specifically the EfficientNets family of models. Notably, EfficientNet exhibits promising transferability in classifying various categories of lung nodules. As the field progresses, future research endeavors should explore the integration of patient-specific metadata for enhanced nodule classification.

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