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AUTOMATED LUNG CANCER RECOGNITION BY A CONVOLUTIONAL NEURAL NETWORK

Rida Ali [1], Adeel Shahzad [2], Mohsin Ali Tariq [3], Muhammad Fuzail* [4], Ahmad Naeem [5], Naeem Aslam [6]

[1,3,4,5,6] *Department of Computer, NFC Institute of Engineering and Technology, Multan, Pakistan*

[2] *Department of Computer Science, Virtual University of Pakistan.*

[*]***Corresponding author: Muhammad Fuzail (*** mfuzail@nfciet.edu.pk***)***

Article Info

Abstract

Cancer of the lung is a massively common fatal kind of cancer in not only medical practice but also the world. It is the second common cancer diagnosed and causes more than 71 % of deaths as a result of non-communicable diseases (NCDs). It is also important that early and accurate diagnosis should be made in order to increase the survival rates of patients and their desired outcome. One of the most valid methods of establishing a certain type and stage of lung cancer is to carry out a histopathological examination of the lung tissue. Manual examination of histopathological slides, however, consumes time, expertise is required, and it is prone to errors by the person performing the task. In this paper, two approaches to automate the classification of lung cancer based on histopathology images using deep learning have been proposed: a Convolutional Neural Network (CNN) built to address the problem and transfer learning, using the EfficientNetB3 pre-trained model. This is aimed at helping the pathologists to come up with the correct diagnosis that is a timely manner. Relatively low computational complexity. The Simple CNN model achieved an accuracy of 94.66%, indicating its potential, even though it is computationally not demanding. EfficientNetB3, in turn, demonstrated excellent results and could reach an accuracy of 100%, with high precision, recall, and F1-scores, proving how strong transfer learning can be in this task. Contrary to most of the earlier works, which dealt with either CT or X-ray pictures, our study focuses on histopathological pictures, which present the cellular detail. The results demonstrate the criticality of model architecture to the increase in diagnosing accuracy and emphasize the potential of deep learning in medical diagnosis. Such models can relieve the diagnostic load, reduce mistakes, and guarantee a quicker clinical judgment, which is why they can be highly helpful to the wider medical sector.

Keywords:

Lung cancer, Histopathological Pictures, Convolutional Neural Network (CNN), Transfer Learning, and Lung Cancer Detection.

Introduction

Cancer is a major global health challenge and a leading cause of death. It is marked by uncontrolled cell growth, where abnormal cells invade nearby tissues and often spread to other parts of the body. Unlike normal cells, cancer cells bypass the body's natural control systems, allowing them to multiply endlessly. A class of diseases known as cancer is defined by aberrant cell proliferation brought on by haphazard mutations in the body. Uncontrollably, these cells proliferate and disperse throughout the body. If untreated, the majority of malignancies can be fatal. After cardiovascular diseases, cancer is the world's largest cause of mortality. Nearly 18 million new cases of cancer were diagnosed worldwide in 2018, and 9.55 million people died from the disease. According to the American Cancer Society, there will be over 606,000 cancer-related deaths and 1.8 million new cases of cancer in the US alone year 2020[1].

Cancer is a group of diseases caused by abnormal cell growth due to random mutations. These cells grow uncontrollably and can spread to other organs. If untreated, most cancers can be deadly. Globally, cancer is the second leading cause of death after heart disease. Nearly 18 million new cases of cancer were diagnosed worldwide in 2018, and 9.55 million people died from the disease. According to the American Cancer Society, there will be over 606,000 cancer-related deaths and nearly two million new cases of cancer in the US alone year 2020[2]. The American Joint Committee on Cancer (AJCC) uses the Tumor-Node-Metastasis (TNM) system to classify cancers into stages 0 to IV, based on tumor size, lymph node involvement, and spread. Survival rates differ by stage, with early detection offering the best outcomes. For colon cancer, survival is around 93% with early treatment, dropping from 87% at stage 0 to 18% at stage III. The survival rate for people with colon cancer drops from seventy percent at Stage 0 to a startling 13% at Stage IV. As stated earlier, there is no proven cure for cancer. Thus, early diagnosis increases the patient's likelihood of survival and enables physicians to create a treatment plan. Reducing cancer-related deaths requires early detection and treatment.[3]. Machine learning is now used not only for diagnosis but also to suggest treatment plans by analyzing patient symptoms and histories. It offers scalable, cost-effective tools to support doctors and improve global access to healthcare. Because it allows for earlier detection, more accurate diagnoses, and individualized patient care—all of which are vital for improving outcomes in diseases like lung cancer—machine learning is thus emerging as a crucial element of contemporary pathology.[4].

Globally, cancer of the lungs is the leading cause of cancer-related fatalities and the second most common type of cancer. The GLOBOCAN assessment 2020 states that the annual incidence as well as death rates of lung cancer worldwide are 11.4% and 18%, respectively [5]. According to the incidence rate, it is the second most common cancer after breast cancer. However, according to the GLOBOCAN report 2018, 2018 saw the highest number of lung diagnoses and fatalities from the disease.[6]Figure 1.1 shows the rates of occurrence and death among the eight most prevalent cancers in 2020. The overall survival rate after five years for all patients with lung cancer is 21% worldwide[7]. Patients at advanced stages have a much lower chance of survival. Lung cancer must be identified early to increase the individual's chances of survival. Nevertheless, it is usually discovered later on. More than 90% of lung cancer patients in the country received a diagnosis in an advanced stage, according to a 2020 study conducted by Indian hospitals.[8].

When aberrant cells grow out of control in the lungs, lung cancer results. A tumor is the bulk formed by these abnormal cells. Malignant lung tumors can spread outside of the lungs and produce new tumors, whereas benign lung tumors do not spread to nearby organs or body parts. The benign tumor is generally regarded as non-cancerous, whereas the malignant tumor is cancerous. A lung tumor with a diameter ranging from 3mm to 30mm is commonly referred to as a lung nodule or pulmonary nodule. Lung nodules can be classified according to two criteria. There are two factors to consider: the intensity profile of nodules and their placement about neighboring pulmonary structures.[9]

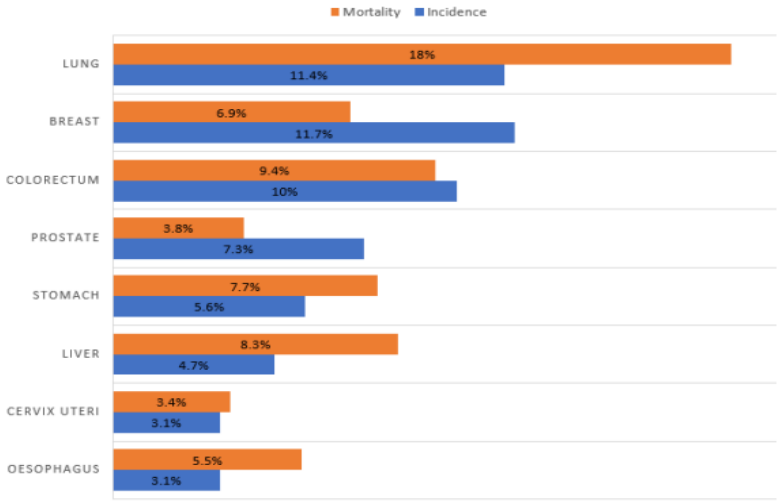

Figure 1 Incidence and fatality rates for the eight most common malignancies.

The intensity profile determines whether nodules are solid, subsolid, or ground-glass (GGN). Solid nodules are lung nodules with homogeneous intensity distribution. The nodules, also known as GGN or subsolid nodules, have a non-uniform intensity distribution, lower density, and do not hide the underlying parenchymal features. Figure 2 illustrates these two forms.

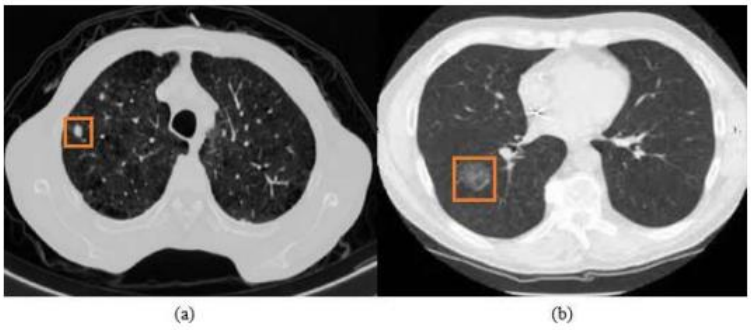

Figure 2 Based on intensity profiles, nodules can be classified as either solid or ground-glass nodules (GGN)

The second criterion classifies lung nodules into four types: well-circumscribed, juxta-pleural, pleural tail, and juxta-vascular. A well-circumscribed nodule is round and surrounded by aerated lung. Juxta-pleural nodules are attached to the lung wall, pleural tail nodules connect narrowly to the pleura, and juxta-vascular nodules are closely linked to nearby blood vessels. Nodules over 30mm are typically seen as malignant. Lung cancer is divided into two main types based on cell appearance: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC), with NSCLC accounting for 80–85% of cases. The staging method used by TNM is followed in the phases of both types.[10]

While an X-ray is first used to investigate cases, CT (computerized tomography) imaging is the recommended technique for detecting lung cancer. This is due to the fact that X-ray images can show any irregularity in the lungs, but they are unable to identify the exact location since they are 2D images. CT images provide a comprehensive picture of malignancy, including the tumor's location, shape, and kind[11]. CT images are 3D imaging methods that diagnose illnesses by taking cross-sectional pictures of

organs using X-rays. Three different perspectives of a lung's CT scan are shown in Figure 3.

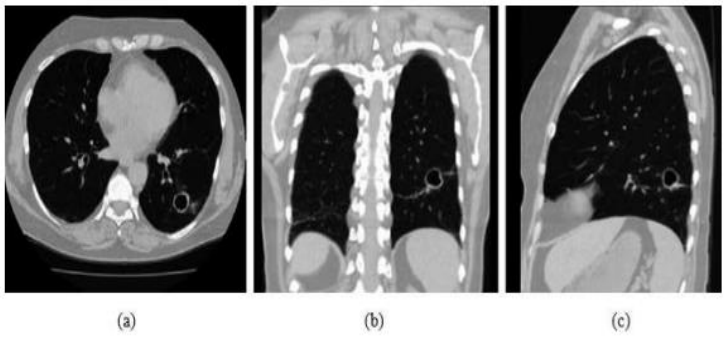

Figure 3shows axial, coronal, and sagittal views of a lung CT picture

Treatment response is evaluated based on tumor reduction and disease progression time. The RECIST guidelines [12] They were released in 2000 and amended in 2009 to standardize the response threshold for solid tumors. The RECIST (Response Evaluation Criteria in Solid Tumors) guidelines define measurable disease as having at least one lesion that can be quantified to evaluate treatment response. Lesions must meet specific size criteria based on imaging techniques. Both target and non-target lesions are reported at baseline, with non-target lesions monitored but not measured during follow-up. Responses are categorized into four groups: full response (FR), partial response (PR), progressive disease (PD), and stable disease (SD), as shown in Table 1.

Table 1 Demonstrates the target and non-target lesions' RACIST criteria.

Response	**Assessment of the target lesions**	**Evaluation of the non-target**
Full Reaction (CR)	The elimination of every target lesion.	Elimination of every non -target lesion
Response in Part (PR)	Using the baseline total as a guide, minimize the LD sum of the target wounds by at least 30%.	
PD, or progressive disease	at least a 20% increase in the target lesions' LD total, as measured by the lowest LD sum observed since th e start of treatment, or the appearance of new lesions.	The emergence of fresh n on-target tumors.
Stable Disease (SD)	Lesions do not shrink or grow sufficiently.	Multiple non-target lesions persist.

Literature Review

Introduced to the world in recent decades, non-communicable diseases (NCDs) have become a serious threat. Cancer is one of the deadliest and fastest-spreading diseases, alongside skin infections and diabetes, which are among the NCDs that threaten the health and life expectancy of human beings. Cancer of the lung, in particular, has seen a worrying increase in the prevalence and the death rate in different parts of the globe. It is the most diagnosed cancer in most countries, and it is one of the greatest causes of death attributed to cancer. This devastating trend is mainly because there has been a lot of complexity in detecting and diagnosing lung cancer at an early, curable stage. Another of the biggest problems associated with lung cancer is the early detection. It is one form of cancer that can advance in silence, whereby,

unlike some of the other forms of cancer that may show apparent signs and damages in the early stages, lung cancer can go without detection. The mild symptoms occurring at an early stage in it, i.e., long cough, slight shortness of breath, or pain in the chest, are often confused with other less serious respiratory illnesses such as bronchitis or asthma. Due to this, people often start to address doctors after the disease has already become quite serious, which dramatically decreases the quality of the treatment process and chances of gaining victory over the disease. By the time the symptoms have become bad enough to consider, the cancer is usually in stage III or IV, where treatment options are more complicated, expensive, and would not necessitate complete recovery. [13].

The survival chances of individuals with lung cancer are greatly increased by early identification and precise diagnosis. When lung cancer is detected early, it can be treated more quickly and effectively, which can significantly lower the disease's death rate. The use of medical imaging techniques to improve the accuracy of lung cancer classification has been one of the major developments in recent years. Because it may produce sharper and more detailed images of lung structures, computed tomography (CT) imaging has become a popular alternative to traditional chest X-rays. Medical practitioners may now identify even tiny nodules that might be signs of early-stage cancer thanks to this advancement.

Recent advancements in Computer-Aided Diagnostic (CAD) systems have enhanced lung cancer detection through improved machine learning algorithms and preprocessing methods, particularly using CT scans. These systems reduce human error and support radiologists in making accurate decisions. Makaju et al. [14] achieved 92% accuracy in classifying cancerous CT scan lesions using a CAD approach. Nanglia et al. [15] introduced a more complex hybrid model, the Kernel Attribute Selected Classifier (KASC), combining SVM with a Feed-Forward Back Propagation Neural Network (FFBPNN) for improved diagnosis.

Deep learning is increasingly important in medical imaging, especially for the early detection and staging of lung cancer. Researchers have developed models using CT and PET/CT data for accurate classification. Kirienko et al. [16] used FDG-PET/CT images to classify lung cancer types. However, model performance may vary due to imaging and patient differences. Sajja et al. [17] applied a pre-trained CNN model (GoogleNet) for lung cancer detection.

Maleki et al. [23] used a k-Nearest Neighbors (k-NN) and GA hybrid technique to determine cancer stages, reaching 100% accuracy. Bhatia et al. [24] employed deep residual learning, Random Forest, and XGBoost within an ensemble framework, achieving 84% accuracy on the LIDC-IDRI dataset. Lastly, Song et al. [25] compared CNN, DNN, and SAE models on CT images, with CNN yielding the best performance—84.32% accuracy, 84.15% sensitivity, and 83.96% specificity.

Table 2 A comparative overview of relevant previous research.

Ref	Paper Year	Preprocessing	Technique used	Finding
[18]	2020	Noise reduction with a Gabor filter	Multi-swarm optimizer for particle swarms	Accuracy: 98%
[19]	2020		Algorithm for Velocity-Enhanced Whale Optimization	Accuracy: 84%
[20]	2019	Noise reduction histogram showing	Instantaneously trained neural	Accuracy: 98.42%

		image quality improvement	networks for deep learning (DITNN)	
[21] **[22]**	2020 2020	eliminates illegible scans that identify cancerous regions.	An innovative residual neural system Deep network ensemble approach	Accuracy: 85.71% Accuracy: 87.35%
[23]	2021	Normalization, Extracting, and Cropping the Sample	fusion of the malignancy evaluation network (R2MNet) with radiological analysis	Accuracy: 89.90% AUC: 96.27%
[24]	2020	Separation of images Segmentation of nodules	Deep Learning methodology	Accuracy: 97.27%
[25]	2021		Optimization based on metaheuristics	Sensitivity: 99.12%
[26]	2017	Partitioning	The CNN Approach, deep belief network (DBN), stacked denoising autoencoder (SDAE)	AUC: 89.9%
[27], [40]	2021		The new EOSA metaheuristic algorithm	With a Friedman test score of 1.60, EOSA ranks first when compared to other tests.
[28]	2015	Conversion to Gray Scale Normalization Reduction of Noise Binary Picture Eliminate the Unwanted Area of the Picture	A neural network	Accuracy: 96.67%
[29]	2019	Uses of morphological procedures and region growth	ResNet, XGBoost	Accuracy: 84%

[30] **[31]**	2017 2018	Augmenting Data	CNN Deep Neural Networks DNN SAE CNN's Inception V3-based architecture	84.15% accuracy 83.96% sensitivity 84.32% specificity AUC: 97%
[32]	2017	thresholding clustering (K-means and Meanshift) to convert the pixel values. Zero-center the data using watershed normalization interpolation of a spline.	Standard CNN in 3D 3D CNN built on GoogleNet	Accuracy: 75.7%
[33]	2021	Image Level Balancing and Noise Elimination	The metaheuristic technique known as marine predators, AlexNet, CNN, VGG-19, ResNet-18, Google LeNet	93.4% accuracy 98.4% sensitivity 97.1% specificity
[34]	2019	Average, Median, Adaptive histogram equalization and adaptive median	Inertia-weighted particle swarm optimization, k-median clustering, k-means clustering and particle swarm optimization, and guaranteed convergence particle swarm optimization (GCPSO)	Accuracy: 95.89%
[35]	2021	denoising and normalizing the input pictures	Improved Optimization of Thermal Exchange	Accuracy: 92.27%
[36]	2020	Normalization of min–max	Optimal modular neural network for harmony	Accuracy: 98.9%

[37]	2021	Partitioning	CNN-based metaheuristic with a bat-inspired design	Accuracy: 97.43%
[38]	2019	Partitioning	The Bat algorithm	94.6% accuracy 88.3% is the Kappa.
[39]	2021	Morphological operation of a normalized Gabor filter	Transfer learning-integrated DNN model.	94.38% precision

Materials and Methods

Developing successful, computer-assisted diagnostic (CAD) systems demands large, varied, and strongly labeled data that are scarce in the histopathological classification of cancer. This is done to combat this by using data augmentation techniques, e.g., flipping, rotating, and scaling the data to increase variability in the dataset and decrease overfitting. In this experiment, it was done on the LC25000 dataset, which started with 750 lung histopathology images, followed by augmentation to create 15,000 images. Having enriched data allowed training deep learning models, such as CNN and EfficientNetB3, with improved accuracy and generalization. The following Table 1 provides a list of other frequently used data on lung cancer that formed part of the improvements in cancer detection via AI systems.

The LC25000 data set has been the common data set used in the training and testing of AI models in the detection of lung and colon cancer. It initially included 750 histopath imaging (250 lung adenocarcinoma, 250 squamous cell carcinoma, and 250 benign tissue) resolution in 1024x768 content that was standardized to 768x768 pixels. To mitigate the lack of data, augmentation processes such as random rotations and flips were applied to increase the size of the dataset to 15,000 photos. Borkowski et al. (2019) created it to be HIPAA compliant and provide balanced classes and quality photos. It is diverse and ethically designed, which makes it good to train deep learning models to accurately classify lung cancer.

In this research paper, the Lung and Colon Cancer Histopathological Image Dataset (LC25000) is used in the classification of the lung tissue using histopathology images. Considering the exclusive existence of lung images, the study is aimed at a multi-class classification task with three unique types of classes presented here, namely, lung adenocarcinoma, lung squamous cell carcinoma (lungs), and lung benign tissue (lung). Non-small cell lung adenocarcinoma grows in glands on the lung tissues, and it is one of the common cancerous cells in non-small cell lung diseases, usually called the non-small cell lung cancer (NSCLC). Squamous cell carcinoma of the lung occurs in the squamous cells lining the airways. Normal tissue, benign lung tissue, is cancer-free, healthy, and it is the negative category in such a classification exercise.

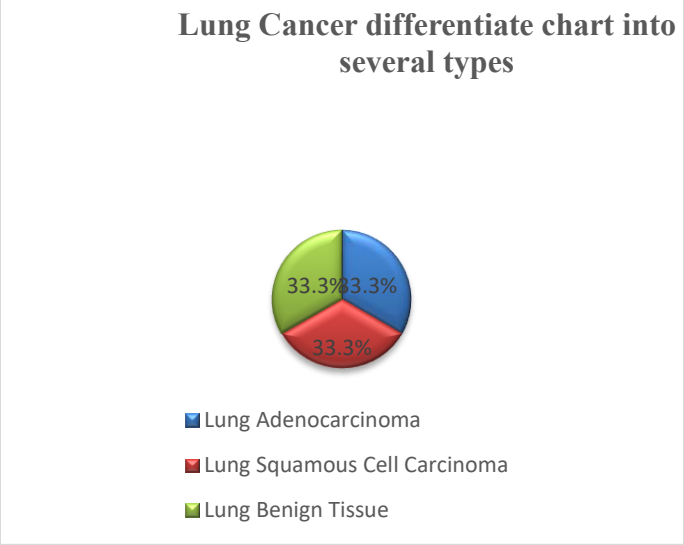

Figure 4. Lung Cancer differentiates into several types

Results

For the duration of the thesis's studies, a laptop with an Intel Core i5-4310U CPU, 16 GB of RAM, and a 16 GB P100 GPU was used. When experimenting with the technological setting of a Jupyter notebook utilizing Google Colab, the investigations were carried out using Python 3.6.9. The entire experiment's approach, which resulted in the creation of this model to address the lung cancer detection decision-making challenge, is detailed in Figure 5.

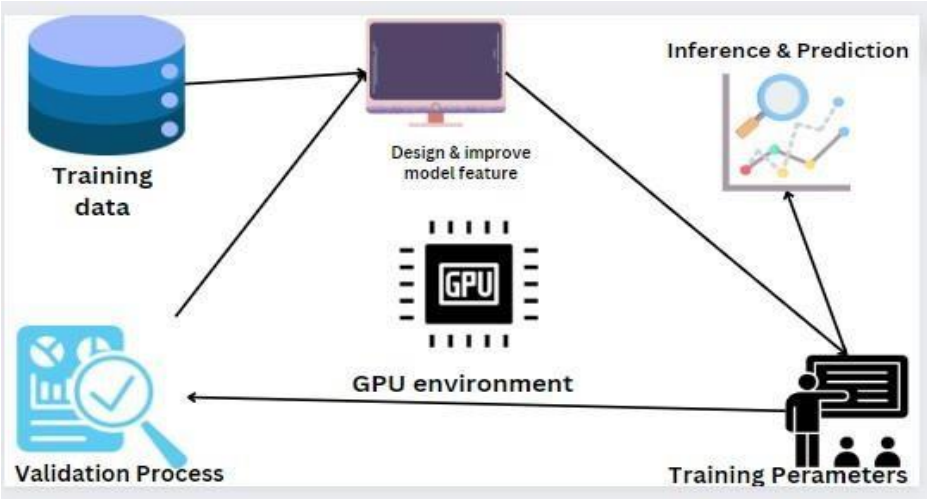

Figure 5: Experimental setup

Custom CNN Model Performance

To classify histological images of lung tissue into three different categories—lung adenocarcinoma, lung squamous cell carcinoma, and benign lung tissue—a specially created Convolutional Neural Network (CNN) architecture was created. The early and precise diagnosis of lung cancer types, which has a substantial impact on treatment choices and patient outcomes, depends on this categorization task. Through a sequence of layered processes, the suggested CNN model was designed to extract intricate features from high-resolution histopathology pictures.

Five convolutional blocks made up the model's architecture; each block had convolutional layers, activation functions, and pooling layers to gradually lower spatial dimensions while capturing important visual information. The model was able to identify patterns specific to each type of lung tissue, including texture, shape, and cell structure, thanks to these convolutional layers. Three fully connected dense layers were added after the convolutional stages in order to evaluate the features that were recovered and aid in decision-making. In order to transfer the high-level features to the proper output class, these layers were essential.

A softmax output layer was used at the network's last stage, which enabled the model to classify data into several classes by giving each class a probability. The ability to accurately discriminate between benign and malignant lung tissue types was established by this well-structured architecture.

The obtained training accuracy of 96.10% indicated that the model's learning capacity was dependable. Additionally, the validation accuracy was 94.66%, indicating that the model did not considerably overfit the training set and was able to generalize quite well on unknown validation data. According to the performance, the CNN model was able to differentiate between several types of lung tissue by successfully extracting spatial features from histopathology pictures. Although there is still an opportunity for improvement, the comparatively small discrepancy between training and validation accuracy suggests a well-balanced model. When compared to state-of-the-art networks, the architecture's depth and representational capacity constraints or variations in histopathological textures may be the cause of the somewhat lower validation accuracy, as shown in Figures [6-13].

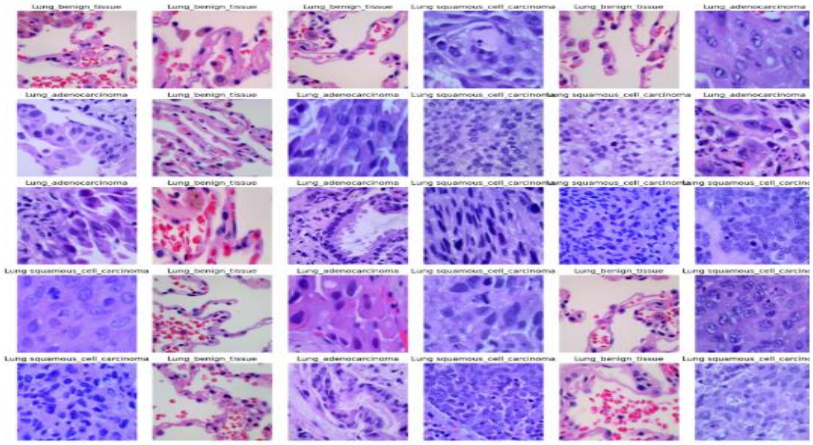

Figure 6. Images, particularly in terms of visualization.

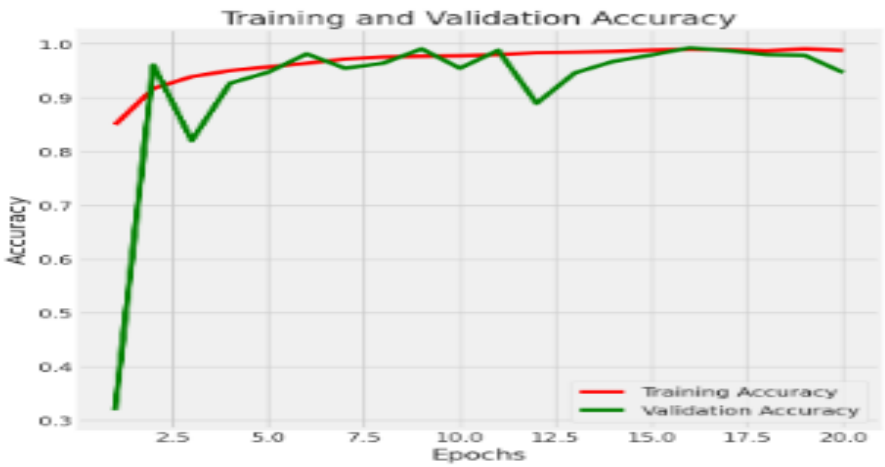

Figure 7. Model Accuracy

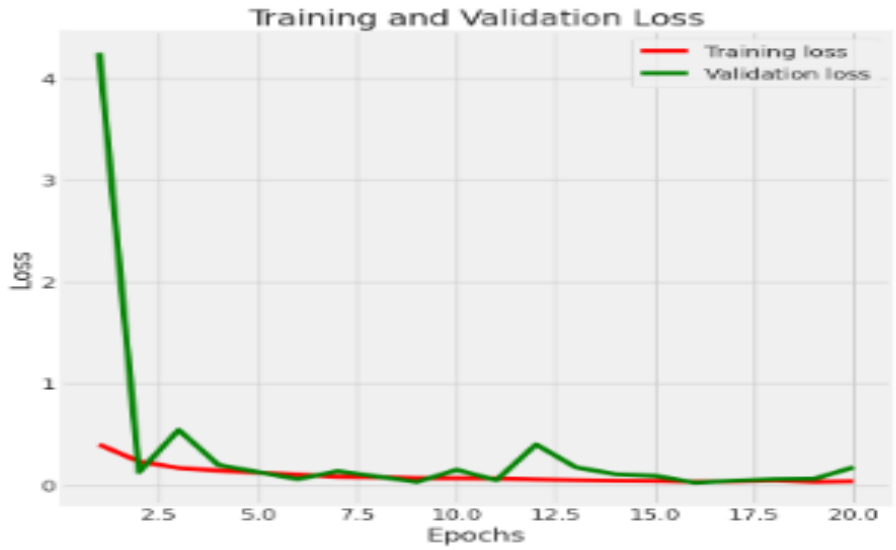

Figure 8. The Model loss.

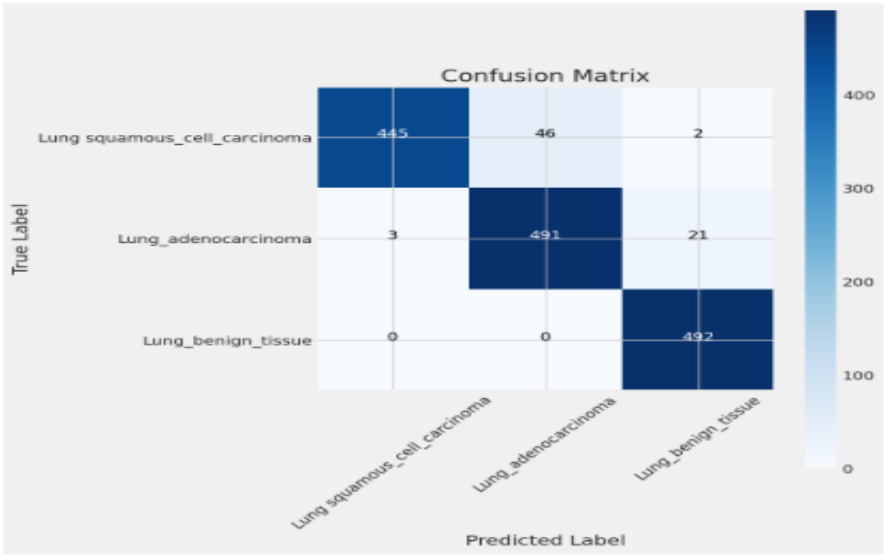

Figure 9. Confusion Matrix for CNN

The CNN model can be utilized as a baseline deep learning model for the classification of lung cancer histopathological images, as it showed strong, consistent performance in recognizing lung cancer classes and high generalization.

Furthermore, by normalizing the inputs to each layer, the model incorporates batch normalization layers that aid in stabilizing and speeding up training and enhance the model's capacity to generalize across various datasets. By minimizing internal covariate shifts, this normalization method speeds up convergence and lowers the chance of overfitting. Additionally, standard fully linked layers are replaced with global average pooling before the final classification layer, significantly lowering the number of parameters. By making the model simpler and making it learn more generalized spatial properties instead of memorizing noise or unimportant details, this method helps avoid overfitting.

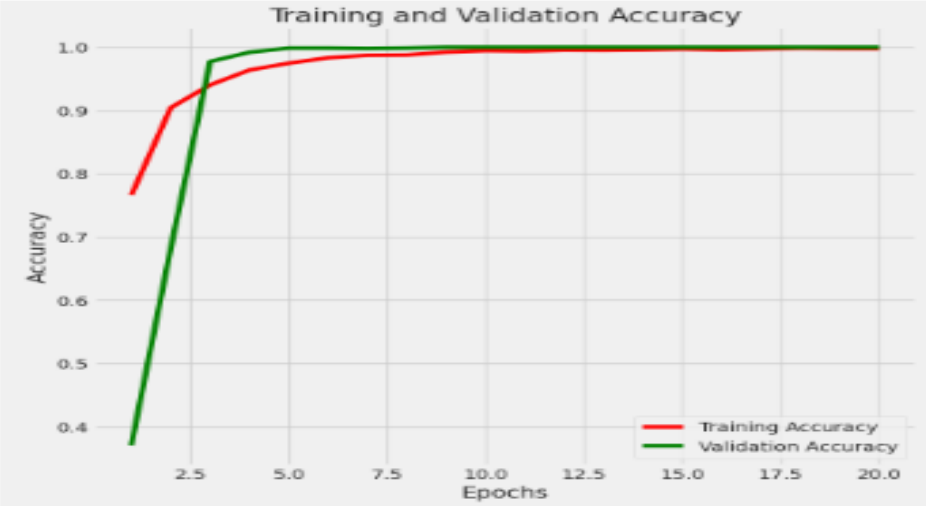

Figure 10. Model Accuracy

Figure 11. Model Loss

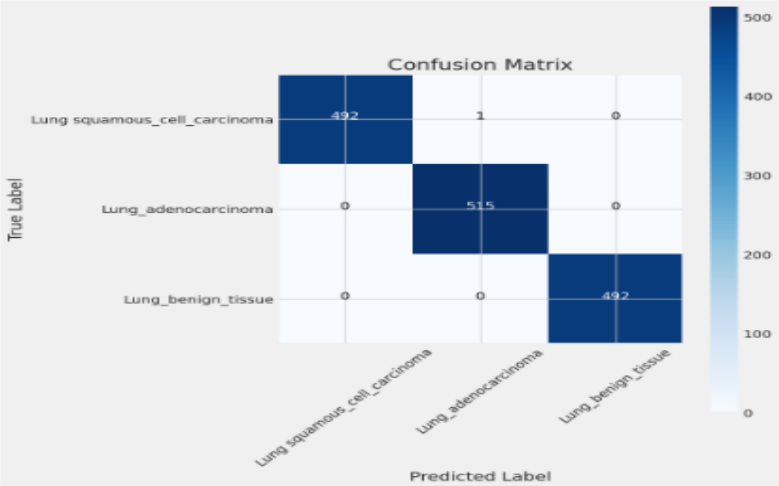

Figure 12. Confusion Matrix for EfficientNetB3

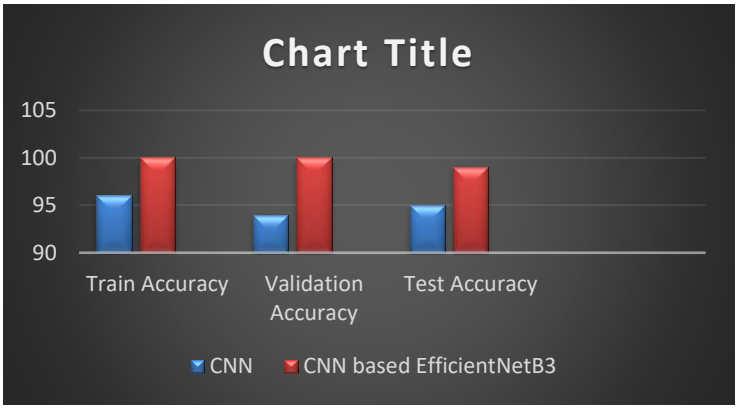

Figure 13. Comparison of CNN and CNN-based EfficientNetB3

Table 3. Following up on a previous part, the table below contrasts the effectiveness of many cutting-edge techniques.

Authors	**Method**	**Accuracy**
Pathan et al [41]	CNN	Test Accuracy:95%
Pal et al [42]	EfficientNetB0	Test Accuracy: **~95%**
Ochoa-Ornelas et al [43]	Mobile Net + Efficient Net + GWO	Validation Accuracy: 97.8%, Test Accuracy: 95.6%
L. Wang [44]	3D Attention U-Net	Validation Accuracy: 93.10%, Test Accuracy: 94.43%
Wahab Sait [45]	DenseNet-121	Validation Accuracy: 97.0%, Test Accuracy: 96.4%
Hejbari Zargar et al., n.d. [46]	VGG16	Test Accuracy: 91.0%
Proposed	CNN-based EfficientNetB3	Validation Accuracy 100%, Test Accuracy 99.93%

Conclusion

This study compared the performance of two deep learning models, Simple CNN and EfficientNetB3, for detecting lung cancer from histopathology images. The results clearly showed that EfficientNetB3 outperformed the Simple CNN in all aspects, achieving 100% training and validation accuracy and 99% test accuracy. This indicates that the model is not only good at learning from data but also generalizes well to new, unseen samples. Its architecture, which uses compound scaling, helps capture complex patterns in medical images better than simpler models and avoids common problems like overfitting. The Simple CNN, while still effective, achieved lower accuracy—96% in training, 94% in validation, and 95% in testing—suggesting it struggles more with capturing the complex features found in histopathology images. These differences emphasize how important advanced architectures are for deep learning in medical imaging.

This study has important implications for clinical practice. Lung cancer is deadly and widespread, and

diagnosis often relies on manual examination of slides by pathologists. This process is time-consuming and can be error-prone. Using automated systems like EfficientNetB3 could reduce human error, speed up diagnosis, and make healthcare more accessible, especially in areas with few experts. The study also highlights how public datasets and deep learning tools can be used to build powerful diagnostic systems without expensive resources. Techniques like data augmentation, model tuning, and careful evaluation made the model reliable. Future research should test these findings on more diverse data and consider combining image data with clinical records to improve results further. Advanced models and ensemble methods could be explored, and user-friendly tools should be developed to help integrate these systems into real-world clinical settings.

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