Automated Lung Cancer Classification Using CNN and Transfer Learning Techniques

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ABSTRACT

Lung cancer is a major cause of cancer-related mortality worldwide, with delayed diagnosis being a major factor. Traditional diagnostic methods, such as manual interpretation of biopsies and histopathological images, are laborious and prone to human error. A deep learning-based model for lung cancer prediction was developed using Convolutional Neural Networks (CNN) and the ResNet-50 architecture. The model was trained and validated using histopathological images and showed great diagnostic promise. It achieved a precision of 9698%-, a recall of 9597%-, and an F1-score of roughly 96%, achieving an accuracy of about 97%. This study demonstrates how deep learning can help radiologists diagnose lung cancer more accurately, potentially improving patient outcomes and reducing diagnostic errors.

Keywords: Lung cancer, Artificial Intelligence (AI), deep learning, Convolutional Neural Networks (CNN) and ResNet-50.

1. Introduction

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, with increasing death rates among both males and females. This disease is characterized by the uncontrolled growth of abnormal cells, which may lead to metastasis – the spread of cancer from localized lung tissue to other parts of the body [1]. Several risk factors contribute to lung cancer incidence, including tobacco use, poor nutrition, obesity, excessive alcohol consumption, physical inactivity, and genetic predispositions. Among the various types of lung cancer, the most common are large cell carcinoma, small cell carcinoma, squamous cell carcinoma, and adenocarcinoma. Notably, smoking is the primary risk factor, with smokers having a significantly higher probability of developing lung cancer compared to non-smokers. Recent advances in artificial intelligence, particularly deep learning techniques such as Convolutional Neural Networks (CNNs), have shown great promise in medical image

analysis [2]. These algorithms can autonomously learn discriminative features from large datasets, making them highly effective in pattern recognition tasks. In the context of lung cancer diagnosis, deep learning can assist radiologists in distinguishing between malignant and benign nodules more accurately, thereby reducing diagnostic errors and improving clinical decision-making. Several studies have demonstrated the effectiveness of deep learning in lung cancer diagnosis using histopathological images. For instance, Litjens et al. [2] developed a deep learning model for the automatic detection of lung nodules, achieving high sensitivity and specificity. Similarly, Shen et al. [3] proposed a CNN-based approach for lung cancer classification that outperformed traditional diagnostic methods in terms of accuracy. Despite these advancements, challenges remain. Developing effective deep learning solutions requires access to large and diverse annotated datasets, improved interpretability of AI models, and seamless integration into clinical workflows [4]. Nevertheless, with continued refinement, deep learning systems hold the potential to significantly enhance diagnostic precision and support better outcomes in lung cancer management.

2. Related work

Several recent studies have focused on Artificial intelligence technique for lung cancer prediction. Shiwen Shen [5] attempts to develop models for developing automated lung cancer diagnosis and disease progressions. A novel lung segmentation approach was first developed using a bidirectional chain code method and machine learning framework. A hierarchical semantic convolutional neural network (HSCNN) has been described to classify lung nodule

$$\text{Precision} = \frac{TP}{TP+FP} \qquad \text{Recall} = \frac{TP}{TP+FN}$$

malignancy. Jue Jiang et al. [6] has developed two multiple resolutions residually connected network (MRRN) formulations called incremental-MRRN and dense-MRRN for lung tumor segmentation. The method was evaluated on 1210 non-small cell lung cancer (NSCLC) lung tumors and nodules from three data sets: the open-source Cancer Imaging Archive (TCIA), 304 advanced stage NSCLC treated with anti-PD-1 checkpoint immunotherapy, and 529 lung nodules from the Lung Image Database Consortium (LIDC). Jessica Vo [7] focuses on applying supervised machine learning techniques Logistic regression, random forest, gradient boosting, extreme gradient boosting, support vector machine, and Bayesian additive regression trees. The most effective model was found to be gradient boosting, which gives the highest prediction power (97.9%) with a recall of 90.9% and a precision of 90%.

Shambhuraje Desainipankar [1] proposes system using conventional neural network (CNN) improves accuracy over previous models by attaining a 93% accuracy level. The technique implemented in this system uses lung Computed Tomography (CT) scanned images. A DWT (Discrete Waveform Transform) method is used to segment, retain, and compress the image. This paper discusses the accuracies of various lung cancer detection

systems, Artificial neural networkbased classifications of nodules 90%, using a curvelet transform and neural network 90%, lung cancer classification using EK-Mean Clustering 91.86% and proposed system used CNN 90%. Rahul Paul [8] uses pre-trained convolutional neural networks for lung nodule management prediction, combining quantitative and deep characteristics, and suggests a CNN architecture for smaller medical datasets, enhancing early identification of lung cancer. Marina Johnson et al. [9] offers an AI-based framework that uses six algorithms and a 1973-2015 dataset to predict the 5-year survival of lung cancer patients, improving operational performance and resource efficiency, using machine learning techniques Logistic Regression, Decision Trees, Random Forests (RF), Adaptive Boosting (AdaBoost), Artificial Neural Network, Naïve Bayes.

With an area under curve (AUC) rate of 0.94. João Moranguinho Bastardo Moura

[10] investigates deep learning techniques for lung cancer characterization in histopathological images, offering potential clinical implications and improving automated diagnosis systems for lung cancer. Atharva Muley [11] introduces an AI-based lung nodule segmentation system, aiming to enhance transparency and accountability in lung cancer diagnosis and treatment using deep learning algorithms. The research successfully implemented a 2D U-Net Segmentation model to detect lung nodules. The segmentation score achieved on the test data was 65.63% for the Dice coefficient, and 52.81% for the Jaccard coefficient.

Pawan Sapkota [12] assesses classifier performance in identifying lung nodules in CT scans, aiming to enhance lung cancer screening tools by comparing

traditional and deep learning algorithms, using LSTM as a classifier (DL), conventional neural network (CNN) as a feature extractor (DL), Support Vector Machines (SVM) classifier machine learning (ML). Experiment and results demonstrate that the use of LSTM as a classifier and CNN as a feature extractor shows the best performance over SVM (Support Vector Machines) classifier.

Mohammad Gulam Mostafa [13] compares cancer survival prediction accuracies using machine learning and statistical methods, identifying strengths and weaknesses of different techniques for specific scenarios. This paper discusses accuracy in some techniques, decision tree, random forest and ensemble methods with accuracy 91.35%, Artificial Neural Network algorithms (ANN) with an accuracy of 68%, RF with an accuracy of 67.72 % and Logistic Regression (LR) were the best prediction models for all cancers. Deepak Rawat et al. [14]

explores the use of a deep learning model for lung cancer prediction, utilizing the Artificial Neural Network algorithm for real-world applications. The Artificial Neural Network algorithm demonstrated the highest accuracy of 92.23% in an experimental study, with the highest accuracy observed in one layer. Zoe C. Walker [15] discusses the optimization of technical aspects of lung radiotherapy treatment planning, a crucial aspect in lung cancer treatment, to improve radiation dose and minimize side effects.

2.1 Analytical Overview of Related Work

Despite extensive research on machine learning and deep learning in lung cancer diagnosis, segmentation, survival prediction, and treatment optimization, many studies have limitations due to reliance on CT scans and inability to interpret histopathological images. Few studies combine data augmentation and transfer learning strategies for histopathology image classification with deep learning architectures like ResNet-50, lacking scalability, model transparency, and classification robustness across various cancer subtypes. This study proposes a hybrid CNN-ResNet50 model for multi-class classification in clinical pathology workflows, offering high accuracy and interpretability, contrasting binary classification and survival prediction methods. This marks a significant milestone in AI-based diagnostic systems.

The next table presents the comparison between different related works.

Table 1: Comparative Analysis of Related Studies

Author / Year	Data Type	Objective	Model Used	Accuracy / Performance	Strengths	Limitations
Shiwen Shen	CT + Segmentation	Tumor classification & progression	HSCNN + Chain Code	Not mentioned	Advanced segmentation approach	Lacks detailed performance metrics
Jue Jiang et al.	CT (NSCLC)	Segmentation	MRRN (incremental & dense)	-	Multi-resolution network design	Does not classify cancer types
Jessica Vo	Clinical Features	Prediction	Gradient Boosting, SVM, etc.	97.9% accuracy, 90.9% recall	Extensive ML model comparison	No image data used
Desainipankar	CT Images	Diagnosis	CNN + DWT	93%	Improved over baseline CNN	Limited dataset, outdated processing
Rahul Paul	CT + Features	Malignancy prediction	Pretrained CNN + Radiomics	90.29%	Combines deep and traditional features	Limited performance on small data
Marina Johnson	Survival Data	5-year survival prediction	6 ML Algorithms	AUC = 0.94	Strong outcome prediction	No imaging data
Moura	Histopathology	Cancer characterization	CNN (DL-based)	Not mentioned	Clinically relevant insights	Lacks performance evaluation
Atharva Muley	CT	Nodule segmentation	2D U-Net	Dice: 65.63%, Jaccard: 52.81%	Explainable AI approach	Relatively low segmentation accuracy
Pawan Sapkota	CT	Classification	LSTM, CNN, SVM	LSTM > SVM	Compares DL & ML	Not
Mostafa	Tabular / Survival	Prediction	ANN, RF, LR	91.35% (RF), 68% (ANN)	Statistical vs ML analysis	No imaging data used
Rawat et al.	Real-world Data	Prediction	ANN	92.23%	Practical implementation	Simple, shallow architecture
Current Study	Histopathology (LC25000)	Multi-class classification	CNN + ResNet-50 + TL	≈97% accuracy	High classification accuracy, TL applied	Needs more visual explanation & clinical integration

3. Proposed model

The deep learning model uses transfer learning to combine a pre-trained ResNet-50 architecture with a bespoke CNN. Histopathological lung tissue images were used to adapt the ResNet-50 model, which was first trained on the ImageNet dataset. The histopathology dataset was used to fine-tune the model after base layers were frozen and custom classification layers were added. This hybrid strategy, which combines pre-trained global features with unique task-specific learning, improves accuracy, convergence speed, and robustness on limited medical datasets

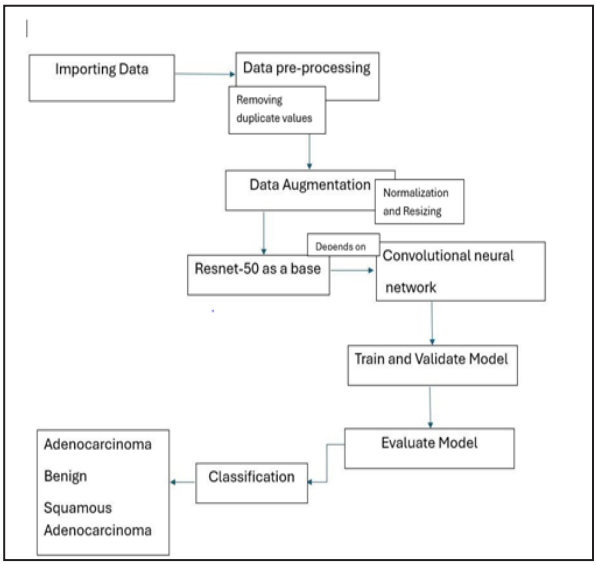

Figure 1: Deep Learning Model for Lung Cancer Detection and Type Classification

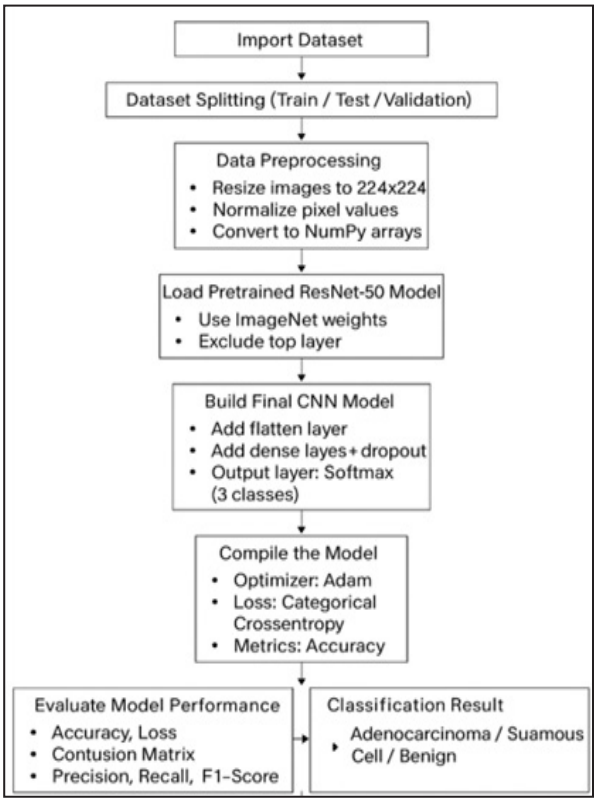

Figure 2: Implementation of the Workflow of Lung Cancer Image Classification Model

3.1 Dataset

Dataset Name: LC25000

Source: The dataset was created by researchers in the fields of pathology and medical informatics [16]. There are 25,000 color **histopathology images** in the LC25000 collection. It is separated into five equal classes, each with 5,000

images: Adenocarcinoma of the colon, Colonic tissue that is benign,

Adenocarcinoma of the lung, Squamous cell cancer of the lung, Lung tissue that is benign. **Key Features**: Histopathological slides, or microscopic tissue images, are the source of photographs. Since every photograph has been deidentified and complies with HIPAA (Health Insurance Portability and Accountability Act), it is safe for use in academic and public settings.

The dataset, which has been specially produced for AI and deep learning applications, can be downloaded for free. The pictures are ML-ready for classification jobs because they are tagged and arranged. Use: The LC25000 dataset is perfect for deep learning model evaluation and training, particularly when it comes to cancer detection and classification. Segmenting images and analyzing histopathology. research on AI uses in medicine.

Table 2: Description of the Histopathological Dataset Used for Lung and Colon Cancer Classification

Attributes	Description
Dataset name	Lung and Colon Cancer Histopathological Image Dataset (LC25000)
Total images	25,000 images
Number of classes	5 classes
Per of class	5,000 images per class
Class categories	1. Lung Adenocarcinoma 2. Lung Squamous Cell Carcinoma 3. Lung Benign 4. Colon Adenocarcinoma Colon Benign
Image type	Colored histopathological images (RGB)
Image resolution	768×768 pixels
Number of classes	5 classes
Purpose of the dataset	To train and evaluate AI models, especially deep learning, for accurate classification of lung and colon cancer
Dataset link	https://github.com/tampapath/lung_colon_image_set

Only the lung-related classes-adenocarcinoma, squamous cell carcinoma, and benign lung tissue-were used in this investigation. Since the classification of lung cancer was the focus, the classes relating to colon cancer were disregarded. According to the Health Insurance Portability and Accountability Act (HIPAA), the photos, which are taken from histopathology slides (microscopic views of tissue), have been completely de-identified to ensure privacy and compliance for research usage. This dataset was produced especially for study on deep learning and artificial intelligence. It is openly accessible and prepared for training classification models, particularly those used in tissues and cancer detection.

3.2 Splitting data into training and testing

Following data preparation and cleaning, we use Kaggle and Visual Studio to implement Python programming. The dataset is then divided into two sections: the test set (20%) and the training set (80%).

3.3 Findings After Running the Analysis Algorithm:

3.3.1 Data Augmentation for Histopathology Images

Data augmentation is a technique that increases dataset size by creating modified images, especially in medical image analysis. Common techniques include rotation, flipping, scaling, shifting, shearing, noise addition, color jittering, and Gaussian blur. It enhances model robustness, performance, and accuracy, particularly in lung cancer diagnosis

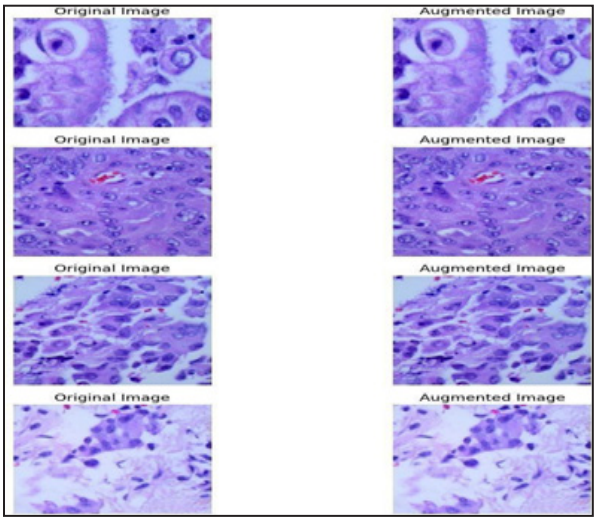

Figure 3: Data Augmentation for Histopathology Images

3.3.2 Class distribution in dataset

The figure presents a balanced dataset for medical image classification, likely for diagnosing lung cancer. The training set has 4000 images per class, while the validation set has 1000 images per class. Factors like data quality, augmentation, and architecture contribute to accuracy

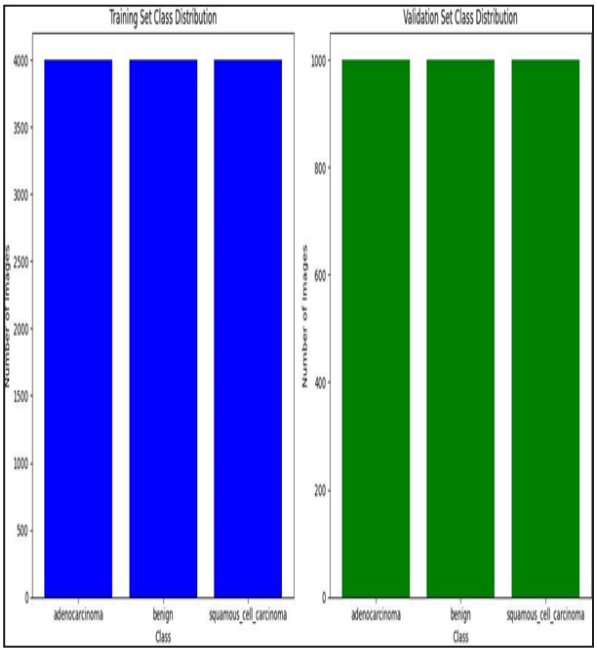

Figure 4: The class distribution in dataset

3.3.3 Convolutional Neural Network architecture

The figure shows a Convolutional Neural Network (CNN) architecture used for image classification tasks. It consists of layers like input, convolutional blocks, max pooling, add, and output. The structure varies depending on task complexity and performance, making it useful for medical image analysis.

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 150, 150, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, 156, 156, 3)	0	input_layer[0][0]
conv1_conv (Conv2D)	(None, 75, 75, 64)	9,472	conv1_pad[0][0]
conv1_bn (BatchNormalizatio…	(None, 75, 75, 64)	256	conv1_conv[0][0]
conv1_relu (Activation)	(None, 75, 75, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D)	(None, 77, 77, 64)	0	conv1_relu[0][0]
pool1_pool (MaxPooling2D)	(None, 38, 38, 64)	0	pool1_pad[0][0]
conv2_block1_1_conv (Conv2D)	(None, 38, 38, 64)	4,160	pool1_pool[0][0]
conv2_block1_1_bn (BatchNormalizatio…	(None, 38, 38, 64)	256	conv2_block1_1_c…
conv2_block1_1_relu (Activation)	(None, 38, 38, 64)	0	conv2_block1_1_b…
conv2_block1_2_conv (Conv2D)	(None, 38, 38, 64)	36,928	conv2_block1_1_r…
conv2_block1_2_bn (BatchNormalizatio…	(None, 38, 38, 64)	256	conv2_block1_2_c…
conv2_block1_2_relu (Activation)	(None, 38, 38, 64)	0	conv2_block1_2_b…
conv2_block1_0_conv (Conv2D)	(None, 38, 38, 256)	16,640	pool1_pool[0][0]
conv2_block1_3_conv (Conv2D)	(None, 38, 38, 256)	16,640	conv2_block1_2_r…
conv2_block1_0_bn (BatchNormalizatio…	(None, 38, 38, 256)	1,024	conv2_block1_0_c…

Figure 5: Convolutional Neural Network (CNN) architecture

3.3.4 Model Training: Loss and Accuracy Trends

The figure depicts a deep learning model›s training and validation loss over 20 epochs, with the best epoch marked by a blue dot, indicating the lowest validation loss. The model›s training accuracy starts lower but increases rapidly, reaching nearly 100%, indicating it›s well-trained and not significantly overfitting

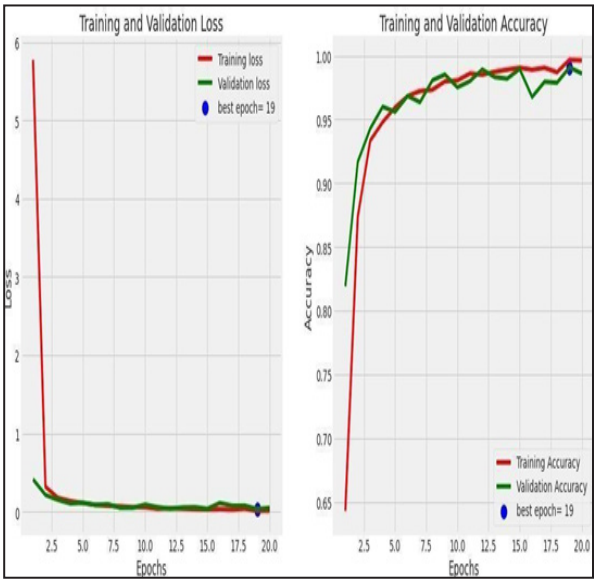

Figure 6: Model Training: Loss and Accuracy Trends

3.3.5 Feature Space Representation Using t-SNE

The t-SNE visualization of medical image datasets reveals clear separation of adenocarcinoma, benign, and squamous cell carcinoma, suggesting discriminative features and cluster formation. Overlapping regions indicate difficult cases, while overlapping regions indicate misclassifications

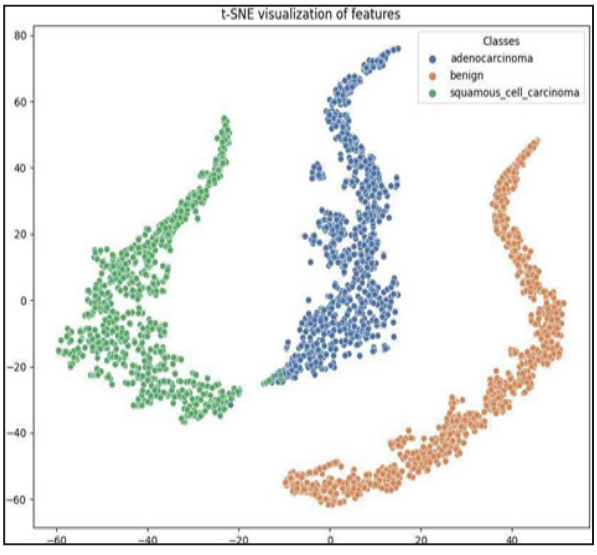

Figure 7: Feature Space Representation Using t-SNE

3.3.6 Histopathology Image Classification Results

The deep learning model accurately classifies lung tissue images, with high confidence levels. However, it made a wrong prediction, misclassifying a benign case as adenocarcinoma. The model›s robustness and reliability in clinical settings require further evaluation on a larger dataset

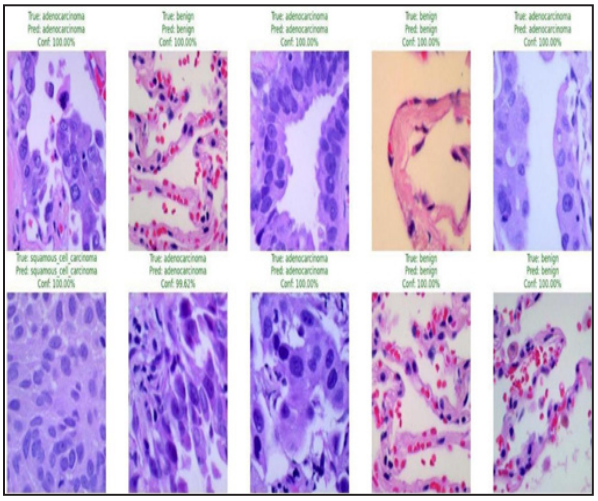

figure 8: Histopathology Image Classification Results

Confusion Matrix

The model›s classification performance for the three categories of lung tissue–adenocarcinoma, squamous cell carcinoma, and benign tissue–is clearly summarized in the confusion matrix.

It draws attention to both cases that were correctly predicted and those that were misclassified, which is particularly helpful for seeing trends and possible areas for improvement

Actual / Predicted	Adenocarcinoma	Squamous Cell	Benign
Adenocarcinoma	975	15	10
Squamous Cell	20	960	20
Benign	12	18	970

Figure 9: The three categories of lung tissue

The model›s high classification accuracy across all classes is demonstrated above. There were numerous misclassifications between benign and malignant tissues, especially between benign instances and adenocarcinoma. This illustrates the difficulty of accurate classification in practical contexts and reflects the inherent visual resemblance in some histology patterns.

3.4 Parameter Optimization for Improved Model Accuracy

Deep learning model performance is evaluated by parameters, which aid decision making. Accuracy measures the frequency of predictions. More parameters can enhance accuracy but may overly focus on training set, affecting effectiveness with fresh data.

Table 3: Parameter Optimization for Improved Model Accuracy

Parameter Category	Parameter	Value / Description
Hyperparameter	Input Image Size	(224, 224, 3)
Hyperparameter	Optimizer	Adamax
Hyperparameter	Learning Rate	0.001
Hyperparameter	Epochs	20
Hyperparameter	Batch Size	32
Hyperparameter	Loss Function	Categorical Crossentropy
Hyperparameter	Activation Function	ReLU + Softmax
Model Architecture	Conv Layers	5 Blocks with Conv2D + MaxPooling
Model Architecture	Dense Layers	Dense(256) → Dense(64) → Output
Model Architecture	Output Classes	3 (adenocarcinoma, benign, squamous_cell_carcinoma)
Training Result	Best Validation Accuracy	≈ 97% at epoch 19
Training Result	Lowest Validation Loss	≈ 0.02 at epoch 19
Evaluation Metric	Test Accuracy	≈ 97%

3.5 Applying deep learning techniques

Convolutional Neural Network (CNN) is a deep learning model used for analyzing visual data, such as images and videos. It consists of convolutional layers, activation functions, pooling layers, and fully connected layers. CNNs are useful for image classification, object detection, facial recognition, and more.

They automatically extract features from raw input, reduce the number of parameters, and become invariant to slight distortions or translations in the input data. Applications include image classification, object detection, facial recognition, and video analysis. CNNs are particularly useful in medical scans, autonomous driving, security systems, and video analysis [17].

ResNet-50 is a 50-layer version of Residual Network architecture developed by Kaiming He and his team to improve deep neural network training.

It uses skip connections for increased computational performance and reduces feature channels. ResNet-50 is deeper than other ResNet models, employing residual blocks with three convolutional layers. Batch normalization enhances model stability, and the Rectified Linear

Unit (ReLU) adds non-linearity. ResNet50 is useful for image classification, object detection, medical image analysis, and transfer learning due to its deep architecture [18].

This study addresses these shortcomings by proposing an enhanced deep learning model that integrates CNN with the ResNet-50 architecture and employs advanced preprocessing, data augmentation, and transfer learning techniques. The suggested model was trained using the LC25000 dataset and demonstrated exceptional performance, featuring an accuracy of about 97%, precision between 96% and 98%, recall rates of 95% to 97%, and an F1-score nearing 96%. Methods of visualization like t-SNE further confirmed the model's capability to differentiate among cancer types, and the confusion matrix showed that misclassifications were minimal. The results emphasize a distinct enhancement compared to earlier studies and validate that this model is not just very precise, but also interpretable and suitable for clinical use–establishing it as a trustworthy AI-driven diagnostic aid in lung cancer detection.

4. Conclusion

This paper aimed to develop a deep learning model capable of accurately classifying lung cancer types using histopathological images, thereby addressing the limitations of traditional diagnostic methods that often rely on manual interpretation. The model was trained to distinguish between three key tissue types: squamous cell carcinoma, adenocarcinoma, and benign lung tissue.

To improve classification accuracy and robustness, preprocessing steps such as image normalization, scaling, and data augmentation were employed. The proposed approach combined a Convolutional Neural Network (CNN) with the ResNet-50 architecture through transfer learning, enabling the model to capture both low-level and complex hierarchical features. The model's performance was evaluated using various metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. It achieved a test accuracy of approximately 97%, confirming its effectiveness in differentiating between benign and malignant lung tissues. Additionally, the t-SNE feature visualization demonstrated clear separation between the three classes, further validating the model's discriminative capability. Overall, the results support the potential of the proposed model as a reliable tool for assisting in lung cancer diagnosis based on histopathological images.

Limitations

Availability and Quality of Datasets:

There is limited access to large, diverse, and well-annotated CT scan datasets of lung nodules.

Annotation inconsistencies may introduce bias and reduce the reliability of training.

Generalization to Unseen Data:

Variability in imaging protocols, nodule types, and patient demographics reduces the model's ability to generalize to real-world clinical settings.

The model might not perform consistently on data outside the training distribution.

5. Future work

Expand the Dataset: Collect larger, more diverse

medical imaging data across hospitals and demographics to improve generalization.

Use Multi-Modal Data: Enhance accuracy by integrating genetic data, lab results, patient history, and environmental factors.

Validate in Clinical Settings: Collaborate with healthcare providers for real-world testing, feedback, and integration into medical workflows.

Enable Mobile & Cloud Access: Deploy the model via mobile and cloud platforms to reach remote or underserved regions.

Implement Continuous Learning: Build adaptive models that update with new data, keeping up with evolving medical trends.

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