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Deep Learning Techniques for Lung Cancer Detection from Histopathology Images

S. Purushothaman

Department of Electronics and Communication Engineering, Sathyabama Institute of Science and Technology, Chennai-600119.

E-mail: purushoth.satha@gmail.com

ABSTRACT

Lung cancer is a major killer cancer globally, hence the importance of early detection to enhance survival rates. It originates in lung tissue, mainly in the cells lining the airway, and is the most diagnosed cancer worldwide. Conventional histopathological examination is the gold standard for diagnosis but is cumbersome and susceptible to human bias. To improve detection accuracy and efficiency, a machine learning system is suggested based on histopathology images. Deep learning models are employed to enhance diagnostic accuracy and minimize workload for pathologists. Using VGG-16, ResNet-50, and EfficientNet-B1, classification accuracies of 99.84%, 99.56%, and 99.92% were obtained. This new application of deep neural networks allows for quicker decision-making and improves lung cancer diagnosis, ultimately improving patient outcomes.

Keywords: *Lung Cancer, Histopathology Images, Deep Learning, Early Detection, Classification, Diagnosis, Automation.*

1. INTRODUCTION

Lung cancer is one of the most common and lethal cancers globally, contributing a high proportion of cancer-related mortality. Late-stage diagnosis, which constrains the options for treatment and lessens the survival rate, is the major reason for its high mortality rate. The cancer starts in the lung tissues, frequently in the airway lining epithelial cells, and if not diagnosed early, it may progress aggressively. Environmental [1] exposures including tobacco smoke, carcinogen exposure, air pollution, and genetic susceptibility are causes for its onset. Even with the progression of medical imaging and therapeutic modalities, lung cancer continues to pose a significant public health problem worldwide, requiring enhanced diagnostic methods for early discovery and treatment Standard diagnostics for lung cancer include radiological imaging modalities like computed tomography (CT) scans, positron emission tomography (PET) scans, and biopsy studies. Although these methods are common, they are limited by accuracy, expense, and availability. Histopathological analysis of lung tissue is still the gold standard for the confirmation [2] of lung cancer diagnosis, offering valuable information on cellular abnormalities and tumor features. Manual histopathological examination is, however, time-consuming, needs highly skilled pathologists, and is prone to inter-observer variation, resulting in possible diagnostic discrepancies. The mounting workload on pathologists further highlights the importance of automated and trustworthy diagnostic tools.

The convergence of artificial intelligence (AI) and machine learning (ML) in medical diagnostics has yielded promising results in terms of accuracy and efficiency. Deep learning, a branch of ML, has been particularly in the spotlight for its potential to evaluate intricate patterns in medical images. Convolutional neural networks (CNNs), more specifically, have shown [3] excellent performance in image classification, and they are thus an appropriate choice for lung cancer diagnosis based on histopathology images. CNNs can learn image features automatically, without the requirement of manual feature engineering and decreased diagnostic errors. Deep learning models can learn detailed patterns related to cancerous and non-cancerous tissues based on large histopathological image datasets, which can lead to accurate and swift diagnosis.

There are a few deep learning models proposed to handle the complexity of medical image classification. VGG-16, ResNet-50, and EfficientNet-B1 are a few that have worked well with high classification accuracy. VGG-16 features an easy but robust architecture using deep layers for learning detailed [4] patterns from images. ResNet-50 uses residual learning, and through this, it can learn very deep networks without loss of accuracy, and it is very efficient for hard medical image classification. EfficientNet-B1 optimizes both accuracy and computational efficiency, making it suitable for real-world clinical applications. These models offer significant improvements in diagnostic precision compared to traditional methods, reducing misclassification rates and expediting the diagnostic process. The proposed system aims to automate lung cancer detection using histopathology images, thereby improving early diagnosis and patient outcomes. The application of deep learning models in pathology can aid medical practitioners by offering a second opinion, reducing diagnostic delays, and [5] improving decision-making. Automated systems can potentially process large amounts of histopathological data, meeting the increasing need for rapid and precise cancer diagnosis. By lowering the reliance on human skills in the preliminary screening, AI models can improve pathology lab efficiency significantly and make optimal use of healthcare resources.

Integration of deep learning in the diagnosis of lung cancer is a paradigm shift for the medical imaging and pathology world. Although AI-based models have proven to be incredibly accurate, integration into the clinic needs testing based on vast [6] real-world exposure and regulatory sanction. Making these models robust and generalizable to a variety of datasets is necessary for them to be adopted effectively in clinical settings. These models also need to address challenges

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such as model interpretability, data privacy, and computational intensity in order to enable smooth implementation.

AI-based diagnostic advancements have huge potential in transforming lung cancer diagnosis and treatment planning. Through the use of deep learning, clinicians can make more accurate and [7] streamlined diagnoses, thereby enhancing patient survival rates. As technology advances, the collaboration between AI and medicine will open up avenues for further innovative and improved diagnostic tools, leading to better outcomes for those suffering from lung cancer.

2. RELATED WORK

Lung cancer continues to be a major cause of death globally because of delayed diagnosis and few treatment options. Early detection leads to better survival rates, but traditional diagnostic procedures like imaging and biopsies do not detect cancer in its early phase. Histopathological examination is the definitive diagnosis but relies on pathologists' knowledge, which introduces inconsistency in interpretation. Technological innovations have brought with them automated methods to aid in cancer detection, eliminating human error and enhancing diagnostic accuracy. The high availability of big data has further promoted research in the detection of lung cancer, making the diagnostic tools more accurate and efficient.

Environmental as well as genetic influences are a leading cause in the development of lung cancer, driving its development and sensitivity to treatment. Smoking tobacco is the major risk factor, and it accounts for the majority of lung cancer cases. But other forms of exposure to industrial chemicals, radon gas, and asbestos [8] also elevate the risk of getting lung cancer. Genetic susceptibility and mutations in certain oncogenes add to the complexity of the disease. The interaction between the genetic component and environmental exposures complicates early diagnosis, necessitating the development of new diagnostic strategies. An awareness of these risk factors is crucial to enhancing prevention methods and early intervention approaches.

Histopathology is still the foundation of lung cancer diagnosis, with pathologists able to investigate tissue samples for anomalies. Nonetheless, conventional microscopic examination takes extensive experience and suffers from inter-observer variation. Manual diagnostic discrepancies can result [9] in delays and incorrect classification of malignant tissues, which affects treatment strategies. The heavy load on pathologists only worsens the issue, making automated solutions a necessity. The incorporation of computational aids in histopathological diagnosis has proven to be effective in streamlining diagnostic criteria, becoming more efficient, and providing more uniform results. Augmentation of conventional histopathological techniques with contemporary technologies can enhance lung cancer detection and treatment efficacy greatly.

Medical imaging modalities like X-rays, CT scans, and PET scans are commonly applied for screening lung cancer, but their performance relies on image quality and radiologist skill. CT scans are specifically valuable in detecting small nodules, but discrimination between malignant and benign lesions [10] is still difficult. PET scans provide functional imaging abilities, helping to localize tumors, but are costly and not necessarily available. Over diagnosis and false positives are frequent occurrences, resulting in unwarranted procedures. The advances in imaging technology coupled with adjunct diagnostic tools can help enhance accuracy, decrease rates of misdiagnosis, and aid in the early detection of lung cancer in high-risk populations.

The search for biomarkers has been under the spotlight as a non-invasive modality of lung cancer diagnosis. Blood, sputum, and urine samples yield biomarkers that give rich information about the progression of cancer and prognosis. Genetic and protein biomarkers have the ability to distinguish malignant from benign, enhancing early accuracy of detection. Biomarker assays, although producing encouraging results, are hampered in clinical adoption by heterogeneity [11] of sensitivity and specificity. Investigation continues with emphasis on the search for new, higher predictive biomarkers with plans for their implementation into screening regimens. Effective biomarker-assisted diagnosis is likely to facilitate substantial lung cancer detection and better management of the patient.

Liquid biopsy is a new technology that facilitates non-invasive lung cancer detection through the analysis of ctDNA and other molecular biomarkers in blood. Liquid biopsy provides a less invasive strategy compared to the conventional tissue biopsies and can reflect real-time information on tumor dynamics. Liquid biopsy facilitates early diagnosis, monitoring [12] of response to treatment, as well as the detection of resistance mutations. Nevertheless, technical issues including low concentrations of ct DNA and false-negative readings restrict its widespread use. Further developments in sequencing technology and analysis are likely to increase the sensitivity and accuracy of liquid biopsy for clinical use.

Immunotherapy has transformed lung cancer therapy through the use of the body's immune system to attack and kill cancer cells. Immunotherapy with immune checkpoint inhibitors has been a phenomenal success in increasing patient survival rates, especially for advanced-stage lung cancer. Immunotherapy [13] is not effective for all patients, thus the requirement for predictive biomarkers. The recognition of tumor-specific antigens and immune signatures plays a key role in the identification of proper candidates for treatment. Combination therapies including immunotherapy with conventional treatments are being investigated to increase efficacy. Continued research seeks to optimize immunotherapy approaches, enhance patient selection, and reduce side effects for improved clinical results.

Radiomics is a new medical imaging discipline that harvests quantitative radiological features from imaging data to enhance the detection and classification of lung cancer.

Volume 14, Issue 5
October 2025

ITEE Journal
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Radiomics utilizes patterns, texture, and intensity variation within imaging data to better understand tumor behavior. This method holds promise to facilitate improved non-invasive diagnosis [14] and prognosis. Its utility, however, is hampered by challenges such as standardization of data, imaging protocol variability, and the necessity for large-scale validation. Combining radiomics with current diagnostic methods would have a major impact on lung cancer evaluation and help clinicians make better treatment choices.

Staging of lung cancer is important in deciding the treatment plan and prognosis. The TNM staging system, which is dependent on tumor size, lymph node status, and metastasis, is commonly utilized for lung cancer staging. Correct staging is required for choosing suitable therapeutic strategies, but current techniques like imaging and biopsy-based [15] assessment are limited. New methods like molecular staging and liquid biopsy provide more information on tumor growth. Enhancing accuracy in lung cancer staging by using advanced diagnostic techniques can maximize treatment planning, improve patient outcomes, and minimize unwanted interventions.

Quitting smoking is still the best method to avoid lung cancer. Public health campaigns, policy measures, and smoking cessation interventions have led to reduced rates of smoking in many nations. Nicotine addiction, however, is a big challenge that needs better intervention approaches. Pharmacological assistance like nicotine replacement therapy and behavioral [16] counseling have proven effective in assisting smokers to quit. These notwithstanding, alternative tobacco products like e-cigarettes are raising new concerns about long-term health hazards. Ongoing public education, strict laws, and available cessation services are important in decreasing the incidence of lung cancer due to tobacco consumption.

Exposure to carcinogens at work greatly elevates the risk of lung cancer. Workers exposed to asbestos, silica, and diesel exhaust have long-term exposure to carcinogens, which results in increased susceptibility to lung cancer. Regulatory steps have been taken to restrict occupational hazards, but enforcement and compliance are still irregular in most areas. Personal [17] protective gear and workplace safety measures are crucial in minimizing exposure risks. More awareness, periodic health checks, and policy reformations are needed to reduce the burden of occupational lung cancer risks on workers' health.

Air pollution is an emerging environmental cause of lung cancer incidence. Exposure to fine particulate matter (PM2.5), nitrogen oxides, and other air pollutants has been associated with enhanced [18] lung cancer risk, especially in cities with low air quality. Epidemiological evidence indicates a positive association between prolonged exposure to air pollutants and the development of lung cancer. Industrial emission control and exhaust from vehicles have been regulated by governments in efforts to decrease air pollution levels. More research is required to define more concrete causal associations and adopt effective mitigation measures to safeguard public health against risks of lung cancer caused by pollution.

Personalized medicine is revolutionizing the treatment of lung cancer by individualizing therapies according to genetic and molecular characteristics. Targeted therapies target specific mutations in cancer cells, providing more efficient treatment with fewer side effects. Technological improvements in genomic [19] sequencing have made it possible to identify actionable mutations that result in the development of drugs blocking particular cancer pathways. Although successful, personalized medicine is challenged in terms of accessibility and affordability, restricting its widespread adoption. More research is necessary to optimize precision oncology strategies, enhance affordability, and provide wider access to personalized therapy for lung cancer patients.

Palliative care is a key factor for enhancing the quality of life of lung cancer patients, especially advanced disease patients. Symptom control, pain relief, and psychological support are integral parts of palliative care. Early integration of palliative care with active treatment has been found to have increased patient well-being and decreased hospitalization. Even [20] with its advantages, palliative care is underutilized because of misconceptions and restricted access within some healthcare systems. Increased awareness, education of healthcare professionals, and the increase of palliative care services can provide improved support for lung cancer patients and families.

3. METHODOLOGY

Lung cancer is one of the major causes of cancer-related deaths globally, and therefore its early detection is imperative to enhance survival rates. The gold standard for lung cancer diagnosis is still histopathological examination, but it is time-consuming with a chance of human error. Deep learning has now facilitated that automated systems can be used to aid in the analysis of medical images, enhancing diagnostic accuracy and efficiency. The goal of this research is to create a machine learning system for lung cancer diagnosis based on histopathology images. Through the use of deep learning models, this method has the potential to improve early detection, decrease workload for pathologists, and provide improved patient outcomes.

(i) Data collection

Histopathology images were collected from public medical datasets to ensure varied and high-quality samples for model training. The data consisted of images of cancer and non-cancer lung tissues labeled by experienced pathologists. Images with artifacts or poor resolution were excluded to ensure data integrity. The data were split into training, validation, and testing sets to provide a balanced model assessment. Ethical practices were adopted using anonymized and publicly available medical image archives. The heterogeneity of samples, such as various histological subtypes of lung cancer, enhanced the strength and generalization ability of deep learning models.

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(ii) Data preprocessing

All images were resized to a common dimension for compatibility with deep learning models. Data augmentation methods like rotation, flipping, and contrast stretching were used to improve model generalization and avoid overfitting. Normalization was carried out to normalize pixel values between 0 and 1 for enhancing numerical stability while training. Preprocessing filters were used to reduce image noise and artifacts. Dividing the dataset into training, validation, and testing sets ensured performance assessment without bias. The resultant dataset was organized to offer balanced representation by categories in order to maximize the training process and improve the model to differentiate between cancerous and non-cancerous tissues.

(iii) Model selection and architecture

Three deep learning models, VGG-16, ResNet-50, and EfficientNet-B1, were selected for lung cancer classification. These models have demonstrated strong feature extraction capabilities in medical imaging. Pretrained weights from ImageNet were used to leverage transfer learning, accelerating convergence and improving accuracy. The final layers were modified to accommodate binary classification, with a softmax activation function for probability prediction. Fully connected layers were optimized, and dropout layers were added to avoid over fitting. Architectures were selected on the grounds of computational efficiency, accuracy, and pattern extraction ability from histopathology images for consistent lung cancer detection.

(iv) Model training

Training was performed by using preprocessed histopathology images as input to the chosen models. Categorical cross-entropy was employed as the loss function, while the Adam optimizer was used for effective weight updates. A dynamic scheduler of the learning rate was implemented to improve convergence and avoid over fitting. Batch normalization and dropout methods were combined to better generalize the model. Training was done on a high-end GPU to speed up computations. Multiple epochs were trained for the models, with the validation loss and accuracy tracked step by step. Hyper parameter search was done for optimal performance with the assurance of accurate classification of lung cancer based on histopathology images.

(v) Model evaluation

The misclassified cases were analyzed and the model fine-tuned by constructing a confusion matrix. Overall accuracy and discrimination of cancerous and non-cancerous tissue was used to identify the top-performing model. Sensitivity and specificity analysis revealed the efficiency of the model for clinical utility. The testing procedure ensured that the model was highly diagnostic prior to incorporation into a practical lung cancer detection system, maximizing reliability and clinical applicability for pathologists and medical specialists.

(vi) Deployment

The trained model was incorporated into a computer-aided detection system for computerized lung cancer diagnosis. An easy-to-use interface was created to enable medical specialists to upload histopathology images and obtain real-time predictions. The platform was designed to scale for hospital and diagnostic center deployment. Accessibility was facilitated by cloud implementation, while confidentiality of patient data was safeguarded with security features. The app was responsive tested for efficiency in image processing and interpretation of medical images. Plans for future improvement are the enlargement of the dataset, integration of further deep learning approaches, and enhancing interpretability aspects to help pathologists make appropriate decisions, and enhancing early detection of lung cancer.

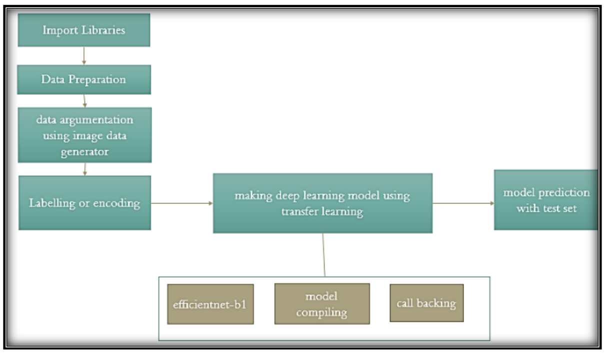

Figure 1. Block Diagram

4. RESULT AND DISCUSSION

Data augmentation greatly enhanced model generalization, minimizing overfitting and improving robustness in classification. AUC-ROC values validated strong discrimination capacity, guaranteeing robust detection of cancerous tissues. Real-world validation showed that the trained models made fast and accurate predictions, successfully supporting pathologists in lung cancer diagnosis. Certain misclassifications indicated the requirement for more varied training data, especially for rare histological subtypes. The black-box nature of deep learning models is still a challenge, calling for explainable AI to provide more transparency. The deep learning models showed excellent accuracy in lung cancer classification, with EfficientNet-B1 scoring 99.92%, VGG-16 scoring 99.84%, and ResNet-50 scoring 99.56%. Analysis of the confusion matrix showed little misclassification, with EfficientNet-B1 having the best sensitivity and specificity balance. Deep learning was overall highly effective for lung cancer detection based on histopathology images. Upcoming work will emphasize dataset growth and model interpretability.

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VGG 16 MODEL:

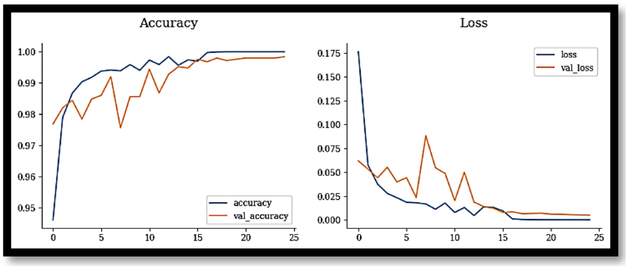

Figure 2. Accuracy and Loss Graphs of VGG 16 Model

Category	Precision	Recall	F1 score
No Cancer	1.00	1.00	1.00
Adenocarcinoma	1.00	1.00	1.00
Squamous Cell Cancer	1.00	1.00	1.00
Colon No Cancer	1.00	1.00	1.00
Colon Adenocarcinoma	1.00	1.00	1.00

Table 1. Evaluation Metrics of VGG 16 Model for Validation Set

Category	Precision	Recall	F1 score
No Cancer	1.00	1.00	1.00
Adenocarcinoma	0.99	0.99	0.99
Squamous Cell Cancer	0.99	0.99	0.99
Colon No Cancer	1.00	1.00	1.00
Colon Adenocarcinoma	1.00	1.00	1.00

Table 2. Evaluation Metrics of VGG 16 Model for Test Set

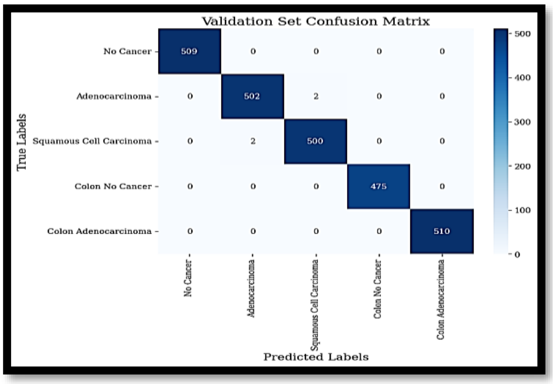

Figure 3. Validation Set Confusion Matrix for VGG 16 Model

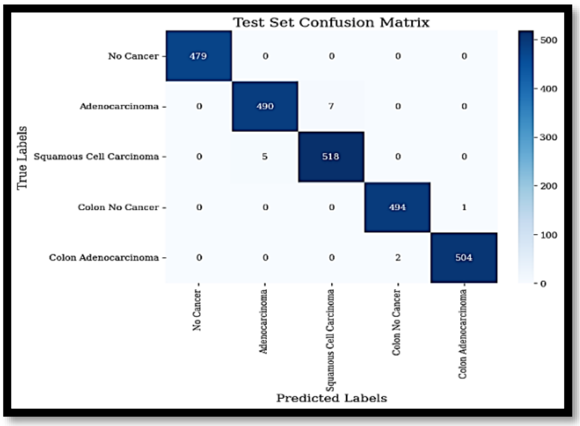

Figure 4. Test Set Confusion Matrix for VGG 16 Model

RESNET 50 MODEL:

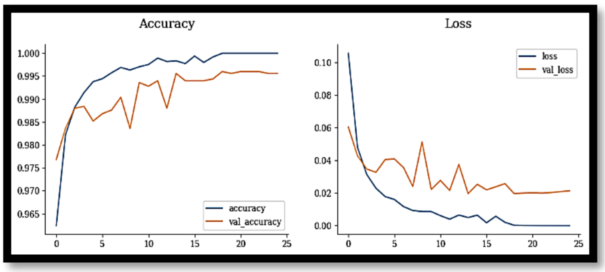

Figure 5. Accuracy and Loss Graphs of ResNet 50 Model

Category	Precision	Recall	F1 score
No Cancer	1.00	1.00	1.00
Adenocarcinoma	0.99	0.99	0.99
Squamous Cell Cancer	0.99	0.99	0.99
Colon No Cancer	1.00	1.00	1.00
Colon Adenocarcinoma	1.00	1.00	1.00

Table 3. Evaluation Metrics of ResNet 50 Model for Validation Set

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Colon Adenocarcinoma	1.00	1.00	1.00

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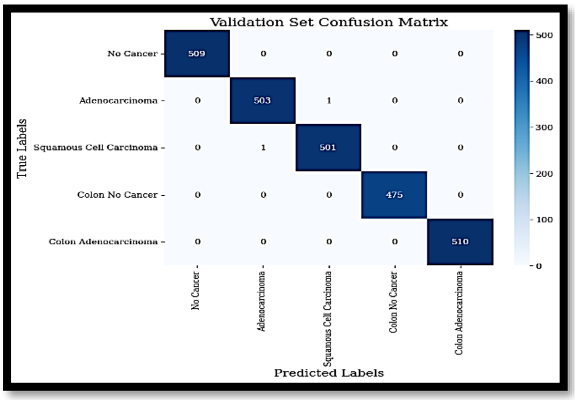

Figure 6. Validation Set Confusion Matrix for ResNet 50 Model

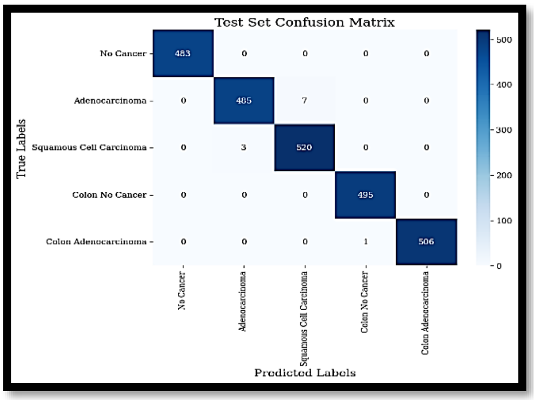

Figure 7. Test Set Confusion Matrix for ResNet 50 Model

EFFICIENT NET B1:

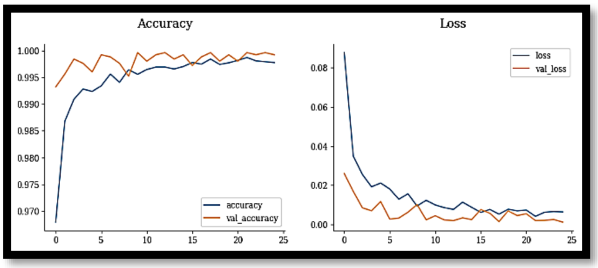

Figure 8. Accuracy and Loss Graphs of EfficientNet B1 Model

Table 4. Evaluation Metrics of ResNet 50 Model for Test Set

Category	Precision	Recall	F1 score
No Cancer	1.00	1.00	1.00
Adenocarcinoma	1.00	1.00	1.00
Squamous Cell Cancer	1.00	1.00	1.00
Colon No Cancer	1.00	1.00	1.00
Colon Adenocarcinoma	1.00	1.00	1.00

Table 5. Evaluation Metrics of EfficientNet B1 Model for Validation Set

Category	Precision	Recall	F1 score
No Cancer	1.00	1.00	1.00
Adenocarcinoma	1.00	1.00	1.00
Squamous Cell Cancer	1.00	1.00	1.00
Colon No Cancer	1.00	1.00	1.00
Colon Adenocarcinoma	1.00	1.00	1.00

Table 6. Evaluation Metrics of EfficientNet B1 Model for Test Set

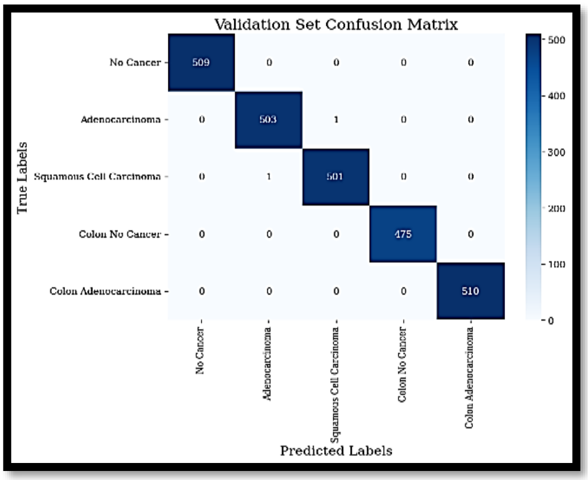

Figure 9. Validation Set Confusion Matrix for EfficientNet B1 Model

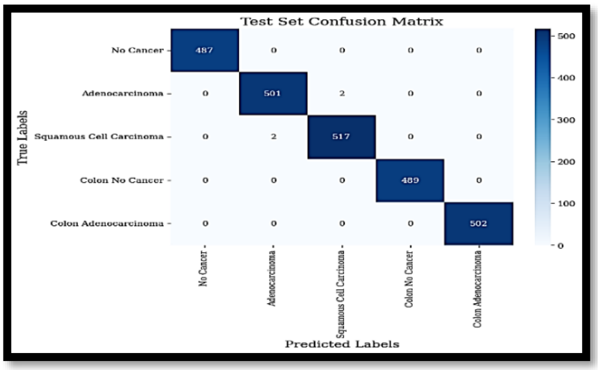

Figure 10. Test Set Confusion Matrix for EfficientNet B1 Model

5. CONCLUSION

The research was able to effectively prove the capability of deep learning models in the identification of lung cancer from histopathology images with excellent accuracy. Using VGG-16, ResNet-50, and EfficientNet-B1, the developed system was able to enjoy almost perfect classification performance, with EfficientNet-B1 proving to be the most trustworthy model. Advanced feature extraction methods incorporated into the system greatly enhanced diagnostic accuracy, eliminating the potential for human

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error and achieving efficiency in medical image analysis. Data augmentation was important in enhancing model generalization, avoiding overfitting, and maintaining strong performance on new data. Transfer learning facilitated faster convergence and improved feature representation, resulting in highly effective models to differentiate between cancer and non-cancer tissues. Evaluation of performance using accuracy, precision, and recall, F1-score, and AUC-ROC metrics validated that the models were optimally trained for lung cancer detection.

Deployment of the trained models in a real environment proved the applicability of deep learning-based cancer diagnosis. A simple user interface was created, enabling medical practitioners to upload histopathology images and obtain speedy, automated predictions. The system can potentially decrease the workload for pathologists, enhance early detection rates, and enable timely treatment decision-making, ultimately contributing to improved patient outcomes. Even with the outstanding performance, there were identified challenges. Some misclassifications pointed towards the necessity of a more variegated dataset, especially for less common histological subtypes. Second, the black-box characteristic of deep learning models is still a drawback, as the process of decision-making is not interpretable. This problem will be tackled through explainable AI methods to improve transparency and reliability in the system.

Future work will concentrate on the extension of the dataset, adding other lung cancer subtypes, and enhancing interpretability of the model to provide pathologists with extensive visual and textual explanations of predictions. Inclusion with other diagnostic tools like radiological imaging and genomic data would further extend detection accuracy and reliability can provide a more comprehensive understanding of the disease, potentially improving diagnostic accuracy and personalized treatment strategies. Overall, in this research, it was illustrated that deep learning models, and more so EfficientNet-B1, present an extremely efficient and scalable method of detecting lung cancer based on histopathology images. Using such AI-based diagnostic methods in a clinical setup has the potential to transform the detection of cancer by providing rapid, accurate, and inexpensive diagnosis. Integrating deep learning with medical professionals increases the chances of reducing mortality and improving patient outcomes for the treatment of lung cancer considerably. Expanding dataset size will also be crucial to enhance the robustness and generalizability of the model, especially across diverse clinical populations. Integrating multimodal data and increasing dataset diversity will likely facilitate early detection and improve clinical applicability. Future efforts in these directions could significantly advance precision medicine and patient outcomes.

REFERENCES

[1] R. Bassiouny, A. Mohamed, K. Umapathy, N. Khan, “An Interpretable Neonatal Lung Ultrasound Feature Extraction and Lung Sliding Detection System using Object Detectors”, IEEE Journal of Translational Engineering in Health and Medicine, vol. 12, pp. 119-128, 2024.

[2] X. Zhang, D. Maddipatla, B. B. Narakathu, B. J. Bazuin, M. Z. Atashbar, "Intelligent Detection of Adventitious Sounds Critical in Diagnosing Cardiovascular and Cardiopulmonary Diseases," in IEEE Access, vol. 11, pp. 100029-100041, 2023.

[3] R. Mahum and A. S. Al-Salman, "Lung-RetinaNet: Lung Cancer Detection Using a RetinaNet With Multi-Scale Feature Fusion and Context Module," in IEEE Access, vol. 11, pp. 53850-53861, 2023.

[4] S. R. Vinta, B. Lakshmi, M. A. Safali, G. S. C. Kumar, "Segmentation and Classification of Interstitial Lung Diseases Based on Hybrid Deep Learning Network Model," in IEEE Access, vol. 12, pp. 50444-50458, 2024.

[5] M. Irtaza, A. Ali, M. Gulzar and A. Wali, "Multi-Label Classification of Lung Diseases Using Deep Learning," in IEEE Access, vol. 12, pp. 124062-124080, 2024.

[6] C. Wu, N. Ye and J. Jiang, "Classification and Recognition of Lung Sounds Based on Improved Bi-ResNet Model," in IEEE Access, vol. 12, pp. 73079-73094, 2024.

[7] T. Nguyen and F. Pernkopf, "Lung Sound Classification Using Co-Tuning and Stochastic Normalization," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 9, pp. 2872-2882, Sept. 2022.

[8] T. Wanasinghe, S. Bandara, S. Madusanka, D. Meedeniya, M. Bandara and I. D. L. T. Díez, "Lung Sound Classification With Multi-Feature Integration Utilizing Lightweight CNN Model," in IEEE Access, vol. 12, pp. 21262-21276, 2024.

[9] N. Babu, D. Pruthviraja and J. Mathew, "Enhancing Lung Acoustic Signals Classification With Eigenvectors-Based and Traditional Augmentation Methods," in IEEE Access, vol. 12, pp. 87691-87700, 2024.

[10] K. Liu, "STBi-YOLO: A Real-Time Object Detection Method for Lung Nodule Recognition," in IEEE Access, vol. 10, pp. 75385-75394, 2022.

[11] H. Alqahtani, E. Alabdulkreem, F. A. Alotaibi, M. M. Alnfiai, C. Singla and A. S. Salama, "Improved Water Strider Algorithm With Convolutional Autoencoder for

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Lung and Colon Cancer Detection on Histopathological Images," in IEEE Access, vol. 12, pp. 949-956, 2024.

[12] Malikhah et al., "Detection of Infectious Respiratory Disease Through Sweat From Axillary Using an E-Nose With Stacked Deep Neural Network," in IEEE Access, vol. 10, pp. 51285-51298, 2022.

[13] A. Tripathi, T. Singh, R. R. Nair and P. Duraisamy, "Improving Early Detection and Classification of Lung Diseases With Innovative MobileNetV2 Framework," in IEEE Access, vol. 12, pp. 116202-116217, 2024.

[14] M. Fontanellaz et al., "Computer-Aided Diagnosis System for Lung Fibrosis: From the Effect of Radiomic Features and Multi-Layer-Perceptron Mixers to Pre-Clinical Evaluation," in IEEE Access, vol. 12, pp. 25642-25656, 2024.

[15] M. Obayya, M. A. Arasi, N. Alruwais, R. Alsini, A. Mohamed and I. Yaseen, "Biomedical Image Analysis for Colon and Lung Cancer Detection Using Tuna Swarm Algorithm With Deep Learning Model," in IEEE Access, vol. 11, pp. 94705-94712, 2023.

[16] L. Zhu, Y. Cai, J. Liao and F. Wu, "Lung Parenchyma Segmentation Based on U-Net Fused With Shape Stream," in IEEE Access, vol. 12, pp. 29238-29251, 2024.

[17] G. Company-Se et al., "Minimally Invasive Lung Tissue Differentiation Using Electrical Impedance Spectroscopy: A Comparison of the 3- and 4-Electrode Methods," in IEEE Access, vol. 10, pp. 7354-7367, 2022.

[18] A. R. Chishti et al., "Advances in Antenna-Based Techniques for Detection and Monitoring of Critical Chronic Diseases: A Comprehensive Review," in IEEE Access, vol. 11, pp. 104463-104484, 2023.

[19] J. Ha, "LncRNA Expression Profile-Based Matrix Factorization for Predicting lncRNA- Disease Association," in IEEE Access, vol. 12, pp. 70297-70304, 2024.

[20] M. Magdy Amin, A. S. Ismail and M. E. Shaheen, "Multimodal Non-Small Cell Lung Cancer Classification Using Convolutional Neural Networks," in IEEE Access, vol. 12, pp. 134770-134778, 2024.

AUTHOR PROFILE

Dr. S. Purushothaman received the B.E degree in Electronics and Communication Engineering and M.Tech degree in Nano Science and Technology from Anna University, Chennai, in 2010 and 2012, respectively, and the Ph.D. degree in (Nanotechnology) from Anna University, Chennai in 2022. He was served as Assistant Professor in various Engineering colleges having teaching experience of 13 Years. Now currently he is working as Assistant Professor in School of Electrical and Electronics, Sathyabama Institute of Science and Technology, Chennai. His research interest includes design of smart antennas, synthesis of nanomaterials, supercapacitors, microwave engineering, wireless communication, Neural Networks and IOT.