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A Systematic Review On Lung Cancer Detection Using Machine Learning Techniques

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***Abstract*— Lung cancer remains one of the leading causes of cancer-related mortality worldwide, highlighting the urgent need for accurate and reliable diagnostic methods. Recent advances in machine learning (ML) have made it a valuable tool for lung cancer diagnosis by leveraging various imaging modalities, datasets, preprocessing techniques, feature extraction methods, classification algorithms, and segmentation strategies. This literature review systematically examines the application of ML techniques in lung cancer detection, emphasizing the progress achieved across these areas. It also identifies the strengths and limitations of existing ML approaches, underscoring the need for multi-modal learning, hybrid artificial intelligence models, and heterogeneous datasets to improve diagnostic performance. Despite notable progress, challenges in early detection remain, warranting further research on integrating deep learning with radiomics, multi-scale analysis, and enhanced feature representation to strengthen early diagnosis and support more effective clinical decision-making.**

***Keywords*— Lung cancer detection, Machine learning techniques, Feature extraction, Lung nodules classification, segmentation, Preprocessing, Modality.**

I. Introduction

Lung cancer is one of the leading causes of cancer-related mortality worldwide, making early and accurate detection essential for improving patient survival. Conventional diagnostic methods, including biopsy, chest X-rays, and computed tomography (CT) scans, often face challenges such as subjectivity, delayed diagnosis, and high false-positive rates. In recent years, machine learning (ML) has transformed medical imaging and lung cancer diagnosis by enabling automated, data-driven, and highly accurate diagnostic solutions.

Machine learning algorithms have been widely applied to lung cancer detection using various imaging modalities, including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and X-rays.

These modalities provide valuable information about lung nodules, their morphology, and potential malignancy. The availability of large public datasets, such as LIDC-IDRI, LUNA16, NLST, TCGA, along with private hospital datasets, has greatly supported the development and validation of ML-based diagnostic models.

The effectiveness of machine learning in lung cancer detection relies on a well-defined pipeline comprising preprocessing, feature extraction, classification, and segmentation. Preprocessing methods such as image normalization, noise reduction, contrast enhancement, and lung field segmentation enhance image quality while minimizing artifacts. Feature extraction techniques, including radiomics, deep feature embeddings, and statistical texture analysis, capture meaningful information from medical images. Classification methods such as Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), Convolutional Neural Networks (CNNs), and Transformer-based models have demonstrated strong performance in distinguishing malignant from benign nodules. In addition, segmentation models including U-Net, V-Net, Generative Adversarial Networks (GANs), and Graph Neural Networks (GNNs) effectively isolate lung nodules from surrounding tissues, improving diagnostic accuracy and prognosis.

This literature review presents a comprehensive analysis of machine learning techniques for lung cancer detection, covering recent advances in imaging modalities, datasets, preprocessing methods, feature extraction techniques, classification models, and segmentation approaches. By examining recent research, it identifies existing challenges, current limitations, and promising future directions for enhancing ML-based lung cancer diagnosis.

The remainder of this paper is organized as follows. Section 2 reviews studies based on CT scan images, Section 3 discusses research using X-ray images, Section 4 summarizes work on histopathological images, Section 5 reviews studies combining multiple imaging modalities, and Section 6 concludes the paper.

II. Related Work Using CT Scan

Liangyu Li et al. [1] proposed a hybrid feature extraction framework that combined Gray-Level Co-occurrence Matrix (GLCM), Haralick descriptors, and autoencoder features using CT scan images from the Lung Cancer Alliance (LCA) dataset. The polynomial SVM achieved the highest accuracy of 99.89% with the combined feature set, while the Gaussian and RBF SVM classifiers attained accuracies of 99.56% and 99.35%, respectively, using GLCM and Haralick features. Muwei Jian et al. [2] introduced the Channel Shuffle Slice-Aware Network (CSSANet) for lung nodule detection on CT images from the LUNA16 dataset. The network effectively captured both intra-slice features and inter-slice contextual information by exploiting spatial relationships between adjacent slices. A Group Shuffle Attention (GSA) module was incorporated to fuse inter-slice features and enhance the extraction of shape-related characteristics of different nodules within the same slice group. The proposed model achieved a Competition Performance Metric (CPM) score of 89.8%, outperforming several existing detection methods. Abe et al. [3] developed an ensemble deep learning framework based on convolutional neural networks using the relatively small IQ-OTH/NCCD CT dataset for automated lung cancer diagnosis. The proposed model achieved an accuracy of 98.17%, with a sensitivity of 98.21% and specificity of 98.13% in distinguishing cancerous from non-cancerous CT scans. For classifying scans into normal, benign, and malignant pulmonary nodules, it reported an accuracy of 95.43%, a sensitivity of 93.40%, and a specificity of 97.09%.

Chaoxi Jiang et al. [4] developed a partial attention module based on Kolmogorov–Arnold Networks (KAN), integrating global representation learning into convolutional neural networks. They also introduced an adaptive feature fusion module combined with a multi-slice partition channel priority attention mechanism to improve the detection of small lung nodules. When evaluated on the LUNA16 dataset, the proposed method achieved a Competition Performance Metric (CPM) score of 90.32% and an Average Precision (AP) score of 89.19%. On the TIANCHI dataset, it further recorded CPM and AP scores of 69.42% and 67.99%, respectively. N. Velmurugan et al. [5] proposed the RSPO algorithm by combining the Rat Swarm Optimizer (RSO) and Political Optimizer (PO) for CT-based lung cancer detection.

A Laplacian filter was employed for image preprocessing, while lung lobe segmentation was performed using a Pyramid Scene Parsing Network (PSPNet) trained with the proposed RSPO algorithm. Lung nodule identification was carried out using a grid-based approach, followed by feature extraction through the proposed RSPO_ShCNN model, which achieved accuracy, precision, and F-measure values of 94.8%, 92.6%, and 93.7%, respectively. V. G. Anisha Gnana Vincy et al. [6] proposed an optimized 3D residual network (ResNet50) for segmenting malignant lung regions from healthy chest tissue in CT images. A dense feature extraction module utilized all encoded feature maps to capture multi-scale information, while a U-Net decoder addressed the vanishing gradient problem and the residual network encoded CT slices into feature maps. Experimental results on the LUNA16 dataset demonstrated that the proposed approach effectively segmented lung nodules from CT images.

Mohammad Q. Shatnawi et al. [7] focused on the automated classification and prediction of lung cancer from CT scan images using deep learning, particularly Enhanced Convolutional Neural Networks (CNNs), for rapid and accurate diagnosis. The study developed and evaluated several pre-trained models, including ConvNeXtSmall, VGG16, ResNet50, InceptionV3, and EfficientNetB0. The dataset comprised four classes: 338 adenocarcinoma images, 187 large cell carcinoma images, 260 squamous cell carcinoma images, and 215 normal images. Among all the evaluated models, the enhanced CNN achieved a testing accuracy of 100%, outperforming ConvNeXt (87.00%), VGG16 (99.00%), ResNet50 (94.50%), InceptionV3 (76.90%), and EfficientNetB0 (97.90%). Xuemei Shi and Zifan Zhang [8] proposed MAST-UNet, a novel pulmonary nodule segmentation model built on the U-Net architecture. The network incorporates a Local Aware Attention module to enhance focus on nodule regions, a Pixel Transformer module to improve semantic feature representation, and a Perceptual Adaptation Module to achieve adaptive receptive field scaling. Experimental evaluation on the publicly available LIDC-IDRI dataset demonstrated that MAST-UNet outperformed existing approaches in terms of Dice Similarity Coefficient (DSC), Intersection-over-Union (IoU), and Pixel Accuracy (PA).

Mengyi Zhang et al. [9] proposed SPC-UNet, a Res U-Net-based lung nodule detection framework incorporating a self-calibrated multi-scale attention mechanism.

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The network employs a Self-Calibrated Pyramidal Squeeze Attention (SC-PSA) module to extract features at multiple scales, while the Coordinate Attention (CA) module and SC-PSA module jointly capture discriminative spatial and channel information. This combination enhances the differentiation of benign and malignant lung nodules. The proposed SPC-UNet achieved an accuracy of 96.18% and a Competition Performance Metric (CPM) score of 0.924 on the LUNA16 dataset. Shidi Miao et al. [10] developed a multimodal deep learning nomogram (DLN) by integrating pulmonary nodule and intrathoracic fat (ITF) features to distinguish benign from malignant nodules. A dedicated segmentation method was designed to accurately delineate the intranodular and perinodular (IPN) regions, while the Swin Transformer was employed for feature extraction and LASSO regression for feature selection. The combined IPN and ITF signatures provided better diagnostic performance than the IPN signature alone, with a net reclassification improvement of 0.134 ($P < 0.05$) and an integrated discrimination improvement of 0.078 ($P < 0.05$). The DLN achieved an area under the curve (AUC) of 0.913 (95% CI: 0.870–0.952) on the internal test cohort and 0.906 (95% CI: 0.867–0.938) on the external test cohort. Calibration analysis showed no significant difference from the ideal calibration curve across all cohorts ($P > 0.05$), confirming the effectiveness of the proposed model, while the inclusion of ITF features further improved its diagnostic performance.

Jiade Tang et al. [11] proposed LN-DETR, a Transformer-based lung nodule detection framework that integrates a Partial Convolution-based Efficient Multi-scale Attention (PC-EMA) module, a Grouped and Shuffled Convolutional Cross-scale Feature Fusion (GS-CCFM) module, and a Channel Transformer (CTrans) module. The PC-EMA module combines Efficient Multi-scale Attention with partial convolution to enhance multi-scale feature extraction while reducing computational cost. The GS-CCFM module employs Grouped and Shuffled Convolution (GSConv) for efficient cross-scale feature fusion, whereas the CTrans module utilizes a cross-channel attention mechanism to further strengthen feature integration. Experimental evaluation on the LUNA16 and Tianchi lung nodule datasets showed that LN-DETR outperformed existing object detection models in terms of detection accuracy, computational efficiency, and model complexity. On the LUNA16 dataset, the model achieved an F1-score of 91.5% and a mean Average Precision (mAP) of 93.1%, while on the Tianchi dataset it attained an F1-score of 87.4% and an mAP of 86.4%.

The reduced parameter count and lower computational overhead further improve its suitability for clinical applications. Mohamad M. A. Ashames et al. [12] investigated the feasibility of adapting conventional deep learning architectures to generate feature nodes with similar magnitudes that facilitate Canonical Variates Analysis (CVA) fine-tuning. Their findings showed that standard deep learning models, even without being specifically designed for this purpose, achieved classification accuracies comparable to state-of-the-art methods after CVA fine-tuning. The study further explored the relationship between the indifference subspace and node values across a wide range of deep learning architectures, with and without ImageNet pre-training. The results demonstrated that CVA fine-tuning not only challenges conventional deep learning classification strategies but also provides a promising approach for improving biomedical image classification, particularly in lung nodule detection.

Wenhu Liu et al. [13] introduced CSEA-Net, a fully automated lung nodule segmentation model designed for high-precision analysis of CT images. The proposed architecture incorporates a dual-branch channel–spatial feature enhancement network along with a coordinate attention mechanism to address the challenges associated with small and poorly defined lung nodules. Experimental evaluation on multiple publicly available datasets demonstrated that CSEA-Net achieved excellent lung tumor segmentation performance, with high Dice Coefficient and Intersection over Union (IoU) scores. Hussain Dawood et al. [14] proposed an Improved CenterNet framework specifically developed for lung cancer detection. The model combines ResNet-34 with an attention mechanism, enabling it to learn discriminative lung cancer features despite complex backgrounds and varying imaging conditions. The proposed approach achieved precision, recall, and F1-scores of 99.89%, 99.82%, and 99.85%, respectively, on the LUNA16 dataset, while corresponding values of 98.33%, 98.02%, and 98.17% were obtained on the Kaggle dataset. However, the model showed limited performance in accurately detecting samples affected by significant lighting variations. R. Sudha and K. M. Uma Maheswari [15] proposed a deep learning framework integrated with swarm intelligence algorithms to overcome the limitations of existing lung cancer detection methods. CT images from the LIDC-IDRI dataset were first preprocessed using a Wiener filter for effective noise removal, followed by lung tissue segmentation using U-Net to identify abnormalities in soft tissues.

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Classification was then performed using the Convolutional Neural Network Fish Swarm Optimization (CFSO) algorithm, which minimizes misclassification while improving computational efficiency through its metaheuristic optimization strategy. The proposed approach also reduced feature dimensionality, thereby accelerating both training and inference without compromising accuracy. Experimental results reported an IoU of 0.7822, along with an accuracy of 97.80%, recall of 98.49%, precision of 96.8%, and an F1-score of 97.32%.

Chaosheng Tang et al. [16] proposed Circle-YOLO, an anchor-free lung nodule detection algorithm that represents nodules using bounding circles to estimate their center location and diameter. The framework incorporates a Bounding Circle Intersection-over-Union (BC-IoU) loss function to improve training stability and efficiency, along with a Cross-stage Partial Attention (CSPA) module to capture nodule characteristics while reducing false positives and false negatives. Evaluation on multiple datasets demonstrated strong performance. On the LUNA16 dataset, the model achieved an accuracy of 97.6%, precision of 96.1%, recall of 97.2%, and mean Average Precision (mAP) of 97.7%. On the LIDC-IDRI dataset, it recorded an accuracy of 95.3%, precision of 95.6%, recall of 95.1%, and mAP of 95.8%, outperforming several state-of-the-art (SOTA) methods. Furthermore, inference speeds of 62 FPS and 52 FPS satisfied real-time processing requirements (>30 FPS). Geethu Lakshmi and Nagaraj [17] proposed a Squeeze-Inception V3 with Slime Mould Algorithm-based Convolutional Neural Network for lung cancer classification. The proposed classifier integrates the lightweight SqueezeNet architecture with Inception V3 to improve feature learning and classification performance. Experimental results showed that the model achieved an accuracy of 95%, sensitivity of 98%, and specificity of 93%, demonstrating its effectiveness for CT-based lung cancer detection.

Lakshmana Rao Vadala et al. [18] proposed SpiLenet for lung cancer detection using computed tomography (CT) scan images. Image preprocessing was performed using the Savitzky–Golay (SG) filter, followed by lung lobe segmentation through Dense-Res-Inception Net (DRINet). Lung nodule identification was carried out using a grid-based approach, and the final classification was performed using SpiLenet, which combines the SpinalNet and LeNet architectures. Experimental results demonstrated that SpiLenet achieved an accuracy of 92.10%, an F-measure of 90.40%, and a precision of 91.10%.

Lokanathan Jimson and John Patrick Ananth [19] developed the Neuron Attention Visual Taylor Network (NAVT-Net) for lung cancer detection from CT images. Initially, the acquired CT images were enhanced using homomorphic filtering, followed by lung nodule segmentation using the Dual-Branch U-Net (DB-UNet). Data augmentation techniques, including resizing, flipping, and rotation, were then applied before extracting shape-based features. The final classification was performed using the NAVT-Net framework, which integrates the Neuron Attention Stage-by-Stage Network (NASNet), Visual Geometry Group-16 (VGG16), and the Taylor series. Experimental evaluation showed that NAVT-Net achieved an accuracy of 92.18%, a True Positive Rate (TPR) of 93.99%, a True Negative Rate (TNR) of 92.19%, an F1-score of 90.99%, and a precision of 91.99%, with a computational time of 37.879 s and memory usage of 41.100 MB at a K-value of 9.

Durgaprasad Mannepalli et al. [20] proposed a lightweight Vision Transformer (LwViT)-based deep learning framework for accurate lung cancer classification using CT images. Initially, image preprocessing was performed using Gaussian enclosed Bilateral Filtering (GaBF) to eliminate noise. Feature extraction was then carried out using a Conditional Variational Autoencoder (CVA), followed by classification using a GroupWise Separable Convolution-based Dual Attention Vision Transformer (gSC-DViT). The hyperparameters of the gSC-DViT model were optimized using the Puma Optimizer to reduce classification errors and improve performance. The proposed LwViT-DL model achieved classification accuracies of 99.52% on the Chest CT Scan image dataset and 99.69% on the Lung Cancer Dataset, outperforming several existing lung cancer classification methods. A. Priya and P. Shyamala Bharathi [21] presented a deep learning framework for lung cancer detection and classification based on the SE-ResNeXt-50 architecture combined with Convolutional Neural Networks. The proposed model integrates QDHE-based preprocessing, data augmentation, advanced feature extraction, and hyperparameter optimization to enhance classification performance. Experimental results showed that the model achieved an accuracy of 99.15%, sensitivity of 97.58%, precision of 99.51%, specificity of 99.80%, and an F1-score of 98.54%, demonstrating superior performance compared with many existing lung cancer detection models.

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Tolgahan Gulsoy and Elif Baykal Kablan [22] proposed FocalNeXt, a ConvNeXt-enhanced FocalNet architecture developed for automated lung cancer detection from CT scan images. The model combines the attention capabilities of FocalNet with the feature extraction strength of ConvNeXt within a Vision Transformer framework to improve diagnostic performance. Evaluation on the publicly available Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) CT scan dataset demonstrated excellent results, achieving an accuracy of 99.81%, sensitivity of 99.78%, recall of 99.36%, and an F1-score of 99.56%, outperforming several state-of-the-art lung cancer detection methods.

Nahed Tawfik et al. [23] employed the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm to preprocess CT scan images and enhance their visual quality. The preprocessing stage was further improved by integrating multiple optimization strategies with the CLAHE technique, while the CutMix data augmentation method was applied to increase the robustness of the proposed model. A comparative evaluation was carried out using several deep learning architectures, including Inception-V3, ResNet101, Xception, and EfficientNet, to assess their classification performance with and without CLAHE preprocessing. The study also investigated the performance of Support Vector Machine (SVM), Artificial Neural Network (ANN), Naïve Bayes (NB), and Perceptron classifiers, which achieved accuracies of 100%, 99%, 83%, and 92%, respectively. The experimental results demonstrated a considerable reduction in the false positive rate (FPR) along with an overall improvement in diagnostic accuracy. S. Akila Agnes et al. [24] proposed a lung nodule segmentation framework by integrating the U-Net++ architecture with wavelet pooling to capture both high- and low-frequency image information, thereby improving segmentation accuracy. The Haar wavelet transform was employed to downsample feature maps within the encoder, enabling the preservation of fine structural details. Evaluation on the LIDC-IDRI dataset produced a mean Dice coefficient of 0.936 and a mean Intersection over Union (IoU) of 0.878. Furthermore, the combination of wavelet pooling with Tversky and Cross-Entropy (CE) loss functions enhanced the model's ability to segment small and irregular nodules that are typically difficult to identify. Overall, the proposed framework demonstrated the effectiveness of combining wavelet pooling with the U-Net++ architecture for accurate lung nodule segmentation.

Sneha S. Nair et al. [25] proposed a Modified Adaptive Threshold Segmentation technique for lung cancer detection.

The method was evaluated using CT scan images from the Lung Image Database Consortium (LIDC) dataset, where the images were processed as video frames to validate the proposed approach. Both quantitative and qualitative analyses were performed to assess the segmentation performance. For lung cancer classification, the framework employed Artificial Neural Network (ANN) and Support Vector Machine (SVM) classifiers, achieving detection accuracies of 96.30% and 97.00%, respectively. Lei Ma et al. [26] introduced a novel convolutional neural network architecture, GoogLeNet with Adaptive Layers (GoogLeNet-AL), for lung cancer detection. The proposed architecture incorporates squeeze-and-excitation blocks, dilated convolutions, depthwise separable convolutions, group convolutions, non-local blocks, octave convolutions, inverted residuals, and ghost convolutions within the inception modules to improve multi-scale feature extraction. In addition, data augmentation, stratified sampling, and fairness-aware training were adopted to enhance model robustness and reduce bias. Experimental results demonstrated that GoogLeNet-AL achieved an accuracy of 98.74%, an F1-score of 98.96%, and a precision of 99.74% for lung cancer detection.

G. Mohandass et al. [27] proposed a lung cancer classification framework based on an Attention-based Convolutional Neural Network with DenseNet-201 transfer learning, optimized using the Namib Beetle Optimization Algorithm (NBOA). In the preprocessing stage, Modified Sage-Husa Kalman Filtering (MSHKF) was employed to remove noise and enhance CT images. Feature extraction was then performed using Improved Empirical Wavelet Transform (IEWT), from which six statistical features—mean, variance, entropy, energy, average amplitude, and kurtosis—were extracted. These features were subsequently fed into the Attention-based CNN integrated with DenseNet-201, where the batch normalization layer of the Attention CNN was replaced with DenseNet-201 to improve classification of cancerous and non-cancerous CT images. The proposed NBOA further optimized the AtCNN-DenseNet-201 classifier, resulting in more accurate lung cancer detection. Experimental results showed that the proposed AtCNN-DenseNet-201 TL-NBOA-CT method achieved 18.30%, 21.37%, and 23.07% higher precision, 24.84%, 16.32%, and 31.36% higher accuracy, and 14.32%, 21.97%, and 23.38% higher F1-score than existing approaches, including the Enhanced Deep Belief Network with Gabor Filters (CLC-CT-EDBN), the Three-Dimensional Deep CNN with Multi-layer Filters (CLC-CT-3D-DCNN), and the Hybrid Deep Learning Neural Network model (CLC-CT-3D-CNN).

Sumaia Mohamed Elhassan et al. [28] proposed a dual-model deep learning framework to improve lung cancer detection by combining a Convolutional Neural Network (CNN) for classification with the You Only Look Once (YOLOv8) architecture for real-time tumor detection. The CNN automatically learns hierarchical features from raw CT images, capturing edges, textures, and complex structural patterns essential for identifying lung cancer. Meanwhile, YOLOv8 employs multi-scale feature extraction to detect tumors of different sizes and shapes within a single image, making it particularly effective for identifying small or irregular lesions. To address the challenge of limited training data, the study incorporated Deep Convolutional Generative Adversarial Networks (DCGAN) for advanced data augmentation, enabling the models to learn from a more diverse dataset. The CNN achieved a classification accuracy of 97.67%, while the YOLOv8 model obtained an Intersection over Union (IoU) score of 0.85 for tumor localization, demonstrating high precision in identifying tumor boundaries. Furthermore, the inclusion of synthetic images generated by DCGAN improved both the CNN classification accuracy and YOLOv8 detection performance by approximately 10%.

Richa Jain et al. [30] proposed a hybrid framework that combines deep learning with reinforcement learning to improve the accuracy of lung cancer diagnosis from CT scans. The dataset included CT images from healthy individuals as well as patients with different stages of lung cancer. Class imbalance was addressed using elastic transformation, while data augmentation techniques were applied to improve model generalization. Five pre-trained convolutional neural network architectures, namely DenseNet201, EfficientNetB7, VGG16, MobileNet, and VGG19, were employed for multi-class lung tumor classification and further refined through transfer learning. To enhance diagnostic performance, the study introduced a weighted average ensemble model, DEV-MV, integrated with grid search-based hyperparameter optimization, achieving a diagnostic accuracy of 99.40%. The incorporation of ensemble reinforcement learning also improved the robustness and reliability of the prediction results. Rehan Raza et al. [31] proposed a transfer learning-based framework called Lung-EffNet for lung cancer classification. The model is based on the EfficientNet architecture and was further enhanced by adding additional layers to the classification head. Lung-EffNet was evaluated using five EfficientNet variants (B0–B4) on the benchmark IQ-OTH/NCCD dataset, which contains CT images categorized as benign, malignant, and normal.

To address class imbalance, multiple data augmentation techniques were employed during training. Experimental results showed that Lung-EffNet achieved an accuracy of 99.10% and an ROC score ranging from 0.97 to 0.99 on the test dataset. Shalini Wankhade and Vigneshwari [32] proposed a hybrid neural network framework for the early and accurate diagnosis of lung cancer. The model extracts features from CT scan images using deep neural networks and incorporates an advanced three-dimensional convolutional neural network (3D-CNN) to improve diagnostic accuracy. The proposed approach is also capable of distinguishing benign from malignant tumors. Performance was evaluated using standard statistical measures, and the experimental results confirmed the effectiveness of the proposed hybrid deep learning framework for early lung cancer diagnosis.

Seifedine Kadry et al. [33] evaluated the effectiveness of pre-trained CNN-based segmentation models using both one-fold and two-fold training strategies. The CT images used in the study were obtained from The Cancer Imaging Archive (TCIA) database. Among the evaluated models, VGG-SegNet demonstrated superior segmentation performance, achieving Jaccard values greater than 88%, Dice coefficients above 92%, and an overall accuracy exceeding 96%, outperforming the other CNN-based segmentation methods. A. Gopinath et al. [34] proposed a Deep Fused Features-Based Cat-Optimized Network for lung cancer classification using CT images. The framework employed saliency maps as the initial segmentation technique, followed by a cat-optimized convolutional neural network to improve the diagnosis of malignant lung nodules. Performance evaluation was conducted on the LIDC-IDRI dataset using standard metrics, including accuracy, sensitivity, specificity, precision, and F1-score. Experimental results demonstrated that the proposed framework achieved an accuracy of 99.89%, sensitivity of 99.80%, specificity of 99.76%, precision of 99.80%, and an F1-score of 99.88%, indicating its effectiveness for lung cancer classification.

Negar Maleki and Seyed Taghi Akhavan Niaki [35] investigated three different approaches for lung cancer diagnosis using CT scan images. In the first approach, the images were processed using a Convolutional Neural Network (CNN), while an Artificial Neural Network (ANN) was employed for classification. The second approach incorporated image preprocessing and segmentation before applying the CNN and ANN models. In the third approach, the preprocessed and segmented images were converted into numerical data through dedicated feature extraction algorithms.

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Dimensionality reduction and feature selection techniques were then applied, followed by classification using three machine learning algorithms: Gradient Boosting (GB), Random Forest (RF), and Support Vector Machine (SVM). A comprehensive comparative analysis was conducted using CT images collected from a medical center to identify the most effective approach. Experimental results showed that both the SVM and RF classifiers achieved a diagnostic accuracy of 95% for lung cancer detection.

Shazia Shamas et al. [36] proposed an improved lung cancer segmentation framework by integrating nature-inspired optimization techniques with the conventional K-means clustering algorithm. The high-resolution characteristics of CT images were utilized to differentiate healthy lungs from cancerous tissues, while the limitations of standard K-means segmentation were addressed through four swarm intelligence algorithms: Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CSA), Particle Swarm Optimization (PSO), and Firefly Algorithm (FFA). The proposed methods were evaluated using the Early Lung Cancer Action Program (ELCAP) database, and their performance was assessed using precision, sensitivity, specificity, F-measure, accuracy, Matthews Correlation Coefficient (MCC), Jaccard index, and Dice coefficient. Among the evaluated techniques, K-means combined with the Cuckoo Search Algorithm (CSA) produced the best segmentation performance, achieving a precision of 0.942, sensitivity of 0.964, F-measure of 0.953, and an average accuracy of 93%. Furthermore, K-means integrated with ABC, PSO, FFA, and CSA improved segmentation accuracy by 10.8%, 13.38%, 13.93%, and 15.7%, respectively, compared with the conventional K-means algorithm.

Rashmi Mothkur and B. N. Veerappa [37] presented a deep hybrid learning framework for lung nodule classification to evaluate the performance of several lightweight and low-memory deep neural network (DNN) architectures for medical image analysis. The proposed approach utilized binary classification models, including vanilla 2D CNN, 2D SqueezeNet, and 2D MobileNet, to distinguish CT images of patients with and without early-stage lung cancer. Among the evaluated models, the proposed lightweight deep neural network achieved the best performance with an accuracy of 85.21%, while maintaining a balanced trade-off between sensitivity and specificity. Sarreha Tasmin Rikta et al. [38] introduced an explainable machine learning (XML) framework to improve the transparency and interpretability of lung cancer prediction models.

The experiments were conducted on a lung cancer dataset obtained from Kaggle, where Random Oversampling (ROS) was applied to address class imbalance. The predictive model employed SHapley Additive exPlanations (SHAP) to identify the most influential clinical features contributing to lung cancer prediction. Experimental results demonstrated the robustness of the Gradient Boosting Machine (GBM), achieving an accuracy of 98.76%, precision of 98.79%, recall of 98.76%, F-measure of 98.76%, and an error rate of only 0.16%.

Debnath Bhattacharyya et al. [39] developed a computer-aided diagnosis (CAD) framework to assist radiologists in the accurate detection and diagnosis of lung cancer. The proposed method was based on a novel image feature that considers the spatial interaction among neighboring voxels and was implemented using a U-Net combined with a three-parameter logistic distribution-based technique. When evaluated on the LUNA16 dataset, the model achieved an average Dice Similarity Coefficient (DSC) of 97.3%, sensitivity of 96.5%, and specificity of 94.1%. The study also investigated the integration of different lung segmentation, juxta-pleural nodule inclusion, and pulmonary nodule segmentation techniques for developing efficient CAD systems. Michail Tsivgoulis [40] proposed SqueezeNodule-Net, a lightweight and accurate convolutional neural network designed to rapidly classify lung nodules as benign or malignant while requiring only a mid-range computing system. The model is based on the compact SqueezeNet architecture and its Fire module, which was modified in two different versions. For 2D CT images from the LUNA16 dataset, SqueezeNodule-Net V1 achieved an accuracy of 93.2%, specificity of 94.6%, and sensitivity of 89.2%, whereas V2 achieved 94.3% accuracy, 95.3% specificity, and 91.3% sensitivity. For 3D CT images, V1 recorded an accuracy of 94.3%, specificity of 96.0%, and sensitivity of 87.4%, while V2 achieved 95.8% accuracy, 96.2% specificity, and 90.2% sensitivity. Compared with the original SqueezeNet, SqueezeNodule-Net V1 was 1.2–1.06 times smaller, 1.31–1.5 times faster, and provided 0.8–2.5% better classification performance, whereas SqueezeNodule-Net V2 was 1.4–1.5 times larger, 0.04–1.5 times faster, and achieved 0.1–2.7% higher classification performance.

Iftikhar Naseer et al. [41] proposed an automated lung nodule detection framework, LungNet-SVM, based on a modified AlexNet architecture integrated with a Support Vector Machine (SVM) classifier.

The proposed model consists of seven convolutional layers, three pooling layers, and two fully connected layers for effective feature extraction, while the SVM performs binary classification of lung nodules into benign and malignant categories. Evaluation on the LUNA16 dataset demonstrated that LungNet-SVM achieved an accuracy of 97.64%, sensitivity of 96.37%, and specificity of 99.08%. Yeguo Xu et al. [42] introduced a modified Satin Bowerbird Optimization Algorithm to optimize the AlexNet architecture and select the most informative features from CT scan images. Image preprocessing was carried out using a Wiener filter for noise reduction, followed by AlexNet for classifying healthy and cancerous lung tissues. The framework also incorporated multiple feature extraction techniques, including Gabor Wavelet Transform, Gray-Level Co-occurrence Matrix (GLCM), and Gray-Level Run Length Matrix (GLRM), to improve diagnostic performance. Experimental evaluation on the RIDER Lung CT Collection dataset showed that the proposed method achieved an accuracy of 95.96%, along with a higher F1-score than existing approaches. In addition, the model attained a test recall of 98.06%, indicating its strong capability to identify relevant cancerous cases from CT images.

R. Pandian et al. [43] proposed a deep learning-based framework for detecting abnormal lung tissue growth using Convolutional Neural Networks (CNN) and GoogleNet. The proposed model employs the VGG-16 architecture as the backbone for both the region proposal network and the classifier network, enabling accurate detection and classification of lung abnormalities. Experimental results demonstrated that the framework achieved a detection and classification precision of 98%. Mohammad Alamgeer et al. [44] introduced a deep learning-enabled computer-aided diagnosis framework for lung cancer detection from biomedical CT images, referred to as the DLCADLC-BCT technique. The proposed method utilizes the Gray-Level Co-occurrence Matrix (GLCM) for feature extraction, followed by a Long Short-Term Memory (LSTM) network to classify the presence of lung cancer in CT images. In addition, the Moth Swarm Optimization (MSO) algorithm was employed to optimize key LSTM hyperparameters, including learning rate, batch size, and the number of training epochs. Performance evaluation on a benchmark dataset demonstrated that the DLCADLC-BCT technique consistently outperformed several recently developed lung cancer detection methods.

Ajni K. Ajai and Anitha A [45] proposed a lung cancer classification framework called Shuffled Social Sky Optimizer-based Multi-Object Rectified Attention Network (SSSO-based MORAN).

The proposed Shuffled Social Sky Optimizer (SSSO) combines the Shuffled Shepherd Optimization Algorithm with the Social Ski-Driver (SSD) algorithm to improve classification performance. Initially, Gaussian filtering was applied for image preprocessing, followed by Region of Interest (ROI) extraction. Lung lobe segmentation was then performed using the proposed Deep Renyi Entropy Fuzzy Clustering (DREFC) technique. After identifying the lung nodule regions, classification was carried out using features extracted from Local Gabor XOR Pattern (LGXP), Gray-Level Co-occurrence Matrix (GLCM), Global Binary Pattern (GBP), Tetrolet Transform, and statistical descriptors. The proposed framework achieved an accuracy of 89.6%, Mean Absolute Error (MAE) of 10.4%, sensitivity of 89.69%, and specificity of 84.5%. S. Akila Agnes et al. [46] developed a computer-aided detection (CADe) framework for lung nodule detection from CT scans by combining an enhanced U-Net with a Pyramid Dilated Convolutional Long Short-Term Memory (PD-CLSTM) network. A modified U-Net architecture, Atrous U-Net+, was proposed to identify nodule candidates from axial CT slices using dilation and ensemble strategies, while the PD-CLSTM network utilized both inter-slice and intra-slice spatial features of three-dimensional nodule patches to identify true nodules. Experimental evaluation on the LUNA16 dataset demonstrated that the proposed CADe framework achieved an average sensitivity of 0.930 across seven predefined false-positive rates (FPRs) of 1/8, 1/4, 1/2, 1, 2, 4, and 8 false positives per scan. Furthermore, the framework detected small nodules measuring 5–9 mm with a sensitivity of 0.92 and larger nodules (>10 mm) with a sensitivity of 0.93, demonstrating its effectiveness in detecting lung nodules of varying sizes.

Laxmikant Tiwari et al. [48] proposed an efficient deep learning framework for lung cancer detection based on a Target-based Weighted Elman Deep Learning Neural Network (TWEDLNN) and a Mask Unit (MU)-based Three-Stage Fuzzy C-Means (3FCM) algorithm. The proposed framework includes lung image segmentation using Geometric Mean-based Otsu Thresholding (GOT), contrast enhancement through Modified Clip Limit-based Contrast Limited Adaptive Histogram Equalization (MC-CLAHE), feature extraction, feature classification using TWEDLNN, and lung nodule detection using the MU-based FCM algorithm. Experimental evaluation on the LIDC-IDRI dataset demonstrated that the proposed method achieved a Peak Signal-to-Noise Ratio (PSNR) of 24.2573 and a Mean Squared Error (MSE) of 292.98, outperforming existing techniques.

Mian Muhammad Naeem Abid et al. [49] proposed a Multi-view Convolutional Recurrent Neural Network (MV-CRecNet) for lung nodule detection from CT scans. The framework exploits variations in nodule shape, size, and cross-slice information to improve feature learning and classification performance. By incorporating multiple image views, the model enhances generalization capability and learns more robust feature representations. Experimental results on the Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI) and Early Lung Cancer Action Program (ELCAP) datasets demonstrated that MV-CRecNet outperformed existing models across all evaluated performance metrics.

Wei Chen et al. [50] proposed Multiple Attention 3D U-Net (MAU-Net), a novel deep learning architecture for lung cancer segmentation from CT images. The framework incorporates a dual attention module at the bottleneck of the U-Net to model semantic interdependencies across both spatial and channel dimensions. In addition, a multiple attention gate module was introduced to adaptively recalibrate and fuse multi-scale features obtained from the dual attention module, previous decoder feature maps, and the corresponding encoder features. Experimental results demonstrated that the proposed model achieved an average Dice Similarity Coefficient (DSC) of 0.8667, a 95% Hausdorff Distance of 13.0036, and a Relative Absolute Volume Difference (RAVD) of 0.1552, indicating its effectiveness for accurate lung cancer segmentation. Kamel Hussein Rahouma et al. [52] introduced a computer-aided detection system for lung nodule classification using CT scan images. The proposed framework consists of four stages, including image preprocessing using Gabor and Kuwahara filters, image segmentation through the Chan–Vese active contour model, and feature extraction using the Discrete Wavelet Transform (DWT) with one-, two-, and three-level decompositions. Subsequently, thirteen features were extracted from each wavelet sub-band, and the most discriminative feature set was selected to train a Polynomial Neural Network (PNN) classifier for distinguishing benign and malignant lung nodules. Experimental evaluation demonstrated that the proposed system achieved high performance in both segmentation and classification, with an overall classification accuracy of 96.66%.

P. Surendar and M. Ponni Bala [53] proposed a lung cancer diagnosis framework based on a hybrid deep neural network integrated with an adaptive optimization algorithm. Initially, image preprocessing was performed using the Fast Non-Local Means (FNLM) filter.

Lung nodule segmentation was then carried out using Masi Entropy-based Multilevel Thresholding with the Salp Swarm Algorithm (MasiEMT-SSA). During the feature extraction stage, various texture features were obtained using the Gray-Level Run Length Matrix (GLRLM), followed by optimal feature selection through the Binary Grasshopper Optimization Algorithm (BGOA). Finally, the selected features were classified using a hybrid Deep Neural Network with Adaptive Sine Cosine Crow Search (DNN-ASCCS) algorithm. Experimental evaluation on the LIDC-IDRI dataset demonstrated a high classification accuracy of 99.17%, outperforming several existing approaches. Jinzhu Yang et al. [54] proposed an efficient 3D Multi-Scale Deep Supervision U-Net (3D MSDS-UNet) incorporating a ResNet backbone and a two-pathway deep supervision mechanism to enhance the network's ability to learn comprehensive representations of lung tumors from both global and local perspectives. The proposed model achieved an average Dice score of 0.675, sensitivity of 0.731, and F1-score of 0.682 on the Liaoning Cancer Hospital dataset, while obtaining an average Dice score of 0.691, sensitivity of 0.746, and F1-score of 0.724 on the TCIA dataset. The experimental results demonstrated that the proposed 3D MSDS-UNet consistently outperformed state-of-the-art segmentation models in detecting lung tumors of various sizes, particularly small tumors.

Prasad Dutande et al. [55] introduced a modified and enhanced version of U-Net, termed SquExUNet, for accurate lung nodule segmentation. The proposed model incorporates squeeze-and-excitation blocks to capture fine-grained feature information and improve segmentation performance. Since the segmented nodule candidates require reliable classification, the authors also proposed a dedicated classification framework. Owing to the similar appearance of nodules and non-nodule structures in two-dimensional CT images, a novel detection approach based on cascaded 2D–3D Convolutional Neural Networks (CNNs) was developed. In this framework, the segmentation model first generates potential nodule candidates, which are subsequently classified by a three-dimensional network called 3D-NodNet into nodule and non-nodule volumetric cubes. The study also introduced a substantial Indian Lung CT Image Database (ILCID) clinical dataset in addition to publicly available datasets for comprehensive evaluation. Spoorthi Rakesh and Shanthi Mahesh [56] proposed a lung nodule segmentation framework that employs the Cuckoo Search Optimization algorithm to optimize the initial segmentation of the lung region.

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The segmented lung image is then processed using the Active Contour technique to accurately identify lung nodules. To further refine the segmentation results during post-processing, a Markov Random Field (MRF) model was incorporated. Qingji Tian et al. [57] proposed a deep learning and metaheuristic-based framework to improve the classification accuracy of benign and malignant lung lesions. Initially, CT scan images were preprocessed, and the region of interest was segmented using an optimized Fuzzy Possibilistic C-Ordered Mean clustering method driven by the Converged Search and Rescue (CSAR) algorithm. The segmented features were then classified using an Enhanced Capsule Network (ECN). The proposed method was evaluated against three state-of-the-art models, namely ResNet, KE-CNN, and CNN. Experimental results demonstrated that the proposed framework achieved a precision of 96.35%, recall of 96.07%, F1-score of 96.41%, and overall accuracy of 96.65%,outperforming the compared methods.

Jiaxing Tan,et.al., [58] proposed a novel deep learning Generative Adversarial Network (GAN)-based lung segmentation method (LGAN) with EM distance to perform pixel-wise segmentation. Their experimental results demonstrated that the proposed LGAN method can be used as a promising tool for automatic lung segmentation due to its simplified procedure as well as its improved performance and efficiency.

III. Related Work Using X-Ray Images

N. Divya et al. [59] proposed a novel lung cancer prediction framework based on Convolutional Neural Networks (CNNs) using lung X-ray images. The CNN model was trained to classify chest X-rays into four categories: adenocarcinoma, large cell carcinoma, normal, and squamous cell carcinoma. The proposed methodology includes image preprocessing, feature extraction through multiple CNN layers, and classification using a carefully designed neural network architecture. The model was trained on a diverse dataset to ensure robust feature learning and reliable prediction performance. Its effectiveness was evaluated using standard performance metrics, including accuracy, sensitivity, specificity, and precision. Experimental results on diverse datasets demonstrated that the proposed model effectively distinguished different types of lung cancer while accurately identifying normal cases.\

B. E. Oyovwe et al. [60] presented an enhanced Convolutional Neural Network-based framework for lung cancer detection from chest X-ray images.

During the preprocessing stage, an Adaptive Median Filter (AMF) was employed to remove image noise, while Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to improve image quality. The K-means clustering algorithm was then used to automatically extract the Region of Interest (ROI) by accurately identifying and cropping the lung field. The trained model subsequently classified the detected nodules as either cancerous or non-cancerous. Experimental evaluation demonstrated that the proposed framework achieved an accuracy of 90.77%, precision of 86.65%, and recall (sensitivity) of 95.31%.

K. Nandhini et al. [61] proposed a new artificial intelligence-based multi-class classification framework for detecting lung nodules and pneumonia using an enhanced image localization approach. The proposed system utilizes deep learning techniques to extract discriminative features from chest X-ray images and accurately localize the affected regions, thereby improving both detection and classification performance. The framework integrates an Enhanced Neural Network (ENN) classifier based on VGG19 with the YOLOv8 image localization model to identify regions affected by lung cancer or pneumonia for robust classification. During image acquisition, an Error Hybrid Automatic Repeat Request (EHARQ) mechanism was employed for error recovery, while ensemble learning was incorporated during post-processing to validate the localized regions with low confidence scores. The proposed model was evaluated using a Kaggle chest X-ray dataset containing 5,856 JPEG images categorized into three classes: healthy, lung cancer, and pneumonia, with samples from both male and female patients. A total of 70% of the dataset was used for training, whereas the remaining 30% was reserved for testing and validation. The proposed framework was compared with existing baseline models, including EfficientNet-B0, ResNet-50, and 3D-DLCNN. Experimental results demonstrated that the ENN classifier combined with YOLOv8 achieved an accuracy of 97.3%, precision of 98.7%, recall of 97.3%, F1-score of 98.8%, a true positive rate (TPR) of 0.93, and a false positive rate (FPR) of 0.07 under the AUC-ROC metric, outperforming the existing EfficientNet-B0, ResNet-50, and 3D-DLCNN models.

Ankita Sharma and Sonam Mittal [62] proposed two deep learning models, Sequential and DenseNet, for lung cancer prediction using chest X-ray images. The methodology involved image preprocessing and feature selection prior to model training, testing, and validation.

Comparative analysis demonstrated that the DenseNet model outperformed the Sequential model, achieving an accuracy of 95.86%. Daniel F. O. Onah et al. [63] proposed a ResNet50-based framework for extracting discriminative features from chest X-ray images to detect the presence of pneumonia. The dataset, obtained from Kaggle, consisted of separate training and testing sets. During preprocessing, the dataset was balanced, and the training data were further divided into training and validation subsets. To improve model performance, data augmentation techniques were applied to increase image diversity, while a data generator was employed to reduce memory consumption during training. The ResNet50 architecture was customized through extensive hyperparameter tuning, and the validation dataset was used to optimize model performance. The framework was evaluated using classification reports and confusion matrices with four optimization algorithms: SGD, Adam, Adamax, and Adagrad, which achieved accuracies of 93%, 90%, 92%, and 89%, respectively. The model also incorporated ReLU and ULU activation functions, and different validation split ratios were investigated to determine the optimal configuration. Experimental results showed that the best performance was achieved when 80–90% of the data were allocated for training and the remaining 10–20% were used for validation.

V. Sreeprada and K. Vedavathi [65] proposed a hybrid deep learning framework combined with a Support Vector Machine (SVM) classifier using optimized hyperparameters for lung cancer detection. The proposed approach utilizes a Convolutional Neural Network (CNN), which requires fewer parameters and is easier to train than a fully connected network with an equivalent number of hidden units. The SVM classifier was incorporated to eliminate irrelevant features that negatively affect classification performance. Experimental results demonstrated that the proposed hybrid OCNN-SVM model achieved a classification accuracy of 98.70%, confirming its effectiveness and practical applicability. Furthermore, the model attained a recall of 98.34%, precision of 98.49%, and an F1-score of 98.76%. Mohd Mohsin Ali et al. [66] proposed a lightweight CNN architecture for lung cancer detection that effectively balances computational complexity and predictive performance, making it suitable for deployment on mobile and edge computing platforms. The proposed framework was evaluated using a heterogeneous chest X-ray lung cancer dataset, where the lightweight CNN achieved a training accuracy of 99%, outperforming several existing models. The high sensitivity and specificity of the model significantly reduced false-negative and false-positive predictions, thereby improving the reliability of lung cancer screening. Its lightweight design also enables real-time inference on resource-constrained devices, extending the accessibility of lung cancer screening to rural and underserved regions while supporting earlier diagnosis and improved patient outcomes.

A. Sivasangari et al. [67] proposed a hybrid deep learning-based framework for detecting and classifying different types of lung cancer. Initially, datasets containing various carcinoma categories were collected, after which the images were labeled and processed through feature extraction techniques. The proposed framework employed deep learning, an advanced branch of artificial intelligence, to enhance the performance of Convolutional Neural Network (CNN)-based systems and improve the accuracy of lung cancer classification.

Mohammad Raihan Goni et al. [68] proposed TL-AttSharpNet, a U-Net-inspired architecture that integrates pre-trained VGG16 weights with depthwise convolutions and an attention mechanism for lung image segmentation. The proposed framework effectively combines transfer learning with attention-guided feature extraction to improve segmentation accuracy. Experimental results demonstrated that TL-AttSharpNet achieved a Dice score of 0.9786 and a Jaccard index of 0.9503, outperforming baseline models as well as existing lung image segmentation architectures. A. Asaithambi and V. Thamilarasi [69] investigated the performance of several deep learning architectures, including VGG-16, VGG-19, ResNet-50, and XceptionNet, for lung disease classification using chest X-ray images. The models were evaluated using 5, 10, and 15 training epochs with different optimization algorithms, namely Adam, SGD, and RMSProp, at a learning rate of 0.0001. Initial experiments using the Adaptive Gradient optimizer showed that VGG-16 achieved 68% accuracy, VGG-19 achieved 67%, ResNet-50 achieved 98.67%, while XceptionNet obtained less than 50% accuracy. Further experiments using different epochs and optimizers demonstrated that VGG-16, VGG-19, and ResNet-50 achieved 100% accuracy after 15 epochs, whereas XceptionNet attained a maximum accuracy of 70%.

Rong Fan and Shengrong Bu [70] proposed a deep learning framework for classifying chest X-ray images into fourteen lung-related pathological conditions. To address the challenge of limited training data, the study adopted two strategies: transfer learning using pretrained DenseNet and ResNet models, and comprehensive data preprocessing, including data leakage verification, class imbalance handling, and data augmentation before training the neural networks.

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The proposed framework was evaluated using classification accuracy, Receiver Operating Characteristic (ROC) curves, and Class Activation Maps (CAMs) for visual interpretation. Experimental results using DenseNet121 and ResNet50 demonstrated that the DenseNet121-based model consistently achieved higher classification accuracy than the ResNet50-based model.

Worawate Ausawalaithong et al. [71] proposed a 121-layer Convolutional Neural Network based on DenseNet integrated with a transfer learning strategy for lung cancer classification using chest X-ray images. To address the challenge of limited training data, the model was first pretrained on a lung nodule dataset before being fine-tuned on a lung cancer dataset. The proposed framework achieved a mean accuracy of 74.43 ± 6.01%, mean specificity of 74.96 ± 9.85%, and mean sensitivity of 74.68 ± 15.33%. In addition, the model generated heatmaps to identify the locations of lung nodules, enhancing the interpretability of the classification results. The experimental findings demonstrate the potential of the proposed approach for chest X-ray-based lung cancer diagnosis using deep learning while effectively addressing the limitations associated with small datasets.

IV. Related Work Using Histopathological Images

Computed Tomography (CT), commonly referred to as a CT scan, is one of the most widely used imaging modalities for detecting lung cancer. However, identifying malignant lesions solely from CT images can sometimes be challenging, leading clinicians to recommend a manual biopsy for confirmation. Although effective, manual biopsy procedures are invasive, time-consuming, labor-intensive, and susceptible to medical errors. These limitations have encouraged researchers to develop Computer-Aided Diagnosis (CAD) systems that can assist in the rapid and accurate detection of lung cancer while reducing diagnostic effort and improving clinical efficiency. In such approaches, lung biopsy samples are collected to generate histopathological images, which are subsequently processed using image enhancement and data augmentation techniques to construct a comprehensive dataset for model training and evaluation [72].

Rabia Javed et al. [29] proposed an enhanced EfficientNetB1-based deep learning framework for the accurate detection and classification of lung cancer using histopathological images. The proposed model classifies histopathological images into three categories: benign (no cancer), adenocarcinoma, and squamous cell carcinoma. Performance evaluation was carried out using the LC25000 histopathological lung cancer dataset.

The methodology included image preprocessing through resizing and data augmentation, followed by loading a pretrained EfficientNetB1 model and applying transfer learning. The dataset was divided into training and validation sets, after which fine-tuning and retraining were performed on the training data to improve classification performance. The final model was evaluated using the validation dataset to assess its ability to accurately detect and classify lung cancer into the three predefined categories. Experimental results demonstrated that the enhanced EfficientNetB1 model achieved an exceptional classification accuracy of 99.8%.

Bijaya Kumar Hatuwal and Himal Chand Thapa [64] proposed a Convolutional Neural Network (CNN)-based framework for the identification and classification of different types of lung cancer with improved accuracy and reduced diagnosis time, thereby supporting appropriate treatment planning and enhancing patient survival. The study considered three categories of lung tissue, namely benign, adenocarcinoma, and squamous cell carcinoma. Experimental evaluation demonstrated that the proposed CNN model achieved a training accuracy of 96.11% and a validation accuracy of 97.2%, indicating its effectiveness in histopathological image classification. Jayant Bokefode et al. [72] investigated three deep learning models, namely Convolutional Neural Networks (CNN), Inception-V3, and ResNet50, trained using a histopathological image dataset for lung cancer classification. The authors observed that although the individual models performed well on the training and validation datasets, they exhibited high variance when evaluated on previously unseen data, making the selection of the most reliable model challenging. To address this limitation, ensemble learning techniques were employed to combine the predictions of multiple models, thereby reducing variance and improving overall predictive performance. The study demonstrated that ensemble deep learning approaches provide a more robust and accurate classification framework than individual models, particularly when dealing with unseen data.

V. Related Work Using Multimodalities

Vani Rajasekar et al. [73] proposed a lung cancer detection framework that utilizes both CT scan and histopathological images to evaluate the performance of six deep learning algorithms, namely Convolutional Neural Network (CNN), CNN with Gradient Descent (CNN-GD), VGG-16, VGG-19, Inception V3, and ResNet-50.

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Comparative analysis demonstrated that detection performance was superior when histopathological images were used instead of CT images. Among the evaluated models, CNN-GD achieved the best overall performance with an accuracy of 97.86%, precision of 96.39%, sensitivity of 96.79%, specificity of 97.40%, and an F1-score of 97.96%. Lei Bi et al. [47] proposed a Cascaded CNN-Transformer Network (CCNN-TN) specifically designed for tumor segmentation in PET-CT images. The framework incorporates a Transformer Network (TN) to capture global contextual information through self-attention and image patch embedding, while multiple cascaded CNNs and Transformer Networks are employed to simultaneously learn both local and global feature representations. In addition, a hyper-fusion branch was introduced to iteratively integrate complementary features extracted from the different network components. The proposed framework was evaluated on three datasets, including two non-small cell lung cancer (NSCLC) datasets and one soft tissue sarcoma (STS) dataset. Experimental results demonstrated that CCNN-TN achieved Dice Similarity Coefficient (DSC) scores of 72.25% and 67.11% on the two NSCLC datasets and 66.36% on the STS dataset, outperforming several state-of-the-art CNN-based segmentation methods.

Ashnil Kumar et al. [51] proposed a supervised Convolutional Neural Network (CNN) framework to improve the fusion of complementary information from multimodal PET-CT images for medical image analysis. The proposed method first extracts modality-specific features from PET and CT images and then generates a spatially varying fusion map that estimates the relative importance of each modality across different image locations. These fusion maps are subsequently combined with the corresponding modality-specific feature maps to obtain a comprehensive representation of complementary multimodal information for accurate image analysis. Experimental evaluation demonstrated that the proposed framework achieved a significantly higher foreground detection accuracy of 99.29% ($p < 0.05$) compared with conventional fusion methods, including FS (99.00%), MB (99.08%), and TC (98.92%), while also attaining a superior Dice coefficient. P. Shyamala Bharathi and C. Shalini [74] proposed an image fusion-based lung cancer detection framework incorporating an improved heuristic optimization algorithm. Initially, PET and CT images were acquired and preprocessed using an Adaptive Dilated Convolutional Neural Network (AD-CNN), whose hyperparameters were optimized through the Modified Initial Velocity-based Capuchin Search Algorithm (MIV-CapSA).

The abnormal lung regions were then segmented using the TransUNet3 architecture. Finally, the segmented images were classified using a Hybrid Attention-based Deep Network (HADN) that integrates MobileNet and ShuffleNet architectures to improve lung cancer detection performance.

Mohamed Hammad et al. [75] proposed a novel deep learning framework that integrates advanced feature extraction techniques, improved interpretability, and effective handling of the diverse characteristics of lung cancer. The study developed dedicated models for both chest X-ray and CT images using publicly available Kaggle datasets. By combining feature selection and model optimization techniques, including a Genetic Algorithm and the Tree-based Pipeline Optimization Tool (TPOT), the proposed X-ray model achieved an overall accuracy of 95.47%, while the CT model attained an accuracy of 98.70%. Furthermore, the combined multimodal framework achieved an overall accuracy of 98.93%, demonstrating its effectiveness in lung cancer detection across different imaging modalities. Dehui Xiang et al. [76] proposed a Modality-Specific Segmentation Network (MoSNet) for accurate lung tumor segmentation in PET-CT images. The proposed framework is capable of simultaneously segmenting modality-specific lung tumors from both PET and CT images. A key contribution of MoSNet is its ability to generate modality-specific maps that explicitly quantify the importance of features extracted from each imaging modality. To validate its effectiveness, the framework was evaluated using 126 PET-CT images of patients with non-small cell lung cancer (NSCLC). Experimental results demonstrated that MoSNet consistently outperformed several state-of-the-art lung tumor segmentation methods, confirming its superior segmentation performance.

VI. Conclusion

Thus, the application of machine learning techniques for lung cancer detection using various imaging modalities has demonstrated significant potential to improve early diagnosis, treatment planning, and patient outcomes. Different imaging modalities, including Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), chest X-ray, and histopathological images, have been successfully integrated with machine learning algorithms to enhance the accuracy, speed, and reliability of lung cancer detection. Among these modalities, CT scans, chest X-rays, and PET images remain the most widely used for clinical diagnosis.

Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have further improved the performance of classification, segmentation, and prediction tasks by enabling more precise identification of cancerous lesions. In addition, the integration of multimodal imaging data has further enhanced diagnostic accuracy by providing complementary information that supports a more comprehensive assessment of tumour characteristics.

Despite these encouraging advancements, several challenges remain unresolved, including data variability, limited availability of large and well-annotated datasets, model interpretability, and the ability of trained models to generalize across diverse patient populations and clinical environments. Future research should focus on addressing these limitations by developing robust, reliable, and clinically adaptable machine learning models that can perform consistently across different healthcare settings. Furthermore, integrating imaging data with genomic, molecular, and clinical information through advanced machine learning frameworks has the potential to enable more personalized diagnosis and treatment strategies. Overall, machine learning has emerged as a transformative technology for lung cancer detection, offering substantial improvements in diagnostic accuracy and clinical decision-making. However, continued research, multidisciplinary collaboration among clinicians, data scientists, and researchers, and extensive clinical validation are essential to facilitate the successful translation of these models from research laboratories into routine clinical practice.

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