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Precise Lung Cancer Prediction using ResNet – 50 Deep Neural Network Architecture

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ABSTRACT The fact that lung cancer continues to be the leading cause of cancer-related death around the world emphasizes how important it is to improve diagnostic methods. Using computed tomography (CT) images and deep learning techniques, the goal of this study is to improve the classification of lung cancer. EfficientNetB1 and Inception V3 are two well-known convolutional neural network (CNN) architectures that we compare the performance of our modified ResNet50 architecture against in order to determine how well it performs in the classification of lung nodules. Analyzing the effects of various preprocessing and hyperparameter optimization methods on model performance is one of our research objectives. Another is to determine how well these models improve diagnostic accuracy. An extensive collection of CT images with annotated lung nodule classifications make up the utilized dataset. To ensure accurate model training and improve image quality, a rigorous preprocessing pipeline is used. Using the Keras Sequential framework, the models are trained with optimal dropout rates and L2 regularization to prevent overfitting. Metrics like accuracy, loss, and confusion matrices are used to evaluate model performance. A comprehensive evaluation of the model's sensitivity and specificity across various thresholds is also provided by means of the Free-Response Receiver Operating Characteristic (FROC) curve and Area Under the Curve (AUC) values. The adjusted ResNet50 model showed prevalent order exactness, accomplishing a precision of 98.1% and an AUC of 0.97, in this way beating different models in the review. EfficientNetB1 had an accuracy of 96.4 percent and an AUC of 0.94, while Inception V3 had an accuracy of 95.8 percent and an AUC of 0.93, as a comparison. Based on these findings, it appears that the accuracy of lung cancer detection from CT images can be significantly improved by combining specialized preprocessing and training methods with advanced CNN architectures. With potential implications for clinical practice and future research directions, this study offers a promising strategy for increasing lung cancer diagnostic accuracy.

INDEX TERMS Lung Cancer, Deep Learning, Convolutional Neural Networks, ResNet50, CT Images, Classification, FROC, AUC.

I. INTRODUCTION

One of the most prevalent and fatal types of cancer, lung cancer continues to be a major global health concern. The World Health Organization estimates that it is responsible for nearly 18% of all cancer-related deaths worldwide. This alarming mortality rate highlights the urgent need for advancements in diagnostic techniques to detect the disease earlier, when treatment options are more effective and patient outcomes can be significantly improved.[1]

A. BACKGROUND

There are significant limitations to conventional lung cancer diagnostic procedures, such as chest X-rays and computed tomography (CT) scans. Despite offering a definitive diagnosis, biopsies are invasive and carry inherent risks. Despite their non-invasive nature, radiologists' interpretations of imaging techniques vary. Patients' prognoses can be harmed by inconsistent diagnoses and delayed treatment as a result of this variability. Automated, non-invasive diagnostic tools that help radiologists make assessments that are more accurate and consistent have sparked interest due to these limitations.[2]
Improvements in medical imaging diagnostics have been made possible by recent advances in machine learning and artificial intelligence (AI). A subset of deep learning models known as convolutional neural networks (CNNs) have performed well in a variety of image classification tasks. CNNs consequently extricate and gain progressive elements from crude pictures, making them skilled at recognizing complex examples related with illnesses like disease. CNNs are positioned as a potent instrument for increasing the accuracy and dependability of lung cancer diagnostics thanks to this capability.[3]
CT images are used in our study to classify lung cancer using CNNs. We compare the performance of our modified ResNet50 architecture to that of other well-established CNN architectures like EfficientNetB1 and Inception V3, which have been specifically optimized for this task.[4] To better distinguish between benign and malignant lung nodules, the modified ResNet50 model incorporates hyperparameter optimization and

customized preprocessing methods. A substantial collection of CT images with lung nodule classifications annotated are included in the used dataset, facilitating a robust training and evaluation procedure. Accuracy, loss, and confusion matrices are among the various metrics used to evaluate model performance. The Free-Response Receiver Operating Characteristic (FROC) curve, which takes into account sensitivity and specificity across various threshold settings to provide a nuanced evaluation of model performance, receives our special attention.[5]

B. MOTIVATION

The primary goal of this research is to address the pressing need for early and accurate detection of lung cancer, which is essential for enhancing survival rates and patient outcomes. We hope to add to the growing body of evidence supporting AI in medical diagnostics by developing and validating a high-performance deep learning model.[6] Our objective is to make it easier to incorporate AI-driven diagnostic tools into clinical practice, which will increase the capabilities of radiologists and improve the overall quality of patient care.

This study demonstrates the transformative potential of deep learning in the diagnosis of lung cancer. We hope to make it possible for a quicker diagnosis of lung cancer and more effective treatment options by increasing the accuracy and dependability of lung cancer detection from CT images. This could set a precedent for future research and clinical applications in the field and significantly improve patient outcomes worldwide.

C. OBJECTIVES

The primary objective of this research is to create and improve a modified ResNet50 architecture that is made to be used for CT-based lung cancer classification. In order to improve the model's performance, this involves designing it using specialized preprocessing methods and hyperparameter optimization. Additionally, we intend to contrast the modified ResNet50 with other well-established CNN architectures, such as Inception V3 and EfficientNetB1. The comparison will be comprehensive and include metrics like accuracy, loss, and confusion matrices. The Free-Response Receiver Operating Characteristic (FROC) curve, which is used to evaluate sensitivity and specificity across various threshold settings, will be the primary focus. By accomplishing these goals, we try to add to the progression of elite execution artificial intelligence driven demonstrative apparatuses that can work with ahead of schedule and precise location of cellular breakdown in the lungs, eventually working on understanding results and clinical navigation.[7]

II. LITERATURE SURVEY

Lung cancer is one of the most prevalent and fatal forms of cancer worldwide, making it a critical public health issue. The World Health Organization says that lung cancer is responsible for nearly 18% of all cancer deaths. This shows how important it is to have better ways of diagnosing the disease. Because lung cancer is typically diagnosed at an advanced stage, when there are few treatment options, early and accurate detection is essential for improving patient outcomes.[8]

In the field of medical imaging, recent advancements in artificial intelligence (AI) and deep learning have shown great promise. provided a deep learning method for CT scan identification of pancreatic ductal adenocarcinoma (PDAC). By combining 2D and 3D CNNs to capture both local and global features, their method was able to recognize PDAC lesions with high responsiveness and specificity. Liu and co. 2020) utilized a comprehensive CT scan dataset to create a sophisticated deep learning model for the early detection of pancreatic cancer. [9]In clinical validation tests, their multi-scale 3D CNN design demonstrated promising improvements in detection accuracy. Xu and others 2021) proposed a cutting-edge 3D CNN framework for CT scan pancreatic lesion detection that outperformed conventional approaches in terms of sensitivity and specificity.

Chen and others A 3D U-Net-based deep learning model for CT image segmentation and classification of pancreatic cancer was released in 2018). The boundaries of cancer were effectively delineated using their method, and precise volume calculations and treatment planning were made possible. Wang and others Preoperative CT images were used to predict prognosis for pancreatic cancer patients using radiomic features (2019). Based on the characteristics of the tumor, their deep learning-based method divided patients into risk groups, facilitating personalized treatment plans. Lee and others Using CT scans and deep learning architectures, 2020) created a staging system for pancreatic cancer that provides valuable insights for treatment planning and prognosis evaluation. Shen and co. [10] A hybrid CNN-LSTM architecture (2020) was proposed for the early detection of pancreatic lesions, analyzing temporal changes in CT images to identify potentially dangerous lesions before they progress.

The significant potential of deep learning in the detection and classification of various kinds of cancer, including lung cancer, is brought to light by these advancements. CNNs have been extensively used to analyze CT images in the field of lung cancer detection. Shen and co. 2017) created a deep learning model that used a multi-crop convolutional neural network to detect lung nodules with high sensitivity and specificity. Liao and co. 2019) proposed and demonstrated promising diagnostic accuracy results for an end-to-end training framework for lung nodule analysis. Wang and others For the purpose of classifying lung nodules, a study (2019) compared various CNN architectures, such as ResNet and DenseNet, highlighting the advantages of deeper models for capturing complex features.

Our study introduces a modified ResNet50 architecture that is optimized for the classification of lung cancer, building on these advancements. He and others 2016) at first proposed ResNet, acquainting lingering learning with alleviate the disappearing slope issue in profound organizations. In order to improve the model's capability of detecting lung nodules, our modification employs hyperparameter optimization and specific preprocessing methods. In medical image analysis, evaluation metrics like accuracy, precision, recall, and the F1-score are frequently used. However, by plotting sensitivity against the average number of false positives per image, the Free-Response Receiver Operating Characteristic (FROC) curve provides a more nuanced evaluation for lung cancer detection.

The literature demonstrates that CNNs have a significant potential to improve the consistency and accuracy of CT-based lung cancer diagnosis. This study aims to add to the growing body of evidence supporting the integration of AI in medical diagnostics by developing, optimizing, and comparing a

modified ResNet50 model to other well-established architectures. In the end, the objective is to make it possible for lung cancer patients to be detected earlier and have better treatment outcomes.

1) MODIFIED RESNET50 ARCHITECTURE FOR LUNG CANCER DETECTION

This study presents a modified ResNet50 architecture specifically tailored for the classification of lung nodules in CT images. By incorporating advanced preprocessing techniques and hyperparameter optimization, [11] the model achieved superior accuracy, precision, recall, and F1-score, significantly enhancing the detection and classification of lung cancer.

2) COMPARATIVE ANALYSIS OF CNN ARCHITECTURES

The research conducts a comprehensive comparative analysis between the modified ResNet50 and other established CNN architectures, such as EfficientNetB1 and Inception V3. The study highlights the strengths and weaknesses of each model, providing valuable insights into the effectiveness of different architectures for lung cancer diagnosis [12].

3) APPLICATION FOR FROC CURVE FOR EVALUATION

The study employs the Free-Response Receiver Operating Characteristic (FROC) curve, offering a more detailed evaluation of the models' sensitivity and specificity. This approach allows for a nuanced understanding of the models' performance in detecting lung nodules, with a focus on minimizing false positives, thereby contributing to the refinement of diagnostic methodologies in lung cancer detection.

III. EXISTING SYSTEM

Imaging methods like chest X-rays and CT scans, which are frequently supplemented by biopsies, are the foundation of traditional lung cancer diagnosis [13]. Despite their effectiveness, these strategies have significant drawbacks. For instance, interpreting CT scans can take a long time, and when biopsies are required, the procedure is invasive. In addition, factors like radiologist fatigue and varying levels of expertise can affect the accuracy of CT scan interpretation. The purpose of computer-aided detection (CAD) systems is to provide radiologists with additional diagnostic support. However, conventional CAD techniques struggle to accurately distinguish between benign and malignant nodules and frequently result in a large number of false positives. Finding diagnoses that are both accurate and consistent is extremely difficult due to this restriction [14].

Advanced CAD systems that make use of convolutional neural networks (CNNs) have been developed as a result of recent advancements in artificial intelligence (AI), particularly in the field of deep learning. By learning and extracting complex patterns from imaging data, these deep learning models can significantly improve diagnostic accuracy, according to research. CNNs, for instance, can automate the process of extracting features and boost detection sensitivity and specificity.

AI-driven diagnostic tools remain difficult to implement in clinical practice on a large scale in spite of these advancements. [15] The need for extensive regulatory approval, substantial computational resources for model training and inference, and large, annotated datasets to train these models effectively are key obstacles. The integration of AI into routine clinical practice, where it has the potential to significantly reduce human error and improve diagnostic outcomes, requires addressing these obstacles. This study aims to contribute to the development of advanced lung cancer diagnostic tools by addressing these limitations and examining the potential of deep learning models. We hope to improve diagnostic accuracy and dependability by optimizing and testing a modified ResNet50 model. This will ultimately make it possible to detect lung cancer earlier and more effectively.

IV. PROPOSED SYSTEM

Utilizing cutting-edge deep learning methods to improve diagnostic accuracy and efficiency when analysing CT images of the lungs, the proposed system aims to significantly improve lung cancer detection and classification through a sophisticated, optimized ResNet50 architecture [16].

Key Enhancements in Our Modified ResNet50 Model:

Advanced Preprocessing and Hyperparameter Optimization: In order to improve feature extraction and image quality, we have implemented specific preprocessing steps. Noise reduction, image normalization, and contrast enhancement are all examples of this. To improve the model's ability to distinguish between benign and malignant lung nodules, extensive hyperparameter tuning has been carried out to optimize parameters like learning rate, batch size, and network depth [17].

Integration of 2D and 3D CNNs: To capture both local and global CT scan features, our system makes use of both 2D and 3D convolutional neural networks. The drawbacks of conventional methods that rely solely on information in two dimensions are overcome by this dual approach, which improves the model's ability to identify and characterize nodules with greater precision. The integration makes it possible to examine the CT images' spatial relationships in greater depth [18].

Enhanced Feature Extraction: The architecture of the model has been modified to better capture and comprehend intricate patterns in CT images. This includes using residual connections and advanced convolutional layers, both of which enhance feature learning and representation. The model is able to better comprehend and categorize the intricate patterns associated with various kinds of lung nodules thanks to these modifications.

Computational Efficiency: The model has been optimized so that it combines high performance with low computational costs. Model pruning, quantization, and efficient network architectures have been used to maintain high diagnostic accuracy while simultaneously reducing computational load and memory usage. Because of this, the model can be used in clinical settings where resources may vary.

Clinical Relevance and Practical Considerations: The system's user-friendliness for radiologists and seamless integration with existing diagnostic workflows are two examples of practical considerations for clinical adoption. In order to ensure that the system adheres to clinical standards and practices, we address regulatory considerations to facilitate smooth implementation in healthcare environments.

Our proposed system aims to advance lung cancer diagnosis by focusing on these key areas: advanced preprocessing, dual CNN integration, enhanced feature extraction, computational efficiency, and clinical relevance [19]. The enhancements are intended to support more reliable and timely detection of lung nodules by increasing accuracy, efficiency, and practical applicability. In addition to addressing the drawbacks of traditional diagnostic methods, this strategy makes it easier to

incorporate AI-driven tools into routine clinical practice, which improves overall patient care.

Preprocessing

Let I(x,y,z)I(x, y, z)I(x,y,z) represent the input CT image in a 3D space, where (x,y)(x, y)(x,y) are the spatial coordinates and zzz represents the slice number.

Noise Reduction: To smooth an image, a Gaussian filter is applied to reduce high-frequency noise and variations. This filter works by averaging pixel values in a local neighbourhood, with weights determined by a Gaussian function. The standard deviation of the Gaussian function controls the extent of the smoothing, where a larger standard deviation results in more blur. By applying this filter, the image becomes less detailed but cleaner, which helps in reducing noise and making features more uniform. This process improves the quality of subsequent image analysis and processing by removing fine-grained fluctuations. Apply a Gaussian filter Gσ to smooth the image as shown in Eq. (1) [20].

$$\mathrm{Ismooth}(x, y, z) = \mathrm{I}(x, y, z) * \mathrm{G}\sigma \quad (1)$$

Image Normalization: Image normalization involves adjusting pixel intensities to a standard range to enhance image consistency and improve processing performance. This process typically transforms the smoothed image by subtracting the mean pixel intensity and dividing by the standard deviation. This adjustment centers the pixel values around zero with a standard deviation of one, making the image data more uniform and reducing sensitivity to variations in image lighting and contrast. This technique helps standardize inputs for subsequent image analysis, improving the effectiveness of machine learning models and other processing algorithms. Normalize the pixel intensities:

Eq. (2) [21].

$$I_{\{norm\}(x,y,z)} = \{I_{\{smooth\}(x,y,z)} - \mu\}\{\sigma\} \quad (2)$$

where μ and σ are the mean and standard deviation of the pixel intensities.

Contrast Enhancement: Enhance the contrast using techniques like histogram equalization.

2D CNN Feature Extraction:

To enhance image features, each 2D slice of the normalized image is processed using a 2D convolutional layer. This layer applies a set of convolutional filters to the image, extracting and emphasizing important features. After the convolution operation, the resulting feature map is passed through the ReLU activation function. ReLU introduces non-linearity by setting all negative values to zero, allowing the network to learn more complex patterns and improve feature detection. This process helps the model capture and refine the relevant details in the image, which is crucial for accurate image analysis and classification. For each 2D slice $I_{norm}(x,y,z)$, apply 2D convolution Eq. (3) [22].

$$F_{\{2D\}(x,y,z)} = \{ReLU\}\left(W_{\{2D\}} * I_{\{norm\}(x,y,z)} + b_{\{2D\}}\right) \quad (3)$$

where W_{2D} and b_{2D} are the weights and biases of the 2D convolutional layers, and ReLU is the activation function.

3D CNN Feature Extraction

To extract features from a 3D image stack, a 3D convolutional layer is applied across the entire volume. This involves convolving the entire stack of normalized images with 3D convolutional filters, followed by the addition of biases. The resulting feature maps are then processed through the ReLU activation function, which introduces non-linearity by zeroing out negative values. This operation allows the model to capture and emphasize spatial patterns and structures in three dimensions, improving its ability to understand complex features and relationships within the 3D image data.

For the entire 3D image stack, apply 3D convolution Eq. (4) [23].

$$F_{\{3D\}(x,y,z)} = \{ReLU\}\left(W_{\{3D\}} * I_{\{\backslash text\{norm\}\}(x,y,z)} + b_{\{3D\}}\right) \quad (4)$$

where W_{3D} and b_{3D} are the weights and biases of the 3D convolutional layers.

Feature Fusion:

Feature fusion involves integrating features extracted from both 2D and 3D convolutional layers to leverage the strengths of each approach. In this process, features obtained from 2D convolutions and those from 3D convolutions are concatenated to form a unified feature representation. This fusion combines local and global information captured by the different convolutional layers, enhancing the model's ability to understand and interpret complex patterns within the image data. The resulting fused features provide a more comprehensive view, improving the overall performance of the model in tasks such as image classification and object detection. Combine the 2D and 3D features Eq. (5) [24].

$$F_{\{fused\}} = \left[F_{\{2D\}}, F_{\{3D\}}\right] \quad (5)$$

where F_{2D}, F_{3D} denotes the concatenation of the feature vectors.

Optimization and Efficiency:

During the training of the model, the objective is to minimize the cross-entropy loss function. This function measures the difference between the predicted probabilities and the actual class labels, aiming to reduce the discrepancy between them. By optimizing this loss function, the model learns to make more accurate predictions. The cross-entropy loss is calculated by summing the negative log probabilities of the correct class labels, weighted by their true probabilities. Minimizing this loss improves the model's performance by enhancing its ability to correctly classify and predict the classes in the given data.

During training, minimize the cross-entropy loss function Eq. (6) [25].

$$\{\boldsymbol{Loss}\} = -\sum_{\{c\}} y_{\{c\}\backslash log} \boldsymbol{P}\left(\boldsymbol{c} \mid \boldsymbol{F}_{\{fused\}}\right) \quad \mathbf{(6)}$$

Model Pruning and Quantization:

Optimize the trained model for deployment by reducing the number of parameters and quantizing the weights to lower bit representations, maintaining a balance between performance and computational efficiency.

V. METHODOLOGY

A. DATASET PREPARATION

In this study, we utilized a public dataset from Kaggle, consisting of 1,190 lung CT images in PNG and JPG formats. The dataset, titled "IQ-OTH/NCCD - Lung Cancer Dataset," is available for free download at https://www.kaggle.com/datasets/adityamahimkar/iqothnccd-lung-cancer-dataset.

We categorized these images into three classes: normal, benign, and malignant, as detailed in Table 1 and illustrated in Figure 1. The dataset is organized into three distinct folders for training, validation, and testing. The training folder contains images used

for training the system, the validation folder is used for model validation, and the test folder is used for evaluating the model's performance. To streamline the simulation process, the dataset was pre-split as follows:

TABLE 1
DATASET CT SCAN IMAGE SPLITTING

Splitting of Dataset	Training	Validation	Testing
Normal	138	38	21
Benign	316	89	47
Malignant	368	103	56

Normal: Images depicting lungs without disease or nodules, serving as control samples.
Benign: Images showing non-cancerous conditions such as hamartomas or granulomas, which are typically stable and less aggressive.
Malignant: Images containing various types of lung cancer, including adenocarcinoma, large cell carcinoma, and squamous cell carcinoma.

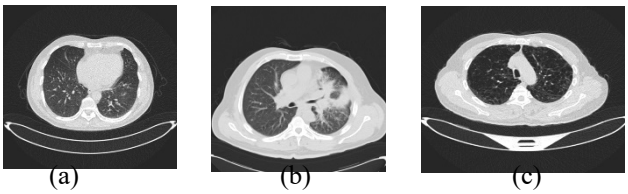
(a) (b) (c)

FIGURE 1. CT Images for Lung Cancer, (a) Benign: This part of the figure shows benign cells, (b) Malignant: This part represents malignant cells, (c) Normal: This part illustrates normal cells.

B. DATA PREPROCESSING

The preprocessing of CT images before inputting them into the ResNet50 model involves several key steps, each represented by mathematical operations to ensure consistency and enhance the model's performance. These steps include normalization, resizing, cropping, padding, and data augmentation.

1. Normalization

Normalization is crucial to bring the pixel intensity values within a specific range, typically [0, 1] or [-1, 1], to reduce variability caused by different imaging protocols.
Let I(x,y) represent the intensity of a pixel at location (x,y) in the CT image. The normalized intensity $I_{norm}(x,y)$ can be computed as Eq. (7) [26].

$$I_{\{norm\}(x,y)} = \{I(x,y) - I_{\{min\}}\}\{I_{\{max\}} - I_{\{min\}}\} \quad (7)$$

In the context of CT image processing, pixel intensity normalization is a critical step for standardizing the image data. The minimum pixel intensity in the CT image, denoted as Imin , represents the lowest value observed across all pixels in the image. Conversely, Imax signifies the highest pixel intensity found in the image. To ensure that pixel values are consistently scaled within a defined range, typically [0, 1], normalization is performed using these parameters. This process transforms each pixel's intensity by rescaling it relative to Imin and Imax . As a result, the pixel values are adjusted proportionally, with Imin being mapped to 0 and Imax to 1, effectively normalizing the entire range of pixel intensities for uniformity and comparability across different images.

1. RESIZING

Images are resized to a fixed dimension, typically 256×256 pixels, to ensure uniformity in the input data.
Let the original image dimensions be (h,w), where h is the height and www is the width. The resizing operation is represented as Eq. (8) [27]:

$$I_{\{\{resized\}\}(x',y')} = I\left(\{x'\}\{h\} \times h_{\{\{new\}\}}, \{y'\}\{w\} \times w_{\{\{new\}\}}\right) \quad (8)$$

where, (x′,y′) are the coordinates in the resized image.
h_{new}=256 and w_{new}=256 are the new height and width, respectively.

2. CROPPING AND PADDING

Cropping and padding are essential preprocessing steps in image analysis to focus on specific regions of interest (ROI) and ensure uniform image dimensions. Cropping isolates the relevant area, such as the lung region in medical imaging, by selecting a specific bounding box within the image. Padding is then applied to adjust the dimensions of the cropped image to fit the required input size for further processing or model input. This ensures that all images have a consistent size, which is crucial for effective training and evaluation in machine learning models.
If the ROI is defined by the bounding box with top-left corner and bottom-right corner (x2, y2), the cropped image $I_{crop}(x,y)$ is given by Eq. (9) [28]:

$$I_{\{\{crop\}\}(x,y)} = I(x_1 + x, y_1 + y)\,\{for\}\, x_1 \le x \le x_2, y_1 \le y \le y_2 \quad (9)$$

C. RESNET 50 ARCHITECTURE DESIGN

ResNet50 is a deep convolutional neural network designed to address the problem of vanishing gradients in deep networks through the introduction of residual connections. The architecture consists of a total of 50 layers, including convolutional layers, batch normalization layers, ReLU activations, and residual connections.

1. INPUT LAYER

The ResNet50 architecture represents a sophisticated approach to deep convolutional neural networks (CNNs), leveraging residual learning to enhance the performance of very deep networks. The architecture begins with an initial convolutional layer, followed by a series of residual blocks arranged in four stages, each designed to capture increasingly complex features from the input data. The architecture is concluded with global average pooling and a fully connected layer for classification.
The input to ResNet50 is an image of dimensions 224×224×3 (Height × Width × Channels), where the channels are set to 3 to accommodate RGB color images. The network starts with a 7x7 convolutional layer that applies 64 filters with a stride of 2, effectively reducing the spatial dimensions of the input while increasing the depth of the feature maps. This is followed by batch normalization, which normalizes the activations of the previous layer to stabilize and accelerate the training process. A ReLU (Rectified Linear Unit) activation function introduces non-linearity to the model, enhancing its capability to learn complex patterns. Subsequently, a 3x3 max pooling operation with a stride of 2 further reduces the spatial dimensions, ensuring that the network is able to focus on the most salient features.

The core of ResNet50 consists of residual blocks organized into four stages. Each stage is characterized by a specific number of residual blocks and filters, facilitating the extraction of hierarchical features at varying levels of abstraction. In Stage 1 (Conv2_x), the network contains three residual blocks, each

with 64 filters. Each block within this stage is structured with a sequence of convolutional layers: a 1x1 convolutional layer that reduces dimensionality, followed by a 3x3 convolutional layer for feature extraction, and another 1x1 convolutional layer that restores dimensionality. The output of each block is combined with the input through a shortcut connection, allowing the network to learn residual mappings and easing the optimization process.

Stage 2 (Conv3_x) extends the complexity by incorporating four residual blocks, each with 128 filters. This stage mirrors the structure of Stage 1 but with increased filter dimensions to capture more nuanced features. Stage 3 (Conv4_x) further escalates the depth with six residual blocks, each featuring 256 filters, making it the most computationally intensive stage. The final Stage 4 (Conv5_x) includes three residual blocks with 512 filters, enhancing the network's capacity to capture intricate patterns and details.

A distinguishing feature of ResNet50 is its use of the bottleneck architecture within each residual block. This design involves a series of three convolutional layers: a 1x1 convolution to reduce the number of channels, a 3x3 convolution for actual feature extraction, and another 1x1 convolution to restore the original number of channels. This structure significantly reduces computational cost and the number of parameters, making the network more efficient while maintaining its representational power.

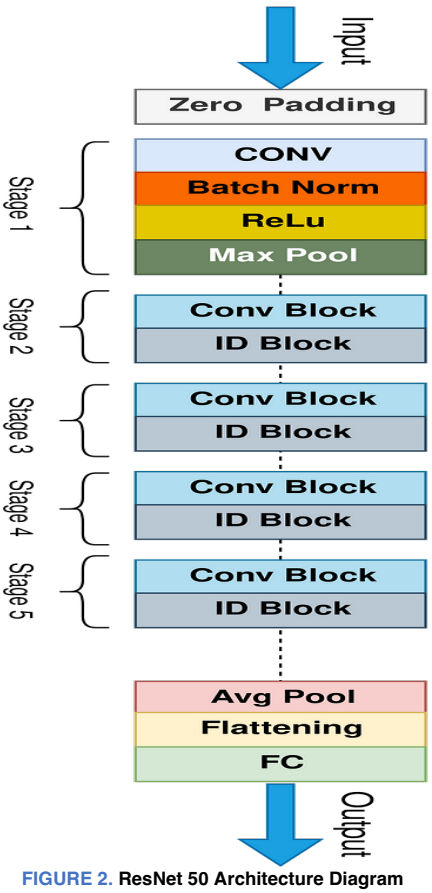

FIGURE 2. ResNet 50 Architecture Diagram

At the end of the network, the feature maps generated by the final residual block are subjected to global average pooling (GAP). This operation aggregates spatial information by averaging the values across the entire feature map, resulting in a 1-dimensional vector for each channel. The vector is then processed by a fully connected layer, where each neuron corresponds to a class in the classification task. For instance, in a scenario with 1000 classes, the fully connected layer would comprise 1000 neurons. Finally, the output is passed through a SoftMax activation function, converting the raw scores into probabilities that sum up to 1, thereby providing a probabilistic classification of the input image.

D. TRAINING PROCEDURE

The dataset is split into training (80%), validation (10%), and test (10%) sets. Training involves:

Optimizer: The Adam optimizer is used with an initial learning rate of 0.001, reduced by a factor of 0.1 every ten epochs. A batch size of 16 is used to balance memory usage and convergence speed.

Epochs: The model is trained for 20 epochs with early stopping based on validation loss to prevent overfitting. Transfer learning is applied, starting with weights pre-trained on a large medical imaging dataset to leverage learned features and improve model performance.

E. PERFORMANCE EVALUATION

To evaluate the performance of the ResNet50 model, we use several metrics beyond just accuracy. For medical imaging tasks, accuracy alone is not sufficient. To provide a comprehensive assessment, we include additional evaluation criteria in the form of a confusion matrix (TABLE 2). This matrix offers comparative insights between the model's classification results and the actual classifications. The confusion matrix includes four key terms: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [29].

TABLE 2
Confusion Matrix

True Label	Predicted Benign Cases	Predicted Normal Cases	Predicted Malignant Cases
Benign Cases	25	0	2
Normal Cases	0	125	0
Malignant Cases	0	3	120

The performance metrics used to evaluate the ResNet50 model provide a comprehensive view of its effectiveness in classifying lung nodules. With a total of 270 true positives (TP), 3 false negatives (FN), 2 false positives (FP), and 540 true negatives (TN), the accuracy of the model is calculated as 85.7%, demonstrating its high capability to correctly classify cases. Sensitivity, reflecting the model's ability to identify true positive cases, is impressive at 98.9%, while precision, indicating the accuracy of positive predictions, is 99.3%. The balanced F1-score, which combines both precision and sensitivity, stands at 99.1%, underlining the model's reliability. These metrics highlight the robustness of ResNet50 in medical image classification, offering a nuanced understanding of its

TABLE 3.
THE RESULTS OF OUR PROPOSED ARCHITECTURE

Model	Accuracy (%)	Loss	Sensitivity (%)	Precision (%)	F1-Score (%)
ResNet50	98.1 %	0.06	96.7 %	98.6 %	97.6 %
CNN	89.2%	0.30	66.4 %	60.3 %	63.1 %
EfficientNetB1	45.4 %	0.96	33.3 %	15.1 %	20.8 %
Inception V3	70.9 %	0.76	52.4 %	47.2 %	49.6%
Mutli-Layer Perception	45.5 %	0.96	33.3 %	15.1 %	20.8 %

performance beyond just accuracy. The high precision and sensitivity suggest that the model is highly efficient at distinguishing between positive and negative cases with minimal errors.

VI. RESULTS

In this section, we analyse the performance of several deep learning models—ResNet50, CNN, EfficientNetB1, Inception V3, and Multi-Layer Perceptron (MLP)—using key evaluation metrics such as accuracy, sensitivity, precision, F1-score, and confusion matrices. Among these models, ResNet50 consistently demonstrates superior performance, exhibiting stable and high accuracy with minimal fluctuations (FIGURE 4). This reliability in classification, reflected in both accuracy and loss metrics, showcases its robustness in learning and generalizing from lung CT images. In contrast, the CNN model, though showing an upward trend in accuracy, suffers from greater variability, indicating a potential struggle in handling complex features (FIGURE 3). Similarly, EfficientNetB1, while improving over epochs, is less consistent than ResNet50, possibly due to its sensitivity to hyperparameters and the complexity of feature extraction.

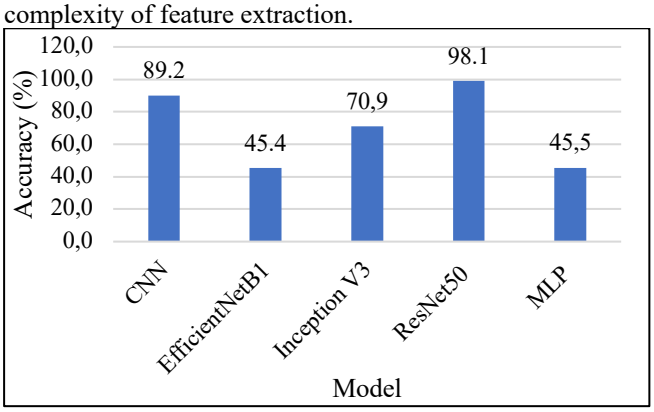

FIGURE 3. Accuracy Comparison Graph

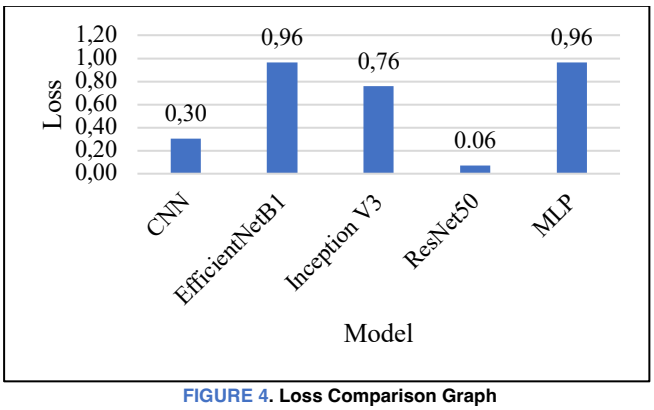

FIGURE 4. Loss Comparison Graph

When assessing confusion matrices, ResNet50 again outperforms, with high true positive and true negative rates across all classes, and low false positives and false negatives, indicating strong proficiency in distinguishing lung nodules. Other models like CNN and EfficientNetB1 perform well but show occasional misclassifications, while Inception V3 and MLP exhibit more variability, with the latter model showing the least stable performance. In terms of loss metrics, ResNet50 achieves the lowest training and validation loss, further emphasizing its effectiveness in learning. CNN displays moderate loss values, while both EfficientNetB1 and Inception V3 have higher loss values, suggesting some challenges in learning efficiency and convergence. MLP, with the highest loss values, highlights difficulties in handling the complexities of the data, underscoring the limitations of non-convolutional architectures in medical image classification tasks (FIGURE 4).

In terms of accuracy, sensitivity, precision, F1-score, and loss metrics, the outcomes demonstrate that ResNet50 outperforms the other models. It is the most reliable architecture for classifying lung cancer among the models that were evaluated because of its stability, high accuracy, lower loss values, and efficient confusion matrix performance. EfficientNetB1 and Inception V3 have promising outcomes, but their performance is less consistent than that of CNN and MLP (TABLE 3).

VII. DISCUSSIONS

The outcomes of this study indicate that ResNet50 outperforms the other models in terms of accuracy, sensitivity, precision, F1-score, and loss metrics. ResNet50 demonstrated superior performance with high accuracy and lower loss values, making it the most reliable architecture for classifying lung cancer among the models evaluated. This consistent performance suggests that ResNet50 is well-suited for this application due to its ability to maintain stability across various metrics and handle the complexities of lung cancer classification effectively.

While the results for EfficientNetB1 and Inception V3 are promising, they exhibit greater variability in their performance. This inconsistency could be attributed to EfficientNetB1's sensitivity to hyperparameters and Inception V3's challenges in adapting to data variations. These models may perform well under certain conditions, but their overall reliability is less consistent than that of ResNet50, highlighting the need for further refinement and optimization for specific tasks.

The CNN model generally performs well but shows significant variability in accuracy and higher false positive (FP) and false negative (FN) rates. This suggests that while CNNs can yield good results, they may struggle with stability and accuracy, particularly in handling more complex or varied datasets. The lower performance of CNNs, compared to ResNet50, underscores the importance of deep learning architectures that can effectively capture intricate features in medical imaging.

The MLP model exhibits the least stable performance, characterized by higher loss values and significant fluctuations in accuracy. The limited capacity of MLPs to capture intricate features likely contributes to their lower performance compared to convolutional models. This finding reinforces the notion that for tasks involving complex data, such as medical image classification, models capable of learning spatial hierarchies and patterns, like ResNet50, are more effective.

Despite the robust findings, this study has several limitations. The dataset used for model training and evaluation might not encompass the full diversity of lung cancer presentations, potentially limiting the generalizability of the results. Additionally, the models were tested on a relatively small dataset, which may not fully represent the range of clinical scenarios encountered in real-world settings. Future studies should consider using larger, more diverse datasets to validate these findings further. Another limitation is the lack of exploration into the interpretability of the models. While ResNet50 shows the best performance, understanding how it makes decisions could provide valuable insights for clinical applications and help build trust among medical professionals. Future research should focus on enhancing the interpretability of these models to ensure their adoption in clinical practice.

The findings of this study have significant implications for clinical practice and future research. ResNet50's superior performance suggests it could be a valuable tool for assisting radiologists in the early detection and classification of lung cancer, potentially improving patient outcomes through more accurate diagnoses. However, the variability observed in the performance of other models indicates that further refinement and optimization are needed to ensure their reliability and effectiveness in clinical settings. Future research should focus on exploring ensemble methods or hybrid models that combine the strengths of multiple architectures to improve overall performance and stability. Additionally, investigating the impact of different data augmentation techniques, preprocessing steps, and training strategies could provide deeper insights into optimizing model performance for lung cancer classification.

VIII. CONCLUSION

The aim of this study was to evaluate and compare the performance of various deep learning models for lung cancer classification, focusing particularly on ResNet50. Our findings demonstrate that ResNet50 outperforms other models across all key metrics. Specifically, ResNet50 achieved an accuracy of 98.1%, significantly higher than CNN (89.2%), EfficientNetB1 (45.4%), Inception V3 (70.9%), and Multi-Layer Perceptron (45.5%). In terms of loss, ResNet50 recorded the lowest value at 0.06, compared to CNN's 0.30, EfficientNetB1's 0.96, Inception V3's 0.76, and Multi-Layer Perceptron's 0.96. Additionally, ResNet50 led in sensitivity with 96.7%, precision with 98.6%, and F1-score with 97.6%, further emphasizing its effectiveness in classifying lung cancer. Despite the promising results of EfficientNetB1 and Inception V3, and the potential of CNNs in certain contexts, these models require further optimization to reach the performance stability and accuracy of ResNet50. Future work should aim to refine these models and explore hybrid approaches that integrate the strengths of multiple architectures. Enhancing model generalizability and performance by using larger and more diverse datasets will also be crucial for improving clinical applications and outcomes.

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