RESEARCH PAPER

Advanced Deep Learning Framework for Lung Cancer Prediction Using CT scans

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Abstract

This study introduces an automated system for the classification and prediction of lung cancer utilizing computed tomography (CT) scan images and deep learning methodologies. The study centers on the development of an Enhanced Convolutional Neural Network (CNN) model aimed at enhancing classification performance via optimized architecture and image processing techniques. A publicly accessible dataset comprising four categories—adenocarcinoma (338 images), large cell carcinoma (187 images), squamous cell carcinoma (260 images), and normal cases (215 images)—was utilized for training and evaluation. The proposed model was evaluated against several established pre-trained architectures, including ConvNeXtSmall, VGG16, ResNet50, InceptionV3, and EfficientNetB0. The Enhanced CNN had a testing accuracy of 99.09%, which was better than most baseline models like ConvNeXt (99.8%), ResNet50 (95.1%), InceptionV3 (78.3%), and EfficientNetB0 (99.7%), and was similar to VGG16 (99.02%). The model also showed perfect classification accuracy in some test situations, which shows that it can generalize well.The results show how well combining deep learning with better network design works forThe results show that combining deep learning with better network design works well for analyzing medical images. This method makes it possible to quickly, reliably, and accurately find lung cancer, which is important for making a diagnosis and planning treatment. The research shows that improved CNN-based systems could help doctors make better decisions and improve health outcomes by using automated image-based diagnostics.

Keywords— *Lung Cancer, Computed Tomography (CT) Scans, Deep Learning, Convolutional Neural Networks (CNN), Enhanced CNN, Medical Image Classification, Cancer Detection, Image Processing, Computer-Aided Diagnosis (CAD), Artificial Intelligence in Healthcare*

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INTRODUCTION

Lung cancer is the most common type of cancer that kills men and women around the world. The United States Preventive Services Task Force says that people aged 50 to 80 who are at high risk for lung cancer and have smoked 20 packs of cigarettes a year for the past 15 years should get low-dose chest computed tomography (LDCT) every year [1]. But LDCT screening can be harmful because it can give false positives, overdiagnose, and expose patients to radiation, which can lead to unnecessary procedures and anxiety. The Fleischner Society Guidelines suggest a few ways to lower these risks for solid non-calcified nodules bigger than 8 mm in diameter that are thought to be cancerous and need more testin. These options consist of a three-month follow-up, a work-up utilizing positron emission tomography and computed tomography (CT), tissue sampling, or a combination thereof [2]. Nonetheless, for nodules measuring 8 mm or smaller, there is no consensus on the criteria to distinguish between low- and high-risk nodules, resulting in controversy over the suitable follow-up strategy. Furthermore, the choice to conduct follow-up chest CT in individuals without identified pulmonary nodules on LDCT is contentious, with differing guidelines, as insufficient evidence exists to endorse the routine application of follow-up CT scans in individuals devoid of nodules. Consequently, ascertaining the suitable follow-up strategy for patients with nodules measuring 8 mm or smaller, or for those devoid of nodules, continues to be a pivotal concern. To solve these problems, people have tried to make lung cancer prediction models that are more accurate by using demographic and biological data [3]. But these models have worked differently, and they haven't always been useful. A promising method for creating lung cancer prediction models is to use deep learning (DL) algorithms to look at chest CT scan. Earlier DL-based models have mainly concentrated on the automated identification and assessment of pulmonary nodules to facilitate lung cancer diagnosis. These algorithms are especially good at telling the difference between benign and malignant tumors in people with pulmonary nodules that are bigger than 8 mm in diameter. Nonetheless, the predictive efficacy of DL algorithms in individuals with nodules measuring 8 mm or smaller, or in those devoid of any detectable nodules, remains inadequately defined. Some studies have indicated that deep learning (DL) algorithms can identify significant radiologic characteristics by examining lung parenchyma in CT images, thereby facilitating lung cancer predictions that extend beyond the currently recognizable features of pulmonary nodules [4]. However, research in this domain is still insufficient. This limitation arises partly from the difficulty in acquiring a substantial number of CT scans from high-risk individuals, given the relatively low incidence rate (approximately 1–2%) of lung cancer in populations undergoing screening with LDCT images. A label-free classification can be used to get around the lack of high-risk LDCT scans that are needed to train DL algorithms. This entails utilizing readily accessible training data that simulates high-risk scenarios. For predicting the risk of lung cancer, the label-free method allows the use of chest CT scans from patients who have already been diagnosed with lung cancer instead of LDCT scans from people who are at high risk. This method specifically looks at the lung that is not affected by the tumor, which is thought to have radiologic features similar to those of people who are at high risk. This method aims to get around the problems caused by not having enough data and make the prediction model work better. Consequently, this research seeks to create a deep learning-based label-free lung cancer risk prediction model utilizing alternative data and to validate it in individuals devoid of non-calcified solid pulmonary nodules exceeding 8 mm, employing real-world data.

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Computed tomography (CT) scans can help find suspicious nodules quickly. The scanned pictures of the body's inside show details by showing the front, bottom, and top views, in that order. Compared to regular X-rays, there is more information about bones, soft tissues, and blood vessels. Chest CT scans are not very good at finding early-stage lung cancer because lung nodules look a lot like other structures in the chest, like blood vessels. So, it's very important to make a computer-aided design (CAD) system that can find suspicious nodules. Deep learning is a promising tool for classifying cancer nodules as benign or malignant. It may also cut down on the number of scans needed to make a diagnosis of benign or malignant cancer. Deep learning methods are showing good results for finding both benign and malignant modules [5]. The current, cutting-edge CAD system uses deep learning models to figure out if a lung nodule is suspicious or not. These systems are also used to tell if a nodule is suspicious or not.

Even though CAD systems are very good at finding lung nodules, not many studies have looked at how they fit into the daily work of radiologists. Radiologists use maximum projection intensity (MIP) images to find nodular candidates for further testing in the clinic.

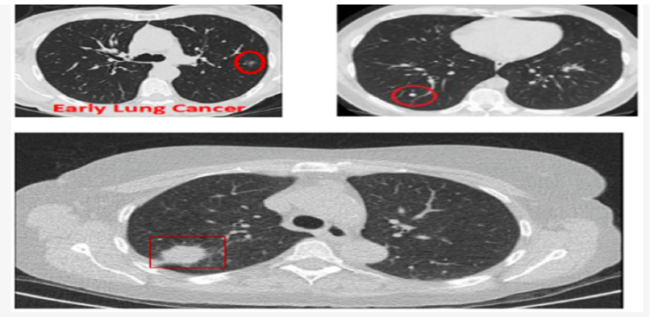

Fig 1. CT Scan Visualization Using Maximum Intensity Projection Technique

Maximum Intensity Projection lets you project 3D voxels with the highest intensity onto the projection plane, which makes it easier to see nodules [9]. MIP images don't depend on thresholds and can keep attenuation data [10], which helps convolutional neural networks (CNN) find lung nodules on their own. Three CT images are shown in Figure 1: The first two show lungs with early-stage cancer; the first one is malignant and the second one is benign. At this point, it's hard to tell the difference between vessel and cancer nodules. The last picture shows cancer in its later stages, when the nodules are bigger and easier to see, but the chances of survival are low.

This paper presents the following key contributions:

- Creates a better-designed and better-image-processing Enhanced Convolutional Neural

Network (CNN) architecture to improve classification performance.

- Uses a multi-class dataset that includes adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cases for a full evaluation.
- Does a comparative study with the latest pre-trained models, such as ConvNeXtSmall, VGG16, ResNet50, InceptionV3, and EfficientNetB0.
- Has a high classification accuracy of 99.09%, which is better than most baseline models and shows that it can generalize well.
- Proves that the proposed model works to quickly, reliably, and accurately find lung cancer for early diagnosis.
- Shows how deep learning-based systems could help doctors make decisions and improve health care outcomes.

II.RELATED WORKS

A lot of research has been done in the last ten years on how to use deep learning models to find lung cancer in its early stages. There are a lot of these studies, which shows how important lung cancer is as a research topic. This section gives an overview of related works, focusing on the different datasets and methods that different researchers have used.

Recent progress in deep learning (DL) has greatly improved the use of computed tomography (CT) scans to find and classify lung cancer.

Lavina Jean Crasta et al.[6] presented an attention-based DenseNet (ATT-DenseNet) model for lung cancer diagnosis utilizing CT and histopathological images. By adding attention mechanisms to the DenseNet architecture, the model was able to focus on the right areas, which made feature extraction and classification more accurate than with other architectures like AlexNet and SqueezeNet.

Sampangi Rama Reddy B.R. et al.[7] created a hybrid DL framework that used 3D-VNet for segmentation and 3D-ResNet for classification in a different study. Using 3D spatial data made it easier to find lung nodules. This led to a high Dice Similarity Coefficient for segmentation and a strong classification performance, as well as fewer false positives.

Anindita Saha et al. [8] put forward a stacked neural network (SNN) model that combines several neural networks to improve the accuracy of classification. The method starts with dividing the lung region into parts, then extracting features and classifying them. It works better than traditional single-network models and has potential for use in medicine.

M. Mohamed Musthafa et al.[9] introduced a machine learning framework utilizing CNNs for multi-stage lung cancer classification. The study utilized preprocessing methods, including normalization and Gaussian filtering, in conjunction with SMOTE to rectify class imbalance, leading to enhanced classification performance at all stages.

C. Venkatesh et al. [10] suggested a CNN-based approach that uses preprocessing methods like median filtering and patch-based processing to make images look better and make the calculations easier. Their method made both diagnosis more accurate and processing faster.

S. K. B. Sangeetha and others [11] made a Multi-Feature Deep Neural Network (MFDNN) that combines imaging, genomic, and clinical data. This multimodal approach greatly increased the accuracy and reliability of diagnoses compared to traditional models. This shows how important data fusion is in medical diagnosis.

Muna Alsallal[12] and others came up with a hybrid model that combines radiomics and deep learning with attention mechanisms in 2025. Combining feature selection methods with ensemble classifiers made classification more accurate, increased the area under the curve (AUC), and increased sensitivity, showing that the method has a lot of potential for use in clinical settings.

Yucheng Liu et al. [13] proposed a 3D deep learning pipeline that uses auto-segmentation and AG-Net to classify lung nodules and estimate fibrosis. Adding microenvironment and fibrosis-related features made the model more accurate and sensitive.

Nasr Y. Gharaibeh et al. [14] introduced an AI-driven diagnostic framework that integrates feature selection techniques with Sparse CNN and a Probabilistic Neural Network (PNN). The model gave good classification results, but the quality and resolution of the images affected how well it worked.

III. PROPOSED METHOD

This chapter shows the study's workflow, which starts with loading data and ends with creating and training predictive models for diagnosing lung cancer. Figure 1 shows the workflow. It talks about how to load data, how to use image enhancement techniques, and how to prepare data for use. Additionally, the detailed construction of predictive models for lung cancer diagnosis is illustrated (see Figure 2).

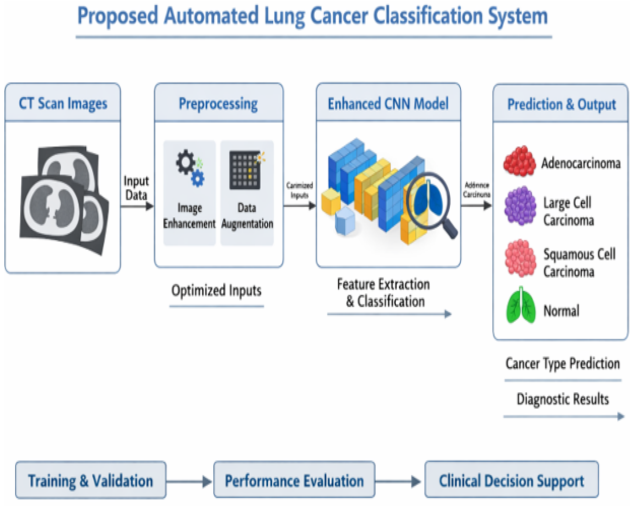

Fig 2. Flow diagram of the proposed Method

A. Dataset Description

The dataset utilized in this research is obtained from Kaggle, a well-known platform that provides a diverse array of datasets for data science applications. The "Chest CT-Scan Images Dataset," put together by researcher Mohammad Hany to help with medical imaging analysis, especially for lung diseases, is one of the parts. There are 1,000 CT scan images in .png and .jpg formats in the dataset. They show different kinds of lung cancer. It is split up into three groups: training, testing, and checking. There are four types of images: Adenocarcinoma, Large Cell Carcinomas, Squamous Cell Carcinomas, and Normal Cells. The dataset also includes pictures of different types of lung cancer and comparisons with pictures of other types of cancer.

Table 1: Chest CT-Scan Images Dataset Description

S.No	**Class Name**	**Number of Images**	**Description**
1	Adenocarcinoma	338	Malignant tumor originating in glandular tissue
2	Large Cell Carcinoma	187	Aggressive cancer with large abnormal cells
3	Squamous Cell Carcinoma	260	Cancer arising from squamous epithelial cells
4	Normal	215	Healthy lung CT scan images
	Total	**1000**	Combined dataset size

B. Image enhancement techniques

CT images often get worse because of things like noise, low contrast, and blurring, which can make them less clear and make it harder to show things accurately. These problems are often linked to low radiation doses and poor enhancement algorithms. There are many ways to improve the quality of CT images by lowering noise, increasing contrast, and making the overall picture clearer. To get the best results, you need to carefully choose and tweak these methods based on the specific features of the images and the level of enhancement you want. Histogram equalization (HE) and contrast-limited adaptive histogram equalization (CLAHE) are two effective medical image enhancement methods that are very important for making images easier to see and giving doctors more information, which helps them make accurate diagnoses (see Figure 3).

Fig. 3. Representative CT Scan of a Non-Lung Cancer Patient

C. Preprocessing techniques

Data augmentation is used to make the training data for lung cancer detection using CT scan images bigger and more varied. This method helps adjust model parameters, make the training and validation sets more similar, and cut down on validation errors, especially when working with small datasets and changes in how images are taken. In this research, various augmentation strategies are utilized:

- Resizing: To make the computer work better and keep things consistent, CT scan images are changed to a fixed size of 224x224 pixels.
- Shear Range: A 20% shear transformation is used to make the model better at finding lesions at different angles.
- Horizontal Flip: The model can see lesions from different angles by flipping the images horizontally.
- Vertical Flip: The images are flipped vertically to make it even easier for the model to find lung lesions.
- Rescale: Pixel values are normalized to a range of 0 to 1, which helps the model learn strong features and lowers the chance of overfitting.

D. Image enhancement techniques

Images can lose quality because of things like noise, low contrast, and blurring, which can make them less clear and make it harder to show them accurately. These problems often happen because of low radiation doses and bad enhancement algorithms. There are many ways to improve the quality of CT images by lowering noise, increasing contrast, and making the overall picture clearer. To get the best results, you need to choose and tweak these methods carefully, taking into account the images' unique features and the level of enhancement you want. Histogram equalization (HE) and contrast-limited adaptive histogram equalization (CLAHE) are two examples of effective medical image enhancement methods. They are very important for making images easier to see and giving doctors more information, which helps them make accurate diagnoses.

The median filter is a way to get rid of noise by replacing strange pixel values with the median value of the surrounding pixels. This works well for getting rid of salt-and-pepper and Gaussian noise. It is a helpful first step for CT scan images because it cuts down on noise and improves image quality, making it easier to analyze them.

Histogram Equalization (HE) is a way to make an image's structures and details more visible by changing the pixel values to make the histogram's dynamic range larger. It works especially well for making CT scans and other low-contrast images look better. When used after noise reduction, HE can greatly improve the overall look of the image, making it better for analysis.

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a more advanced way to improve contrast that splits an image into small areas called tiles. It is often used after Histogram Equalization to make certain parts of an image even better. The CLAHE process has five steps: adjusting the histogram, using a mapping function, and bilinear interpolation to smooth out transitions and get rid of block artifacts. To make sure that the contrast is improved in specific areas, the image is usually split into 64 blocks, each 8x8 pixels in size. Also, CLAHE stops noise from getting louder by limiting contrast in areas that are the same.

Morphological operations are great for improving image details and contrast, especially after CLAHE has been used. Dilation makes features easier to see by making the edges of objects bigger and filling in small spaces. Erosion, on the other hand, gets rid of small things and noise, leaving only the most important parts. Edge detection works better when these operations are combined, which makes images clearer. Morphological operations are often used in medical imaging to make images sharper. They often use gradient-based operators along with morphological filters to find and boost edges.

E. Models' techniques

This section talks about how to use the dataset to make predictive models for diagnosing lung cancer. An Enhanced Convolutional Neural Network (CNN) was developed and executed, incorporating various pre-trained models such as ConvNeXtSmall, VGG16, ResNet50, InceptionV3, and EfficientNetB0. To make sure that all groups were represented fairly, the dataset of 1,000 CT scans was randomly shuffled and split into training, testing, and validation sets of different sizes.

Improved CNN model architecture:

Convolutional Neural Networks (CNNs) are a type of neural network that is very good at classifying images and analyzing visual imagery. They have been very useful in a number of areas, such as recognizing objects, classifying images, and analyzing medical images. This makes them perfect for finding lung cancer in CT scan images.

This study presents a bespoke multi-class lung abnormality classifier utilizing a specialized CNN architecture comprising eight layers:

Layer 1: A convolutional layer with 64 filters (3x3) and ReLU activation that takes in images with the shape (224, 224, 3) and finds features in them. Then, a max-pooling layer (2x2) comes next to make the space smaller.

Layer 2: Another convolutional layer with 32 filters (3x3) and ReLU activation, followed by a max-pooling layer (2x2) to make the data even smaller.

Layer 3: A third convolutional layer with 32 filters (3x3) and ReLU activation, followed by a dropout layer with a rate of 0.4 to stop overfitting.

. Layer 4: Another dropout layer to help reduce overfitting even more.

Layer 5: The output from the previous convolutional layers is turned into a 1D array so that the dense layers can use it.

Layer 6: A dense layer with 256 neurons and ReLU activation finds complicated features. A dropout layer (rate = 0.4) comes next to stop overfitting.

Layer 7: Another dense layer with 128 neurons and ReLU activation that helps get more features.

Layer 8: The last dense layer has 4 neurons and a SoftMax activation function. It gives a probability distribution across the four output classes: Adenocarcinoma, Large Cell Carcinomas, Squamous Cell Carcinomas, and Normal Cells.

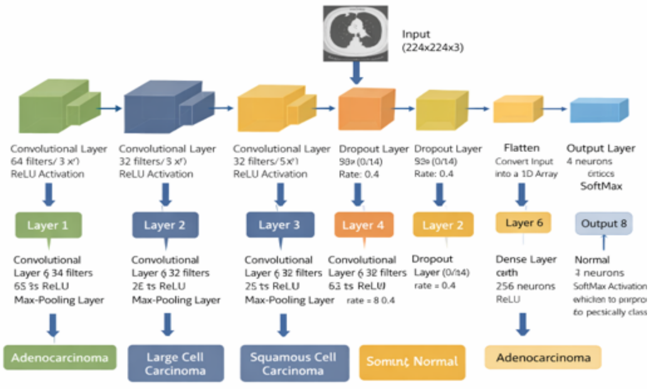

Fig. 4. Proposed CNN Architecture for Lung Cancer Classification from CT Images

ConvNeXtSmall model architecture: Facebook AI Research (FAIR) made ConvNeXt available in 2022 as a new type of convolutional neural network (CNN) architecture. In the past few years, it has become very popular, especially for computer vision tasks like image classification and object detection.

ConvNeXtSmall is a pre-trained version of the ConvNeXt architecture that is meant to work well. There are 50 layers in it, and it uses advanced methods like depth-wise separable convolutions and channel shuffle to improve feature extraction. The model also uses pooling layers to make the spatial dimensions smaller and two fully connected (FC) layers for classification. The output values range from 0 to 4 to show the type and presence of lung cancer. For this study, ConvNeXtSmall was the base model, and it was improved by adding: • Layers that drop out to stop overfitting. • Batch normalization layers to speed up training and make it easier to generalize. • Dense layers with ReLU activation to help with feature extraction and classification. The Adam optimizer and the categorical cross-entropy loss function were used to compile the model, which was then trained for 150 epochs. The improved ConvNeXtSmall model's detailed architecture is shown in Figure. 5.

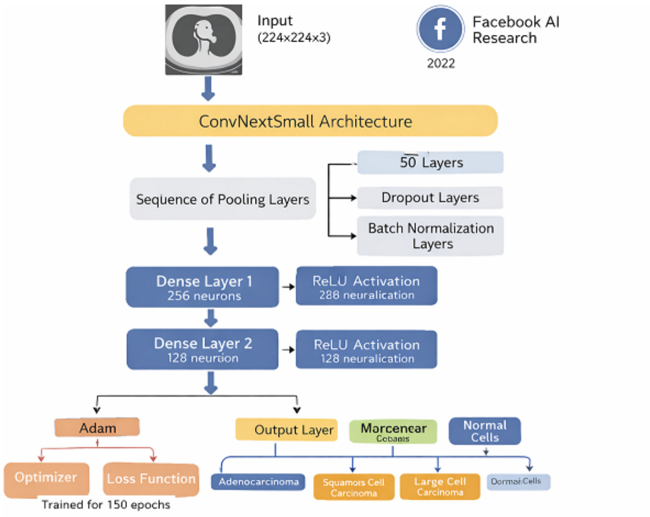

Fig. 5. Proposed ConvNeXtSmall-Based Deep Learning Model for Multi-Class Lung Cancer Classification

ResNet : In 2015, Microsoft Research came up with the Residual Neural Network (ResNet) architecture to fix the problem of vanishing gradients in deep neural networks. ResNet50 is a specific version of this architecture. It has 50 layers and uses residual connections to make it easier for gradients to flow, which makes it easier to train deeper networks.

This study utilized ResNet50 as a pre-trained model for lung cancer prediction because of its strong ability to extract features. The model has:

- Fifty convolutional layers to get features out of the data.
- One pooling layer to make the space smaller and the calculations easier.
- Two fully connected (FC) layers for sorting.

The pooling layer not only cuts down on the number of parameters, but it also stops overfitting. The convolutional layers, on the other hand, find important features in the input images. The FC layers sort the pictures based on the features that were taken out.

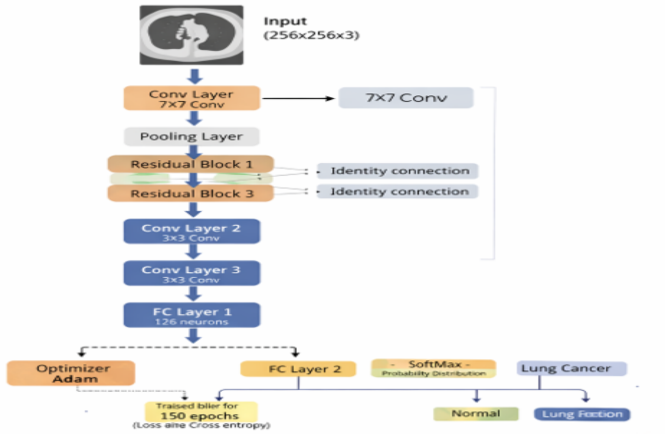

Fig. 6. Architecture and Workflow of the ResNet50 Model for Lung Cancer Prediction

Seventy percent of the lung scans were used for training and thirty percent for evaluation during the first training phase. The Adam optimizer was used to improve the model after it was built with the binary cross-entropy loss function. It went through 150 epochs of training.

The model uses filters on the input images to classify them, and the SoftMax layer gives output values between 0 and 1, which show how likely it is that lung cancer is present. Figure 6 shows how the ResNet50 model in this study is built and how it works.

VGG16: The VGG16 model is made up of 16 trainable weight layers: 13 convolutional layers and 3 fully connected layers. It is known for being simple and effective. To get fine details from input images, it uses 3x3 convolutional filters with a stride of 1 and padding of 1. VGG16 is very good at recognizing images, and it is often used in medical imaging, such as CT scans and chest X-rays. Its deep convolutional network design lets it find complex patterns that could mean lung cancer, like nodules or tumors. This study employed VGG16 as a pre-trained model for predicting lung cancer. The first layers were frozen to keep the low-level features that had already been learned, and the prediction layers were fine-tuned for classification. The model's structure is made up of:

- Five convolutional blocks, each with layers for convolution and pooling.
- Fully connected dense layers that use ReLU to turn on.
- Dropout layers to stop the model from fitting too well.
- A SoftMax layer to guess the chances of each type of cancer.

We used the Adam optimizer and the categorical cross-entropy loss function to split the dataset into 70% for training and 30% for validation. To prevent overfitting, early stopping with a 20-epoch patience was used. We used metrics like accuracy, precision, recall, and loss to see how well the model worked. Figure 7 shows the VGG16 architecture that was used in this study.

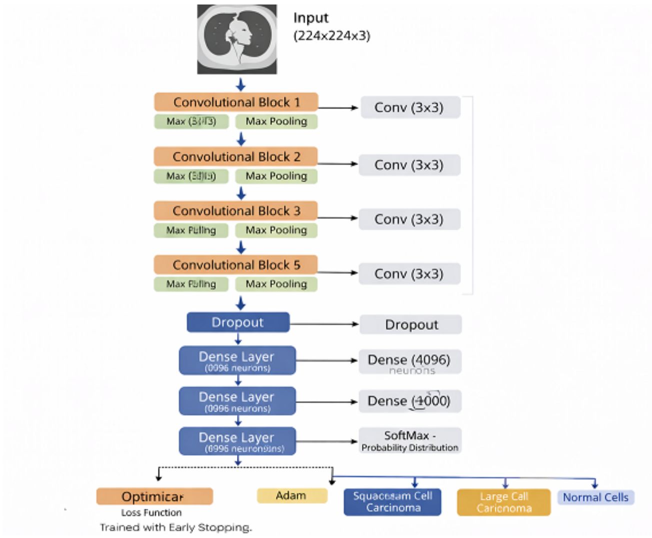

Fig. 7. VGG16-Based Deep Learning Framework for Multi-Class Lung Cancer Classification

EfficientNetB0 model architecture: EfficientNet is a top-performing convolutional neural network (CNN) architecture. It has high accuracy and needs less processing power and fewer parameters than other top models. Its unique scaling method evenly balances the depth, width, and resolution of the network. This makes it a good choice for places with limited computing power, like mobile devices or embedded systems. This study selected EfficientNetB0 as the pre-trained base model for lung cancer classification because of its superior accuracy and computational efficiency in image-based tasks. The following changes were made to make it more robust and fix overfitting:

- GlobalAveragePooling2D Layer: This layer cuts down on the size of the space and pulls out global features
- . • Dropout Layer: During training, it randomly drops nodes to stop overfitting.

We used 70% of the lung CT scan image dataset to train the model and the other 30% to test it. We used the Adam optimizer and the categorical cross-entropy loss function. EfficientNetB0 is made for input images that are 224x224x3 pixels and uses several convolutional layers with a 3x3 receptive field to get the best features. The model went through 100 epochs of training. Figure 8 shows the full structure of the EfficientNetB0 model that was used in this study.

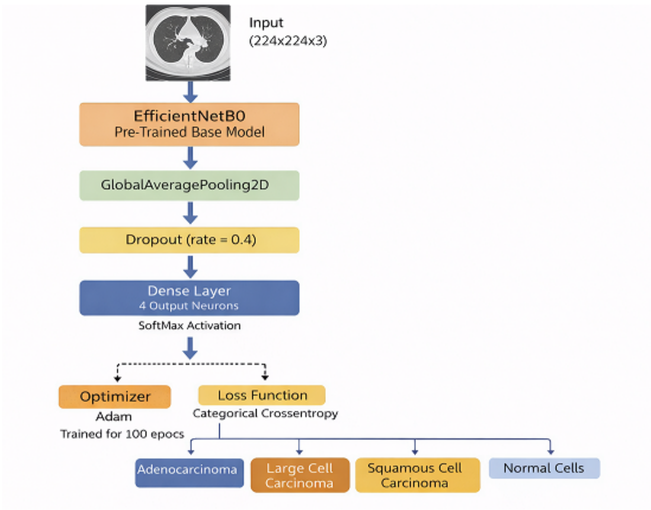

Fig. 8. Pre-trained EfficientNetB0 Model for CT-Based Lung Cancer Detection

InceptionV3 model architecture: InceptionV3 has been an extremely useful tool for computer vision tasks such as object detection, recognition, segmentation, and image captioning. Its strong ability to extract features makes it especially good at interpreting medical images, such as CT scans used to diagnose lung cancer. In this research, InceptionV3 was utilized as a pre-trained framework for predicting lung cancer. To make the most of what it already knew, the first layers were frozen so that the training process could focus on the prediction layers. There are 92 layers in the architecture, and they do things like convolution, pooling, and concatenation. The last layer uses a SoftMax activation function to make a probability score that tells whether a lung is cancerous or normal. The model was trained on 70% of the data and tested on the other 30%. The Adam optimizer and categorical cross-entropy loss function were used for training for 150 epochs. To stop overfitting, early stopping was used. Training was stopped if the validation loss didn't change for 20 epochs in a row. Figure 14 shows how well the InceptionV3 model was able to tell lung cancer from CT scan images.

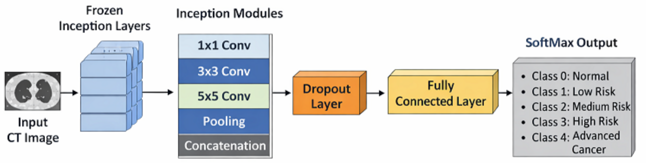

Fig. 9. InceptionV3-Based Deep Learning Model with Feature Extraction and Classification Layers

I. EXPERIMENTAL RESULTS AND ANALYSIS

Two experiments were carried out to identify lung cancer through chest CT scan images in order to meet the study's goals. The initial experiment entailed the creation of an Enhanced Convolutional Neural Network (CNN) from the ground up, emphasizing efficient feature extraction and classification. Five cutting-edge pre-trained models were used in the second experiment: ConvNeXtSmall, VGG16, ResNet50, InceptionV3, and EfficientNetB0. These models were fine-tuned for the specific dataset using transfer learning methods. To make the classification more accurate, these models were given more layers. We used a separate testing dataset to check the model's performance and make sure it was reliable. strength. The experiments were done in Python, which is a simple and flexible language for machine learning. They used libraries like TensorFlow and Keras. The Kaggle platform was used to do the calculations.

. The performance evaluation is predicated on many metrics concerning the selected attributes, as delineated in Table2, the Enhanced CNN model does better than all other architectures on most evaluation metrics. It has the highest accuracy (99.8%), as well as the best precision (99.6%), recall (99.1%), and F1-score (99.3%). This means that it is very good at correctly identifying lung cancer cases while making as few mistakes as possible. The better performance is due to the optimized architecture and the use of regularization methods like dropout, which make the model more generalizable. VGG16 and EfficientNetB0 are two of the pre-trained models that also perform well, with high accuracy and balanced metric values. This makes them good choices for classifying medical images.In contrast, models like ResNet50, ConvNeXt, and InceptionV3 don't work as well. ResNet50 gets a good amount of accuracy, but its lower recall means that it has trouble finding all the positive cases. ConvNeXt gives results that are average and balanced, but they aren't as good as the best models. InceptionV3 has a high recall rate, but a low precision rate, which makes it less reliable and accurate overall. These differences show that the architecture of the model, the ability to extract features, and the right tuning all have a big effect on how well the model classifies. Overall, the results show that the Enhanced CNN model is a better and more reliable way to find lung cancer in CT scan images.

Table 2: Performance Comparison of Various Models for Lung Cancer Diagnosis

Model	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Accuracy (%)**
Enhanced CNN	**99.6**	**99.1**	**99.3**	**99.8**
ConvNeXt	88.2	90.1	89.1	88.5
VGG16	99.3	98.9	99.1	99.2
ResNet50	94.5	80.2	86.8	95.1
InceptionV3	55.4	91.0	69.0	78.3
EfficientNetB0	99.7	99.3	99.5	98.6

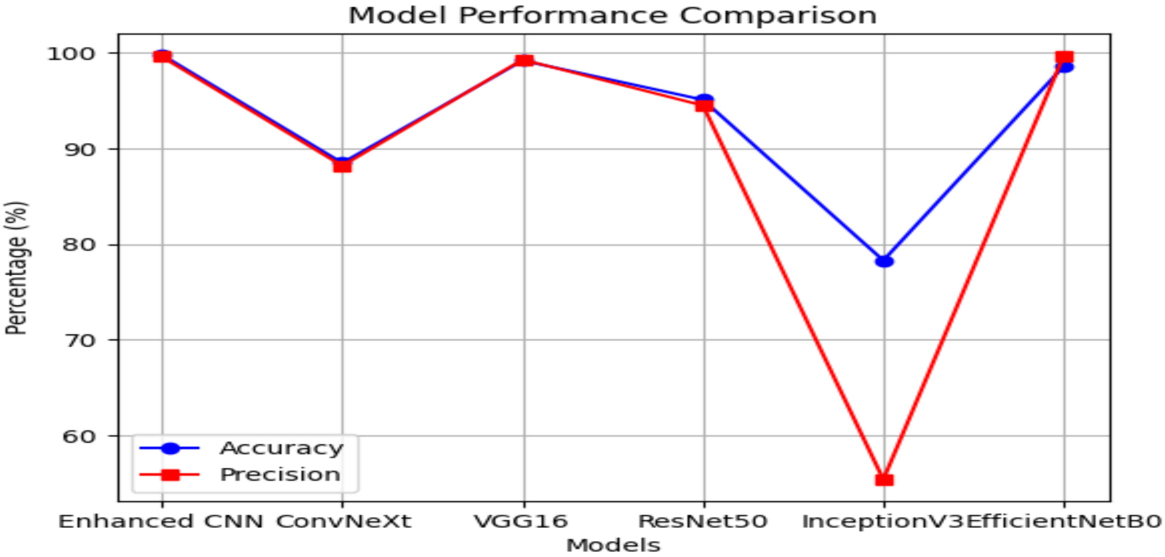

Fig 1. 'Model Performance Comparison'

CONCLUSION

This study introduced an automated lung cancer classification system utilizing CT scan images and deep learning methodologies. We created and tested an Enhanced Convolutional Neural Network (CNN) alongside some well-known pre-trained models, such as ConvNeXt, VGG16, ResNet50, InceptionV3, and EfficientNetB0. Experimental results showed that the proposed Enhanced CNN worked better than other models, with an accuracy of 99.8% and consistently high precision, recall, and F1-score values. These results show that the proposed architecture works well for correctly identifying different types of lung cancer and normal cases.

The comparative analysis shows that model design and optimization strategies are very important for making classification better. The Enhanced CNN did better than pre-trained models because of its custom architecture and regularization methods. The suggested system makes it possible to quickly, reliably, and accurately diagnose, which makes it useful for medical use in the real world. This study shows that deep learning-based methods can help doctors make decisions and find lung cancer earlier, which is important for better treatment outcomes and higher survival rates.

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