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HYBRID DEEP LEARNING MODEL FOR LUNG DISEASE PREDICTION

Sunita Ranadhir Landge[1,] Dr. Lalji Prasad[2]
[1] Research Scholar, Department of Computer Science and Engineering, SAGE University, Indore, MP 453331, India.
[2] Dr. Lalji Prasad, Professor, Computer Science & Engineering, SAGE University, Indore, MP 453331, India.
Email: [1]sunitarlandge@gmail.com, [2]hoi.iac@sageuniversity.in

Abstract

Lung cancer remains the global health concern because millions of people lost their lives in recent years. Traditional diagnostic method depends on manual CT scan interpretation that leads to variation in the diagnosis of lung cancer. This paper proposed advanced deep learning techniques for automated lung cancer prediction using CT scan images. The proposed model uses ResNet50 for the feature extraction and Convolutional Block Attention Module (CBAM) to enhance nodule detection by dynamically weighting critical spatial and channel wise features. This enhanced features then passed to multi-layer perception (MLP) for classification of the images. The proposed hybrid model achieved 98% accuracy for multi classification. The findings validate that hybrid deep learning architectures can significantly enhance accuracy in lung cancer prediction in the medical field.

Keywords: Deep learning (DL), ResNet50, Convolutional Block Attention Module (CBAM), Multi-layer perceptron (MLP)

1. Introduction

The impact of the disease on global health has intensified significantly due to environmental modifications, climate change, lifestyle factors, and other determinants. These changes have substantially elevated population health risks. Lung diseases are a serious global health problem that cause high rates of illness and death worldwide. Cancer is dangerous because it involves the rapid, uncontrolled growth of cells in certain parts of the body. If left unchecked, these abnormal cells can form harmful tumors that leads to life threatening complications [19-20]. Lung cancer is a serious health concern and millions of people die due to lung cancer. Lung cancer requires early diagnosis for better treatment and better outcome of the patient health. CT scan images are used to identify the lung cancer diagnosis by the radiologist. The advanced technologies such as Machine learning (ML),Deep Learning (DL) are used for early diagnosis of the lung cancer.

Deep learning algorithms such as convolutional neural networks (CNN) used for the analysis of the CT scan images. These techniques identify the important pattern from the data and use this pattern for the classification of the image. This technology shows the potential for the early diagnosis of the lung cancer, accurately classify the images and personalized treatment for the patient. The traditional method depends on the radiologist's manual interpretation of the CT scan image. This diagnosis can be bias and limited to individual knowledge. The modern technology such as ML and DL demonstrate the higher predictive accuracy for the lung cancer prediction from the medical images. This increases the reliability and helps the medical practitioners to identify the lung cancer early.

The objectives of this research paper are

- To develop a transfer learning based model using ResNet50 and Convolutional Block Attention Module (CBAM) for accurate lung cancer prediction.
- To enhance the feature extraction from the medical images using CBAM. This will prioritize malignant nodules and suppress irrelevant background features.

- To achieve a higher accuracy than the existing model.

The key contribution of this paper is to develop a novel hybrid architecture using ResNet50, CBAM and multi-layer perceptron (MLP). The CBAM improves the module detection by dynamically weighting important spatial and channel wise features. The proposed system achieved a higher accuracy than the existing model. The proposed model gives a comprehensive multi class classification than the existing models.

2. Literature review

A. N.Patel and others study the DL model for lung disease prediction. They uses deep neural network for the classification of the lung medical images and proves that this technology gives accurate result than medical practitioners. They explore the other techniques that work with images and support computer system for better diagnosis [1]. The authors develop a hybrid model by the combination of lightweight CNN (LPDCNN) and ridge ELM for the classification of the CT scan images. They clear the noise and clean the images using Gaussian blur and CLAHE techniques. This model achieved 98.40% of accuracy [2]. C. Venkatesh and others perform the segmentation of the medical images using Otsu thresholding techniques. They also used cuckoo search optimization for accurate segmentation. After extracting key features from the images they implement CNN model for the classification of the images. This model get the 96.97% of accuracy. This model helps medical practitioners to make accurate predictions and minimize human errors [3]. Jianyu Li and others uses the data from 2115 lung cancer patients. They combine the clinical data with blood based protein biomarkers and used this data for implementing machine learning model. They implemented ML model like random forest (RF), Logistic regression (LR), KNN, adaboost, XGboost and Catboost. Out of these ML model catboost gives higher accuracy of 97% using on given data. These model helps the medical practitioners for personalize the chemotherapy treatments [4]. G. Divya Deepak and others collect the X-ray dataset from the kaggle repository. They used transfer learning pre-trained model such as ResNet50, ResNet 101, DarkNet-53, EfficientNet-bo and DenseNet 201 for model training. They get the higher result by using this transfer learning techniques [5]. Cancer Nexus Synergy (CanNS), a new structure created to enhance early and accurate lung cancer diagnosis, is presented by Durgam R. and colleagues. The suggested method combines three cutting-edge approaches: Devilish Levy Optimization (DevLO) for ideal parameter modification, Xception-LSTM GAN (XLG) CancerNet for improved classification, and Swin-Transformer UNet (SwiNet) for precise tumor segmentation. The system delivers better diagnostic performance with less computing needs by integrating these techniques [6]. Subrato Bharati and others proposed hybrid architecture that combines VGG architectures and CNN model. They perform the data augmentation techniques before train the model. They used NIH chest X-ray dataset from the kaggle repository. The performance of the model is evaluated using precision, recall, F0.5 score and validation accuracy. The model get the 73% of validation accuracy on this hybrid model [8]. Xinrong Lu et al**.** Implemented advance techniques for the lung disease prediction. In the first step they implemented image augmentation. After this they implemented enhanced CNN using the Marine Predator Algorithm (MPA) and optimized the performance. By using this model they improved the model performance and get the higher accuracy [9]. T.I.A. Mohmmad and colleagues proposed a new system that combines Convolutional Neural Networks (CNNs) with smart algorithms. They first build the CNN model to get the pattern from the images. In the next step they fine-tuned CNN model using solution vector approach. They combine CNN model with Earthworm Optimization Algorithm

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(EOSA) to get the better result [10]. The authors uses multi-space reconstruction technique for the accurate lung disease prediction. In this techniques they enhance the quality of the images and after this images are passed through the softmax classifier for the classification of the CT scan images. The accuracy of lung cancer classification increased from 98.9% to 99.5%. In this techniques performance of the system is improved from 10 frames per second to 12 frames per second [11].

Nasser et al. created and tested an artificial neural network (ANN) model for detecting lung cancer using the Survey Lung Cancer dataset. Their method uses clinical symptoms like chronic cough, existing lung conditions, anxiety levels, yellowing of fingers, and allergy history to make predictions. The ANN model showed excellent performance which gives a classification accuracy of 96.67%. This machine learning approach offers an effective way to identify lung cancer early by analyzing various symptom patterns [12]. Sebastian and Dua developed a framework for lung disease classification using medical images. They perform the segmentation using Otsu's thresholding technique. After segmentation they extract the features of the images using Local Binary Pattern (LBP). They implemented CNN model with Improved Moth Flame Optimization (IMFO) which improved the model performance. This hybrid model gives a higher accuracy compared with traditional techniques for lung disease prediction [13]. Nageswaran and others uses CT scan images collected from 70 different patients. In the first stage they apply geometric mean filter to improve image clarity and reduce noise from the images. They perform the segmentation of the images using K-means clustering algorithm that identify regions of interest within the lung images. They implemented classification model using ANN, KNN and RF. The ANN model gives the higher accuracy as compared with the other models [14]. A complex ML-CNN was developed by Yossra Hussain Ali and others to classify lung medical images. They built classifier to discriminate between clinically relevant nodular formations such as malignant and benign nodules and normal lung tissue without nodules. They used Bayesian thresholding and Taylor series approximation to reduce noise and improve image quality. They used particle swarm optimization (PSO) for improving performance of the classification model. This model gives a 98.45% of classification accuracy [15]. Ahmed et al. developed a novel diagnostic approach combining ensemble XGBoost with ResNet101 architecture to distinguish between NSCLC and SCLC. Their methodology incorporated texture features extracted through GLCM analysis. The comparative evaluation revealed significant performance differences between classifiers. The KNN algorithm achieved superior diagnostic accuracy at 97.0%, substantially outperforming SVM which demonstrated 83.0% accuracy in tumor subtype classification [16].

3. Methods and Materials

For this study on lung disease prediction from CT scan images using Deep learning, a comprehensive dataset comprising both healthy and diseased CT scan images were collected form online kaggle repository. A total 1000 MRI images we divided in to the train and test folder. 70% of the images used for train the model, 20% images used to test the model and 10% images used to validate the model. This study uses a medical imaging dataset divided into four categories that includes three types of pathological lung cancers such as Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma along with a control group of normal lung tissue. Adenocarcinoma, type of NSCLC, developed in the glandular cells near the outer area of the lung. It is frequently found in normal person those are not smoke and younger

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individuals. These type of cancer is grow silently and after some tenure it can spread to the other organs of human body. Large Cell Carcinoma, another aggressive form of NSCLC, lacks clear differentiation and consists of large, irregular cells. It can appear anywhere in the lung and progresses quickly. Squamous Cell Carcinoma develops from the squamous cells lining the bronchi. The person who smoke rapidly are a very high chances to fall in to this type of cancer. This typically forms in the central areas of the lung and may create cavities within the tissue. The normal class includes lung images with no signs of cancer, providing a crucial reference point for training and testing classification models. By incorporating these four distinct classes, the dataset allows for a thorough analysis and improved diagnosis of major lung cancer types using deep learning methods.

3.1. Flow of algorithm

Step 1: Data Pre-processing

Input: Chest CT scan medical images having four categories: Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma, and Normal.

Resize each image to fixed dimensions H×W (224 X 224)

Image Normalization: $\frac{I}{255}$

Apply image augmentation

Step 2: Feature Extraction using transfer learning such as ResNet50

Use a pre-trained ResNet-50 model truncated before the classification layer.

Given input image x, the ResNet encoder outputs a high-dimensional feature map

F_{res}=ResNet (x)

Step 3: Attention Refinement Using CBAM

3.1 Channel Attention Module (CAM)

It learns which feature channels (texture, edges) are more important. Uses average and max pooling along spatial dimensions to capture global and local context

$M_c(F)=\sigma(MLP(avgpool(F)+MLP(maxpool(F))$

$F_{cam} = M_c (F_{res}) X F_{res}$

$MLP(x) = W_2. ReLU (W_1. X + b1) + b2$

Where W_1 is reduces the dimensions, W_2 is restore original channel dimension, b1 and b2 are biases and ReLU is the activation function.

3.2 : Spatial Attention Module (SAM)

It learns which spatial regions the model should focus within the image

It applies 2D pooling over channels and a 7×7 convolution

$M_s(F) = \sigma (f^{7x7} (AvgPool (F_{cam}); MaxPool (F_{cam})))$

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The feature map becomes $F_{cbam} = M_s (F) X F_{cam}$

The resulting features are more focused on relevant parts of the lung

Step 4: Global Average Pooling

Converts the feature map $F_{cbam} \in R^{c X H X W}$ to a 1D vector by averaging across spatial dimensions

$$F_{gap} = \frac{1}{H.W} \sum_{i=1}^{H} \sum_{j=1}^{W} \text{Fcbam}(i, j)$$

Step 5: Multi-Layer Perceptron (MLP) Classifier

The 1D feature vector is passed into a fully connected feedforward neural network

Hidden Layer

$H1 = \phi(W1f+b1)$

Where ϕ is a non-linear activation function and W_1, b_1 are learnable weights and biases.

Output Layer

$\bar{Y} = \text{softmax}(W_2 h_1 + b_2)$

Step 6: use categorical cross entropy and minimize the loss using a optimizer like Adam

Step 7: Assess model performance using metric such as accuracy, precision, recall and f1 score.

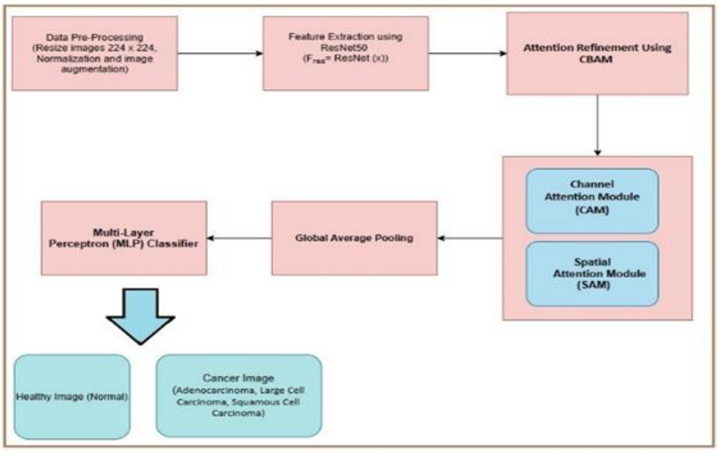

Figure 1: Proposed Model

The figure 1 presents the structural design of a DL based system for classifying lung cancer from CT scan images. The model employs a ResNet50 backbone enhanced with a CBAM, followed by MLP for final classification. In the data pre-processing we resizing the images into 224 x 224 pixels and then perform normalization operation on images. Then we extract the deep spatial features from the images using transfer learning model of ResNet50. To enhance the important extracted features the output of ResNet50 is passed to the CBAM. In the CBAM it uses CAM to identify which features are important and SAM to focuses on where the most

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informative regions are located in the spatial dimensions. Following attention refinement, the feature maps undergo dimensionality reduction by using Global Average Pooling (GAP). This operation mitigates overfitting by consolidating spatial information into a compact representation, significantly lowering parameter count without discarding important features. These features are passed through the MLP classifier which gives output as normal (Healthy) image or abnormal image.

3.2. Convolutional Block Attention Module (CBAM)

The attention module are used to make a model that more focus on the important information of the images rather than the non-useful background information. The CBAM has two sub module such as CAM and SAM.

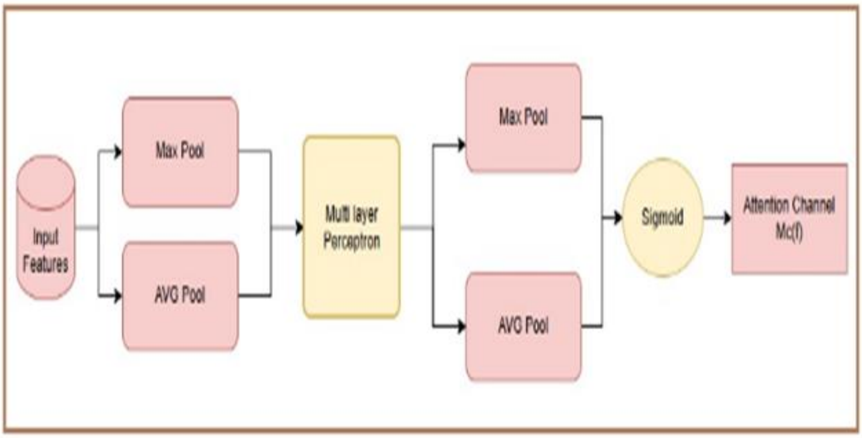

Figure 2: Channel Attention module

The above figure 2 shows the flow of the CAM. In above module input features go through the average pooling and max pooling and then these two descriptors are passed through MLP. After this combine features of max pooling and average pooling are passed through sigmoid activation function and generate channel attention map M_c (f). Then this channel attention map M_c (f) is then multiplied with original feature map F_{res} to obtain F_{cam} as shown in step 3 of the proposed algorithm. The detailed mathematical explanation for this module is shown in the step 3.1 of the channel attention module.

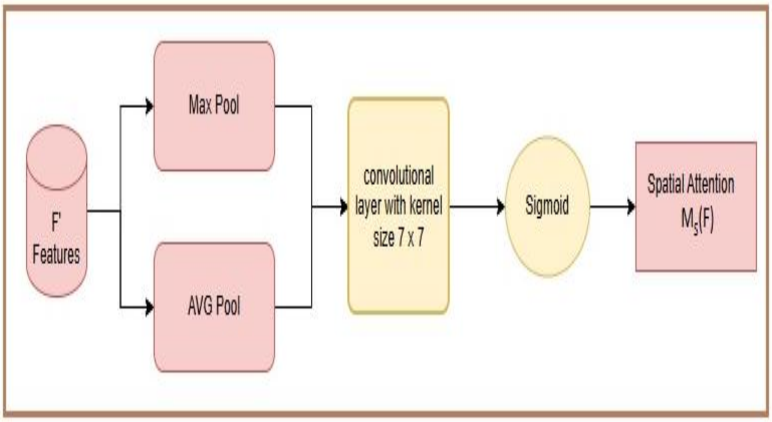

Figure 3: Spatial Attention module

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The above figure 3 shows the flow of the SAM. In above module channel-refined feature map F' is further processed using spatial attention. These features go through the average pooling and max pooling and after these features are concatenated and passed through the convolutional layer with kernel size is 7 x 7. After this sigmoid activation function is applied to this output. The detailed mathematical expression for this module is shown in the step 3.2 of the SAM.

4. Result and Discussion

This chapter introduces a DL framework designed to predict lung diseases by analysing CT scan images. The methodology employs a transfer learning model such as ResNet50 to extract high-level features, which are subsequently processed by multi-layer perceptron algorithms for precise disease classification. The experiments were conducted using Python on the Google colab environment, with T4 GPU acceleration to optimize computational performance.

This chapter assesses the performance of transfer learning methodologies such as ResNet50 to facilitate robust feature extraction from medical images. Subsequently, the derived features are analyzed using a CBAM to highlight discriminative features and localize salient spatial regions within the images that are important for accurate feature representation.

Figure 4: accuracy graph over epoch

The above figure 4 demonstrate the performance of the proposed model which uses ResNet50 for feature extraction, CBAM for enhancing silent features and MLP for classification of the images. The accuracy is evaluated over 25 epoch. The above graph shows that model is rapidly increasing both training and validation accuracy during initial epoch. This indicate that model learns important features from the medical CT scan images. The training accuracy of the model is consistently improved and stabilizing to above 98%. The validation accuracy of the model is cross above 90% after 5th epoch and this indicate that model is generalizes well on unseen data.

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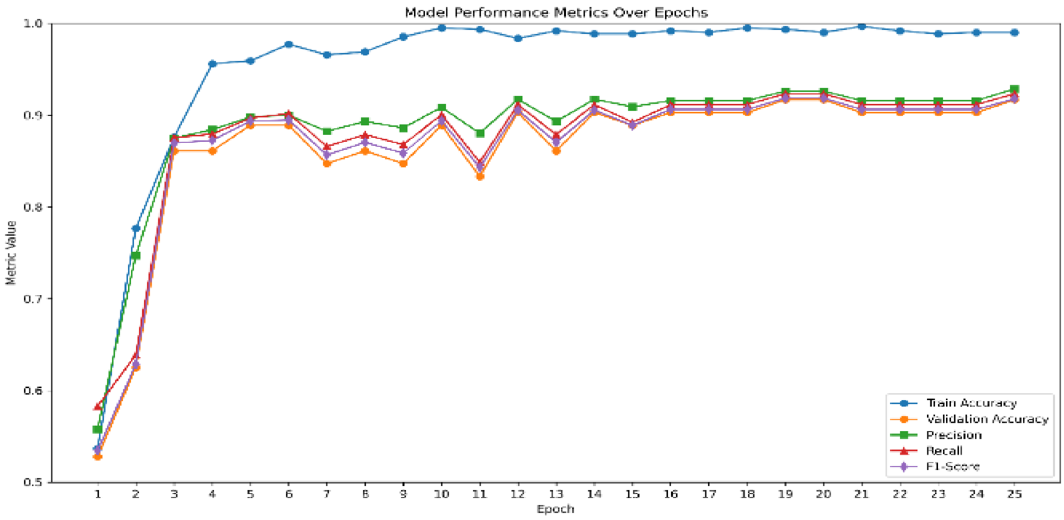

Figure 5: Model Performance Metrics over epoch

The above Figure 5 shows the trend of multiple performance metrics such as train accuracy, validation accuracy, precision, recall and f1 score across 25 training epoch for the proposed model. The performance trends depicted in the graph demonstrate substantial improvement across all evaluation metrics during the initial training epochs, indicating efficient model learning and stable convergence. Precision, Recall, and F1-Score stabilize at approximately 90%, underscoring the classifiers ability to maintain equilibrium between sensitivity and specificity. The high precision indicates that most of the positively predicted cases are correct, while high recall ensures that most actual positive cases are successfully detected. The F1-Score as a harmonic mean of precision and recall, further validates the robustness and reliability of the model.

Table 01: Hyperparameter Table

Hyper parameter	**Value**	**Feature**
learning_rate	1e-4	Controls the step size during weight update.
optimizer	Adam	Adaptive optimizer combining momentum and RMSprop.
loss_function	Cross Entropy Loss	Measures classification error between predicted and true class labels.
Scheduler	Step LR	Reduces the learning rate by a factor such as gamma
step_size	7	Number of epochs before reducing the learning rate
Gamma	0.1	Multiplicative factor for learning rate decay
num_epochs	25	Number of full passes through the training data.
model architecture	Hybrid ResNet CBAM	Combines ResNet50 + CBAM + MLP.
evaluation metrics	accuracy, precision, recall, F1-score	Used to monitor and assess model performance.
Device	GPU	Hardware for the training of dataset

The above table 01 outlines the critical hyper parameter configurations employed in the proposed architecture. The model utilizes an initial learning rate of 0.0001 to maintain steady convergence, coupled with the Adam optimization algorithm for adaptive parameter updates. For multi-class prediction tasks, the Cross-Entropy loss function serves as the optimization objective. Training incorporates a step-based learning rate scheduler that reduces the rate by a factor of 0.1 after every 7 epochs, facilitating improved optimization. The complete training consists of 25 epochs, accelerated through GPU computation. Model efficacy is quantified through standard classification metrics including accuracy, precision, recall, and the F1 measure, providing a performance assessment.

The existing systems use basic CNN model such as LPDCNN [2] and VGG based model [8]. It uses pre-trained model for the ResNet50, DenseNet-201 without adaptive refinement [5]. Our proposed system uses ResNet50 for feature extraction and CBAM for the extracting spatial and channel wise features. Proposed system enhances important features while suppressing irrelevant regions which improve model classification. Our proposed model gives higher accuracy nearly 98% for training and 90% for validation as compared to the existing model like VDSNet which gives nearly 73% accuracy [8]. The existing system uses lightweight models such as LPDCNN that achieve higher accuracy but lack in model generalization. Our proposed model indicating validation accuracy over 90% after 5 epoch which indicating strong epoch. The existing system require high computational cost for U-Net and hybrid PSO-CNN [15]. The proposed system uses optimized GPU and no-manual pre-processing is needed.

5. Conclusion

This study introduces an innovative deep learning framework for lung cancer detection through CT scan medical image analysis. The proposed methodology combines a pre-trained ResNet50 with CBAM and MLP to overcome diagnostic challenges associated with conventional radiological examination. Experimental results demonstrate exceptional classification performance, attaining 98% accuracy in distinguishing between multiple lung cancer subtypes and healthy tissue. These findings substantiate the clinical viability of attention enhanced deep neural networks for improving both the precision and throughput of oncological image interpretation in pulmonary medicine.

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