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Deep Learning-based Lung Cancer Classification of CT Images using Augmented Convolutional Neural Networks

Bushara A. R.* and Vinod Kumar R. S.+

* *Research Scholar, Department of ECE, Noorul Islam Center for Higher Education, Tamil Nadu, India*
+ *Professor, Department of ECE, Noorul Islam Center for Higher Education, Tamil Nadu, India.*

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Abstract

Lung cancer is worldwide the second death cancer, both in prevalence and lethality, both for women and men. The applicability of machine learning and pattern classification in lung cancer detection and classification is proposed. Pattern classification algorithms classify the input data into different classes underlying the characteristic features in the input. Early identification of lung cancer using pattern recognition can save lives by analyzing the significant number of Computed Tomography (CT) images. Convolutional Neural Networks (CNN) recently achieved remarkable results in various applications including Lung cancer detection in Deep Learning. The deployment of augmentation to improve the accuracy of a Convolutional Neural Network has been proposed. Data augmentation is utilized to find suitable training samples from existing training sets by employing various transformations such as scaling, rotation, and contrast modification. The Lung Imaging Database Consortium-Image Database Resource Initiative (LIDC-IDRI) database is utilized to assess the networks. The proposed work showed an overall accuracy of 95% Precision, recall, and F1 score for benign test data are 0.93, 0.96, and 0.95 respectively, and 0.96, 0.93, and 0.95 for malignant test data. The proposed system has impressive results when compared to other state-of-the-art approaches.

Key Words: Lung Cancer Detection, Deep Learning, Convolutional Neural Networks, Computed Tomography, Data Augmentation.

1 Introduction

Lung cancer is the second most lethal cancer in terms of prevalence and first in terms of mortality for women and men all around the world. As per the report, new cases and sexual fatalities estimated in the United States, 2021 [1], 12% (119,100) of all incidents in men (116,660) and 13% (116,660) among women are lung cancer. However, lung cancer is the major cause of mortality in both men (22%, 69410) and women (22%, 62470), and patients with the early-stage disease have a survival rate of five years is 59%, whereas advanced cancer people have a survival rate of 5 years of fewer than 6% [1]. There are two forms of lung cancer, Non-Small Cell Lung Cancer (NSCLC) and Small Cell Lung Cancer (SCLC). Adenocarcinoma (ADC) and Squamous Cell Carcinoma (SqCC) are sub types of NSCLC, which account for 80 to 85 percent of lung cancer cases [2]. The

Correspondence to: <bushara.phd@gmail.com>

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goal of early detection of lung cancer is required because symptoms only arise in advanced stages, and early detection can cure or facilitate treatment, saving many lives [3]. Medical imaging is a critical tool for detecting and diagnosing cancer early on. Medical imaging has been used for early cancer detection, evaluation, and follow-up during procedures, as is well known [4]. Manual interpretation of a large number of medical images can be tedious and time-consuming, as well as prone to human bias and error. Model classification algorithms classify the input data into different classes as the basis for the characteristic features of the input. Early identification of lung cancer using pattern recognition can save lives by analyzing large numbers of CT images. As a result, starting in the early 1980s, Computer-Aided Diagnostic (CAD) systems were implemented to help doctors interpret medical images more efficiently [5].

Image processing methods have been used in the past to diagnose lung cancer [6] & [7]. Machine learning techniques aid in the diagnosis and classification of lung nodules by evaluating CT images obtained using artificial intelligence algorithms. Preprocessing, segmentation, object detection, feature extraction, and classification processes are used by such systems to investigate images. The main step in implementing machine learning is feature extraction, which can be done in a CAD framework. [[8]-[13]] focused on various methods for extracting features and classification for lung cancer. Here Haralick features, Gabor features, Local Binary Pattern [8], Scale Invariant Feature Transform, Histogram Oriented Gradient features [9], and minimum Redundancy Maximum Relevance [10] have been adopted as feature selection, and Support Vector Machine, k Nearest Neighbor [11], Rule-Based Classifier, Naive Bayes Classifier [12], Artificial Neural Network [10], Feed-Forward Neural Network [13] are proposed for classification. A CAD system has been developed that focuses on a new heuristic search technique for optimizing the Back Propagation Neural Network in distinguishing nodules from non-nodules [14]. The Fuzzy C-mean clustering [15] and other active contour models [16] can be used to segment lung nodules in CT data. These approaches primarily concentrate on creating good feature descriptors, many of which must be hand-crafted and machine learning techniques. These feature extraction-based methods have several flaws, like a lower level of accuracy. This flaw prevents CAD systems from improving their performance any further.

Several researchers have proposed the use of Artificial Intelligence (AI), especially Deep Learning to overcome these limitations and improve results. Deep learning has the advantage of being able to perform end-to-end detection in CAD systems by learning the most critical features during training and can learn features from observed data without the need for hand-engineered features[17]. The Convolution Neural Network (CNN), Deep Neural Network (DNN), and Stacked Auto Encoder (SAE) [18] are the three major deep learning structures for cancer detection. CNN yielded the best performance as compared to DNN and SAE [19]. Convolutional Neural Networks[20] (CNNs, or ConvNets) are a type of multi-layer neural network that can distinguish visual patterns from pixel images with little or no preprocessing. AlexNet [21], VGG 16 [22], Inception (GoogleNet) [23], ResNet [24], and DenseNet [25] are the CNN architectures that have been employed to investigate for lung nodule detection and classification.

The objective of this article is to develop a deep learning architecture for early lung cancer diagnosis and classification using Augmented CNN. Presently overfitting is an incredibly common issue in the image classification. Eventhough overfitting learned the features of the training set extremely well, it is unable to generalize and accurately predict the output when given data that differs slightly from the exact data. The purpose of the proposed research work is to alleviate the overfitting problem that occurs in CNN architecture by employing data augmentation. Augmentation is a technique for expanding the size of data sets to improve accuracy. The outcome of the research is a CNN-based lung cancer detection and classification method with better performance matrices in terms of accuracy.

The following is a breakdown of the paper's structure. The second section contains a relation between CNN and the various state-of-the-art as CNN architectures. The third section discusses the architectures of the developed augmented CNN along with model parameters and the performance matrices used. The experimental results and discussion are elaborated in the fourth section. The paper ends with the conclusion in the last section.

2 Background

Early detection is crucial in the diagnosis of cancer and can improve long-term survival chances. As a result, research into lung cancer detection and categorization has become a major area in recent years. Several studies have used CNNs for lung cancer classification and detection to develop a reliable method. Some of them are briefed in this section. S. Bhatia et al. [26] proposed an approach to lung cancer detection and feature extraction using deep residual networks. Features are extracted using UNet and ResNet models which are fed into multiple classifiers. In addition, XGBoost and Random Forest, together with the individual forecasts, predict the probability of malignancy in a CT scan. The accuracy obtained by the research work is 84% on LIDC-IRDI datasets. M. Kriegsmann et al. [27] examined different lung cancer types associated with the University Clinic Heidelberg with assistance from the Tissue Biobank of the National Center of Tumor Disorders has compiled, scanned, annotated, and image patches taken from the Institute of Pathology Archive for 30 skeletal muscles as control. They investigated different configurations of CNN architectures for classification and claimed that the optimized InceptionV3 CNN architecture obtained the greatest classification accuracy. A new approach for automatic pulmonary nodule detection from volumetric CT scans that use 3D CNN to reduce false positives was proposed by Q. Dou et al. [28].

The LUNA16 Challenge, a dataset that was analyzed, achieved the highest Competition Performance Metric 0.827 score in the challenge. On histopathology slides, N. Coudray et al. [29] used convolutional neural networks such as Google's Inception v3 to diagnose lung cancer and classify lung cancer into Adenocarcinoma and squamous cell carcinoma, which are the most common subtypes. The performance of this method is comparable to that of pathologists, with an average area under the curve of 0.97. To address the noise in an image and the morphology of nodules, W. J. Sori et al. [30] developed a "denoising first" two-path CNN and tested it on the Kaggle Data Science Bowl 2017 challenge. This model combines denoising and detection in an end-to-end approach, resulting in improved lung cancer detection. P. M. Shakeel et al. [31] proposed an improved profuse clustering technique and the Deep Learning with Instantaneously Trained Neural Networks method was used to evaluate lung CT images to predict lung cancer. The CT images of the lungs were taken from the Cancer Imaging Archive dataset. The improvised 3D AlexNet with lightweight architecture was used by E. S. Neal Joshua et al [32] to investigate lung nodule classification, and this network made use of the multiview network technique in its entirety. They performed binary classification on CT images from the LUNA 16 database.

Heuvelm et al. [33] suggested deep learning to identify malignant nodules and retrospectively validating the Lung Cancer Prediction CNN on an isolated dataset of indeterminate nodules in a European multicentre, with benign nodules excluded, but preserving a high sensitivity to lung cancer. Masud et al. [34] presented a new supervised learning approach based on deep learning that identifies five different types of tissues found in lung and colon lesions by observing their corresponding pathological data sets using LC25000 datasets to train and validate the method. For image classification, two types of domain transformations were used to extract four sets of features. The resulting features were combined to create a group of features containing both kinds of information. T. L. Chaunzwa et al. [35] suggested a radiomic approach to the prediction of NSCLC non-invasive CT tumor histology. They trained and validated Convolutional Neural Network data on 311 patients undergoing surgery at the Massachusetts General Hospital, prioritizing the two most common forms of histology, named ADC and SqCC.

The complete system for detecting and diagnosing lung cancer has been introduced by O. Ozdemir et al. [36] using low-dose CT scans, model uncertainty characterized by Monte Carlo dropout, and deep ensembles. This has demonstrated that calculating model uncertainty allows the system to deliver calibrated classification chances for diagnostic treatments based on utility or risk reliability. The background of this research paper reveals that many methods for detecting and classifying lung cancer have been developed, with CNN being the most popular. The authors discovered that a CNN system with data augmentation effectively mitigates overfitting and improves accuracy.

3 Materials and Methods

The developed Augmented Convolutional Neural Network for classification consists of three main stages namely i) CT Lung image Data Acquisition ii) Augmentation and iii) Classification using CNN. As shown in Figure 1, the workflow begins with the gathering of a primary dataset containing two picture classes: one for benign CT images that will not become cancer and the other for malignant which is cancerous CT images. The data set was expanded using typical augmentation procedures to increase its size in the research's following step. In the next phase, the dataset was utilized to train the model. After training, the model was put to the test for the performance of the proposed method in terms of cancer identification and classification. The chosen test dataset of LIDC-IDRI was used to access the performance measures of augmented CNN.

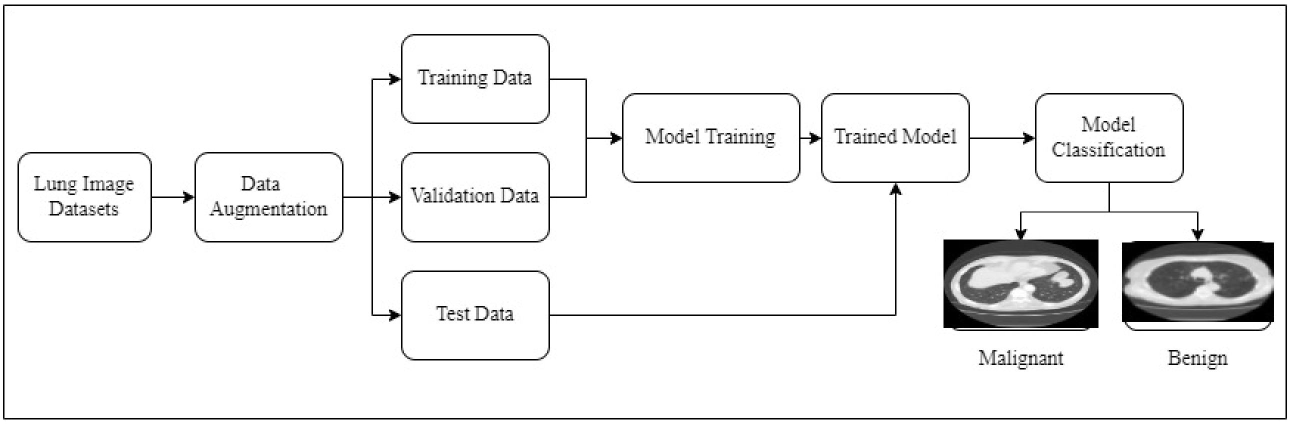


Figure 1: Workflow of the Proposed System

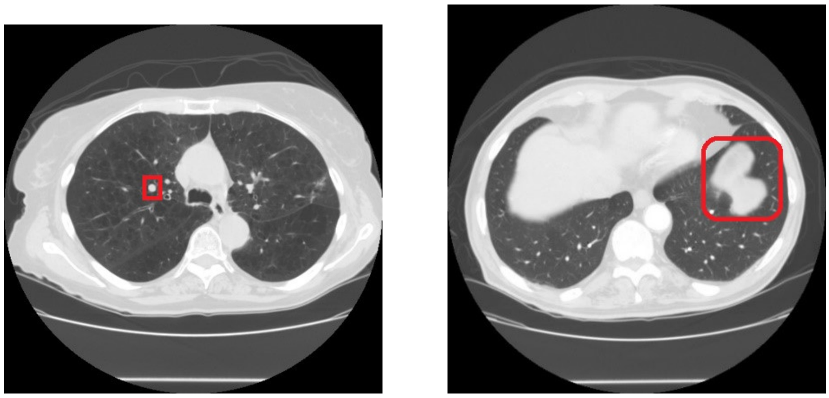
3.1 CT Lung Image Data Acquisition

The images of the lungs were collected from the Lung Imaging Database Consortium-Image Database Resource Initiative (LIDC-IDRI) [37]. DICOM format is used for all images, with slices ranging from 1.25 to 2.5 mm in size, and pixels as small as 512×512 in size [38]. The thickness in LIDC-IDRI ranges from 0.48mm to 0.72mm [39]. Several parameters, including lesion size, tumor type, and location, have been recorded by four radiologists. All images in the LIDC datasets were classified as non-nodules, nodules less than 3 mm in diameter, or nodules greater than 3 mm in diameter. For the proposed investigation, a benign nodule was defined as one that was less than 3 cm in diameter, and a malignant nodule was defined as one that was greater than 3 cm in diameter. Figure 2 depicts the sample images of benign and malignant lungs on Computed Tomography (CT).

The first step in building and training a convolutional neural network that can classify lung images as benign or malignant is to obtain and prepare the datasets for training the model. The images are copied into the train, test, and valid directories, which contain benign and malignant directories, after the datasets from the LIDC - IDRI data sets are downloaded. This experiment used 2066 images, of which 80% (1653) of them were used for training and 20% (413) for testing. Validation data were taken from 20% (330) of the training data.

3.2 Augmentation

In deep learning, data augmentation is used to find adequate training samples from existing training sets using various transformations such as scaling, rotation, and contrast modification to improve the proposed method's accuracy[22]. Figure 3 depicts some of the augmented images used in the proposed work. Data Augmentation allows for the creation of many more images with the same output, and as data size artificially extends, CNN becomes more robust and can avoid overfitting problems. The rescale, shearing, zooming, and horizontal flip



(a) Benign nodule (b) Malignant nodule

Figure 2: Lung Images (Courtesy: LIDC- IDRI Dataset)

are performed for each image. This work employs an image data generator to accomplish the task. Here image manipulation is accomplished through rescaling to normalize the image, and the scaling is accomplished by the value 1/255. Shearing is another method that is used to produce excellent results with values ranging from 0 to 1, and in the proposed work, 0.2 is selected for shearing. The zoom parameter was set to 0.2, which resulted in a random zoom range of 0% to 20%. The image will be randomly flipped if the Horizontal flip is set to true.

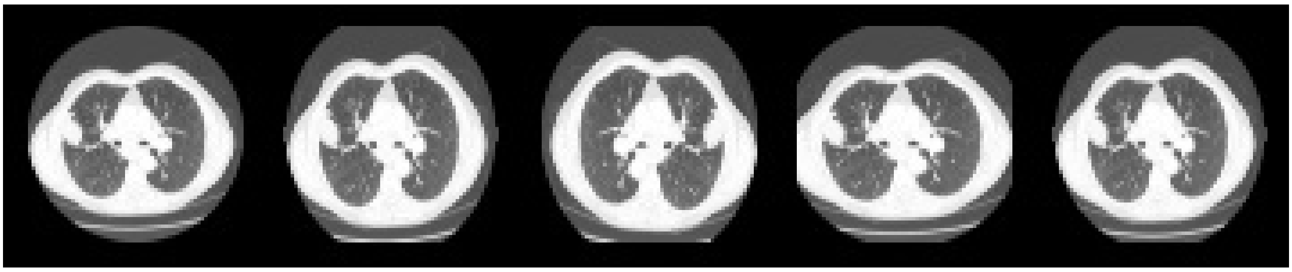


Figure 3: A subset of new images after the image augmentation technique

3.3 Convolutional Neural Networks (CNN)

The CNN is the central component of computer vision, learning feature maps of a given image and categorizing it by detecting a variety of abstract features ranging from simple to complex. The network then uses these discriminatory features to predict the correct image category [38]. The basic functionalities are normalization, convolution, activation, pooling, fully connected layers, and classifier as shown in Figure 4.

Pre-Processing: The data must be pre-processed before being passed to the networks to make the CT scans homogenous. The general pre-processing steps are mean subtraction [28], normalization [39], and local contrast normalization. The pixel values of each image are converted to Hounsfield Units (HU), a radiodensity calculation. Since tumors grow on lung tissue, segmentation can be used to mask the bone, outside air, and other noise-causing substances, leaving only lung tissue details for the classifier [40]. The image data was subjected to isotropic rescaling using a linear interpolator and density normalization using mean subtraction and linear transformation to reduce distortion [35]. Figure 5 depicts Hounsfield Units (HU) of a Lung Image. Air, lipids, blood, and soft tissues are all found in the lungs. Figure 5 shows that HU units range from -1000 to 300, with a normal value of -700 to -600 for the lung. As a preprocessing phase, the proposed approach used normalization and data augmentation.

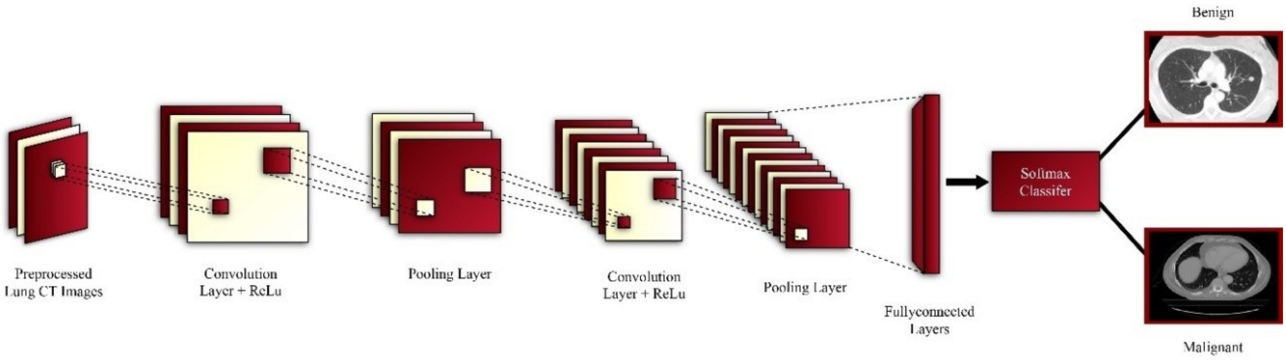


Figure 4: Basic CNN architecture for Lung Cancer Detection

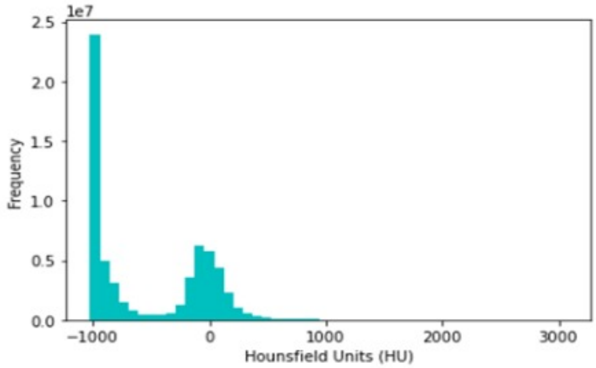


Figure 5: Hounsfield Units (HU) of a Lung Image

Convolution: The convolutional layer, which is at the heart of the network, performs either the convolution of the input image if it is at the input layer or the convolution of the feature map available from previous layers if it is at any other layers[41]. The convolution operation is performed using Equation (1)

$$y(m,n) = \sum_{p=-A}^{A} \sum_{q=-A}^{A} w(p,q)x(m-p,n-q) \tag{1}$$

where y(m,n) represents the image sample at (m,n) in the output image, the convolution kernel coefficients that will be employed as weights are represented by w. All the convolutional layers in the proposed system had a kernel size of w. In the proposed work a 3×3 kernel is chosen. The coefficients are randomly initialized and they get adjusted automatically during iteration for obtaining maximum accuracy.

The pooling layer: The pooling layer uses a downsampling method to achieve spatial invariance following a convolution layer. In Max pooling, the maximum values are used wherein in average pooling the average values are used.

Activation Function: Every node in the convolutional layer has a non-linear activation function. Non-linear mapping's power is that it can map non-linear, non-separable data points into linearly separable data points, which aids classification.

Fully Connected: One or more completely connected layers are included on the output side, and these fully connected layers aim to classify the input data. The fully connected layer works with a flattened input that connects each information to each neuron.

Softmax Classifier: Softmax is the last activation function of the neural network, converting a number vector into a probability vector and assigning decimal probabilities to each class in a multiple-class problem [42]. The proposed CNN model architecture included 14 layers, consisting of 5 Two dimensional Convolutional layers, 3 fully connected layers, ReLu and Sigmoid as Activation Function, 5 Max-pooling layers, and 1 Flattening layer. Table 1 shows the parameters employed in the experimentation.

Parameter	**Value**
Input Image Dimension	(500, 500, 3)
Kernel Size	3×3
Filter	32, 64
Max Pooling	2×2
Activation Functions	ReLU, Sigmoid
Optimizer	Adam
Epochs	20
Loss Function	Binary Cross-Entropy

Table 1: Parameters used in the proposed Augmented CNN

3.4 Performance Matrices Used

The trained models with different metrics assess the performance of the proposed approach. The quality of learning algorithms is usually evaluated by evaluating the performance of testing data. Different evaluation matrices such as Accuracy, Specificity, Sensitivity / Recall [43], Precision, F1-score, and Area under the ROC Curve (AUC) [44] can be used to evaluate the performance of the proposed work and are defined as follows.

Accuracy is the ratio of correct predictions to total predictions and is expressed in Equation (2)

$$Accuracy = (TP + TN)/(TP + FP + TN + FN) \tag{2}$$

where TP = True Positive, FP = False Positive, TN = True Negative, and FN = False Negative

Specificity is the ratio of true negatives to total negatives in the data and is expressed in Equation (3)

$$Specificity = TN/(TN + FP) \tag{3}$$

Sensitivity / Recall is defined as the ratio of true positives to total positives in the data and is expressed in Equation (4)

$$Sensitivity/Recall = TP/(TP + FN) \tag{4}$$

Precision is the ratio of true positives to total predicted positives and is expressed in Equation (5)

$$Precision = TP/(TP + FP) \tag{5}$$

F1-score depends on the precision and recall value, which is expressed in Equation (6)

$$F1 - score = 2 * (Precision * Recall)/(Precision + Recall) \tag{6}$$

The range of area within the ROC curve (AUC) is 0.5 to 1. Higher AUC values mean that the device is performing well. It is expressed in Equation (7).

$$AUC = \int_0^1 ROC(t)dt \tag{7}$$

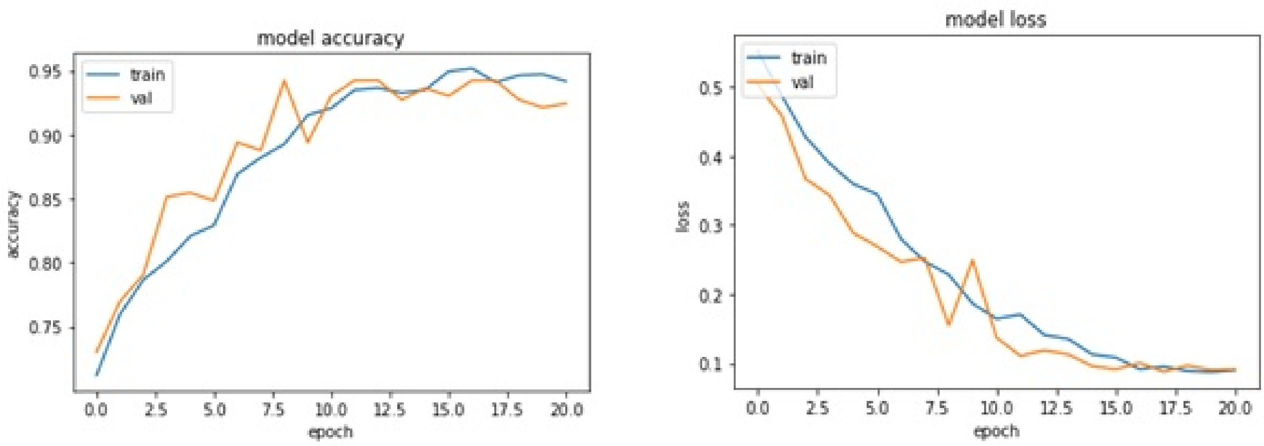
4 Experimental Results and Discussion

The experimentation was carried out using Python libraries such as Keras and TensorFlow on a GPU NVIDIA-MX450, an i5-1135G7 processor, with Windows as the operating system. Lung CT images were collected from the LIDC - IDRI dataset and partitioned into 80:20 for learning and testing during the analysis procedure. The training dataset included 1653 Lung CT images, while the testing dataset comprised 413 CT images. The proposed method allocated a training subset of 1653 CT images with a 20% validation size. Of the 1653 CT images, 1323 images train the method and 330 images evaluate the method for each epoch. Table 2 shows that utilizing these performance parameters with default values is preferred. In addition, the batch size was extended to 16. As a result, the CNN model performed admirably, with an accuracy of 95%. In addition to accuracy, the other critical metrics examined in this work to measure the overall performance include precision, recall, and F1 score. They are summarized in Table 2.

	Recall	Precision	F1-score	Test Data
Benign	0.96	0.93	0.95	203
Malignant	0.93	0.96	0.95	210
Overall Accuracy	0.95			413

Table 2: Performance of the proposed Augmented CNN with LIDC – IDRI dataset

Figure 6 a) and 6 b) depict the accuracy and loss curves between training and validation respectively. Validation accuracy is maximum at epoch 8 and minimum loss at epoch 20. From this, it is known that accuracy increases with an increase in the epoch, and the loss decreases with an increase in the epoch.



(a) Accuracy Curve (b) Loss Curve

Figure 6: Training Progress for Augmented CNN

Figure 7 depicts the confusion matrix of the proposed work. Of the 210 malignant data, 196 are expected to be positive (TP) and 14 are anticipated to be negative (FN), and out of 203 benign data sets, 195 are expected to be positive (TN) and 8 as negative (FP). Benign test data has a recall, precision, and F1 score of 0.96, 0.93, and 0.95, while malignant test data has a recall, precision, and F1 score of 0.93, 0.96, and 0.95 respectively.

The performance of the proposed work is compared with the existing works and the values of the performance are given in Table 3. In the classification of lung cancer, all the existing CAD systems in Table 3 have reasonable accuracy values. While classifying a CAD system, it is pivotal to take into account the small nodule size and the size of the datasets. The proposed work produced better results since a smaller data dimension of

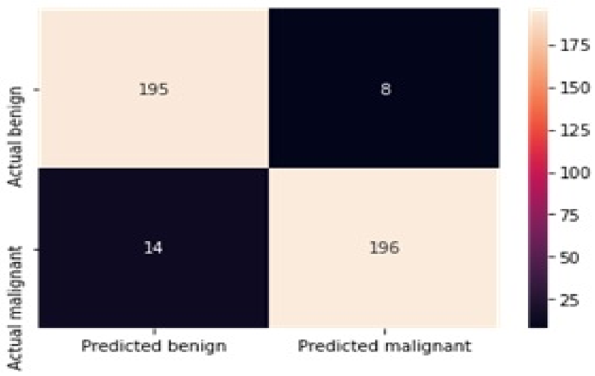


Figure 7: Confusion Matrix of the proposed Augmented CNN

Methods	**Architecture**	**Accuracy** (%)
S. Bhatia et al.[26]	UNet and ResNet	84
Q. Z. Song et al. [19]	CNN	84.15
S. R. Jena et al. [45]	KNG-CNN	87.3
Proposed Work	**Data Augmented CNN**	**95**

Table 3: Performance of the proposed Augmented CNN with LIDC – IDRI dataset

500 $\times$ 500 pixels, a batch size of 16, and a kernel size of 3 $\times$ 3 are used in the experimentation. With these modifications in the architecture and along with the use of augmentation techniques, thereby increasing the size of the datasets, the proposed work provides relatively high accuracy when compared with the existing work.

5 Conclusion

This paper work was carried out to demonstrate the efficacy and accuracy of lung cancer diagnosis using CNN trained on Lung CT image datasets. Because of the promising results of deep learning methods, the LIDC-IDRI dataset was used in this work to detect lung cancer using CT scan images. In this paper, the most current research on deep learning techniques to early detect and diagnose lung cancer using CT images was analyzed. Data augmentation techniques were used to preprocess the data set. Following augmentation, the dataset was trained and tested using a CNN method, and the performance parameters were identified. An accuracy of 95% is obtained in the proposed work.

The Capsule Neural Network (CapsNet), a new deep learning architecture can be deployed to overcome CNN challenges, and it can be trained with a smaller number of data. Through more research on the topic, the computer vision community hopes to construct robust machine vision algorithms by using the triumphs and flaws of CapsNets. So future research would concentrate on CapsNet which could improve the performance measures using a limited number of datasets.

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