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An Approach of AlexNet CNN Algorithm Model for Lung Cancer Detection and Classification

Kavitha B C[1], Dr. Naveen K B[2]
[1]Electronics & Communication Engineering,
Research Scholar, BGSIT, Adichunchanagiri University, B G Nagara, India, 571448
e-mail: kavithabc@bgsit.ac.in
[2]Electronics & Communication Engineering,
Professor,BGSIT, Adichunchanagiri University, B G Nagara, India, 571448
e-mail: naveenkb@bgsit.ac.in

Abstract— As a reliable tool for identifying and classifying different illnesses, including lung cancer, deep learning has grown significantly in popularity. It is crucial to quickly and accurately diagnose lung cancer because different treatment options depend on the type and stage of the disease. Deep learning algorithms (DLA) are used to speed up the critical process of lung cancer detection and lessen the burden on medical professionals. In this study, the feasibility of employing deep learning algorithms for the early detection of lung cancer is explored, using data from the Lung Imaging Database Consortium (LIDC) database. The study introduces the VGG-16 and AlexNet models specifically to identify the presence of cancer in lung images. The AlexNet model is chosen for additional classification tasks based on performance. The suggested technique displays considerable increases in both the prediction and classification accuracy of cancer. The results from using the AlexNet model show the highest levels of accuracy, with classification accuracy of 97.76% and prediction accuracy of 97.02%, both verified using a 5-fold cross-validation method. Moreover, when classifying the forms of cancer, the model gets a remarkable area under the curve (AUC) value of 1 for the Adenocarcinoma class, signaling extraordinary performance. Notably, the proposed model achieves an accuracy exceeding 90% across all classes.

Keywords- Alex Net,Convolutional neural network, Cross validation, Deep Learning, Lung Cancer, Lung Image Database Consortium, VGG 16, Robust.

I. INTRODUCTION

Lung cancer stands as the foremost contributor to deaths related to cancer. It can start anywhere in the respiratory system, which includes the windpipe and lungs. When particular lung cell types proliferate and spread out of control, the illness develops [1]. Lung cancer diagnosis rates are often higher in those who have a history of chest discomfort and lung diseases like emphysema. There is now widespread recognition that, heavy tobacco use, including smoking cigarettes and beedis, increases the chance of developing lung cancer among Indian citizens. However, the fact that lower frequency of smoking among Indian women implies the presence of additional risk factors at play [2]. Uncontrollable proliferation of aberrant cells occurs in a body with a cancer. Normal cells in a human body grow, divide, and die in an orderly manner. The cancer's malignant cells do not die; instead, they grow and disperse rapidly. It leads to unusual accumulation cells that spread uncontrollably [3]. Cancer is the heading sign of death worldwide. As per the world Health Organization (WHO), reports 7,4 million deaths (13% of all deaths) due to carcinoma in 2015. Deaths causes by this disease will reach 13.1 million by 2030 [4]. The main Institute of the United States projects that by 2017, there will be 222,500 new instances of lung cancer identified and 155,870 lung cancer fatalities. Lung cancer (1.8 million diagnoses) is the most frequent kind of cancer worldwide[5]. Exposure to radon gas, workplace toxins, and air pollution are additional concerns. Primary lung cancers start inside the lung, whereas secondary lung cancers start within lung further spread to other organs. Tumor size and cancer spread are two characteristics that affect the disease's stage [6]. Early-stage lung cancer is often simpler to treat than later-stage lung cancer, which is marked by metastasis. To avoid the condition, it is important to comprehend all of its risk factors. In their study, Award M et al. used lung cancer datasets from the authenticated site and Data World [7]. Using k-fold cross-validation, the datasets are initially split into training and test sets. The required classification models are then built utilizing the training data and classification techniques. The authors assess the performance of these models' construction and evaluation using test and training data to get their results [8]. Deep Learning is a cutting-edge machine learning area which claims inspiration from brain anatomy [8]. Deep learning (DL) algorithms have the potential to outperform conventional methods through the utilization of layered, intricate, and hierarchical data representations. While many continue to link deep learning to elementary image classification tasks like identifying handwritten numbers in images , this viewpoint has undergone a transformation in the last decade [9].

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DL is most effectively used in several research to tackle even more difficult categorization challenges. In the Image Net LSVRC-2012 competition, the top-scoring team used DL which classify 1.2 million high-resolution photos into 1000 categories with a 15.3% error rate [10]. Furthermore, the use of DL systems aided teams in winning the ICPR 2012 Contest on Mitosis Detection and the MICCAI 2013 Grand Challenge. Convolution neural networks (CNNs) have designed recent times been effectively used in digital breast tomo synthesis to identify clustered micro calcifications [11]. Understanding the menace factors can greatly aid in preventing sickness. To increase survival rates, DL techniques are mainly accomplished for early diagnosis. It is possible to lessen radiologists' workloads and minimize diagnostic mistakes related to human factors by implementing these strategies to improve radiologists' diagnostic procedures [12].

II. RELATED WORK

A CAD-System was created by Ahmed Shaffie et al., [13] to identify lung cancer nodules. The MGRF model, spherical harmonics shape analysis, and auto encoders are few among the methods used in a unique framework for combining the visual and form characteristics of lung nodules towards precise identification of lung cancer. Finally, the installation of the CAD system produced results with a Sensitivity of around 90.48%, Specificity of 95.95%, and Accuracy of 93.97%.

The image processing system created by K. Gopiel et al., [14] employing advanced transformation tools, feature extraction process and suitable classifier for separation of nodule to state Malignant and Benign, has detected malignant nodule from CT-Lung Cancer picture. Recognition and categorization of lung tumor areas had a 92.46% accuracy rate.

An improved lung cancer classification method was created by Sheenam Rattan et al. [15] for the identification and categorization of lung cancer nodules in chest-CT images. Here, authors states that, a primary lung cancer stage was taken into consideration. The features of the lung nodules were recovered after the nodules were segmented using Watershed Transformations and the BAT technique. The ANNE categorization method is employed. The collected findings showed that nodules are successfully identified by reaching Accuracy of 98.5% and Specificity of 91%.

A Computer-Aided-Diagnosis (CAD) system was created by C. Lakshmi Priya et al. In this system, the picture was improved using a median filter, and the contrast was increased by adjusting the image's intensity using histogram equalization. By employing morphological operations, the lung lobes were extracted, and any leftover tissue on the margins was cut off using a thresholding method [16]. GCLM was utilized for feature extraction, and an ANN-back propagation network was employed to classify lung pattern data.

A CAD-System was created by May Phu Paing et al. [17] to identify lung cancer nodules. Here, the pixels were converted into Hounsfield Units (HU) because of the picture pre-processing. SVM classifier, margin, and shape features are designed to categorize the margin characteristics of 3D pulmonary nodules. Evidence has shown that this combination achieves an accuracy rate of approximately 90.9%.

By analyzing lung CT images, Xiang-Xia Li et al. [18] conceived and created an Automatic CAD-System for timely identification of disease. Using methods such as anisotropic nonlinear diffusion filter, enhanced random walker, intensity, texture, and geometrical feature, in thoracic computed tomography, it was feasible to automatically distinguish between tumor and non-tumor pulmonary nodules using RF classifier. From the statistics, nodules are efficiently diagnosed when it is analysed with an accuracy, sensitivity, and specificity of 90%, 92%, and 83%, respectively.

Using Watershed segmentation and SVM classifier has been proposed by authors. To separate nodule and predict it as Malignant and Benign the image processing system has developed by Pooja R. Katreet et al. [19] which is able to detect malignant nodule from CT-Lung cancer picture. Initially, salt and pepper noise is removed from photos using the Median filter during pre-processing. The laterhigh boost filter is utilized to reduce picture noise.

Taolin Jin et al. [20] developed a CAD-System to automatically recognize lung cancer nodules. In this system, the pre-processing of the image included the conversion of pixels into Hounsfield Units (HU). After feature extraction, the process involves classification using the 3D Convolutional Neural Network (CNN) classifier, termed "Learning Deep Spatial Lung Features," specifically designed for early cancer detection. This classifier demonstrates an accuracy of approximately 87.5%.

The paper's structure is as follows: Section I of the introduction provides an overview of related work. Section II outlines the proposed methods for this study. Section III highlights the system methodology. Section VI discusses the Results and Discussion, focusing on the Alex Net architecture. The conclusion of the proposed work is presented in next section

III. SYETEM METHODOLOGY

. Lung cancer must be detected early and accurately for successful treatment planning since it contributes significantly to cancer-related death. The Alex Net model illustrates the potential of deep learning techniques to outperform conventional methods by taking cues from the complicated structure of the brain. With its deep, hierarchical architecture, the Alex Net model shows promise for deciphering intricate patterns found in medical images and aiding in the early identification of lung cancer. This cutting-edge use of ML aims to get better the competence of diagnosis but also has the potential to lighten the load on medical staff, thereby improving patient outcomes. Convolution layers are developed to figure out the features, and fully connected layers combine the retrieved features to mimic the outputs. Figure 1 displays features of a sample picture throughout of the model using convolution layers.

Using the Alex Net model for forecasting has a lot of potential to improve medical diagnostics, especially for certain kinds of predictions. Getting the cancer kind right in the case of lung cancer is crucial for creating effective treatment regimens. The complex architecture of the human brain served as inspiration for the Alex Net model, which exhibits the ability to decipher complex patterns within medical pictures and enable accurate categorization of various forms of lung cancer.

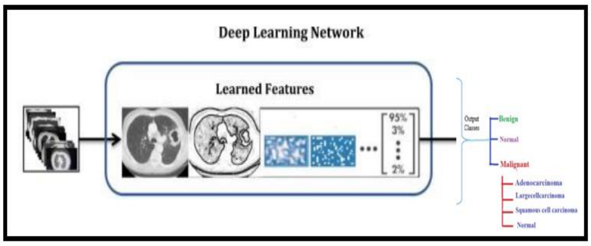

Figure 1. Proposed model to detect lung cancer

The Alex Net model has the capacity to recognize tiny differences that identify diverse types of data by utilizing its hierarchical features and deep design. The following measures are used to assess the model's overall performance.

$$\text{Precision} = \frac{True\ Possitive}{True\ Possitive + False\ Possitive} \quad (1)$$

$$\text{Recall} = \frac{True\ Possitive}{True\ Possitive + False\ Negative} \quad (2)$$

$$\text{F1} = 2\,X\left(\frac{Precision\ X\ Recall}{Precision + Recall}\right) \quad (3)$$

$$\text{mAP} = \left(\frac{1}{N}\right)\sum_{i=1}^{N} APi \quad (4)$$

Here, N is the total number of queries, and APi is the average precision of query. The above said statistical parameter values are range from 0 to 1. The model performs better when the value is higher.

IV. RESULTS AND DISCUSSIONS

Utilizing the LIDC-IDRI Dataset with a Modified Alex Net Architecture for Lung Cancer Detection and Sub typing. The Alex Net-inspired deep learning model we've devised successfully detects lung cancer and classifies its subtypes. Success of the model demonstrates its potential to support early lung cancer diagnosis and individualized treatment approaches. The dataset comprises 500 lung CT images, with 350 images used for training and 150 for testing, all standardized to a resolution of 227x227 pixels.

The cancer detection framework yielded remarkable results, showcasing an impressive overall accuracy of 97.02% after undergoing 25 epochs of training. This signifies the model's ability to effectively distinguish between cancerous and non-cancerous lung CT images. During the training phase, the validation accuracy exhibited an encouraging 97.55% as in table 1, further affirming the model's robustness and generalizability.

Moving on to the equally important task of subtype prediction, the performance remained consistently strong. The model's ability to distinguish between various forms of lung cancer based on visual features present in the CT scans was demonstrated by its accuracy of 97.76% for subtype categorization as in table 2. This enhanced accuracy is reflected in the validation phase as well, where the model attained an impressive accuracy of 99.38%, demonstrating its adaptability to new data.

Further, Alex net model is continued to classify the stages of lung cancer into its subtype. Figure 2 depicts performance Alex net model towards identification of a particular stage of the malignancy. The mAP values are calculated over recall values and are tabulated in table 2 for a specific epoch and iteration. Batch loss and validation loss are also very minimum for this model. The training process for subtype prediction was equally noteworthy, with an accuracy of 98.99%, highlighting the model's capacity to grasp the nuances of different lung cancer subtypes from the provided dataset. The validation accuracy of 98.99% echoes this capability, accentuating the model's reliability and potential application in clinical settings. These outcomes collectively underscore the significance of the proposed Alex Net architecture in both cancer detection and subtype prediction tasks. The consistently high accuracies achieved during training and validation phases lend credence to the model's precision and potential to contribute significantly to early lung cancer diagnosis and individualized treatment pathways.

Moreover, the assessment of deep learning performance metrics is conducted and presented in Table 2 and Table 3 for each specific class across the 5-fold validation. Figure 3 and Table 5 collectively illustrate that the receiver operating characteristic curve's area under the curve (ROC-AUC) value for the proposed model is approximately 0.99. This high value signifies the model's exceptional ability to effectively distinguish between the mentioned classes.

Under consideration of the four classes, the proposed model's accuracy and AUC have been estimated for the LIDC-IDRI dataset. The model's overall performance has been assessed here using 5-fold cross validation, and the findings are displayed in Tables 2 and 3. The accuracy of the fourth fold, which was 99.4%, was the highest, and all classes had AUC values that were almost greater than 0.99.

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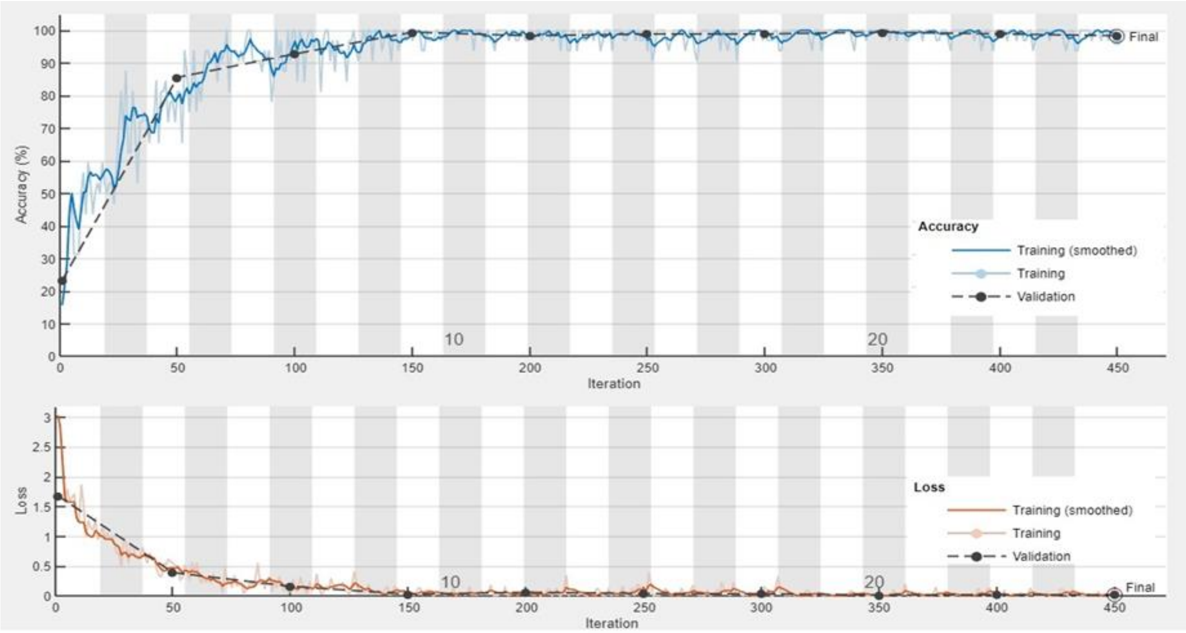

Figure 2. mAP curve for lung cancer analysis

Table 1 Accuracy of Alex Net Model for cancer detection and Sub Type Classification

	Alex-Net Model -Cancer Detection			**Alex-Net Model -Sub Type Classification**		
Fold	**Accuracy%**	**mAP**		**Accuracy%**	**mAP**	
		Training %	**Validation** %		**Training** %	**Validation** %
1	97.8	96.88	98.91	97.8	100	99.44
2	96.7	97	97.83	96.1	100	98.89
3	96	100	96.74	98.3	100	98.33
4	98.9	97	98.91	99.4	100	100
5	95.7	96.88	97.83	97.2	96.88	98.33
Average	**97.02**	**97.55**	**98.04**	**97.76**	**99.38**	**98.99**

Table 2. AUC for each class with 5-Fold Cross validation for Sub Type Classification

Fold\Class	**Adenocarcinoma**	**Large cell carcinoma**	**Squamous cell carcinoma**	**Normal**
1	0.9979	0.9991	0.9918	1
2	0.9897	0.9973	0.9938	1
3	0.9988	0.9904	0.9971	1
4	1	0.9965	0.9972	1
5	0.9983	0.9996	0.9991	1
Average	**0.9969**	**0.9965**	**0.9958**	**1**

Table 3 Alex Net Model Metrics for each class.

Class	**AUC**	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Adenocarcinoma	1	0.9833	0.9833	0.9833	0.9888
Large cell carcinoma	0.9965	1	0.9705	0.9850	0.9944
Squamous cell carcinoma	0.9972	0.9574	0.9782	0.9677	0.9833
Normal	1	1	1	1	1

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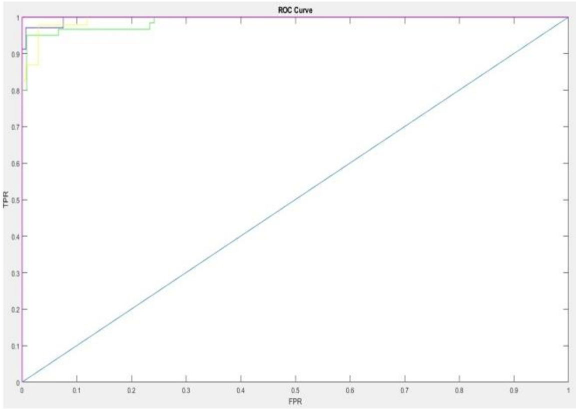

Figure 3 ROC Curve

V. CONCLUSSIONS

This research used the LIDC-IDRI respiratory dataset to develop a CT classification method based on the VGG-16 model for predicting lung cancer. Deep learning networks VGG-16 and Alex Net are used in the proposed study to identify cancer. When it comes to identifying cancer, both networks perform well, but Alex Net's performance is moderately superior to that of existing models across the board. The Alex Net model has a ROC-AUC value more than 0.99, indicating that it can distinguish between malignancy classifications with greater accuracy and lower false-positive rates than other models. The Alex Net model's overall performance is 97.02% for cancer detection and 97.76% for cancer categorization. According to the developers, the suggested diagnostic system would provide top doctors an accurate and rapid diagnosis.

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