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Lung Cancer Detection Using Convolutional Neural Networks from Computed Tomography Images

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Abstract: Lung cancer disease is one of the most common illnesses that should be treated in its early stages to increase the likelihood that patients will survive. A Convolutional Neural Network (CNN) approach is suggested in this study to identify aberrant lung tissue growth. The CNN algorithm uses the textural properties of the images to distinguish between normal and cancerous images. It improves the accuracy of cancer cell detection. An automated tool using VGG-16 techniques is required. Databases have been created for several viewpoints of the CT scanning system, such as axial, coronal, and sagittal, and the suggested algorithm is trained using lung images from both healthy and malignant individuals. The region proposal and classifier network use the VGG-16 architecture as their base layer. The classification of the algorithm and detection accuracy is 98%. A quantitative analysis of the suggested network is carried out based on results from the computation of the confusion matrix and the classification accuracy. By assisting in the early detection of lung cancer and increasing the precision of medical diagnoses, the suggested CNN algorithm can ultimately help to save priceless human lives.

Keywords: Lung Cancer, Machine Learning, CNN, Deep Learning, VGG-16, X-ray, CT scan Images.

1. Introduction

Lung cancer is one of the main causes of cancer-related fatalities globally. Early detection is critical in improving lung cancer patients' prognosis and survival rates. In recent years, machine learning techniques have been increasingly used in medical research to improve the accuracy of cancer detection. The possibility of using machine learning algorithms to identify lung cancer using medical imaging data, such as computed tomography (CT) scans, is examined in this research. The study analyzes the performance of various machine learning models and compares them to traditional methods used for lung cancer detection. The findings of this study could significantly affect the creation of more precise and efficient methods for lung cancer diagnosis, leading to earlier detection and improved patient outcomes.

In a different study, Zhang et al. [1] suggested a VGG-16-based method for identifying and categorizing lung nodules. It is used to identify and categorize lung nodules from CT scans, and the suggested method uses a 3D deep convolutional neural network (CNN). For training and testing the VGG-16 model, the scientists used a sizable dataset of more than 4,000 CT scans of the lungs containing lung nodules. With an AUC of 0.94 for nodule detection and an accuracy of 93.2% for nodule classification, the suggested technique was highly accurate in identifying and categorizing lung nodules.

In order to identify and categorize lung nodules, Chen et al. [2] suggested a hybrid approach combining VGG-16 and conventional machine learning. The suggested method used a 3D CNN for nodule identification and feature extraction, then a support vector machine (SVM) classifier for nodule classification.

For training and testing the hybrid model, the authors used a sizable dataset of more than 1,000 CT scans of lung nodules. With an AUC of 0.96 for nodule detection and an accuracy of 91.6% for nodule classification, the suggested approach successfully identified and classified lung nodules with high accuracy. One of the simplest and most prevalent issues in the discipline of medical imaging is the accurate detection of cancer from the CT scan images. It is difficult to detect whether the cancer is present in the images or not. The most common type of lung tumor, non-small cell lung cancer (NSCLC), is one of the true diseases that cause death in humans. Diagnosing and treating persons with lung cancer greatly benefit from computer-aided diagnosis and survival prediction of NSCLC. Lung cancer still has a terrible prognosis, with a five-year survival rate of only about 10% in many countries. The majority (84%) of cases of lung cancer are NSCLC. Two primary NSCLC kinds are squamous cell carcinoma, which accounts for 25 to 30%, and adenocarcinoma, which comprises bronchi alveolar carcinoma, which is about 40%.

In our study include an intricate approach for improving healthcare. It concentrates on using deep learning to help VGGA-16 algorithms quickly and effectively while utilizing accurate disease identification. By eliminating diagnostic delays, this initiative encourages cost-effective healthcare and highlights the vital requirement for accuracy in disease detection, particularly in the case of widespread illnesses like lung cancer. My study focuses on increasing diagnostic precision to reduce false positives and facilitate early interventions, which are essential for optimal treatment outcomes. Our research is ultimately focused on the possibility of early illness diagnosis to save lives, particularly in situations like lung cancer where prompt discovery can greatly impact patient outcomes.

2. Literature Review

In this research paper [3], the author used VGG-16 techniques for lungs cancer detection. The proposed technique uses the concept of SVM with VGG-16. The proposed technique detects the pathological and physiological changes in the images. Firstly, the model gets trained by measuring the image profile values, then the model gets tested using CT scan images. The research uses 888 images of cancer and non-cancer patients available on LIDC/IDR database 94% accuracy is achieved in the research. It is found out from the research that the VGG-16 techniques are effective for lung cancer detection.

In the lung lobe, pulmonary nodule patterns [4], typically appear as a distinctive texture. Before implementing categorization schemes, most CAD systems carry out feature extraction operations within the chosen region of concern. Depending on the input scale of the classifier (VOIs), the defined area of concern is frequently created as either local regions of interest (ROIs) or volumes of interest. The diagnosis of pulmonary nodules is accomplished by swiping a fixed-scale classifier over ROIs or VOIs [5]. Early studies showed the effectiveness of discriminative characteristics, such as first-order thresholding methods for grey levels.

Gray-level and CT density histograms are used to find lung nodules over ROIs or VOIs. Recently [6], developed CAD systems gave a new perspective on feature extractions in higher dimensional areas since more sophisticated texture descriptions were applied. These techniques made use of the local binary pattern (LBP), the histogram of gradient (HOG), and the scale-invariant feature transform (SIFT).

The feature extraction methods that were previously described relied on hand-crafted features that lacked adaptability when new nodule patterns arose. More recent studies [7] supported using unsupervised feature learning to produce promising outcomes with new data. These qualities made it possible for the systems to find customized features irrespective of input features. These systems use convolution with principal component analysis (PCA) and k-means and pooling procedures as well as [8], the artificial neural network's unsupervised learning strategy, the restricted Boltzmann machine (RBM), (ANN).

Regardless of the retrieved characteristics, it is essential to pick a classifier that best converts the features into the right classes [9]. K-nearest neighbours (kNN) and support vector machines (SVM) and linear discriminant (LD) are three common feature-based classifiers used for pulmonary nodule diagnosis [10]. Additionally, because the output vector is changed from the input dimension to a one-dimensional space, ANN can classify data and extract learned features.

This research uses unsupervised learning systems with linear SVM to successfully detect cancer in pulmonary nodules [11]. The earlier work [12] has shown to perform better than other manually created features tested within the LUNGx database, including LBP on the three orthogonal planes (axial, coronal, and sagittal CT images), LBP with random sampling and the CT density histogram. The entire pulmonary nodule and its surrounding tissues are contained within VOIs, a 3-D cubic bounding box used for feature extraction. As part of feature extraction, the following stages were used: PCA over VOIs.

In [13], Many 3-D convolution kernels pool operations over convolved feature sets. The collected VOIs were first transformed using PCA into 3-D kernels with highly linked unsupervised characteristics. The kernels produced in the previous step were applied to 3-D convolution operations in the following stage. On the second stage, higher-level characteristics were extracted. The final phase used max-pooling and min-pooling to maintain the extracted features while minimizing the number of features that were convolved into one-dimensional feature vectors. The linear SVM was trained using the one-dimensional feature vectors, and the classifier's performance in identifying malignant lung nodules was assessed [14]. ConvNets significantly beat the state-of-the-art in the field of computer vision by utilizing supervised learning algorithms, which led to success in large-scale picture classification [15]. ConvNets can learn and extract a large number of high-level discriminative features from the raw image at various levels of abstraction, transforming representations of input features, while entire networks are trained in a supervised manner to perform classification due to the similar output structure of ANNs. This solves the issue with unsupervised learning techniques. Because predictions made using low-level features were never correct, and the entire classification process should be carried out automatically [16], ConvNet's characteristics are well suited to pulmonary nodule identification.

In [17], ConvNets classification of lung disease patterns has been overcome in early attempts. A shallow ConvNet was created to classify patch-based images of interstitial lung disease (ILD). The ILD patterns contain substantial texture variation within the same class, similar to pulmonary nodule patterns, but distinct classes frequently have similar visual representations. The earlier ConvNet revealed [18], the extraordinary potential of extraction on high-level discriminative features in comparisons of LBP, SIFT, and RBM [19].

However, the prior ConvNet, which only used a single convolutional layer, did not adequately capture high-level characteristics because of the limitations of such a shallow structure [20]. A deeper structure is typically needed for abstraction based on the hierarchy of abstraction.

Song et al. [21] used a deep ConvNet structure with two convolutional layers as opposed to the shallow ConvNet. The ConvNet, a neural network-based unsupervised learning system, achieved substantially better precision on malignancy identification of the pulmonary nodule compared [22] to ANN and Stacked Autoencoder. Since fully connected layers make up the majority of ANN and SAE's design, completely linked layers between hidden layers never allow for the analysis of invariant features within the immediate area. As a result, pulmonary nodule patterns are typically only partially understood [23].

To identify pulmonary nodules, a grouped convolution-based ConvNet was suggested [24]. The grouped convolution was initially presented in [25], the AlexNet model to reduce processing. Cost increases when the convolutional layer's output depth is deep. Group convolution also improves classification performance when a deep convolutional layer breaks into a group of two light convolutional layers. Compared to building the ConvNet model from scratch, using the pre-trained model to train new data has shown nonperformance in categorizing medical photo tasks. Transfer learning is described as the process of teaching previously trained weights to adopt new input. Risks of over-fitting and the convergence problem are reduced by transfer learning. Due to the similarity of their attributes, medical images, in particular, are usually challenging to optimize clusters of the classifier. Recent studies [26], used transfer learning and a pre-trained deeper ConvNet (AlexNet) to categorize pulmonary embolism patterns.

In [27] the high mortality rate of lung cancer, a Convolutional Neural Network (CNN)-based framework [28] was created to detect lung tumors in CT scans [29]. It performed exceptionally well, outperforming previous [30] and [31], research with 98% accuracy, 98.93% sensitivity, and 99% specificity [32]. Lung Cancer Dataset [33], a unique lung cancer detection method utilizing convolutional neural networks (CNNs) [34], and a modified Snake Optimizer produced excellent results [35], exceeding competitive approaches and demonstrating the potential for automated lung cancer identification in CT scans [36]. A deep learning-based Convolutional Neural Network (CNN) [37] framework outperformed other models with an accuracy of 92%, AUC of 98.21%, recall of 91.72%, and a low loss of 0.328, [38] showing promising findings for early lung cancer diagnosis using CT scan images. It [39] strategy has great potential to increase lung cancer diagnosis and decrease mortality rates [40].

2.1 Contribution

The major role of our research work is to use a precise VGG-16 techniques model to predict lung cancer from CT images using CNN techniques by initial augmentation of datasets. In this way, it will permit us to improve the reliability and accuracy of disease detection. The following is the main contribution of our research work:

In order to enhance patient outcomes and save healthcare costs, health institutions can now swiftly construct deep learning algorithms using their already-existing clinical data. The goal of this study is to develop a model for the identification and categorization of lung cancer. Using CNN modeling, the device will assist the radiologist in identifying the proper malignant location and improve accuracy. The method will aid in the early diagnosis of diseases.

Our research focuses on detecting lung diseases, which include both malignant and non-cancerous conditions. This thorough approach guarantees that our model can help in the diagnosis of a variety of lung diseases, helping to more thorough patient management.

Our detecting system's dependability and precision are of the utmost significance to us. Our VGGA-16 model has been carefully created and trained to deliver accurate results with a low probability of false positives or false negatives.

Our CNN model's primary role is to categorize the input images into two categories: malignant images and normal images. Healthcare professionals can take advantage of the useful data from this binary categorization to help with early disease detection and treatment planning.

3. Methodology

Our purpose model used an 868-image main dataset available on GitHub and Kaggle, publicly accessible datasets used in this research. All CT scan images of healthy volunteers and cancer patients with cancer images and non-cancer images are included in the dataset. The images are split 80/20 into training, testing, and validation folders using dataset class subfolders. The three categories of Lung cancer in the dataset included adenocarcinoma, large cell carcinoma, and squamous cell carcinoma, are typical cancer images or non-cancer images.

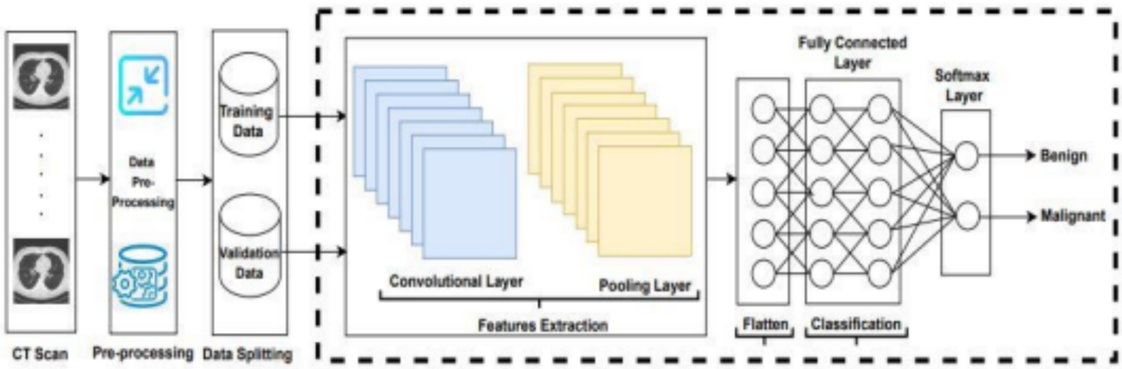

Figure 1. Propose Work

The proposed work involves the development of a VGG-16 model using convolutional neural network (CNN) architecture for the classification of lung nodules as either malignant or benign. The first step involves collecting CT scan images and preprocessing them by data rescale and performing data augmentation to enhance the data quality. Data normalization is also performed to resize and normalize the data. The study used an 868-image main dataset. The dataset was established, which is available on GitHub and Kaggle. The model is then trained on the hidden patterns of the data using 80% of the data, and testing is performed on the remaining 20%. The CNN architecture consists of six layers and 64 nodes, with a kernel size of 3x3 and a max pooling2D layer. The ReLU activation function is used on the hidden layers to convert the data to a non-linear form, and the softmax activation function is used on the output layer for binary classification. The proposed work aims to achieve higher accuracy in classifying lung nodules using VGG-16 techniques and classification algorithms with limited computation power.

CNNs are used in the suggested technique to identify and categorize lung cancer CT scan pictures. A VGG-16 model called a CNN is very good at processing and classifying images. They work by applying a series of convolutional and pooling layers to an input image, which extracts increasingly complex features from the image. The output of the CNN is then typically fed into one or more fully connected layers, which perform the final classification.

Many weak classifiers (in this case, individual CNN models) are combined into a stronger classifier using the AdaBoost algorithm, a common ensemble learning technique. AdaBoost gives samples that are incorrectly categorized by the present set of weak classifiers a higher weight during training and a lower weight to samples that are correctly classified. This enables the algorithm to concentrate on the most difficult samples and raises the accuracy of the algorithm as a whole.

The pipeline you described seems to be an effective method for classifying images because it combines the advantages of ensemble learning with the strengths of VGG-16. The quality of the training data, the CNN models' architecture, and the hyperparameters applied to both the CNNs and the AdaBoost models will all have an impact on the pipeline's specific performance.

In image classification tasks, the AdaBoost algorithm is often employed as a complementary strategy to enhance the performance of an existing CNN-based pipeline rather than as a replacement for convolutional neural networks (CNNs).

CNNs have shown to be quite good at classifying images, particularly when trained on big, varied datasets. While pooling layers help lower the spatial dimensions of the feature maps and produce invariance to tiny translations in the input, convolutional layers learn a series of filters tailored to detect particular features in the input images. At the end of the CNN, fully connected layers are frequently employed to complete the final classification.

Many effective VGG-16 algorithms, including well-known designs like VGG, ResNet, and Inception, use CNNs for image classification. These models have attained state-of-the-art performance on numerous common picture classification benchmarks, including ImageNet. In conclusion, while the AdaBoost algorithm is a potent ensemble learning method, it is not frequently employed as the main VGG-16 image classification algorithm. As an alternative, CNN-based pipelines are frequently employed and have had great success with computer vision jobs.

4. Results and Evaluation

The dataset is divided into M equally sized sections at random in order to avoid the over-fitting problem. After practicing on M-1 parts, the technique is tested on the remaining component. The sum of the measurements from M training cycles yields the total metric.

We calculated precision, accuracy, recall, specificity, and f1-score using a confusion matrix.

The accuracy of the training set given by and is present in Equation 1

$$Acc = \frac{Knegative + Kpositive}{negitive + positive} \qquad 1$$

Specificity is taken from equation 2.

$$Spec = \frac{Knegative}{Kpositive + Kpositive} \qquad 2$$

Recall the training set estimated by equation 3.

$$Recall = \frac{Kpositive}{Pnegative + Kpositive} \qquad 3$$

F1-Score is provided by equation 3.

$$f1 - score = 2\,\frac{Prec - Recall}{Prec + Recall} \qquad 4$$

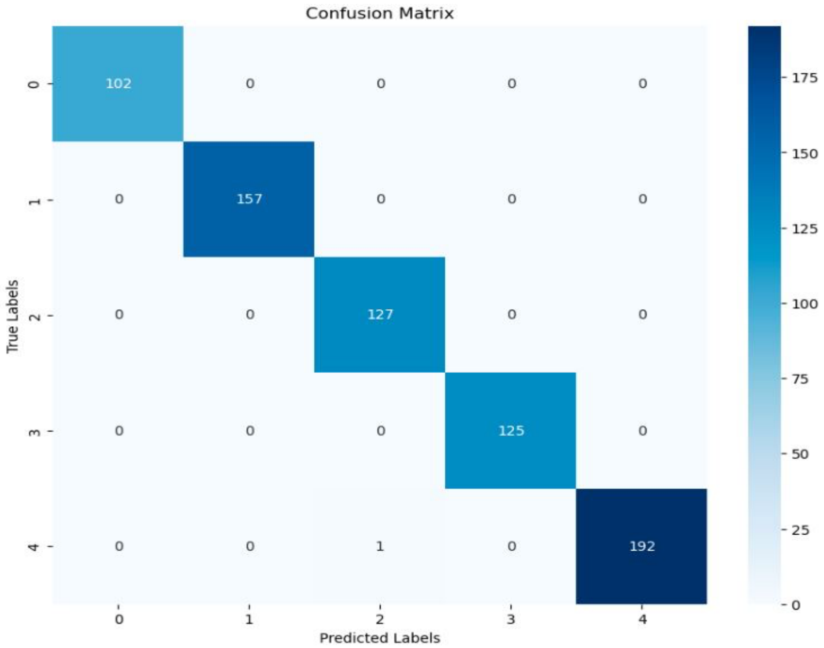

Figure 2. Confusion Matrix Train Data

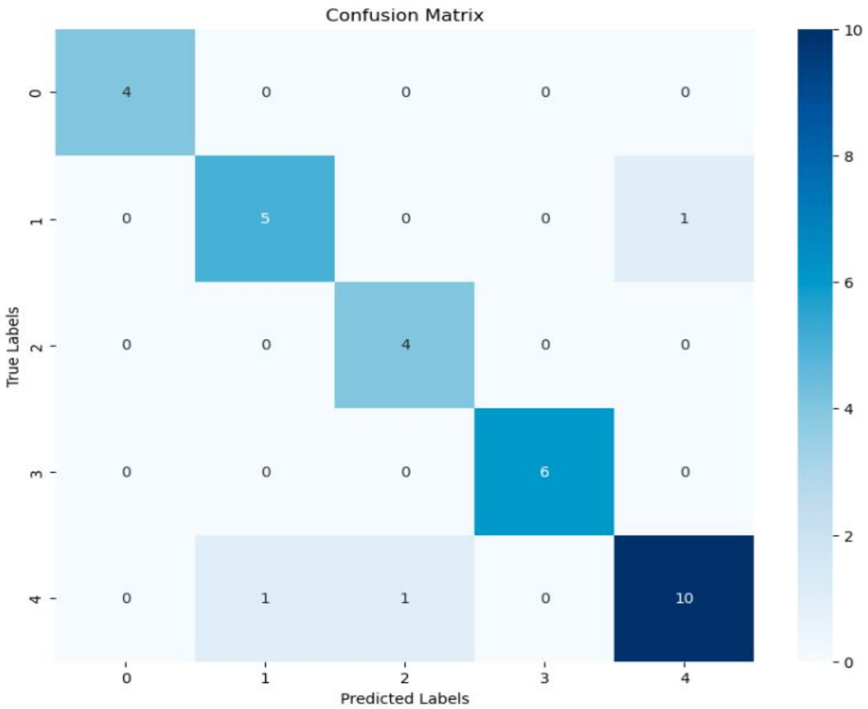

Figure 3. Confusion Matrix Test Data

Table 1. Model Performance

Algorithm	Accuracy	Precision	Recall
Proposed VGG-16 model	99%	99%	98%

4.1 Network Modeling and Training

Using a computer running Windows 10 and an AMD GTX 1080 graphics processor, the suggested 2D CNN model is trained. The selection and removal of features speed up network formation time. As a result, the chosen feature can process learning utilizing the simple corei3 method. Figure 4 displays the error rate of the proposed network during validation. It has been demonstrated that the mistake gets smaller the more epochs there are.

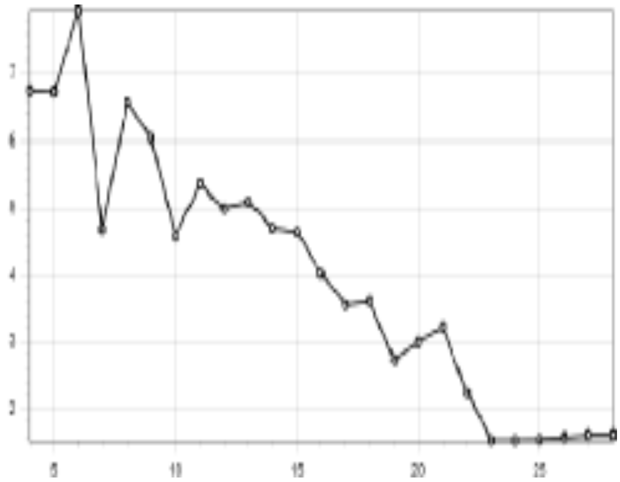

Figure 4. Testing error rate of CNN

In this study, two datasets consisting of 868 CT Scan images were used to categorize the cancers and Normal images. Two datasets were used for training and testing and categorized with the percentage of 80% images for training 20% images for testing, and some data for validation. The datasets were used repeatedly to train the model and boost its precision and accuracy thoroughly. The input size for the proposed models is set to 256 (height) and 256 (width), with 3 channels—RGB—used. To reduce the time-consuming process of training, preprocessing, and data augmentation of datasets, Image Data Generator is used with batches. The 3x3 size filters with explicitly expressed parameters. The CNN model was trained using Jupyter Notebook, and the training results are shown in this section. Plots of loss and accuracy were produced by this model using the training and validation sets. The CNN model's show that training accuracy and validation accuracy are only slightly different, with the model achieving about 98% accuracy on the validation set.

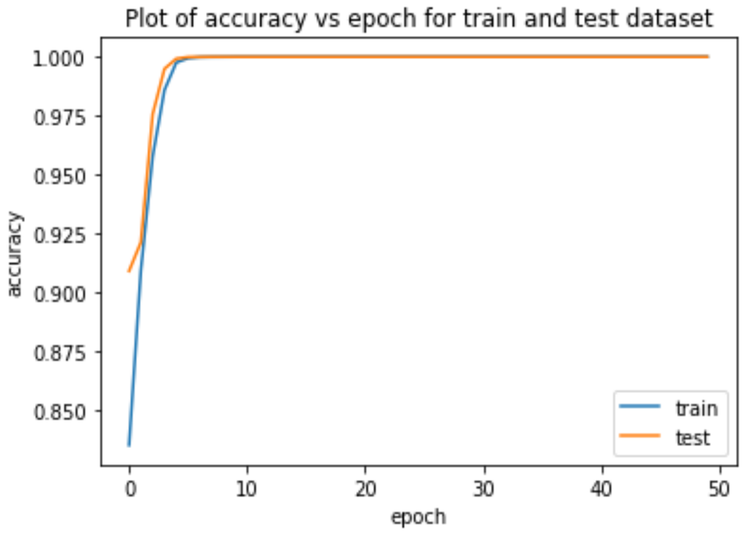

Figure 5. Accuracy Curve of the model

When it comes to cancer detection technologies, the accuracy achieved is very high—nearly 100%. Figure makes it clear that the precision of the suggested model is quite poor during the early stages and that the epochs are small. Epochs represent the total number of training iterations the model has gone through. A balanced and ideal number of epochs is always needed to develop the DL algorithm because a large number of epochs may cause the model to overfit. The accuracy of the model tends to improve as the number of epochs rises. The model's accuracy increases to 100% when the number of epochs exceeds 50. Epochs and batch size determine the accuracy of the DL models. It get the desired outcomes and accuracy, it may be necessary to set up to 1000 epochs in some problems. The number of epochs will vary depending on the task at hand. Because the data is numerical and not very vast, 50 to 100 epochs are sufficient to achieve satisfactory accuracy in the attack detection problems. Batch size is also regulated to the ideal value in attack detection problems.

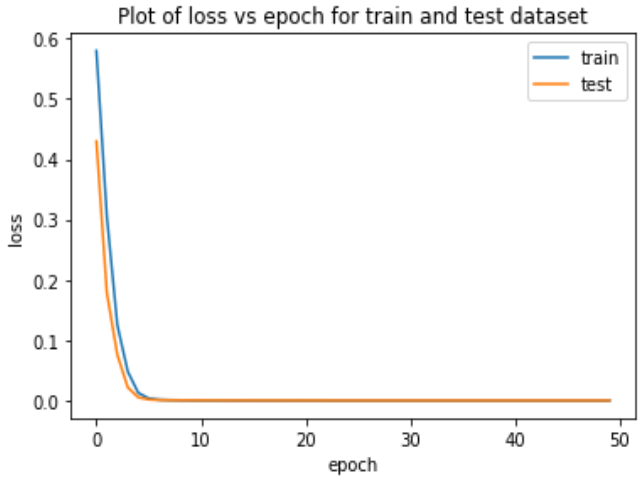

Figure 6. Loss Curve

Loss is one of the most crucial things to consider while solving deep learning challenges. The model's start loss is extremely large, and epochs are also short. The loss of the model is particularly high when the epochs are zero. Loss is a sign that the model has made a mistake. Due to a number of circumstances, initial inaccuracy is relatively significant. Deep learning employs a number of strategies to lower errors. The loss related to the model tends to decrease as the number of epochs rises. When the number of epochs hits 50, the model's loss almost reaches zero, which is ideal for deep learning models. The accuracy and loss the model achieves are the two factors determining how effective deep learning models are. The model needs some parameter adjustment and fine-tuning of the activation functions if the accuracy is high, but the loss is also high. The suggested model needs the training parameters that were used to construct the model to be fine-tuned if the accuracy is low, but the loss is also minimal in this scenario. Therefore, in the research, a high degree of precision was attained with a very small amount of loss. The model also diagnoses cancer with higher accuracy and lower loss when it is used in real-time. The loss function plays a crucial role in assessing how effectively the hybrid algorithm modeling performed on the dataset. It's a mathematical function to define a loss function. The loss is decreased to zero with an increase in the number of epochs.

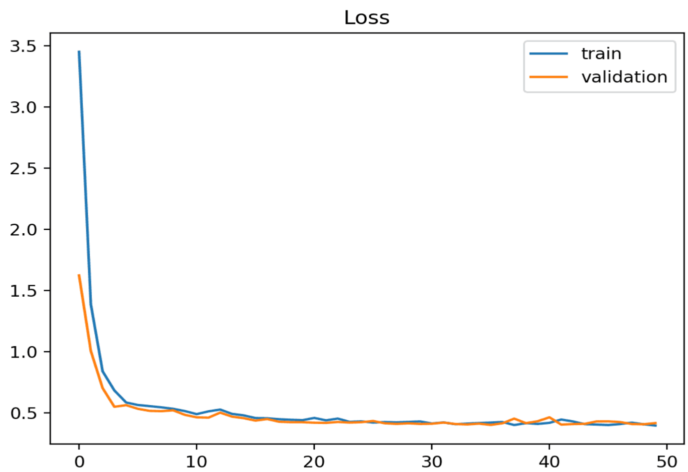

Figure 7. Loss Curve Train and Validation

An appropriate fit, which can be achieved between an overfit and an underfit model, is what the learning algorithm seeks to achieve. A good match is indicated by training and validation losses that stabilize at a modest difference between the two final loss values. The training dataset's model loss will almost always be lower than that of the validation dataset. Therefore, a difference between the train and validation loss learning curves is likely to exist. This distinction is referred to as the "generalization gap." To evaluate the model's performance, utilize the parameters mentioned above. As a result of cross-high validation's reliability, LSVM, NB, and k-NN execute grouping by comparing the results of the extracted features with traits from previously proposed groupings and classification approaches.

Table 2. Classification Performance

Author	Model	Techniques	Accuracy
Zheng, et al. [1]	3D Deep convolutional neural network (CNN)	VGG-16	93.2%
Chen, C., et al. [3]	CNN, DBNs, and SDAE	VGG-16	79%, 81%, 79%
Aamir, M. et al. [8]	CNN Based Model8	Deep Convolutional Network	93.5%
Wang, B., et al. [12]	3D CNN12	Deep residual learning	84%
Song et al [21]	MLP, SVM, Nave Bayes, and Neural Network	Machine learning and ensemble learning techniques	90%
Proposed Model	Convolutional neural network (CNN)	VGG-16	98.3%

5. Conclusion and Future Research

This research investigates how developing a classification system with the VGG-16 algorithm has been researched to produce the best outcomes and a high accuracy rate. The study used a CNN model with six layers, 64 nodes, a kernel size of 3x3, and a MaxPooling2D layer for the classification task of diagnosing lung cancer. Due to the binary classification nature of the problem, the model used the ReLU activation function in the hidden layers and the Softmax activation function in the output layer. The study found that CNN model was best for lung cancer detection and was successfully used in real-time for this purpose. LeNet and VGGNet, two further CNN variations, were also discovered to be successful at spotting lung cancer. It indicates that CNN models can be useful for detecting lung cancer, which is a significant discovery in medical imaging. Although this research offers a number of valuable tips for detecting lung cancer, it is not without flaws that call for additional study in the future. First, this study illustrates three key factors influencing engagement behavior: data collection, preparation, and model construction. Future studies can expand CNN by adding influencing, model enhancing, etc. Second, the research model can be examined in additional contexts because this study deals with the CNN algorithm's machine-learning involvement. Thirdly, this study focuses specifically on utilizing CNN models to identify lung cancer; future studies can compare CNN models with other machine learning models like ANN models etc. Fourthly, while the data in this study is specific to Kaggle, it may be expanded to include Luna 16, to produce more comprehensive conclusions. The model can also be examined using different datasets. Fifth, an analysis of detection that compares the behaviors of cancers and non-cancers on such a model can be done in future studies. Sixth, because this study concentrated on the CNN model, further studies may look at other deep-learning methods.

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