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Lung Cancer Image Classification using CNN with SVM

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ABSTRACT: Deep learning and machine learning are increasingly being utilized to evaluate medical Images and address machine intervention difficulties. While existing deep-learning and machine learning technologies are adaptive, they need medical image analysis-specific capabilities and need substantial research before they can be applied in this sector. Consequently, several research teams have built incompatible infrastructure and spent critical time repeating their work. This article offers to detect and classify the lung cancer based on deep learning framework. Lung cancer is one of the major causes of cancer-related deaths due to its aggressive nature and delayed detections at advanced stages. Early detection of lung cancer is very important for the survival of an individual, and is a significant challenging problem. Generally, chest radiographs (X-ray) and computed tomography (CT) scans are used initially for the diagnosis of the malignant nodules; however, the possible existence of benign nodules leads to erroneous decisions. At early stages, the benign and the malignant nodules show very close resemblance to each other. In this paper, a novel deep learning-based model with multiple strategies is proposed for the precise diagnosis of the malignant nodules. Due to the recent achievements of deep convolutional neural networks (CNN) in image analysis, we have used SVM algorithm for classification of lung cancer image. The deep learning model for nodules' detection and classification, combined with clinical factors, helps in the reduction of misdiagnosis and false positive (FP) results in early-stage lung cancer diagnosis. The proposed system was evaluated on LIDC-IDRI datasets in the form of sensitivity (95%) and specificity (93%), and better results were obtained compared to the existing methods

KEYWORDS: Machine learning, Lung cancer, SVM

I. INTRODUCTION

Researchers developed automatic analysis techniques as soon as medical images could be processed and submitted. Medical image processing throughout the 1970s and 1990s included successively applying low-level imaging techniques (edge and line detection filters, region expansion) and mathematical modeling (fitting lines, circles, and ellipses) to solve specific issues. Expert systems that used if-then-else statements were standard in Intelligence at the time. In the late 1990s, medical image classification increasingly embraced supervised techniques, in which a machine-learning model is employed to build a system. Examples include active shape models (for segmentation), atlas techniques (fitted atlases using data for training), extraction and classification, and statistical classifiers (for computer-aided detection and diagnosis). This classification methodology, also known as machine learning, is still widely utilized in many computer-aided diagnostic categorization systems. As a result, we have seen a shift from human-designed to computer-trained systems that use example data to extract feature vectors. The optimal high-dimensional classification function is determined using computer algorithms. The extraction of image features is a critical stage in the design of such systems. This is still done by people; thus, specialized systems are utilized.

Medical imaging is an important part of many clinical decisions and patient journeys. Computer-aided screenings, diagnosis, patient management, intervention, and therapy all make use of medical images. Medical imaging remains an important aspect of many clinical tasks. Still, a scarcity of qualified radiologists to interpret complex images highlights the need for trustworthy automated solutions to alleviate the increasing load on healthcare practitioners. Because of the competence and prior knowledge required to deal with so much data, there is usually significant inter- and inter-observation variation in categorizing medical data. As a result, there is disagreement on what constitutes a gold-standard testing dataset annotation. Because we require several expert datasets (oracles) to reach an agreement, these problems raise the cost of labeling and re-labeled medical picture datasets. Researchers in medical image analysis are using DL (Deep Learning) and ML (Machine Learning) algorithms for various applications, and the results are encouraging. The use of DL and ML in medical imaging recently received a lot of attention.

Medical imaging, such as CT, MR, PET, mammography, ultrasound, X-ray, and others, has been more significant for early sickness diagnosis, detection, and treatment in recent decades. Technologists and physicians in the

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medical field examine medical pictures. Researchers and doctors are increasingly embracing computer-assisted therapy due to disease unpredictability and expert fatigue. Machine learning, as well as deep learning technologies, have recentlyenhanced computerized medical image analysis, which was late. Optimized feature extraction or representations is critical to machine learning's efficacy. Relevant or task-related qualities were typically developed by human architecture and were influenced by their grasp of targeted domains, making machine learning approaches challenging for non experts to implement. Deep learning has addressed these obstacles by using feature engineering throughout training. Deep learning, rather than hand-designing features, requires a gathering of data with little pre-processing and then self-teaching relevant interpretations. Because feature engineering is now performed by a machine, non-experts in computer vision may use machine learning and deep learning to conduct their own research and/or implementations, notably medical picture analytics.

II. DEEP LEARNING

The convolutional neural network is a popular deep learning architecture inspired by visual cortex of animals [1]. Initially, was mostly used for object detection, but it is currently being used in other areas, including object tracking, pose estimation, text detection and recognition, in visual salience detection, action recognition, scene labelling and many others. The eocognitron, which was developed in 1980, is regarded the forerunner of ConvNets. LeNet was Le Cun et al., pioneering work in convolutional neural networks in 1990 [2], which was later enhanced [3].It specially designed to categorize handwritten digits and managed to recognize visual motifs directly from the input image without any previous processing. This approach, unfortunately, has not performed well enough in complicated tasks due to a lack of appropriate training data and computational capacity. Later in 2012, Krizhevsky et al. [4] developed a CNN model that reduced the ILSVRC competition's mistake rate. Over the years, his work has become one of the most dominant in the field of artificial vision and many use it to test changes in CNN architecture. AlexNet has been able to achieve remarkable results compared to the previous model of ConvNets [5], using purely supervised methods learn and without any prior training without supervision to keep the network simple. The system, which comprises five convolutional levels followed by three fully linked levels, can be a major variation of LeNet. AlexNet has gone through multiple iterations since its enormous victory in the ILSVRC-2012 contests. This work will serve as an initial point for newcomers to the field. The set of sections mentioned below are section II describes the network levels.

This level constitutes the basic unit of a ConvNet in which most of the calculation is involved. It is a set of characteristic maps with neurons arranged inside it. Level parameters are a set of filters or cores that can be learn. These filters are involved with feature maps to produce a separate two-dimensional activation map, which, if grouped along the depth dimension, produces the output volume. The neurons that are on the same characteristic map share the weight (exchange of parameters) thus reducing the complexity of the network while keeping the quantity of parameters low [6]. The spatial extension of poor connectivity between two-layered neurons is a hyper-parameter called the receptive field. The depth (number of filters in a layer), pitch (for filter movement), and zero fill hyper-parameters affect the output volume size (to control the spatial size of the output).The ConvNets are trained with backward propagation and the backward passage implies a convolution operation but with spatially inverted filters. Fig.1. shows the basic convolution operation of a convnet.

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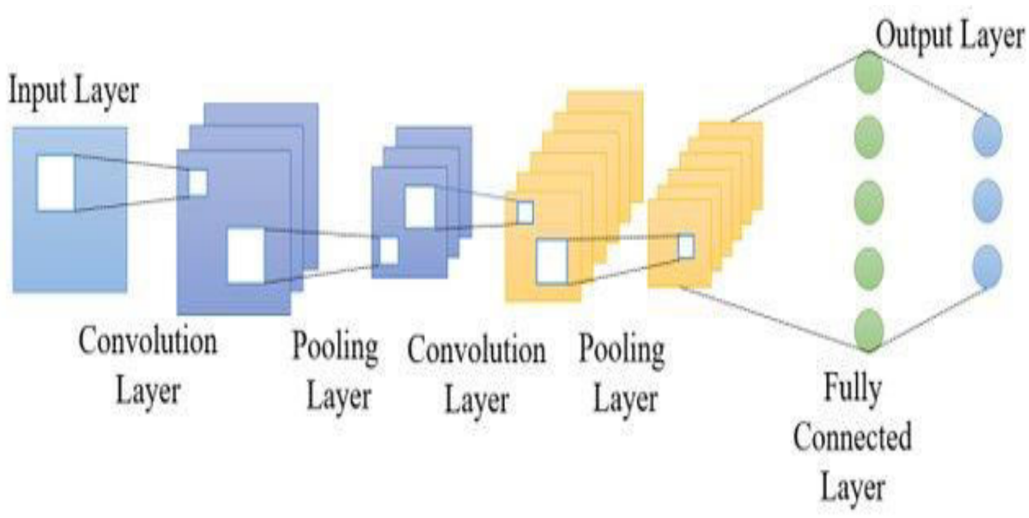

Fig.1 Architecture of CNN showing alternating convolution and pooling layers.

The "Network In Network" (NIN) suggested by Lin et al. [7] is a version of the regular CNN in which the 1*1 convolution filter is a Multi-Layer Perceptron (MLP) instead of typical linear filters, and the fully linked layers are replaced with a global average pooling layer. Because the micro network is made up of a stack of MLPCONV layers, the final structure is termed MLPCONV layer. Unlike CNN, NIN can improve the ability of latent notions to be abstracted. They were successful in demonstrating that NIN's final MLPCONV layers were confidence maps of the categories, allowing them to conduct object recognition using NIN

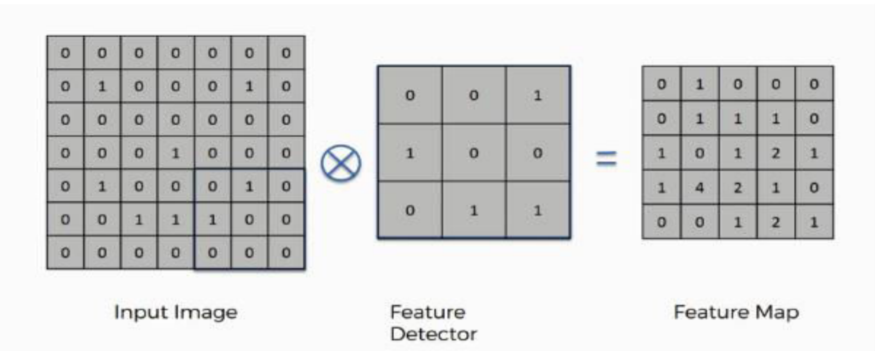

Fig.2 Convolution Operation

CNN has been developed for dense prediction tasks, such as semantic segmentation, which is fundamentally different from image classification. Dilated convolutions are used that support exponential enlargement of the accessible field without loss of resolution. They have dilated the convolution operator but do not develop dilated filters. The structure designed specifically for dense prediction is organized as a rectangular prism of convolution layers without grouping or sub-sampling in contrast to the traditional pyramidal structure used in image classification and this has led to innovative results for tight forecasts.

Deep learning is a branch of artificial intelligence and machine learning (AI) that aims to replicate how individuals learn specific aspects of information. Deep learning is a critical component of the subject of data science, which also includes statistics and predictive modeling. Deep learning makes the process of acquiring, analyzing, and interpreting massive amounts of data faster and easier, which is beneficial to scientists who are tasked with carrying out these tasks. Deep learning may be thought of as a method for automating predictive analytics at its most basic level. In comparison to the linear arrangement of standard machine learning algorithms, deep learning algorithms are layered in a hierarchy of organizing several complicated and abstraction

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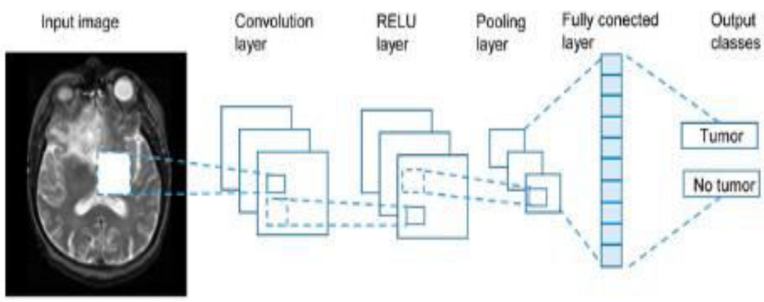

Fig.3 CNN Architecture

III. METHODOLOGY

Forming a multi-tiered CNN is a tedious process due to the non-convex nature of the loss function [11] and requires a high processing GPU if the datasets are huge. CNN is rarely trained from scratch with random initialization. Convergence can be accelerated with proper network initialization. The transfer learning technique can be used to have significant weight initialization or if the training data set is small. In this case, it is only necessary to prequalify the classifier or the last layers, thus dipping the total training time. With a careful selection of parameters such as learning speed, number of iterations, number of training and test samples, batch size, etc., a good model can be achieved. An assembly model can be designed to obtain more accurate results when training the same network in different parameter configurations. The net is trained with Back-propagation and descent gradient to update the weight. Back-propagation training is affected by a key problem: decreased gradient flow (also called prolonged delay or disappearance gradient problem) [12], which makes it difficult to train the lower layers of a multilayer neural network, since the rate of error breaks or explodes exponentially to the lower levels. This problem can be adequately addressed by selecting a sparse activation function such as sigmoid or tanh. But recently rectified linear units (ReLU) have proven more effective for ConvNets due to their dispersion properties and suffer less from the reduced gradient flow [14].The final layer of a convnet is the classifier. One of the most used is the softmax classifier which generates probabilities for each class, adding up to 1. But according to the needs, other classifiers such as SVM, probabilistic classifiers, etc. are also used. SVM is used for structured forecasting. Classifier sets are also widely used.

ALGORITHM :1

Pseudo-code of SVM Algorithm
Input: determine the various TESTING AND TRAINING image data.
Output: determine the calculated ACCURACY of the data set.
Select the **optimal** values for SVM.
WHILE (stopping condition is not met) **DO**
Implement SVM train step for each data point.
Implement SVM classify for testing data points.
END WHILE
RETURN *accuracy*

ALGORITH: 2
Pseudo-code for CNN algorithm
INPUT :medical image data
OUTPUT: integrity status
For each response of the image
Check the accuracy value
If(result)== empty or incorrect then
Integrity == false

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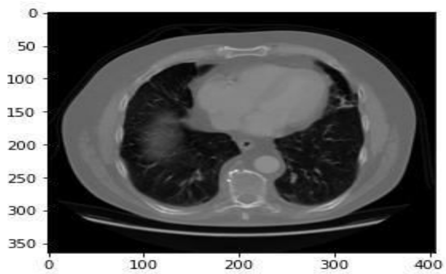
Else
Integrity == true
End if
End for
Return status
End

IV. RESULTS AND DISCUSSION

We trained, tested, and validated our model using datasets from the Kaggle website. For the four folders used for training, testing, and validating the model, we used distinct files to store the various cancer types according to the type of cancer. Total 613 photos from 4 classes are found during the training phase, 83 images from 4 classes are found during the testing phase, and 351 images from 4 classes are found during the validation phase. The model underwent training over 120 epochs with 25 steps each. Following the training stage, the model is evaluated using example photos and categorized in accordance with the assigned category. The model has been compiled using cross entropy loss function, Adam optimizer and the following metrics. Setting the data set path for training, testing and validation of our model created with the layers of convolutional neural networks.

The purpose of this study was to evaluate the clinical efficacy of the model using a deep convolutional neural network algorithm for the classification of lung cancer using the chest CT images. Here we classified the chest CT images based on the type of cancer such as adenocarcinoma, large cell carcinoma, squamous cell carcinoma and normal CT image. Our model has produced the result as he model has produced the following results as training accuracy= 94.13%, training loss= 0.3254, training precision= 95.45%, training recall= 92.5%, training AUC= 0.9756.



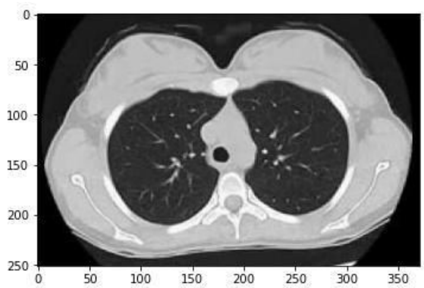


Fig-4 Input image

Fig-5 The given lung CT image is found as normal

V. CONCLUSION

In this work, CT images and trained using SVM. SVM is used to classify the images into two classifications by testing and training 10 images for disease. The same images are examined and trained using CNN technologies, and the outcomes are measured by accuracy. Deep learning outperforms machine learning in accuracy. Deep learning is the best image classifying approach, although machine learning is used occasionally. Deep learning algorithms may use more data. Less data improves machine learning. The classification about normal and malignant

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status from CT/MRI images is subjective and might vary from specialist to specialist. CAD systems largely help in making an automated decision from the MRI/CT images and allow both the patient and doctors to have a second opinion. A conventional image classifier utilities hand-crafted local features from the image for the image classification. However, the recent state-of-the-art above model mostly employs global information using the layer based working techniques, which act to extract features from the images for the classification. Using this model, this paper has classified a set of lung cancer images into adenocarcinoma, large cell carcinoma, squamous cell carcinoma and normal CT image. This model can be use with other dataset with huge images to get a good result with high efficacy and accuracy.

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