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LUNG CANCER PREDICITION USING MACHINE LEARNING

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Abstract: Lung cancer is one of the most lethal cancer types; thousands of peoples are infected with this type of cancer, and if they do not discover it in the early stages of the disease, then the chance of surviving of the patient will be very poor. For the suggested reasons above and to help in overcoming this terrible, early diagnosis with the assistance of artificial intelligence procedures most needed. Through this research, a computer-aided system introduced for detecting lung cancer in a dataset collected from hospitals by using a convolutional neural network technique. The accuracy of prediction has always been a challenge, despite the many algorithms proposed in the past by many researchers. Using Convolutional neural networks, this study proposes a methodology to detect abnormal lung tissue growth. In order to achieve great accuracy, a tool with a higher probability of detection is taken into account. The manual interpretation of results is incapable of avoiding.

During the course of this research, lung images from both healthy and malignant individuals were analyzed. An effective training function is used for proposed neural network construction. This proposed method provides High accuracy of detection. This improved result is comparatively better than other existing detection techniques. The basic reasons for getting magnificent results are the utilization of perfect preprocessing steps and effective training function.

Keywords: Lung cancer, Convolutional Neural Network, Contrast enhancement, Local Binary Pattern (LBP).

1. INTRODUCTION

The abnormal growth of cells in human Lung is called as Lung Cancer. Lung cancer is one of the most serious diseases in the world today, and it is the leading cause of mortality in the previous several decades. It also kills more people each year than breast, prostate, and colon cancer put together. The addiction to cigarettes is one of the leading causes of lung cancer. Furthermore, carcinogenic surroundings such as radioactive gas and air pollution contribute to the spread of this disease. In addition, genetic factors also have a major contribution to lung cancer. Uncontrolled magnification of tissue creates lung cancer. Primary originate from cells within secondary cancer begin in another part of the body and therefore spread to lungs. Lung cancer can be cancerous or noncancerous. Lower-grade cancers are

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classified as Grades I and II. In some cases, cancer grades III and IV are regarded to be of higher severity. In the human body, there are two types of cells. Normal cells are small and confined, whereas cancer- affected cells are rapidly forming and can be easily spotted. These cells appear to be aberrant and dissimilar to regular cells.

Lung cancer is the most commonly [1] discovered dangerous cells and additionally one of the most perilous cancer tissues that lead to fatality among males in 2019. Exactly, bronchi cancer tissues have actually happened to be a primary risk to personal everyday lifestyle. Low-dose computed tomography (CT) is actually a valuable method for pinpointing lung cancer tissues [2] early. A choice to recognition through these predefined features is by using component finding methods to find first-class depictions straight from the instruction [3] and relevant information. Convolutional neural networks (CNNs), like a swiftly, scalable, and also end-to-end finding-out neural network, considerably evolved the landscape of goal findings, such as in image classification, medical diagnosis[4], and semantic division.

Thoracic CT creates a volume of pieces that may be regulated to reveal several volumetric pictures of physical structures in the bronchi. 2D convolution dismisses the 3D spatial size, indicating that it is actually incapable of making complete usage of the 3D condition pertinent [5] information, and 3D CNN can, definitely, be in harmony with this. Our goal is to check empirically the trouble of determining bronchi acnes captured through computed tomography (CT) in an end-to-end means making usage of the 3D convolutional neural network (CNN) effectively to perform a binary distinction [6] (benign and malignant) on CT pictures [7] from the Lung Image Database Consortium picture variety (LUNA 16 Dataset). Our major contributions are as follows:(1)3D CNN is used for the automated distinction of bronchi blemishes. Reviewed with the 2D design, 3D CNNs can effortlessly encode richer spatial information to eliminate additional unique symbols.(2) Multiview places are actually utilized in our designs. Our staff use the multiview-one-network strategy that contrasts and arises from the one-view-one-network technique used in the study. Completion leads to the fact that our technique may achieve a decreased mistake rate than the one- view-one-network approach while using far fewer requirements. Note that while the layout used a similar approach and 2D CNN is simply utilized, our group used 3D CNN in this paper.

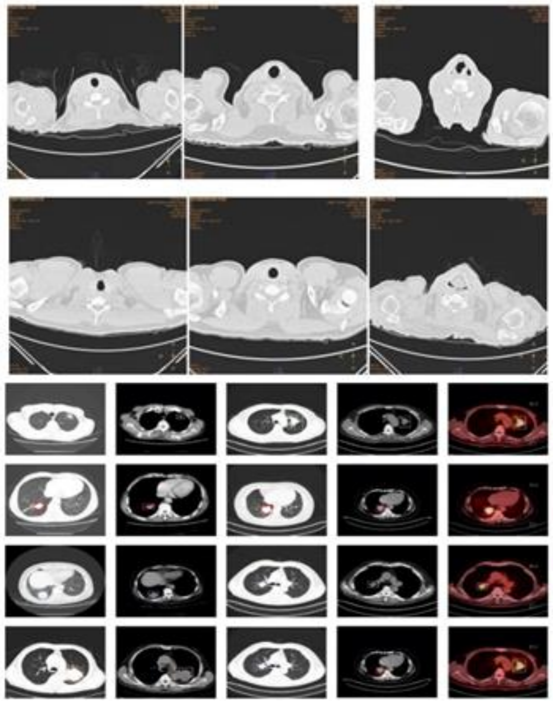
Fig. 1.1 CT lung images of different person with various age groups.

This type of cell grows quickly and is more prone to spread. Poorly differentiated or high grade are terms used to describe them. Lung cancer can be life-threatening; thus, a patient’s exact diagnosis and treatment are critical. Cancer analysis is performed in a pathological laboratory. Microscopic investigation, such as

biopsy, and electronic modalities, such as CT, Ultrasound, and others are used to examine cancer tissue. CT scan is the most commonly utilized pathological test, and it is very popular for diagnosis. It uses high resolution, high-contrast pictures of the lung in various positions to provide a three-dimensional assessment of the lesion. An automated strategy for cancer diagnosis was developed in this research work, which used CT Scan Grayscaleimages.

CNNs are a machine-learning technique based on an artificial neural network with deep architecture relying on convolution operations (the linear application of a filter or kernel to local neighborhoods of pixel/voxels in an input image) and down sampling or pooling operations (grouping of feature map signals into a lower-resolution feature map). The final classification or regression task relies on higher-level features representative of a large receptive field that is flattened into a single vector. The development of an algorithm entails (a) selection of the hyperparameters, (b) training and validation, and (c) testing. The hyperparameters include the network topology, the number of filters per layer, and the optimization parameters. During the training process, the dataset of input images (divided into training and validation sets) is repeatedly submitted to the network to capture the structure of the images that is salient for the task. Initially, the weights for each artificial neuron are randomly chosen. Then, they are adjusted at each iteration, targeting minimization of the loss function, which quantifies how close the prediction is to the target class. The performance of the trained model is then evaluated using an independent test dataset. This is also aimed at assessing whether an “overfitting” has occurred.

The overfitting problem can arise in the case of limited datasets with too many parameters compared with the dataset size, in which case a model “memories” the training data rather than generalizing from them [1].

Lung cancer dataset

In the field of lung imaging, CNNs have been tested in nodule segmentation from CT images. Average dice scores of 82% and 80% for the training and test datasets, respectively, have been reported [2]. CNNs have been demonstrated to achieve better results than conventional methods for the purpose of nodule detection [3, 4]. Moreover, a model for assessment of cancer probability in patients with pulmonary nodules has been proposed. The area under the curve (AUC) was found to be 0.90 and 0.87 for the training and test sets, respectively [5]. Stage assessment has not yet been described. The present study, as a first step towards complete TNM parameter assessment, aimed to develop an algorithm for the classification of lung cancer as T1- T2 or T3-T4 on staging fluorodeoxyglucose positron emission tomography (FDG-PET)/CT images.

2. RELATED WORK

Lung cancer is the leading cause of cancer deaths for both men and women, making up almost 26% of all cancer deaths worldwide. The survival rate for five years is just 17 percent. Early diagnosis increases the probability of success and prognosis dramatically. Owing to the amount of data involved, diagnosis of lung nodules is time-intensive and often suffers from interradiology heterogeneity. A commonly used method for screening for lung cancer is computed tomography (CT). The purpose of screening is to diagnose infection at the earliest possible point.

The Author [1] conducted study on cancer lungs detection using artificial neural network back propagation based gray level occurrence matrices characteristics on CT scan images. The perspective of the lung pictures is one of the key advantages of employing CT scan images in this technique. The results demonstrate that the system can recognize CT images of normal and cancerous lungs with an accuracy of 80%. Hopefully, it will be used to assist medical workers and researchers in detecting lung cancer.

The Author [2] focused on the effect of input size on the categorization of lung nodules using convolutional neural networks. The goal of this study was to employ convolution neural networks to evaluate CT lung screenings in order to decrease false positives and demonstrate their power and influence on overall accuracy. Various functions were applied.

The Author [3] conducted a study focused entirely on the identification of lung cancer medical images using deep neural networks. The goal of this study was to see if there was

2581-4575
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any evidence of cancer in a patient's lungs. To aid clinicians in visual diagnostics by training deep neural networks to detect lung cancer. The key benefit is that doctors will have more assistance in detecting and treating lung cancer in its early stages.

The Author [4] worked in using LUAD and LUSC for Classification and Mutation Prediction from Non-Small Cell Lung Cancer Histopathology Images.

The Author [5] wrote a paper titled Optimization of features using artificial neural networks for categorization of type of lung cancer. The overall goal is to decrease human error in CT scans of lung cancer patients and to diagnose them.

The Author [6] studied and featured the use of convolutional neural networks in Deep Learning for the detection and classification of lung cancer nodules in CT scans.

The Author [7] showed how they used Convolution neural networks, Autoencoders, and Deep Belief Networks for Lung Nodule Classification on Computed Tomography Images Using Deep Learning.

The Author [8] completed their research and study focused on lung cancer detection using 3D convolution deep neural networks. Using CAD is one of the key benefits. The convolution neural network is one such technique, which best defines a series of deep learning models with filters that can be built with local pooling processes alternating on input CT images to build an array of hierarchical complicated features.

Kanavati [9] Lung Disease screening using low-dose CT scans using a deep learning methodology was applied. Computed tomography scans are used for identifying lung diseases because they offer a thorough view of the tumor in the body and follow its progress.

The Author [10] explained drawbacks include that they can't help with disease detection at an early stage.

The Author [11] proposed algorithm for Lung Diseases Detection Using Co-Learning from Chest CT Pictures and Clinical Demographics is a technique for detecting lung diseases in CT scan images that uses an automated approach.

The Author [12] used an algorithm for diagnosing lung illnesses is being developed using various methods. The following are some of the restrictions: Allows the radiologist to spend more time assessing the patient. Implementing neural network systems is complex. In [12], LIDC/IDRI dataset is used where the researchers have used the intrinsic CNN features, and 431 malignant nodules and 795 benign nodules were extracted, and the input for SVM was sequential forward feature method to construct the classifier. The researchers attained an accuracy of 85%.

OBJECTIVES OF THE THESIS

Three types of Lung cancer classification technique is proposed in this paper Convolutional neural network. The novelty of this work is increasing the accuracy level without any complexity. The remaining part of this paper is arranged as follows. The literature review is discussed in section II, the workflow of method is explained elaborately in section III. The result of proposed method is presented in section V, proposed technique is concluded in section VI.

3. IMAGE PROCESSING

In the next few decades, cancer is expected to be the leading cause of death and is one of the biggest threats to human life (Tang et al, 2009). To improve the efficiency and speed of cancer diagnostics, Computer aided diagnosis (CAD) was applied to the analysis of clinical data. There has been vast development in the field of CAD and many machine learning techniques are developed for the diagnosis purpose. Among all machine learning techniques, neural networks have shown increased performance in the detection of medical images. In the classification of lung cancer images, different CNN algorithms are used to improve the accuracy of the prediction and classification. Such accurate predictions aid doctors by reducing the workload and prevent human errors in the process of diagnosis. a) Computer aided diagnosis in medicine: Computer-aided diagnosis (CAD) is cutting edge technology in the field of medicine that interfaces computer science and medicine.

TYPES OF IMAGE PROCESSING

1. Analog Image Processing
2. Digital Image Processing

Analog Image Processing
Simple picture preparing identifies with the change of a picture through simple or electrical signs. A typical case of this procedure is the TV picture. The adequacy levels of the voltage differ to represent the brilliance of a picture. Through the use of differed electrical signs, the appearance of the showed picture is adjusted (or) changed. The brilliance what's more, differentiate levels in the picture are changed with the guide of both the controls accessible on sufficiency and the reference of the video motions in a TV set.

Digital Image Processing
Advanced picture handling by and large signifies the strategy of handling a two-dimensional picture by an advanced PC. A computerized picture is contained a variety of genuine numbers symbolized by a limited number of bits. In advanced picture handling, computerized PCs are utilized to process the input picture. The picture would be changed over to an advanced frame utilizing an electronic gadget, say scanner, and after that the further preparing upon the picture is finished. It can likewise be specified as the numerical portrayals of the pictures to empower an arrangement of operations to infer a coveted outcome. Computerized picture preparing starts the handling with one picture lastly; an improved adaptation of a similar picture is acquired.

CLUSTERING TECHNIQUES:
A Clustering is one of the most useful techniques in MRI Segmentation, where it classifies pixels into classes, without knowing previous information or training. It classifies pixels with highest probability into the same class. Clustering technique training is done by using pixel features with properties of each class [Wang. (2008)].

K-means K- means clustering algorithm is the simplest unsupervised learning algorithm that can solve clustering problem. The procedure followed to classify a given set of data through a certain number of clusters is very simple. In K means ‘K’ centers are defined, one for each cluster. These clusters must be placed far away from each other. The next step is to take a point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and early grouping is done. The second step is to recalculate ‘k’ new centroids as bary center of the clusters resulting from the previous step. After having ‘K’ new centroids a new binding has to be done between the same data set points and the nearest new center. A loop has been generated. As a result of this loop, the k centers change their location step by step until centers do not move any more. Finally this algorithm aims at minimizing an objective function known as squared error function given by,

$$J(V) = \sum_{i-1}^{c} \sum_{j-1}^{c_j} \left\| x_i - v_j \right\|^2$$

Where, is the Euclidean distance between xi and yj ‘ i c ’ is the number of data points in ith cluster. ‘C’ is the number of cluster centers.
Feature Extraction and Feature Reduction
This proposed method used two-dimensional DWT and the utilized level was three-level decomposition wavelet.
After preprocessing, 2D-DWT is utilized to extract multiple features from the clustered images. Fourier transformation is also used for feature extraction in image processing but FT is unable to accommodate information of time domain [18]. Each scale of DWT contains four sub-bands: LL, LH, HH, and HL. Input layer of feed-forward network consisted of 13 neurons for 13 features, hidden layer consisted of 20 neurons. For three types of tumor classification, output layer had 3 neurons. The fastest training function ‘Levenberg-Marquardt’ was applied in neural network construction.

2581-4575
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ANN firstly performs the learning process and then predicts in the testing stage. Neural network took 70% sample for training, 15% sample was used for validation and 15% was used for the test. The basic artificial neural network model is displayed in Fig. 4.
ANN consists of main three layers: input layer, hidden layer and output layer. Here, x is the input of the network and y is the classification types.

Edge Detection Methods
Edge discovery has its own particular notoriety in the space of picture preparing. Area limits and edges are very comparable since there is an iterative adjustment of power at the area limits. The edges perceived by edge location strategies are frequently not - consistent. To section an question or an area of want from a picture, one requires shut district limits. The normal edges are the limits which lie between such objects. Thus, edge based discovery underpins picture division. One such edge identification method was proposed by Canny, which uses ideal smoothing channel to save the edges while performing picture division.

4. INTRODUCTION TO MATLAB
MATLAB® is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include
Math and computation Algorithm development
Data acquisition
Modeling, simulation, and prototyping
Data analysis, exploration, and visualization
Scientific and engineering graphics
Application development, including graphical user interface building.

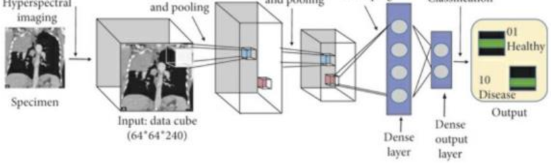
MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non interactive language such as C or FORTRAN.
The name MATLAB stands for matrix laboratory. MATLAB was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects. Today, MATLAB engines incorporate the LAPACK and BLAS libraries, embedding the state of the art in software for matrix computation. MATLAB has evolved over a period of years with input from many users. In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis.

5. PROPOSED SYSTEM
This proposed paper Deep CNN for three types of lung cancer classification. The proposed technique was executed in MATLAB R2019a. Overall method can be split up into four steps: pre- processing steps, feature extraction, classification step with CNN.

Algorithm of Proposed Method

Step 1: Taking MRI brain tumor image from dataset
Step 2: (a) Resize the input image
(b) Use of Median filter to remove nois
(c) Enhance the image contrast
Step 3: Image segmentation using k-means clustering Step 4: Feature extraction using LBP
Step 5: Collecting features data for training
Step 6: Train the CNN with those data and see accuracy result.

Framework of proposed methodology is demonstrated in below Fig.



Architecture of CNN

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2581-4575
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Framework of Proposed Methodology

Image preprocessing

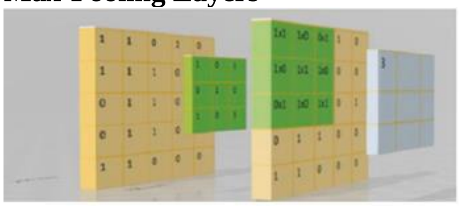
This model comprise of following phases.

• Image Processing:- A picture is comprised of RGB hues. In Image processing, some operations are performed on image in order to get an enhanced image or to extract some valuable data from it. Thus the input is usually the image and output may be image or certain properties associated with the image.
• Image Filtering :- Filtering is a procedure to change or improve the picture, for example to show certain features or eliminate other features. It incorporates smoothing, honing, removing noise and edge upgrade. Picture can be filtered in frequency or spatial domain. It is a process in which value of any given pixel in output image is found out by applying some algorithm to values of pixels in neighborhood of corresponding input pixel.
• Feature Extraction:- It includes extraction, by which certain features of interest within an image are detected and represented for further processing. It is a critical step as it marks the transition from pictorial to alphanumerical data representation. In our framework, CNN is incorporated.
• Segmentation :- It is a method of partitioning a digital image into multiple segments(set of pixels) and so is used to locate objects and boundaries viz. lines, curves etc in an image. All pixels in a region or segment share a common property. One simplest method is thresholding.
• Edge Detection :- Edge Detection is most fundamental tool in image processing and computer vision that is used to identify points in digital image at which the image brightness changes sharply and has discontinuities. It is most well-known method to find significant discontinuities in intensity values precisely. Edges appear on boundary between two regions. Most of the shape information of an image is hidden in edges of the image and needs to be extracted. Algorithm utilized in our exploration is canny edge detection operator.

6. CNN Development and Analysis
Convolution Layer
The kernel will convolve [24] over the input, so it will start at the
left and will go to the next layer, and then dot product is taken between the kernel and the input. This output feature map like convolution neural layers can detect certain features in the image. Figure 2 explains the working of 2D Kernal and the sliding of Kernal over the input image. The feature was extracted from the convolution layer.

Input and output feature maps over convolutional layer.

Max-Pooling Layers



The idea is that convolution layers can detect the edges of the little edges on the CT scan. The convolutional layers can detect certain parts of the CT scan which may be the benign nodule or the malignant nodule, and finally, the last few layers will detect the entire benign nodule. Figure 3 shows a 3D kernel for the proposed architecture. So, this is the main layer that makes up the convolutional neural network.

2581-4575
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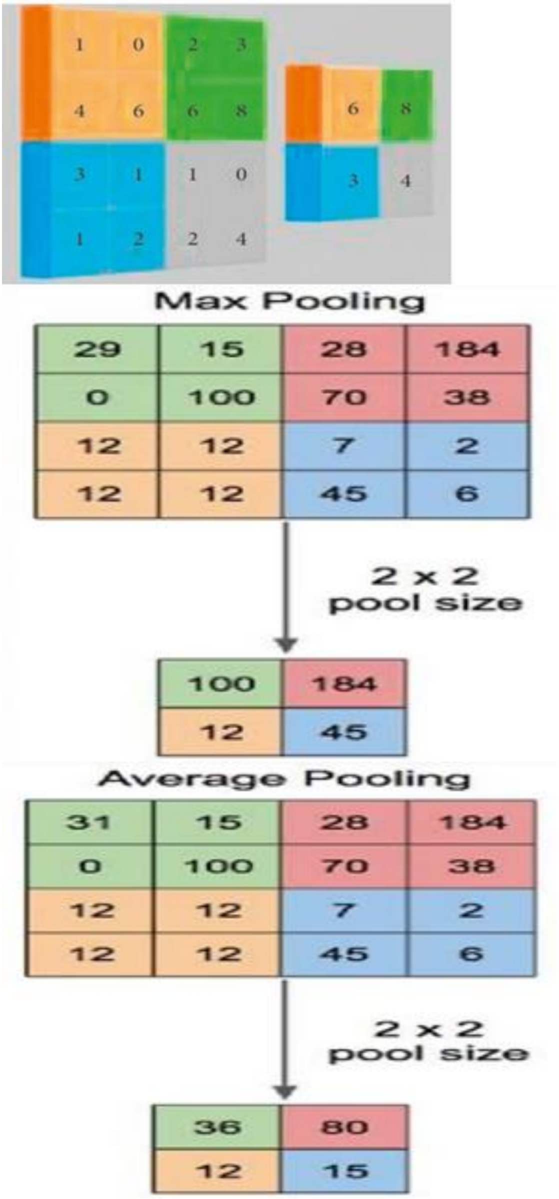
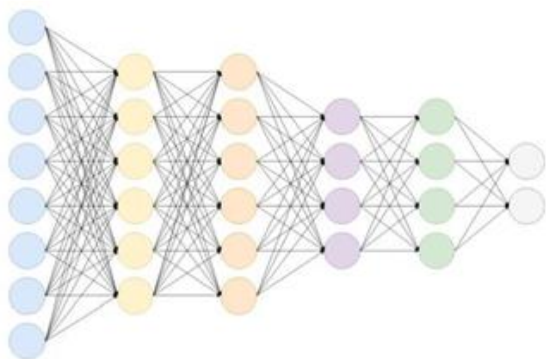
Max pooling



Max pooling is actually a merging procedure that decides on the maximum component coming from the area of the attribute chart dealt with due to the filter. Hence, the outcome after max- pooling level would certainly be a feature chart having the most prominent highlights of the previous feature map. The max- pooling layer reduces the dimensions [25] of the data and this allows for quicker computation.

Max-pooling layers which reduce dimensions allow for better computational speed and reduce overfitting. So, each CNN layer has features of increasing complexity. The first layer learns edges and corners things like that, and then, as we go further, the intermediate layers will learn more complex parts of the object, and finally, the last layers will detect full objects. We keep move the kernel down till it reaches the bottom border of the input matrix (image). Then, we return the kernel to the top, and move the kernel to its right by one element (pixel). We repeat the convolution for every possible pixel location until we have moved the kernel to the bottom right corner of the input image, as shown in Figure 3. For order 3 tensors, the convolution operation is defined similarly. Suppose the input in the l-th layer is an order 3 tensor with size Hl × Wl × Dl. A convolution kernel is also an order 3 tensor with size H × W × Dl.. Similarly, we use index variables $0 \leq i < H$, $0 \leq j < W$, $0 \leq d$ $l < Dl$ and $0 \leq d < D$ to pinpoint a specific element in the kernels. Also note that the set of kernels f refers to the same object as the notation wl. We change the notation a bit to make the derivation a little bit simpler. It is also clear that even if the mini-batch strategy is used, the kernels remain unchanged.



7. FEATURE EXTRACTION LBP-FEATURES

LBP is a texture descriptor used for the property of high discrimination power. LBP labels each pixel in an image by comparing the gray level with the neighboring pixels and then assigning a binary number. A value of unity is assigned to the neighbors with gray level greater than the center pixel in a predefined patch otherwise a value of zero. A binary number is then obtained and assigned to the center pixel. The original LBP operator considers a 3 × 3 patch so the surrounding pixels form a binary number of 8 digits. After all the pixels in an image are labeled, LBP feature map, and a histogram that consists of 256 bins is obtained. The LBP histogram can

2581-4575
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be used as a feature vector for classification where each bin represents one feature.

LBP feature vector, returned as a 1-by-N vector of length N representing the number of features. LBP features encode local texture information, which you can use for tasks such as classification, detection, and recognition. The function partitions the input image into non-overlapping cells. To collect information over larger regions, select larger cell sizes . However, when you increase the cell size, you lose local detail. N, depends on the number of cells in the image, num Cells, the number of neighbors, P, and the Upright parameter. LBP descriptors efficiently capture the local spatial patterns and the gray scale contrast in an image.

1- Convert the image into grayscale space.
2- For each pixel(gp) in the image, select the P neighborhoods that surround the central pixel. the coordinates of gp are given by
3- Take the center pixel (gc) and set it as a threshold for its P neighbors.
4- Set to 1 if the value of the adjacent pixel is greater than or equal to the value of the center pixel, 0 otherwise.
5- Now compute the LBP value: Sequentially counterclockwise, write a binary number consisting of digits adjacent to the center pixel. This binary number (or its decimal equivalent) is called LBP-central pixel code and, further, is used as a characteristic selected local texture.

$$LBP(gp_x, gp_y) \sum_{p=0}^{P-1} S(gp - gc) \times 2^p$$

gc- the intensity value of the central pixel
gp- the intensity of the neighboring pixel with index p the function S can be expressed as:

$$s(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0. \end{cases}$$

threshold (step) function
P- number of sampling points on a circle of radius R(circular neighborhood).
P- controls the quantization of the method.
R- determines the spatial resolution of the method or operator. The gray values of neighbors which do not fall exactly in the center of a pixel(block) are estimated by interpolation.

Now let's take, for instance, the following chunk of a grayscale image:

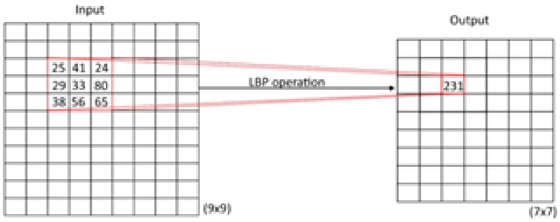

image by the author
you can express the size of this window(3x3) in terms of The radius of the circle which equals (2*R + 1), if the radius is 1, then we get a 3x3 matrix.
The coordinates of the central pixel denoted by gc (gc_x,gc_y) are (1,1) according to the coordinated axis of the matrix(3x3). The value of this pixel is 33(center) gc =33. Let's take for our example 8 neighbor samples (P=8)

8. CONVOLUTIONAL
The convolution layer.
Next, we turn to the convolution layer, which is the most involved, what is convolution? Let us start by convolving a matrix with one single convolution kernel. Suppose the input image is 3 × 4 and the convolution kernel size is 2 × 2, as illustrated a 2 × 2 kernel. The convolution input and output: Illustration of the convolution operation. If we overlap the convolution kernel on top of the input image, we can compute the product between the numbers at the same location in the kernel and the input, and we get a single number by summing these products together.

CLASSIFY: Classifies each row of the data in sample into one of the groups to which the data in training belongs. The groups for training are specified by group. The function returns class, which contains the assigned groups for each row of sample.

As in many other learning systems, the parameters k in both directions. We first run the network in the forward pass to get to achieve a prediction using the current CNN parameters. Instead of outputting a prediction, we need to compare the prediction with the target t corresponding to − 1, that is, continue running the forward pass till the last loss layer. Finally, we achieve a loss z. In most CNN materials, a

International Journal For Recent Developments in Science & Technology
2581-4575
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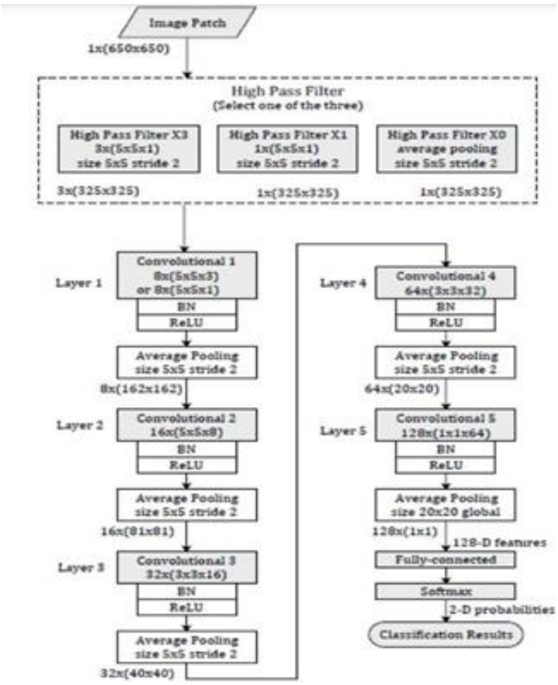
superscript indicates the "time" (e.g., training epochs). But in this note, we use the superscript to denote the layer index. Please do not get confused. We do not use an additional index variable to represent time.. This partial derivative vector is called the gradient in mathematical optimization. Hence, in a small local region around the current value of wi , to move with in the direction determined by the gradient will increase the objective value z. In order to minimize the loss function, we should update wi along the opposite direction of the gradient. This updating rule is called the gradient descent. Gradient descent is illustrated in Figure, in which the gradient is denoted by g. If we move too far in the negative gradient direction, however, the loss may increase. One update based on − 1 will make the loss smaller for this particular training example if the learning rate is not too large. However, it is very possible that it will make the loss of some other training examples become larger. Hence, we need to update the parameters using all training examples. When all training examples have been used to update the parameters, we say one epoch has been processed.

Proposed Convolutional Neural Network architecture



images shown in Fig. 1. 2.1. Proposed method An algorithm has been proposed for Automatic detection of Lung cancer using Deep Learning Techniques. The Base network has chosen from VGG-16 Architecture. In this work, classification of lung cancer such as Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma has been differentiated from the normal lung images through deep learning techniques. To train and test the performance of the network, 100 samples images are taken from each class. Out of which 70 images are used for training and the remaining 30 are used for validation purpose. The depth of 28 layers with Memory Size of 27 MB and 7.0 million parameters which accepts the image with the size of 224x224 pixels. On the other hand.

Image Acquisition and Postprocessing

FDG-PET/CT was performed according to the standard institutional procedures, previously detailed [6]. Post acquisition processing was performed to generate an adequate dataset for the CNN. The original CT and PET image size was 512 × 512 × N slices and 128 × 128 × N slices, respectively, where N slices is the number of slices in which the lesion appears. The CT images were clipped between −1000 and 400 Hounsfield units. PET images were resampled in the CT space. Then, both images were rescaled to lie between 0 and 1. Consequently, the dataset consisted of 3D bounding boxes on both PET and CT images, cropped around the lesion center, identified by two nuclear medicine physicians (M.S. and M.K.) with dimension 128 × 128 × N slices. Data augmentation, a strategy commonly used by deep-learning methods, was performed. Image patches were rotated in 2D space around the lesion center about the z-axis by an angle randomly selected in a range of [−10°, 10°]. This processing step artificially expands the size of the training set and reduces the overfitting phenomena.

The study workflow and the networks' architecture are summarized in Figure 1. During the training phase, a fivefold cross-validation strategy was adopted by dividing the cohort into a training dataset and a validation dataset. To assess the performance of the final model, the cohort was divided into training, validation, and test datasets. The algorithm was composed of two networks: a feature extractor and a classifier. The feature extractor was a CNN that took a CT-PET image patch of 128 × 128 pixels as input and performed classification (T1-T2 with label = 0 and T3-T4 with label = 1) according to the appearance of the image patch. The feature extractor aimed to extract the most relevant

2581-4575
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features from a single patch. The classifier took as input the mean of the second to last layer of features extracted from all slices of a single patient and aimed to perform a classification (T1-T2 vs. T3-T4) for that patient. The softmax function was applied to the last layer of both networks, in order to obtain the probability of being T1-T2 and T3-T4. The class having the highest probability was assigned to each patient. Both models were trained with the Adam algorithm.

If the next layer is a ReLU layer, the output of the next layer in fact defines many "edge detection features"
which activate only at horizontal or vertical edges in certain directions. If we replace the Sobel kernel by other kernels (e.g., those learned by SGD), we can learn features that activate for edges with different angles. When we move further down in the deep network, subsequent layers can learn to activate only at horizontal or vertical edges in certain directions. If we replace the Sobel kernel by other kernels (e.g., those learned by SGD), we can learn features that activate for edges with different angles. A CNN feature may activate frequently for dogs' heads and often be deactivated for other types of patterns. However, there are also possible false activations at other locations, and possible deactivations at dogs' heads. In fact, a key concept in CNN (or more generally deep learning) is distributed representation.

9. Fully connected layer as a convolution layer

As aforementioned, one benefit of the convolution layer is that convolution is a local operation. The spatial extent of a kernel is often small (e.g., 3 × 3). One element in x l+1 is usually computed using only a small number of elements in its input xl. A fully connected layer refers to a layer if the computation of any element in the output x l+1 (or y) requires all elements in the input xl. A fully connected layer is sometimes useful at the end of a deep CNN model.

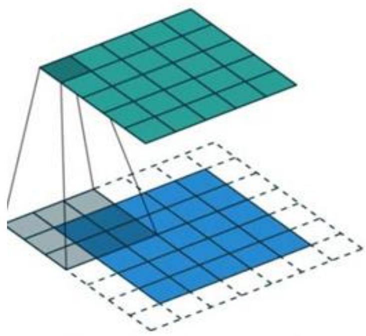
10. The pooling layer

We will use the same notation inherited from the convolution layer. Let x l ∈ R Hl ×Wl ×Dl be the input to the lth layer, which is now a pooling layer. The pooling operation requires no parameter (i.e., wi is null, hence parameter learning is not needed for this layer). The spatial extent of the pooling (H × W) is specified in the design of the CNN structure.

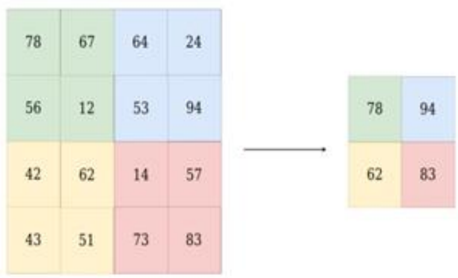
Max Pooling 2d Layer:

A 2-D max pooling layer performs down sampling by dividing the input into rectangular pooling regions, then computing the maximum of each region. SYNTAX layer = maxPooling2dLayer (pool Size, Name, Value)

• The proposed method consists of two primary steps: image preprocessing and CNN-based model training.
• In the first step, the input images—including the computer-generated graphics and the natural images— are clipped to image patches, then three types of high- pass filter (HPF) are applied to the image patches.
• ***These filtered image patches constitute the positive andnegative training samples.***
• In the second step, the filtered image patches are fed to the proposed CNN-based model for training. The proposed CNN-based model is a five-layer CNN.



Calculation of output using 2D Convolution



Pooling Stage

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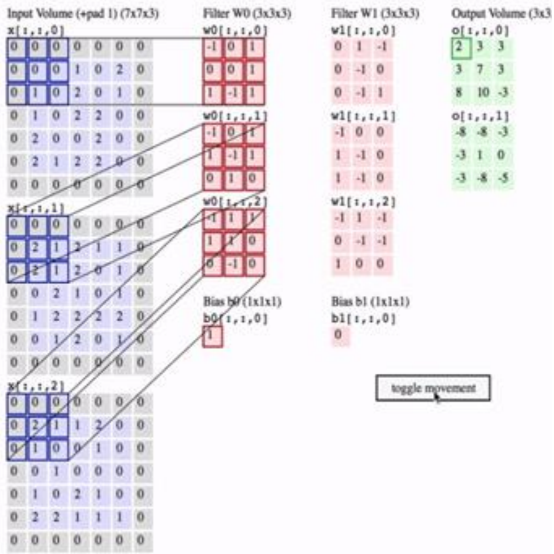

may not give the same results in the case of the test dataset. Generally, 80% of the total dataset is used as the training dataset.

c) Validation Set: Fine-tuning helps to train the model. If for the training dataset the accuracy is increasing then a certain portion of data from the training dataset which is unknown to the model is selected to check that for that dataset also the accuracy is increasing. If accuracy is not increasing for the validation set then the program is overfitting the model. In that case, the developer needs to check the value of the parameters or he/she may have to reconsider the model.

d) Test Set: The test set is used to take the output from the model. After the training, it issued to check how accurate the model is. The rest of the 20% of the dataset is used as a test set.

11. CONCLUSION

This paper discusses about the automatic Cancer detection and classification of CT Images using deep learning algorithm. The CNN algorithm is chosen for detecting the cancer regions and classifying them into normal and abnormal. For the CNN algorithm implementation, a deep convolution network architecture was used as base network. The proposed algorithm efficiently identifies the Lung Cancer.

12. FUTURE SCOPE

The CNN uses max-pooling to address the problem which is class invariants, but for the biomedical images, we need class equivalence, but the major issue here is that a lot of significant data is lost in the process, and also CNN is a bad representation to the human visual system. Capsule neural network is the best and uses class equivalence to store and mimic the human vision system. Its significance indicates that capsule neural networks can train on far less data and produce more accurate results.

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