ORIGINAL ARTICLE

Detection of Brain Tumor from MRI Images Base on Deep Learning technique Using TL Model

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Abstract: A brain tumor is a collection or mass of abnormal cells in the brain, which cause an increase in intracranial pressure, which can cause brain damage and can be life threatening. Among all imaging techniques, MRI image analysis is a powerful tool for brain tumor diagnosis. In the past, segmentation algorithms were mainly used to diagnose this disease, but they are mostly problematic due to the complex structure of the brain and the presence of similar lesion areas. In this paper, we use these images to train the transfer learning (TL) model. We subsequently test this model with 5000 T2-weighted contrast-enhanced images with three types of brain disease. The results show that the TL model has high classification performance and accuracy in terms of brain tumor identification in medical images.

Keywords: Disease, Brain, Transfer Learning, MRI Images, Tumor detection.

Introduction

A brain tumor is an abnormal mass in the brain that can be benign or malignant, by the nature of its constituent cells. The origin of the tumor may be from the brain tissue or spread to another brain or so-called metastasis. In other words, a brain tumor is a type of hard, full-blown intracranial neoplasm, or a tumor (abnormal cell growth), inside the brain or the central canal of the spinal cord [1]. Brain tumors include all intracranial tumors or tumors within the central canal of the spinal cord [2]. Uncontrolled and abnormal cell division, and typically either in the brain itself cause these tumors (including neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells, myelin-producing Schwann cells), lymphoid tissue, or blood vessels), In the cranial nerves, the meninges, skull, pituitary, and spruce are produced [3]. These tumors can also be the result of the spread of malignancies that have primarily involved other organs, which is called metastatic or metastatic Although any brain tumor is inherently serious and life-threatening because of its invasive and diffuse nature in the confined skull space, brain tumors (even malignant types) are not always fatal and deadly[4]. Brain tumors or intracranial tumors can be cancerous (malignant) or non-cancerous (benign); however, the definition of malignant or benign neoplasm in the brain is different from the definitions typically used in other types of cancerous or non-cancerous tumors body parts are used [5]. The extent of threatening a tumor depends on a combination of different factors, such as the type of tumor, the location and size of the tumor, and how it spreads and develops [6]. Because the brain is completely covered by the skull, rapid and early detection of the brain tumor is only available and used promptly if appropriate preclinical tools and diagnostic tools are available to identify the intracranial cavity [7]. However, typically, brain tumor diagnosis occurs at advanced stages of the disease and when the tumor has caused unexplained signs and symptoms in the patient [8].

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Related Works

Many researches have been conducted in the field of brain tumor diagnosis, in which only the class of images with tumors has been investigated. We examine some of them in this section. In the study done by Chowdhary and, it is suggested to use fuzzy logic to diagnose breast tumor by using C-means algorithm, which did not have the necessary accuracy and sensitivity to check the exact location of the tumor[9].In another study by Chowdhary and Acharjya suggested to use intelligent computational hybrid system for diagnose breast tumor,this method used another fuzzy logic system using intuitionist possibilistic fuzzy C-mean clustering and fuzzy SVM algorithm,this method havent the necessary accuracy for cancer detection[10].In another study Odusami and et al, suggested Resnet-18 for Alzheimer's detection from brain shape they fine-tuned ResNet-18 model is used for deep feature extraction on 138 subjects of Alzheimer's, and it provides 99.9% classification accuracy[11]. Havaei et al. introduced deeper convolutional neural network based brain tumor automatic segmentation technique this method have not high Sensitivity and Specificity [12]. In another study, Oliveira et al. introduced brain tumor segmentation model comprising genetic algorithm and AdaBoost classifier and achieved low accuracy results performed their experiment using FLAIR MRI modalities [13]. Havaei and et al, introduced multimodal brain tumor classification based on segmentain, this method promising results achieved over existing neural nets models [14]. A. Yang et.al utilize also Convolution Neural Network (CNN) as Xception and Dense Net for extreme features extraction to sift out the imagery surface information using local binary pattern (LBP)[15]. Mittal et al. utilized deep learning CNN method to tumor's detection the as benign by extracting feature [16]. Different authors have used different CNN structures for tumor classification despite the various proposed approaches for classifying brain tumors, these methods have a number of drawbacks as mentioned above. Many techniques for classifying tumors relied on manually defined tumor regions, preventing them from being fully automated. Algorithms that used CNN and its derivatives were able to increase the speed and accuracy significantly. As a result, performance evaluation based on indicators other than accuracy becomes increasingly important. To overcome the limitations in brain tumor diagnosis, a model using transfer learning is proposed for brain tumor classification using three data classes.

Transfer Learning

Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task. It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks given the vast compute and time resources required to develop neural network models on these problems and from the huge jumps in a skill that they provide on related problems. While many details of how these models work still remain a mystery, we are by now aware that lower convolutional layers capture low-level image features, e.g. edges, while higher convolutional layers capture more and more complex details and other compositional features, The final fully-connected layers are generally assumed to capture information that is relevant for solving the respective task, e.g. Pre-trained features are in practice mostly used for adaptation scenarios where we want to adapt to a new task. For the other scenarios, another way to transfer knowledge enabled by Deep Learning is to learn representations that do not change based on our domain. This approach is conceptually very similar to the way we have been thinking about using pre-trained CNN features: Both encode general knowledge about our domain. However, creating representations that do not change based on the domain is a lot less expensive and more feasible for non-vision tasks than generating representations that are useful for all tasks.

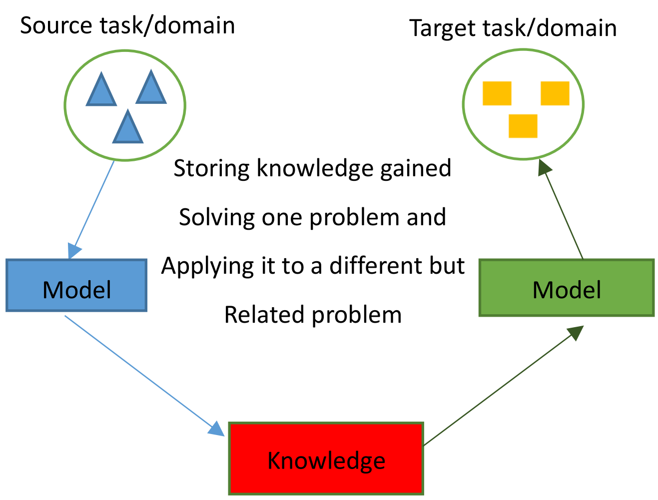

Figure 1. Solving one problem and applying it to related problem with TL model.

Convolutional Neural Network

A convolutional neural network consists of an input layer, an overlay layer, and a number of hidden layers. The basic layer in the grid used is the cannula sand layer, because of the use of the cannula sand layer to create a variety of variations the convolution layer causes the immutability and stability of the object to shift. Just as the human brain needs to respond to stress, so does artificial intelligence. We used the activator function. In the past, the sigmoid function was used for most issues, but in recent years we have introduced The Relu function has given Sigmoid its own address. Relu's function is economically feasible and saturated It also does not converge and it converges much faster than sigmoid. Our second layer is the Relu layer after the convolution layer, which It is presented as an activation function. Pooling, to reduce computational burden and make the network perform better [14]. After the Pooling Layer Using Optimization with Toure we have to invert any value for the layer parameters. We are using a fully connected layer. We apply this layer before the softmax layer so that we can set Assign classes to the given image to the net. Network design includes 5000 input image with dimensions of 128 * 128 * 3 of images input layer contains 49,152 neurons to feed images to the network. The convolution layers apply one canopy action to the input, and then give the result to the next layer. This convolution actually simulates the response of a single neuron to a visual excitation. New networks prefer to use ReLU activation functions for hidden layers instead of sigmoid. This function is defined as follows:

$$F(x) = \max(x, 0) \tag{1}$$

The pooling layer is usually placed after a layer of cannulas and can be used to reduce the size of feature maps and network parameters. Like the convoluted layers, the pooling layers are unchanged (stable) because of the neighboring pixels in their calculations. Pooling layer implementations using the max pooling function and the average pooling function are the most common implementations. We have used max pooling [17-19].
Accurate diagnosis of brain tumors in MRI imaging has many applications, including disease diagnosis, progression of treatment and disease, or design of radiotherapy interventions. This is done manually today. With the advancement of science, much research has been done into introducing computer processing into the medical sciences, and in particular medical image processing [20]. In general, MRIs in the intracranial cavity produce a complete picture of the brain. A physician to diagnose a brain tumor examines this visual image. However, this method of detection is exactly different in location and size Contract. On the other hand, as we know, accurate diagnosis of disease in images, especially in the field of medical images, is becoming increasingly important [21]. Accurate diagnosis of brain tumors from the data suggests key useful markers in disease progression to improve this approach; we introduce a circular neural network that is very accurate in addition to reducing the analysis time. In less than a decade, convolutional neural networks have been able to contribute significantly to the development of computing power in the field of deep learning, with significant success in applications such as medical imaging and self-propulsion systems [22]. The use of convolution neural networks such as Alexnet, due to the use of deeper layers than conventional neural networks, can dramatically change the category of brain tumor detection in medical image processing.

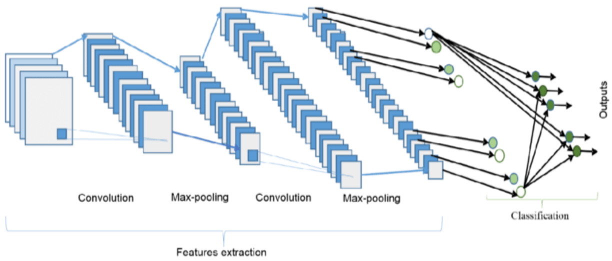

Figure 2. The overall architecture of the CNN includes an input layer, multiple alternating convolution and max-pooling layers, one fully connected layer and one classification layer.

Materials and Method

This study tests its methodology with 5000 T2-weighted MR images from 1283 meningioma Tumor 1457 Normal 2260 Brain clot. The image has a resolution of 512*512 Pixels yet; it is reduced to 128*128 pixels to decrease the computational cost of the model. Three examples are shown in figure 3.

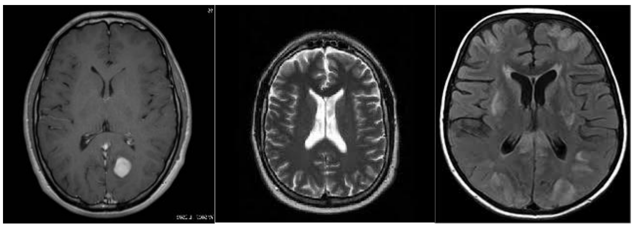

Figure 3. Tumor, normal and brain clot images.

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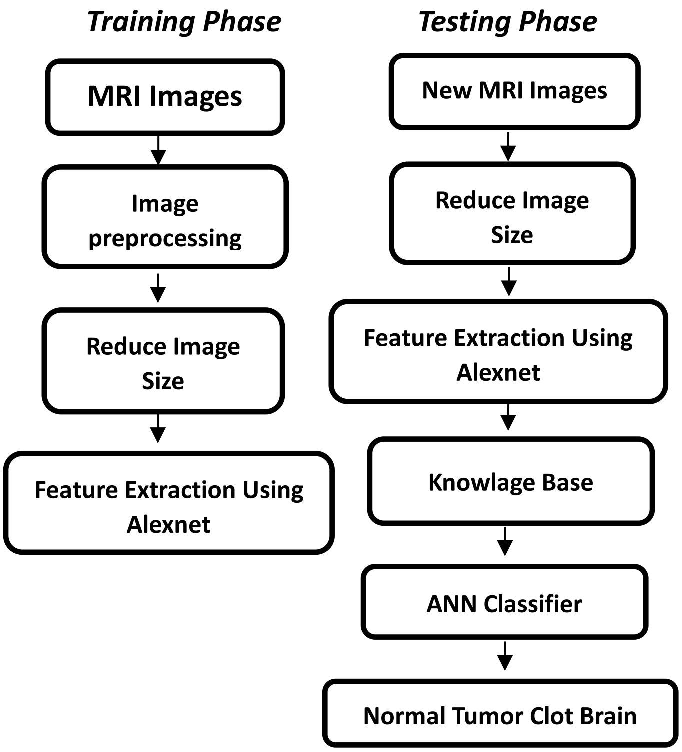
Experimental Setup

In this section, the proposed experimental setup for classification is described the TL model has been developed in Matlab 2020a due to the availability of the most common machine learning and ANN toolbox. In the work used both CPU and GPU 14.9GB RAM 3868 GB hard and runtime for deep learning and free of charge access to robust GPU.

Proposed Method



The architecture consists of eight layers: five convolutional layers and three fully connected layers. Nevertheless, this is not what makes AlexNet special these are some of the features used that are new approaches to convolutional neural networks:
ReLU Nonlinearity. AlexNet uses Rectified Linear Units (ReLU) instead of the tanh function, which was standard at the time. ReLU's advantage is in training time; a CNN using ReLU was able to reach a 25% error on the dataset six times faster than a CNN using tanh. Overlapping Pooling. CNNs traditionally "pool" outputs of neighboring groups of neurons with no overlapping.

The Over fitting Problem. AlexNet had 60 million parameters, a major issue in terms of over fitting. Two methods were employed to reduce over fitting Data Augmentation. The authors used label-preserving transformation to make their data more varied. Specifically, they generated image translations and horizontal reflections, which increased the training, set by a factor of 2048. They also performed Principle Component Analysis (PCA) on the RGB pixel values to change the intensities of RGB channels, which reduced the top-1 error rate by more than 1% dropout. This technique consists of "turning off" neurons with a predetermined probability (e.g. 50%). This means that every iteration uses a different sample of the model's parameters, which forces each neuron to have more robust features that can be used with other random neurons. However, dropout also increases the training time needed for the model's convergence.

Neural Network Detail

Back propagation algorithms are a family of methods used to efficiently train artificial neural networks (ANNs) following a gradient-based optimization algorithm that exploits the chain rule. The main feature of back propagation is its iterative, recursive and efficient method for calculating the weights updates to improve the network until it is able to perform the task for which it is being trained. It is closely related to the Gauss–Newton algorithm. Back propagation requires the derivatives of activation functions to be known at network design time. Automatic differentiation is a technique that can automatically and analytically provide the derivatives to the training algorithm. In the context of learning, the gradient descent optimization algorithm to adjust the weight of neurons by calculating the gradient of the loss function commonly uses backpropagation; back propagation computes the gradient(s), whereas (stochastic) gradient descent uses the gradients for training the model (via optimization). In other words, The Back propagation algorithm looks for the minimum value of the error function in weight space using a technique called the delta rule or gradient descent. The weights that minimize the error function is then considered a solution to the learning problem.

Calculate weight correction parameter
Calculate weight and bias correction value
Bias correction parameter calculation
Receive Delta Entries by Hidden Units from Output Units
Multiply the derivative of the activation function to calculate the parameter for the error information
Updating the weights and bias of the output units
Updating the weights and bias of hidden units

$$\delta k=(tk-yk) \tag{2}$$

Δwjk=αδkZj (3)

ΔW.k=αδk

$$\delta - inj = \sum_{k=1}^{m} \delta k \;\; wjk \tag{4}$$

Δvij=αδjxi Δv.j=αδj (5)

Stochastic Gradient Descent is a simple yet very efficient approach to discriminative learning of linear classifiers under convex loss functions such as (linear) Support Vector Machines and Logistic Regression. Even though SGD has been around in the machine learning community for a long time, it has received a considerable amount of attention just recently in the context of large-scale learning. Stochastic Gradient Descent has been successfully applied to large-scale and sparse machine learning problems often encountered in text classification and natural language processing.

Stochastic gradient descent in contrast performs a parameter update for each training example x(i) and label y(i)

$$E(\vec{W}) \equiv \frac{1}{2} \sum_{d \in D} \sum_{k \in outputs} (t_{kd} - o_{kd})^2 \tag{6}$$

$$\theta = \theta - \eta . \nabla \theta J(\theta; x(i); y(i)) \tag{7}$$

Gradient descent is a way to minimize an objective function J(θ) parameterized by a model's parameters θ∈Rd by updating the parameters in the opposite direction of the gradient of the objective function ∇θJ(θ) w.r.t. to the parameters see in Equation(4). The learning rate η determines the size of the steps we take to reach a (local) minimum. In other words, we follow the direction of the slope of the surface created by the objective function downhill until we reach a valley. The result of using this chain rule is written in the following way:

$$\frac{\partial f(u(t), v(t), w(t))}{\partial t} = \frac{\partial f}{\partial u}\frac{\partial u}{\partial t} + \frac{\partial f}{\partial v}\frac{\partial u}{\partial t} + \frac{\partial f}{\partial w}\frac{\partial w}{\partial t} \tag{8}$$

$$\delta_c = \frac{\partial Q}{\partial_{ac}} \tag{9}$$

$$a_c = \sum_p w_{pc} \times b_{pc} \tag{10}$$

$$b_c = \theta_c(a_c)$$

$$\frac{\partial Q}{\partial w_{pc}} = \frac{\partial Q}{\partial_{a_c}} \frac{\partial_{a_c}}{\partial w_{p_c}} = \delta_c b_p \tag{11}$$

$$\delta_c = \frac{\partial Q}{\partial a_c} = \frac{\partial Q}{\partial b_c}\frac{\partial b_c}{\partial a_c} = \frac{\partial Q}{\partial b_c} \times \theta_c'(a_c) = \left(\sum_n \frac{\partial Q}{\partial a_n}\frac{\partial a_n}{\partial b_c}\right) \times \theta_c'(a_c) = \left(\sum_n w_{an}\delta_n\right) \times \theta_c'(a_c)$$

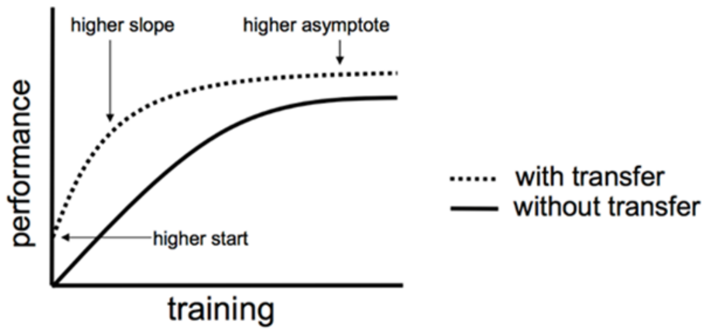


Figure 4. Training with transfer learning

Results

A Convolutional Neural Network are a special kind of multi-layer neural networks, designed to recognize visual patterns directly from pixel images with minimal preprocessing Convolutional Neural Network or CNN Conventional Neural Network is widely used in pattern swimming and It has images and is a sort of synthetic neuron that exchanges data between them. Weighted Communication this is a number that is adjusted during the training process, so that the learned network for swimming the pattern with the least Answer the error. This network consists of several layers of characteristic neurons, each layer having multiple neurons and it responds with inputs from previous layers. In the convolutional neural network, the layers play a characteristic detector role Play but not set by the user. The core of the weight filter is the decision maker of the training process. Conves layers they have the ability to extract local attributes because they restrict layers locally. Basic neural networks the core of deep learning is that in discrete spaces such as pattern anchoring, CERN anchoring, natural language processing and analysis the video is in use. The balance between depth, accuracy and

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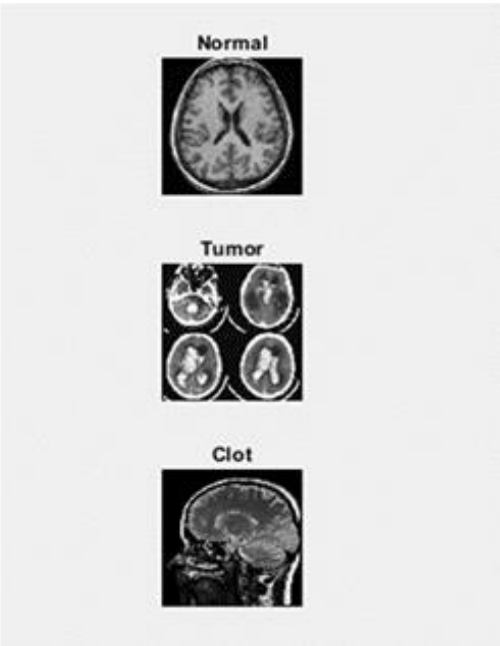
network speed is very simple. The more layers used, the greater the overall accuracy, but it makes your slope slower as the number of calculations increases. In general, you can have depth look and find the best place to get the highest score. After a bit of testing you can probably go"Decline yield" well guess this point. In some cases you have to be aware that the balance between accuracy and regularity is regulated (diminishing returns) the more layers we add, the less precision in each individual layer. The world's most accurate network remains unclear.

Convolutional neural networks use preprocessing to a lesser degree than other image classification approaches. This means that the network encompasses the criteria learned in previous approaches to data. This Independence from prior knowledge and human manipulations in torsional neural networks is a major advantage.



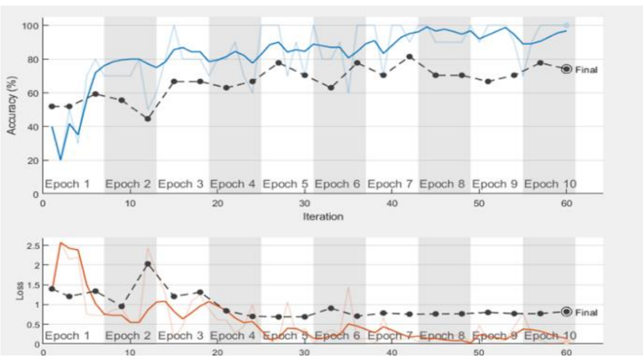


Figure 6. Network training process

Table 1. The accuracy obtained in the simulation

Experiment	MeanSensitivity (%)	Mean Accuracy (%)
Image1	90.54	88.25
Image2	90.65	89.76
Image3	78.87	76.98
Image4	89.09	82.75
Image5	85.98	83.15
Image6	89.32	86.99
Image7	88.59	81.76
Image8	98.75	92.8
Image9	90.99	82.81
Image10	87.22	85.98
Image11	87.70	85.93
Image12	87.13	84.82

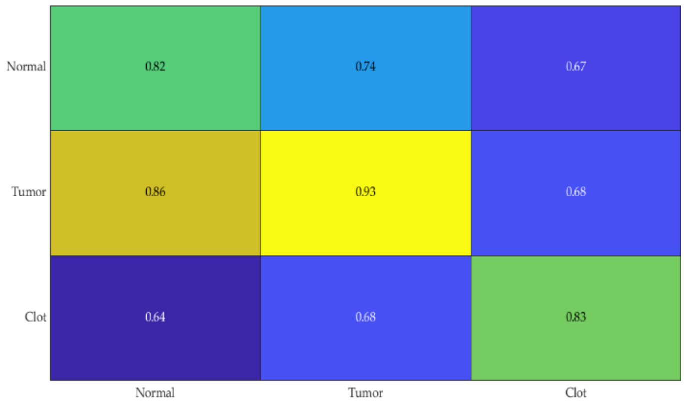


Figure 7. Mean accuracy (%) in brain tumor detection

Conclusion

For an accurate diagnosis of brain tumor patients, the proper Detection method is required to be used for MR images to carry out an improved diagnosis and treatment. Currently, information is provided by many images from various slices required for accurate diagnosis, planning, and treatment purpose. The volume of the available information requires computation processing to inform the decision-making. Now-e-days, the speed of computation is no longer an issue for researchers. Therefore, the focus is directed toward the improvement of information from images obtained through the slice orientation and perfecting the process of Detection to get an accurate picture of the brain tumor. Therefore, in the next work in the framework of brain tumor identification, more attention will be paid to improving the quality of images obtained from the brain in order to receive more accurate information from the image, so that it can be very useful in diagnosis. In addition, accelerate the treatment of this disease. The field of medical image processing includes a wide range of applications from the automated screening of diabetic retinopathy based on retinal images to MRI segmentation for tumor recognition. Various machine learning classification and clustering approaches have been studied in literature to improve the accuracy of the screening methods. Some studies used manually feature extraction of fundus images by image processing experts. In recent years, a new approach for image classification and diagnosis without using any manual feature extraction is proposed based on a convolutional neural network (CNN). The CNNs are based on deep learning concept have more convolutional and hidden layers and are more powerful envolving the high dimension inputs such as medical images. In medical imaging and diagnosis, training a deep CNN from scratch is difficult because it requires a large amount of labeled training data and the training procedure is a time-consuming task to ensure proper convergence. Therefore, a very common method to train CNNs for medical diagnosis is fine-tuning a pre-trained CNN. Some of these powerful pre-trained CNNs are the GoogleNet, CifarNet and AlexNet, which have been trained on theImageNet as a large database.

Chart 1. Comparing Alexnet with past Methods in Machine Learning.

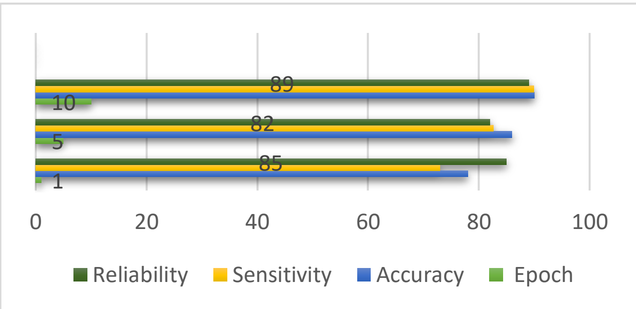


Chart 2. Comparing Alexnet features with past Methods in Machine Learning.

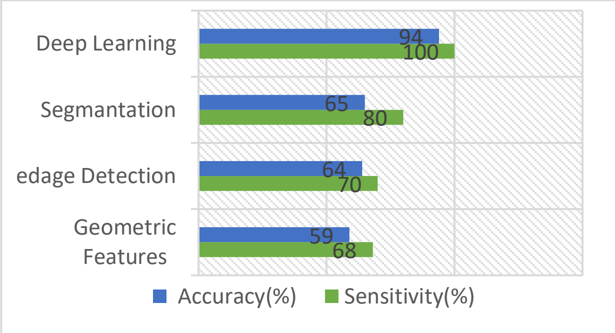
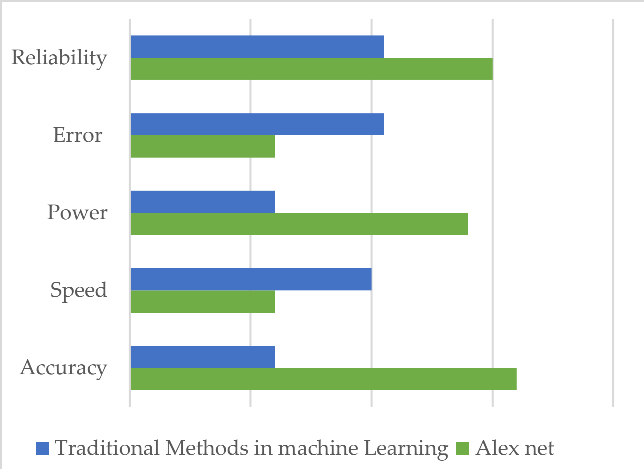


Chart 3. Comparing deep learning with past Methods in Machine Learning.



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