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Brain Tumor Classification Using Machine Learning and Deep Learning Algorithms

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ABSTRACT- Early identification and diagnosis of brain tumors have been a difficult problem. Many approaches have been proposed using machine learning techniques and a recent study has explored deep learning techniques which are the subset of machine learning. In this analysis, Feature extraction techniques such as GLCM, Haralick, GLDM, and LBP are applied to the Brain tumor dataset to extract different features from MRI images. The features which have been extracted from the MRI brain tumor dataset are trained using classification algorithms such as SVM, Decision Tree, and Random Forest. Performances of traditional algorithms are analyzed using the accuracy metric and stated that LBP with SVM produces better classification accuracy of 84.95%. Brain tumor dataset is input to three-layer convolutional neural network and performance has been analyzed using accuracy which is of 93.10%. This study proves that CNN performs well over the machine learning algorithms considered in this work.

Keywords: Brain Tumor, Deep Learning, Machine Learning, GLDM, HARALICK, GLCM, LBP,SVM, Random Forest, Decision Tree, CNN.

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1. INTRODUCTION

The brain is defined to be a complicated physical organ in humans that has billions of cells. The tumor in the brain begins with the unusual development of cells that multiply in a usual manner. The tumor develops through brain cells on the walls of the brain, inner glands region, or on nerves. Brain cells become weak and get damaged by giving additional pressure to the skull during the developing stage of the tumor (Varuna Shree, N., & Kumar, T. N. R., 2018) [1].

The masses that develop in human brains can broadly classified as benign and malicious, is depicted in *figure 1*. Brain tumors have been diagnosed and treated at various stages. Based on the severity, the tumors have categorized into different grades given by the standards of the World Health Organization (Louis, D. N., et al. 2016) [2]. The early detection of brain tumors at the beginning stages can increase the longevity of the individuals affected by this type of tumor. The rapid growth of brain tumors produces the number of brain MR images that have accurately analyzed.

In medical image processing, CT, PET and MRI have been used for the early identification of cancer cells. Diagnoses of MRI images are very effective compared with the other medical imaging methods (Patel, J., &Doshi, K.., 2014) [3].

Artificial intelligence has been used in recent years to automate the detection processes utilizing deep learning and neural networks. These methods have been frequently employed to detect and locate tumor cells. (Lundervold, A. S., & Lundervold, A., 2019) [4] Convolutional is the term referring to a mathematical linear action in CNN. At each layer of CNN, the image's size is decreased without sacrificing the data necessary for training. The model is created using a variety of processing techniques, including convolution, maxpooling, flatten, and dense layers. In this research, the MRI brain images have been classified into three categories. The performances of traditional classifiers on brain tumor classification against CNN have been analyzed.

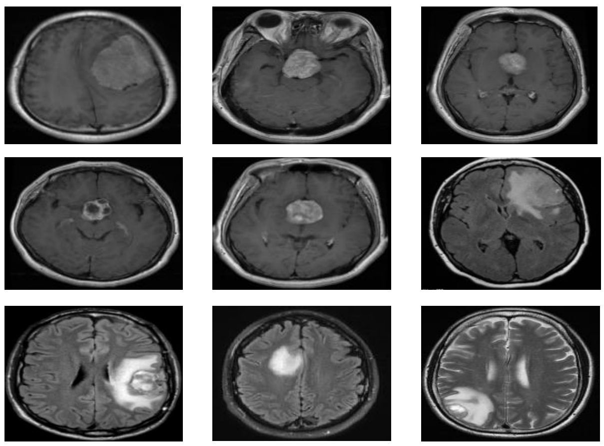

Figure 1: MR images of T1-Weighted-Contrast-Enhanced-MR Brain-Tumor

The brain tumor classification follows 3 steps (*i*) Pre-processing (*ii*) Feature Extraction (*iii*) Classification. Efficient feature extraction algorithms like GLDM, Haralick, LBP and GLDM are used to extract features. They have been trained by SVM, Decision Tree and Random Forest classifiers. The proposed work concerns an eminent comparison between the classifier performances on MRI brain images, specifically for brain tumor classification. Our motive is to conclude the best classification technique and the best feature extraction algorithm that supports effective decision-making in clinical practice.

In this paper (Khalil, M., Ayad, H., &Adib, A., 2018) [5] the brain images are categorized as ordinary and unusual by extracting the features of the image using various feature extraction algorithms like HOG, GLCM, LBP and adopted K-NN classifier for classification. The obtained simulation results showed that HOG in combination with k-NN has been producing the best classification results. The authors of (Vijayarajeswari, R. et al. (2019) [6] presents a classification method for mammograms using features extracted by the Hough transform. The results are effective with SVM classifiers. In this paper (Anitha, R., & Siva Sundhara Raja, D., 2018) [7] an automatic classification technique has been proposed, that differentiates different grades of cancer in MRI images. The features have been considered on both region-wise and subject-wise information. Finally, Random Forest is incorporated for training and testing the classifier. In this paper (Swati, Z. N. K., et al., 2019) [8] authors built a model for brain tumor classification that focuses on transfer learning and segment-wise fine-tuning. This approach presents a classification model that is suitable for any human organ of anMRI image. The paper (Venkatesan, E., &Velmurugan, T., 2015) [9] analyses the performances of Decision theTree Algorithm for Breast Cancer Classification. The system examines only the specific important regions of breast cancer by the classification algorithms such as ADTree, CART, J48 and BFTree. The performance of J48 has been proven to be better in performance than the other three algorithms.

Traditional classifiers and several neural network architectures have been used in recent studies on cancer detection. It is observed that SVM has outperformed several (Abe, B. T., Olugbara, O. O., &Marwala, T., 2014) [10] datasets. Random forest and Decision tree also gives better accuracy in detection and classification problems. Author (Shanmuga Priya, S., et al., 2021) [11] analyze the performance of Multilayer Perceptron (MLP) and Pre-trained Alexnet model with an MRI brain tumor dataset. Texture features are extracted with help of GLCM and the haralick method and the higher classification accuracy of 82% is compared with the previous model and Alexnet model. In addition to this, Convolutional Neural Network gives better classification in various cancer detection problems. Though many proposed methods give good results, still there is a need to explore the best-suited methods for the brain tumor classification. The following list highlights the main research advancements made by the proposed method:

- Implementing a CNN Algorithm using the Data Augmentation technique for training the dataset, making slight adjustments to brightness, rotation, and flipping. As a result, the quantity of the training data grows, with these slight differences being treated as independent images
- Providing improved efficacy for spotting leaf diseases

The article is organized is follows *Section 2* defines the Materials and Methods, *Section 3* gives the Result and Discussion and *Section 4* concludes the brief analysis of the work.

2. MATERIALS AND METHODS

2.1 Dataset

The experimentation of brain tumor detection was carried out in two folds (*i*) Existing feature extraction with different classifiers (*ii*) Proposed Three Layer Convolutional Neural Network. In the proposed work, Training and testing were conducted using the T1-weighted CE-MR brain dataset, contains 3064 MRI images with 512 width and 512 heights in size from 233 patients. The dataset contains these three distinct types of tumors—pituitary tumors, gliomas, and meningiomas—as shown in *table 1*.

Table 1: MRI Image Data set [17]

T1-weighted CE-MR brain dataset	
Tumors Types	**Number of MRI images**
Meningiomas	708
Gliomas	1426
Pituitary	930
Total	3064

The varied types of pre-processing techniques are applicable for different circumstances. This pre-processing technique applied on the MRI images to remove the noise which creates difficulty in direct image analysis. Initially preprocessed images were converted into gray scale images. There were solely 256 gray colors. The main reason for grayscale imaging methodology employed was, it contains solely luminance data and not color data (Mas, S., et al., 2019) [12]. All the images were resized to 128 x 128 pixels.

2.2 Existing Feature Extraction and Classification Algorithm

Feature extraction is a set of methods to extract important features from corresponding MRI. The considered feature extraction algorithms were LBP, GLDM, GLCM and Haralick.

Feature Extraction

2.2.1 Local Binary Pattern (LBP)

LBP is used to describe the different texture information in the image. Kernel with the size of 3X3 moves over the image pixel (Korkmaz, S. A., &Binol, H., 2018) [13]. The center point pixel value was compared with the neighbor pixel and returned binary value 0 or 1. If the value of the center pixel point is greater than the neighbor pixel value, it returns 1 otherwise 0 binary values of the neighbor pixel was considered and converted into decimal value to the center point of the pixel which was the LBP feature of the given 3X3 matrix. By taking 3X 3 matrix over the greyscale image, Compare the grey level value of pixel [1,1] with its neighbor pixel value to find the feature [1,1] pixel point. The process of obtaining the LBP feature from the grey level was achieved by taking 3X 3 matrix over the greyscale image as shown in *figure 2*, Compare grey level central pixel with 8 neighbors pixel value to replace binary value 0 or 1 as neighbor pixel values. The binary pattern can be achieved for neighbors and converted into equivalent decimal values for the central pixel. Let Ip be the gray level value of the central pixel p and I_j represent the j^{th} grey level pixel value of the neighbor.

$$LBP(p) = \sum_{j=0}^{7} \binom{n}{k} 2^i a(I_j - I_p) \quad (1)$$

Where, j from 0 to 7.

Threshold function K(t) used for converting neighbor pixel values to binary values where, t denotes the central pixel value in the equation (2),

$$K(t) = 1, t \geq 0 \quad otherwise \;\; 0 \quad (2)$$

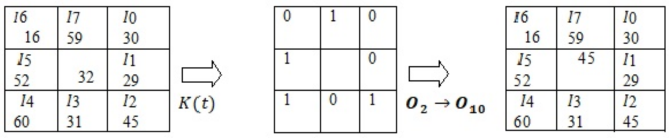

Figure 2: Local Binary Pattern

2.2.2 Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) is responsible for extracting statistical features from MRI images. It uses the Gray Level Co-occurrence Matrix to obtain statistical features from MRI images (Öztürk, Ş., &Akdemir, B., 2018) [14]. Texture features were obtained from the two-dimensional matrix of joint probabilities among pairs of pixels divided by a distance in a given direction. The texture features of Haralick were determined from GLCM. This haralick works better with gray level image.

2.2.3 Gray Level Difference Method (GLDM)

In Gray_Level _Difference Method (GLDM) digital image function is written as *i(x.y)* and $\delta = (Dx, Dy)$ for any given displacement. Where,dn and dm were the integer, so that $i\delta(x, y) = |i(x, y) - i(x+ \Delta x, y+ \Delta y)|$. The function $f'(.|\delta)$ is to estimating the probability with the desirable values of $i\ \delta$. For the expriments four vectors δ was considered. For example, *(0, s), (-s, s), (s, 0), (-s, -s)*. where d is the sampling space distance (Kitanovski, I., et al., 2011) [15].

Classification: The process of classifying the images as Tumor cells based on the trained features. The different features extracted were given to the classifiers and built. Later the test data was given for classification and the accuracy of classification were computed.

2.2.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) classifier that works by splitting the data into groups by generating lines in between the data points. The best line was considered for the separation of a class of data by considering the maximum space to separate two classes. A hyperplane was chosen by measuring the margin of the hyperplane. The largest distance margin from the hyperplane will be the best choice to choose for the classification problem. The hyperplane could be defined by $g(\vec{x})$ the weight of vectors given below *equation 3*,

$$g(\vec{x}) = \vec{w}\vec{x} + w_0 \quad (3)$$

Weight vector can be defined by $w(p, 2p)$

$$g(\vec{x}) \geq 1, \forall \vec{x} \in class1$$
$$g(\vec{x}) \leq -1, \forall \vec{x} \in class0$$

2.2.5 Decision Tree

A Decision tree is a Hierarchical tree-shaped structure that had to define a plan of action. Every tree branch is a possible decision. Entropy is used to find the unpredictability in the dataset. Entropy was measured for class attribute and each attribute was used to decide the root node of the decision tree from *equation (4)*. Information gain was measured for the selected attribute as the same as the entropy class measured by *equation (5)*. Once information gain was calculated the entropy for the selected attribute is computed by *equation (6)*, Highest Entropy (attribute) was considered to be a root node in the decision tree.

$$Entropy(Class) = \frac{-Pvalue}{Pvalue-Nvalue} log_2\left(\frac{Pvalue}{Pvalue-Nvalue}\right) - \frac{-Nvalue}{Pvalue-Nvalue} log_2\left(\frac{Nvalue}{Pvalue-Nvalue}\right) \quad (4)$$

$$InformationGain(P_i, N_i) = \frac{-Pvalue}{Pvalue-Nvalue} log_2\left(\frac{Pvalue}{Pvalue-Nvalue}\right) - \frac{-Nvalue}{Pvalue-Nvalue} log_2\left(\frac{Nvalue}{Pvalue-Nvalue}\right) \quad (5)$$

$$Entropy(Attribute) = \sum \frac{-P_i+N_i}{Pvalue+Nvalue} InformationGain(P_i, N_i) \quad (6)$$

2.2.6 Random Forest

A group of classifiers with tree like structure makes up the Random Forest Classifier. The Gini Index is used by the Random Forest. Based on relatively little Gini Index, the Gini Index limit has been broken. The number of *trees(n)* formed with a variety of factors in each node served as a good *partition indicator(m)*. Each node's initial value was selected by the user and subsequently depending on the defect, its corresponding values were either extended or shrunk.

2.3 Convolution Neural Network

2.3.1 Convolution Layer

The convolution layer learns the feature from the source of the input image. It consists of future maps. future maps in every neuron were used for extracting local attributes of various locations in the prior layer. initially, future maps were convolved with the kernel then results were transferred to nonlinear activation functions such as sigmoid, tanh and Relu (Chandrakar, M. K., & Mishra, A., 2020) [16].

2.3.2 Pooling Layer

The pooling layer, which is a secondary future extraction, can increase the strength of future extraction while simultaneously reducing the components of future maps. Most of the time, it was positioned between two Convolution layers. The movement of the kernel across the image was used to determine future maps. High level properties can be effectively extracted by utilising many pooling layers and convolution layers.

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2.3.3 Fully Connected Layer
The fully connected layer, which receives the convolutional result from the pooling layer, flattens it, and then determines the classification. Weights were used to connect every output neuron to every input neuron. Flatten feature maps passed to the fully connect layer. The traits were integrated into more properties via a fully connected layer, which improved the ability to identify different types of tumor cells.

Medical image processing makes heavy use of convolutional neural networks. A separate CNN model was developed by researchers to test its utility in identifying brain regions likely to develop tumours. (Deepak, S., & Ameer, P. M., 2019) [17]

2.4 Data Augmentation
The data augmentation idea is used to artificially increase the dataset size depending on the data already there. The training procedure for deep learning concepts involves significant amount of data with precise parameter settings, as is well known. Because there are less samples in the suggested dataset, this research incorporates the idea of data augmentation for the training process, making slight adjustments to the brightness, rotation, and flipping, as depicted in *figure 3*. As a result, the quantity of the training data rises, taking into account these slight variations as a different image and aiding the model in better learning unobserved data.

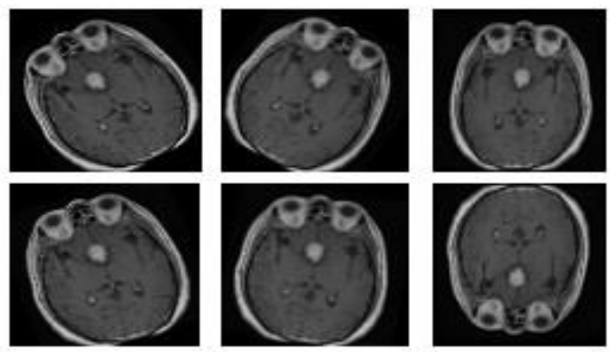

Figure 3: Augmented MR images

3. PROPOSED 3 LAYER CONVOLUTION NEURAL NETWORK
In this work, tumor detection by the proposed CNN model of the Three Layer Convolutional Neural Network in Figure 4. The model has developed with five layers which consist of an input layer and an output layer. Data augmentation is complete before training the CNN model in translation invariance. Max_Pooling takes place after convolute the input source at each layer. Input images converted into a homogenous size of 128*128 are used to load in the input layer. The kernel of 3*3 size was applied to the input image with a stride of 2 to extract the features. Max_pooling was applied over the convoluted image and resulted in the future maps of an input image. Feature maps were stretched to a single-dimensional vector and taken as a dot product of the vector by applying a filter to get scalar output. A fully connected layer takes the decision classification of tumors.

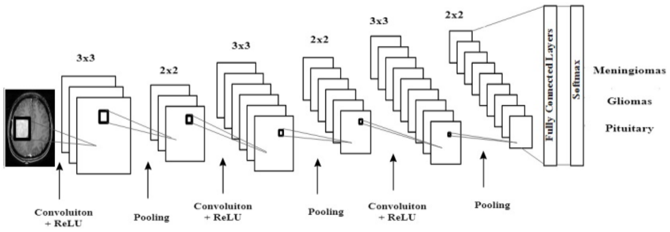

Figure 4: Three Layer Convolutional Neural Network Architecture

We accomplish 93.10% of accuracy for 70:30 splitting ratio where the training accuracy is 99.31%. So our proposed model gives the best result when comparing with the traditional machine learning approach.

4. RESULTS AND DISCUSSION
4.1 Performance Analysis of Existing Methods
One of the toughest system applications that proved useful in sophisticated computer-aided diagnosis was the identification of brain tumors in MRI images. Numerous feature extraction and classification methods have been tested in the need to find malignancies. Different features have been collected on one side using various feature extraction methods. These features were tested on samples after being trained using various classifiers with 10-fold cross-validation. On the other hand, the accuracy results of a Three Layer Convolutional Neural Network for tumor identification were assessed.

The accuracy of the features extracted from the MRI images using LBP, haralick, GLCM, and GLDM, which were then provided to SVM, Random Forest, and Decision Tree, was measured. *Table 2 and 3* contain the findings of experimental comparisons among LBP, haralick, GLCM, GLDM, feature extraction methods employing SVM, Decision tree, and Random Forest.

Table 2: SVM classifier accuracy for various features set

Feature Extraction	SVM Accuracy (%)
GLCM	73.98
GLDM	71.13
HARALICK	76.01
LBP	84.95

Table 3: Decision Tress classifier accuracy for various features set

Feature Extraction	Decision Tree Accuracy (%)
GLCM	74.39
GLDM	69.10
HARALICK	70.32
LBP	78.45

Table 4: Random Forest classifier accuracy for various features set

Feature Extraction	Random Forest Accuracy (%)
GLCM	75.20
GLDM	77.64
HARALICK	75.60
LBP	83.73

Table 5: Comparing each feature extraction method with each classifier

Feature Extraction	SVM Accuracy (%)	Decision Tree Accuracy (%)	Random Forest Accuracy (%)
GLCM	73.98	74.39	75.20
GLDM	71.13	69.10	77.64
HARALICK	76.01	70.32	75.60
LBP	84.95	78.45	83.73

LBP (local binary pattern) feature extraction algorithm excelled with all the classifiers and provided better accuracy. It was proved that LBP combination with SVM provide better performance than other classifiers. Furthermore, from Table 5 also observed that SVM in combination with LBP gave 84.95% accuracy, Random Forest with LBP gave 83.73% accuracy, and Decision Tree with LBP gave 78.45 % accuracy. Thus, it is concluded that SVM yields better results than the Random Forest and Decision Tree.

4.2 Performance Analysis of Existing Methods with Proposed Method

As *figure 5* depicts, Three Layer Convolutional Neural Networks yield 93.10% accuracy for the pre-processed Brain-Tumor dataset shown in *table 6*. Therefore, Three Layer CNN performed better than other traditional machine learning algorithms such as Support Vector Machine, Random Forest, and Decision Tree.

Table 6: Accuracy comparison of LBP+SVM with Three-layer CNN

Methods	Accuracy (%)
Three-layer CNN	93.10
LBP+SVM	84.95

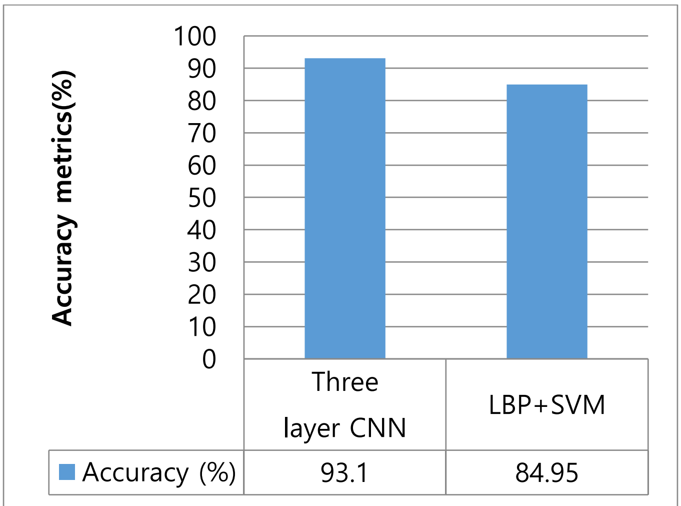

Figure 5: Accuracy comparisons of LBP+SVM with Three-layer CNN

Any ML methods are capable of completing the task of image categorization. However, all ML algorithms needed the right features to do classification. The classifier won't be able to categorize the images accurately when inputting the raw images and its accuracy will suffer.

The CNN manages the entire feature engineering process by extracting the attributes from the images. In a typical CNN design, the initial layers extract the image's low-level features, and the last layers extract the image's high-level features.

5. CONCLUSION

One of the difficult and demanding topics in medical image processing is brain tumour detection. For the purpose of identifying and categorising brain tumours, numerous researchers have recently devised a variety of techniques. However, the majority of techniques rely on standard-sized MRI scan, which are used to train neural network models. The dataset of size 128X128 has been taken into consideration in this study. By contrasting several feature extraction techniques and classifiers, comparison studies have been made. This study establishes that extraction of features and classifying them as Meningiomas, Gliomas, and pituitaryusing three-layer convolutional neural network is superior to traditional machine learning algorithms.

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