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THE EFFECTIVENESS OF FEATURE EXTRACTION AND MACHINE LEARNING CONCEPT IN DETECTION OF BRAIN TUMOR

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Abstract
The human body's regulating center is the brain. It regulates processes that include problem-solving, personality, knowledge, vision, hearing, and memory. The stalled development of brain cells is the primary cause of brain tumors. Numerous health organizations have identified brain tumors as the second most common condition that results in a significant number of fatalities worldwide. Early detection of a brain tumor provides the possibility for efficient medical care. Magnetic resonance is used Comparing imaging images to computed tomography images, imaging images have been found to be more consistent and detailed. There are numerous methods for finding brain tumors or other neoplasms. This paper reviews several relevant research papers and discusses the most capable and efficient algorithms. The majority of studies use pre-processing, segmenting, feature extraction, clustering, and cancer identification as their approaches. The model presented in this study uses machine learning methods to accurately identify brain tumors in magnetic resonance imaging.

Keywords: Machine Learning, Feature Extraction, Brain Tumor, Support Vector Machine.

I. Introduction

In this study work, the various stages of brain tumours have been covered. The division of cerebral cancer is a crucial task in the management of clinical images. Early detection of brain tumours plays a critical role in expanding treatment options and increasing the patients' endurance rates. One of the most crucial tools surgeons employ to identify brain tumours is medical imagery. It can be quite beneficial to have a tool that automates this operation with excellent precision.

Such a tool, however, cannot take the place of the qualified medical opinions of trained professionals due to concerns over legal obligations.

It is a difficult and time-consuming task to manually separate the mind growths for disease discovery from the massive amount of MRI images created in clinical daily practise. Furthermore, mind growth analysis calls for a high degree of precision because even a small error in judgement could have disastrous consequences. As a result, cerebrum cancer division is challenging for clinical uses.The specifics of brain tumour grades are as follows in this regard.

Grade I : Tumours develop gradually and do not spread quickly. These can nearly entirely be removed through surgery and are linked to greater long-term survival chances. Grade 1 pilocyticastrocytoma is an illustration of one such tumour.

Grade II: These tumours have a similar slow growth rate but have the potential to spread to nearby tissues and progress to higher grades. Even after surgery, these tumours are prone to recurrence. An example of one of these tumours is the oligodendroglioma.

Grade III: These tumours can penetrate the surrounding tissues and grow more quickly than grade II tumours. Such tumours require post-surgical radiotherapy or chemotherapy as surgery alone is ineffective in treating them. Anaplastic astrocytoma is an illustration of one such tumour.
Grade IV: The most aggressive and easily spread tumours fall into this category. They might even exploit blood vessels to develop quickly. One such tumour is glioblastoma multiforme.
Different machine learning algorithms were employed in the work to find patterns in magnetic resonance images. Less data was lost, and the model was built using a simplified architecture to create a thin deep neural network. In comparison to earlier models, it is more accurate and takes less time to compute.
The remainder of the essay is structured as follows: The literature review is presented in Section II, the proposed system is presented in Section III, the findings and discussion are shown in Section IV, and the conclusion and future work are presented in Section V.

II. Literature

Designing methods for brain tumour diagnosis has drawn more attention in recent years. Magnetic resonance imaging (MRI) tumour analysis heavily relies on medical picture segmentation. Several methods have been suggested to find tumours in MRI scans. Here is a summary and presentation of some current research findings.
Gopal and Karnan[1] used image processing clustering methods to separate images into two groups: those with brain tumours and those without. The dataset used in this study is made up of 42 MRI pictures that were taken from the hospital's database at KG. The authors eliminate the film artefacts (labels and X-ray markings) during the preparation stage. They also take out high frequency elements from the MRI image using the Median filter. The authors then employ a Genetic Algorithm (GA) as a clever optimisation tool in addition to the Fuzzy C Means (FCM) algorithm as an image clustering approach.
In order to reduce complexity and improve performance, N. Varuna Shree et al. [2]focus on noise reduction techniques, the extraction of GLCM (gray-level co-occurrence matrix) features, and brain tumour region growing segmentation (DWT-based). After segmentation, noise that may have accumulated is removed with the help of morphological filtering. The accuracy performance for detecting tumour site in relation to brain MRI images is tested and trained using the probabilistic neural network classifier.
A new framework for MAS (Multi-atlas segmentation) for MR tumour brain images is presented by Zhenyu Tang et al. [3] In essence, MAS creates a new brain picture for segmentation by recording and merging label data from many normal brain atlases. Although the majority of its frames are for normal brain imaging, tumour brain images continue to be a challenging worry for it. At the first level of the MAS framework, a new low-rank algorithm is being used to retrieve the recovered picture of the normal brain from the MR tumour brain image by using the information from the normal brain atlas. The following stage involves registering normal brain atlases to restore the image without tumour interference.
To categorise and analyse the image de-noising filters used to remove additive noises present in MRI images, such as speckle noise, Gaussian noise, and salt-and-pepper noise, Garima Singh et al. present the Adaptive filter, Median filter, Un-sharp masking filter, Averaging filter, and Gaussian filter. The de-noising performance of all the considered techniques is compared using PSNR and MSE. A novel approach is suggested by using normalised histogram and segmentation via K-means clustering algorithm for successful brain tumour diagnosis. The MRIs are successfully classified using the Naive Bayes Classifier and SVM, providing accurate prediction and classification [4].
J. Seetha et al. suggested using MRI images to diagnose brain tumours. The MRI scan typically generates a large amount of data, which makes the human procedure of classifying a tumour as

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opposed to a non-tumor quite time intensive. Despite only providing exact quantitative measurements for a small number of photos. As a result, automated classification methods that can be trusted are required to lower the human fatality rate. The automatic classification of brain tumours is frequently quite complicated due to the significant structural and geographical heterogeneity of adjacent tumour sites. Here, a method for automatically detecting brain tumours is proposed [5] using the CNN classification.

The concept of soft thresholding DWT for improvisation and genetic algorithms for image segmentation is presented by G. Rajesh Chandra et al. These algorithms can be used for grey-level magnetic resonance imaging, it has been found. The suggested method makes use of GA's potential to solve optimisation problems with a broad search space (which reflects the label of every single image pixel). The suggested solution also incorporates any previously known information (such as the local ground truth). On the basis of ground truth, the established approach was able to segment tumour pixels with an accuracy of 82% to 97% and an SNR value of 20 to 44 [6].

III. Proposed Methodology

The use of machine learning approaches come in a variety of forms. Different machine learning methods, including SVM, Adaboost, and various classification algorithms have been implemented for brain tumour detection.

3.1 Data acquisition

The data collected had been separated into two categories as healthy and non-healthy ones. Further, the images are of different dimensions so they are converted into the same dimensions of 224*224.

3.2 Pre-processing

In this stage noise removal will be done from the MRI images to increase the accuracy of the model. MRI images often consist of noise which will increase the redundancy and hence decrease the accuracy of the model. There is a high chance of a tumour not getting detected because of the noise present on the borders of an MRI. Hence affects the accuracy of the model. Pre-processing was done by scaling, reducing and converting them into grayscale. Image Pre-processing is done to enhance the quality, look and characteristics of the image.

3.3 Feature Extraction

It is the method of aggregation higher-level info of a picture like form, texture, colour, and distinction. In fact, texture analysis is a very important para3meter of human perception and machine learning system. It’s used effectively to enhance the accuracy of designation system by choosing distinguished options. Haralick et al. introduced one in all the foremost wide used image analysis applications of grey Level Co-occurrence Matrix (GLCM) and texture feature. This system follows 2 steps for feature extraction from the medical pictures. Within the commencement, the GLCM is computed, and within the alternative step, the feel options supported the GLCM square measure calculated.

3.4 Classification

9The classification of imaging pictures is more difficult task for the automated detection of neoplasm pictures. Classification may manufacture the solution whether or not the image contains neoplasm or not. For classification purpose several classifiers are going to be used. Doubtless, every approach has its blessings and inconvenient. The use of different machine learning classification algorithms can be used to detect brain tumour disease in early stages such as KNN, ANN, Support Vector Machine, Naïve Bayesian classification.

3.4.1 K-Nearest Neighbour

The K-Nearest Neighbour classifier uses the lowest distance between two points to identify which class a given point belongs to. The objective is to determine the distance between each training sample and the query sample and select the neighbour with the least distance.

3.4.2 Decision Tree

In order to increase the projected accuracy of the input dataset, the Random Forest classifier averages the results from multiple decision trees applied to various subsets of the input dataset.

3.4.3 Support Vector Machine

Support vector machine, or SVM for short, is a non-linear classifier and a more recent development in machine learning techniques. SVM is frequently used to address a variety of pattern recognition problems, including texture classification. Only two classes were considered when developing SVM. By increasing the margin of the hyper plane, this is achieved. When solving an issue, multiclass classification is helpful and is basically made up of several two-class SVMs that either employ one-versus-all or one.

3.4.4 Naïve Bayesian

The Bayes theorem, which is utilized to solve the classification algorithm, gives rise to the idea of a naive Bayesian algorithm. Based on the likelihood of a data point, it makes predictions about the outcomes. In a naive Bayesian method, where Bayes law establishes the probability of a hypothesis with prior knowledge, the occurrence of an exact feature is completely independent of the occurrence of the other features**.**

3.4.5 Random Forest

Random Forest is a classifier that uses many decision trees on different subsets of the input dataset and averages the results to increase the dataset's predicted accuracy.

3.4.6 Logistic regression

It is a predictive model that uses independent factors to forecast the outcomes of dependent variables. When the dependent variable is binary, we analyze the data using this procedure. The link between one dependent binary variable and multiple independent binary variables is examined using this regression. The class membership probability is determined by this algorithm.

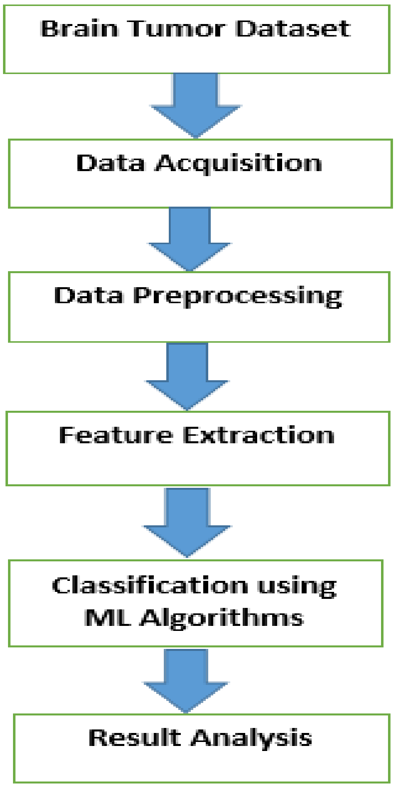

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Fig 1: Proposed Methodology for Brain Cancer Tumor

IV. Results

The burden on the healthcare systems may be reduced by the early diagnosis of brain tumors. In this paper, many machine learning methods have been examined, and the efficacy and performance of every classification model have been examined. When compared to other models like KNN, Naive Bayes, and Decision Tree, which have 61.90%, 76.19%, and 61.90% accuracy respectively as shown in Fig. 2, the model that was developed using the support vector machine concept is the best model among all classification models in terms of accuracy with 80.95%, while Figs. 3 and 4 show the model accuracy and model loss accuracy of Support Vector Machine.

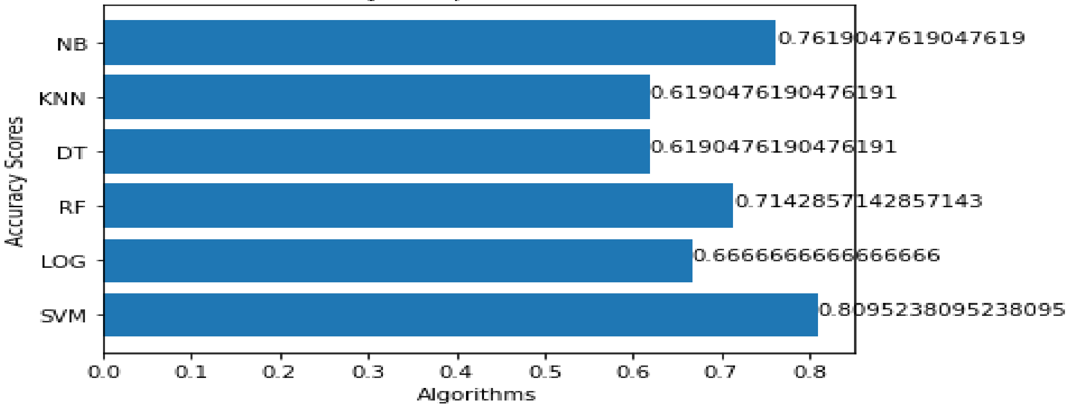

Fig 2: Result of Machine Learning Algorithms

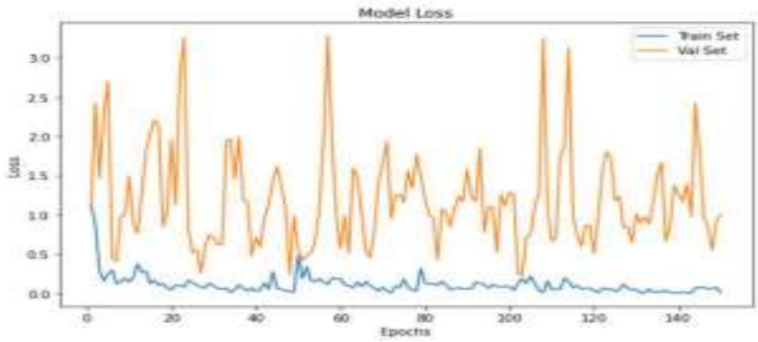

Fig 3: Model accuracy for SVM

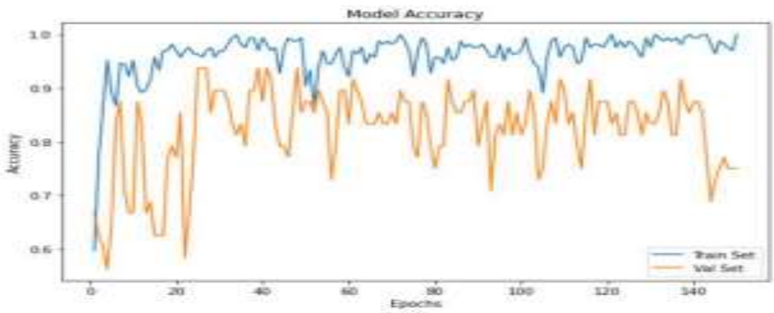

Fig 4: Model loss accuracy for SVM

Conclusion

The goal of this research endeavour is to create a model that can recognise brain tumours with accuracy from MRI data. The model is built on a machine learning technique. It enables to simply trim and resize the image without losing any essential information that will be used for prediction. The developed model has an accuracy of 80.95% and 82.86% when applied to the training set and the validation set, respectively. The loss gradually begins to decrease as the number of epochs increases. The model loss is relatively little when applied to the training set, but it is significant when applied to the validation set. Future uses of this method on different datasets would boost its overall accuracy

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