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Design and development of an effective classifier for medical images based on machine learning and image segmentation

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ABSTRACT

Recently, there has been an increase in the death rate due to encephaloma tumours affecting all age groups. Because of their intricate designs and the interference they cause in diagnostic imaging, these tumours are notoriously difficult to spot. Early and accurate detection of tumours is crucial because it allows for identifying and predicting malignant regions using medical imaging. Using segmentation and relegation techniques, medical scans can aid clinicians in making an early diagnosis and potentially save time. On the other hand, the identification of tumours may be a laborious and extended process for professional doctors owing to the complex nature of tumour formations and the presence of noise in the data produced by Magnetic Resonance Imaging (MRI) since it is pretty imperative to locate and determine the site of the tumour as quickly as feasible. This research proposes a method for detecting brain cancers from MRI scans based on machine learning. It uses the Support Vector Machine, K Nearest Neighbor, and Nave Bayes algorithms for image preprocessing, picture segmentation, feature extraction, and classification. According to the findings, the SVM algorithm accomplished the best level of accuracy, which is 89 %.

1. Introduction

The occurrence of encephaloma tumours has caused an increase in the death rate across all age groups. According to conventional understanding, tumours can be categorized as benign or malignant depending on their growth rate in the encephalon. Tumours are classified as malignant due to their non-uniform growth patterns, indicating cancerous cells. In contrast, benign tumours consist of normal, non-cancerous cells, as defined by the American Society of Clinical Pathology.

The complex structure and inherent noise in medical imaging make it challenging for experts to diagnose tumours physically, which is time-consuming and labour-intensive. Therefore, locating and identifying the tumour's site as soon as possible is crucial. Medical scans may help detect and forecast malignant lesions at various levels and can work together with segmentation and relegation techniques to give a prompt analysis [1,2].

To identify brain tumour tissues, it is necessary to perform the intricate and time-consuming task of segmenting an MRI image. Medical illustrations often have complex structures that can be challenging to identify and diagnose clinically, but segmentation can help. Increasing the precision of tumour identification and decreasing the possibility of human mistakes during the radiologist's physical examination is feasible by utilizing extra pictures and an automated method for assessing and classifying medical images [3].

Digital image processing is a broad field that encompasses various subjects, including geology, medicine, microscopy, astronomy, and computer vision. Since it facilitates the automatic segmentation of medical images and the creation of computer-aided designs, medical imaging plays a crucial role in scientific and medical research. These tools can enhance surgical treatment planning and accuracy through human–machine interaction, providing practical diagnostic tools for the medical industry by developing imaging technologies and implementing treatment plans. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are the two non-invasive imaging procedures most often employed to produce human body pictures. Using medical instruments, segmented images of the human body are created [4,5].

Brain tumours form over time when aberrant tissue accumulates, inhibiting average tissue growth, development, and death. These deviant tissue types cause cancer to increase uncontrolled and grow. Medical imaging methods such as CT and MRI are employed to find and

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diagnose brain tumours, with CT being the ideal prevalent technique. Physicians and radiologists utilize MRI/CT scans to generate 3D pictures for brain tumour detection. In addition, an automated or semi-automated tumour segmentation technique may be employed to identify the characteristics of a brain tumour in the 3D image, saving time for healthcare professionals and producing more reliable results. This approach provides several benefits, allowing human healthcare providers to focus on other tasks while planning patient treatment [6]. Fig. 1 below illustrates many MRI image processing procedures.

Various preprocessing techniques are required for MRI images to address noise, non-brain tissues, and bias fields. This time-consuming step is necessary to eliminate unnecessary elements and ensure the photos are correctly processed. This procedure begins with picture preparation, which includes operations such as grayscale conversion, noise reduction, and image reconstruction. Converting the image to grayscale is the most commonly used preprocessing technique. Once the image is in grayscale, various filtering techniques remove noise. Reducing noise is critical to obtaining effective results after retrieving images from the database. However, there is still room for improvement in existing noise reduction techniques [1,4].

Segmentation: Throughout the scanning procedure, large pictures were created. In a reasonable time, medical practitioners can manually identify the subjects of these photographs. It is a must-have for clinical diagnostic, pre-operative planning or computer-assisted surgery.

Feature Extraction involves acquitting each character to an attribute vector that will serve as the character's identification. Its challenging aims are to extract the features with the fewest components that maximize the recognition rate while simultaneously establishing the same quality set for several occurrences of the same symbol. Regrettably, the feature extraction techniques currently in use cannot select the essential elements for a future diagnosis.

Classification Method classifies every single item in a batch of data into one of a predetermined number of classes or groups of things. This method is frequently used to distinguish between benign and cancerous brain images. The primary objective of classification is to predict the target class for each data sample correctly. This is accomplished by separating brain pictures into tumours and non-tumours. Our proposed effort will substantially emphasize this phase since current approaches must concentrate more on accurately classifying MRI images.

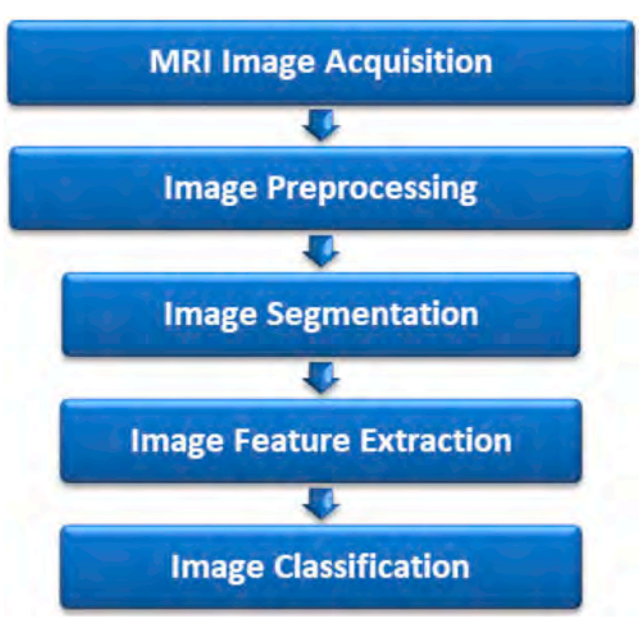

Fig. 1. Shows the procedures for processing MRI images.

2. Literature survey

2.1. Preprocessing techniques

Brain pictures may be examined via image processing. Medical professionals perform diagnostic and therapeutic techniques using magnetic resonance imaging (MRI). The following actions involve preprocessing a photo: improving artefact removal and noise reduction. The tumours should be easy to find with this picture. Suryavamsi et al. [7] developed many techniques: Histogram Equalization, Adaptive Histogram Equalization, and Brightness-Preserving Dynamic Fuzzy Histogram Equalization for MRI brain imaging linked to astrocytomas. These three techniques have been tested, and performance measurements have been used to calculate the findings. PSNR, RMSE, and MSE.

Before the necessary signal can be extracted from the MRI data, background noise must be removed. Several preprocessing procedures use independent component analysis and nuisance regression. De Blasi and her colleagues use a variety of LD cleaning procedures to check and ignore non-BOLD signs from healthy people and patients by using temporal lobe epilepsy. Compared to data that had just been preprocessed, all preprocessing methods tested improved temporal features, such as SNR and power spectrum density in the resting-state frequency range (0.01–0.1 Hz). The preprocessing pipeline was examined as part of the pre-ICA approach to find the DMN. These pipelines and groups could describe the posterior portion of the cingulate cortex more accurately than other pipelines and groups.

The improved preprocessing techniques developed by Poornachandra and Naveena can successfully separate glioma tumours [8]. In addition, medical imaging of brain tumours has been produced using recent developments in deep learning. Therefore, researchers with a better understanding of brain tumours can better identify the disease and provide treatment alternatives to individuals diagnosed with it due to improved segmentation findings.

Much has been said about employing brain MR imaging to analyze and identify the anatomy of the tumour. However, since the image is constant, segmenting it is difficult. Setyawan Widyarto et al. [9] improved the Region Scalable Fitting (RSF) method for image segmentation to include preprocessing before a region with an active contour model. The 2D-sigmoid function is enforced by preprocessing at the tumour border. In addition, a second 2D-sigmoid function was added during the preprocessing stages of the brain MRI image to boost the contrasts.

In [10] describes the design of an investigative protocol for layer-optimized image compression in a telemedicine environment. The study's primary goal is to enhance medical image compression to enable more effective transmission and storage of pictures such as those from CT and MRI scans. The proposed method employs layer optimization to preserve image quality and reduce transmission bandwidth. The authors highlight the potential benefits of this approach for telemedicine applications, including faster transmission and reduced storage requirements.

The paper presents an improved unsupervised clustering technique for identifying unstructured clusters of oncological images. The proposed method utilizes a hybrid approach that combines K-means clustering with the non-negative matrix factorization technique to improve the accuracy of cluster identification. The authors also introduced a new evaluation metric to evaluate the effectiveness of the clustering method. According to the research findings, the suggested approach beats current strategies from the perspective of cluster identification precision and computing power. The authors conclude that the proposed method can be applied in oncological imaging analysis and diagnosis [11].

2.2. Feature extraction techniques

Extracting crucial attributes is one of the most significant tasks in tumour segmentation systems. [12]. Jui et al. created an improved feature extraction technique to increase brain tumour identification precision, considering the relationship between intracranial structural deformation and compression resulting from brain tumour development. In the LaV area of the brain, 3D volumetric images are deformed using non-rigid registration and deformation modelling. Often used classification techniques, such as k-means, may be used to confirm and enforce LaV deformation feature data on brain tumour segmentation. The suggested component underwent a quantitative and qualitative analysis, and the author obtained encouraging findings. The application stage of the landmark-based feature for AD diagnosis utilizing longitudinal structural MR images developed by Jun Zhang does not call for nonlinear registration or tissue segmentation. We use a fast landmark detection method to rapidly and accurately find the landmarks in test images without requiring tissue segmentation or nonlinear registration. We then use these characteristics, high-level statistical qualities, and longitudinal contextual data to check the brain's structural absorption in the spatial domain. The Alzheimer's Disease NeuroImaging Initiative database gives 88.30 % classification precision for Alzheimer's disease and MCI when having the recommended strategy, which is more successful and beneficial. [13].

Gabriele Piantadosi and colleagues developed an automated breast CAD system to identify breast cancer. Mammographic segmentation blueprints, dampening of motion distortion, lesion Identification of the precise location, and categorization of the cancer are included in the design, which Michael Osadebey and colleagues created. To ensure a fair comparison, cross-validation was performed on 42 patients with confirmed histological lesions. The experimental results indicate no human interaction is required for any processing steps involved in the BLADeS system's breast lesion diagnosis. [14].

Hsin-Yi Tsai and colleagues [15] suggested employing the Gray-Level Co-Occurrence Matrix to parallelize feature extraction in their study (GLCM). The strategy is built and implemented on many GPUs rather than optimizing the code on a single computer. Geforce GTX 1080 graphics cards were used to test single-precision and double-precision MR brain pictures of various sizes. The findings demonstrate that the suggested method is faster than 25 to 105 times the other methods.

2.3. Segmentation techniques

Sérgio Pereira et al. [16] suggested an automatic segmentation technique that depends on Convolution Neural Networks (CNN) work on 3 x 3 kernels. The network's smaller weight distribution prevents overfitting and creates more complex designs. Even though this method is uncommon in CNN-working in segmentation algorithms, it was very effective when used in conjunction with data augmentation to separate brain tumours from surrounding tissue in MRI images. A semiautomatic segmentation technique was described by Jinyoung Kim et al. [17] and used in high-quality images given by ultra-high field (7 T) MRI. The complementary edge data from several structural MRI modalities were used in this technique. A unique edge indicator function is presented that integrates the information from all three modalities—susceptibility-weighted, T2-weighted, and diffusion MRI—. The development of active geometric surfaces is made more accessible with a prior understanding of the shape and organization of the subcortical systems. Adjacent structures were segmented repeatedly to avoid misuse at their borders. According to Antonios Makropoulos et al. [18], 50 different brain areas should be from early preterm up to term-equivalent age. In this work, we apply a state-of-the-art segmentation technique to reliably reproduce intensity over the whole brain, accounting for structural hierarchy and physical constraints. Compared to standard atlas-based approaches, this approach increases label overlaps in light of manual reference segmentations. The results demonstrate the proposed method's high reliability throughout a wide range of gestational ages, from 24 weeks to the term-equivalent age.

2.4. Proposed framework

Fig. 2 below shows the framework that has been suggested. To make the image better, you need to filter and improve it. Many things can affect the results when mobile phone photos are used for segmentation. During preprocessing, pictures are resized, noise is removed, and images are improved. Different sounds can be stored in digital images. This could lead to image noise, which would make the thresholding technique without any benefit. Image noise is when the lighting or colours in a picture change randomly. Images can have Gaussian, salt-and-pepper, shot, quantized, and other types of noise. For example, median and Wiener filters can eliminate these blips. There are many ways to reduce noise that have to do with shape. Median and Gaussian filtering have different effects on the brightness of each pixel. In this case, GF was used to reduce the amount of noise. In Gaussian filtering, the intensity of each pixel is less critical than a weighted average of the brightness of nearby pixels [19].

After filtering, images are improved to improve how information reflects or how humans can understand them. With the input image's histogram set to 1, the intensity distribution will be uniform across the picture. This method will often improve the overall image contrast, especially when the image's experimental data is close to the contrast. The histogram's intensity could be distributed evenly using this technique. Low-contrast areas thus acquire local contrast. The image is finished by spreading the most prevalent powers using histogram equalization [20].

Before segmenting the picture to get the optimal ROI, the image benefits from a dynamic fuzzy histogram equalization. The analysis of these portions may reveal essential characteristics. Image segmentation involves detecting and grouping related picture regions. There are both edge-based segmentation and region-based techniques. For instance, when analyzed, intensity patterns ringed by a cluster of neighbouring pixels may indicate anatomical or functional characteristics.

The ROI is segmented based on its texture or pattern utilizing region-based segmentation. In k-means clustering, the local mean is used as a cluster pattern for k-distinct interpretations of a given data set. Taking into account the full complement of classes that k may represent, data groups are identified. Then, the closest data is found using the Euclidean distance method. The supplied qualities are used to classify data points into one of the k groups. K Nearest Neighbor (KNN) is a technique for classification and regression applications in machine learning. It finds

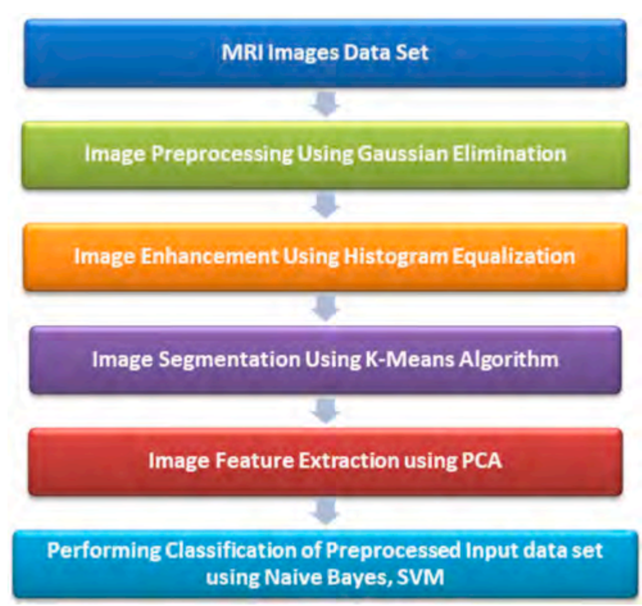

Fig. 2. A Methodology for Classifying and Segmenting MRI Images.

the K closest data points in the training dataset to a new data point and assigns it the label or value of most of its K neighbours. K is a hyperparameter whose value must be optimized for the best performance. KNN is a non-parametric method that makes no assumptions about the distribution of the underlying data. It is a straightforward and obvious approach, but it might be computationally costly for big datasets [21,22].

The creation of SVM by Vapnik has piqued the curiosity of scientists worldwide. The SVM classifier is used for data collecting and classification. After a classifier has been trained using training data, a model is constructed for evaluation. It is common to categorize anything into more than one class. Binary classifiers will be highly sought. Many studies have shown that SVM performs better than other popular classification methods. Photographs may be categorized using SVM. SVMs outperform a range of different classifiers in terms of accuracy. [23] The mathematical model for PCA is shown below:

1-centring the data: Subtract the mean from each feature in X to centre the data around the origin.

$$X\_c = X - mean(X, axis = 0) \tag{1}$$

2- Computing the covariance matrix: calculate the covariance matrix S of the centred data.

$$S = 1/(n-1)^{*}X\_c.T@X\_c \tag{2}$$

3- Calculate the covariance matrix S's eigenvectors and eigenvalues. Eigenvectors reflect the main components, whereas eigenvalues indicate the variance collected by each principal member.

$$eig\_vals, eig\_vecs = np.linalg.eig(S) \tag{3}$$

4-Selecting the top k eigenvectors: Sort the eigenvectors in decreasing order of eigenvalues, and select the top k eigenvectors to retain. These k eigenvectors represent the new feature space that captures the most important information in the original data.

$$idx = np.argsort(eig\_vals)[::-1][:k]eig\_vecs\_k = eig\_vecs[:, idx] \tag{4}$$

5- Transforming the data: Project the original data X onto the k eigenvectors to obtain the new feature space Y, an n x k matrix.

$$Y = X^{*}V\_k \tag{5}$$

6- The resulting new feature space Y can be used for various tasks such as clustering, classification, and visualization. The equations above show how PCA may extract the most critical features from image data and reduce its dimensionality while retaining its most essential information.

3. Result analysis

We have examined “Dataset-160 and Data-255″ from Harvard’s clinical college of ”architecture“. After analysis, we investigated datasets 160, 255, and 35, which comprised pictures of the ”Normal-20″ and “Abnormal-140″ MR256x256 axial aircraft encephalon, respectively. The ”Dataset-255″ Irregular Encephalon Magnetic Resonance metaphors represent eleven symptoms related to the “Dataset-160″ by combining the seven syndromes. ”Dataset-160″ comprises, in addition to Huntington’s syndrome, Alzheimer’s disease, and Alzheimer’s infection, agnosia, glioma, meningioma, pick’s condition, and sarcoma. The four unique illnesses described in “Dataset-255″ include herpes encephalitis, persistent subdural hematomas, and several types of sclerosis. ”Dataset-255″.

Sensitivity:

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{6}$$

True Positive is represented by TP, whereas FN represents False Negative.

Specificity:

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \tag{7}$$

False Positive is represented as FP and True Negative as TN

Accuracy:

$$Accuracy = \frac{TN + TP}{(TN + TP + FN + FP)} \tag{8}$$

Fig. 3 and Table 1 display the performance comparison of several classifiers. For the comparison research, three metrics are used: accuracy, specificity, and sensitivity.

The table above provides the performance evaluation of three different algorithms for a particular task, where each algorithm is evaluated based on three metrics: Accuracy, Sensitivity, and Specificity. Here’s a description of each metric and algorithm:

- SVM (Support Vector Machine): a classification method that seeks to identify the optimal border (hyperplane) between the various classes in the data.
  - o **Accuracy:** SVM had an accuracy of 0.89, which indicates it categorized 89 % of the total cases in the data correctly.
  - o **Sensitivity:** With a sensitivity of 0.57, SVM successfully detected 57 % of the data’s positive cases..
  - o **Specificity:** The specificity of SVM is 0.99, which means that it accurately detected 99 % of the negative cases in the data..
- Naive Bayes: Naive Bayes is a probabilistic algorithm that determines the likelihood of each class given the input attributes and makes a prediction based on the type with the most excellent possibility.
- o **Accuracy:** With an accuracy of 0.51, Nave Bayes accurately categorized 51 % of the total cases in the data.
- o **Sensitivity:** With a sensitivity of 0.85, Nave Bayes was able to properly identify 85 % of the positive cases in the data.
- o **Specificity:** With a specificity of 0.42, Nave Bayes successfully recognized 42 % of the data’s negative occurrences.
- KNN (K-Nearest Neighbors): KNN is a classification algorithm that assigns a label to each model based on the tags of its k nearest neighbours in the feature space.
  - o **Accuracy:** KNN classified 85 % of the total cases in the data with an accuracy of 0.85.
  - o **Sensitivity:** KNN correctly detected 65 % of the positive cases in the data with a sensitivity of 0.65.
  - o **Specificity:** KNN detected 92 % of the negative cases in the data with a specificity of 0.92, making it highly accurate.

In summary, SVM has the highest accuracy and specificity but a lower sensitivity than the other algorithms. Naïve Bayes has a high sensitivity but low accuracy and specificity. KNN has a balanced performance in accuracy, sensitivity, and specificity. The choice of algorithm depends on the specific task and the trade-off between different performance metrics.

4. Conclusion

The mortality rate has risen as the prevalence of encephalic tumours has grown across all age groups. In addition, physical tumour detection is challenging for medical professionals due to the complexity of tumours and the evolution of noise in MR imaging data. Early tumour localization and identification are, therefore, crucial. With segmentation and relegation techniques, medical scans may enable the early diagnosis of malignant tumours at different levels. Our approach employs machine learning to segment and categorize MRI images to identify brain tumours. Preprocessing, segmentation, feature extraction, and classification using SVM and Nave Bayes algorithms are all included in this

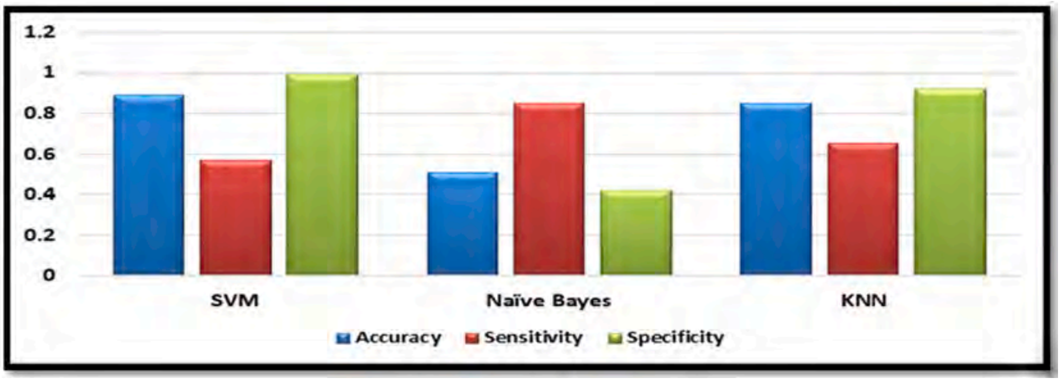

Fig. 3. Classifier Results.

Table 1
Medical Picture Classification Using Support Vector Machines and Naive Bayes.

Algorithm	Accuracy	Sensitivity	Specificity
SVM	0.89	0.57	0.99
Naïve Bayes	0.51	0.85	0.42
KNN	0.85	0.65	0.92

system.

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