International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
OPEN ACCESS
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST241124

Study and Performance Evaluation of Brain MRI Images Using Aartificial Intelligence

Pornima B. Niranjane[1], Vaishali B. Niranjane[2], Krushil M. Punwatkar[3]

[1]Department of Computer Science & Engineering, Babasaheb Naik College of Engineering, Pusad, Maharashtra, India.

[2]Department of Electronics and Telecommunication, Yeshwantrao Chavan College of Engineering, Nagpur, Maharashtra, India

[3]Department of Electronics and Telecommunication, Babasaheb Naik College of Engineering, Pusad, Maharashtra, India

ARTICLEINFO

Article History:

Accepted: 05 Feb 2024
Published: 28 Feb 2024

Publication Issue :
Volume 11, Issue 1
January-February-2024
Page Number :
570-576

ABSTRACT

The limits and potential of medical imaging are expanded by artificial intelligence. Therefore, in an effort to improve the performance and accuracy of diagnosing brain abnormalities, researchers are constantly working to create an effective and automated diagnosis method. Tumour identification and diagnosis have been achieved by the use of magnetic resonance imaging (MRI). Medical professionals can identify and categorise tumours as normal or abnormal with the aid of digital image processing. This research focuses on various neural networks for brain MRI tumour and non-tumour image categorization and confusion matrix performance evaluation. Otsu's thresholding approach is used for segmentation out of all the segmentation techniques. For feature extraction, a grey level co-occurrence matrix (GLCM) is employed. The classification techniques utilized in this study produce the necessary results in terms of confusion matrix parameters, which may be used to assess the classifier's performance in terms of F1 score, accuracy, sensitivity, and precision.

Keywords: Tumour, Otsu's thresholding , Grey level co-occurrence matrix, Confusion matrix

I. INTRODUCTION

Medical Image Processing is a challenging and emerging field that involves the use of various machines such as MRI, CT scan, ultra scan, and X-rays to diagnose patients. The human body is composed of different types of cells, and the brain is a highly specialized and sensitive organ. A brain tumor is a fatal neurological condition that occurs when cells in the brain or skull grow abnormally and uncontrollably. The mortality rate of individuals with this disease is increasing gradually. Brain tumors are a serious problem in the medical field, and MRI imaging is commonly used in their treatment. Image processing techniques, including various segmentation algorithms, are employed to detect brain tumors. The scanned MRI image is first enhanced in quality, and then different segmentation techniques, such as Otsu's thresholding algorithm, are applied to identify the tumor in the image. Otsu's method is a widely used technique for image thresholding. It divides an image into two categories, foreground and background, by analyzing the grayscale intensity values of its pixels. MATLAB software is used to process the MRI images. These techniques allow for the determination of the tumor's area, execution time, and number of pixels.

II. LITERATURE SURVEY

Researcher worked with SVM Classifier to detect brain tumours. Additionally, they compare the precision of various classifiers, such as SVM and neural networks, in classification learning applications. [3] In this paper researcher uses Knearest Neighbour (K-NN) classifiers in an attempt to identify and categorise brain tumours in a benign stage. Up to 96.15% overall recognition rate or classification accuracy is attained. [4].Researchers developed the technique meant to differentiate between benign and malignant brain tumours. Various wavelet transforms and support vector machines are employed in the recognition and categorization of magnetic resonance imaging brain tumours. [7] In this study examined a number of techniques that shed light on the benefits and drawbacks of various approaches for using MRI images to identify brain tumours. [9] In an proposed algorithm that uses Otsu's segmentation method to detect brain tumours, and support vector machines are used to classify images.

III.PROPOSED METHODOLOGY

In this research, we proposed an efficient and simple algorithm for detecting brain tumours and compared the texture parameters of normal and tumor-detected MRI images. Pre-processing, computing segmentation using Otsu's thresholding algorithm, and feature extraction using grey level co-occurrence matrix (GLCM) are the main modules. The proposed algorithm has two major phases: training and testing. The training phase is the first stage of working in the proposed system. The known MRI images are first processed through various image processing steps such as image pre-processing, segmentation, and textural feature extraction using Grey Level Co-occurrence Matrix (GLCM) in this phase.The extracted features are used in the training phase. They aid in the correct classification of unknown images. During the training phase, known data represents the nature of the data, whether normal or abnormal, in order to teach and train the classifier. During the testing phase, the unknown MRI image samples are first segmented, and then textural features are computed for each input MRI image using the Grey Level Co-occurrence Matrix. The discrete wavelet transform (DWT) coefficients are used as feature vectors in the proposed system, and principal component analysis (PCA) is used to reduce dimensionality. In the proposed method, the confusion matrix and the receiver operating characteristic (ROC) are important tools for evaluating the performance of the classifiers.

Steps of proposed methodology.

A. Image Enhancement

The main aspects of image enhancement are:

- Highlighting the edges
- Improving the brightness and contrast
- De-blurring and sharpening
- Noise removal

B. Image Segmentation

One of the difficult tasks in image processing is dividing the image into different sub images, which includes,

- Lines various types of shapes in an image, finding circles,
- Recognising tumours, different objects, and detections in an image

In this work, segmentation is used extensively for the detection of tumours in the human brain.

C. Otsu's Thresholding

Image thresholding is a technique for binarizing images based on pixel intensities. A grayscale image and a threshold are typically used as input to such thresholding algorithms. The end result is a binary image. Image thresholding is used as a preprocessing step in many applications. The disadvantage of simple thresholding is that the threshold value must be manually specified. We can manually test how good a threshold is by experimenting with different values, but this is time-consuming. The Nobuyuki Otsu technique, named after its creator, is a good example of auto thresholding. This method was proposed by N. Otsu in 1975 and has since become popular. MATLAB employs the graythresh function, which computes a global threshold that can be used to convert an intensity image to a colour image.

level = graythresh(I)

It computes a global threshold (level) for converting an intensity image to a binary image. Level is a normalised intensity value in the [0, 1] range. The graythresh function employs Otsu's method, which selects the threshold based on the intraclass variance of the thresholded black and white pixels.

D. Principal component Analysis

Principal component analysis is one of the most successful and widely used image recognition and compression techniques. The goal of using PCA is to reduce the extracted features' high dimensionality. Rather than incorporating all of the features, a feature selection is performed as a preprocessing step using PCA to ignore the redundant features. Because the feature selection is based on statistical data, only the most informative features extracted from MRI images are used in this process. These chosen features are known as principal components (PC). The PC retains the most variation in the samples. The reconstructed data's variance is preserved. These primary components result in an efficient classification algorithm that employs supervisory learning.

E. Feature Extraction

A frequency matrix, the gray-level co-occurrence matrix (GLCM), is a useful method for enhancing details and is frequently used as an aid in image interpretation. The GLCM is a tally of how frequently various combinations of pixelbrightness values (grey levels) appear in an image. The frequency of a pair of pixels that are exactly the same distance and direction as the displacement vector is indicated by the GLCM. It computes the relationships of pixel intensity to the intensity of its neighbouring pixels based on the hypothesis that the same grey level configuration is repeated in a texture and pixels that are close together tend to be more related than pixels that are far apart.

Independent Features

- Mean: It gives the contribution of individual pixel intensity for the entire image.
- Variance: It is used to find how each pixel varies from the neighbouring pixel.
- Standard Deviation: It measures the deviation of measured values or the data from its mean.
- Skewness: It measures of symmetry, or more precisely, the lack of symmetry.
- Kurtosis: It describes the peakiness e.g., a frequency distribution.

The above features are first order features which rely only on the values of individual pixels in the image, and do not express their relationship to other image pixels

Second order features or texture features

- Contrast: It is the difference in luminance or colour across the image.

- Correlation: Correlation is the process of moving a filter mask often referred to as kernel over the image and computing the sum of products at each location. ♣ Energy: It is the rate of change in the colour/brightness/magnitude of the pixels over local areas.
- Homogeneity: Homogeneity expresses how similar certain elements (pixels) of the image are.
- Entropy: It is a statistical measure of randomness that can be used to characterize the texture of the image.
- ASM (Angular second moment): It is a measure of textural uniformity of an image.
- Dissimilarity: It is a numerical measure of how different two data objects are coarseness: It describes the roughness/harshness of a texture.

F. Image Classification

The process of categorising and labelling groups of pixels or vectors within an image based on specific rules is known as image classification. Artificial neural network classifiers are used in this work. Classifier Using an Artificial Neural Network Since training, processing, optimisation, and time-consuming calculations are no longer required, neural networks are very fast and precise. The network's outputs are generated directly from the provided inputs. Different types of neural networks are used to categorise inputs into a set of target categories [10].

Perceptron

Multi-layer perceptrons are neural networks that have several hidden layers and activation functions. The learning occurs in a supervised setting, with the weights updated using gradient descent. The multi-layer perceptron is bi-directional, with inputs propagating forward and weight updates propagating backward. The activation functions can be altered depending on the type of target. Softmax is commonly used for multi-class classification, while sigmoid is used for binary classification. Because all neurons in a layer are connected to all neurons in the next layer, these are also known as dense networks. They are used in deep learning applications, but because of their complex structure, they are generally slow.

Radial Basis Function Networks (RBF)

Radial basis function networks (RBN) predict targets in a completely different way. It is made up of three layers: an input, a layer with RBF neurons, and an output. For each training data instance, the RBF neurons store the actual classes. The radial function used as an activation function distinguishes RBN from traditional multilayer perceptrons. The RBF neurons compare the euclidian distance of the feature values with the actual classes stored in the neurons when new data is fed into the neural network. This is similar to determining which cluster the specific instance belongs to. The predicted class is assigned to the class with the shortest distance. RBNs are mostly used in function approximation applications..

IV. PERFORMANCE EVALUATION

This is an important tool for assessing performance. They are most frequently applied to binary classification problems. The relationship between the true positive rate (TPR) and the false positive rate (FPR) is depicted by the ROC curve. The TPR is the rate at which the classifier predicts "positive" for observations that APerformance evaluation can be achieved by the confusion matrix parameters and receiver operating characteristic curves (ROC).

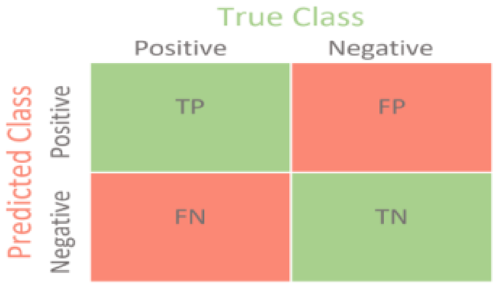

Figure 1 : confusion matrix for two classes

A. Performance Metrics

An algorithm's performance metrics are accuracy, precision, recall, and F1 score, which are calculated using the TP, TN, FP, and FN.

- Accuracy is a general measure of the model's performance. The ratio of correctly classified patients (TP+TN) to the total number of patients (TP+TN+FP+FN) represents an algorithm's accuracy.

  Accuracy = (TP+TN) / (TP+FP+FN+TN)

- Precision is a measure of the accuracy with which a positive outcome is predicted. The precision of an algorithm is represented as the ratio of correctly classified disease patients (TP) to total patients predicted to have the disease (TP+FP).

  Precision = (TP) / (TP+FP)

- Recall: It measures the proportion of true positives correctly classified by the model. The ratio of correctly classified diseased patients (TP) divided by the total number of patients with the disease is defined as recall. The perception of recall is the number of patients who have been diagnosed with the disease. Sensitivity is another term for recall.

  Recall = (TP) / (TP+FN)

- The F1 score: The F1 score represents the balance between precision and recall. It is also referred to as the F Measure. It is a measure of the accuracy of a model on a dataset. It is defined as the arithmetic mean of precision and recall. It is used to rate performance statistically. A perfect model has an F1-score of 1.

F1-score = 2 *(precision * recall) / (precision + recall)

B. Receiver Operating Characteristic Curves (ROC Curve)

This is an important tool for assessing performance. They are most frequently applied to binary classification problems. The relationship between the true positive rate (TPR) and the false positive rate (FPR) is depicted by the ROC curve. The TPR is the rate at which the classifier predicts "positive" for observations that are "positive." The FPR measures how often the classifier predicts "positive" for observations that are actually "negative." A perfect classifier has a TPR of one and an FPR of zero.

V. RESULTS

The neural network pattern recognition tool will assist in the selection of data, the creation and training of a network, and the evaluation of its performance using mean square error and confusion matrices in pattern recognition problems. Given enough neurons in its hidden layer, a two-layer feed-forward network with sigmoid hidden and output neurons can classify vectors arbitrarily well. The workspace variables are used to select the dataset for input and targets. The following step is to select training, validation, and test data. During training, training samples are presented to the network, and the network is adjusted based on its error. Validation samples are used to assess network generalisation and to stop training when generalisation no longer improves. Because testing samples have no effect on training, they provide an independent measure of network performance during and after training. Figure 2 to 7 depicts ROC curves and Confusion matrices for PNN, perceptron and radial basis function network respectively.

A.PNN

Figure 2 Confusion Matrix for PNN

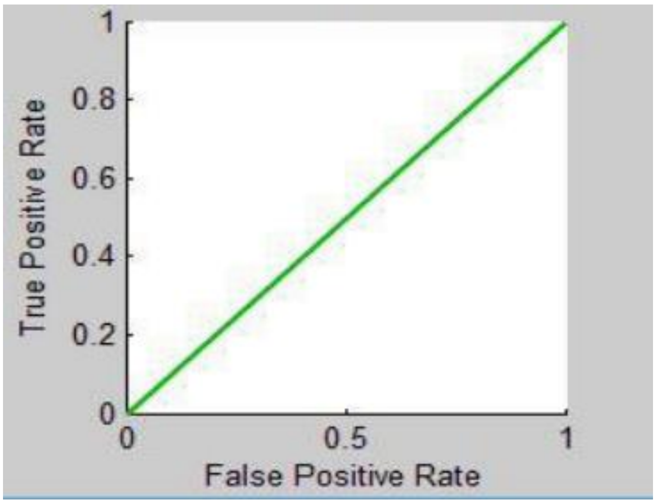

Figure 3: ROC Curve for PNN

B. Perceptron

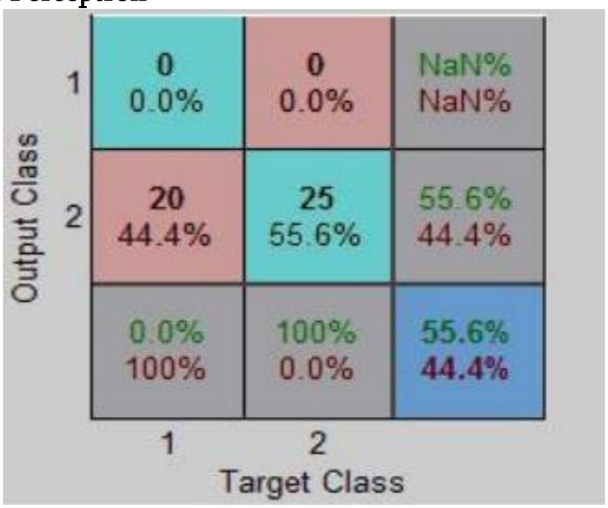

Figure 4. Confusion Matrix for Perceptron

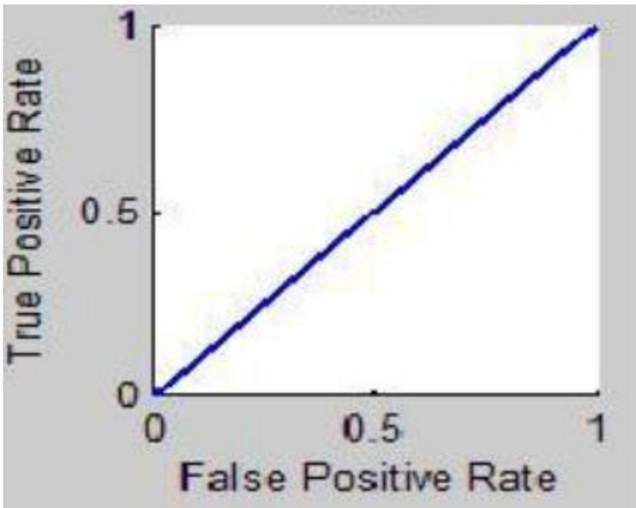

Figure 5 : ROC Curve for Perceptron

C. RBF Network

Figure 6 Confusion Matrix for RBF

Figure 7: ROC Curve for RBF

VI. CONCLUSION

In this study, we studied and evaluated an efficient artificial intelligence techniques for detecting brain tumours and compared the texture features of normal MRI images and tumor-detected MRI images. The methods used for brain tumour detection produce good tumour classification results. The texture features are analysed using the confusion matrix results in terms of accuracy, precision, recall, and F1 score for the ANN classifiers PNN, Perceptron, and RBF. Among the various classifiers used here, RBF produces results with 97.8 percent accuracy. The ROC curve demonstrates that all of the classifiers perform well. The research can be expanded to look for different grades of cancer. As a result, we can use the same techniques for multiple classes.

VII. REFERENCES

[1]. Komal Sharma, Akwinder Kaur, and Shruti Gujral,. 2014, "A review on various brain tumour detection techniques in brain MRI images", IOSR Journal of En gineering (IOSRJEN) ISSN (e): 2250-3021, ISSN (p): 2278-8719 Vol. 04, Issue 05, ||V3|| PP 06-12

[2]. S.H.Lavate, Rutuja Bhasme, Amit Gore, and Tejas Deshmukh ,2018, "Brain Tumour Detection Using Segmentation and Classification Technique " , IJSART - Volume 4 Issue .

[3]. B.Smith Suhartono, Phong Thanh Nguyen, K. Shankar, Wahidah Hashim, Andino Maseleno , 2019, "Brain Tumour Segmentation and Classification using KNN Algorithm", International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 –8958, Volume-8, Issue-6S

[4]. Mr. T. Sathies Kumar ,K. Rashmi , Sreevidhya Ramadoss , L.K. Sandhya , and T. J. Sangeetha , 2017, "Brain Tumour Detection Using SVM Classifier " , IEEE 3rd International Conference on Sensing, Signal Processing and Security (ICSSS) 978-1-5090-4929-5© IEEE

[5]. Dr. Umar Alqasemi, Mohammed Bamaleibd, and Abdullah Al Baiti 2021, "Classification of Brain MRI Tumour Images",International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181,Vol. 10 Issue 03

[6]. J. Seetha and S. Selvakumar Raja. 2018, "Brain Tumour Classification Using Convolutional Neural Networks ",Biomedical & Pharmacology Journal, Vol. 11(3), p. 1457-1461

[7]. Nikita V. Chavan B.D. Jadhav and P.M. Patil 2015, "Detection and Classification of Brain Tumours ",International Journal of Computer Applications (0975 – 8887) Volume 112 – No. 8,

[8]. V. Anitha , and S. Murugavalli , 2015"Brain tumour classification using two-tier classifier with adaptive segmentation technique " ,IET computer vision journals ISSN 1751-9632

[9]. S.S. Dharun Raj , and S. Hariharan.2021, " Brain Tumour Detection and Classification Using SVM", International Journal of Computer Science Trends and Technology (IJCST) – Volume 9 Issue 3, ISSN: 2347-8578

[10]. Aryan Sagar Methil, "Brain Tumour Detection Using Deep Learning and Image Processing ", in International Conference on Artificial Intelligence and Smart Systems (ICAIS) ,Coimbatore, Tamil Nadu, India March 2021

Cite this article as :

Pornima B. Niranjane, Vaishali B. Niranjane, Krushil M. Punwatkar, "Study and Performance Evaluation of Brain MRI Images Using Aartificial Intelligence", International Journal of Scientific Research in Science and Technology (IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 11 Issue 1, pp. 570-576, January-February 2024. Available at doi : https://doi.org/10.32628/IJSRST241124

Journal URL : https://ijsrst.com/IJSRST241124