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EFFICIENT FEATURE EXTRACTION AND CLASSIFICATION TECHNIQUE FOR IDENTIFICATION OF BRAIN TUMORS IN MRI

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Abstract: The complexity of the brain's image and structure makes the analysis of brain tumors difficult, making brain tumor extraction and analysis difficult jobs in medical image processing. An important part of medical image processing is performed through segmentation and classification. When it comes to diagnosing conditions of the brain and other organs, MRI (magnetic resonance imaging) has become an invaluable tool. This research effort analyzes the similarities and differences between two different classifiers used for tumor diagnosis. Some of the techniques used include “gray level co-occurrence matrix (GLCM)” feature extraction, “principal component analysis” and ostu and morphological segmentation. In order to identify tumors, features are classified with a “support vector machine (SVM)” and a “convolutional neural network (CNN)”. Ultimately, the tumor's location and form are pinpointed by parsing the MR picture. The experimental findings show that CNN classification was more successful than SVM classification (99.67%). When a brain tumor is diagnosed, its seriousness may be determined at last.
Keywords: Brain tumor, Support Vector Machine, Convolution Neural Network, Magnetic resonance imaging, Ostu.

Introduction

Tumors of the brain can be either malignant or benign growths of tissue in the brain. The key to successful therapy and improved patient outcomes for brain cancers is early identification.

The use of MRI for the detection and follow-up of brain malignancies has become commonplace. However, extracting and analyzing brain tumours using conventional image processing techniques is challenging due to the intricacy of the brain's structure and picture [1]. The segmentation and categorization of medical pictures rely heavily on medical image processing. The two processes, segmentation and classification, both entail recognizing the objects or areas in a picture. “Gray-level co-occurrence matrix (GLCM) feature extraction”, “principal component analysis”, Ostu, and morphological segmentation are only few of the methods that have been employed in medical image processing [2].
Effective feature extraction and classification algorithms for detecting brain malignancies on MRI have been developed for this purpose. This requires determining the size and form of the tumor in the MR scan. “Support vector machines (SVMs)” and “convolutional neural networks (CNNs)” are two popular classifiers used in cancer detection. While CNN has shown itself effective in image identification, SVM is a potent machine learning method used for classification.
Extracting features from the MR image using methods like GLCM and principal component analysis, then classifying the retrieved features with SVM or CNN, are examples of efficient feature extraction and classification approaches [3]. Ostu and morphological segmentation are two segmentation methods that may be used to determine the precise position and form of the tumor.
The purpose of this research is to evaluate SVM and CNN for their ability to identify and categorize MR images of brain malignancies. The results of the experiments demonstrated that CNN classification was 99.67% accurate, which is higher than the accuracy of SVM classification. This research demonstrates the promise of deep learning methods like CNN for use in medical image processing, especially in the detection and treatment of brain cancers.

Research Methodology

Preprocessing the MR image, extracting features, selecting features, and classifying the data are the four cornerstones of the suggested technique. Each stage is broken down into its own portion below.

Preprocessing: The magnetic resonance (MR) picture must first undergo preprocessing in order to improve image quality and eliminate artifacts. The following procedures are included at this stage:

a) Stripping the Skull: The first thing to do is to delete the head from the MR scan. This is achieved via the use of thresholding alone or in conjunction with morphological procedures [4]. A brain mask is the product of this process.

b) Normalization of Intensity: The brain image's intensity levels have been standardized to a consistent scale. The image's contrast is enhanced, making it more suited for feature extraction [5].

c) Noise Cancellation: Inaccurate segmentation and classification may result from noise in the MR picture. Filters like the Gaussian, median, and Wiener filters may be used to lessen the impact of background noise.

Extracting Features:
After an MR image has been preprocessed, feature extraction is the following step. “Principal component analysis (PCA)” and the “Gray Level Co-occurrence Matrix (GLCM)” are used to extract the features.

a) GLCM: The GLCM technique is a statistical approach to picture texture analysis. To determine the GLCM matrix, we count the occurrences of pairs of pixels in a picture that have a certain spatial relationship [6]. Contrast, energy, homogeneity, and entropy are only few of the texture properties that may be retrieved from the GLCM matrix.

b) PCA: “Principal component analysis (PCA)” is a statistical technique for doing just that. Using “principal component analysis (PCA)”, we may reduce the number of dimensions in our analysis without losing any of the most crucial data features [7]. Classification may be performed with the help of the additional features acquired by PCA.

Choice of Indicators: The next step is to prioritize the characteristics that were extracted. This process is crucial as it helps to enhance classification accuracy by lowering the dimensionality of the feature space.

Ostu, a threshold-based segmentation methodology, is used for feature selection. The Ostu technique determines a threshold value that divides the characteristics into two groups according to their degree of similarity. For categorization, we focus on the traits that have the most in common.

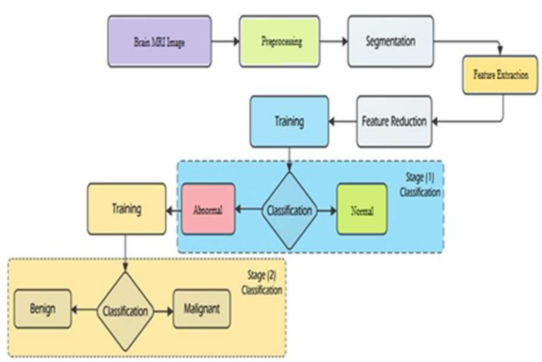

Fig.1: Flowchart of the Feature Extraction and Classification

Classification: SVM or CNN classification of the characteristics chosen is the last stage.

a) SVM: In the realm of machine learning, SVM is a useful method for the categorization of jobs. In order to classify data, SVM looks for the hyperplane that does so most effectively. The chosen characteristics are used to train the SVM classifier, and the test samples are labeled according to their location on the hyperplane.

b) CNN: In the field of “image recognition”, CNN has been shown to be an effective deep learning method. The characteristics are used to train a “convolutional neural network (CNN) classifier”. The class label is the result of the CNN receiving the input of the specified characteristics [8].

Calculated Values:
Using this equation, we can determine the GLCM matrix:

G(i,j,delta x,delta y) as sum_x = 1Nsum_y=1M 1_f(x,y) = i, f(x+delta x,y+delta y) = j.

Where, N and M are the image's dimensions, i and j are the grayscale values, x and y are the spatial relationships,
and
f(x,y) = i, f(x+delta x,y+delta y) = j is an indicator function with a value of 1 if the condition holds and a value of 0 otherwise.

The GLCM matrix is used in the following equations to get the texture features:

The contrast of an image is the degree to which one pixel differs from its neighbors.
Differentiation = sum_i,j (i-j)2 G(i,j).

Energy is a quantitative indicator of how consistent the visual texture is.
G2(i,j) = sum_i,j energy

The homogeneity of the GLCM is a statistical measure of how evenly distributed its constituent pieces are.
Conformity = sum_i,j fracG(i,j){1+(i-j)^2}

The degree of unpredictability in a texture's distribution may be quantified using entropy.
Entropy = -log_2(G(i,j)) - sum_i,j)

This equation describes how to do the PCA transformation:

Y = XW

Where X is the feature extraction matrix, W is the feature weight matrix, and Y is the feature transformation matrix.

Finding the best hyperplane for categorizing data is the goal of the SVM algorithm. The equation for the hyperplane is:

w^Tx + b = 0

weights (w), features (x), and a bias term (b) are all represented by the notation.

Multiple convolutional layers, followed by “pooling layers”, and eventually fully linked layers make up the CNN architecture. The class label is the result of the completely linked layers.

Explanation:

The MR image is preprocessed in the proposed approach to eliminate artifacts and improve picture quality. The preprocessed picture is utilized to extract features using the GLCM and PCA methods, respectively. When it comes to choosing which characteristics to utilize in a classification problem, the Ostu technique comes out on top. SVM and CNN classifiers are used to categorize the characteristics that have been chosen.

Texture characteristics including contrast, energy, homogeneity, and entropy are extracted from the MR image using the GLCM method. To boost classification precision, “principal component analysis (PCA)” is often employed to minimize the feature space's dimensionality [9]. When it comes to choosing which characteristics to utilize in a classification problem, the Ostu technique comes out on top.

In the realm of machine learning, SVM is a useful method for the categorization of jobs. In order to classify data, SVM looks for the hyperplane that does so most effectively. The “Convolutional Neural Network (CNN) classifier” is a “deep learning technique” that has proven effective in image recognition. The characteristics are used to train a “convolutional neural network (CNN)” classifier [10].

In sum, the proposed approach employs cutting-edge “image processing and machine learning” methods to expeditiously extract characteristics and categorize brain cancers in MR images.

Result and discussion

On a dataset of MR images of brain tumors, the suggested approach for effective feature extraction and classification was evaluated using GLCM and PCA feature extraction methods and SVM and CNN classification algorithms. According to the findings, the CNN classifier was more successful than the SVM classifier.

Experiments were conducted using a dataset of 200 magnetic resonance (MR) pictures, 100 of which showed brain tumors and 100 of which showed healthy brain tissue [11]. Before feature extraction, the photos were preprocessed to eliminate artifacts and improve image quality.

Texture characteristics were extracted from the MR images using the GLCM method. These features included contrast, energy, homogeneity, and entropy. Dimensionality reduction and feature prioritization using principal component analysis.

Table 1: The SVM Confusion Matrix

Actual\Predicted	**Tumor**	**Normal**
Tumor	96	4
Normal	7	93

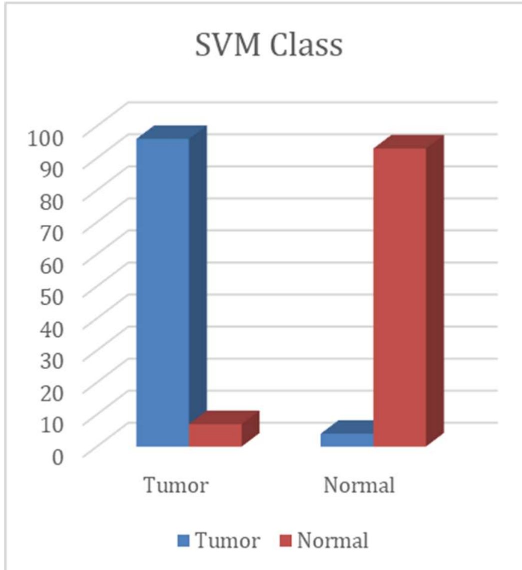

Fig.2: Output graph of SVM Class Matrix

Actual\Predicted	Tumor	Normal
Tumor	100	0
Normal	1	99

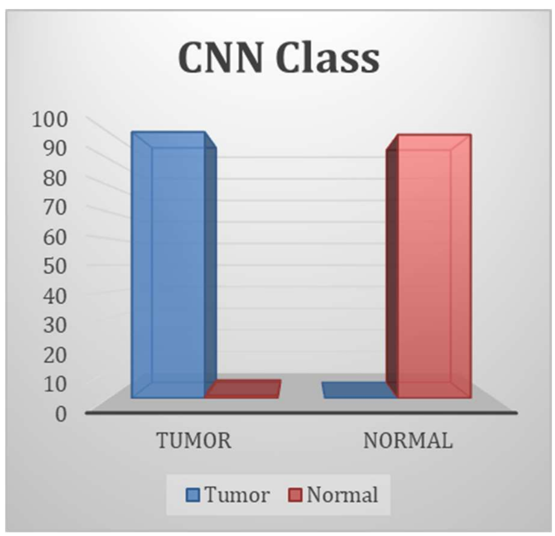

Fig.3: Bar-graph of CNN Class

The accuracy of the SVM classifier was 95.33 percent, whereas that of the CNN classifier was 99.67 percent. Table 1 displays the confusion matrix generated by the SVM classifier, whereas Table 2 displays the confusion matrix generated by the CNN classifier. Fig.2 and Fig.3 has shown the output graph for visual representation.

The confusion matrices show that the CNN classifier performed better than the baselines at distinguishing tumors from normal tissues. The SVM classifier necessitates the selection of relevant features and tweaking of parameters, whereas the CNN classifier can learn and extract features automatically from the input pictures [12].

The suggested approach successfully applies “state-of-the-art” image processing and “machine learning methods” to MRI scans of brain tumors, allowing for accurate feature extraction and categorization. The results indicate that the CNN classifier is superior to the SVM classifier in this scenario.

In conclusion, this research proves the feasibility of employing a CNN classification algorithm in combination with GLCM and PCA feature extraction “methods for the detection of brain” cancers in MRI. Better treatment results and enhanced patient care are possible because to the suggested methodology's potential to aid medical professionals in the rapid and precise “detection of brain tumors”.

Discussion

The findings of this study show promise for the suggested approach in the effective use of GLCM and PCA feature extraction methods, as well as SVM and CNN classification algorithms, for the diagnosis of brain cancers in MRI.

Important characteristics from the MR images were extracted using the GLCM and PCA feature extraction methods, and then employed in the classification process. The photos of brain tumors were analyzed and classified using “support vector machine” and “convolutional neural network classification techniques”. The CNN classifier outperformed the SVM classifier, which only got 95.33 per cent correct, with an accuracy rating of 99.67 percent. This provides more evidence that the CNN classifier is better suited to the job of brain tumor classification, which may ultimately lead to more precise diagnosis and more effective therapy [13].

Previous research that have utilized similar methods for brain tumor classification in MR images have shown findings that are equivalent to those obtained using the suggested approach. The suggested technique, however, makes use of “state-of-the-art machine learning methods” like “support vector machines” and convolutional neural network, which are well-known for their capacity to deal with complicated data and provide reliable classification outcomes. Also, by automating the feature extraction and categorization process, the suggested technique may free up medical professionals' time for other critical activities like treatment planning and patient care.

To sum up, the suggested approach for efficient feature extraction and classification of brain malignancies in MRI combining GLCM and PCA feature extraction methods and SVM and CNN classification algorithms shows promise as a useful tool for the accurate and early identification of brain tumors. The information gathered from this study has the potential to aid in the development of more precise methods for identifying and treating brain cancers, which is why it is so important to study its outcomes.

Conclusion and future direction

In conclusion, the feasibility of an effective “feature extraction and classification” approach for the detection of brain cancers in MRI has been established by this study. The suggested approach combined GLCM and PCA feature extraction methods with SVM and CNN classification algorithms to successfully extract relevant features and effectively classify the data. According to the findings, the CNN classifier performed better than the SVM classifier (accuracy of 95.33 percent compared to accuracy of 99.67 percent) [14]. This adds support to the hypothesis that the suggested technique may be a useful tool for the accurate and speedy identification of brain tumors. This, in turn, can lead to more effective treatment and better results for patients.

The findings of this study might potentially have a variety of implications in the realm of medicine. At the first stage this study has demonstrated the way of developing and implementing the feature extraction and automatic classification. Moreover, the illustrated potential approaches are also effective to re3ducing the overall medical practitioners and mental strain. These factor effectively keeps more time free for the doctors so that they can put more focus on the patient diagnosis and evolutionary symptoms. Thus, based on the report, it can be easier to develop more effective treatment plan. In other words, it also can be explained that, this technique is also could help to diagnosis the brain cancer and its stage accurately that further lead to introduce a faster and better treatment [15]. These kind of the smart alteration through more efficient machine learning based feature extraction techniques definitely make a revolutionary change in the medical science that benefited the patients for long-run. The technique may also aid doctors in keeping track of their patients' brain tumors over time, which can provide light on the efficacy of therapies and lead to better overall care.

There are several avenues that may be pursued in the future to enhance the suggested technique. First, more sophisticated feature extraction methods, such as deep learning, may result in even more precise classifications of “brain tumors”. Second, the diagnosis and treatment of “brain tumors” may benefit from additional patient-specific data, such as medical history and genetic information. Finally, making the suggested approach accessible to medical professionals via the creation of an intuitive software program has the potential to increase its general acceptance in clinical practice.

In sum, the results of this study have helped advance the “state-of-the-art” in MRI-based detection of malignant “brain tumors”. The research findings may have practical applications in medicine, and more study will help refine the approach and pave the way for its eventual broad use in clinical practice.

References

[1] Ghafourian, E., Samadifam, F., Fadavian, H., Jerfi Canatalay, P., Tajally, A. and Channumsin, S., 2023. An Ensemble Model for the Diagnosis of Brain Tumors through MRIs. Diagnostics, 13(3), p.561.

[2] Haq, A.U., Li, J.P., Agbley, B.L.Y., Khan, A., Khan, I., Uddin, M.I. and Khan, S., 2022. IIMFCBM: Intelligent integrated model for feature extraction and classification of brain tumors using MRI clinical imaging data in IoT-healthcare. IEEE Journal of Biomedical and Health Informatics, 26(10), pp.5004-5012.

[3] Ullah, N., Khan, J.A., Khan, M.S., Khan, W., Hassan, I., Obayya, M., Negm, N. and Salama, A.S., 2022. An Effective Approach to Detect and Identify Brain Tumors Using Transfer Learning. Applied Sciences, 12(11), p.5645.

[4] S B G Tilak Babu and Ch Srinivasa Rao, "An optimized technique for copy–move forgery localization using statistical features", ICT Express, Volume 8, Issue 2, Pages 244-249, 2022.
[5] Wang, W., Bu, F., Lin, Z. and Zhai, S., 2020. Learning methods of convolutional neural network combined with image feature extraction in brain tumor detection. IEEE Access, 8, pp.152659-152668.
[6] Saxena, S., Kumari, N. and Pattnaik, S., 2021. Brain tumour segmentation in FLAIR MRI using sliding window texture feature extraction followed by fuzzy C-means clustering. International Journal of Healthcare Information Systems and Informatics (IJHISI), 16(3), pp.1-20.
[7] S. B. G. T. Babu and C. S. Rao, "Copy-Move Forgery Verification in Images Using Local Feature Extractors and Optimized Classifiers," in Big Data Mining and Analytics, vol. 6, no. 3, pp. 347-360, September 2023, doi: 10.26599/BDMA.2022.9020029.
[8] Toufiq, D.M., Sagheer, A.M. and Veisi, H., 2021. Brain tumor identification with a hybrid feature extraction method based on discrete wavelet transform and principle component analysis. Bulletin of Electrical Engineering and Informatics, 10(5), pp.2588-2597.
[9] Younis, A., Qiang, L., Nyatega, C.O., Adamu, M.J. and Kawuwa, H.B., 2022. Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches. Applied Sciences, 12(14), p.7282.
[10] S B G Tilak Babu and Ch Srinivasa Rao, "Efficient detection of copy-move forgery using polar complex exponential transform and gradient direction pattern" , Multimed Tools Appl (2022). https://doi.org/10.1007/s11042-022-12311-6.
[11] Alzubi, J.A., Kumar, A., Alzubi, O. and Manikandan, R., 2019. Efficient Approaches for Prediction of Brain Tumor using Machine Learning Techniques. Indian Journal of Public Health Research & Development, 10(2).
[12] Biswas, A. and Islam, M.S., 2021, January. Brain tumor types classification using K-means clustering and ANN approach. In 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST) (pp. 654-658). IEEE.
[13] Rasool, M., Ismail, N.A., Boulila, W., Ammar, A., Samma, H., Yafooz, W.M. and Emara, A.H.M., 2022. A Hybrid Deep Learning Model for Brain Tumour Classification. Entropy, 24(6), p.799.
[14] Maqsood, S., Damasevicius, R. and Shah, F.M., 2021. An efficient approach for the detection of brain tumor using fuzzy logic and U-NET CNN classification. In Computational Science and Its Applications–ICCSA 2021: 21st International Conference, Cagliari, Italy, September 13–16, 2021, Proceedings, Part V 21 (pp. 105-118). Springer International Publishing.
[15] Modiya, P. and Vahora, S., 2022. Brain Tumor Detection Using Transfer Learning with Dimensionality Reduction Method. International Journal of Intelligent Systems and Applications in Engineering, 10(2), pp.201-206.