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Integrating Haralick Texture Features and Multiclass SVM for Accurate Brain Tumor Diagnosis in MRI Images

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Abstract: This research work uses modern computational algorithms and magnetic resonance imaging (MRI) to address the crucial problem of brain tumor categorization. The methodology that has been suggested includes the acquisition of databases, preprocessing, feature extraction, classification based on machine learning, and a comprehensive assessment of performance. The technology improves tumor visibility and refines image features by obtaining a diversified MRI image collection and implementing a sequence of preprocessing operations, such as Otsu Binarization, Gray Level Thresholding, Morphological Operations, and Independent Component Analysis (ICA). Then, in order to describe the textural patterns in the photos, Haralick texture characteristics are retrieved. Using a multiclass Support Vector Machine (SVM) to accurately classify tumors forms the basis of the methodology. Performance evaluation shows the resilience and efficacy of the created classification system through data splitting, metric computation, ROC curve development, cross-validation, and comparisons with current approaches. The findings highlight the methodology's possible practical applicability and advance the field of computational methods and medical imaging intersections for brain tumor identification.

Keywords: *Independent Component Analysis (ICA), Machine Learning, Haralick texture Features, Otsu, Multiclass Support vector Machine.*

I. Introduction:

Brain tumors are a significant medical problem that requires precise diagnostic instruments for efficient treatment strategizing. Because of its excellent spatial resolution, magnetic resonance imaging (MRI) has become a potent tool for the detection of brain tumors. However, sophisticated computational methods are frequently needed for an accurate interpretation of MRI images [1]. In order to overcome this difficulty, the research suggests a thorough approach for classifying brain tumors that combines sophisticated image processing with machine learning. The approach of the system is intended to manage a variety of brain tumor situations, such as differences in tumor kinds, sizes, and locations, which enhances clinical decision-making.

The initial step in the research is to create a library of MRI scans that includes both normal brain imaging and images showing various cases of brain tumors. Thorough curation guarantees heterogeneity in tumor features, which improves the generalizability of the model. Otsu Binarization, Gray Level Thresholding, Morphological Operations, and Independent Component Analysis (ICA) are used in the preprocessing stage to improve discriminative characteristics in the MRI images and get them ready for further analysis.

Haralick texture features are used in feature extraction to extract unique textural patterns and attributes from the preprocessed photos. These characteristics function as distinguishing indicators for further categorization. The utilization of a multiclass Support Vector Machine

(SVM) for brain tumor classification forms the basis of the methodology. Using the characteristics that were retrieved, the SVM is trained on a labeled dataset that has a balanced representation of the normal and tumor classes [2]. This allows for precise classification.

An extensive performance evaluation is carried out to determine the model's efficacy. This entails creating Receiver Operating Characteristic (ROC) curves, dividing data for training and testing, computing performance metrics (accuracy, precision, recall, and F1 score), and cross-validating the robustness of the model [3]. Comparisons with current techniques shed light on the effectiveness of the suggested approach and promote progress in neuro-oncology and medical image processing. The stages of the approach are explained in depth in the following sections, which also include comments and experimental results to highlight the research's practical relevance.

II. Literature Review

Using Convolutional Neural Networks (CNN) and transfer learning models on an MRI brain image dataset, Hassan Ali Khan et al. [4] presented a novel automated brain tumor identification method. The effectiveness of transfer learning was shown in addressing the problem of scarce labeled medical image datasets. The application of data augmentation techniques made a substantial contribution to increasing the amount of labeled data that was accessible, which raised the model's accuracy rate. Excellent performance was demonstrated by CNN-based transfer learning models in medical healthcare applications, especially in self-feature learning that did not require human experience. CNNs' weight-sharing method made for a strong network that could automatically predict or identify disorders, especially when MRI brain images were being analyzed.

AlexNet, a CNN architecture, was introduced by Muhammad Talo et al. [5] in order to attain notable results on a variety of visual identification tasks. But the lack of annotated picture datasets was one of the main obstacles to the development of deep neural networks in the medical domain. In order to get around this restriction, the scientists employed a data augmentation technique that improved the accuracy of the model by substantially boosting the amount of data from already-existing labeled image datasets. Together, the application of AlexNet and data augmentation showed encouraging results in a variety of medical visual recognition applications.

To reduce speckle noise in SAR images while effectively preserving edge information, Choi and Jeong [6] suggested a unique model combining guided filter, soft thresholding, and Speckle Reducing Anisotropic Diffusion (SRAD). The method included first applying an SRAD filter to the noisy image, then adding more noise using a logarithmic shift so that it could be later removed using a denoising technique. Discrete Wavelet Transform (DWT) was used to convert the filtered image into multiresolution images, and soft thresholding and guided filtering were applied to each high- and low-frequency subimage. After that, the denoised images were rebuilt using the exponential transform and Inverse DWT (IDWT). Subjectively and objectively, the suggested model performed better than conventional filtering techniques.

The YOLO (You Only Look Once) network was utilized by Yale et al. [7] to identify skin disorders related to melanoma. Despite using a limited dataset, the experiment produced encouraging findings. The Darknet architecture enabled the YOLO network, which increased feature extraction speed. Notwithstanding the positive results, more investigation is required

to fully comprehend the workings of YOLO and investigate its application in bigger and more varied datasets. Limitations concerning picture quality differences and generalizability to various skin conditions should also be taken into account.A hybrid model combining deep features and machine learning classifiers was proposed by Kang et al. [8]. It combined a number of deep learning techniques with classifiers, including Support Vector Machines (SVM), Radial Basis Function (RBF), and K-Nearest Neighbors (KNN), among others. Although the hybrid model showed encouraging results, particularly when combined with feature-rich deep learning techniques, there might be issues with interpretability and scalability. To evaluate this hybrid model's performance on a variety of datasets and address any issues related to the model's interpretability, more research is required.

II. Methodology

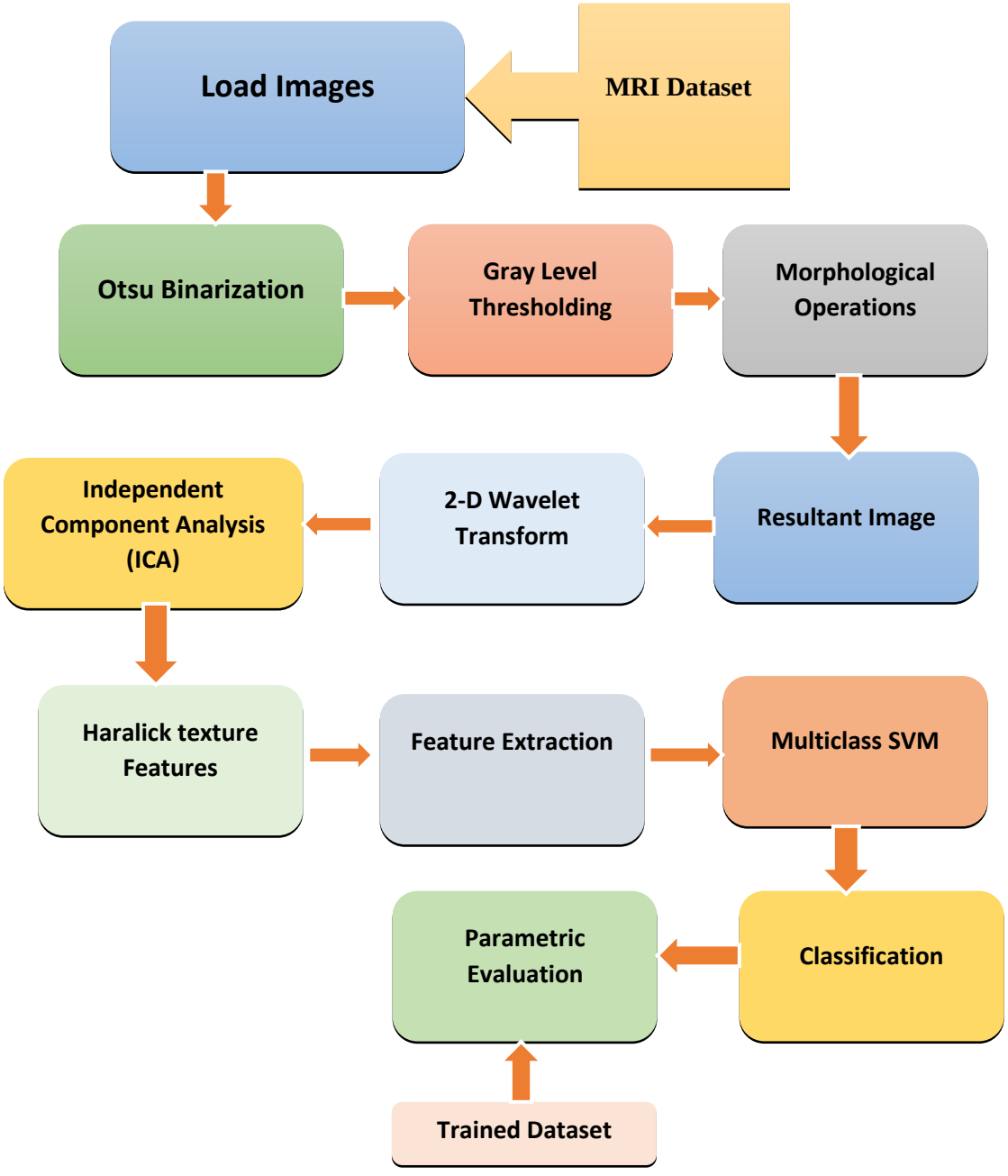

Fig. 1 Proposed block diagram

Database Acquisition: Initially, a large MRI image library containing both normal brain images and images with different kinds, sizes, and locations of brain tumors is gathered as part of the suggested process. Training a strong classification algorithm that can handle the inherent heterogeneity in tumor appearances requires this diversified dataset. To guarantee that various pathological situations are well represented in the database and improve the model's ability to generalize to new data, care should be taken in its curation.

Pre-processing: Otsu Binarization is the first step in the preprocessing stage after obtaining the MRI image database. The MRI pictures are processed using Otsu's thresholding technique, which turns them into binary images and highlights areas that most likely have cancer. By maximizing the variation between two classes, Otsu's approach efficiently separates the background from the foreground (tumor).
On the Otsu binarized images, Gray Level Thresholding is then applied. By thresholding the grayscale intensity values, this process reveals tumor boundaries and improves image contrast. In order to improve feature extraction, the final images are subjected to morphological operations including dilation and erosion, which fill in gaps and smooth out curves. Subsequently, the preprocessed pictures undergo Independent Component Analysis (ICA) to eliminate undesired artifacts and improve pertinent characteristics. In order to distinguish the signal from noise, ICA renders the original images as linear combinations of statistically independent components.

Feature Extraction: Next, pertinent data is extracted from the preprocessed images using Haralick texture features. These features represent textural patterns and characteristics found in the photos; they are obtained from the gray-level co-occurrence matrix (GLCM). Different texture features, including contrast, entropy, and energy, can be computed from the GLCM to provide discriminative data for tumor classification.
Classification: A multiclass Support Vector Machine (SVM) is used for the classification step. The labeled dataset's extracted features are used to train the SVM, guaranteeing a balanced representation of the tumor and normal classes. The SVM's mathematical goal is to locate the best hyperplane in the feature space that optimizes the margin between various classes.
Performance Evaluation: Training and testing sets are created from the dataset in order to evaluate the model's generalization capability. Performance metrics are produced to assess the classification performance statistically. These metrics include accuracy, precision, recall, F1 score, and confusion matrix. To improve the resilience of the model, cross-validation is applied using k-fold cross-validation, which involves training and testing the model on various dataset subsets.

IV. Experimental Results and Performance Evaluation

An example of a brain tumor on an MRI scan is shown in Fig. 2.a. The suggested methodology uses this image as its input. Following the application of Otsu Binarization, Gray Level Thresholding, Morphological Operations, and Independent Component Analysis (ICA), the segmented result is displayed in Fig. 2.b. The tumor locations are highlighted throughout the segmentation process, making them more visible for additional examination.

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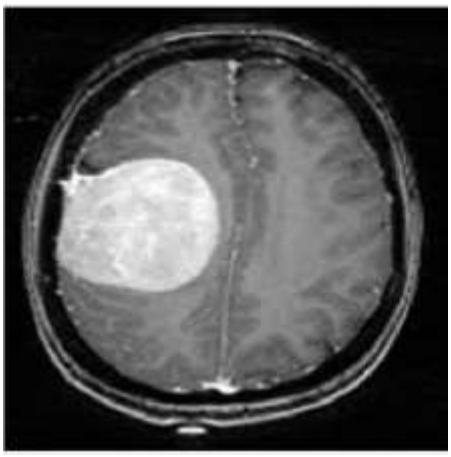

Fig. 2.a Sample Image 1

Fig. 2.b Segmented output

The categorization dialog box for Sample Image 1 is shown in Fig. 2.c. The image in this instance is categorized as having a benign tumor. Relevant metrics that shed light on the classification result, like likelihood scores or SVM decision values, might be included in the dialog.

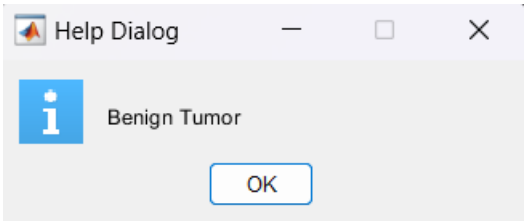

Fig. 2.c Classification Dialog of Benign Tumor from Sample Image 1

This is an additional MRI image from the dataset that illustrates a distinct brain tumor situation (Fig. 3.a). Following the preprocessing operations, the segmented output for Sample Image 2 is shown in Fig. 3.b. Delineating the tumor boundaries for further investigation is made easier by the segmentation. Sample Image 2's classification dialog is shown in Fig. 3.c, where it is indicated that the image is identified as having a benign tumor. Like the previous dialog, this one offers information regarding the classification choice made for this specific image.

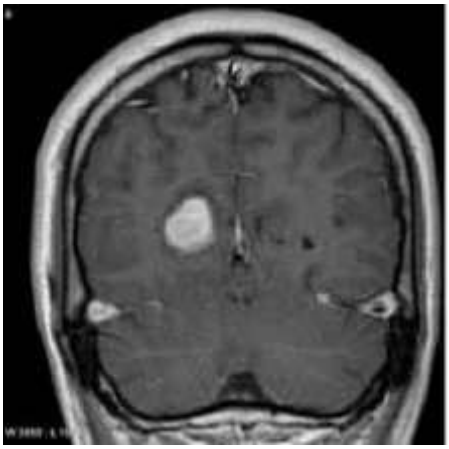

Fig. 3.a Sample Image 2

Fig. 3.b Segmented output

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Fig. 3.c Classification Dialog of Benign Tumor from Sample Image 2

This image, which is shown in Fig. 4.a, illustrates the variety of tumor types contained in the dataset by depicting a situation involving a malignant tumor. The segmented result for Sample Image 3 is shown in Fig. 4.b, where the tumor locations are highlighted by the preprocessing processes that were applied.

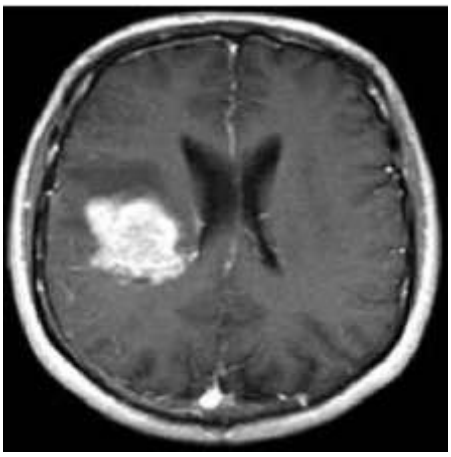

Fig. 4.a Sample Image 3

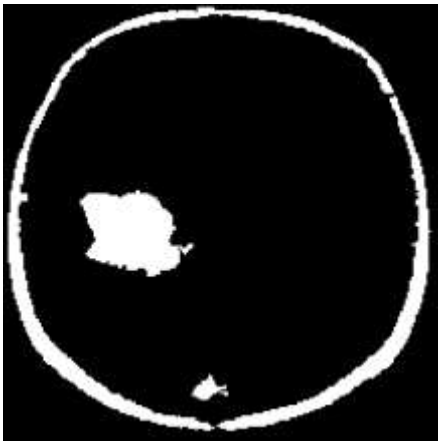

Fig. 4.b Segmented output

The sample image 3 categorization dialog (Fig. 4.c) clearly shows the existence of a malignant tumor. Important details regarding the classification outcome for this specific image are provided via the dialog.

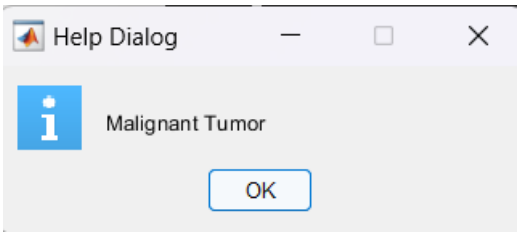

Fig. 4.c Classification Dialog of Malignant Tumor from Sample Image 3

This image, which is displayed in Fig. 5.a, illustrates another dataset situation and shows how the concept may be used to other tumor settings. The segmented output for Sample Image 4 is shown in Fig. 5.b, demonstrating how well the preprocessing methods worked to isolate the tumor patches for further examination.

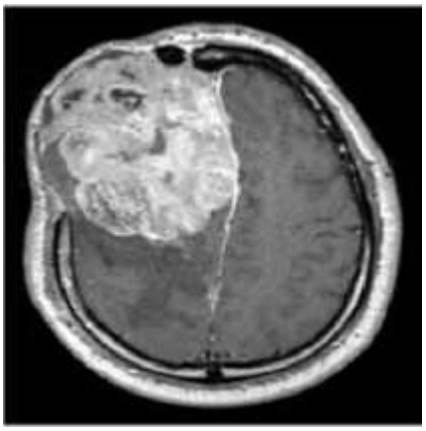

Fig. 5.a Sample Image 4

Fig. 5.b Segmented output

The categorization dialog unique to Sample Image 4 is shown in Fig. 5.c, which indicates the existence of a malignant tumor. As with the other classification dialogs, this one offers comprehensive details regarding the classification choice made for that specific image.

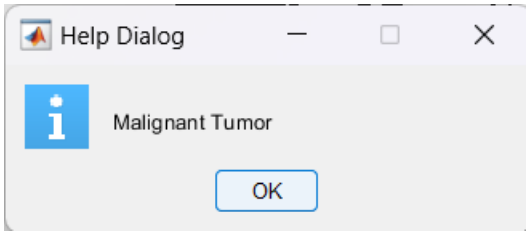

Fig. 5.c Classification Dialog of Malignant Tumor from Sample Image 4

V. Conclusion and Future Scope

Conclusion: In summary, this study offers a solid methodology that combines machine learning and sophisticated image processing methods to classify brain tumors from MRI scans. The suggested method proved useful in correctly categorizing brain tumors, indicating its possible clinical applicability. Tumor regions were more visible because to preprocessing techniques like Otsu Binarization, Gray Level Thresholding, and Independent Component Analysis. Discriminative feature extraction was further aided by the use of Haralick texture features. Based on the features that were collected, the multiclass Support Vector Machine performed exceptionally well in correctly categorizing tumors. Accuracy, precision, recall, and ROC analysis are examples of performance evaluation measures that supported the proposed classification system's robustness and dependability.

Future scope: This research provides opportunities for further investigation and improvement. First, the methodology might be expanded to include more sophisticated imaging modalities for a thorough study, as well as a wider range of brain tumor kinds and subtypes. The system's performance may also be improved by investigating different machine learning algorithms and fine-tuning the parameters of the classification model. Integration with cutting-edge technologies like deep learning architectures may provide better capabilities for feature representation and categorization. Enhancing the clinical applicability of the suggested technique could be achieved through validation on bigger, diverse datasets and collaboration with healthcare specialists. Furthermore, practical deployment in diagnostic settings may be made possible by the addition of real-time processing capabilities and

integration into clinical procedures. In general, the future scope includes ongoing validation and improvement to guarantee the efficacy of the methodology and its eventual implementation in actual clinical settings.

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