

A Study on Computer-Aided Diagnosis of Human Brain Tumor Detection and Classification using Binary Genetic Algorithm and Deep Learning Techniques

Prashantha S.J¹, H.N. Prakash² and Padmajadevi G³

¹Department of Computer Science and Engineering, NCE Hassan, Visvesvaraya Technological University, Belagavi, India
Email: prasi.sjp@gmail.com

²Department of Computer Science and Engineering, RIT Hassan, Visvesvaraya Technological University, Belagavi, India
Email: prakash.hn98@gmail.com

³Department of Electronics and communication and Engineering, MCE Hassan, Visvesvaraya Technological University, Belagavi, India
Email: padmajadevi@gmail.com

Abstract—Computer-aided detection (CAD) frameworks enable doctors diagnose faster and more accurately. The objective of paper is to present a hybrid learning approach for a CAD system for automatically detecting brain tumors using magnetic resonance (MR) images. The methodology focuses on four computational techniques: (1) the Conventional and deep learning (DL) for Feature Extraction (2) select a deep features by last fully connected layer and conventional optimal feature sets are from Genetic Algorithm (GA) (3) combine the features that were chosen by employing a fusion approach and (4) the support vector machine (SVM) is used to classify inputs as either normal or abnormal. A total of 125 flair MR images, 50 normal and 75 abnormal, were used in the experiments. These images were taken from a real-world of brain MRI dataset. The results demonstrated that the proposed method efficiency compared with the other MR images state of the art techniques. The outcomes demonstrated how specific and robust the proposed hybrid technique. At last, some probable next steps are proposed.

Index Terms— Brain tumors, Genetic Algorithm, Deep learning, Fusion and Support vector machine.

I. INTRODUCTION

Brain cancer, often known as a tumor, is one of the most fatal illnesses that can affect life for an individual. The advancement of medical image processing has renewed interest in the study of brain tumor. The most notable frequent significant causes of the rise in death rates among adults and children around the globe is brain tumor. Tumors of the brain are masses of abnormal cells that can form anywhere in or around the brain. A primary malignant tumor of the brain or spinal cord will be identified 24,810 adults (10,530 women and 14,280 men) in the United States in 2023. In addition, 5,230 young children under the age of 20 are expected to receive a CNS tumor diagnosis in the United States in 2023. In 2023, primary CNS and brain tumor fatalities are predicted to total 18,990 in the US (11,020 males and 7,970 women) [1].

In India, the prevalence of brain tumors is gradually increasing, and more cases of brain tumors are reported each

year among people of all ages. According to studies, among Indians, brain tumors are the 10th most prevalent type of cancer. According to the International Association of Cancer Registries (IARC), India reports about 28000 cases of brain cancer every year, and sadly, 24000 individuals pass away from brain tumors. A brain tumor is a serious medical illness that, if found and treated improperly, can be fatal [2]. Based on the GLOBOCAN projections of incidence, death, and prevalence for year 2020 in 185 countries or territories for 36 cancer types by sex and age group, CANCER TODAY offers a thorough assessment of the cancer burden globally [3]. Figure 1. Shows the Brain central nervous system fact sheet.

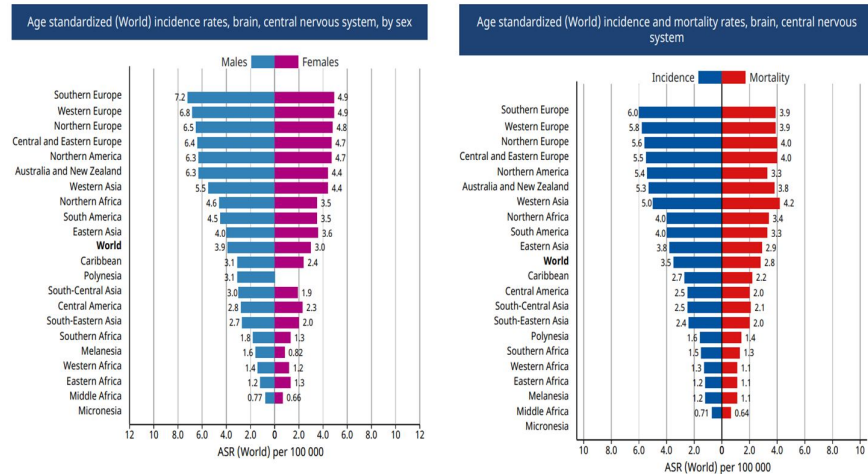


Figure 1. Brain central nervous system fact sheet[3]

In the past twenty years, computer-aided detection (CAD) has advanced quickly. By using specialized computer systems to offer "second opinions," the major goal of CAD is to aid radiologists in analysing medical images. Studies on CAD technology and systems demonstrate that they can reduce cancer missed due to fatigue, overlooking, or data overload, improve inter- and intra-reader variability, and assist radiologists diagnose more accurately. The process of extracting features from objects (such as lesions) in raw data and making a decision based on the output of a classifier, such as categorizing each object into one of the available categories of multiple patterns, is known as pattern recognition.

There are two kinds of computer-aided detection systems for brain examination in general: those that distinguish between diseases (benign or malignant lesions) and those that identify lesions (normal or abnormal brain). A CAD scheme is developed using a variety of methods, many of which have been compiled for review purposes. In general, all imaging modalities and examination types can use CAD systems. The incorporation of several image processing processes (techniques) such image segmentation, feature extraction and selection, and classification is crucial to the creation of a CAD system. A number of researchers, including [4][5] have recently developed a variety of brain CAD methods by brain MR images constructed on various kinds of classifiers.

Providing CAD models that function in all circumstances, irrespective of the level of detail and data base size, continues to be a difficulty. The requirement to achieve the greatest degree of precision drives the development of computerized systems for MR images of the human brain. The goal of this work is to enhance the capability of a detection system for the detection of brain tumors. CAD systems are still a challenge. We devised an efficient classification method that can quickly and automatically distinguish between normal and abnormal brain images from MRI images in response to the aforementioned needs.

The following describes the way the paper is structured: Section II describes related efforts on conventional feature selection and extraction, deep learning techniques to feature selection, and feature level fusion frameworks. Section III provides an overview of the proposed framework methodology. It describes feature extraction, feature vector selection, feature fusion, and classification. Section IV discusses the experimental setup, results, and techniques used in this study. Section V gives the conclusions.

II. RELATED WORKS

Researchers have proposed various brain MR imaging detection and classification approaches over the last fifteen years, but there are significant disparities in datasets used, segmentation targets, features, and recognition.

In the field of medical imaging, there is an extensive corpus of literature on medical image analysis and the design of differentiated features for high-level tasks like classification and segmentation [4][5]. Recent work demonstrated that categorization of the human brain in magnetic resonance (MR) images is achievable utilizing a 2-tier classifier with an adaptive segmentation technique [9], and gives via neural network and the central moments[10]. Based on wavelet-Entropy and the Naive Bayes Classifier proposed categorizing MRI images as either normal or pathological [11]. Fully automatic differentiation between healthy and diseased human brains, essential for research.

A hybrid image enhancement-based brain MRI image classification approach to distinguish into normal and pathological classes was proposed by Z. Ullah et al.,[12](2020). The median filter, CLAHE, wavelet transform, color moments, and feed-forward NN are used to design this system (i.e., Median + CLAHE + DWT + CM + ANN) methods. It is used for this purpose and consists of four steps: (1) remove noise using a median filter, improve contrast, and sharpen the image using the histogram equalization approach and Grayscale images are converted to RGB color space. (2) Discrete wavelet transform feature extraction followed by color moments (i.e., mean, skewness, and standard deviation). Additionally, (3) a deep neural network (DNN) can classify MRI scans of the human brain as healthy or diseased. In comparison to prior state-of-the-art methodologies, the methodology achieved 95.7 % accuracy. It goes on to say that the image enhancing approach can help other medical image analysis methods perform better.

El-Sayed A et al., [13](2014) introduced a hybrid learning approach for a CAD system to automatically identify brain tumors using MRI images. The system is developed based on a feed-forward back-propagation neural network for input classification as abnormal or normal. The tests were conducted on an actual MRI dataset of the human brain, comprised a total of 101 images, 14 of which were normal and 87 of which were abnormal (benign and malignant tumors). Several potential possibilities for the future of human brain MR image CAD systems include: (1) the acquisition of sizeable archives from many universities with various image quality for use in clinical testing and CAD system innovation. (2) Enrich classification precision by expanding the training data set and extracting more effective features. (3) Many academics have not yet explored the potential of combining various machine learning methods into a single, hybrid framework. (4) More testing and analysis is needed to determine if the offered methods can be applied universally.

A data-constrained method for brain tumor identification was proposed by Sethy, P.K., and Behera, S. K. [14](2021). In this study, the potential of deep characteristics is examined. The use of deep features in combination with deep classification approaches is addressed in this work. The suggested method uses three different pre-trained networks and the deep features they have to offer (these networks are vgg19, Alex net, and vgg16. For better model output, we use a deep fusion strategy. In addition, PCA is used to investigate how well classifiers work by reducing the dimensionality of feature vectors. This investigation makes use of a modest dataset retained in its original format. Using a linear SVM classifier and a fusion feature of fc6 and fc7, VGG16 performs competitively (accuracy of 0.9798) with state-of-the-art studies.

J. Horwath et al., [15](2020) utilized cutting edge deep learning methods for physical applications. In generalizable and convincing models where methodically learning dataset preparation, neural network design, and accuracy assessment are required. Understanding crucial deep features and critically assessing the use of multiple deep learning methods, on the other hand, is of stimulating decisive process design. H. Mohsen et al., [16](2017) proposed an effective strategy for classifying brain MRIs as Normal, glioblastoma, sarcoma, or metastatic bronchogenic carcinoma by combining DWT features with a Deep Neural Network. This method was used to classify a dataset made up of 66 brain MRI images by deep neural network classifier. In the future, design novel methods could be employed with DWT, CNN, and principal components analysis (PCA) techniques for large-size (256 x 256) images.

The detection of malignancies in the brain includes a number of critical steps, one of which is the extraction of features. These features would be helpful in determining whether or not a tumor exists. The computer diagnostic method depends heavily on accurate classification of brain tumors in order to make accurate diagnoses. For MRI images of the brain, several different feature extraction techniques have been created during the past few decades. Despite the availability of several methods, the extraction of characteristics and the diagnosis of brain tumors remain difficult tasks. Because techniques that are effective for one individual may not be effective for another, it is challenging to develop a system that can recognize and diagnose brain tumors in all people. Furthermore, a technique can be used to classify images of developing at various ages, unlike the research on brain image classification described above. This shows that the proposed technique may be used to complete the tasks of classification using axial FLAIR MR training images. Therefore, we give a classification strategy for the interpretation of brain MR images.

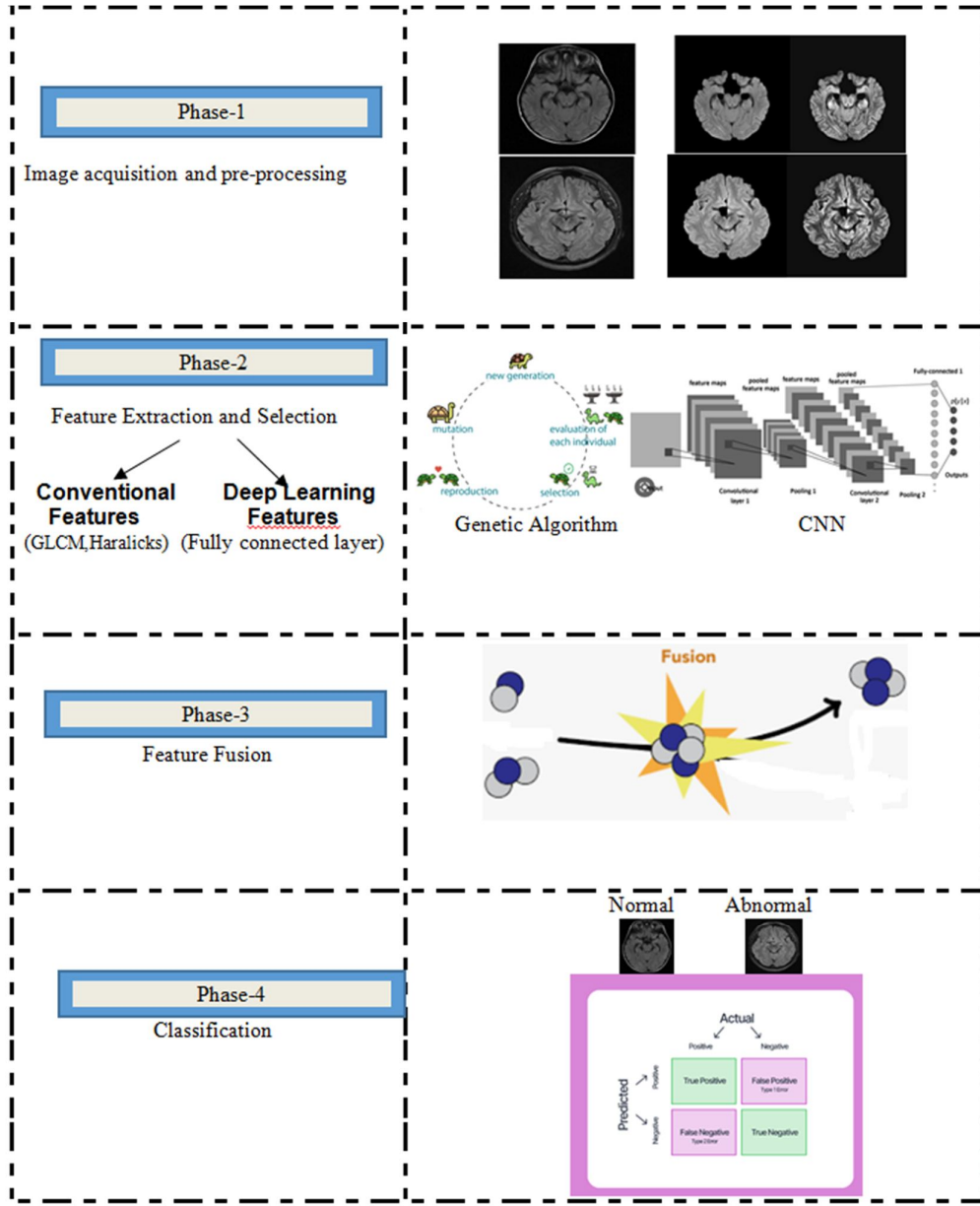


Figure 2. The proposed CAD brain MRI methodology

III. THE PROPOSED METHODOLOGY

We presented a hybrid intelligent system to design a low-cost CAD system. Figure 2 shows the overall system architecture of the proposed CAD brain MRI system. It consists of four primary procedures: (1) image acquisition and pre-processing (2) feature extraction and selection (3) feature fusion (4) classification and evaluation of performance.

A. Image acquisition and pre-processing

Digital images are produced using computer technology by image acquisition techniques like MRI. After acquiring digital images, analysis can continue to be performed using image pre-processing techniques. The radiopaedia.org web database is used to collect the MRI FLAIR images. Radiologists have specifically assembled the dataset's resources from all over the world. Pre-processing is a crucial step that ensures the

effectiveness of the classification technique. We used pre-processing techniques including grayscale image conversion, bicubic method used for image resizing, skull stripping, and contrast enhancing. The Contrast Limited Adaptive Histogram Equalization (CLAHE) approach [6] is employed in the proposed work to enhance the contrast of MRI slice images.

B. Feature Selection and Extraction

The proposed approach computes an image's Haralick textures patterns and grey level co-occurrence matrix (GLCM) based on the directions or orientations of the image [7] [8]. A number of features of the spatial correlations of the gray levels in the image are revealed by the GLCM matrix. The co-occurrence matrix is used to compute the Haralick features, which are used to describe an image's textures. The elements of the image are located within the region of interest (ROI). It spread in one of the image orientations while taking into account the relationship between discretized intensities of nearby pixels. We employed a Genetic Algorithm Feature Selection (GAFS) wrapper model to choose which features had the most significant features [4]. There are three further steps. Subsets of features were found in the first step. Second, to assess the importance of the chosen subset of features in light of the classifier's performance. Finally, repeat the first and second stages until the target iteration is reached. Choosing an optimal features subset by GAFS module is one of the key goals of this work. In order to extract the deep-rooted features, we start a feature extraction technique based on convolutional neural networks (CNN). An input layer, two convolutional layers, two subsampling layers, and two fully linked layers make up the proposed CNN architecture. Investigating the contributions of input dimensions and feature maps of each layer is the major goal of the proposed feature selection and extraction approach. The CNN architecture employed in this work is depicted in Figure 3.

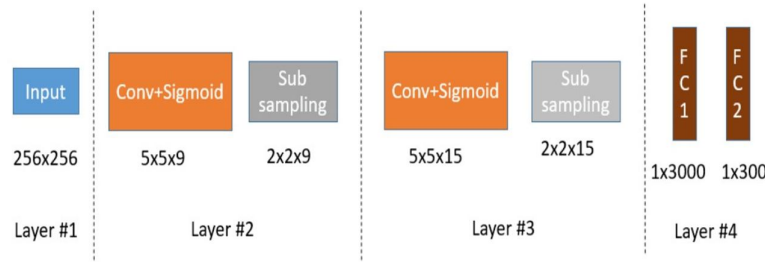


Figure 3. Architecture of CNN as Feature Selector and Extractor

C. Feature Fusion

One of the crucial steps in creating the most effective combination of features for this proposed methodology is fusion. In the proposed study, feature-level fusion has been taken into consideration. Getting a set of fused features aids in classifying objects as normal or abnormal. Let $X_{i,...,n}$, $Y_{i,...,m}$ represent the feature vectors gathered from two distinct instances. Here, conventional features and deep features, respectively, are represented by the feature vectors X and Y that were generated from the two distinct sources. The $Z_{i,...,k}$ stands for the appropriate fused feature vectors. The detection of correlated feature values produced through several methodologies and the identification of a small selection of salient characteristics that can increase recognition accuracy are the main advantages of feature-level fusion. After extracting conventional and high-level deep features, we fused the features using a linear feature fusion strategy, setting up a fixed proportion as the feature fusion. The following formula is used to calculate the classifying feature:

$$FV = \beta \cdot X + (1 - \beta) \cdot Y \quad (1)$$

Where X stands for traditional feature vectors, Y for high-level deep feature vectors, and FV for fusion feature vectors. The weight parameter, β , specifies the relative relevance of two separate features. In order to complete the final classification task, the feature fusion will be fed into the classifier. Figure 4 depicts the structure of these feature fusion vectors.

D. Classification

SVM is a robust supervised technique that performs optimally on moderately sized datasets. In the present work, we classified data using a SVM. In this supervised machine learning issue, we look for the optimal hyper plane to divide the two classes. The SVM is a two-stage process that includes training and testing that uses a binary

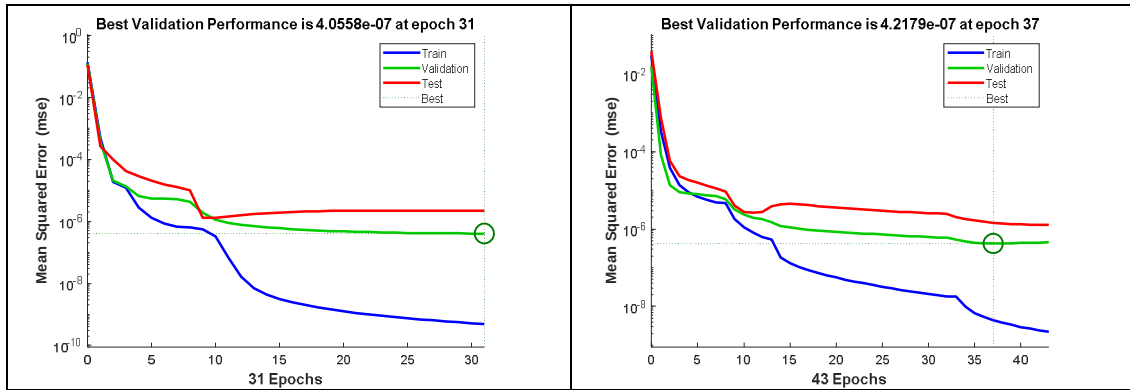


Figure 6. Examples of GAFS wrapper model 2 runs for Haralicks features

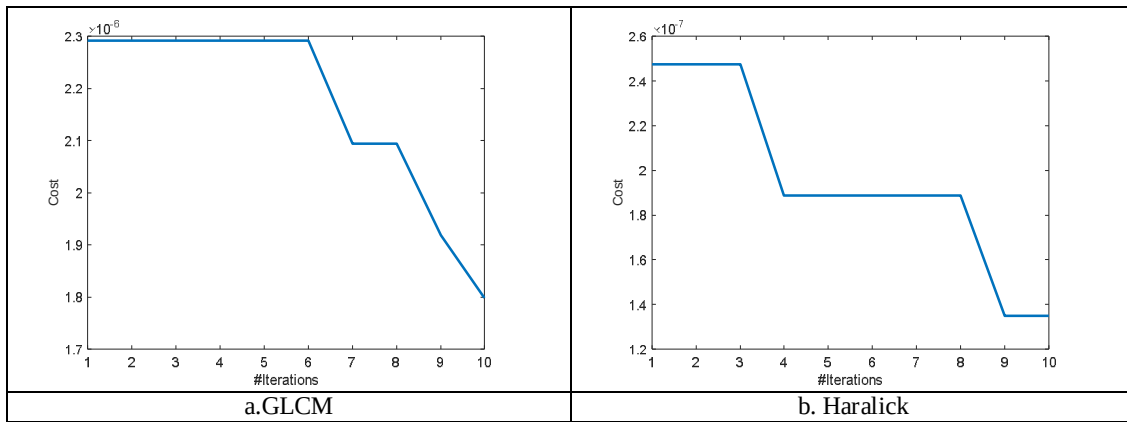


Figure 7. Best fitness cost plot for (a) GLCM and (b) Haralick features by GA

wrapper model 2 runs for GLCM features and Haralicks features respectively. The Genetic Algorithm is used to choose the best features from among the original features (GLCM and Haralicks) depending on the fitness cost. The results of the best feature cost versus iteration plot by GA to choose the best feature set are shown in Figure 7.

TABLE I. SELECTED FEATURES

Feature vectors	All Features (D)	GAFS selected Features (K)
	Dimensions	Dimensions
GLCM Features	96	32
Haralick Features	52	22

The purpose of these experiments is to explore the framework of a CNN. In order to set up the network, the following hyper parameters are employed: The batch size is 100, the learning rate is 0.001, and there are 50 epochs in total. Sigmoid is the activation function; Randomization is used for the weight initialization. The settings are selected based on the results of multiple previous experiments. Table I displays the total number of features that were chosen for this study by employing the GAFS wrapper approach. From the first conventional feature group, we were able to extract 54 best feature subsets at the conclusion of the feature selection process. Additionally, the first fully connected layer FC1 and the second fully connected layer FC2 yield 3000 and 300 deep features, respectively. Figure 8 displays the total number of features that were chosen using deep learning. For the experimental setup, there are three different types of normal brains and five different types of abnormal brains in the data set, total 125 images, of which 50 are images of normal brains and 75 are images of abnormal brains. The images were chosen at random. A table called a confusion matrix is frequently used to evaluate the effectiveness of a classification model. Since there are two target classes in the experimental instance, we made a 2x2 confusion matrix in order to evaluate the effectiveness of the proposed classification model. The outcomes of the confusion matrix are displayed in Table II. The performance of the proposed classification model is shown

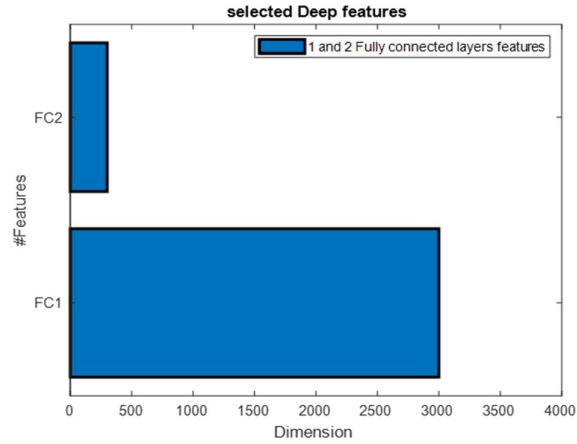


Figure 8. Deep Features of the proposed method

TABLE II. CONFUSION MATRIX

#optimal features set	#classes	Accuracy (%)
354	2	92.80

in the Table III. We developed the robustness of the given strategy by comparing the proposed work with other recently released research classification accuracy results in Table IV.

TABLE III. PROPOSED MODEL PERFORMANCE

#optimal features set	#classes	Accuracy (%)
354	2	92.80

TABLE IV. STATE-OF-THE-ART COMPARISON OF THE PROPOSED METHOD

Study	Number of images	Accuracy (%)
[9]	65	94.28
[11]	64	92.60
[10]	60	88.33
[4]	100	97.00
Proposed Method	125	92.80

V. CONCLUSION AND FUTURE WORK

In this study, we devised a new automatic computational technique for the classification of MR brain images that produces reliable classification outcomes in images taken at various ages. In the proposed framework, both the GAFS approach and the deep learning CNN architecture are used for feature extraction and selection. Then, a fusion method was used to create the paired fusion feature set, which is considered the key contribution of this paper. Conventional and deep learning methods extracted 354 features from each MRI image. When applied to the acquired FLAIR of MRI brain scans, the experimental results revealed a classification accuracy rate of 92.80%. Future work in numerous areas could help CAD systems for MR images of the human brain become even well. (1) Acquiring huge databases from many institutions with a range of image characteristics for clinical assessment and CAD system enhancement. (2) increase the training data set and extract more effective features to increase classification accuracy. (3) There is still a lot of scope for researchers to use different transfer learning approaches and incorporate them into an intelligent hybrid system. (4) To determine whether the proposed approaches have broad applicability, it would be good to conduct additional research and analysis.

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