Enhanced Classification and Detection of Brain Tumor using Hybrid Deep Learning and Machine Learning Models

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Abstract. In recent years, deep learning has become an influential tool in medical imaging,especially the present work illustrates a new technique for brain tumor identification based on magnetic resonance images(MRI) using the combination of convolutional neural networks and support vector machine techniques. The proposed model combines CNNs performing feature extraction effectively, while SVMs classify with high precision. To begin with, some preprocessing methods like adaptive gamma correction, adaptive contrast enhancement, and median filtering are applied to MRI images so as to improve image quality and minimize noise interference. Fuzzy c-means clustering technique is used to extract important texture features like energy, mean values or entropy from GLCMs represented as matrices of grey levels co-occurrence pairs. CNN helps with acquiring deeper features from segmented images which serve as inputs during training phases of SVM classifiers based on those features thus obtained from them (CNN), eventually yielding high performance levels. An hybrid model using CNN-SVM showed an accuracy rate of 97 .94%, sensitivity 95% , specificity 98.1% when it came to distinguishing between normal and abnormal brain tissue. Therefore, this hybrid model demonstrates its capability in tumor detection due to combination of both CNN and SVM hence providing an alternative automated approach for early diagnosis.

Keywords: Magnetic Resonance(MRI) Images,Fuzzy c-means Segmentation,CNN-SVM Hybrid Model,GLCM Feature Extraction

1 Introduction

Among the most terrible types of cancer, brain tumors necessitate immediate detection for successful treatment. MRI is crucial in spotting brain tumors because of its best quality and precision. However, manual interpretation by radiologists can be time-consuming and inconsistent, necessitating automated systems to detect and classify malignant brain tumors with high accuracy. This improves diagnosis and treatment outcomes. In India, the incidence of brain tumors is on the rise, with around 40,000 new cases projected annually. Early and precise detection is essential to improve survival rates, as delays or errors can lead to misdiagnosis and further suffering. Accurate classification of tumors, such as glioma,meningioma, and pituitary tumors [1], ensures patients receive the in evaluation of healthcare images,particularly advanced Convolutional Neural Networks [2] and Support Vector Machines are used. SVMs are known for their classification accuracy as well as their ability to generalize while CNNs excel in image classification by automatically learning hierarchical features.This research paper suggests a hybrid model integrating CNN with SVM for tumor recognition in brain [3]. There are several advanced preprocessing methods such as Adaptive Contrast Enhancement Algorithm (ACEA), adaptive gamma correction, normalization, equalization, median filtering , and data augmentation which improve performance. Fuzzy C-Means (FCM) segmentation and GLCM technique are used to precisely select tumor areas and extract features. This hybrid model neural networks aims at achieving higher accuracy and reliability in detecting and classifying brain tumors as shown in Fig 1, so as to provide more effective and personalized treatments approaches.

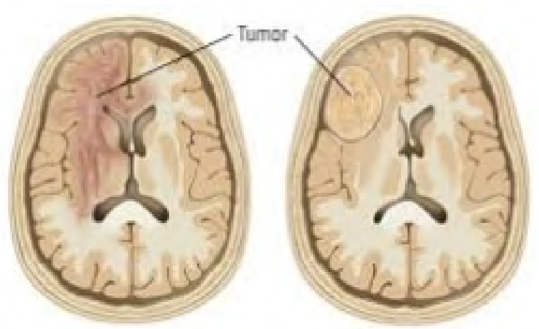


Fig. 1. Classification of healthy brain tissues and tumor brain tissue

The major contributions of this study consist of:

1. Incorporation of cutting-edge preprocessing algorithms such as Adaptive Contrast Enhancement Algorithm (ACEA), non-linear gamma enumeration tool, scaling, histogram modification, all within a single scan, to enhance image resolution and facilitate the extraction of features from MRI images.
2. Utilization of Fuzzy C-Means (FCM) segmentation for more accurate tumor region extraction, along with Grey Level Co-Occurrence Matrix (GLCM) for reliable feature extraction.
3. Development of a hybrid CNN-SVM model for better classification and differentiation of brain tumors using MRI scans.
4. Comprehensive analysis of the effectiveness of our proposed model based on a dataset of MRI images, with comparisons to conventional methods.

5. Examination of different evaluation metrics to assess the performance and reliability of the suggested approach.

This entails evaluating several performance metrics to ascertain the validity and stability of the said model. Particularly, the study will explain the model's reliability and its capability of brain tumor detection through the exploration of other metrics like accuracy, sensitivity, specificity, and precision. The goal of the suggested model with hybrids systems incorporated is the improvement of the detection and classification of brain tumors coupled with machine learning and deep learning techniques alongside a lot of pre processing techniques. This would provide a lot of improvements in the dissociative diagnosis enabling health care workers to make appropriate decisions in a short period, thereby reducing the chances of patient mistrust. To wrap up, this CNN-SVM model offers a great opportunity to be successfully employed for the goal of treating brain tumors by optimizing the existing treatment resources.

2 Related Works

Solanki S. addresses techniques for identifying and classifying brain tumors using CNNs and transfer learning models including RESNET-100 and VGGNET.Traditional methodologies like SVMs and RFs present difficulties in automation while CNN's enhance accuracy of classification by a margin of 10-15%. Furthermore, propelling up its performance is transfer learning which adds an additional 5-10% .M. Imran [4]enhanced CNN-based detection with a DCNN and a three-stage preprocessing technique, lead for enhanced output evaluated to models like VGG16 and VGG19.According to Ahmad S. and Choudhury P.K. [5], they have conducted a systematic examination of the progress made in machine learning and deep learning with respect to identifying tumors based on MRI, whereby it was shown that models which had undergone training before, like Inception-v3 and DenseNet201, can attain above 90% level of accuracy although there still remain some optimization challenges that must be addressed. To solve problems in single-modal techniques, Shah H. A [6]presented a CNN aimed at multi-modal MRI fusion. As noted in [8], EfficientNet-B0 is also considered to be one of the best models on tumor detection; therefore, it is recommended to use transfer learning and data augmentation methods to deal with limited datasets.M. Agrawal proposed enhanced brain tumor detection and classification using deep learning models used inception V3 model for better results [9]. Sireesha,M. used cnn for better tumor classification [10] used magnetic resonance images with this efficient techniques brain tumor detection and classification is done efficiently to secure more accuracy.The article discusses an approach to detecting brain tumors using the Faster R-CNN [11] model which efficiently performs tumor identification in MRI images by region proposal networks enabling real time detection. This technique is shown to be highly precise making it possible to reduce the time taken in diagnosis in the imaging process.

2.1 Problem Statement:

Brain tumors quite serious, could cause paralysis and long term treatments. Their implications vary based on their size, location and type. Early diagnosis prevents complications.There is therefore a need for better instruments for quick, precise diagnosis to facilitate prompt treatment with improved out comes for patients.

3 Proposed methodology

The emphasis of this investigation is to detect brain tumors in MRI images [12] by employing deep and machine learning methods [14] as in Fig 2. The pre-processing phase is performed through the ACEA algorithm and median filter after segmented using fuzzy c-means and features are extracted through GLCM. Following this, a hybrid CNN-SVM model is applied to classify these features thereby increasing the accuracy of detection.

3.1 Dataset collection:

We assessed our model employing Kaggle dataset [2]encompassing T1-sequenced improved MRI scans [7] obtained from individuals diagnosed with brain tumors, as shown in Fig 3. This dataset contains meningioma, glioma, pituitary, and no tumor slice images, respectively collected from `https://www.kaggle.com/datasets/vivekp7039/figshare-brain-tumor-dataset-converted-to-png`.

3.2 Preprocessing:

ACE - Adaptive Contrast Enhancement Algorithm (improvised algorithm) ACE algorithm improves the image contrast by means of local statistics such as mean pixel intensity and standard deviation. ACE adjusts the image's brightness depending on its different parts. Hence, while some areas may be highlighted more than others, each one remains clear and easily visible than before.

The first step is to slice the picture into segments for localized contrast modification by(1).

$$\mu = \frac{1}{N} \sum_{i=1}^{N} p_i \tag{1}$$

Next, we calculate the standard deviation,the mean using equation (2):

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (p_i - \mu)^2} \tag{2}$$

After gathering local averages and standard deviations (equations 1 and 2),as shown in equation (3). The modified pixel value can be expressed by this formula:

$$p_{\text{new}} = \mu + k \cdot (p - \mu) \tag{3}$$

With the use of local means and contrasts, this method improves pixel and image quality thereby giving a better appearance to the whole image.

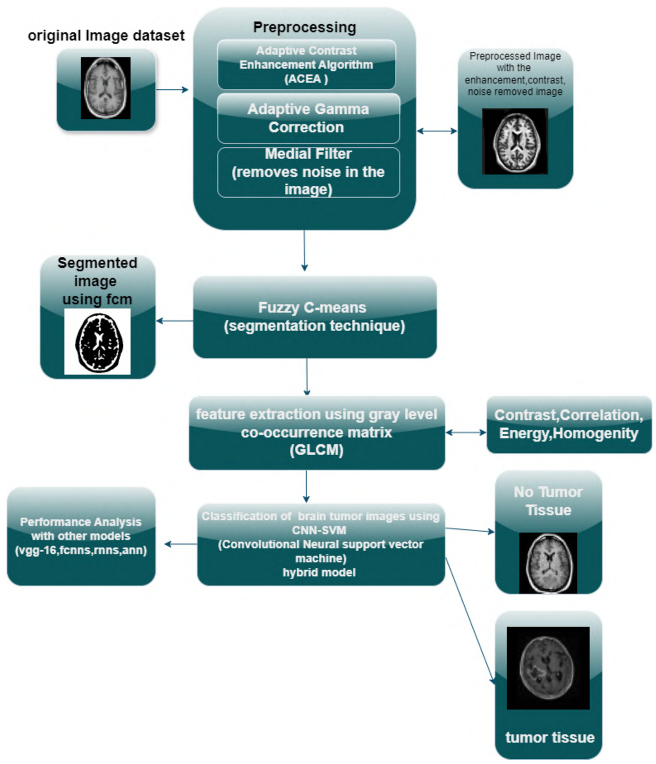


Fig. 2. Procedure Outline for the Developed Technique.

Adaptive Gamma Correction Algorithm(AGC): AGC alters brightness and contrast locally to enhance MRI images for brain tumor detection; it enables better visualization of tumors than their neighboring tissues. In contrast to conventional gamma correction, AGC adjusts the value of gamma for each zone.The formula used to determine the corrected pixel intensity $I_{\text{corrected}}$ (equation 4) is as follows:

$$I_{\text{corrected}}(x, y) = I(y)^{\gamma_{\text{local}}} \tag{4}$$

To obtain clear, high resolution images, AGC is used to increase local gamma value, $gamma_{\text{local}}$, in MRI images.

Median filter: Median filtering is a widely used technique for reducing noise. It helps clean up images while preserving important details.At each position, the central pixel's value is replaced by the median of the values within the window. The new pixel value is computed using the formula(5):

$$u_{\text{updated}}(a, b) = \text{median}\{p(a - m, b - n), \ldots, p(a + m, b + n)\} \tag{5}$$

Here,$u_{\text{updated}}(a, b)$(5)represents the new parameter of (a,b) where (a,b) is the updated parameter of the pixel at position (a,b). This median takes account of the pixel values gathered from a window around (a, b) such that k represents half the window size.

3.3 Enhanced Image Segmentation Through Fuzzy C-Means Clustering:

The Fuzzy C-Means (FCM) segmentation is an often-used unsupervised clustering technique Certainly, brain tumors can be detected and segmented using fuzzy c-means method (FCM). This is an improvement over conventional methods because FCM takes into account the inbuilt fuzziness of data unlike traditional techniques that apply hard classifications.
In the process of Cluster Centre Computation, new cluster centers are computed through the formula (6):

$$\mu_j = \frac{\sum_{i=1}^{N} v_{ij}^m x_i}{\sum_{i=1}^{N} v_{ij}^m} \tag{6}$$

Then, update the membership values based primarily on the distance between data points and cluster centers (6) using the formula:

$$p_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|a_i - x_j\|}{\|a_i - x_k\|} \right)^{\frac{2}{v-1}}} \tag{7}$$

The objective function can be calculated to check for convergence using formula (8):

$$j_m = \sum_{i=1}^{N} \sum_{j=1}^{C} v_{ij}^m \cdot \|x_i - \mu_j\|^2 \tag{8}$$

This process ends when it reaches a predetermined level of the objective function (8) or when it has carried out its maximum number of iterations. Otherwise, the processes are repeated.

3.4 Feature Extraction using GLCM :

A gray level co-occurrence matrix known as GLCM is a common textual study method that examines spatial correlations of pixel intensities in MRI images. This statistical technique captures texture information, helping to differentiate tissues and detect pathological features like tumors in medical MRI scans. The

Following several statistical features can be obtained from GLCM to characterize the MRI image texture. In this approach was suggested, contrast, dissimilarity, homogeneity, energy, correlation.

1.Contrast: It measures the intensity difference between neighboring pixels. A

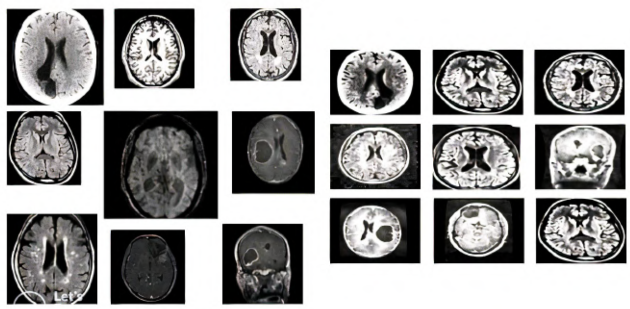


Fig. 3. Comparisons of Different and Same Sizes Sample MRI Images

higher contrast value from (9) which may be useful in differentiating tumor areas from normal tissue.

$$\text{contrast} = \sum_{p,q} (p-q)^2 a(p,q) \tag{9}$$

2.Correlation:In an image, correlation measures of how much image data points(pixels) are related linearly to one another. This indicative bare skeleton measure (10) indicates how intensity correlates with the pixel map of different positions in any given place.

$$\text{correlation} = \frac{\sum_{l,m}(l-\mu_x)(j-\mu_y)P(l,m)}{\sigma_x \sigma_y} \tag{10}$$

3.Energy: It represents (11) the combination of the class features in the GLCM, which means that the text is identical.

$$\text{energy} = \sum_{i,j} R(i,j)^2 \tag{11}$$

4.Homogeneity:In (12) measures how close the distribution of features in the GLCM is to the diagonal.

$$\text{homogeneity} = \sum_{i,j} \frac{Q(i,j)}{1+(i-j)^2} \tag{12}$$

3.5 Integrated Hybrid Models WithCNN and SVM for Enhanced Classification:

This model Combines the feature extraction of CNN neural network with the classification of SVM; hence optimizing image analysis and category boundaries.

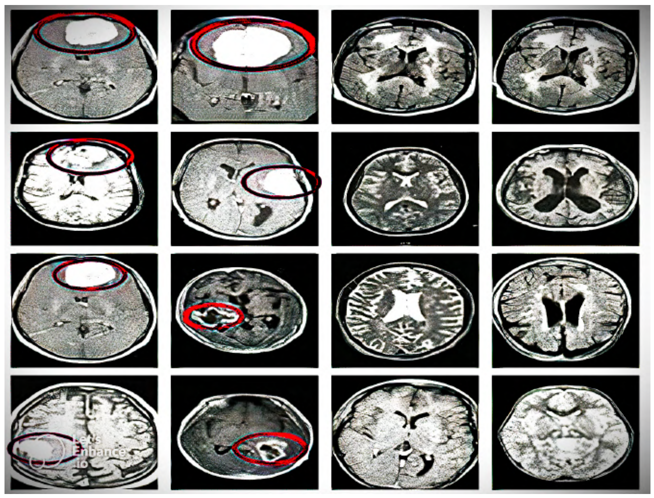


Fig. 4. Hybrid CNN-SVM Model for Classification Approach

Designing Approach for Hybrid CNN - SVM system: The CNN-SVM model in it, various raw images are passed through a CNN [13] where rectified linear unit (ReLU) activations and pooling layers help to maintain important information while reducing dimensions. After that, a fully connected layer(13) compresses the flattened output which is then classified by the SVM machine learning model that searches for the best hyperplane for class separation.

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{n} \beta_i z_i \mathit{\Phi}(x_i, x) + c\right) \tag{13}$$

Implementation of CNN-SVM Hybrid Model Architecture: In order to effectively create a CNN-SVM structure , the initial step is teaching a CNN using a loss function, for instance cross entropy loss, in order to achieve the extraction of useful features.

This training consists of image segmentation which improves the feature extraction and the entire system performance(14).

$$\mathrm{LCNN} = -\sum i = 1^n \left[y_i \log(p_i) + (1 - y_i) \log(1 - p_i)\right] \tag{14}$$

Model Output: The outcome model of CNN-SVM combine CNN to extract features and SVM for the ultimate classification which enhances prediction accuracy, as in Fig 5.

Developing the CNN-SVM Hybrid Model A Training Methodology: The training mode for CNN-SVM hybrid model uses dual optimization strategy making use of the two. The CNN [11] is initially trained to extract feature vectors from input MRI images. These are fed into SVM [15] for classifying purposes.This system performs alternating updates of both CNN and SVM based on metrics a. results than when only CNN or SVM were used separately. The developed model identifies and detect the tumor as shown in Fig 4 efficiently.

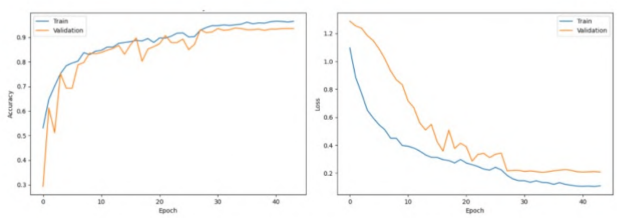


Fig. 5. CNN-SVM model accuracy and loss

4 Results and Discussions:

Using Python 3.10 based deep learning or Machine Learning methods,this section is devoted in brain tumor detection from MRI images. The evaluation of models has been done through TP, TN, FP and FN metrics that compare CNN-SVM model with other models such as CNN, VGG, RNN, RFC, FCNN and ANN. Accuracy, Jaccard index as well as sensitivity are used to measure performance.

4.1 Accuracy

The performance of a model in accurately distinguishing between tumor types and normal tissue is referred to as the accuracy(15).It is a key metric for measuring performance.

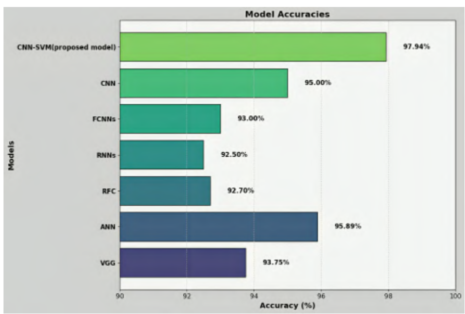
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

Comparing the suggested method shows clearly higher accuracy at 97.94% as shown in Fig 6.

4.2 Specifivity:

Specificity(16) measures the proportion of true negatives, indicating how well a test identifies the absence of disease. As shown in Fig 7, CNN-SVM achieved the highest specificity of 98.1 %, excelling in MRI classification.

$$\text{Specificity(TNR)} = \frac{TN}{TN + FP} \tag{16}$$



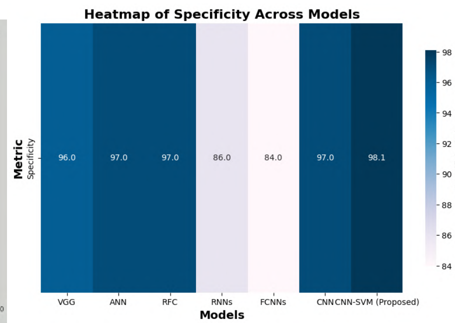


Fig. 6. Accuracy comparison.

Fig. 7. Specificity comparison.

4.3 Sensitivity:

True positive probability is what sensitivity assesses. In the design of the CNN-SVM model, the sensitivity value(17) was obtained as minutely as 95% which exceeds that of traditional approaches.

$$\text{sensitivity} = \frac{TP}{TP + FN} \tag{17}$$

4.4 Jaccard Coefficient

Jaccard coefficient, commonly referred to as the Jaccard index or intersection over union (IoU) (18), is a primary measure in image segmentation and analysis. Here,Fig 9 shows Jaccard index of the analysis of the different models.

$$\text{jaccardcoefficient} = \frac{|p \cap q|}{|p \cup q|} \tag{18}$$

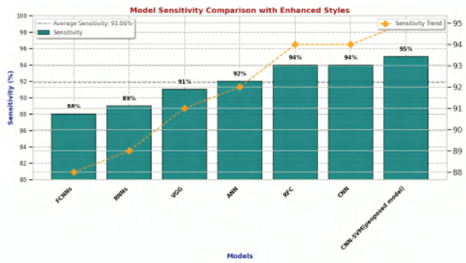


Fig. 8. Sensitivity Comparison.

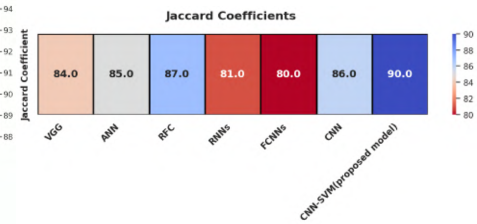


Fig. 9. Jaccard Coefficient.

5 Discussion:

In Table 1, the performance measures of several machine learning techniques are compared. These techniques include CNN, ANN,RFC,RNN,FCNN among others and the proposed model CNN-SVM plus the VGG architecture. Though each model has its level of accuracy, speed and overall performance, the costs in terms of computational power also differ across the models. For example, high-performance ANN models require sophisticated hardware where they are deployed and are dependent on tuning of hyperqualities which often results to differences in their performances. Random Forest Classifiers have a reputation for being versatile and capable of dealing with diverse data, the ensemble methods tend to be expensive in terms of computing power as the number of trees increases which in most cases leads to delays especially with bigger data sets. RNNs are great for tables and graphs that have all the data points in a particular order, but they cannot handle farther back gaps so well and tend to be heavier on the processing.

Table 1. Performance comparison of different models.

Model	Accuracy	Jaccard Coefficient	Sensitivity	Specificity
VGG	93.75	84	91	96
ANN	95.89	85	92	97
RFC	92.70	87	94	97
RNNs	92.5	81	89	86
FCNNs	93	80	88	84
CNN	95	86	94	97
CNN-SVM(propsed)	97.94	90	95	98.1

The hybrid model that combines CNN [16] and SVM proves to be a suitable contender that is less time-consuming and more efficient in terms of performance by combining the feature extraction advantage of CNNs and the classification prowess of Support Vector Machines (SVM). An in-depth presentation of the performance metrics, such as accuracy, specificity, sensitivity, and Jaccard's index for each model across experiences with various datasets is demonstrated in the Fig 6-9. Such figures indicate the performance capabilities of each model in various scenarios.Visual assessments of the models under review further confirm the superiority of the combined CNN-SVM model in terms of performance metrics with respect to the discussed other models.

6 Conclusion:

Developed CNN-SVM model is very effective at detecting brain tumors with an accuracy of 97.94% Through advanced types of deep neural networks enabling easier approach to automatic feature extraction by using a supporting vector machine classifiers combination, it becomes quite simpler than traditional methods thereby offering faster and easier way out. This model was found by simulations to have potential for better accuracies, and future researchers should focus on incorporating it into clinical software by using color images or 3D scans in order to achieve better tumor segmentation. Simulations have shown how viable this method is thus promising improved accuracy levels in regard to brain tumor detection using CNN-SVM models. Future research here is most important however; incorporating these algorithms into clinical software would enhance their practical uses in hospitals while working with colored photographs or three-dimensional scans could also assist better tumor segmentation leading to a more comprehensive instrument for diagnosing and planning treatment of brain tumors. As a whole, the CNN-SVM model is a promising step forward in the detection of brain tumors; it includes hybrid approaches that utilize deep learning techniques as well as machine learning ones for effective and accurate results. To enhance its usefulness in medical imaging, subsequent studies must seek to diversify its usage and implement it in health care systems

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