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Ensemble Model for Brain Tumor Classification from MRI Data

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Abstract: Human brains are sophisticated and control the central nervous system. Brain abnormalities can disrupt organ processing and coordination. There are several ways to diagnose brain illnesses. Brain tumors in brain tissues are caused by uncontrolled cell proliferation. Brain tumors are among the deadliest disorders. Medical imaging is important in treating and mending crucial disorders. Medical brain imaging provides anatomical and functional information for diagnosis. This study classifies brain tumors using an ensemble of two pre-trained CNN RestNet-50 and GoogleNetclassifiers. We form the pre-trained CNN features into feature vectors for each MR brain image in the training and testing datasets. BRATS 2021 dataset is utilized in this research and model accuracy is compared with other pretrained models on these feature vectors to assess the performance of the classification system. Proposed Model (RES-GNET) achieves 97.9% accuracy for BRATS dataset on Kfold value 20. The model classifies medical pictures based on natural scene categorization. The suggested model has the maximum accuracy of 97.9%, surpassing other state-of-the-art algorithms. Future studies must integrate more recent datasets and use finer individual-level data. We need to conduct further research to understand the impact of healthcare access, treatment modalities, genetic predispositions, and socioeconomic factors on mortality outcomes.

Keywords: Brain tumor, CNN, Deep learning, Machine learning.

I. Introduction

Medical imaging and analysis of many organs improved radiologists' diagnosis and treatment planning in patients. The brain controls the neurological system and is a basic organ. Diseases affecting distinct organs may spread or remain localised. Most brain illnesses affect other organs, which can put patients at risk and cause death [1]. Thus, brain disease diagnosis and therapy are crucial. Medical image diagnosis and analysis automation is crucial to treatment decisions. We analyse medical images using image processing techniques. To analyse such medical photos, one must know organ anatomy. A brain tumor's cells proliferate and reproduce rapidly, appearing unchecked by normal cell mechanisms. A stiff skull encases the brain. In such a small space, aberrant cell development is problematic. Malignant and noncancerous brain tumors exist. As benign or malignant tumors grow, they can increase skull pressure. Brain tumors account for 2% of malignancies and can be fatal [2]. Over 150 brain tumors exist. The two main tumor groups are primary and secondary. Most initial brain tumors are benign and arise in brain tissues or adjacent areas [3]. Secondary brain tumors, or metastatic brain tumors, originate in other organs and spread to the brain. Metastatic cancers are malignant [4]. Research Inspiration Brains are complicated and crucial to the neurological system. It controls most body motions, stores, processes, and coordinates sense organ information, as well as deciding what commands to give the rest of the body. A tumor arises from irregular brain cell development, causing a powerful swelling or enormous cell growth. Fig. 1 below shows the systematic approach for brain tumor classification.

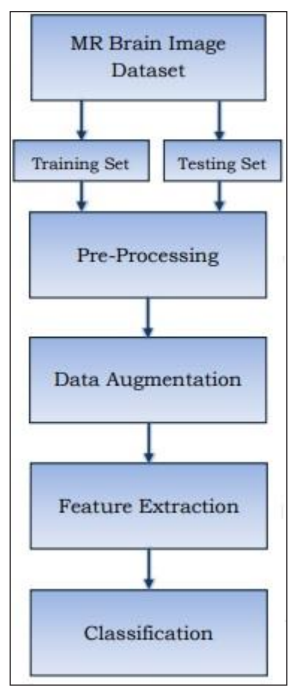

Fig. 1: Systematic Approach to Classification

The classification system demonstrates the simultaneous execution of the fundamental stages of data processing. It is possible to see the processed data travel between stages through the feed-forward link. One step's output serves as the input for the subsequent stage in the process. Each stage can be implemented using a variety of processing approaches. Following is a thorough description of each stage of this approach:

Pre-Processing: The data both the uneven borders and the misclassification are the result of the random noise that is present in the MR pictures. Two possible explanations for the noise exist: either the image underwent compression, or it originated from an outdated magnetic resonance imaging scanner. We apply the DnCNN and median filters to the dataset to perform the denoising process. The magnetic resonance images, in addition to the noise, include anomalies in the brightness of the intra and inter images. We use the min-max normalisation approach to standardise the intensity.

Data Augmentation: Fitting the dataset into the training model necessitates data augmentation. This category encompasses various techniques such as resizing, turning, adding salt and pepper noise, scaling illumination, shifting, rotating, and modifying viewpoints.

The Extraction of Features: Classifiers will receive data from extracted features. This involves training a CNN from the start, fine-tuning block-wise pre-trained CNN features, and extracting off-the-self characteristics from CNN models.

To classify data by attribute, the classification classifier uses the training set and values. Machine learning and deep learning can classify MR brain tumors. This is achieved by feeding brain MR image characteristics into algorithms.

Objectives

This study compares urban and rural brain cancer mortality rates and sees if demographic variables affect them. The second goal of this study is to evaluate the ensemble model and compare it to state-of-the-art methods.

II. Literature Review

Brain tumor cases have increased in recent years. Scientists and researchers are developing advanced tumor type and stage identification technologies. Brain imaging uses several methods to view the nervous system's structure, function, or pharmacology. It is modern in medicine, neurology, and psychology. Resection and examination of brain tissue form, size, and location anomalies using magnetic resonance imaging (MRI) help discover tumors. There are many medical image classification algorithms. We review some of the main image categorization methods below. Fuzzy logic-based expert system strategy integrates all improved picture pre-processing approaches and allows type II fuzzy logic to be used for approximate reasoning [5]. Image processing is used to classify type II astrocytoma's in MRI brain images. This Method performed better with successive MRI scan planes. This approach had 89% accuracy, 89% recall, and a 90% true negative rate [6]. This research introduces three Fuzzy C-Means methods conventional, modified, and multi-scale and compares their performance on the McGill brain dataset [7]. The Fuzzy C-Means (FCM) algorithm outperforms conventional clustering methods in segmentation competency but fails to locate tumorlesions [8]. We used the Adaptive Neuro Fuzzy Interference System (ANFIS) for computerised seed point assurance. The type of tumor does not affect the planned count's pixel drive. To see how well the tumor division worked, the authors compared the Likeness Index (SI), Overlap portion (OF), and Extra part (EF) to 0.817, 0.817, and 0.182, respectively [9]. The proposal for pre-processing involved aggregating fuzzy rule-based filtering. The authors extend the Possibilistic C-Mean (PCM) approach, the Mahala Nobis distance, and the Kwon validity index for segmentation using Type-II fuzzy notions. Thresholding extracts features, while Type-II approximate reasoning categorises brain MRI tumor grades [10].

Authors proposed a Bayes-based district development calculation that assesses parameters based on neighbourhood features and clusters them using the Bayes factor. Both of these methods are error-prone because poor starting arrangements and seed images can affect results. Factual and fuzzy logic methods are dependable and provide the best alternatives to the above techniques [11].

Probabilistic neural network and fuzzy probabilistic neural network classifiers achieve 91.3%, 96.3%, and 97.2% accuracy for the radial bias function, respectively [12]. Based on accuracy Naive Bayes algorithm was 91% accurate [13].

Authors compared graded brain tumors using convolutional neural networks and demonstrated an 18% improvement in CNN performance [14].

The authors suggested a hybrid MRI classification method employing ANN and KNN. ANN has 97% accuracy. The Harvard Medical School website provides the data [15].

Authors suggested brain tumors using FFNN, MLP, and BPN. They compare these three approaches for accuracy, specificity, and sensitivity. BPN leads with 96.7% accuracy, 84% specificity, and 72% sensitivity. The accuracy is solely dependent on the appropriate training features [16]. The authors proposed the use of ANN for brain tumor detection. This work also includes a comparison of ANN methods. Three ANN methods are BPNN, RNN, and Elman Network. Elman Network took first place with 88.24% overperformance [17].

Traditional image processing and machine learning involve pre-processing, feature extraction, selection, and classification. Noise removal, skull stripping, and intensity bias correction are standard pre-processing steps. After pre-processing, image processing extracts tissue-specific characteristics [18-20].

Conventional classification algorithms use visual features, whereas convolutional neural networks (CNN) automatically learn complicated features from the data. Recently, deep learning models have become popular for classification [21-24].

The categorization system technique outlines the data processing steps. A feed-forward link illustrates the transfer of processed data between stages [25-29]. Stage output becomes stage input. Different processing algorithms can implement each stage. A thorough description of each identification system stage follows:

Brain Image Database (MRI): We acquired MRI brain images from the BRATS website, http://braintumorsegmentation.org [30].

Pre-Processing Data: Imaging compression or acquisition from an obsolete MR imaging scanner may produce noise. We denoise the dataset using CNN and median filters.

Augmenting Data: Augmentation is crucial for training the model on the dataset. Various approaches solely use resizing to integrate the dataset into the DL model.

Features Extracted: We use three feature extraction methods: off-the-shelf features from pre-trained CNN models, block-wise fine-tuned CNN features, and CNN training from scratch. *Classification:* Classifier uses training sets and values to categorise new data into a specific attribute. Deep learning classification algorithms use MR brain image attributes to classify tumors.

III. Dataset Used

This investigation uses the IEEE data port-available BRATS MICCAI BRAIN TUMOR DATASET [30]. The Glioma and No tumor analyses yielded 2787 samples. We also evaluated and instructed using 10 and 20-fold cross-validation of data samples. Fig. 2 shows several brain tumors.

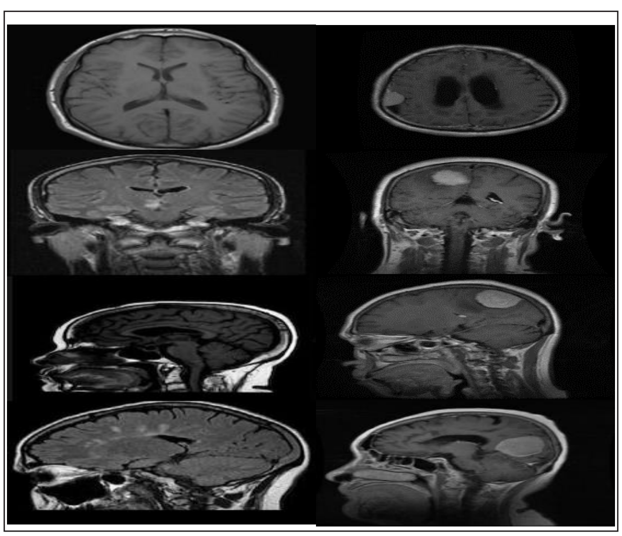

Fig. 2: Sample Pictures (Left) Normal & (Right) Glioma

IV. Proposed Methodology

This section represents the proposed algorithm and proposed methodology. The design of conventional ML algorithms is to train on a single task at a time. We need to develop and train a whole new algorithm for all the other jobs. Starting from scratch with a fresh model for each job is a tedious and laborious procedure. One solution to this difficulty is the idea of transfer learning, which allows one to apply what they've learnt to solve related problems. Fig. 3 shows the proposed methodology.

Proposed Algorithm (RES-GNET)

Step 1. Pre-Processing:

Load the MRI brain images.

Resize images to 224×224 pixels.

Normalize pixel values (scale to [0, 1]).

Step 2. Initialize Pre-Trained Models:

ResNet-50: Load the ResNet-50 model pre-trained on ImageNet without the top classification layer.

GoogleNet: Load the GoogleNet model pre-trained on ImageNet without the top classification layer.

Step 3. Feature Extraction:

For each MRI image:

Pass the image through ResNet-50 to get a feature vector.

Pass the image through GoogLeNet to get a feature vector.

Step 4. Feature Fusion:

Concatenate the feature vectors from both models: fensemble=Concatenate(fresnet,fgooglenet)

Step 5. Define Classification Head:

Flatten the concatenated feature vector fensemble.

Fully Connected Layer: Add a dense 128 layers with and ReLU activation.

Dropout Layer: Apply dropout to prevent overfitting.

Output Layer: Add a dense layer with the two numbers of classes and a softmax activation to output class probabilities.

Step 6. Build and Compile the Model:

Create a new model with the input layer, feature extraction layers, fusion, and classification head.

Compile the model with a loss function suitable for classification using Adam optimizer.

Step 7. Training:

Train the model using the training dataset.

Validate the model using a validation dataset to tune hyperparameters and avoid overfitting.

Step 8. Evaluation and Prediction:

Evaluate the model on a test dataset.

Use the trained model to classify MRI images.

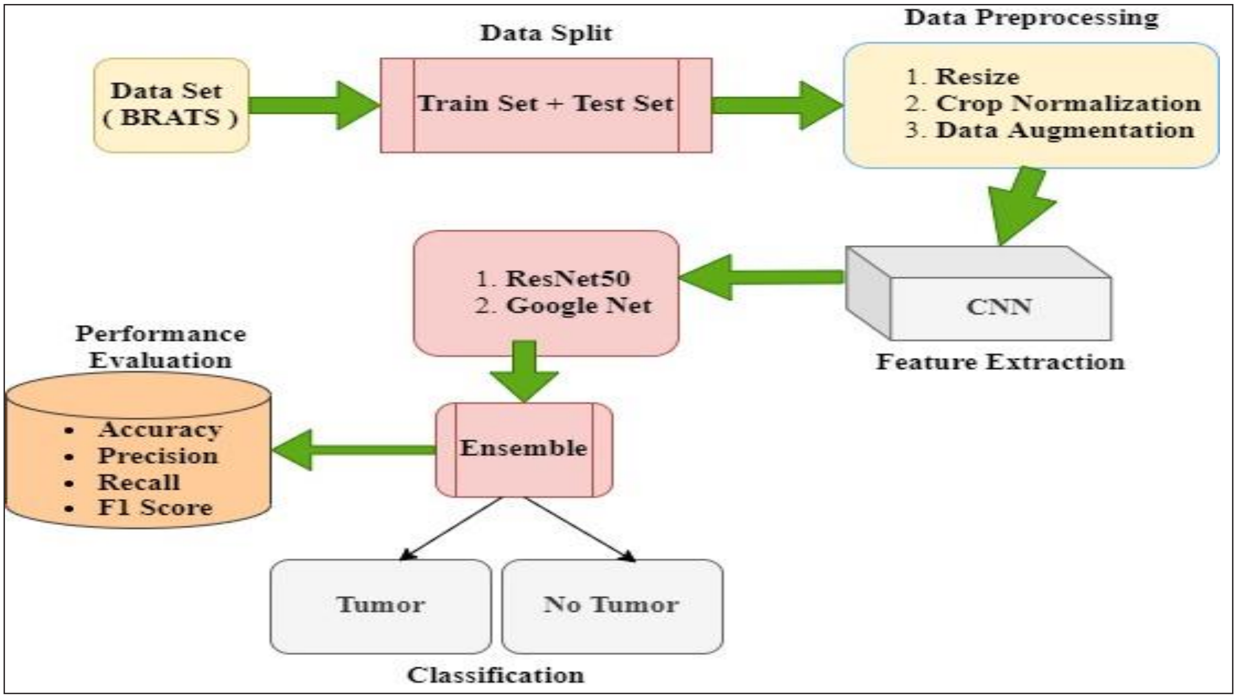

Fig. 3: Proposed Methodology

V. Performance Metrics

Measurements of Classification Performance: There are several ways to assess classifier performance. We use four numbers from the classifier's test set for supervised learning with two classes to measure performance. We refer to these numbers as True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN).

TP A True Positive Test outcome is one that identifies the disease when there is a disease.

TN A True Negative test outcome is one that has not identified the disease when there is no disease.

FP A False Positive test outcome is one that identifies the disease when there is no disease.

FN A False Negative test outcome is one that has not identified the disease when there is a disease.

Four matrices to assess RES-GNET's performance are as follows:

AUC-ROC Basically, the ROC curve is a graph that shows the performance of a classification model. The curve is plotted between two parameters TP and FP.

Accuracy Equation 1 defines accuracy (CA)

$$CA = (TP + TN) / (TP + FP + TN + FN) \quad (1)$$

Precision Equation 2 defines Precision (Pre)

$$Pre = TP / (TP + FP) \quad (2)$$

Recall Equation 3 defines Recall (Rec)

$$Rec = TP / (TP + FN) \quad (3)$$

F1-Score Equation 4 defines F1

$$F1 = (2 \times Precision \times Recall) / (Precision + Recall) \quad (4)$$

VI. Results and Discussions

This study trains two deep learning models, ResNet50 and GoogleNet, for classification using BRATS datasets. We test these models to classify brain tumors as benign (no brain tumor) or malignant (tumor). Experiments indicate that the ensemble model's strong performance is significantly higher when compared to other state-of-the-art algorithms. The proposed algorithm. We tested the results on two different K-fold validation values: K = 10 and K = 20. It has an AUC value of 99.7%, an accuracy value of 97.8%, an F1-score of 98%, a precision value of 97.7%, and a recall value of 97.7% at K-fold value 10. Check out Table I for more information. The proposed model (RES-GNET) gives an AUC value of 99.7%, classification accuracy of 97.9%, F1-score of 98%, precision value of 97.9%, and recall value of 97.9% at a K-fold value of 20. We compare the proposed model with other state-of-the-art algorithms like SVM, Naive Bayes, AdaBoost, SGD, ResNet50, and GoogleNet, and the results demonstrate its high accuracy. Fig. 4 represents a comparison of accuracy level with literature work, and the Fig. 5 shows a comparison with state-of-the-art algorithms. In both figures, the proposed model surpasses the other model in terms of accuracy.

Table I: Results

	K-Fold=10					*K-Fold=20*				
Model	*AUC*	*CA*	*F1*	*Pre*	*Recall*	*AUC*	*CA*	*F1*	*Pre*	*Recall*
SVM	97.8	92.2	92	92.2	92.2	98.5	94.6	95	94.6	94.6
Naïve Bayes	81.8	77.3	77	77.4	77.3	80.7	76	76	76.1	76
AdaBoost	85.5	85.5	86	85.5	85.5	84.8	84.8	85	84.8	84.8
SGD	94	94	94	94	94	94	94	94	94	94
ResNet50	99.7	97.7	98	97.7	97.7	99.6	97.6	98	97.6	97.6
GoogleNet	99.6	97.7	98	97.7	97.7	99.6	97.6	98	97.6	97.6
Proposed	99.7	97.8	98	97.7	97.7	99.7	97.9	98	97.9	97.9

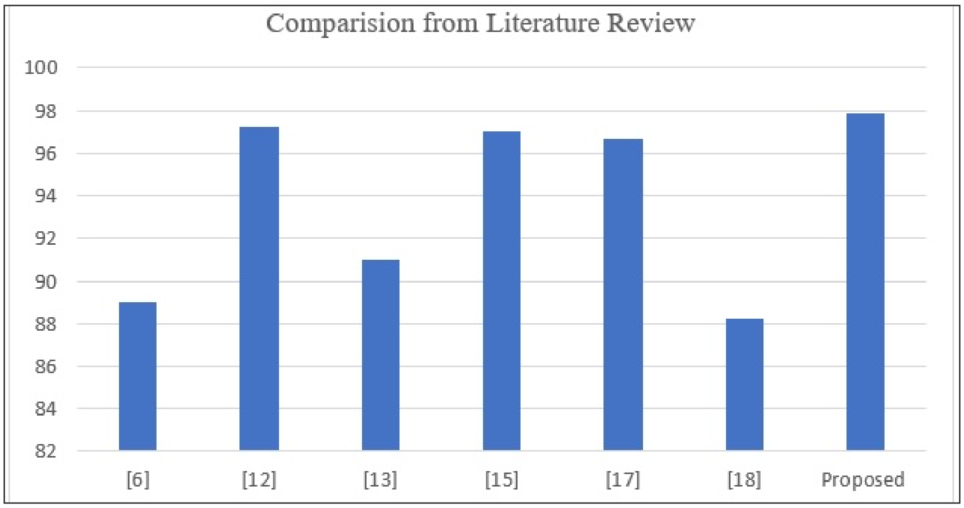

Fig. 4: Comparison between Literature Review and Proposed Model

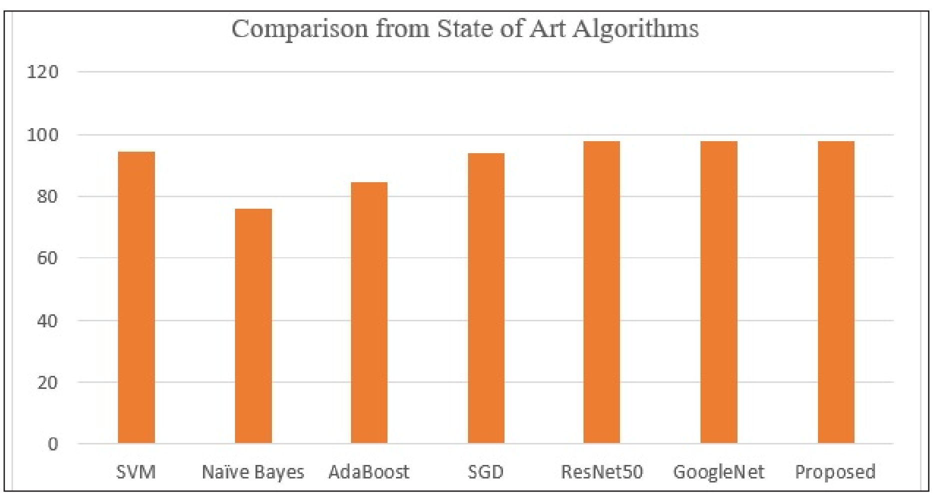

Fig. 5: Comparison between State of Art Algorithms and Proposed Model

VII. Conclusion

In this study, we suggested an ensemble model based on feature fusion that does a better job of dividing MR images into two types (benign and malignant) in the BRATS dataset. The suggested model uses two pre-trained CNN-based models, ResNet-50 and GoogleNet. We use CNN as a ready-to-use feature extractor from the input layer to create a new fully connected layer and classifier for class forecasting. The model illustrates how natural scene image classification transforms into medical image classification. The suggested model had the highest accuracy of 97.97%, which is significantly high when compared with other state-of-the-art algorithms.

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