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Brain Damage Detection Using Ensemble Classifier for Children Health Progress



Abstract: - Magnetic Resonance Imaging (MRI) is a medical imaging technique used to detect brain damage, particularly in children. Previous classification techniques for brain damage had low accuracy, complex edge detection, and high noise levels. In this proposed work, use an ensemble classification technique to analyze MRI brain images of 6-10 year old children. The input data is preprocessed using a Median filter to remove noise and improve image quality before being sent to a segmentation technique. Each part of the segmented image, such as tissue, inner layer, overall shape, and texture, is classified based on pixel size. The classification is done using an ensemble of Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) techniques. The ensemble prediction is multiplied with several input values to classify the MRI image, aggregating different layer values. The output classified image is validated and developed using Mat Lab software simulation, with an accuracy of 97.86%. This method can accurately classify various types of brain damage and aid in early detection in children.

Keywords: Brain magnetic resonance imaging (MRI), PSO-based K means segmentation, Feature Extraction, Ensemble Classifier, Support Vector Machines (SVM), KNN (K-Nearest Neighbors).

I. INTRODUCTION

Brain damage is a serious medical condition that poses significant challenges for healthcare professionals due to its complex nature and potentially life-threatening consequences. The intersection of medical imaging and image processing techniques has led to innovative approaches in brain damage detection. These methods offer a non-invasive way to identify and characterize abnormalities in the brain. While traditional diagnostic methods are valuable, they have limitations in terms of precision and efficiency. Image processing has emerged as a transformative tool, particularly in medical imaging, for improving the accuracy of brain damage detection. This intersection combines computational algorithms and advanced image analysis techniques to extract meaningful information from medical images, enabling the identification of even the smallest abnormalities that may be difficult to detect using conventional methods.

The integration of cutting-edge technologies has revolutionized brain damage detection, significantly enhancing diagnostic capabilities. Advanced imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), coupled with sophisticated image processing algorithms, have opened up new possibilities for precise and automated brain damage detection. These developments have transformed the way doctors diagnose brain damage, leading to earlier and more accurate diagnoses.

The auto-encoder network was used to improve the performance of the Ensemble Classifier, which had previously been trained using specific hyper parameters. This was achieved by adding multiple convolutional layers to the classifier. Each layer in this hierarchical network is controlled by a kernel function. The network consists of eight convolutional layers and four standard layers. Batch-normalization networks were also incorporated after the convolutional layers.

The improved auto-encoder network includes two convolutional networks: one for classification and the other for auto-encoding using the final output encoder layers from the first phase. With advancements in medical image processing techniques, it is now possible to extract complex features, making it easier to identify boundaries, size, and characteristics of brain damage. Additionally, machine learning algorithms have been integrated to

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enhance diagnostic accuracy by training models on diverse datasets, allowing for the recognition of patterns that can indicate the presence of brain damage.

A. Objective

The primary contributions of this approach are as follows. An efficient clustering segmentation algorithm is given in the present work to enhance the unstable clustering and reduce its sensitivity to noise. To remove Noise from the MRI Input image and improve the image quality, reduce the noise using Median filtering. PSO-based K-means algorithm is utilized to initialize the clustering midpoint, which is significant and improves the stability of the algorithm. The K-means algorithm combined with PSO segmentation further improves the each edges of segmentation. Ensemble based combination of KNN-SVM is proposed to classify brain damage of children from different age.

II. LITERATURE REVIEW

A multi-wavelet band The Weiner filter is used to improve and reduce noise in the input slices. The application of Potential Field (PF) clustering identifies subsets of cancerous pixels. Furthermore, this cancerous region is segregated using a global threshold and other quantitative morphological approaches, with pixel values for the background at 0.98 (BG) and foreground pixels at 0.93 (FG). The average Q value and variation for product quality are 0.88 and 0.017, respectively. [1]-[2].

Deep learning models have sparked interest in the biomedical industry for illness detection and therapy. They used filter algorithms to remove noise from the photos as part of the dataset's preparation. They then retrieved characteristics from each image's average colored moment. These classifications are abnormal image data with a detected mass and regular visual information. The Brain LSTM model's classification accuracy outperformed prior research that used the same dataset classification success outcome 91.8% [3].

In the BRATS 2013 dataset, convolutional neural network architecture uses a patch-based method that employs local and surrounding input to predict output labels, resulting in dice scores of 0.86, 0.86, and 0.91. Segment outcomes were assessed in terms of fused features, individual features, and pixels. The recommended method was compared at the pixel level to ground truth slices and verified in terms of Error Region (ER), Pixel Quality (Q), Background (BG), and Foreground (FG) values with an accuracy of 0.93 FG, 0.98 BG, and 0.010 ER. [4].

Differentiating between brain damage types using two publicly accessible datasets, MRI images based on DNN are used to attempt to create a new model that determines the kind of Brain damage and the tissue grades of the detected image. Timely diagnosis is essential due to the severe circumstances, aberrant development, and complexity of brain anatomy associated with cancer. Magnetic Resonance Imaging (MRI) is beneficial for examining Brain damages since it produces high-quality brain images, DWA, or Discrete Wavelet Auto encoder, achieves 96% accuracy [5].

Input data set and attained an Intersection over Union (IoU) level of 0.9504. The ideas of data augmentation and preprocessing were introduced in order to increase the classification rate. Brain damages in the head are classified into several categories using evolutionary algorithms and reinforcement learning through transfer learning. Additional deep learning techniques include Mobile Network V2, DenseNet201, InceptionV3, and ResNet50. The resulting data showed that the suggested outperformed state-of-the-art reports, with Mobile Net V2 achieving 91.2% [6].

The human visual assessment of tiny biopsy photos is time-consuming, subjective, and contradictory because of variations within and between observers. In this way, the cancer and its composition will be identified at the outset for final therapy and correction. This Machine Learning-Based Back Propagation Neural Network (MLBPNN) brain cancer Classification method helps doctors identify threats more accurately and proficiently while reducing the variety of onlookers. Additionally, the Method might help physicians evaluate the image on the cell by using the phones' recoloring capabilities to aid in order and bunching calculations [7].

The Transfer Learning Model The Visual Geometry Group (VGG-19) is fine-tuned to collect the attributes, which are then concatenated with handmade (shape and texture) features using a serial-based approach called the Grab-cut Method to properly segment the actual lesion symptoms. Entropy is employed for optimizing these properties for faster and more accurate classification, and classifiers are given a fused vector [8].

In a multicenter, prospective clinical investigation, the user determined that the CNN-based diagnosis of SRH visuals was not inferior to the pathologist-based evaluation of conventional histologic images ($n = 278$; overall accuracy, 94.6% versus 93.9%). Furthermore, interpreting intraoperative histologic images relies on a pathology workforce that may be better dispersed, reducing a parallel strategy in the current research that combines Stimulated Raman Histology (SRH) [9] - [10].

Consequently, it is advised to divide and identify brain malignancies using an active deep learning-based feature selection strategy. The first phase involves contrast enhancement, which is then provided to SbDL for saliency map generation. SbDL then applies basic thresholding to turn the enhanced contrast into binaries form. Deep feature extraction is done using the pre-trained CNN model Inception V3 during the classification stage. Afterwards, the classification approach is used in the second stage with a median accuracy more significant than 92 on BRATS2013, 2014 [11]-[12].

The soft computing procedure is the Extended Linear Boosting (ELB) classification method, which is employed to identify disease cells in Brain MRI. The ELB classification system is used to identify and segment the Brain damage. The Curvelet transform is applied to the original brain MRI image, which converts the spatial domain pixels into multi-resolution pixels. The spectral and linear identifying characteristics are built using the Curvelet converted coefficient matrix. The PCA methodology decreases the dimensionality of the generated features, which are subsequently classified using the ELB classification algorithm. [13].

The treatment of a deadly illness depends on the early diagnosis of brain damages. Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans are typically used to identify the presence of a Brain damage. The MRI/CT scans require a great deal of data and are quite sophisticated. Neurologists must go through a very lengthy and laborious procedure in order to discover tiny malignancies. Entropy Images with low entropy have large areas of darkness with constant pixel values. The entropy of an image with a perfect low level will be zero [14].

The effectiveness of the two skilled radiologists who manually delineated the lesion boundaries against the recently proposed automated lesion segmentation model. The database, which included 80 real-time Magnetic Resonance Imaging (MRI) brain scans containing glioma growths, was used for the experiments. To compare the lesions found manually by specialists with those found automatically by the automated technique, extensive statistical analysis is carried out using tests like the two-tailed T-test, analysis of variance (ANOVA) test, Mann-Whitney U test, regression and correlation tests, etc. The automated lesion identification approach is also assessed using three quantitative metrics: the Jacquard coefficient, and the dice similarity index [15].

Deep learning architectures such as VGG19, Resnet50, and EfficientNetB0 are being utilized to recognize and detect brain damages. The dataset consists of human brain images with and without Brain damages, which are provided as training, testing, and validation data. Based on the results obtained in our proposed work, the EfficientNetB0 architecture achieved an accuracy of 96.50% and a loss value of 0.021 when compared to the other three models [16]. Individuals applied transfer learning on the second dataset, combining the VGG16 architecture with our suggested "23 layers CNN" design. Our models outperformed all existing state-of-the-art models, with classification accuracies of up to 97.8% and 100% for the first and second datasets, respectively. [17].

Convolutional neural networks (CNN) are effective in learning complex features from multimodal MRI images of both healthy and Brain damages brain tissues. The accuracy of the CNN. Attempted to implement SVM on CNN, but it only provided an accuracy of 20.83%. Experimented with different parameters, such as changing the final layer parameter to soft-max and the optimizer to Ada-Max, which improved the accuracy to 98.10%. However, wanted to improve the results even further, so we changed the optimizer to RMS-Prop, which

gave us an impressive accuracy of 99.74%. Our model was trained on 2473 images with a 9:1 ratio of testing data (273 images) and 11 epochs. The model consists of a 9-layer CNN model with 14 stages [18].

According to one experiment, a Convolutional Neural Network (CNN) architecture may efficiently identify brain cancer using MR images. The models include ResNet-50, VGG16, Inception V3, and the recommended architecture. The analysis evaluates the models' performance using a variety of measures such as accuracy, recall, loss, and area under the curve (AUC). The research concludes that the proposed model outperforms the other models in the comparison. The CNN model achieves an accuracy of 93.3%, an AUC of 98.43%, a recall of 91.19%, and a loss of 0.25 using a dataset of 3264 MR images. [19].

Deep learning is applied to develop an efficient malignancy detection system. The technique goes as follows: Data was gathered from well-known databases for the brain, lung, and liver, total 10,000 records, and preprocessed using the following techniques: CLAHE for brightness enhancement, Thresholding (Grayscale), Filtering (ADF), and Skull Masking for noise and anomaly removal from raw images. Using Principle Component Analysis (PCA) to extract features. The VGG16 network is used to select attributes, which are subsequently classified using the Deep Dense Neural Network (Dense Net 164). Experimental tests have shown that the proposed model outperforms other state-of-the-art models under different measures, with an accuracy of 0.97, sensitivity of 0.98, specificity of 0.98, and detection rate of 0.94 [20].

Six widely used machine learning algorithms, a convolutional auto-encoder network, and a new 2D CNN architecture were constructed to detect brain damages. A T1-weighted, contrast-enhanced MRI dataset comprising three different types of abnormalities and a healthy brain free of abnormalities was used for this kind of classification. Magnetic Resonance Imaging (MRI) brain scans of healthy brains, meningioma's, gliomas, and pituitary gland abnormalities were employed in this investigation. First, MRI brain images were subjected to preprocessing and augmentation methods. Subsequently, created a convolutional auto-encoder network and a new 2D CNN, which had previously been trained using the hyper parameters we had been given. Then, many convolution layers are included in 2D CNN; each layer in this hierarchical complex has a 2*2 kernel task [27].

Here, various images processed for noise reduction, smoothing, and image resizing are utilized as the input. Convolutional operation constructed fuzzy clustering with multilevel thresholding of the input image to segment the processed image. Gradient multilevel Kernel zed perceptron combined with Darwinian optimization (GMKP-DO) was then used to classify this image. The findings from several experiments validated by statistical analysis demonstrate the ability of the recently developed Method to generate precise forecasts [28].

A. *Problem statement*

With the fast growth of communication technology, mobile phones steadily gained popularity in the mid-1990s and are now widely used in many nations. Children from 2 to 10 are continuously using mobile phones for specific hours, which causes headaches, eye problems, and, later brain damage. Children become increasingly dependent on their mobile phones due to the advent of numerous apps. Mobile phones were required to operate in many parts of life, including purchasing items. As an outcome, whether using mobile phones harms human health has gained much attention.

III. MATERIALS AND METHOD

The proposed attempts focus primarily on brain imaging analysis in order to reduce fatalities. MRI segmentation and Ensemble Classifiers are used to detect brain sickness. The proposed Method is separated into four phases. The first stage is filtering preprocessing is improve image quality, the clustering approach is employed for segmentation, the Grey-Level Co-occurrence Matrix (GLCM) is used for feature extraction, and the Ensemble classifier, a neural network combiner, is used for classification. KNN, as well as Support Vector Machine (SVM) and. Image segmentation, is a critical preparatory step in the complex and composite image handling technique used in Brain Magnetic Resonance Imaging (MRI). Segmentation plays an acceptable role in medical image segmentation; the overview of the proposed methodology is shown in Figure 1.

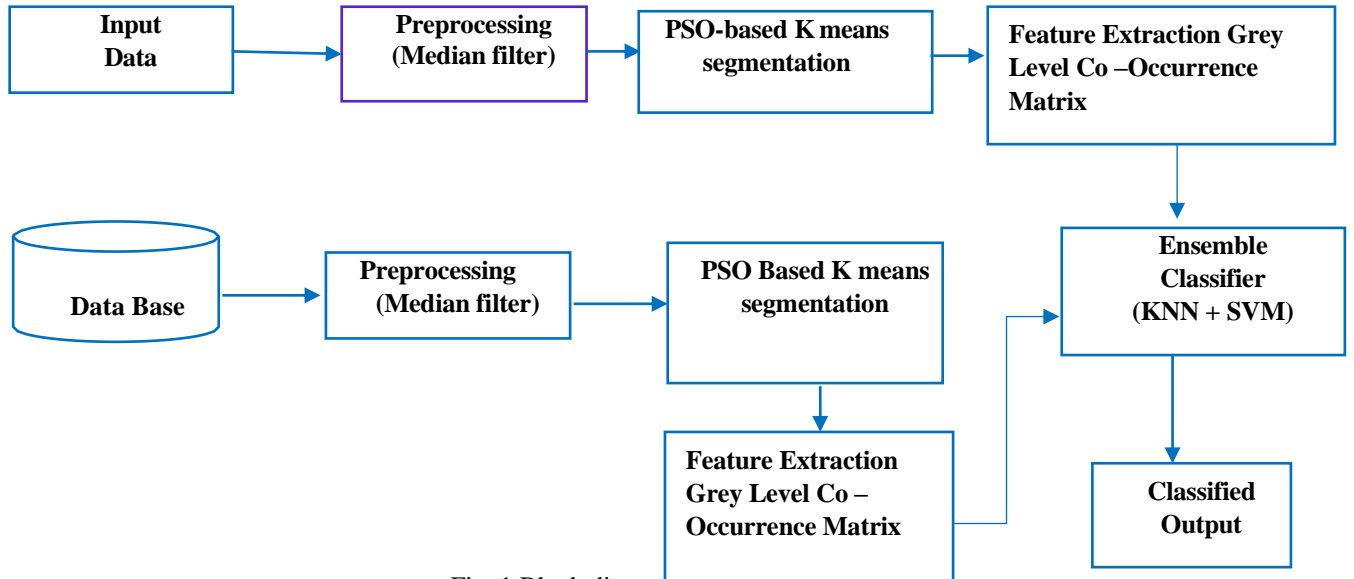


Fig. 1 Block diagram of proposed Method

A. Preprocessing

Preprocessing is a set of operations used to enhance the overall quality of an input brain MRI image. Eliminating any potential noise from the image, such as irregular pixel values or dark areas, is the initial stage in the process. The image's clarity may suffer as a result of this noise. The second step is contrast enhancement, which analyzes each pixel and adjusts the contrast to improve the overall appearance of the image. This process takes into account the size and shape of structural elements within the image. By using preprocessing techniques, we are able to eliminate unwanted distortions and enhance specific elements that are crucial to the quality of the image. This is achieved by using quantitative characteristics from the image as training data

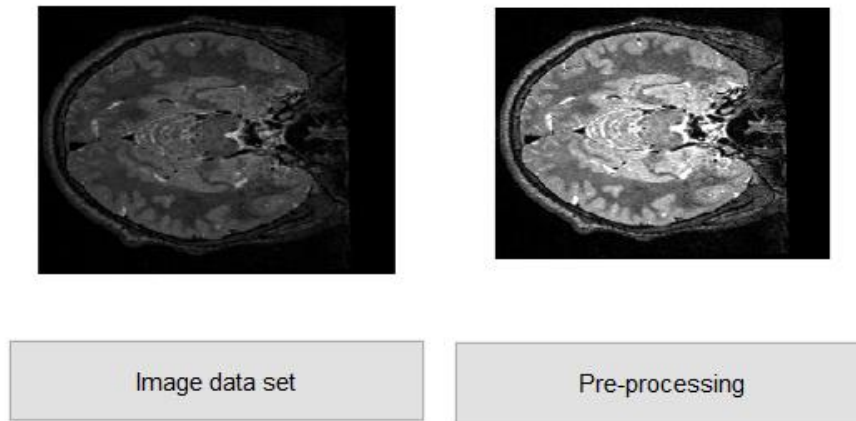


Fig. 2. (A) Input Brain MRI Image (B) Pre - Processing

Median filter technique

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \tag{1}$$

Filtering is a discrete operation in which a computation is applied to the estimates of the pixels in the blurred surface of the corresponding input pixel to regulate the estimation of a random pixel in the gained image

of each layer. The Median filter has proven to be an effective method for eliminating noise extracted from a regular dispersion. Median smoothing with increasing difference can be a helpful technique for obtaining a multi-scale spatial representation of an image.

B. PSO-based K means segmentation.

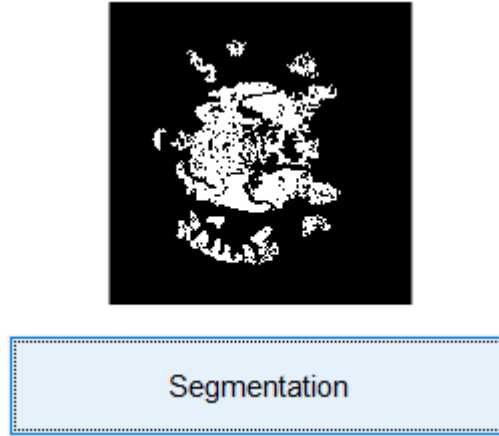


Fig. 3. Segmented Output Image

Segmentation enhances object recognition based on Step 1: Similarity segments are divided by determining similarity between pixels, as the name indicates. Step 2: In this scenario, Discontinuity segments are generated based on variations in pixel intensity levels across the frame. This idea is used by algorithms that identify lines, points, and edges. The Particle Swarm Optimize (PSO) approach is applied on a malignant brain imaging, and the type of malignant brain malignancy is difficult to diagnose with existing technology.

$$d = || p(x, y) - c_k || \tag{2}$$

$p(x, y)$ Is a pixels in a visual are edge pixels and selecting those pixels from a dataset big enough to capture the variety of the objects segmenting are the steps of the edge-based approach, referred to as edge identification. C_k Clustering technique for segmenting images is K-means clustering. Using this Method the pixels of an image are seen as data points, which the computer divides into K clusters according to how similar.

$$d = \sqrt{\sum_{k=1}^n (p_k - q_k)^2} \tag{3}$$

Where d is a dimension of image, p_k and q_k indicate, respectively choose the number of clusters, K, depending on data gathered during the K-means clustering procedure itself. Using an objective assessment metric eliminates the need for trial and error by suggesting appropriate values for K. Consequently, a list of values may be used in place of a single predetermined K. The number of elements taken into consideration must be sufficiently high to represent the unique qualities of the datasets accurately.

$$O (I * k * m * n) \tag{4}$$

The medical community needs help to manually delineate visuals and pinpoint the precise location of malignant borders or limits. It in addition required anatomical expertise, but it also faced economic and human error concerns. Following the publication of a 3D automated segmentation model, an encoder-decoder convolutional neural network applying an MRI scanner could give predicted segmentation results comparable to the ground truth.

C. Feature extraction using grey level co-occurrence matrix (GLCM) technique.

Feature extraction is calculated method that extracted from the brain-segmented image; a different stage of data analyses in feature extraction, The GLCM filter analyses the Mean data from MRI segmented image of distribution as edge of pixel function data bases also varies as there has been no normal gathering protocol.

$$f(x) = Z^T \phi(y) + b \tag{5}$$

An end-to-end technique for evaluating images, image splits a $f(x)$ digital image into many segments and classifies the data in each one to classify individual pixels in the image to identify the exact limits and shapes of various objects and regions and calculating based on mean and n^{th} movement

$$\text{Mean} = \frac{\sum_{i=1}^N P_i}{N} \tag{6}$$

The dataset for training and testing samples, or they can use any openly available dataset using this Method. A classification algorithm may over-fit to training instances and become unable to be applied to new samples if there are a lot of variables, which also means a big number of variables demands a lot of memory and processing resources.

$$\text{Energy} = \sum_i (P_i = P)^n f(P_i) \tag{7}$$

By evaluating these characteristics, the classifier finds it easier to differentiate between various classes since it can do so with minimal effort. They may be roughly classified into two categories: spectral texture method for feature extraction and spatial texture feature extraction methods, depending on the domain from which the surface texture characteristic is collected.

D. Ensemble Classifier

Brain damage classification is performed using a combined classification technique-based machine-learning methodology that employs an ensemble classifier, which combination of SVM and KNN is employed in classifiers.

Support Vector Machines (SVM)

Support Vector Machines (SVM) are learning algorithms that are dependent on supervised learning algorithms. It calculates the space between the input data fact and all the training instances, The SVM algorithm was developed to find the optimum edge with the biggest difference between classes in an n-dimensional classification point in each axis. The segmentation image is a combination of significant dimension and changes in the training information.

Training Data Set

Each MRI brain image model is tested using layer calculation-based soft max layer (with scores) for the ensemble model. The soft-max classifier's score values are averaged using the state-of-the-art ensemble networks to perform prediction.

$$f(x) = \max(0, x) \tag{8}$$

Where,

$f(x)$ is N^{th} layer as a function which is calculated in SVM

A probabilistic classifier has been developed, in which the maximum score of the soft-max classifier from each pipeline is chosen, along with $\max(0, x)$ is a maxima of all the maximum numbers.

KNN (K-Nearest Neighbors)

During the training period, the KNN algorithm maintains the complete training dataset as an indicator. When creating predictions, it computes the distance across the input points of information. Two factors in order to obtain distinct K-values: the training error rate and the validation error rate.

Testing Data Set

The brain image dataset is tested using eight classes, twenty-five classes, and the entire dataset. The parameters that provide the best cross-validation performance are less likely to be ideal when fewer training samples are available.

$$F = \sum_{i=1}^n W_i * P_i \tag{9}$$

By using learning algorithms ensemble techniques W_i generate a group of classifiers and use a P_i weighted voting system for classifying incoming data points based on their predictions or classifications. An ensemble learning methodology involves training many learners to answer one problem at a time. Unlike standard machine learning techniques, that attempt to extract a single hypothesis from the F training dataset, ensemble techniques aim to generate multiple possibilities and integrate them for purposes of prediction.

IV. RESULT AND DISCUSSION

For our experiment evaluation, user used a widely accessible brain MRI dataset. Ages taken 6-10 years old children groups into which the user will classify the brain damages. Carried out an identification of techniques from the Image Processing Toolbox to preprocess our dataset. Image scaling, random a rotation, and skull shape are examples of pre-processing procedures.

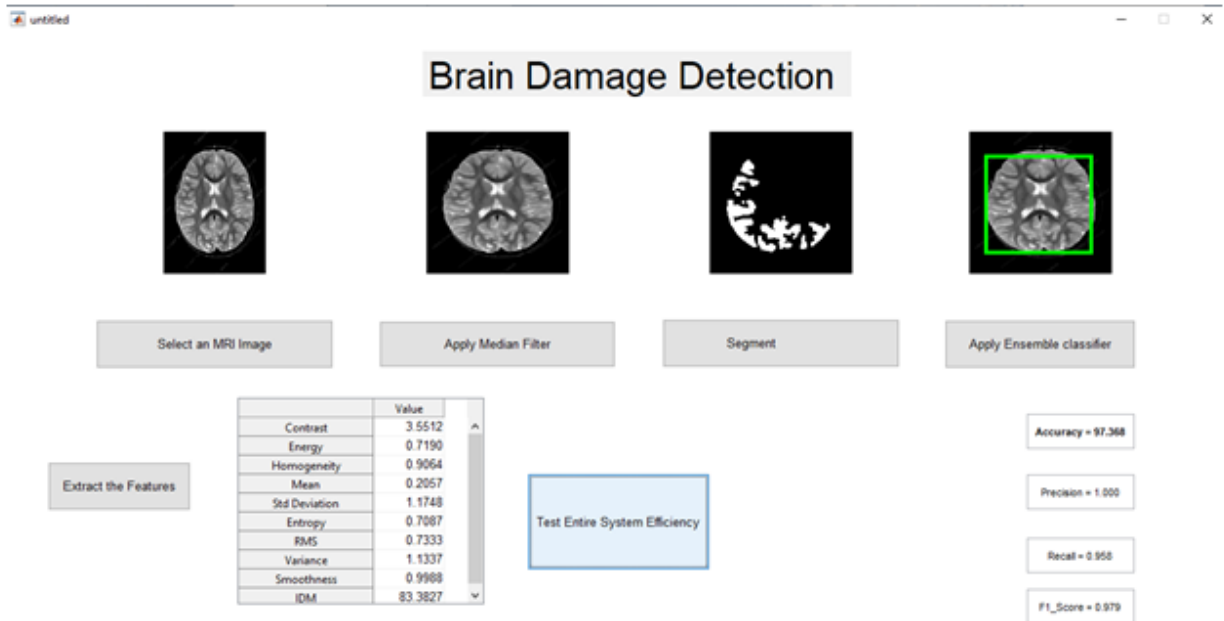


Fig. 4. Simulation output of Brain damage detection from 6–10-year-old children MRI data set

Figure 4 shows the output simulation based on three significant findings: segmented image, feature extraction and neural network ensemble classifier in mat lab. Input MRI images from the dataset as the input image, using a Median filter-based preprocessing, the image is resized, and the label is encoded.

Every image separated the data, allocating 80% of the images to training and 20% to testing. Next, a deep neural network model is trained for ROI (Region of Interest) using the ensemble classifier construct approach. Next, the image was classified into accuracy using a confusion matrix if that Brain damage was positive, otherwise, it was negative.

One classification and one segmentation approach were used information is gathered using various imaging methods, including MRI, CT, and X-rays. It takes much effort for medical professionals to segregate Brain damage's using data from Magnetic Resonance Imaging (MRI). Segmenting-based PSO-based K means segmenting brain damages from complicated MRI brain images, a meaningful way to retrieve information. The

high-intensity pixel cluster is separated from the MRI image to construct the cancerous area. Then, characteristics like the Brain damage's perimeter and size are retrieved from the Ensemble classifier technique

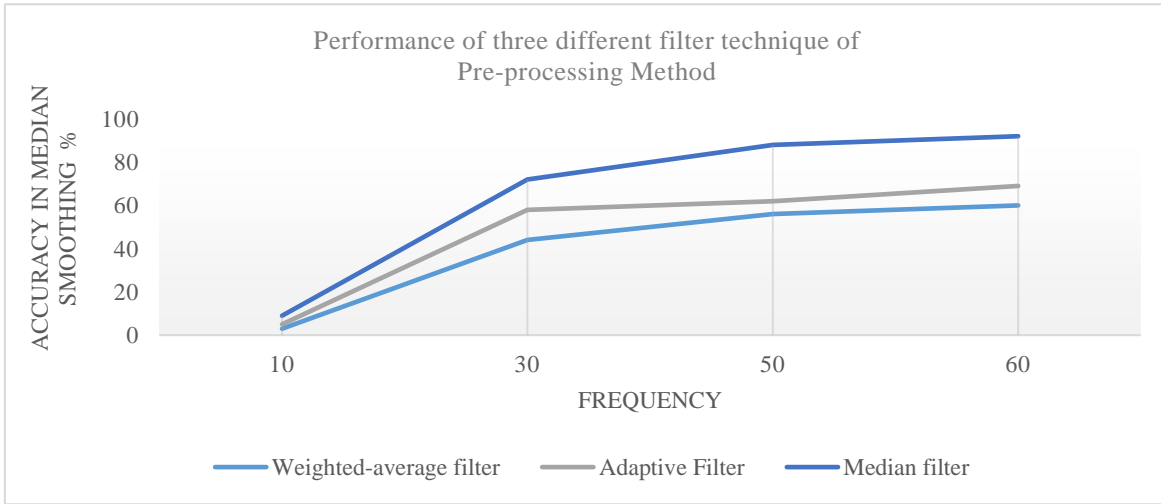


Fig. 5. Comparison of existing two different filter technique using proposed Median filter technique.

Figure 5 graph shows median filter performs better noise removal when compared to previous Weighted-average filter, adaptive filter, based on output categorization Filtered

Table 2. Analysis of two existing classification techniques with three confusion matrix parameters.

Parameters	Fuzzy Clustering With Neural Network	K means segmentation with neural network	Ensemble classifier [KNN+SVM]
Accuracy (%)	80 %	95 %	97 %
Sensitivity (%)	80 %	92%	95 %
Specificity (%)	89%	94%	96 %

Table 2 shows the confusion matrix calculation

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{10}$$

Which is $(50+50) / (50+51+1+2) = 0.97245 \times 100 = 97\%$ are gained in Ensemble classifier of classification output

$$\text{Specificity} = \text{TN} / \text{TN}+\text{FP} \tag{11}$$

specificity = $100 / (100+5) = 0.98\%$ The number of data points accurately predicted to be in the negative class out of all values in the dataset that are really in the group that is negative.

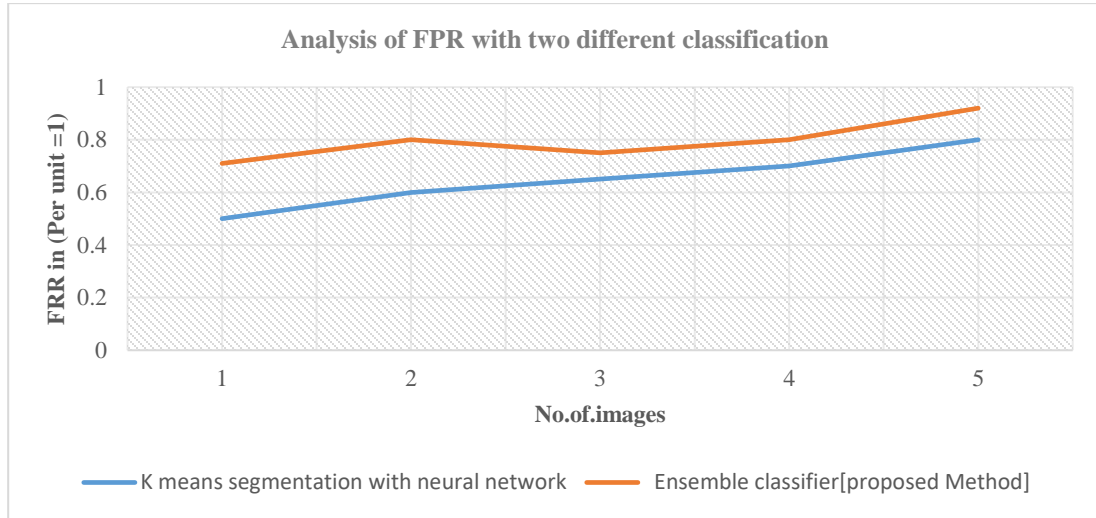


Fig. 6. Analysis of False Positive Rate (FPR)

$$\frac{FP}{N} = \frac{FP}{FP+TN} \quad (10)$$

Figure 6. Demonstrates how to compute the ratio of false positives to all anticipated outcomes (the sum of false positives and true positives) in a binary classification issue to get the false positive rate in the analysis of the data. The rate of false positives is based on how many real negatives the model predicts.

V. CONCLUSION

In this study, which focuses on using image processing to detect brain damage, early diagnosis is crucial for improving treatment outcomes. Once a brain infection is diagnosed, a radiological assessment is necessary to determine the exact location, extent, and impact of any adjacent conditions. To achieve accurate results, the brain disease analysis involves four processes: preprocessing the image data from a database using Median filtering, segmentation using the PSO-asked k-means clustering algorithm, feature extraction using the Grey Level Co-Occurrence Matrix (GLCM), and classification using ensemble classifiers. The latter is a combination of two different techniques, SVM + KNN. The output of this study showed a 97% accuracy rate in detecting the specific area, which is significantly higher than conventional methods

A. Future scope

In future, MRI image classify with inspection V3 based deep neural networks for image classification, which was developed to address issues like computational and memory demand that arise while training deep networks. Inception-v3 has been fine-tuned to yield high accuracy in tasks like image classification while remaining computationally angle. The inspection V3 is modular and uses numerous Inception modules that conduct pooling and inversion with different kernel measurements, enabling the network to learn broad and particular information. This background has succeeded in several computer vision tasks after being trained on large ImageNet datasets.

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