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Brain Tumor Classification using MRI Images and AI

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Abstract: *Brain tumors pose a significant challenge in both pediatric and adult healthcare landscapes, constituting a majority share of primary Central Nervous System (CNS) tumors and annually affecting approximately 11,700 individuals. Survival rates for those diagnosed with cancerous brain or CNS tumors hover at 34 percent for men and 36 percent for women over a 5-year period. These tumors are diverse, spanning from benign to malignant, including pituitary tumors among others. Effective treatment planning and accurate diagnostics are pivotal in improving patient outcomes. Magnetic Resonance Imaging (MRI) serves as the cornerstone for tumor detection, generating vast amounts of imaging data for interpretation by radiologists. However, manual examination of these images can be error-prone due to the complexities inherent in brain tumor characteristics. Automated classification techniques powered by Machine Learning (ML) and Artificial Intelligence (AI) offer a promising avenue, consistently demonstrating superior accuracy compared to manual approaches. Thus, proposing a system integrating Deep learning techniques such as artificial neural networks (ANNs) and convolutional neural networks (CNNs) algorithms and Transfer Learning (TL) could revolutionize brain tumor detection and classification globally. This innovative approach would provide invaluable support to medical professionals, enhancing diagnostic accuracy and ultimately improving patient outcomes in the battle against brain tumors.*

Keywords: FCM, CNN, segmentation, SVM, Medical Image

I. INTRODUCTION

Medical imaging stands as beacon of innovation, offering a myriad of non-invasive techniques to explore the inner workings of the human body, thereby shaping the landscape of modern healthcare [1]. This diverse field encompasses an array of imaging modalities and methodologies finely tuned to visualize anatomical structures, driving informed medical decisions and ultimately fostering improved patient well-being.

At the heart of this technological marvel lies image segmentation, a cornerstone process within the realm of image processing, wielding profound significance, particularly in the domain of medical imaging [2]. Its primary mission? To meticulously identify and delineate tumors or lesions, serving as the bedrock for efficient machine vision and paving the way for precise diagnostic outcomes. Yet, amidst its complexity, the pursuit of enhancing the sensitivity and specificity of tumor detection remains an ongoing endeavor, one met with innovative solutions such as Computer-Aided Diagnostic (CAD) systems.

In the realm of disease burden, brain and nervous system cancers cast a shadow of concern, ranking among the top causes of mortality worldwide, with survival rates remaining stubbornly low [3]. The World Health Organization (WHO) sheds light on the staggering statistic of approximately 400,000 individuals globally grappling with the complexities of brain tumors and their associated complications annually [4]. Thus, the quest for timely detection and accurate segmentation of these tumors emerges as a critical imperative, offering a lifeline for effective treatment strategies and improved patient prognoses.

Within the arsenal of medical imaging modalities lie stalwarts such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET), each wielding its unique prowess in the pursuit of brain tumor detection and segmentation. These modalities, akin to skilled artisans, craft detailed portraits of anatomical and functional nuances, empowering clinicians with the precision needed for optimal tumor localization and characterization.

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To unravel the mysteries hidden within these images, a diverse array of segmentation algorithms step into the spotlight, from the nuanced dance of region growing to the intricate orchestration of methods based on deep learning. Convolutional neural networks (CNNs) are one of these. emerge as heralds of a new era, harnessing the power of vast datasets to automate the intricate task of brain tumor segmentation with unprecedented accuracy.

In summation, the interplay between medical imaging and image segmentation unfolds as a tale of ingenuity and perseverance, forging pathways to early tumor detection and precise delineation, ultimately illuminating the path towards improved patient outcomes. As the journey continues, fueled by innovation and collaboration, the future holds promise for a paradigm shift in the diagnosis and management of brain cancer, driven by the unyielding spirit of human ingenuity.

III. LITERATURE REVIEW

Segmenting the region of interest (ROI) from an object poses significant challenges, especially when it comes to extracting tumors from MRI brain images. This task is ambitious and intricate, prompting researchers globally to explore various approaches from distinct perspectives. In recent times, neuralnetwork-based segmentation has shown remarkable results, leading to a growing trend in its adoption. The use of this model is steadily increasing, driven by its effectiveness and the potential to transform medical image segmentation practices

Yantao et al. [8] embarked on a formidable journey in the realm of medical image analysis, focusing their efforts on the intricate task of brain tumor segmentation. Armed with a Histogram-based segmentation technique, they endeavored to tackle the challenge of classifying brain tissues into three distinct categories: tumor (encompassing necrosis and active tumor tissue), edema, and normal tissue. Central to their methodology was the utilization of two modalities—FLAIR and T1—to discern subtle nuances in tissue characteristics and delineate regions of interest. Leveraging the FLAIR modality, they employed a region-based active contour model to detect abnormal regions, while the contrast-enhanced T1 modality facilitated the differentiation of edema and tumor tissues using the k-means method. Through meticulous analysis and validation, they achieved commendable performance metrics, including a Dice coefficient of 73.6% and a sensitivity of 90.3%, underscoring the effectiveness of their approach in accurately segmenting brain tumors from MRI images.

In a parallel endeavor, Badran et al. [9] embarked on a quest to refine the process of ROI extraction in medical imaging, with a specific focus on brain tumor segmentation. Their methodology, rooted in the fusion of aimed to precisely delineate the boundaries of the region of interest. With a dataset comprising 102 images, they meticulously preprocessed the data before subjecting it to a two-step neural network approach. The first neural network leveraged the canny edge detection method to extract edges, while the second neural network applied adaptive thresholding to refine the segmentation process. Feature extraction using the Harris method further enhanced the characterization of the segmented images, enabling the differentiation between healthy and tumor-containing brain tissues. Through rigorous evaluation and comparative analysis, their study unveiled the superiority of the canny edge detection method in achieving accurate and reliable brain tumor segmentation, thus offering a valuable contribution to the field of medical image analysis.

Pei et al. [10] embarked on an innovative endeavor aimed at enhancing texture-based tumor segmentation in longitudinal MRI scans. Recognizing the inherent challenges posed by the dynamic nature of tumor growth, they proposed a novel approach centered on leveraging tumor growth patterns as unique features for segmentation. By integrating label maps to model tumor growth and predict cell density, alongside extracting texture and intensity features, they devised a comprehensive methodology capable of capturing the complex interplay between tumor morphology and growth dynamics. Performance evaluation revealed promising results, with the Mean DSC metrics reflecting high accuracies of 0.819302 and 0.82122 for leave-one-out (LOO) and three-fold cross-validation, respectively, thereby underscoring the efficacy of their approach in accurately segmenting brain tumors in longitudinal MRI scans.

Dina et al. [11] introduced a pioneering segmentation model rooted in the Probabilistic Neural Network (PNN) framework, augmented by Learning Vector Quantization. Their study, conducted on a dataset comprising 64 MRI images, showcased the efficacy of their approach in significantly reducing processing time by 79% compared to

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conventional methods. By incorporating a Gaussian filter for image smoothing, they optimized the segmentation process, demonstrating the potential for substantial efficiency gains in medical image analysis tasks.

Othman et al. [12] undertook a bold exploration into brain tumor segmentation, harnessing the power of a Probabilistic Neural Network (PNN) model integrated with Principal Component Analysis (PCA). Their methodology, anchored in feature extraction and dimensionality reduction, aimed to enhance the efficiency and accuracy of segmentation their study yielded promising results, with accuracy ranging from 73% to 100% based on the spread value. Through meticulous analysis and performance evaluation, they highlighted the potential of their approach to achieve robust segmentation outcomes in clinical settings.

In summary, these studies underscore the diverse approaches and methodologies employed in the challenging task of brain tumor segmentation. From Histogram-based segmentation to neural network-based techniques, researchers continue to push the boundaries of medical image analysis, striving to improve accuracy, efficiency, and ultimately, patient outcomes. As advancements in technology and methodology continue to unfold, the future holds promise for further innovations in the field of medical image segmentation, paving the way for enhanced diagnostic capabilities and personalized treatment strategies.

III. PROPOSED METHODOLOGY

In our scheme, two different models are used for brain tumor segmentation and detection. The first model segmented tumors according to FCM and classified them with traditional machine learning algorithms; The second model focused on deep learning for tumor detection. FCM segmentation provides better results for segmenting noisy data [15]. Although it requires more time to complete, it stores more information.

A. Plan for segmenting and classifying tumors using conventional classifiers

In our future model, brain segmentation and detection will be done using machine learning algorithms and the performance of our model will be compared with the classifier. Our brain image segmentation system has seven stages: skull stripping, filtering and reliability, fuzzy C-means algorithm segmentation, morphological tasks, tumor contours, feature extraction, and normal classifier classification. The results of our study are interesting. The following section provides a description of the primary phases of our suggested model (Figure 1).

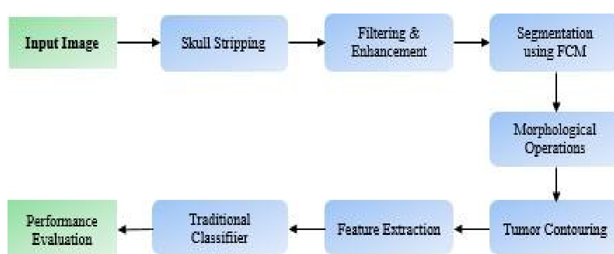

Fig. 1.Proposed methodology of classification using Classifiers

1) Skull Stripping: Removing the skull is an important step in the treatment of medical imaging because the history of MRI images does not contain important information and only increases the duration of the operation. CNN is used in the plan Convolutional neural networks are widely used in medical imaging. Over the years, many researchers have tried to develop models that could detect tumors more effectively. We attempted to propose a focus algorithm that can classify tumors from 2D brain MR images. Convolutional neural networks can detect tumors, but due to jointness and uniformity, our model uses CNN.A five-layer convolutional neural network is designed and used to diagnose tumors. The seven-stage collective model along with the hidden process provides the most significant insights about the tumor.

Instructions and a brief description are below -progressively deleting the cranium from the MRI pictures. The following are these steps:

a) *Otsu Thresholding:* To remove the skull, we first applied Otsu's Thresholding technique, which divides the image into the foreground and background by automatically determining the threshold value. This method's chosen threshold reduces the intra-class variance, which is the weighted total of the variances between the two classes.

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b) *Connected Component Analysis:* During the last stage of the skull stripping process, we eliminated the skull portion by using connected component analysis to isolate the brain region.

Improvement and filtering: Helps in better processing, we need to improve the quality of low-noise MRI images because brain MRI images are noisier than other image processing pains.

Use FCM for segmentation: For segmentation, use Fuzzy C-Means clustering algorithm which allows one file to be split into two files or multiple clusters. At this stage, we obtain fuzzy group segmented images, which provides good segmentation.

Morphological study: We only need the brain, not the skull, to divide the tumor. To do this, we use morphological functions of images. First, erosion is performed to isolate weak areas of the MRI image. After corrosion, we will get many connected areas in the picture.

Tumor contour: Removal of the tumor is done by the initial effort method. In the tumor area with a dark background, the image's output is crucial.

Feature extraction: For categorization, extract two different kinds of characteristics. From the segmented MRI data image, extract tissue attributes such as dissimilarity, homogeneity, power, correlation, and ASM, as well as statistical values like mean, entropy, centroid, standard deviation, skewness, and kurtosis.

Conventional classifiers: To fully test our designs, we employed six conventional machine learning models, including logistic regression, K closest neighbors, multilayer perceptrons, naive Bayes, random forests, and support vector machines.

Phase evaluation: Correctly categorize the tumor by comparing our segmentation method with our ROI segmentation model using alternative regional segmentation techniques. The entire procedure is depicted in Figure. We use it for classification after tumor segmentation and feature extraction.

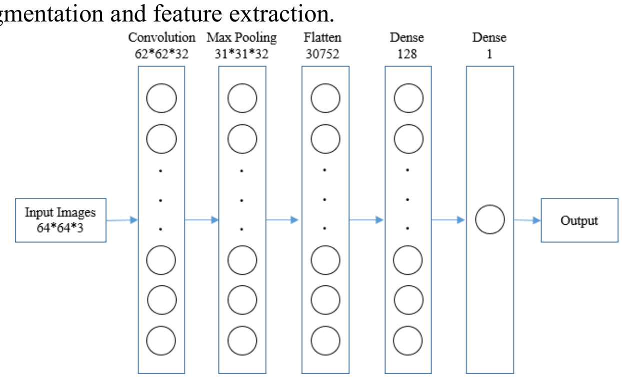

Fig.2.Suggested Approach for 5-Layer Convolutional Neural Network-Based Tumor Detection

B. Suggested Approach Making use of CNN

Convert the entire image to size using the convolutional process as the main process to create the MR image that is 64*64*3. After gathering each and every picture with same appearance, we create a convolution kernel with input layer - we control it using 32 convolution filters of size 3 * 3, each filter supports a 3-channel frame amount. Since ReLU is used as a function, it does not match the output. In this ConvNet architecture, the description space is gradually shortened to reduce the parameter block and computation time of the network.

Processing of MRI images of the brain can also be subject to excessive contamination, and the maximum pooling layer is good in this regard. We use MaxPooling2D as the model for accurate spatial information in the input image. This convolution technique works on dimensions 31*31*32. Since the input image is split into two dimensions, the size of the pool becomes (2, 2), which means that a tuple of two numbers is scaled down vertically and horizontally. After layering, the aggregate features get the map.

Flattening is an important part of layers following pooling since the whole matrix corresponding to the input image must be transformed into the vector line needed for rendering. After that, the neural network processes this data. Two full layers Dense-1 and Dense-2 are used to represent the density layer. In Keras, the density function is used to of layers following pooling since the whole matrix corresponding to the input image must be transformed into the vector line needed for rendering. After that, the neural network processes this data.

Since ReLU exhibits superior integration, it is utilised as a function. The second layer serves as the structure's final layer after the first. The activation function in this process is the sigmoid function. where all nodes are 1 because we need to reduce the use of computational resources to reduce the running time a lot.

Since using sigmoid as a function affects the examination of deep networks, we adjusted the sigmoid function and the deep network has fewer nodes and can be monitored

Working Flow Devised for Proposed Methodology

1. Load the input dataset
2. Adding a Convolution Layer with 32 convolutional filter
3. Passing the Convolutional kernel into the Max Pooling layer
4. Pooled feature map is used to get the single column vector
5. Processing of the vector in dense layer with 128 nodes
6. Final dense layer applying Sigmoid as the Activation function
7. Validation stage and Performance evaluation

Fig.3.The proposed CNN Model's workflow.

We assembled models using Binary cross-entropy and Adam's optimizer as a function of failure were discovered to be accurate in tumor detection. Figure 4 shows an algorithm where we measure the effectiveness of the model.

Algorithm 1: Evaluation process of CNN model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
    for each batch in batchSize do
        ŷ = model(features);
        loss = crossEntropy(y, ŷ);
        optimization(loss);
        accuracy();
        bestAccuracy = max(bestAccuracy, accuracy);
return
```

Fig.4.The performance evaluation algorithm

Table I contains the values for each hyper-parameter. An accuracy of about 97.87% is attained.

TABLE 1: CNN Model Hyperparameter Value

Stage	Hyper-parameters	Value
Initialization	bias	Zeros
	Weights	glorot_uniform
	Learningrate	0.0001
	beta_1	0.8
	beta_2	0.989
	epsilon	None

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Training	decay	0.0001
	amsgrad	False
	epoch	9
	Parameters	Values
	Batch_size	35
	steps_per_poch	81

IV. EXPERIMENTAL RESULTS

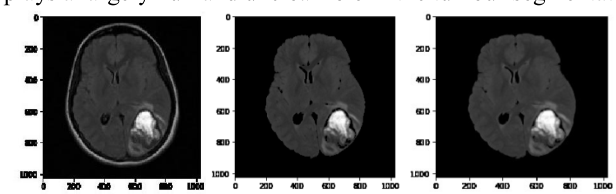
In order to support our proposed model, a comparative analysis of our proposed models of classification using machine learning and deep learning is presented, along with steps for segmenting the tumour from 2D brain MRI (Fig. 5). Using SVM, we obtained 92.42% accuracy, while CNN yielded 96.87% accuracy.

Trial Dataset

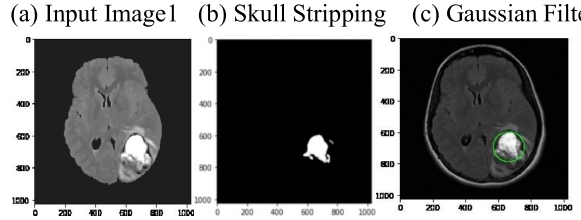
We use the BRATS dataset [16], which is the dataset in the field of brain segmentation, to assess the efficacy of our proposed model. Class-0 and class-1 in this dataset represent MRI images of tumours and non-tumors, respectively. Thirty-seven and 187 MR images with and without tumours were categorised as category 0 and 1, respectively. we divide the data into 70 by 30 and 80 by 20, and we compare the outcomes. B. Image processing technology for segmentation We divided the tumour in accordance with our plan without erasing any important details. We remove the skull because its function in the tumour segmentation process is essentially nonexistent and unclear.

Segmentation utilising methods from image processing

We were able to segment the tumour using our suggested methodology while retaining all of the subtle details. We removed the skull because it plays a largely null and unclear role in the tumour segmentation process



(a) Input Image1 (b) Skull Stripping (c) Gaussian Filtering



(d) Image Enhancement (e) Segmentation (f) Tumor Contouring

Fig.5.Segmentation process of MRI Images

From the data, An input image of a 2D MRI was obtained, and in order to interpret the features of the scan, skull structure analysis (Figure 1b) and image enhancement (Figure 1c) were applied to the input picture. Next, noise was eliminated using a Gaussian filter (Figure 1d), and lastly, the FCM segmentation procedure was simulated (Figure 1d). 1e) Next, use tumor contouring (Figure 1f) . After dividing the tumor into segments, we classify the tumor according to different machine-learning algorithms.

Using Machine Learning to Classify

Regions of interest (ROIs) are frequently defined using texture and feature-based statistics. These characteristics allow us to differentiate between neoplastic and non-neoplastic MRI images.

For classification, we employ statistics and texture as features.

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From segmented brain tumors, tissue-based properties including dissimilarity, homogeneity, power, correlation, and ASM are retrieved, along with statistical features like mean, entropy, centroid, standard, deviation, skewness, and kurtosis. In addition, we remove the tumor's diameter and convex body region. Mr. The next step is categorization after feature extraction. We used six models: SVM, random forest, naive Bayes, multilayer inference, logistic regression, and KNN. SVM performance produced the best accuracy. The effectiveness of classification and approaches to reduce confusion are described in Table 3. The performance markers listed here are

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Sensitivity(recall) = \frac{TP}{TP+FN} \quad (2)$$

$$Speficity = \frac{TN}{TN+FP} \quad (3)$$

$$Precision\ (PPV) = \frac{TP}{TP+FP} \quad (4)$$

TABLE 2: SEGMENTED TUMOR EXTRACTED FEATURES

ImageNo	Contrast	Dissimilarity	Homogeneity	Energy	Correlation	ASM	Label
1	281.18	1.37	0.97	0.90	0.97	0.81	1
2	97.36	0.53	0.98	0.98	0.94	0.96	1
3	337.39	1.68	0.98	0.97	0.82	0.95	1
4	357.59	2.34	0.94	0.92	0.90	0.86	1
5	149.37	0.82	0.98	0.96	0.96	0.93	0
6	357.59	2.34	0.95	0.93	0.90	0.86	0

TABLE 3. CONFUSION METRICS' OF THE CLASSIFIERS

Classifiers	Accuracy	Recall	Specificity	Precision	Dice Score	Jaccard Index
K-Nearest Neighnout	92.5	0.959	0.448	0.9393	0. 999	0.809
Logistic Regression	87.998	0.939	0.296	0.938	0.973	0.845
Multilayer Perception	89.49	**1.000**	0.001	0.844	0.964	0.896
Naïve Bayes	79.89	0.747	**0.737**	**0.979**	0.901	0.790
Random Forest	89.78	0.952	0.169	0.933	0.973	0.871
SVM	**93.52**	0.973	0.448	0.975	**0.969**	**0.931**

As can be seen from Table 3, With an accuracy rate of 92.42% among the six conventional machine learning models, SVM produces the best results. While accuracy and specificity are significantly improved by Naive Bayes, the difference with SVM is negligible and does not warrant consideration of other performance metrics. C. Categorization With an accuracy rate of 92.42% among the six conventional machine learning models, SVM produces the best results. While accuracy and specificity are significantly improved by Naive Bayes, the difference with SVM is negligible and does not warrant consideration of other performance metrics. CNNOther performance tests also include SVM's Jaccard Index, Dice Score, Precision, Recall, etc. We concluded that it achieved good results in these subjects.

CNN Reclassification

The proposed five-layer approach provides us with cancer screening results. Convolution, max pooling, Smoothing, and two thick layers are five-layer CNN techniques. Since CNNs are translation invariants, data augmentation is performed before fitting the model. We evaluate the performance of the two methods based on segmented data. We achieved 93.98% accuracy and 99.01% training accuracy at 70:30 split ratio. Later, in the second iteration, when 80% of the images were allocated to training and the remaining images were allocated to testing, we found that the accuracy rate was 97.87% and the training accuracy was 98.47%. Therefore, our formula gives the best results when the split is 80:20. Table IV shows the performance

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TABLE 4. PERFORMANCE OF THE PROPOSED CNN MODEL

No	Training Images	Testing Image	Splitting Ratio	Accuracy (%)
1	155	69	68: 28	92.98
2	184	43	85: 15	**97.87**

Using a five-layer CNN, we achieved an accuracy of 97.87%; This is an incredible number. We performed our analysis using multiple layers, but the difference in results was not significant when using the CNN model with five layers. Among the outcomes of adding more layers are that the computation time, batch size, and complexity of each step are very high. We also use 0.2 as the output value but do not compensate the model as the accuracy looks flat. Therefore, the model provides the best accuracy without the need for any versioning.

The model's training and validation outcomes are displayedin Figure. The Keras callback function computes it. We conducted several evaluations of the training and validation procedures. We found that the training and validation accuracy of the model reached its maximum after 9 times

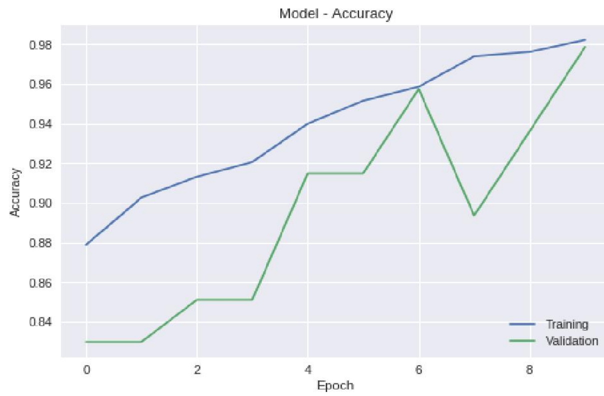

Fig.6.The proposed CNN model's accuracy.

Achievement Comparisons

Lastly, we compare our classification methods utilizing CNNs and conventional machine learning. Using the same data, we also contrasted our findings with those of a few other studies.. Seetha et al. [17], researchers achieved 88.0% accuracy when utilizing CNN and 97.5% accuracy when using SVM-based classification. Our proposed method provides better results for machine learning and CNN-based classification. Meryem et al. [18] achieved a dice coefficient of approximately 95%, while we have a score of 96%.

V. CONCLUSION AND FUTURE WORK

Due to the wide range of medical pictures, image segmentation is essential to medical image processing.

For brain segmentation, we use images from CT and MRI scans. Brain segmentation and classification are common uses for MRI. With fuzzy C-means clustering, tumor cells can be accurately predicted. is a method we use in our study to segment tumors. Classification with neural networks and normal distributions forms the basis of the segmentation process. In the section on traditional classifiers, we proposed and compared the outcomes of several traditional classifiers, including naive Bayes, random forest, multilayer perceptrons, Support vector machines, K-nearest neighbour, and logistic regression.

With an accuracy of 92.42%, SVM is the most accurate of these rules.

We also used CNN, which achieved an accuracy rate of97.87%, to obtain better results. To further enhance brain tumour segmentations, we intend to work in conjunction with 3D brain imaging in the future.

In this case, using larger data will become more difficult, and we hope to create data that addresses intangible problems affecting our country and increases the responsibility of our business.

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