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Brain Tumor Detection in MRI Images Using CNN With U-NET

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Abstract:
Human brain tumors are exceptionally hazardous and devil of the advanced period, prompting definite death. Likewise, when a brain tumor progresses, the patient's life turns out to be more muddled. Early tumor diagnosis is subsequently vital for save the patient's life and expanding their personal satisfaction. In this way, further developed brain tumor recognizable proof is required in the clinical space. Magnetic resonance imaging (MRI)programmed ID of human brain tumors is fundamental for a few indicative and remedial applications. The ongoing techniques, for example, wavelet transform, random forest, fuzzy C-means, and artificial neural networks (ANN), may identify brain tumors, however they need additional opportunity to execute (in minutes) and have less accuracy. In this work, we give a better technique to distinguishing brain cancers in people that utilizes principal component analysis (PCA) and super pixels related to the format-based K-means (TK) calculation to rapidly track down growths more. To increase exactness, we will expand this and use CNN with U-Net. To start with, we use PCA and super pixels to remove key qualities that guide in the exact recognition of cerebrum cancers. Then, a channel that guides in expanding exactness is utilized to improve the image. To recognize the mind growth, the TK-means grouping strategy is utilized to lead picture division. The discoveries of the examination exhibit that, in contrast with other current strategies, the proposed detection system for brain tumor recognizable proof in attractive reverberation imaging accomplishes higher exactness and more limited execution times (measured in seconds).

Keywords: Magnetic resonance imaging, Segmentation, Feature extraction, Superpixels Principal component analysis, Template based K-means algorithm, CNN.

1. Introduction

The brain is the most important anatomical component of the human body, with between 50 and 100 trillion neurons. It is sometimes referred to as the body's center. Moreover, it functions as the nervous system's processor or kernel, playing the most important and crucial role (Alam et al., 2019; Islam et al., 2020). To the best of our knowledge, the skull's presence makes diagnosing brain illness too difficult and complicated (Gondal & Khan, 2013). In general, the human body's most delicate organ is the brain. In contrast to other disorders, brain growth—whether it be aberrant or mass—causes a variety of alterations in brain physiology and behavior. Additionally, it creates resistance to brain function. This anomaly or malfunction is a sign of a brain tumor. Stated differently, an unchecked proliferation of brain cells leads to the development of a brain tumor. "It causes cancer, which accounts for about 13% of all deaths worldwide and may be the cause of death." A brain tumor's degree of danger is contingent upon several

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characteristics, including the tumor's size, location, growth status, style, and behavior. More people have died from brain and other cancers than from other nervous system illnesses. It ranks as the tenth most common cause of death for both men and women. "It is estimated that 23,890 adults (13,590 men and 10,300 women) in the United States will be clinical tested with primary cancer of the brain and spinal cord in the current year," according to estimations on brain tumors. Furthermore, primary malignant brain and central nervous system tumors are predicted to be the cause of 18,020 adult deaths (10,190 males and 7830 women) in 2020. Furthermore, "the survival rate is approximately 36% for five years and 31% for ten years for people with a cancerous brain or CNS tumor." (Cancer.net, 2020; Bhahadure et al., 2017). There are primarily two kinds of brain tumors: benign and malignant.

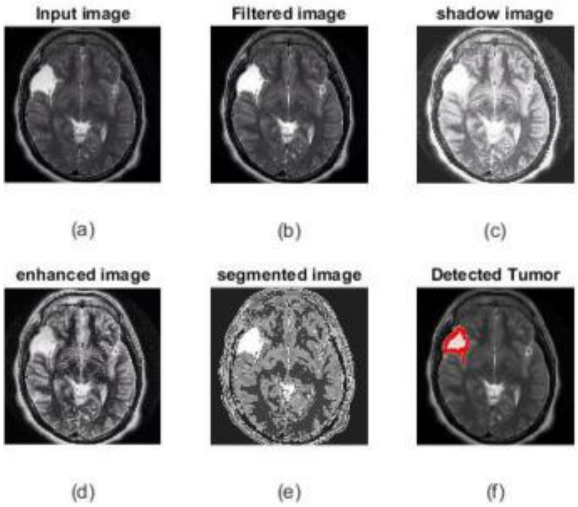

Fig. 1, Example figure.

Benign tumors are those that are less dangerous to humans and do not include malignant cells. Nonetheless, a tumor is viewed as malignant in the event that it incorporates more hazardous cancerous cells for people (Ali et al., 2021; Borole et al., 2015). To learn the area, size, behavior, and growth status of a brain tumor, clinically thought, radiological investigation are vital when the tumor is clinically thought. The data offered works with dynamic on the patient's proper care, including radiation, chemotherapy, the best course of treatment, and surgery. Most importantly, a patient's chances of survival may be increased by accurately detecting a brain tumor in its early stages (Coatrieux et al., 2013). The medical industry is undergoing a significant transformation as a result of several novel imaging methods. Magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT), ultrasound, and X-ray are the most widely used imaging modalities. According to Borole et al. (2015), these medical imaging approaches are utilized to identify complicated disorders such as brain tumors, COVID-19, malignant cells, and CNS cancer in people. MRI is a non-invasive method that is increasingly often used to find anomalies in the composition of tissue. Because it provides the finest contrast pictures of cancerous tissues and the brain, it is preferred above other medical imaging techniques. Rich information and high-quality anatomical picture structures are provided by MRI for the diagnosis of diseases that are clinically suspected. Furthermore, it is playing an extremely important part in scientific and medical research (Liu et al., 2014).

2. Literature Review

In [1], the author proposed that Simple linear iterative clustering (SLIC), which modifies k-means clustering to produce superpixels, is the novel superpixel approach we suggest. Although strikingly SLIC is demonstrated to produce state-of-the-art adherence to picture limits for the Berkeley benchmark**.**

In [2], a model for identifying human brain tumors in an MRI image is provided. It uses the template-based K means and enhanced fuzzy C means (TKFCM) technique. The fuzzy C-means (FCM) algorithm is used in this proposed method to update membership while contacting its best result. Lastly, tumor positivity is determined using the refined FCM clustering technique. Initially, segmentation is greatly initialized using the template-based K-means method, which selects a perfect template based on the image's gray-level intensity.

In this study, Ali, M. S., and Miah [4] developed a deep convolutional neural network (DCNN) model that makes precise use of deep learning methods to classify skin lesions as benign or malignant. It includes a thorough preparation workflow that includes feature extraction, picture normalization, and the removal of noise and artifacts. Additionally, data augmentation is used to improve classification accuracy. With training and testing accuracies of 93.16% and 91.93%, respectively, on the HAM10000 dataset, this DCNN model performs better than popular transfer learning models like AlexNet, ResNet, VGG-16, DenseNet, MobileNet, etc. It is acknowledged as a more dependable and complete method of identifying skin cancer.

The author of [5, 17] suggested a completely new approach for using the k-means algorithm. Our method yields similar or equal results..This study was funded by Hitachi America, Ltd.'s Information Technology Lab (ITL) when K. Alsabti and S. Ranka were visiting ITL. Because of the round-off errors, the clustering's results were similar to the straight k-means approach's. It outperforms the straight k-means technique in the majority of cases.

In order to achieve improved execution and reduced complexity in the medical picture segmentation process, we focused on Berkeley wavelet transformation (BWT) based brain tumour segmentation in [6]. In order to increase the accuracy and quality rate of the support vector machine (SVM) based classifier, pertinent features are also constructed from each separated tissue.

In this study, the most recent machine learning (ML) methods for interpreting brain cancer images from mpMRI scans were assessed during the duration of the seven prior editions of the International Brain cancer Segmentation (BraTS) competition, which ran from 2012 to 2018. In particular, [7, 20] analyzed the segmentation of different glioma sub-regions in pre-operative mpMRI checks, surveyed the chance of tumor sub-regions developing over the long haul to evaluate conceivable tumor progression past the use of RECIST/RANO criteria, and forecasted generally endurance in view of pre-operative mpMRI sweeps of patients going through gross all out resection.

Filtering, contrast enhancement, edge detection, and postprocessing techniques including histogram, threshold, segmentation, and morphological operation are only a few of the approaches for MRI image preprocessing and postprocessing that are covered in this article [8, 9].

This study expands on efforts to detect and classify tumors in their benign stage [10,15–16]. The proposed approach consists of two stages: feature extraction and classification. First, texture characteristics were extracted from the MRI images using Grey Level Cooccurrence Matrix (GLCM) based techniques. Next, the images were classified using the K-nearest Neighbour (K-NN) classifier.

The application of deep learning algorithms to segment brain tumors and their surrounding regions in MRI sequences will be further examined in [11].

We at first show in [12] that each neighborhood change might be approximated to the closest summed up 2-D Gaussian utilizing geometric moments. We next show how proportions between the first and recomputed geometric moments might be utilized as picture highlights in a classifier-based way to deal with pick the suitable sort of global image processing.

The goal of this research, as stated in [13], is to emphasize the advantages and disadvantages of earlier suggested segmentation techniques that have been looked at in current literature. In addition to providing a summary of the literature, the paper provides a critical evaluation of the examined material, highlighting new directions for future research. To describe a new method is beyond the scope of this work.

In this work, an intelligent system is developed to identify brain tumors using MRI by combining image processing clustering techniques like fuzzy C Means with intelligent optimization tools including genetic algorithms (GA) and particle swarm optimization (PSO)[14]. The first and second steps in the tumor detection process are preprocessing and enhancement and segmentation and classification, respectively.

The suggested FIS approach provides a potential addition to the identification of tumors in brain imaging in[14, 18]. The FIS approach develops fuzzy rules to help in picture segmentation.
By introducing a unique method for the automated segmentation of prostate MRI data, Jin, Yang, and Fang [19] address a crucial gap in the diagnosis and treatment planning of prostate cancer. The suggested technique, dubbed 3D PBV-Net, combines a specific 3D neural network for segmentation with bicubic interpolation for preprocessing. Tested on clinical datasets (PROMISE 12 and TPHOH) using hand delineations as the ground truth, it shows remarkable performance with low Hausdorff and boundary distances, high Dice metric scores, and high average accuracy. This method greatly improves prostate MRI data segmentation accuracy, which makes it appropriate for telehealth applications in the treatment of prostate cancer.
Alonso-Álvarez D., Wu Y., and Hatipoglu S. [21] With cardiac magnetic resonance (CMR) imaging, the suggested system offers a novel method to improve the precision of left ventricular myocardial velocity mapping (3Dir MVM). This quick and automated method uses multi-channel data, such as magnitude and phase velocity mapping, to enrich a U-Net-based model with cross-channel fusion via the use of an attention module. Moreover, it uses post-processing based on shape information to accurately define the contours of the endocardium and the epicardium. Myocardial longitudinal peak velocities are measured and Dice Scores are used to assess the system's performance. The system performs better than single-channel U-Net-based networks. This method has the potential to enhance the analysis of 3Dir MVM CMR data in clinical settings.
By using a multi-encoder model, Zhang W., Yang G., and colleagues' suggested approach [22] tackles the

difficult job of 3D MRI-based glioma segmentation. This model allows for efficient feature extraction and consists of four encoders, each of which corresponds to a different MRI modality. A single decoder is then created by combining the extracted characteristics. To address the problem of voxel imbalance, we provide a new loss function called "Categorical Dice" and use weighted segmentation for various areas. Our technique outperforms state-of-the-art methods in assessments on the BraTS 2020 Challenge, showing encouraging results with Dice scores of 0.70249, 0.88267, and 0.73864 for complete tumor, tumor core, and improved tumor segmentation, respectively.

Yang G., Hosseiny M., Liu Y., and [23] Using multi-parametric MRI (mpMRI), our suggested approach automatically segments the prostate's transition zone (TZ) and peripheral zone (PZ) while estimating uncertainty. This is achieved via the use of spatial attentive Bayesian deep learning. Utilizing both internal and external testing datasets, we assessed our approach and obtained mean Dice Similarity Coefficients (DSC) for PZ and TZ segmentation on the internal testing dataset of 0.80±0.05 and 0.89±0.04, and 0.79±0.06 and 0.87±0.07 on the exterior testing dataset. Our technique demonstrated better diagnostic potential for prostate cancer assessment than previous approaches and surpassed them in highlighting segmentation ambiguity at important intersections.

3. Methodology

They have recently recommended a Multi-Encoder Network (ME-Net) design for segmenting 3D MRI images that reduces the test of feature extraction. This engineering utilizes an original misfortune capability called "Categorical Dice." Furthermore, they involved different loads for unmistakable divided region of the 3D MRI check to address the voxel imbalance problem. By the by, this model's division results are inadequate for the multi-class division challenge and the tumor's increasing tumor area. They recommended a FCM strategy for distinguishing brain MR images in one more system that was at that point set up. However, for the group individuals to impart naturally, this procedure was expected for exact part definition. The researchers recommended utilizing gray level co-occurrence matrix(GLCM) based highlights, which extricate data from brain images, to lessen this issue.

Drawbacks:

1. 1. There is inadequate improvement of the brain tumor area by the ongoing Multi-Encoder Network (ME-Net) plan with the 'Categorical Dice' deficit capability. This limitation might bring about wrong diagnosis and insufficient preparation for therapy.
2. 2. Multi-class segmentation issues, which are significant for separating between various brain tumor kinds or locations, are a test for the ongoing methodology. Its powerlessness to give a careful assessment of the MRI images is hampered by this requirement.
3. 3. Albeit the ongoing strategy gives different loads to different segmented areas with an end goal to address the voxel imbalance issue, it will be unable to completely resolve this issue, which could bring about inaccurate tumor diagnosis.
4. 4. In another system that is as of now being used, precise human determination of bunch individuals is important to utilize the FCM calculation for brain MR images distinguishing proof. This manual inclusion might add subjectivity to the cycle and consume a large chunk of the day.

Human brain tumors provide a significant and sometimes fatal challenge in modern medicine, often with disastrous outcomes. The lives of individuals affected by these tumors get more difficult as they grow, highlighting how crucial early discovery is to prolonging and maintaining life. With a unique technique to brain tumor identification in magnetic resonance imaging (MRI) data, our suggested system meets this urgent requirement. By using the template-based K-means (TK) algorithm together with principal component analysis (PCA) and superpixels, our system can identify human brain cancers with remarkable efficiency and at a much shorter execution time. Accuracy is increased by carefully extracting important characteristics using PCA and superpixels. TK-means clustering enables accurate tumor segmentation, while image enhancing algorithms further improve the findings. The system's superiority is confirmed by the experimental results, which demonstrate increased accuracy and significant execution time savings. Our suggested method is ready to transform MRI-based brain tumor diagnosis, providing promise for better patient outcomes and lives saved. We will integrate U-Net with CNN as an extension to obtain higher accuracy, and we will embrace sophisticated algorithms like K-means. Furthermore, thorough exploratory data analysis—which includes scaling and resizing images—helps prepare the dataset and guarantees the stability and dependability of the system.

Benefits:

1. 1. The proposed system provides better tumor detection capabilities, particularly with regard to enlarging the tumor area. This improvement may result in more accurate diagnosis and improved patient treatment planning.
2. 2. The suggested approach outperforms the proposed system in multi-class segmentation, making it possible to identify different brain tumor kinds and locations. This thorough examination offers a more thorough and informative assessment of MRI images.
3. 3. The proposed system successfully addresses the voxel imbalance problem, delivering more exact and adjusted tumor detection outcomes. This ensures that during the segmentation process., each area of interest is sufficiently considered during the segmentation process.
4. 4. The proposed system utilizes state of the art calculations like K-means, CNN, and UNet for automated brain tumor diagnosis, which decreases the prerequisite for human cluster formation. This assists the potential for human error and l streamlines out the detection process.

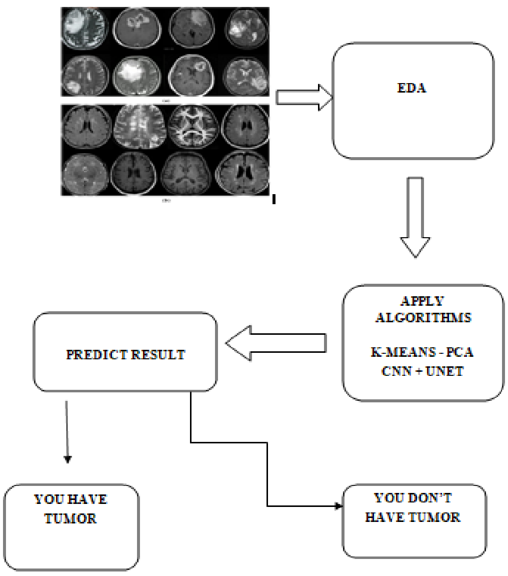

Fig. 2: Proposed Architecture.

Modules:

1. Data exploration: We will bring information into the system utilizing this module.
2. Processing: We will peruse information for Processing by utilizing the module.
3. Splitting data into train and test: This module will be utilized to isolate information into train and test.
4. Model generation: Model building – K – Means, CNN + UNET. Algorithms accuracy calculated.
5. User signup & login: By utilizing this module, you might enroll and sign in.
6. User input: Predictions might be made with the assistance of this module.
7. Prediction: the last Prediction is shown.

4. IMPLEMENTATION

K-MEANS:

One sort of unsupervised machine learning technique that assembles equivalent information focuses is called K-means clustering. To work, the information is partitioned into a predetermined number of clusters, with every information guide having a place toward the bunch whose mean worth is nearest to the cluster's centroid.

The objective of K-means clustering is to partition the information into k groups with the end goal that the data of interest in each group are more scattered and the data of interest in a similar cluster are more comparable. The separation between two focuses decides how comparative they are. There are multiple ways of ascertaining the distance.

The following procedures are usually performed in order to execute K-means clustering:

1. Decide on K, the number of clusters.
2. Set the cluster centroids in motion.
3. Assign every data point to the cluster whose centroid is nearest.
4. Determine the mean of the data points allotted to each cluster in order to update the cluster centroids.
5. Until the cluster assignments remain constant, repeat steps 3 and 4 once more.
6. K-means clustering is a straightforward and effective technique, but it's crucial to remember that it works best with data that is clearly divided into distinct groups. Inaccurate findings using K-means clustering might arise if the data is inaccurate results.

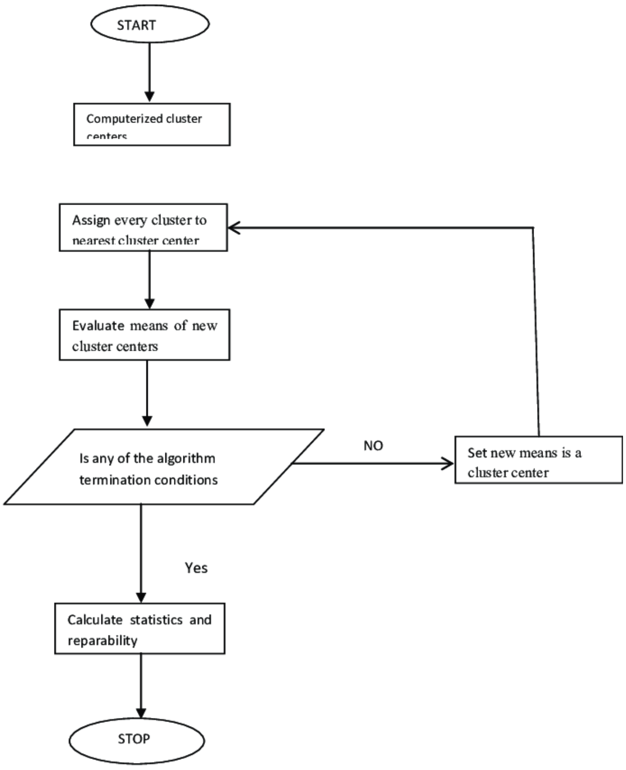

Fig. 3: Algorithm of K -clustering method.

CNN + UNET:

CNN+UNet is a hybrid deep learning design that consolidates UNet and Convolutional Neural Networks (CNNs). While UNet is a specific sort of CNN that is planned for image segmentation, CNNs as a class are unmistakably appropriate for image processing applications.

In various image segmentation tasks, for example, medical image segmentation, remote sensing image segmentation, and natural picture segmentation, CNN+UNet designs might be used to accomplish very high accuracy when consolidated.

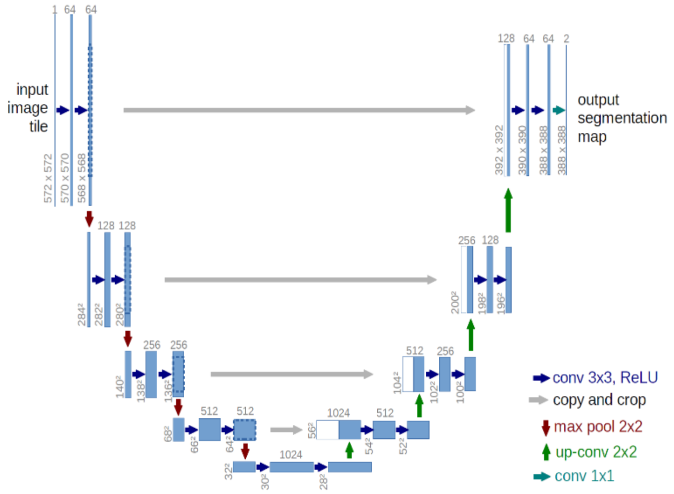

Fig. 4: CNN with UNet model.

5. EXPERIMENTAL RESULTS

The primary webpage of a website is called the front-end home page. It is often the most significant page on a website and is usually the first page people view when they visit it. The screen provided is below:

Fig. 5: Home page.

A webpage that enables visitors to register for an account on a website is known as a front-end registration page. The screen that is seen below is normally found on the website's public pages, making it simple for visitors to register and begin using the site's functions.

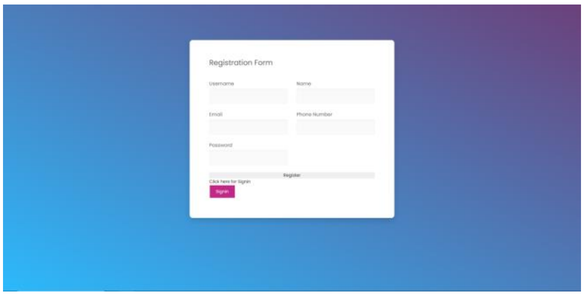

Fig. 6: Registration page.

A web page that enables users to access their accounts on a website is known as a front-end login page. Usually, it is shown on the public sections of the website, making it simple for visitors to register and begin using the resources available there. The displayed screen is under

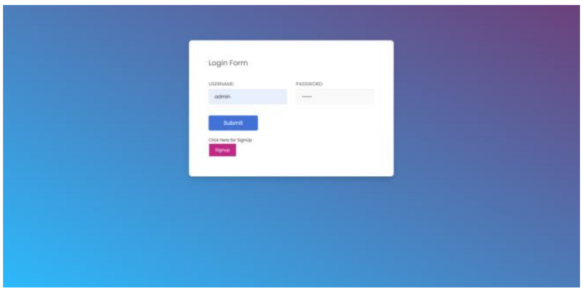

Fig. 7: Login page.

The home page, or front-end main page, is the primary webpage of a website. It is often the most significant page on a website and is usually the first page people view when they visit it.

Usually, the front-end home page is made to be both interesting and educational. It should make it simple for visitors to locate the features or information they're searching for and provide a clear summary of the website's goals. The screen provided is below:

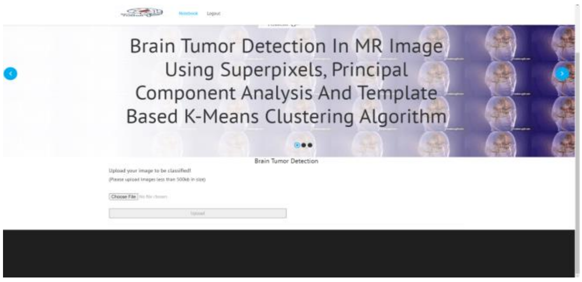

Fig. 8: Main page.

An HTML element known as a front-end upload input picture enables users to choose and upload an image file from their computer to a web server. Usually, the <input> element is used to construct it, with the type attribute set to file. The screen provided is below:

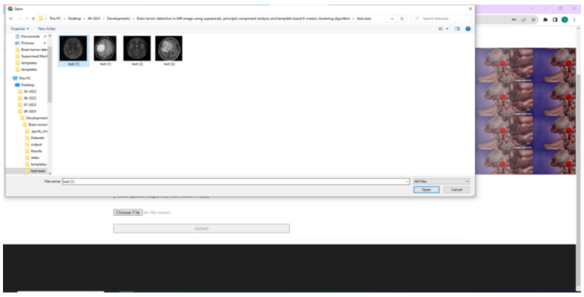

Fig. 9: Upload input image.

The output of a machine learning model that is shown to a user in a web application is called a front-end prediction result. It gives the user details about the forecast, including its likelihood and the model's confidence, and is usually shown as a text box, table, or chart. The screen provided is below:

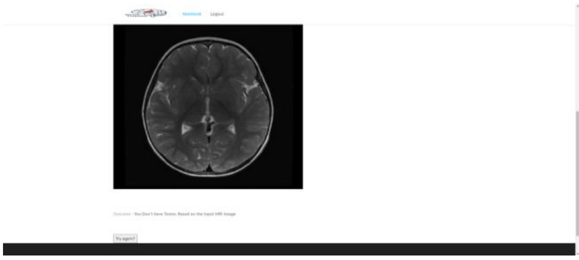

Fig. 10: Prediction result.

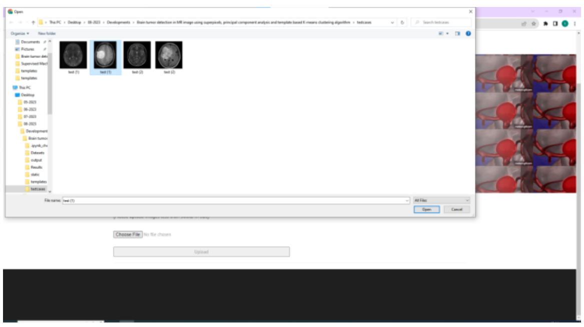

Fig. 11: Upload another input image.

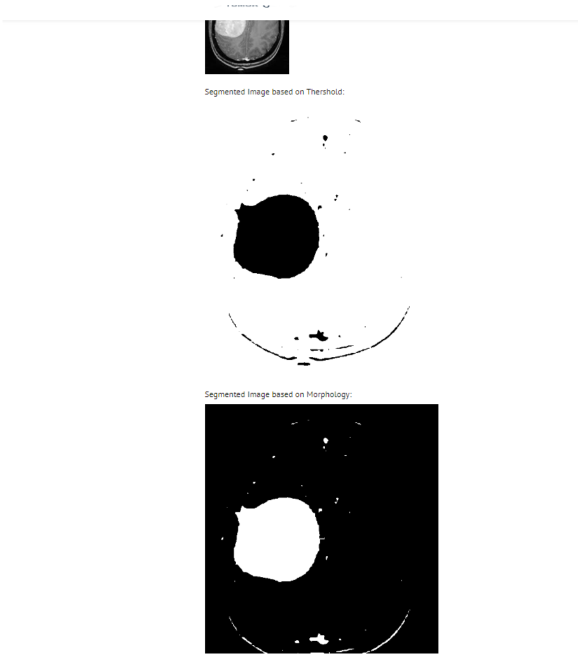

Fig. 12: Input image.

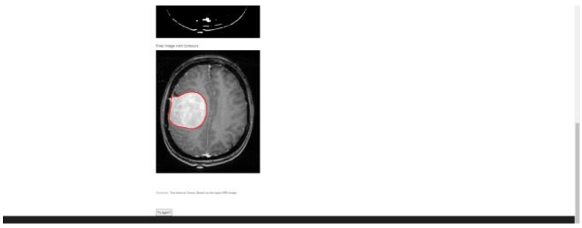

Fig. 13: Prediction result.

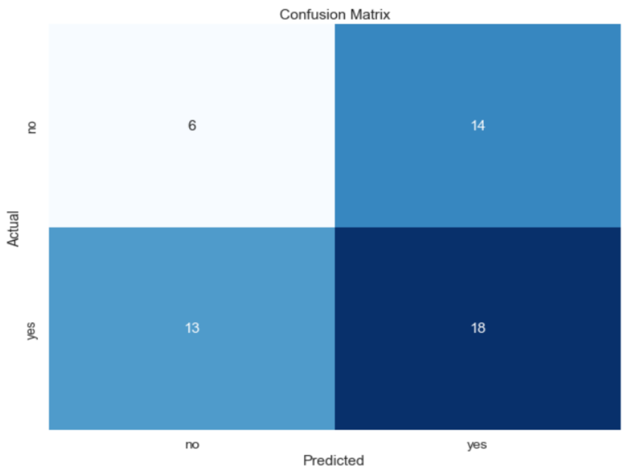

Fig. 14: Confusion Matrix.

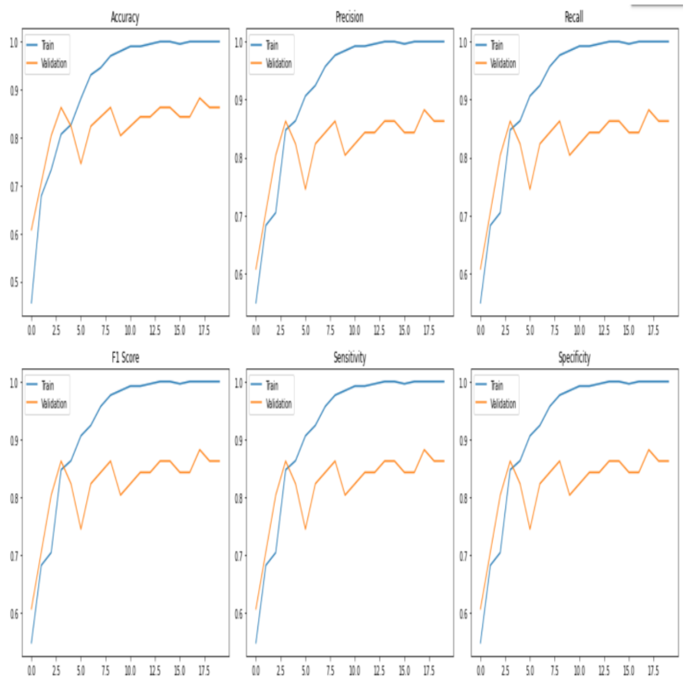

Fig. 15: Accuracy results.

5.CONCLUSION

The performance of the CNN + UNET, PCA & TK-means, and superpixels techniques suggested in this study outperforms that of other detection systems already in use. When compared to other current detection systems, the suggested scheme for brain tumor detection had the greatest accuracy. Additionally, superpixels and PCA are essential for feature extraction, which lowers the MR pictures' size and complexity. Consequently, our proposed technique successfully detects brain cancers from MR images in 35–60 seconds of execution time. A limitation of this research is that it was conducted using a limited dataset and did not use the 2019 WHO International Classification of Diseases (ICD11) system with actual clinical magnetic resonance imaging data.

6. FUTURE WORK

To enhance the detection system, we will examine genuine clinical MR images in the future and extract high-dimensional characteristics from them. Additionally, by identifying the tumor's stage, we will improve the accuracy of detection and categorization. Furthermore, we need to work on the similarity of the plan by integrating a deep learning system that can be utilized to radio imaging modalities like MRI, CT, PET, and SPECT notwithstanding multi-sequential BRATS 3D images.

References

[1]. R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua and S. Süsstrunk, "SLIC Superpixels Compared to State-of-the-Art Superpixel Methods," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 11, pp. 2274-2282, Nov. 2012, doi: 10.1109/TPAMI.2012.120.

[2] Acharya, J., Gadhiya, S., & Raviya, K. (2013). Segmentation techniques for image analysis: A review. International Journal of Computer Science and Management Research, 2(1), 1218–1221.

[3] Alam, M. S., Rahman, M. M., Hossain, M. A., Islam, M. K., Ahmed, K. M., Ahmed, K. T., Singh, B. C., & Miah, M. S. (2019). Automatic human brain tumor detection in MRI image using template-based k means and improved fuzzy c means clustering algorithm. Big Data and Cognitive Computing, 3(2), 27.

[4] Ali, M. S., Miah, M. S., Haque, J., Rahman, M. M., & Islam, M. K. (2021). An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models. Machine Learning with Applications, Article 100036.

[5] Alsabti, K., Ranka, S., & Singh, V. (1997). An efficient k-means clustering algorithm.

[6] Bahadure, N. B., Ray, A. K., & Thethi, H. P. (2017). Image analysis for MRI based brain tumor detection and feature extraction using biologically inspired BWT and SVM. International Journal of Biomedical Imaging, 2017.

[7] Bakas, S., Reyes, M., Jakab, A., Bauer, S., Rempfler, M., Crimi, A., Shinohara, R. T., Berger, C., Ha, S. M., Rozycki, M., et al. (2018). Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge. arXiv preprint arXiv:1811. 02629.

[8] Borole, V. Y., Nimbhore, S. S., & Kawthekar, D. S. S. (2015). Image processing techniques for brain tumor detection: A review. International Journal of Emerging Trends & Technology in Computer Science (IJETTCS), 4(2), 1–14.

[9] Byale, H., Lingaraju, G., & Sivasubramanian, S. (2018). Automatic segmentation and classification of brain tumor using machine learning techniques. International Journal of Applied Engineering Research, 13(14), 11686–11692. cancer. net (2020). https://www.cancer.net/cancer-types/brain-tumor/statistics, Brain Tumor: Statistics.

[10] Chavan, N. V., Jadhav, B., & Patil, P. (2015). Detection and classification of brain tumors. International Journal of Computer Applications, 112(8).

[11] Chithra, P., & Dheepa, G. (2018). An analysis of segmenting and classifying tumor regions in MRI images using CNN. International Journal of Pure and Applied Mathematics, 118(24), 2018.

[12] Coatrieux, G., Huang, H., Shu, H., Luo, L., & Roux, C. (2013). A watermarkingbased medical image integrity control system and an image moment signature for tampering characterization. IEEE Journal of Biomedical and Health Informatics, 17(6), 1057–1067.

[13] Gondal, A. H., & Khan, M. N. A. (2013). A review of fully automated techniques for brain tumor detection from MR images. International Journal of Modern Education and Computer Science, 5(2), 55.

[14] Gopal, N. N., & Karnan, M. (2010). Diagnose brain tumor through MRI using image processing clustering algorithms such as Fuzzy C Means along with intelligent optimization techniques. In 2010 IEEE international conference on computational intelligence and computing research (pp. 1–4). IEEE.

[15] Hebli, A., & Gupta, S. (2017). Brain tumor prediction and classification using support vector machine. In 2017 international conference on advances in computing, communication and control (ICAC3) (pp. 1–6). IEEE.

[16] Husein, E. M., & Mahmoud, D. M. A. (2012). Brain tumor detection using artificial neural networks. Sudan University of Science and Technology.

[17] Islam, M. K., Ali, M., Das, A., Duranta, D. U., & Alam, M. (2020). Human brain tumor detection using K-means segmentation and improved support vector machine. 11, (p. 6).

[18]Janani, V., & Meena, P. (2013). Image segmentation for tumor detection using fuzzy inference system. International Journal of Computer Science and Mobile Computing, 2(5), 244–248.

[19] Jin, Y., Yang, G., Fang, Y., Li, R., Xu, X., Liu, Y., & Lai, X. (2021). 3D PBV-net: an automated prostate MRI data segmentation method. Computers in Biology and Medicine, 128, Article 104160.

[20]kaggle. com (2018). https://www.kaggle.com/navoneel/brain-mri-images-for-braintumor-detection, kaggle datasets

[21] Wu Y., Hatipoglu S., Alonso-Álvarez D., Gatehouse P., Li B., Gao Y., Firmin D., Keegan J., Yang G. Fast and automated segmentation for the three-directional multi-slice cine myocardial velocity mapping, Diagnostics, 11 (2) (2021), p. 346.

[22]Zhang W., Yang G., Huang H., Yang W., Xu X., Liu Y., Lai X. ME-net: Multi-encoder net framework for brain tumor segmentation, International Journal of Imaging Systems and Technology (2021).

[23]Liu Y., Yang G., Hosseiny M., Azadikhah A., Mirak S.A., Miao Q., Raman S.S., Sung K. Exploring uncertainty measures in Bayesian deep attentive neural networks for prostate zonal segmentation, IEEE Access, 8 (2020), pp. 151817-151828.