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BRAIN TUMOUR IDENTIFICATION USING CNN

M. Sandeep[*1], C Bheem Raju[*2], Akireddy Varshini[*3], Battula HimaBindu[*4]

[*1]Associate Professor, Department Of Computer Science And Engineering Malla Reddy College Of Engineering & Technology Hyderabad, India.

[*2,3,4]Final Year Student Department Of Computer Science And Engineering Malla Reddy College Of Engineering & Technology Hyderabad, India.

ABSTRACT

Brain Tumor division is one of the foremost crucial and challenging errands within the territory of therapeutic picture preparing as a human-assisted manual classification can result in wrong forecast and diagnosis. Moreover, it is an exasperating assignment when there's a huge sum of information display to be helped. Brain tumors have tall differences in appearance and there's a likeness between tumor and ordinary tissues and in this way the extraction of tumor locales from pictures gets to be immovable. In this paper, we proposed a strategy to extricate brain tumor from 2D Attractive Reverberation brain Pictures (MRI) by Fluffy C-Means clustering calculation which was taken after by conventional classifiers and convolutional neural organize. The test ponder was carried on a real-time dataset with different tumor sizes, areas, shapes, and diverse picture force. In conventional classifier portion, we connected six conventional classifiers specifically Bolster Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Calculated Relapse, Naïve Bayes and Arbitrary Woodland which was executed in scikit - learn. A while later, we moved on to Convolutional Neural Network (CNN) which is actualized utilizing Keras and Tensorflow since it yields to distant better; a much better; a higher; a stronger; an improved"> an improved execution than the conventional ones. In our work, CNN picked up an exactness of 97.87%, which is exceptionally compelling. The most point of this paper is to recognize between ordinary and unusual pixels, based on surface based and factual based highlights.

I. INTRODUCTION

Medical imaging involves various non-invasive techniques to examine the internal structures of the body, encompassing different modalities and processes for diagnostic and treatment purposes. This plays a crucial role in healthcare by facilitating actions for improving people's health.

Image segmentation is a vital step in medical image processing, significantly influencing the success of higher-level processing. In the medical field, it is particularly crucial for tasks such as tumor or lesion detection, enhancing machine vision, and achieving satisfactory results for further diagnosis. Addressing the challenge of improving sensitivity and specificity in tumor or lesion detection has become a central concern, often tackled through Computer-Aided Diagnostic (CAD) systems.

Brain and other nervous system cancers rank as the 10th leading cause of death, with a five-year survival rate of 34% for men and 36% for women with cancerous brain conditions. According to the World Health Organization (WHO), approximately 400,000 individuals worldwide are affected by brain tumors, resulting in 120,000 deaths in recent years. Additionally, it is estimated that around 86,970 new cases of primary malignant and non-malignant brain and Central Nervous System (CNS) tumors were expected to be diagnosed in the United States in 2019.

A brain tumor is a result of abnormal cell formation within the brain, classified into two main types: Malignant and Benign. Malignant tumors, originating in the brain, grow rapidly, invade surrounding tissues aggressively, and can spread to other parts, affecting the central nervous system. They are further categorized into primary tumors (originating in the brain) and secondary tumors (spreading from elsewhere), known as brain metastasis tumors. In contrast, benign brain tumors consist of slowly growing cell masses.

Detecting brain tumors early is crucial for improving treatment possibilities and increasing survival rates. However, manually segmenting tumors or lesions is a time-consuming and challenging task due to the large number of generated MRI images in medical routines. Magnetic Resonance Imaging (MRI) is commonly used for brain tumor detection. The segmentation of brain tumors from MRI images is a critical task in medical image processing, given the substantial amount of data involved and the often ill-defined boundaries of tumors with soft tissues.

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The paper proposes an efficient method for automated segmentation and detection of brain tumors without human assistance. The approach combines traditional classifiers and Convolutional Neural Networks (CNNs) to enhance the accuracy of tumor segmentation from MRI images, addressing the extensive and complex nature of the task.

II. LITERATURE REVIEW

Segmenting the region of interest (ROI) from an object, particularly when dealing with tumor segmentation in MRI brain images, is a challenging and demanding task. Researchers worldwide are actively working on advancing this field, exploring various approaches to achieve optimal segmented ROIs from distinct perspectives. The use of Neural Network-based segmentation has gained prominence due to its notable outcomes, and its application is increasing day by day.

Devkota et al. [1] proposed a segmentation process based on Mathematical Morphological Operations and the spatial FCM algorithm, aiming to improve computation time. However, their solution has not been evaluated thoroughly, showing a 92% cancer detection rate and an 86.6% classifier accuracy.

Yantao et al. [2] employed a Histogram-based segmentation technique for brain tumor segmentation, treating it as a three-class classification problem involving FLAIR and T1 modalities. They achieved a Dice coefficient of 73.6% and a sensitivity of 90.3% by using region-based active contour models on FLAIR and k-means method on T1 for detecting abnormal regions.

Badran et al. [3] utilized edge detection approaches, combining Canny edge detection with Adaptive thresholding to extract the ROI. Their method, applied to a dataset of 102 images, showed improved accuracy in comparison to other models.

Pei et al. [4] introduced a technique incorporating tumor growth patterns as novel features for longitudinal MRI tumor segmentation. The model, using label maps and various texture features, demonstrated promising results with Mean DSC values of 0.819302 and 0.82122.

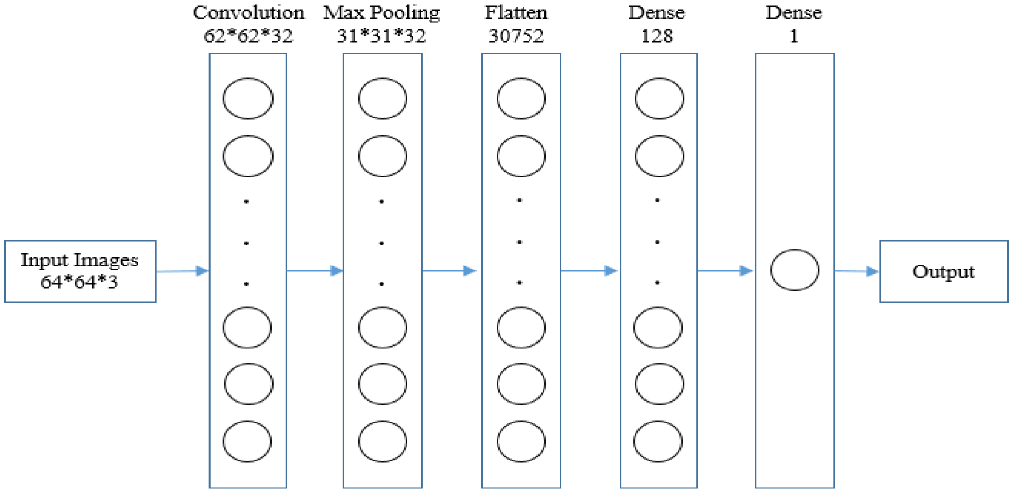
Dina et al. [5] proposed a model based on the Probabilistic Neural Network and Learning Vector Quantization, reducing processing time by 79%. Othman et al. [12] implemented a Probabilistic Neural Network with Principal Component Analysis, achieving accuracy ranging from 73% to 100%.

Rajendran et al. [6] focused on Region-based Fuzzy Clustering and deformable models, achieving 95.3% and 82.1% of ASM and Jaccard Index based on an Enhanced Probabilistic Fuzzy C-Means model. Zahra et al. [14] used the LinkNet network for tumor segmentation, achieving a Dice score of 0.73 for a single network and 0.79 for multiple systems, without requiring preprocessing steps rewrite it.

III. METHODOLOGY

PROPOSED METHODOLY USING CNN

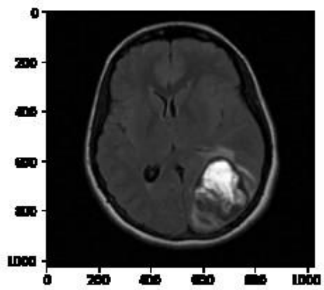
Convolutional Neural Network is astronomically used in the field of Medical image processing. Over the times lots of experimenters tried to make a model which can descry the excrescence more efficiently. We tried to come up with an exemplary which can directly classify the excrescence from 2D Brain MRI images.



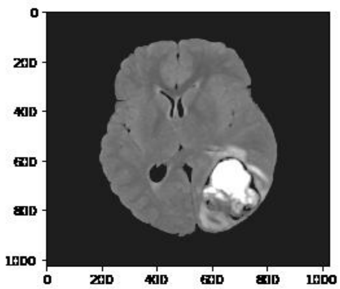
A completely- connected neural network can descry the excrescence, but because of parameter sharing and sparsity of connection, we espoused CNN for our model. A Five- Subcaste Convolutional Neural Network is introduced and enforced for excrescence discovery. The added up model conforming of seven stages including the retired layers provides us with the most prominent result for the apprehension of the excrescence. Following is the proposed methodology with a brief narrationUsing convolutional subcaste as the freshman subcaste, an input shape of the MRI images is generated which is 64 * 64 * 3 converting all the images into a homogeneous dimension. After accumulating all the images in the same aspect, we created a convolutional kernel that's convoluted with the input subcaste — administering with 32 convolutional pollutants of size 3 * 3 each with the support of 3 channels tensors. ReLU is used as an activation function so that it's not corroborating with the affair. In this ConvNet armature, precipitously dock the spatial size of the definition for dwindling the knob of parameters and computational time of the network. Working on the Brain MRI image can also bring the impurity of the overfitting and for this Max Pooling subcaste impeccably works for this perception. For spatial data which substantiate with our input image, we use MaxPooling2D for the model. This convolutional subcaste runs on 31 * 31 * 32 dimension. Because of peak the input images in both spatial confines, the pool size is(2, 2) which means a tuple of two integers by which to downscale by vertically and horizontally. After the pooling subcaste, a pooled point chart is attained. leveling is one of the essential layers after the pooling because we 've to converted the whole matrix representing the input images into a single column vector and it's imperative for processing. It's also fed to the Neural Network for the processing. Two completely connected layers were employed thick- 1 and thick- 2 represented the thick subcaste. The thick function is applied in Keras for the processing of the Neural Network, and the attained vector is work as an input for this subcaste. There are 128 bumps in the retired subcaste. Because the number of dimension or bumps commensurable with the computing coffers we need to fit our model we kept it as moderate as possible and for this perspective 128 bumps gives the most substantial result. ReLU is used as the activation function because of showing better confluence performance. After the first thick subcaste, the alternate completely connected subcaste was used as the final subcaste of the model. In this subcaste, we used sigmoid function as activation function where the total number of the knot is one because we need to lower the uses of computing coffers so that a more significant quantum assuages the prosecution time. Though there's a chance of hampering the literacy in deep networks for using of the sigmoid as the activation function, we gauge the sigmoid function, and the number of the bumps is important lower and easy to handle for this deep network.

IV. RESULT AND ANALYSIS

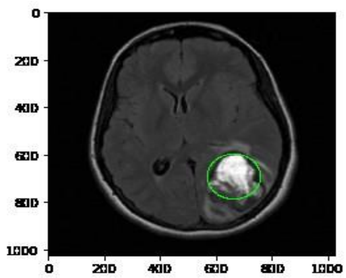
To justify our proposed model, way of segmenting the excrescence from 2D Brain MRI is and a relative analysis of our proposed models of bracket using machine literacy, and deep literacy is shown. We got92.42 of delicacy using SVM and97.87 of delicacy is achieved using CNN. For Performance Evaluation of our proposed model, we used the brain excrescence dataset in the field of Brain Tumor Segmentation, conforming two classes ' — class-yea and class- no represents the Non-Tumor and Tumor MRI images. 187 and 30 MRI Images containing excrescence andnon-tumor independently classified as class- 1 and class- 0. All the images are MRI images from different modalities like- T1, T2, and faculty. For traditional machine learning classifiers, we attained the superlative result unyoking the dataset by 70 to 30 in terms of training to testing images, and for CNN, we divided the dataset in both 70 to 30 and 80 to 20 conformation and compared the issues. Grounded on our proposed methodology, we segmented the excrescence without loss of any subtle information. We removed the cranium because for excrescence segmentation the part of cranium is roughly null and nebulous in this process.



1. Input image



2. Image segmentation



3. Tumor Decetion

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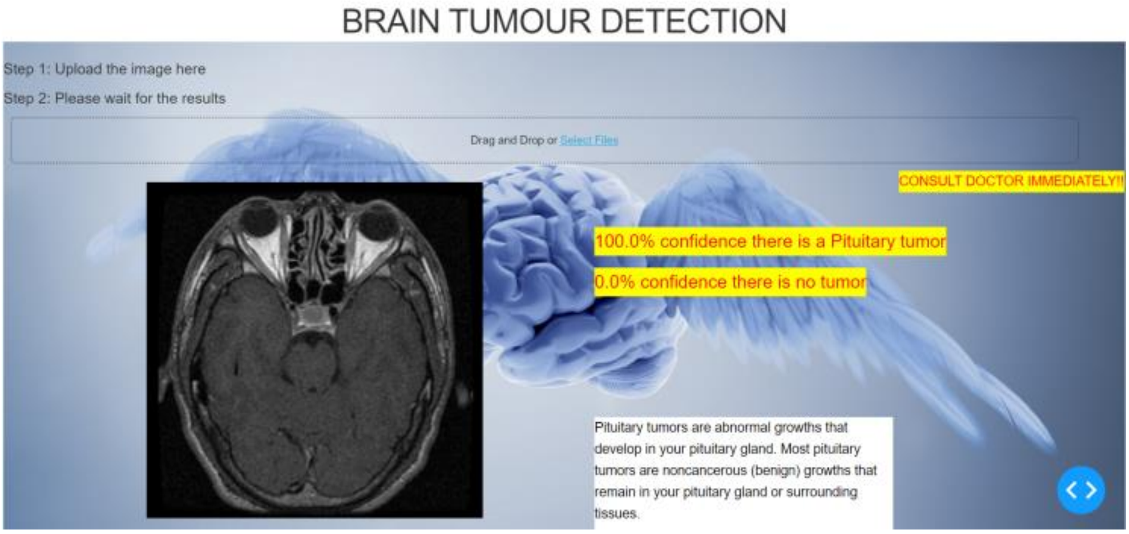
PERFORMANCE OF CNN MODEL

SNO	Training image	Testing image	Splitting ratio	Accuracy
1	162	45	70:30	96.8
2	153	67	80:20	97.0
3	176	53	60:40	95.7

SAMPLE OUTPUT SCREEN



V. CONCLUSION

In conclusion, our proposed method for brain tumor extraction from 2D Magnetic Resonance Imaging (MRI) has demonstrated promising results in addressing the challenges associated with manual classification and the variability in tumor appearance. The utilization of Fluffy C-Means clustering algorithm as a preprocessing step, followed by a combination of traditional classifiers and Convolutional Neural Network (CNN), has proven to be effective in accurately identifying tumor regions.

We conducted extensive experiments on a real-time dataset, encompassing diverse tumor sizes, locations, shapes, and image intensities. The traditional classifiers, including Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Linear Regression, Naïve Bayes, and Random Forest, were employed in the initial stage. However, the subsequent integration of Convolutional Neural Network (CNN) using Keras and Tensorflow demonstrated superior performance, achieving an impressive accuracy of 97.87%.

The primary objective of our work was to differentiate between normal and abnormal pixels based on both texture-based and statistical-based features. By leveraging the power of deep learning through CNN, we achieved a robust and efficient system for brain tumor extraction, overcoming the limitations associated with manual classification. The high accuracy obtained with our proposed method signifies its potential for aiding medical professionals in accurate and timely diagnosis, ultimately contributing to improved patient outcomes in the field of neuroimaging. The successful integration of advanced image processing techniques and machine learning algorithms in this study opens avenues for further research and development in the domain of medical image analysis for brain tumors.

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