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An Artificial Intelligence System for Brain Tumor Detection from Medical Imaging

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***Abstract* - Any part of the brain might get affected by tumors, which can have irregular shapes and borders. In around twenty-five days, their size doubled due to their rapid growth. Patients may experience a number of health issues, including mortality, if they are not identified in their early stages. Consequently, early detection of brain tumors is one of the most important factors. Furthermore, a successful imaging sequence is essential for the diagnosis of tumors. Among the several scanning techniques, magnetic resonance imaging, or MRI, is frequently utilized.**

Researchers have recently developed numerous methods; however, they yield limited accuracy due to the variations in tumor characteristics, image noise variations, irregular boundary pixels, and intensity non-uniformity in MRI images. Hence, this paper suggests three Computer-Aided Diagnosis (CAD) frameworks for classifying and detecting brain tumors from MRI images.

The suggested framework employs Convolutional Neural Networks (CNN) with ResNet50 encoding to develop an automated methodology for detecting brain tumors from MRI images. Initially, we use the skull-stripping process to remove non-brain matter like muscle, skin, fat, and eyeballs. After that, we employ the CNN model to predict the abnormalities of brain MRI images. From the experimental outcomes of the approaches mentioned above, we observed that they significantly enhance the diagnosis performance compared to the state-of the-art methods by minimizing the impact of noise and intensity non-uniformity in MRI images. Hence, the proposed models provide the Percentage Correct Classification by CNN+ResNet50 for radiologists to diagnose brain tumors.

Index Terms* - *Magnetic Resonance Imaging (MRI), Brain tumor, Computer-Aaided Diagnosis (CAD), Support Vector Machine (SVM), Principal Component Analysis (PCA), Convolutional Neural Networks (CNN), etc.

I. Introduction

Malignant growths that either originate in the brain or migrate there from different portions of body are known as brain tumors. Numerous types of brain cells, such as neurons, glial cells, and supporting tissue, can give rise to these tumors. Medical researchers find it challenging to study brain tumors because of the complexity of the brain's anatomy. In order to accurately diagnose, plan treatment, and manage patients, it is necessary to have a good grasp of the anatomy of brain tumors. The brain is a very complicated organ with many different parts and structures, each of which has a specific job to do. The size, position, and shape of brain tumor can have a substantial impact on a person's symptoms and potential course of therapy.[1]. Understanding the different parts of the brain is essential to understanding the anatomy of brain tumors. The medulla, diencephalon, cerebellum, and cerebrum are the four main parts of the brain. Higher cognitive processes including thinking, memory, and voluntary movement are controlled by the cerebrum, the biggest part of the brain. Coordination and motor control depend on the cerebellum. Essential functions like breathing and heart rhythm are controlled by the brainstem, which joins the brain to the spinal cord. The thalamus and hypothalamus are both located in the diencephalon, two organs essential in hormone regulation and sensory processing. The diencephalon contains the thalamus and hypothalamus, two organs essential in hormone regulation and sensory processing.

Cerebral tumors, for example, might result in seizures, motor impairments, personality abnormalities, and cognitive impairment. On the other hand, cerebellar tumors can impair fine motor skills, balance, and coordination [2]. While diencephalic tumors can disrupt hormone balance and endocrine functioning, brainstem tumors can impair speech, breathing, and facial movement. Additionally, brain tumors can be categorized based on their histology, behavior, and place of origin. Gliomas, meningiomas, pituitary adenomas, and other types are further classifications for primary brain tumors. However, tumor cells that have spread to other parts of body are the source of secondary brain tumors. Brain tumors are often diagnosed and treated by neurosurgeons, neurologists, oncologists, radiologists, and other medical specialists. In order to visualize and characterize brain tumors and enable precise diagnosis as well as treatment therapy, advanced imaging methods like Positron Emission Tomography exams and Magnetic Resonance Imaging are essential [3].

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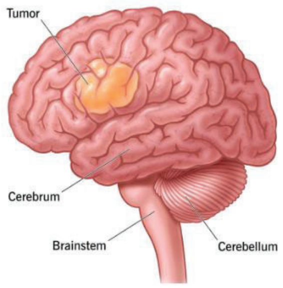

Fig 1 Brain Tumors

A. *The Brain Tumor*

A mass of living cells is called a brain tumor that develop uncontrollably in or around the brain. A tumor, on the other hand, is a mass of abnormal tissues that is filled with fluid. The principal brain tumors as well as secondary brain tumors, also referred to as metastatic brain tumors, are the two principal types of brain cancer. Primary tumors cannot expand to other parts of the body; they start in the brain. They are often divided into two categories: malignant (cancerous) and benign (non-cancerous).

Benign tumors slowly grow, have different boundaries, and rarely spread to nearby brain tissues. However, being placed in a vital area may lead to death. Similarly, malignant tumors proliferate, have uneven boundaries, and spread into nearby tissues. Secondary tumors originate somewhere in the body and disseminate into the brain. Typically, they arise when the active cells are carried in the bloodstream. The most frequent cancers that diffuse into the brain are breast and lung cancers [4].

Brain tumors are categorized by the WHO as Grade I through IV [5]. Tumors that are classified as Grade I and II are referred to as LG tumors, whereas those that are classified as Grade III and IV are mentioned to as HG tumors. Grade - I tumors are typically treated as benign, whereas Grade-II tumors can develop into HG and exhibit recurrent behavior. Malignant tumors of grades III and IV have been identified.

B. *Brain Tumors Types*

The USA National Brain Tumor Society (NBTS) reports that there are over 130 different types of brain tumors. Here, we identified a few types of brain tumors provided by the America Association of Surgeons (AANS) (Tiwari et al., 2020). Figure 2 illustrates different kinds of brain tumors; Figure 1.2 represents the classification of gliomas; and Figure 3 shows the different types of brain tumors provided by the WHO [7].

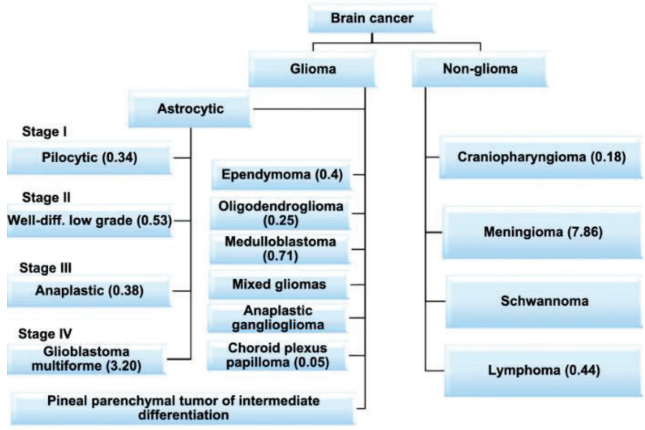

Fig 2 The brain tumors Classification

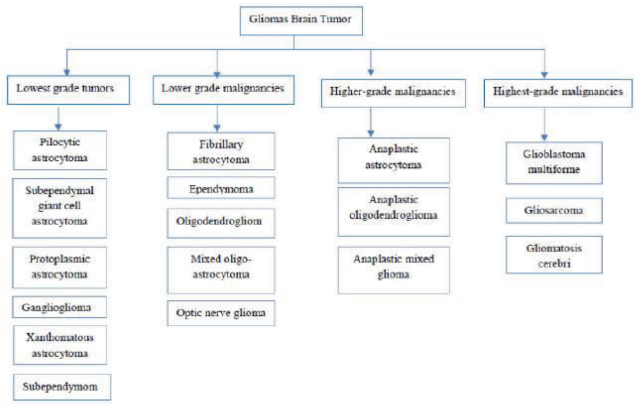

Fig 3 The glioma brain tumors Classification

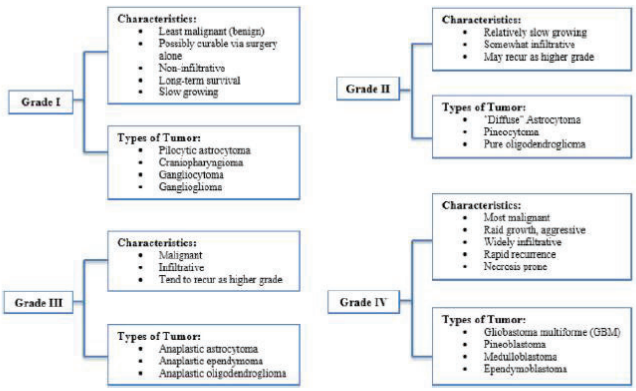

Fig 4 Classification of brain tumors according to WHO

C. *Symptoms of Brain Tumors*

The kind of brain tumor determines the symptoms, location, and size; however, most brain tumors have the following symptoms:

1. Headache: It was the predominant symptom, as reported by 46% of the patients. A tension-type headache is a common initial symptom of a brain tumor and is often the most prevalent manifestation in the context of cancer. Headaches resulting from a brain tumor exhibit distinctive characteristics compared to other headaches. The discomforts mentioned above frequently exacerbate over time and may not respond to non-prescription analgesics. The symptoms may include

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nausea or vomiting, exacerbating when assuming a supine position, bending forward, or straining during defecation.

2. Seizures: The second most frequently reported symptom was a seizure, as reported by 33% of patients before diagnosis. Epilepsy, high fevers, stroke, trauma, and other disorders are just a few additional causes of seizures. This manifestation should be given due attention and not disregarded, irrespective of its underlying etiology. In individuals with no prior history of seizures, such an event typically suggests a severe underlying condition, necessitating a cerebral imaging procedure. A seizure is an abrupt and involuntary alteration in behavior, muscle coordination, consciousness, and perception. The manifestations of a seizure can vary from abrupt, forceful convulsions and complete loss of awareness to muscular spasms or minor tremors in a limb. Some other behaviors that an individual may display during a seizure include gazing into the distance, visual distortions, and impaired speech. It has been reported that around 10% of individuals residing in the United States will encounter a solitary episode of seizure during their lifetime.

3. Vision or hearing problems: Twenty-five percent of the people reported experiencing issues with their vision. It is imperative to seek medical attention to detect auditory or visual impairments. It is frequently asserted that ophthalmologists are often the first medical professionals to identify elevated intracranial pressure, as the ocular examination may reveal indicative manifestations that warrant further investigation.

4. Nausea and vomiting: Similar to headaches, the symptoms of nausea and vomiting are non-specific, indicating that most individuals experiencing these symptoms are not afflicted with a brain tumor. As per the MUSELLA Foundation for Brain Tumour Research and Information findings, a significant proportion of individuals, i.e., 22 %, reported experiencing nausea and vomiting symptoms. The presence of nausea or vomiting in conjunction with the other symptoms delineated herein may suggest a higher likelihood of a brain tumor.

5. Behavioral, cognitive, and neuromuscular problems: Numerous behavioral and cognitive alterations have been reported, including difficulties with short-term memory, impaired concentration, and verbal fluency; impulsive behavior characterized by low patience and tolerance; and decreased inhibitions leading to inappropriate verbal or physical actions. People might have issues with the weakness of their upper or lower extremities, facial musculature, and strange sensations in the cranial or manual regions. Twenty-five percent of the patients reported experiencing weakness in their upper or lower extremities. Approximately 16 % of the participants reported experiencing anomalous sensations in the cranial area, while 9 % reported experiencing anomalous phenomena in the manual extremities. The conditions mentioned above may lead to modifications in the individual's gait, unintentional release of objects, loss of balance, or a facial expression that is not symmetrical. These symptoms could also indicate the occurrence of a stroke. The abrupt manifestation of these symptoms necessitates urgent medical attention, prompting a visit to the emergency department. If you observe a gradual alteration, you must notify your physician.

II. LITERATURE REVIEW

A crucial area of medical is detection and classification of brain cancers, which entails analyzing brain images and determining the existence of tumors using sophisticated imaging methods and machine learning algorithms. Benign (non-cancerous) or malignant (cancerous) brain tumors are aberrant cell growths in the brain or surrounding tissues. The steps used to detect and categorize brain tumors are pre-processing, segmentation, feature extraction, and classification. This chapter aims literature survey on above stages. For the Image Acquisition or Image modalities stage, survey of the different modalities; like, MRI, CT scan, PET etc. For Pre-processing of the MRI Brain Images, survey of the different filters; like, wiener filter, anisotropic filter, median filter, non-local means filter, combined filters, etc. was described. For Segmentation of the MRI image, survey of the various multithresholding algorithm of the MRI images was described. For Feature extraction of Brain MRI Images, survey of different Feature Extraction methods; like, DWT, GLCM, LBP, etc. was described. In For Feature Classification of the MRI Images, survey of different classification methods; like, SVM, CNN, etc. was described.

ASSAS Ouarda, et.al (2023) conducted study on "Fuzzy Segmentation of MR Brain Real Images Using Modalities Fusion" This work aims to improve brain MRI segmentation by fusing information from different modalities using Fuzzy C-Means approach. With the availability of more data from different sources, multi-modality image fusion seeks to obtain more inferences than a single modality can provide. The adopted fusion approaches were compared using four criteria, and the experimental results on real MR brain images showed that the fusion approaches were more accurate and robust than the standard FCM approach [7].

Guoyang xie,et.al (2022) presented study on "Cross-Modality Neuroimage Synthesis: A Survey" Multi-modality imaging can improve disease diagnosis as well as reveal clear variations in tissues, but gathering fully-aligned as well as paired data is costly and impractical. Cross-modality synthesis using unsupervised or weakly-supervised learning approaches can be an alternative solution to synthesize missing neuroimaging data. This work offers a thorough analysis of cross-modality synthesis for neuroimages, covering datasets, synthesis-based downstream applications, evaluation metrics, loss functions, weakly-supervised and unsupervised situations, and modality ranges. The paper also highlights the challenges for cross-modality image detection [8].

Javaria Amin et.al (2022) presented study on "Brain tumor detection and classification using machine learning: a comprehensive survey" Brain tumor detection remains a difficult endeavor because tumors differ in size, shape, and position. The goal of this survey is to present an extensive assessment of the literature on MRI's use in brain tumor identification. The survey discusses DL, TL, and quantum ML for brain tumor analysis, and the anatomy of brain tumors, publically available datasets, augmentation methods,

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segmentation, feature extraction, and classification. To assist researchers in this area, it also offers significant survey on the detection of brain tumors, along with information on its benefits, drawbacks, advancements, and future trends [9].

Tulasi Gayatri Devi, et.al (2023) conducted study on "Analysis & Evaluation of Image Filtering Noise reduction technique for Microscopic Images" This paper discusses the use of advanced digital image processing techniques in the area of microscopy for accurate cell classification. To eliminate noise and other unwanted material that could lead to errors in image processing methods, preprocessing is a crucial step. The Wiener and Median filters are suggested in the paper as ways to reduce noise in microscopic images. The median filter outperformed the Wiener filter in terms of PSNR, which may be utilized for improved picture classification in subsequent stages, when the filters were evaluated for denoising accuracy. 35 real-time photos with Gaussian noise were used to test the suggested approach [10].

Anitha S, et.al (2023) conducted study on "Analysis of Filtering and Novel Technique for Noise Removal in MRI and CT Images" MRI is a non-invasive procedure that creates sharp images of tissue and organs using radio and magnetic waves without the use of dangerous radiation. It is essential for the detection and management of prostate, foot, ankle, and brain cancer. However, a variety of noise sources, including Gaussian noise, salt & pepper noise, as well as speckle, can make it difficult to get precise images. Noise removal filters such as Wiener, KSL, and median filters are employed to address this. This article discusses and compares the performance of median and Wiener filtering algorithms in removing noise from MRI and CT images, and evaluates the image quality using metrics like PSNR, RMSE, and MSE [11].

Md. Alamin Talukder a, et.al (2023) presented study on "an effective identification and analysis for brain tumor diagnosis using an efficient machine learning technique". The use of machine learning diagnostic image detection can assist surgeons in clinical diagnostic of brain tumor disease, but it needs a bulk amount of labeled data for effective detection. Diagnosing the disease is crucial to prevent its rapid rise, and a novel Tiger-based Support Vector Machine technique was proposed for this purpose. The technique involves preprocessing, feature extraction, prediction, and segmentation stages, which utilize the wiener filter and GLCM feature extraction method to provide accurate results. The proposed model was compared with other methods using various metrics [12].

S. Ayshwarya Lakshmi, et.al (2023) conducted study on "Enhanced Cuckoo Search Optimization Technique for Skin Cancer Diagnosis Application" The improved cuckoo search algorithm that has been suggested, is used for skin cancer segmentation in a clinical decision system. This algorithm is an effective global optimization strategy that outperforms other conventional approaches in terms of accuracy, precision, specificity, and sensitivity. The enhanced optimization approach accomplished 98.75% as well as 98.95% for Dice & Jaccard coefficient, respectively. The proposed method offers a 23% to 29% improvement over other optimization algorithms and achieves an accuracy of 99.26%. When it comes to segmenting skin cancer image data, the model trained using this measure performs better than those trained with traditional techniques [13].

III. PROPOSED METHODOLOGY

Environmental and genetic factors have contributed to a significant increase in brain tumor-related clinical cases in recent years, especially in adults. There is a chance of serious health issues, including death, if they are not detected in the early stages. Therefore, a patient's health can be improved and treatment therapy is greatly aided by early brain tumor identification. Brain tumors can have different sizes and characteristics, and there are several treatments available for them. Among these, brain tumor identification and categorization by hand is difficult, takes a lot of time, and likely to make errors. On the basis of these findings, we created an automated process for MRI-focused brain tumor detection as well as classification. Three stages make up the suggested work: segmentation, classification, and preprocessing. We began the preprocessing by removing non-brain components including skin, muscle, fat, and eyes by using morphological and thresholding methods to strip the skull. Then, in order to reduce overfitting and increase model accuracy, we used picture data augmentation. We created a new convolutional neural network (CNN) with Resnet50 model later in the classification process to identify aberrant and normal characteristics in enhanced brain MR images without a skull. Lastly, during the segmentation stage, we extracted contaminated tumor areas from the brain MR images [14].

Matlab is used to implement the suggested gland segmentation system. For training and evaluation, we make use of the publicly available Warwick-QU dataset [15]. The dataset consists of two distinct parts (SectionA: 60 images as well as SectionB: 20 images) with 85 color training and 80 test images. Our training dataset needs to be supplemented because we don't use a pre-trained network.

Since the sizes of the 85 training photos in the Warwick-QU dataset vary {(589 × 453), (775 × 522)}, we first resize each one to the nearest multiple of 64 (832 × 576), so that it can be used in LinkNet's subsequent downsampling layers.

Four essential processes are included in the suggested model: classification, feature extraction, tumor extraction, and noise reduction, illustrated in Figure 5.

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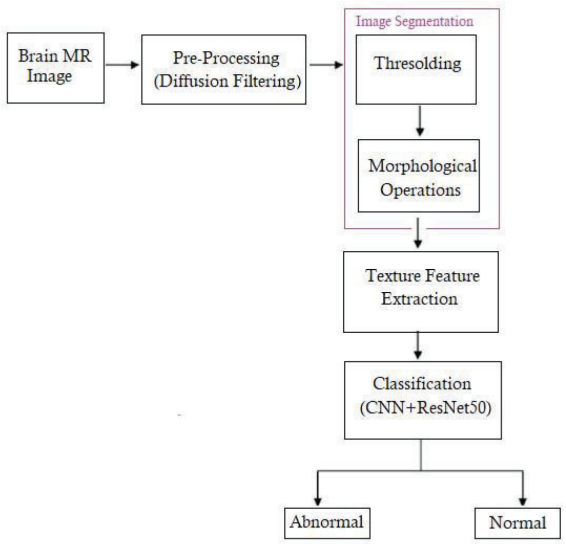

Fig 5 Workflow of the proposed system

A. Preprocessing

The resistance of the coil, weak magnetic fields, dim lighting, and inductive losses in a preamplifier all contribute to noise in MRI image capture. These variables make it difficult for doctors to recognize abnormalities in the brain from MRI images. Therefore, numerous methodologies have been introduced over the last few decades to deal with this issue. Among these, ADF and Non-Local Means (NLM) are often employed strategies.

B. Segmentation and morphological process

The Multi-thresholding Algorithm is explained in the Segmentation Stage. Brain tumor identification and segmentation using MRI are challenging but crucial tasks for a number of medical analytic applications. Many recent methods have used the four brain imaging modalities T1, T2, and FLAIR because each modality provides distinct and important information about each area of the tumor. They have a complicated structure that makes training and testing them take longer, even if several of them achieved a decent segmentation outcome on the Warwick-QU dataset. Professional neuroradiologists are now the only ones able to execute the laborious and laborious process of manually classifying and evaluating brain tumor structural MRI images. As a result, brain tumor detection and therapy will be greatly impacted by automatic and reliable brain tumor segmentation.

Watershed segmentation is used for good cranial MRI segmentation. This technique finds cancer. Watershed lines are determined by geography as well as water basins. It uses the mechanism of the object's topology within an image to evaluate gray data and identify the boundaries of the object. The watershed transformation technique based on submersion is improved. *hmin* and *hmax* are the lowest and highest values of I, respectively. Recursion can be seen when *hmin* moves to *hmax*. At the beginning of the recursion, *Xh* basin clusters have been similar to dot clusters having *hmin*. In equation 1, the threshold cluster's *Xh* basin cluster gradually expands.

$$X_h = min\left(\bigcup_{i=1}^{ZTh+1} f(X_h)\right), \forall h \in \ [h_{min}, h_{max} - 1] \quad (1)$$

C. Texture Feature Extraction

Image intensity is one of the most widely used elements for interpreting brain MRI images since grayscale picture levels differ depending on the texture. Nevertheless, there are no encouraging outcomes when utilizing this function. Because various tumor areas have distinct textural patterns, texture features are therefore frequently exploited. Over the last few years, a number of strategies were developed [16]. Statistical texture features are the most widely used among them. The spatial link between the various local texture patterns is left out.

D. Classification

One type of artificial neural network, sometimes referred to as a multilayered sensor, is CNN. The visual cortex served as the model for its architecture. DL in the convolutional neural network, or CNN, is one of key concepts. CNN is frequently utilized in image recognition applications and is composed of two fundamental techniques known as convolution and pooling. When a higher degree of accuracy is achieved, more number of convolution as well as pooling layers are inserted as needed. Furthermore, each convolutional layer has specific feature maps, and convolutional nodes, which are housed within the samilar map share weights. These designs enable the learning of many network features while reducing the number of traceable parameters [17]. Unlike more conventional techniques, CNN may be able to learn to fully extract characteristics while also carrying out fewer specialized tasks. Fig. 6 displays a CNN's entire process plan.

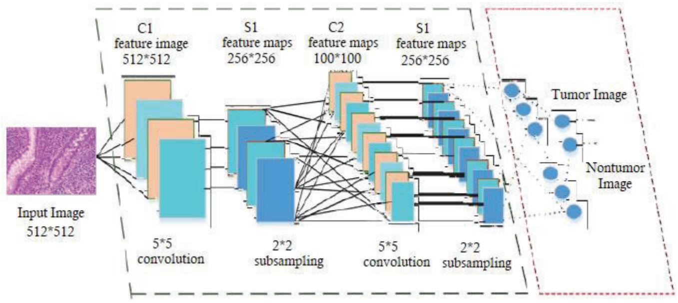

Fig. 6 The CNN Procedures

A tumor can be detected in MRI scans using the suggested five-layer CNN model. The five-layer CNN approach is shown in Fig. 7. First, add photos of the same size to the input dataset. Five-layer CNN is utilized to identify tumors early. It has seven phases (eight if the hidden layers are included) and yields the most accurate tumor detection results. By breaking down procedure into seven parts, CNN can identify brain tumors. The procedure is explained in the step-by-step directions below. The suggested 5-layer CNN tumor detection approach is shown in Fig. 7. Five discrete dimensions are used.

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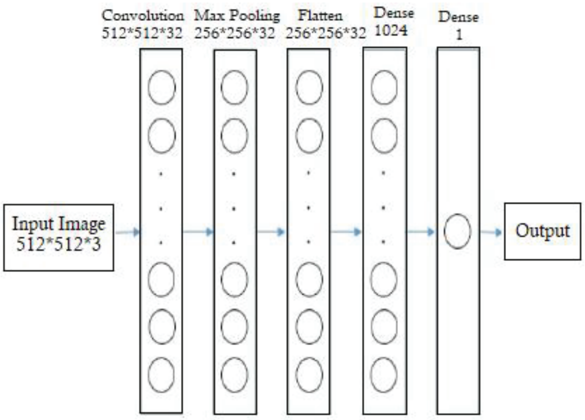

Fig. 7 The Five layer CNN for Brain Tumor detection

The foundation of CNN is a convolutional layer. First, MRI images are resized using a convolutions layer. This creates an input shape of 512 x 512 x 3. Utilizing 32 3 × 3 convolution filters and 3 channels tensors, a convolution kernel was created after collecting all input images with the same orientation. ReLU is the activation function. The 512×512×3 input volume is tripled by the filter size.

In addition to one for the bias parameter, each neuron in the convolutions layer carries three × three × three = 27 weights. Evaluate zero-padding, stride, and depth. The model has a 33 spatial filter and a 512×512×3 input volume. Padding and stride are both 1 because border padding was not specified. If the stride is set to 1, the input volume will be deeply changed by the CONV layers, whereas only the pooling layers will downsample. Maximum pooling was implemented after the convolutions layer.

Max Pooling Layer: By gradually reducing the spatial dimensions of representation, the pooling layer's main goal is to lower the network's parameter count and computational burden. Its capacity to reduce the parameters may help control over-fitting. If the input is deep enough, it can be enlarged spatially using the max pooling layer, which can do so on a per-slice basis. From a different perspective, The Max Pooling layer is very good at preventing over-fitting, which during editing could taint the brain MRI image (Fig.7). Consequently, MaxPooling2D is utilized as a pre-processing step to examine the impact of the pooling operation on the input image. This convolutions layer has 32 nodes in total, producing a 256 × 256 × 31 matrix.

Flatten Layer: Refer to Fig. 7 to see how pooling produces a pooling features map that eliminates unnecessary features and only extracts essential characteristics. After pooling, flattened layer is essential as it converts feature maps in the input into a single-column vector that can be processed. It is processed by the neural network. Pixels in Layer 256 × 256 × 32.

Fully Connected Layer: In Fig. 7, the dense-1 as well as dense-2 layers have been connected. This layer receives the output vector after Keras uses the dense function to process the neural network. There are 128 nodes in each tier. The number of dimensions or nodes was reduced to 128 because to the high processing expenses.

Because of its high convergence, ReLU is utilized. The final layer in model has been the second fully linked layer, which used to expedite execution, it uses a single node and the sigmoid function as its activation function. Deep network learning may be hampered by sigmoid activation. This deep network contains fewer nodes because the sigmoid function has been decreased.

ResNet-50 Architecture: The 50 layers that make up ResNet-50 are split into 5 blocks, containing a collection of residual blocks. The network may preserve data from previous levels thanks to the leftover blocks and learn better representations of the input data [18-19].

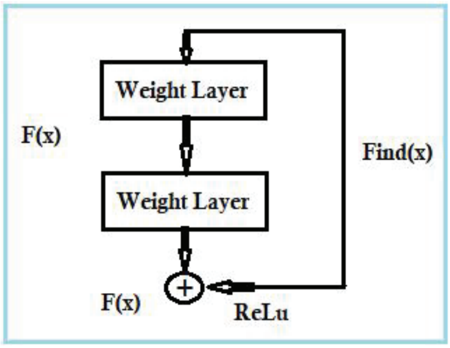

Fig. 8 The learning block of residual learning

Two 3*3 convolutional layers make up each residual block, which are then a ReLU layer activation function as well as a normalization layer come next. The output of second convolutional layer is then merged with input of the residual block, which is subsequently exposed to yet another ReLU activation function. The outcome of the residual block is then sent to next block.

ResNet50 is superior to other networks in a number of ways. One of its main advantages is its ability to train incredibly complicated networks with hundreds of layers.

This is made feasible by the retention of data from earlier layers through the use of remaining blocks and skip connections.

Another advantage of the network is ResNet50's ability to generate state-of-the-art leads to a variety of image-related tasks, having segmentation, object recognition, and image classification.

IV. RESULTS ANALYSIS

This part described the full suggested technique from loading image to identify the tumor step-by-step using the Graphic User Interface (GUI) widow results.

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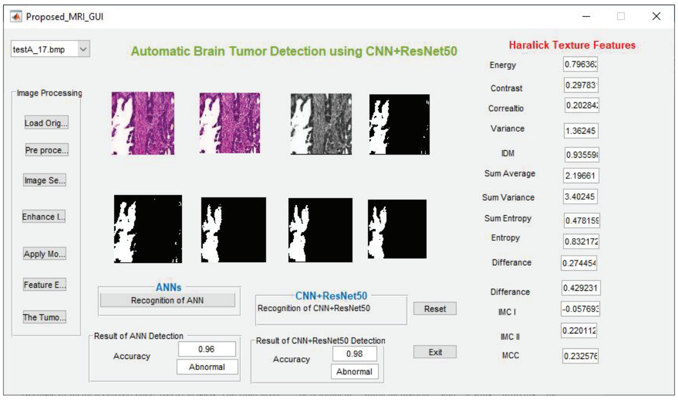

Fig. 9 The System GUI

All steps like load image, pre-processing, segmentation, image enhancement, morphological operation, feature extraction, tumor detection, and Harlick Texture Features have been shown here.

Results of Haralick's Features

Plotting the attributes curve for each of Haralick's attributes should come after you have completed computing them all. As shown in figures 10 through 23, this will enable you to establish the ideal settings that work well and produce accurate results for cancer detection.

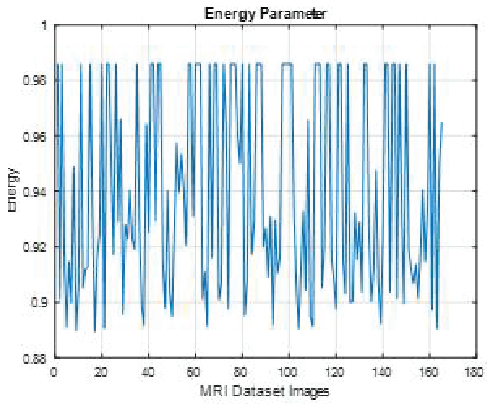

Fig. 10 The Energy's feature

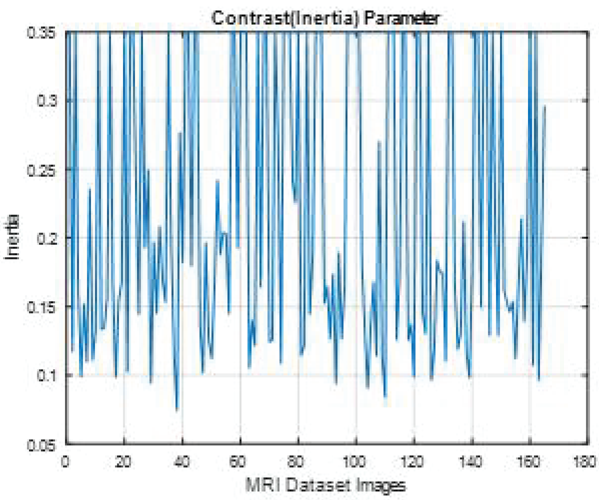

Fig 11 Contrast Parameter

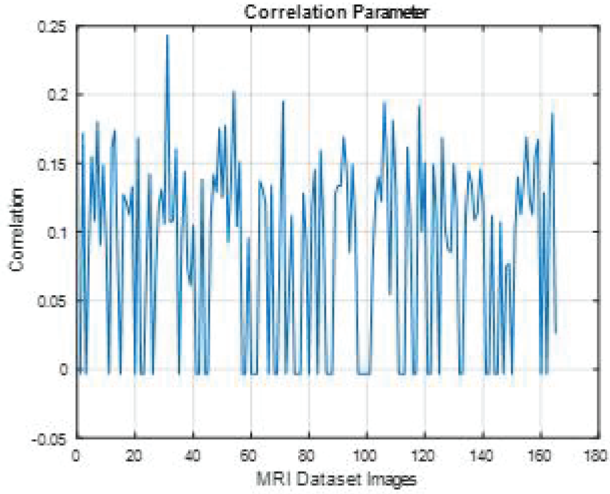

Fig 12 Correlation Parameter

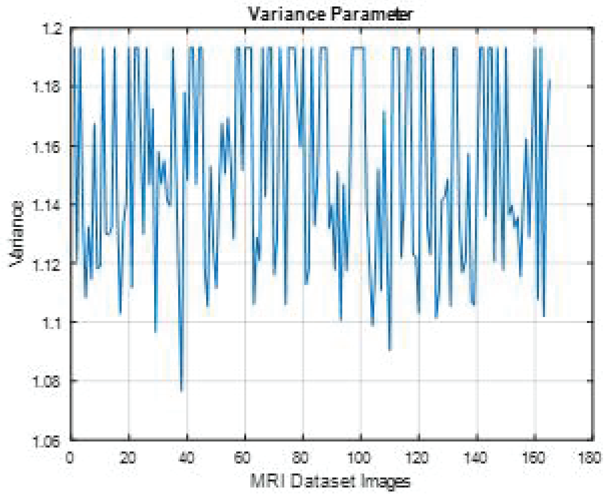

Fig 13 Variance Parameter

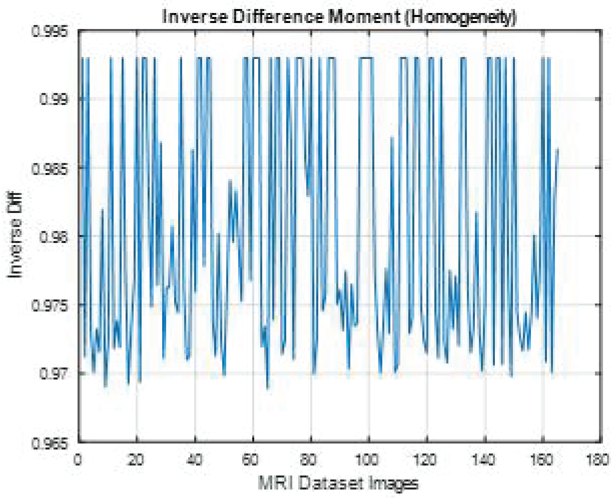

Fig 14 Inverse Difference Moments Parameter

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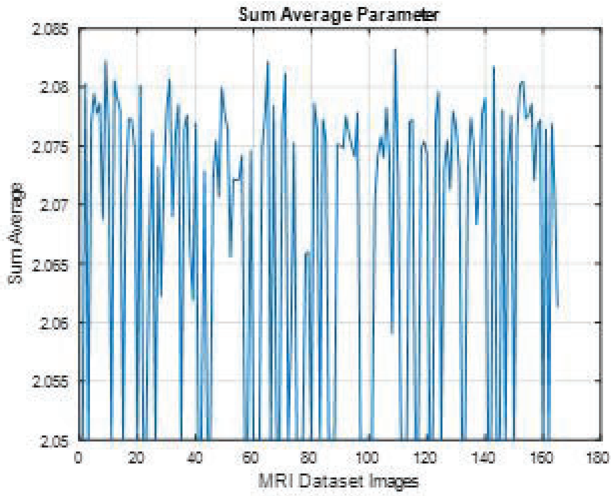

Fig 15 Inverse Sum Parameter

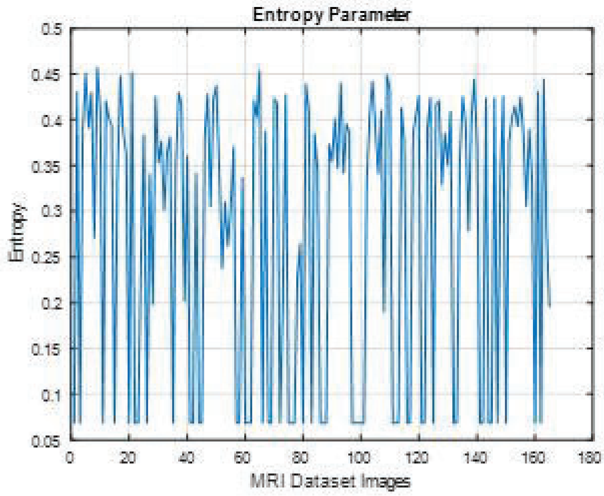

Fig 18 Entropy Parameter

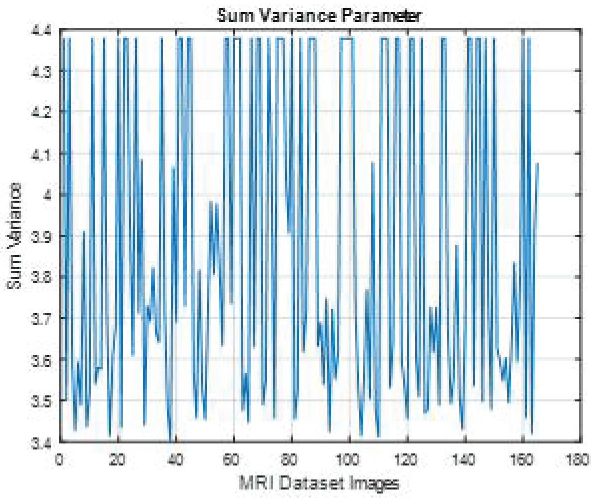

Fig 16 Sum Variance Parameter

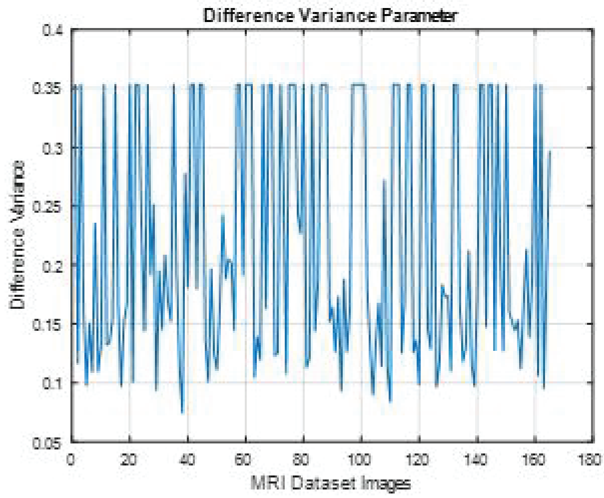

Fig 19 Difference Variance Parameter

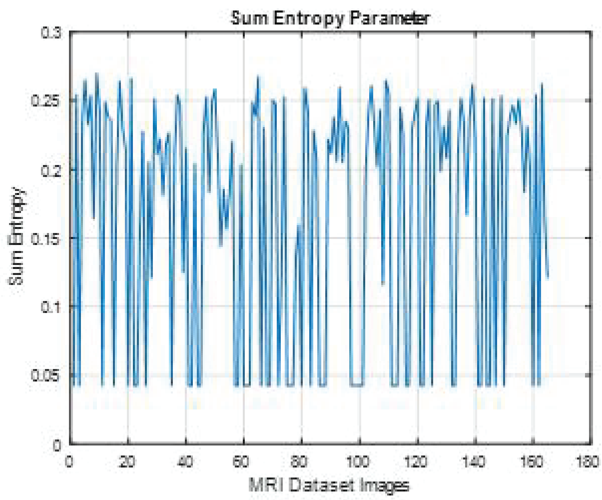

Fig 17 Sum Entropy Parameter

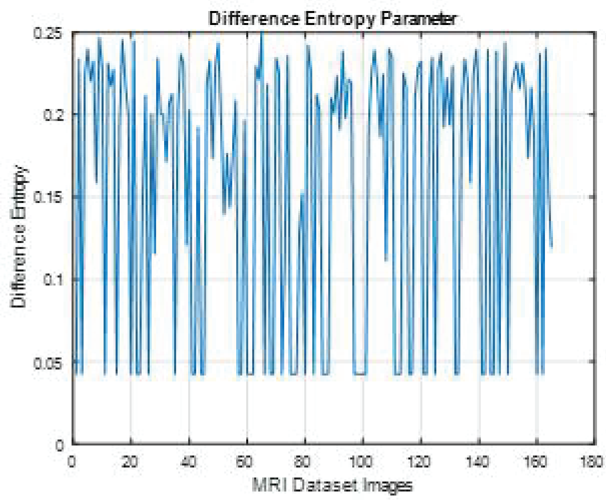

Fig 20 Difference Entropy Parameter

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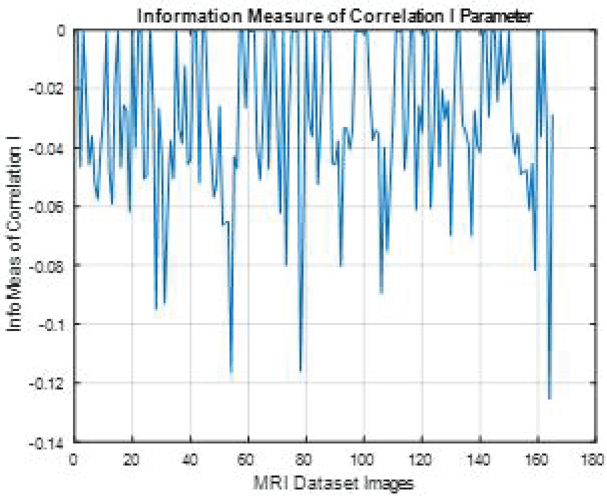

Fig 21 Information Measure of Correlation-I Parameter

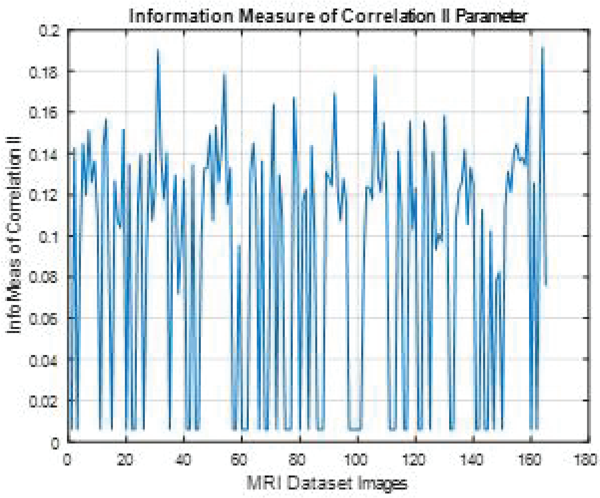

Fig 22 Information Measure of Correlation-II Parameter

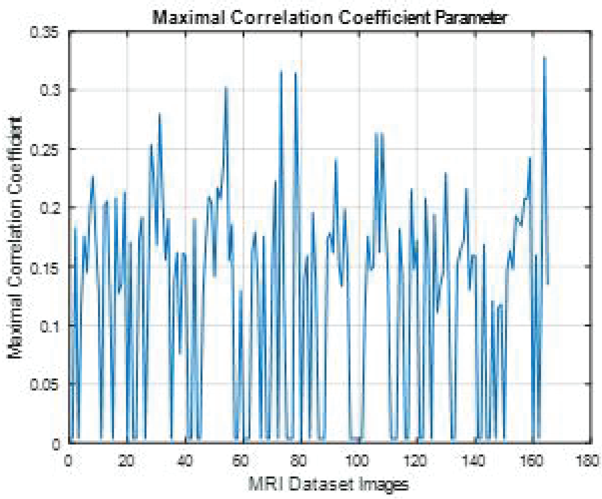

Fig 23 Maximal Correlation Coefficient Parameter

Percentage Correct Classification by CNN+ResNet50: 98.00000%.

Percentage Incorrect Classification by CNN+ResNet50: 2.00000%.

V. CONCLUSION

The main objective of this paper was to use MRI data with convolutional neural networks to create an autonomous approach for brain tumor detection. It has been determined that the algorithm's development, implementation, and testing utilizing the available brain tumor MRI data was successful. This decision was reached when the procedure was completed. The purpose of this task has been to develop a set of image segmentation algorithms and feature extraction approaches that can produce user-satisfactory results. The data that has been collected and processed in order to prepare it for detection. Statistical feature analysis was utilized to extract information from the submitted images. These characteristics were produced by utilizing Haralick's feature equations, which were derived from the SGLD image matrix. To assess if the images were cancerous, it was chosen to use a convolutional neural network with supervised learning. The findings show that the used strategy is beneficial for both identifying cancers that are expanding and limiting tumors to the actual tumor site. The method's application is an example of this.

REFERENCES

[1] P. K. Chahal, S. Pandey, and S. Goel, "A survey on brain tumor detection techniques for MR images," Multimed. Tools Appl., vol. 79, no. 29–30, pp. 21771–21814, 2020, doi: 10.1007/s11042-020-08898-3.

[2] Ayane, T. H. et al. (2021), 'Brain tumor detection and classification using frfcm segmentation and pso based extreme machine learning and it's implementation through embedded system', Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12(13), 452–465.

[3] Agrawal, R., Sharma, M. and Singh, B. K. (2019), 'Segmentation of brain tumour based on clustering technique: performance analysis', Journal of Intelligent Systems 28(2), 291–306.

[4] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain tumor detection and classification using machine learning: a comprehensive survey," Complex Intell. Syst., vol. 8, no. 4, pp. 3161–3183, 2022, doi: 10.1007/s40747-021-00563-y.

[5] 5 P. S. Ganesh, T. S. Kumar, M. Kumar, and M. S. R. Kumar, "Brain Tumor Detection and Classification Using Image Processing Techniques," Int. J. Adv. Res. Sci. Commun. Technol., vol. 2, no. 3, pp. 32–38, 2021, doi: 10.48175/ijarsct-v4-i3-005.

[6] Tiwari, A., Srivastava, S. and Pant, M. (2020), 'Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019', Pattern Recognition Letters 131, 244–260.

[7] A. Ouarda, "Fuzzy Segmentation of MR Brain Real Images Using Modalities Fusion," Int. J. Adv. Comput. Sci. Appl., vol. 7, no. 1, pp. 267–273, 2023, doi: 10.14569/ijacsa.2016.070137.

[8] G. Xie et al., "Cross-Modality Neuroimage Synthesis: A Survey," vol. 1, no. 1, 2022, [Online]. Available: http://arxiv.org/abs/2202.06997

[9] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain tumor detection and classification using machine learning: a comprehensive survey," Complex Intell. Syst., vol. 8, no. 4, pp. 3161–3183, 2022, doi: 10.1007/s40747-021-00563-y.

[10] T. G. Devi, N. Patil, S. Rai, and C. S. Philipose, "Gaussian Blurring Technique for Detecting and Classifying Acute Lymphoblastic Leukemia Cancer Cells from Microscopic Biopsy Images," Life, vol. 13, no. 2, 2023, doi: 10.3390/life13020348.

[11] A. V. P. Sarvari and K. Sridevi, "An optimized EBRSA-Bi LSTM model for highly undersampled rapid CT image reconstruction," Biomed. Signal Process. Control, vol. 83, no. December 2022, p. 104637, 2023, doi: 10.1016/j.bspc.2023.104637.

[12] M. A. Talukder et al., "An efficient deep learning model to categorize brain tumor using reconstruction and fine-tuning," Expert Syst. Appl.,

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

vol. 230, no. August 2022, p. 120534, 2023, doi: 10.1016/j.eswa.2023.120534.

[13] S.A.Lakshmi and K.Anandavelu, "Enhanced Cuckoo Search Optimization Technique for Skin Cancer Diagnosis Application," Intell Autom.Soft Comput.,vol.35 ,no .3,pp .3403–3413,2023,doi:10 .32604 /iasc /iasc.2023 030970.

[14] S. Dey, R. Bhattacharya, F. Schwenker, and R. Sarkar, "Median filter aided CNN based image Denoising: An ensemble Aprroach," Algorithms, vol. 14, no. 4, pp. 1–11, 2021, doi: 10.3390/a14040109.

[15] Sirinukunwattana, K., et al., 2017. Gland segmentation in colon histology images: The glas challenge contest. Medical image analysis 35, 489–502. doi:10.1016/j.media.2016.08.008.

[16] Humeau-Heurtier, A. (2019a), 'Texture feature extraction methods: A survey', IEEE access 7, 8975–9000.

[17] Murthy, M. Y. B., Koteswararao, A. and Babu, M. S. (2022), 'Adaptive fuzzy deformable fusion and optimized cnn with ensemble classification for automated brain tumor diagnosis', Biomedical engineering letters 12(1), 37–58.

[18] Sanjay A. Agrawal, Vaibhav D. Rewaskar, Rucha A. Agrawal, Swapnil S. Chaudhari, Yogendra Patil, Nidhee S. Agrawal, "Advancements in NSFW Content Detection: A Comprehensive Review of ResNet-50 Based Approaches", International Journal of Intelligent Systems and Applications in Engineering IJISAE, 2023, 11(4), 41–45.

[19] Zhang L, Bian Y, Jiang P, Zhang F. A Transfer Residual Neural Network Based on ResNet-50 for Detection of Steel Surface Defects. Applied Sciences. 2023; 13(9):5260. https://doi.org/10.3390/app13095260.

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