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Domain Specific ANN Heuristic Edge Detection Algorithm for CNN based MRI Classification [DAHEDA]

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Abstract:

The Artificial Intelligence (AI) edge detection phase is a multi-step technique for detecting edges in any images. The use of machine learning models to explore medical data and reveal insights to assist improve health outcomes and patient situations is known as edge detection in artificial intelligence. The proposed algorithm which is named as "Domain Specific ANN Heuristic Edge Detection algorithm for CNN based MRI Classification" (DAHEDA) is the amalgamation of four intertwined functional algorithms. They are Tabu Search Heuristics Symmetrical Pattern Identifier (ASHSPT), Fuzzy Symmetric Pattern Table Manager (FSPTM), ANN Edge Detection Algorithm Selector (AEDA) and CNN MRI Classifier. These algorithms are interlaced in a way to improve the MRI classification metrics without significant difference in processing speed.

Keywords: Edge detection, TSHSPI, ASHSPI, FSPTM, CNN

I. INTRODUCTION

Artificial intelligence (AI) makes it possible for computers to perform previously human tasks. In this process, AI algorithms are created for analyzing, predicting data based on classification, analysis, and predictions. Additionally, it involves discovering new data, enhancing with time, analyzing data and acting on it. In its most basic form, AI is a branch of computer science that merges computer science with large datasets to solve problems. Data science is characterized by the use of Machine Learning (ML). Computers learn from mathematical models of data without direct instruction by using Machine Learning. It's considered a subset of Artificial Intelligence. Data is analyzed using algorithms in order to identify patterns, and these patterns are used to create predictive models. The output results of Machine Learning is great accurate as a result of enhancing data and experience, just as humans increase in skill with practice. Machine learning and Deep Learning are subfields within AI that are frequently mentioned. AI algorithms are used in these fields, so that expert systems can predict data or recognize it based on the input. Neuronal networks are actually the foundation of Deep Learning. Deep learning is the process of learning through a network composed of more than three layers. It involves the uses of Neural Network (NN) to deliver results. DL recognizes information in the same way as a human brain and is what powers the most human-like Artificial Intelligence Systems. Using deep learning to analyze large amounts of data has proven to be an extremely effective tool. In the field of pattern recognition, hidden layers have become more popular than traditional techniques. Deep neural networks, such as Convolutional Networks, are a popular type of Deep Learning.

II. RELATED WORKS

Diagnoses improved by reducing time and improving quality with computer-aided diagnostic applications. The research describes an edge identification technique that was created specifically for processing brain MRI data. The introduction of the log filer was the first step in the modified canny algorithm. Adjusting both the gradient magnitude and kernel gradient improved MRI image edge detection. The algorithm is based on Canny's classic method. When compared to other common edge detection methods, it was discovered that the suggested method produces more detailed edge detection [1]. On MRI images of a patient's brain, a technique is described for detecting tumor edges. The Balance Contrast Enhancement Technique (BCET) is the first step in removing noise from medical images in order to provide reliable diagnosis and improve the features in medical images. The fuzzy C-Means (FCM) clustering is used to segment the results of the second stage. The final step is to apply the canny edge method to identify fine edges. The experimental investigation included photographs of brain tumors that were differentiated by their location, pathology, form, size, density, and the size of the injured area near the tumor region [2]. Developed using GTIKF, a Gabor transform integrated with K means and Fuzzy C means, the proposed method detects edges even in noisy environments. MRI and CT were used as examples to validate the proposed method. When compared to other approaches, the results were more convincing. The fuzzy C means is extremely poor compared to the K means and are prone to noise when only considering spatial information [3]

Edge detection problems such as fragmentation, dislocation of position, and loss of thinness can be greatly reduced by the proposed algorithm. Noise is not a concern with the detector, and it can accurately extract critical edge features. The new operator is called the WL operator (Wang and Lin). Pratt's figure of merit was used to compare the WL operator with other edge detectors. Furthermore, a visual analog scale was used to confirm the performance with experts. In addition to X-rays, CTs, and MRIs, the WL operator showed promising results with various forms of medical imaging [4]. Depending on the symmetric encryption process, the healthcare cloud server is being built. The healthcare information administrator encrypts the healthcare information and the encryption key with the encryption algorithm. Then sends that data out after encrypted medical outsourcing. The decryption mechanism must be used once the health workers or patient user obtains the cipher text [5].

In this research, a new fuzzy edge symmetry-based genetic clustering approach. It is used to offer an automatic segmentation process for multispectral magnetic resonance brain images. Fuzzy-VGAPS is a real-coded variable string size genetic fuzzy clustering technique that automatically identifies clusters. It is presented in a data set based on the number of real-coded variables [6]. CADD or DSS can be developed based on human X-Ray images or other types of digital images by using the proposed algorithm in the medical field. The proposed mechanisms are improved in this work to improve PSNR and reduce MSE, RMSE, and edge time complexity. The proposed method is improved and analyzed by adding more comparison mechanisms and parameters [7]**.** In this research, artificial neural networks and histogram thresholding are used to detect brain tumors using Magnetic Resonance Imaging (MRI). The research summarizes and compares the results from each method. In addition to detecting the shape of the tumor, the presented approach can determine its geometrical dimensions. In addition, a new Artificial Neural Network (ANN) strategy based on learning vector quantization along with image, data analysis and manipulation method. It is presented to perform automated brain cancer classification using MRI images in this study. The proposed approach for recognizing the tumor location from T1, T2-weighted Brain images is more efficient and faster. Feature extraction, dimensionality reduction, identification, localization, and classification are some of the stages in the proposed neural network technique. In this study, the purposed strategy for brain tumor identification and segmentation is shown to be more accurate and effective [8].

A feature selection strategy based on the integration of GA and TS is presented in this paper (GATS). With the current mutation operator enhanced by TS, the new GATS approach focuses on improving the GA's computational complexity. Other feature selection approaches, such as a standard GA, multi-start TS, and Relief F. It is used to evaluate the reliability and efficiency of the suggested feature extraction technique. The proposed suggested algorithm outperforms another methods are compared of final classification accuracy [9].

The goal of this research is to provide a fast edge recognition system for MRI medical pictures using an artificial neural network (ANN). First, created features based on differences in the diagonal, vertical, and horizontal directions. Then, as a training output, the Canny edge detector was used. Finally, optimum parameters such as the number of hidden nodes and final threshold are obtained. The proposed methodology produced improved pixel density while processing quicker than other existing procedures such as Sobel and Canny edge detectors, according to the results [10]. A breast images are always low contrast and are not uniform in the background, analysis of these images is difficult. This reduces the contrast between the ROI and the background by scanning, digitizing, and processing the breast images.

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Furthermore, the occurrence of noisy, organs, and joints causes differences in background brightness. The estimated cancer area's limits are always blurry and inaccurate. The goal of this paper is to create an effective edge sensor system that is used to separate a tumor region on breast pictures [11]. Proposed methods use the pre-trained neural network to recognise additional edge pixel values. A CNN is used to calculate the edge of an image patch. As a result, while using such systems, the canny technique and the SUSAN filter become better efficient while maintaining image quality. The edge accuracy and efficiency improve as more edges are detected [12]. The smoothing filter, pixel identifier, and feature selection are all improved in this study, which looks at the canny edge technique. Tabu Search Heuristic Pattern Identifier (TSHPI), a Britwari approach, improved edge identification employing the SUSAN Filter. To improve the canny edge technique, feature selection has been used. To locate more edge pixels, a Deep Learning technique is employed to classify pre-trained neural networks. The results suggest that the Britwari presented technique outperformed beat classic Canny Edge Detection algorithms. The results showed that edge detection in MRI images improved based feature selection [13]. Edge detection removes unneeded information in a picture while keeping its structure by using the structure information from the image surrounded in edges. The goal of this work was to provide a clear explanation of the CNN classification model and its impact on edge detection. Furthermore, many previously proposed strategies for overcoming edge detection concerns were examined [14].

III. PROPOSED METHOD

The proposed method which is named as "Domain Specific ANN Heuristic Edge Detection algorithm for CNN based MRI Classification" (DAHEDA) is the amalgamation of four intertwined functional modules. They are Tabu Search Heuristics Symmetrical Pattern Identifier, Fuzzy Symmetric Pattern Table Manager, ANN Edge Detection Algorithm Selector and CNN MRI Classifier. These algorithms are interlaced in a way to improve the MRI classification metrics without significant difference in processing speed.

a. Tabu Search Heuristics Symmetrical Pattern Identifier (TSHSPI)

Tabus are recorded in the search's short-term memory (the tabu list), and only a fixed and very limited type of data is normally stored. There are various options for the exact information that is recorded in any given situation. The most basic tabus include storing the most recent few changes applied on the current approach and restricting reverse changes solutions or moves. A Tabu is nearby neighbor classifier's leave-one-out exact classifier percentage is used to calculate the value of a subset of features. When interacting with diagnostic photographs, symmetry is one of the most important characteristics. In the case of MRI scans, this symmetrical characteristic has a better index. The presented method enhances the efficiency of feature extraction. The standard Tabu search algorithm is given below in Equation 1.

$$s' \in N(s) = \{N(s) - T(s)\} + A(s)$$
Equation (1)

Where, s is the initial solution, s' is the achieved solution, $N(s)$ is new set of results of Tabu List $T(s)$ and $A(s)$ is the Aspiration Criteria.

Canny and Sobel edge detection algorithms are used to find the edges from the MRI Images and their results will be labeled separately for the successive functional modules. A new Tabu search algorithm is introduced in this module to optimize the edge detection process in MRI Images. The key of this meta-heuristic optimization exists in the selection of symmetrical edges from an MRI image in different directions. This process begins with finding the center of an MRI Image.

The Tenure T_d is set to be dynamic for the proposed Tabu search with the condition$T_{min} \leq T_d \leq T_{max}$. There is rare chance to the Tabu search memory change in the appropriated domain, thus 'Restart Diversification' memory frequency is selected rather continuous diversification. The Aspiration Criteria $A(s)$ is set to the directional position correlation which is represented as$A(D)$. The aspiration criteria are selected based on the Horizontal Symmetrical Pair (HSP) and Vertical Symmetrical Pairs (VSP) of the position blocks. The pair listings are given in following Table.

	Horizontal Pair	**Vertical Pair**
0	8	16
1	7	15
2	6	14
3	5	13
4	4	12
5	3	11

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6	2	10
7	1	9
8	0	8

Table 1: Blocks, HSP and VSP pairs

The HSP is calculated using Equation 2 and the VSP is calculated by Equation 3.

$$\forall x = 0 \rightarrow 8: HSP(x) = 2^{n-1} - x$$

Equation (2)

$$\forall x = 0 \rightarrow 8: VSP(x) = 2^{n} - x$$

Equation (3)

Where n is the number of regions split by the virtual directional axis

The symmetrical patterns identified by TSHSPI are maintained individually for both Canny and Sobel edge detection processes.

b. Fuzzy Symmetric Pattern Table Manager (FSPTM)

FSPTM module is used to trim the symmetrical patters identified by the TSHSPI module. Discovered symmetrical patters are classified into two categories based on the match between the symmetrical pairs. Patterns with more matching are marked as the beneficial symmetrical patterns whereas less match patterns are tagged as non-beneficial patterns. A simple segment flips and X-OR operation is identified to calculate the similarity index between the pattern pairs. Every edge block is captured from an MRI image as RGB matrix and it is converted into grayscale to reduce the computation complexity by $\frac{1}{3}$ by equation 4 – given below.

$$\forall i = 1 \rightarrow w: \forall j = 1 \rightarrow h :: \ m_{ij} = \frac{r_{ij}+g_{ij}+b_{ij}}{3}$$

Equation (4)

where w, h are the number of row and columns of the source edge block (width and height of the image), m is the grayscale pixel element value, r, g and b are the red, green and blue pixel element values in order.

For HSP block, the pair is found through Equation 2 and a horizontal flip operation is applied to the pair. Similarly, for VSP, Equation 3 is used and a vertical flip operation is applied. Let M_{Δ} be the source edge block matrix with members $\{\{m_{\Delta_{00}}, m_{\Delta_{01}}, \dots m_{\Delta_{0w}}\}, \{m_{\Delta_{10}}, m_{\Delta_{11}}, \dots m_{\Delta_{1w}}\} \dots \{m_{\Delta_{h0}}, m_{\Delta_{h1}}, \dots m_{\Delta_{hw}}\}$ and M'_{Δ} be the pair edge block matrix with members $\{\{m'_{\Delta_{00}}, m'_{\Delta_{01}}, \dots m'_{\Delta_{0w}}\}, \{m'_{\Delta_{10}}, m'_{\Delta_{11}}, \dots m'_{\Delta_{1w}}\} \dots \{m'_{\Delta_{h0}}, m'_{\Delta_{h1}}, \dots m'_{\Delta_{hw}}\}$, then the member values are normalized to 0 and 1 using the following equation.

$$m_{\Delta_{ij}} = \begin{cases} 1\ if\ \left(m_{\Delta_{ij}} < 2^{7}\right) \\ 0\ otherwise \end{cases}$$

Equation (5)

Let the X-OR result matrix $M_x = M_{\Delta} \oplus M^{1}_{\Delta}$, then it is quantized as follows

$$Q_{M_x} = \sum_{i=0}^{i<w} \sum_{j=0}^{j<h} M_{x_{ij}}$$

Equation (6)

Then the beneficial factor f of source edge block M_{Δ} and the pair edge block M'_{Δ} is determined as follows

$$f = \begin{cases} Beneficial\ if\ \left(\frac{Q_{M_x}}{hw}\right) > \frac{3}{4} \\ Non-beneficial\ otherwise \end{cases}$$

Equation (7)

This module uses fuzzy logic to distinguish beneficial and non-beneficial symmetrical patterns for both Canny and Sobel Edge detection algorithms. The pattern table is enrolled with only beneficial symmetrical patterns and non-beneficial patterns are discarded from the entry. The Fuzzy Symmetric Pattern Table will contain the details about all beneficial HSP and VSP along with the source edge block name Δ_x.

c. ANN Edge Detection Algorithm Selector (AEDAS)

AEDAS is used to reduce the execution time while sustaining the classification accuracy. During the training process, AEDAS module optimizes its weight between the neurons to select the edge detection algorithm. The symmetrical edge block label Δ_x, pair block label Δ'_x, type of the symmetric pattern $\rho = \{HSP|VSP\}$, edge detection algorithm type $\varepsilon = \{Sobel \mid Canny\}$ and number of beneficial identified patters N_b are given as the input to the network. The network gains knowledge through multiple iterations performed during the training process.

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The output of the network is the type of preferred edge detection algorithm. The architecture of AEDAS is given in Figure 1. The initial weights of the primary edges (from input layer to hidden layer) ω_0^{l1} to ω_{29}^{l1} are initialized with random values. Similarly, the secondary edges (from hidden layers to output layer) weights ω_0^{l2} to ω_{11}^{l2} be also initialized with random values. The initial bias values β_0^{l1} to β_4^{l1}, and β_c, β_s are set to 0.5 to maintain a neutral state. Further these values will be updated based on the successive approximations during the back-propagation phase. The hidden layer neuron values are calculated as follows

$$L_x = \Delta_x \omega_{(x-1)*5+1}^{lx} + \Delta'_x \omega_{(x-1)*5+2}^{lx} + \rho \omega_{(x-1)*5+3}^{lx} + \varepsilon \omega_{(x-1)*5+4}^{lx} + N_b \omega_{(x-1)*5+5}^{lx} + \beta_{x-1}^{l1}$$

Equation (8)

The activation function for the hidden layer neurons is given in Equation 9

$$L_x^A = \frac{1}{1+e^{\frac{1}{L_x}}}$$

Equation (9)

Where $x \coloneqq 1 \rightarrow 6, step\ 1$

Equation for Canny output neuron is given below in Equation 10 and Sobel output neuron equation is given as Equation 10.

$$Canny = \left(\sum_{i=0}^{5} L_{i+1} \omega_{i+1}^{l2}\right) + \beta_c$$

Equation (10)

$$Sobel = \left(\sum_{i=0}^{5} L_{i+1} \omega_{i+6}^{l2}\right) + \beta_s$$

Equation (11)

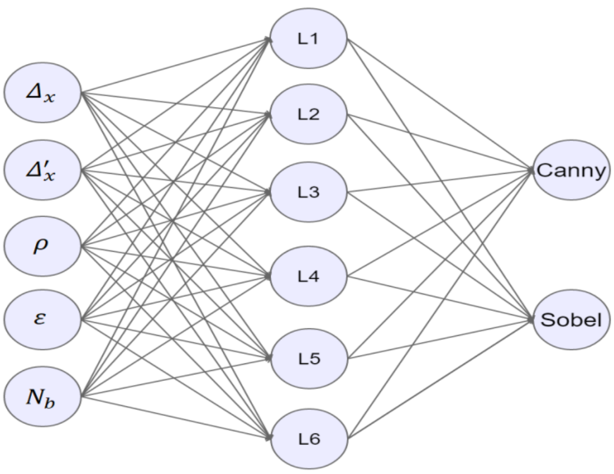

Fig 1: AEDAS Architecture

This AEDAS module is used to select either Canny or Sobel edge detection algorithm based on the input criteria while running in the test phase. Since the selected edge detection process is optimally chosen based on the beneficial symmetrical edge blocks, AEDAS can reduce the computational complexity from $O(2n)$ to $O(n)$ without compromising the accuracy performance parameters.

3.4 CNN MRI Classifier (CMC)

The architecture of CMC is given in Figure 2.

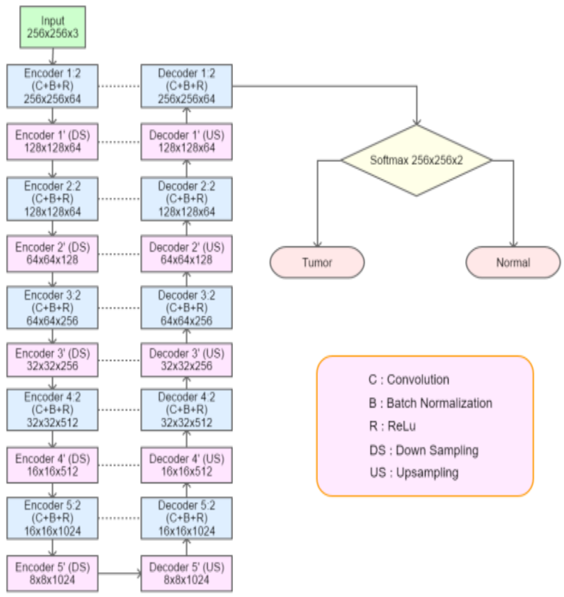

Fig 2: CMC Architecture

Convolutional Neural Network architecture is used in this work to measure the performance of the proposed edge detection method. The filter matrices are generated based on the beneficial symmetrical patterns from the Fuzzy Symmetric Pattern Table. The maximum number of permitted filters is 16 which are derived based on Step No.6 of Tabu Solution Set Formation algorithm as $\frac{22.5}{2\pi}$.

IV. RESULTS AND ANALYSIS

The proposed DAHEDA work result is compared with other traditional approaches, they are "An improved canny edge detection algorithm for detecting brain tumors in MRI images [1]", "Edge detection in MRI brain tumor images based on fuzzy C-means clustering

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[2]", and "Gtikf-gabor-transform incorporated k-means and fuzzy c means clustering for edge detection in CT and MRI [3]" and "Edge detection in medical images with quasi high-pass filter based on local statistics [4]". DAHEDA work is result calculated by the accuracy, precision, sensitivity, specificity.

4.1 Accuracy

Accuracy is a measure of how often a model correctly classification of the data points based on the machine learning algorithm. This is calculated from the numerator, which is the number of correct predictions. As a result, only TP and TN will be included in the numerator and TP, TN, FP, and FN will be included in the denominator. The number of successfully classified data divided by the total number of classifications made by the model is called accuracy. In classification problems, one of the significant factors is the accuracy of how the model predicts the correct outputs. Proposed DAHEDA work is great accuracy results for when compared with other existing methods. DAHEDA accuracy has achieved 99.8 levels.

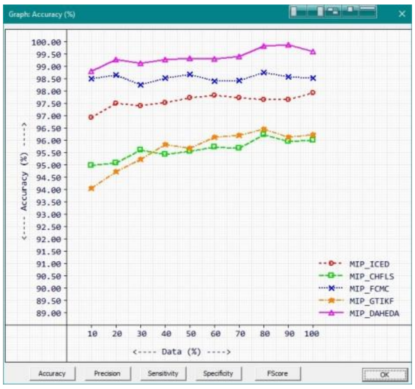

Fig 3: Accuracy plot levels

4.2 Precision

Precision is calculated as the ratio of True Positives to all points classified as Positives in the most basic sense. Positive and negative values from the binary classification are used to measure a model's precision. The DAHEDA algorithm has achieve 98.88 percentage of better performance.

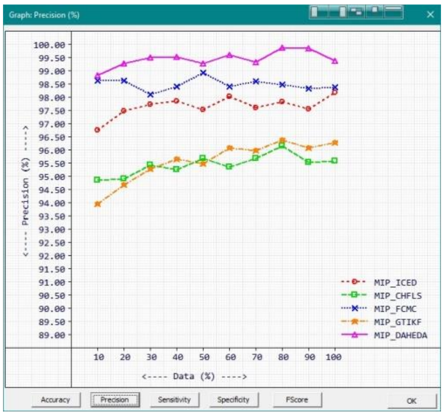

Fig: 4 Precision graphs

4.3 Sensitivity

Sensitivity is the True Positive values, is refers to the probability of positive test values, and rule on truly being positive values. A diagnostic test's sensitivity is defined as the probability (in percentage) that a sample will test positive if the patient has the disease. It has been described as a test's capacity to correctly identify all persons who have the illness, often known as "true-positive". A classifier's sensitivity is the ratio between the number of positives correctly identified and the number of positives that actually occurred. This proposed DAHEDA algorithm is grate achieve results of 98.88 percentages in better performance.

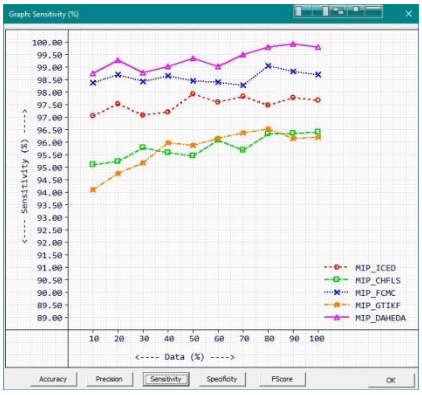

Fig 5: Sensitivity result graph

4.4 Specificity

Specificity is the True Negative values, refers to the probability of negative test phases, and rule on truly being negative values. It is described as a test's ability to accurately identify those who may not have the cancer, or "true-negatives. Classifier specificity is the ratio between the numbers of times that were correctly categorized as negative to the number of times that were actually negative. Proposed DAHEDA work is

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good specificity of when compared with other traditional methods.

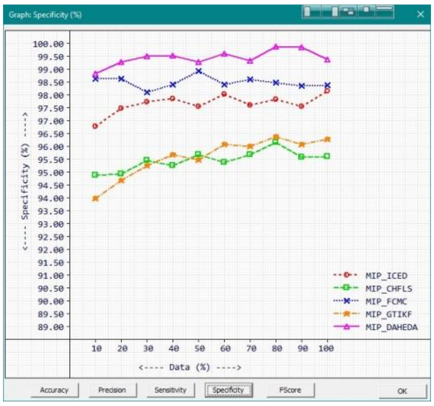

Fig 6: Specificity result graph

V. CONCLUSION

The research highlights a technique for identifying the edges of a brain tumor using MRI scan images of the patient's brain. This approach comprises several functions of enhancing the efficiency of feature extraction and noise removal in the initial stage, which improves pixel properties of medical images for accurate diagnosis using TSHSPI. The image pattern segmentation output from the second stage is done using the Fuzzy Symmetric Pattern Table Manager (FSPTM) approach. The ANN Edge Detection Algorithm Selector (AEDAS) is the third step, which is aimed at minimizing the experimental running time and benefiting the edge detection algorithm in identifying pixel patterns. Finally, the presented edge detection algorithm's performance is classified by CNN. An MRI image of the brain can be analyzed using VC++ software to detect and extract tumors. These DAHEDA work accuracy results are obtained.

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