Computational Analysis based on Advanced Correlation Automatic Detection Technology in BDD-FFS System

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Abstract—**Big Data-Driven Fabric Future Systems (BDD-FFS) is currently attracting widespread attention in the healthcare research community. Medical devices rely primarily on the intelligent Internet to gather important health-related information. According to this, we provide patients with deeply supportive data to help them through their recovery. However, due to the large number of medical devices, the address of the device can be modified by intruders, which can be life-threatening for serious patients (such as tumor patients). A large number of abnormal cells in the brain can lead to brain tumors, which harm brain tissue and can be life-threatening. Recognition of brain tumors at the beginning of the process is significant for their detection, prediction and therapy. The traditional approach for detecting is for a human to perform a biopsy and examine CT scans or magnetic resonance imaging (MRI), which is cumbersome,unrealistic for great amounts of resource, and requests the radiologist to make inferential computations. A variety of automation schemes have been designed to address these challenges. However, there is an urgent need to develop a technology that will detect brain tumors with remarkable accuracy in a much shorter time. In addition, the selection of feature sets for prediction is crucial to realize significant accuracy. This work utilizes an associative action learner with an advanced feature group, Partial Tree (PART-T), to detect brain tumor recognition grades. The model presented was compared with existing methods through 10-fold cross-validation. Experimental results show that partial trees with advanced feature sets are superior to existing techniques in terms of performance indicators used for evaluation, such as accuracy, recall rate and F-measure.**

Keywords—*Big data-driven fabric future systems (BDD-FFS); magnetic resonance imaging (MRI); partial tree*

I. Introduction

Reliable and efficient collection and communication of observations from physical information systems that support the Internet of Things (IoT), for example sensors laid at faraway locations, to dominate centers are the current issues facing data detection in big data areas [1-3]. With the heavy use of devices in the healthcare trade, low-power communication equipment, and restricted reliability availability, there will be a variety of security threats. The most serious life threat facing the healthcare industry is brain tumors, which have a survival rate of less than 35 percent. With device management in the Internet of Things (IoT) [4-6], more specifically, in the Medical Internet of Things based on big data-driven future fabric (BDD-FFS) [7-8] systems, patient data can be hacked via botnets. As the result of, the security of BDD-FFS facilities is essential [9]. The disordered expansion of tissue in the brain was called a brain tumor, and it can lead to main (benign) or minor (malignant) tumors. A main tumor is a non cancer condition that does not propagate from one piece of the brain to another, yet a minor tumor is a cancer condition that maybe spread to other sections of the brain. In benign or malignant cases, the skull can compress and expand, causing damage to the brain and potentially life-threatening problems [10-11]. Therefore, accurate early prediction of brain tumors is crucial for their detection, prediction and therapy, which can only be ensured by exploiting safety schemes on the BDD-FFS device.

Brain tumors are often detected via biopsy, MRI or CT scan. In a biopsy test, a pathologist removes a few amount of material and checks it in line with a microscope to identify if there are signs of a tumor. While biopsy can accurately detect the presence of abnormalities, it can be unlucky for the patient. Second, the surgeon must be familiar with the accurate position and scale of the tumor when performing surgical tests.Therefore, MRI or CT scan is very important. One of the biggest merits of MRI compared with CT scan is that it is radiation-free, so it is healthy for human health. In addition, MRI can accurately detect tumors. However, extensive human MRI is a complex and unrealistic task, which relies on the technical awareness of doctors and technicians. In addition, a small number of radiologists will lead to higher cost and labor intensity of MRI analysis. Studies of approximations also suggest that radiologists filter out 15 to 25 percent of tumor treatments during screening [12]. Therefore, automatic recognition of brain tumors by MRI is a big change in medicine. Automatic recognition will allow doctors to predict the disordered growth of cells and tissues in the brain and

help repair early abnormalities. Many algorithms have been developed for calculating automatic recognition of brain tumors from MRI.

Although much of the work described above has validated various algorithms using computation to detect brain tumors, and some other experimental techniques have been executed to investigate brain tumors, the raised approach is known to be more accurate and precise. The method designed in this work has not been used to explore brain tumors in the above results. The complexity of partial trees is superior to all previous schemes. Partial trees showed better medical outcomes in terms of baseline and advanced features compared to other previous work.

The major contributions of the paper are the following:

(1) Aiming at the problem that traditional methods of brain tumor detection are cumbersome, unpractical and require radiologists reasoning time, a new technology is developed that can detect brain tumors with high accuracy in a shorter time.

(2) Since the selection of feature sets for prediction is crucial for real apparent accuracy. This work proposes an associative action trainer with a high-level feature union-PART tree (PARTT), to investigate the grade of brain tumor recognition.

(3) The results show that the partial trees with advanced feature sets are superior to the existing techniques in performance indicators such as accuracy, recall rate and F-measure.

The architecture of the rest of the papers is the following: Section II depicts the connect done in concerned areas, Section III portrays the materials and schemes involving the data union structure and raised mould, Section IV describes the outcomes and argument, and Section V supplies an survey of the paper and proposes some prospect discuss orientations.

II. RELATED WORK

In literature [13], a computer assistance completely automated skill is exploited to detect glioma from multi-modle MRI images segment the tumor area from whole image. To diagnose tumors from brain MRI, a classifier called Naive Bayes is introduced. After detection, k-mean clustering and boundary prediction were served as collect brain tumor regions. The accuracy rate is more than 80%. In literature [14], large feature extraction proposals, in other sayings histogram of oriented gradients and gray rank concurrence matrix are applied to describe the graphicses. a segmentation scheme on account of color and edge detection was raised to investigate brain tumor regions. Budati aims at the problem that MRI is used as a result of low ionization and radiation in various medical imaging technologies, while manual detection takes a lot of trouble. Therefore, a machine learning technology is introduced to achieve the classification, recognition and detection effect of tumor or non-tumor areas in view of brain MRI dataset [15].

Automatic brain tumor detection, which graphics is segmented and classification is executed on brain MRI graphics applying genetic sequence that is meta-heuristic optimization scheme and support vector machine is proposed in [16]. The approach uses tumor attributes in genetic algorithms support

vector machines feature extraction sociology. The tumor data classification is close to the user's views that are in view of dynamic style. The best Fuzzy in the light of Bayesian classification is a qualified method that has been raised to more the classification accurateness, only in case of the richness of details on these terraces allow them available for use as source data, in implantations depend on tumor cancer research fields [17]. Uma has a large number of violations in a specific website, and it is hard to analyze the data of the website. A new feature extraction method based on dependency parsing and sentiment dictionary is proposed. This feature is used in conjunction with dictionary-based features to classify specific data [18].

Pries et al. [19] concentrates on analysis of those research which comprise segmentation, detection and classification of brain tumors. The general process for a scheme which designed to classify brain tumors on FMRI or MRI scans is: Pre-processing the graphics such as though eliminating the noise, then segmenting the image, which generates the area which might be a brain tumor, and eventually classifying features like intensity, shape and texture of the area. The existing ML methods with regard to brain tumor detection have already been built. However, the above methods, even if emerging well outcomes, are not also employed. Therefore, all spatial pixels need to be converted into multi-directional ones.The application of Gabor transform for spatial to multidirectional image conversion is reflected in [20]. Gabor transform was applied to convert the noise filtered image into multi-dimension brain image. Mixed features such as GLCM, grayscale co-occurrence matrix and LDP, local derivative mode statistics and texture properties were calculated from the transformed brain images. Lu has developed a new computer-aided diagnostic system, called PBTNet, to validate the detection of primary brain tumors in MRI images because of the large differences between observers in the interpretation of MRI images [21].

Hazra was drawn in the detection and localization of tumor districts in the brain exploiting schemes raised by MRI images of patients [22]. The design scheme involves three steps: preprocessing, edge detection and segmentation. The pre-processing process relates converting the primitive graphics to grayscale image and eliminating the noise when it exists or sneaks in. This is accompanied with edge detection utilizing Sobel, Prewitt and Canny strategies with graphics enhancement technologies. Segmentation is then utilized so that the regions influenced via the tumor are obviously evident in the MRI image. Finally, K-means scheme is exploited to cluster images. Considerations on the correctness of tumor recognition and realistic placement of MRI images are given in literature [23]. A method for detecting brain tumors by easily utilizing magnetic resonance imaging (MRI) data was exploited in the research. Improve the quality of picture frame, convenient for patients to carry out tumor treatment and diagnosis. The proposed protocol improves MR image quality and the detection of brain tumors, making it easier for doctors to diagnose tumors. Due to the combination of automated image segmentation technology and automated and efficient brain tumor detection technology implemented on positron emission tomography (PET) images, Hagargi developed the operation and technology to detect brain tumors from PET images using artificial neural network (ANN). The network applies most artificial intelligence to the classification and

TABLE I. Outline the Framework and Feature Set Described

Method	Segmentation	Features	Reference
Thresholding	Threshold	Area Set	Das et al. [8]
K-mean Clustering	Canny edge detection	Edge Det	Jos et al. [17]
Genetic Algorithm	Threshold	Region	Halder.[14]
Watersheding	Sobel Value	Metabolic threshold	Mus et al.[16]
MultiLayer Perceptron	Threshold	Fuzzy Algorithm	Sharma et al.[19]
OTSU	Threshold	Intensity Gray	Singh et al.[15]
CART	EM Algorithm	K segmentation	Bh and Ch [11]
SVM	Threshold	Tumor area	Sing et al.[18]

recognition of biomedical images [24].

Tahir [25] studied an image filtering and grayscale segmentation method for feature extraction. The extracted feature union are transmitted to a deep neural network to identify tumor areas. A strategy combining threshold segmentation, feature extraction and filtering procedure is designed in literature [26]. Solidity, area, and bounding box are the features used for classification. In [2], a hybrid kernel-based support vector machine (HKSVM) was designed to identify brain tumors from MRI. At first, anisotropic filters are applied to images to isolate them from noise, and morphological operators are used to complete image segmentation. Isolate tumor areas using area prop algorithms. Feature vectors were extracted from isolated tumor regions according to GLCM and strength-based histogram. In the end, the extracted feature union was transmitted to HKSVM for tumor classification. The above schemes mainly emphasis on MRI segmentation, which is used to detect brain tumors.

In addition, the above method focuses on the binary classification of brain tumors as normal and abnormal, and does not involve level 1 (i.e., meningioma, metastasis), level 2 (i.e., low-level glioma), level 3 (i.e., glioma), and level 4 (i.e., glioma) in the light of the World Health Organization. However, in the above discuss, this paper adopts a new computational strategy, an association rule learner, Partial Tree, which makes use of some advanced feature sets that have not been used before to classify brain tumors into multiple categories. The set of advanced features exploited in the research are cell count, angle, density, perimeter, and center of mass, which are described in subsection 3. As can be seen from Table I, this feature group has not been used for tumor detection and judgment in previous studies. However, experimental results show that, compared with currently approaches (namely, Bayesian networks, random trees, Rep trees, random forests and Naive Bayes), the use of advanced feature set partial trees performs better in terms of time complexity and accuracy.

III. System Model

A. Data Collection

The MRI was downloaded from various online sites. A total of 70 MRI samples were collected, including 32 samples of grade I, 10 samples of grade II, 8 samples of grade III and 20 samples of grade IV. Above all, the picked MRI was preprocessed to extract the feature group, and then the extracted feature information was delivered to the partial tree system to gradually classify brain tumors. The flow chart of the proposed approach is shown in **Fig.1**.
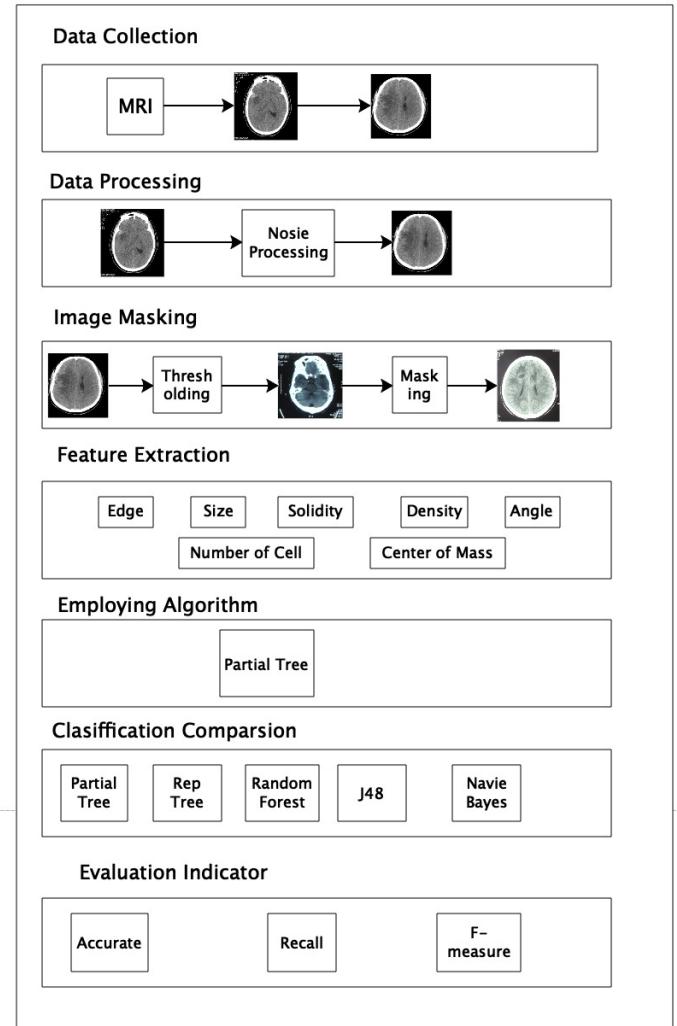

Fig. 1. Proposed Method Framework Diagram.

B. Feature Extraction

For the nature of feature extraction, some pre-processing processes are used for MRI, namely threshold segmentation and masking. According to the threshold segmentation, pixels are separated into different classification in view of their gray levels. The classification is regulated though the intensity value called the threshold. Pixels with larger intensity values fall into one classification, and pixels with smaller intensity values fall into another classification. It can be seen from the above literature that threshold is a common scheme that can successfully segment images. Therefore, the image can be segmented by threshold technology. In addition, the above data has not found the use of masking technology to identify brain tumors. The masking technology is introduced here as the preprocessing operation for detecting brain tumors, since in the case of the masking technology is appropriate for the image following the threshold, it will help to extract the features effectively.

Masking technology extracts features more effectively than other image processing schemes such as edge detection, mo-

tion detection and noise decrease, and is an effective performance of image processing. It can effectively measure the regional features and organizational structure in the image. Construct a duplication of the primary image and perform different AND, OR operations to meet its requirements. However, first use threshold segmentation on MRI, then construct a duplication of the image to employ the masking technique, and then use AND function to extract the required region. At the last, extract the features of the desired region. The feature set involves the number of cells, angular position, area, solidity, density, size, center of mass, perimeter, and so on. All of the above features are described the following.

1) Cell Number: Cell count refers to the entire amount of cells in the tumor area extracted. Use these factors to calculate the cell count using the following formula [27].

(1) The amount of small squares for counting according to the number of cells

(2) Count the number of large squares (tumor squares)

(3) Cell solution dilution

$$\text{The amount of cells} = \frac{\text{Number of large squares} \times \text{Cell solution dilution}}{\text{Number of small squares}}$$

2) Angle Position: The angle position shows details about the direction of tumor expansion in the skull. Tumors grow in a proportion of the brain that can travel vertically or horizontally through the brain at an angle.

3) Area: The size of the proportion shows particular details regarding the spatial spread of the tumor, namely, how much space the tumor can consume, in which S defines the region of the target (tumor) in the graphics, and x indicates the pixel value bigger than 1 and reaching N items in the region.

$$\sum_{x=1}^{N} Sx \qquad (1)$$

4) Solidity: Solidity represents the density of the tumor and can be used to measure the number and size of depressions in the target boundary. The proportion of the brain tumor in the graphics target partitioned into the region of its convex hull is the solidity of the target graphics, which is expressed via formula (3)

$$Solidity = \frac{\text{Area Size}}{\text{Brain Convexhull}} \qquad (2)$$

5) Density: Density is the key property applied to separate interest in an image region, which provides important information about image density.

6) Size: The size is considering the height and width of the objective image, which is built via multiplying though the number of horizontal and vertical pixels, as depicted in the Eq (4).

$$Size = \text{Horizontal pixels} \times \text{vertical pixels} \qquad (3)$$

(a) Original (b) Thresholding (c) Segmention-1
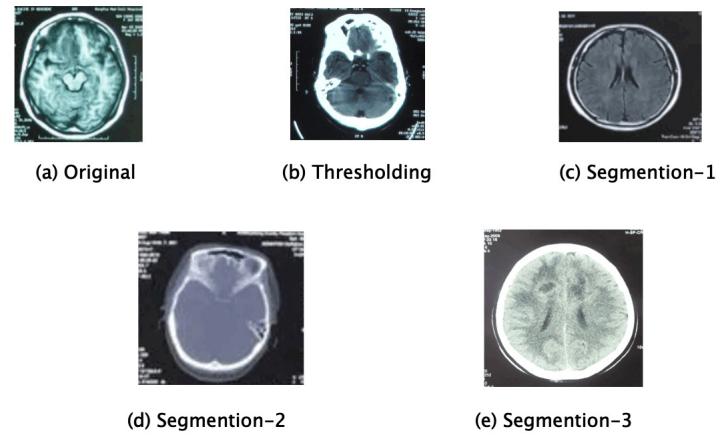
(d) Segmention-2 (e) Segmention-3

Fig. 2. Results from the Previous Process of Feature Extraction.

7) Center of Mass: The average value of each dimension in the target graphics is called the centroid, which is the median value of horizontal coordinate (x) and vertical coordinate (y) in the target graphics . The centroid is set by Eq. (5), which x, y and C respectively indicate the ordinate, abscissa and centroid of the object in the target image.

$$\text{Center of mass} = C \times \text{mean}(x \, or \, y) \qquad (4)$$

8) Perimeter: The perimeter refers to the sum of all external pixel boundaries in the target graphics. The most feasible approach to estimate the circumference of a brain tumor is to calculate the entire amount of edge pixels in the target graphics. Eq. (6) explains the representation of the perimeter.

$$\text{Perimeter} = \sum_{x,y} C(x,y) \qquad (5)$$

which x and y define horizontal and vertical pixel values, while C represents the perimeter of the target in the target graphics.

The feature extraction procedure is shown in **Fig.2**. After feature extraction, the feature vector is transferred to the association rule learner, namely partial tree. The results demonstrate that the performance of partial tree is better than other algorithms, i.e., Random Trees, Rep Trees, Random Forests, and Naive Bayes are as above high-level feature collections on accuracy and time complexity.

IV. PARTIAL TREE

Association rule learning tool has the ability to predict effectively. Therefore, this paper applies association rule mining model, that is, partial trees are used for grade detection of brain tumors. Partial tree is a mould designed by [28-29], which combines the merits of C4.5 and Ripper [30], and is used to yield a group of rules for efficient and accurate prediction. It takes advantage of Ripper's dial-and-conquer nature and

integrates it with C4.5 to prevent global optimization. C4.5 first builds an unpruned decision tree and transforms it into a rule union, and then simplifies rules by using a rule ordering strategy for each rule isolation. Finally, rules are set aside from the rule union to prevent global optimization until the rule set error is reduced. Ripper applies a divide-and-conquer approach to the set of rules. Only one rule can be introduced at a time, and the entities protected by this rule will be removed from the training sample. The rule generation process lasts up to the last entity of the training union. By combining the top features of C4.5 partial trees, a partial decision tree is initially constructed for the entities supplied in the dataset. Convert the leaves in the constructed tree with the largest coverage to rules, and then process the constructed partial tree to prevent global optimization. Entities protected by the yielded rule union are yet removed, and this process lasts until the final remaining entity in the dataset.

At first, some of the intelligibility of trees stimulated the use of them in hierarchical brain tumor detection in this paper. Second, it avoids global optimization, resulting in more noteworthy function in smaller time. In addition, it makes use of C4.5, which is a tree-based rule creation method, and from the existing research, tree-based method has the latent ability of identification. Therefore, a hybrid approach as a partial tree may perform better at extrapolating predictions. However, in this work, partial trees were found to have significant recognition of brain tumors and replace other existing methods such as Bayesian networks, random trees, Rep trees, random forests and naive Bayes in the light of time complexity and correctness.

V. Performance Evaluation

To verify the effectiveness of the algorithm, the following performance indicators are defined: accuracy (i.e., Acc), recall rate (i.e., Rec) and F-measure (i.e., F-mea). We use mathematical expressions (7), (8) and (9) respectively to describe the equations of these indicators.

$$Acc = \frac{TP}{TP + FP} \qquad (6)$$

$$Rec = \frac{TP}{TP + FN} \qquad (7)$$

$$F - mea = 2 \times \frac{Pre \times Rec}{Pre + Rec} \qquad (8)$$

where TP represents true positive rate and is classified as brain tumor, FP is false positive rate, for instance, non-brain tumor is classified as brain tumor, FN is false negative rate, namely, brain tumor is classified as non-brain tumor. Consequently accuracy is the ratio between familiar instances of brain tumors that are correctly classified and all instances of brain tumors that are classified. Recall rate is the ratio between the amount of brain tumor instances that have been properly assorted and the whole amount of known brain tumor cases. The F-measure is the harmonic average of accuracy and recall rate.
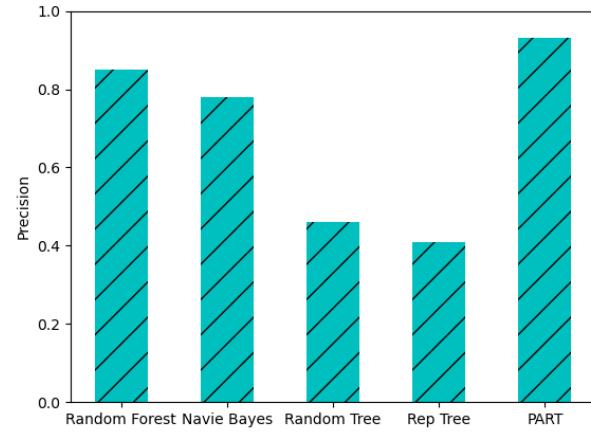

Fig. 3. Comparison of Accuracy between Partial Tree and Other Schemes.
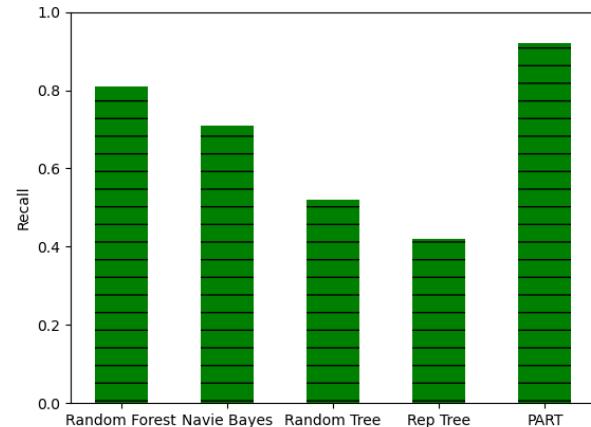

Fig. 4. Comparison of Recall with Partial Tree and Other Schemes.

A. Analysis of Experimental Results

To verify the efficiency of partial trees, it is compared with other competitive models such as random tree, Rep tree, random forest and naive Bayes. The performance comparison in accuracy, recall rate and F-measurement is shown in **Fig.3-5**. Compared with other technologies, partial tree will produce better results according to accuracy, recall rate and F-measure.

1) Performance Robustness: To verify the robustness of partial Tree performance, this paper compares it with the true positive (TP) rates of random Tree, Rep Tree, random forest and naive Bayes under different thresholds. The thresholds used are $t = 0.25$ to 0.95. **Fig.6** shows that the performance of some trees is more robust than that of other schemes because the TP rate is close to 1 while the TP rate of other methods is less than 0.85.

2) Computation Performance Cost: To verify the function of partial tree in computing cost, it is analyzed using mathematical and experimental algorithms respectively. The
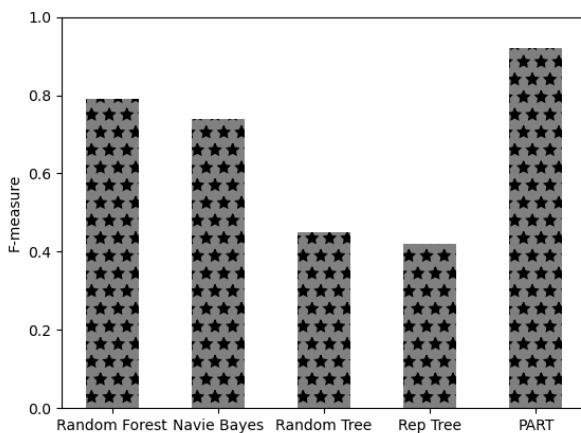
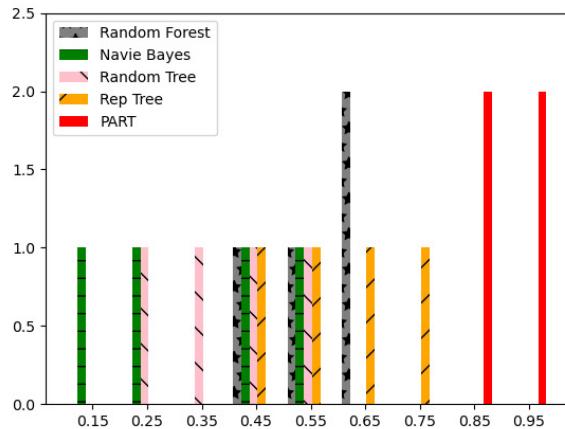Fig. 5. Comparison of F-Measure with Partial Tree and Other Schemes.

TABLE II. ANALYSIS OF EXPERIMENTAL RESULTS

Algorithm	Correct Instances	Incorrectly Instances	Time (seconds)
Partial Tree	60	5	0.03
Rep Tree	30	35	1
Random Tree	32	27	1
Random Forest	50	15	0.3
Naive Bayes	48	18	0.2

TABLE III. THEORETICAL ANALYSIS OF DIFFERENT ALGORITHMS

Algorithm	Sample Size	Time Complexity (seconds)
Partial Tree	N+M	$O(S \times NlogN)$
Rep Tree	N+M	$O(N^2)$
Random Tree	N+M	$O(N^2)$
Random Forest	N+M	$O(M_{tree} \times N_{tree} \times NlogN)$
Naive Bayes	N+M	$O(D \times N)$

Fig. 6. Robustness Comparison of Algorithms under Different Thresholds.

correct naive Bayes classification is smaller than the number of partial trees that may pose risks to the diagnosis, prevention and treatment of brain tumors.

Therefore, by studying an association rule learner with a different analysis called a partial tree, it can be concluded that some trees are superior to existing the most advanced technologies for instance Rep Tree, Random Tree, Random Forest and Naive Bayes in accordance with the correctness and computing expense. In addition, the set of high-ranking features described in the research, namely cell count, angular direction, density, centroid, and perimeter, still play a critical part in significantly making better the function of the brain tumor category-based model.

3) Impact of State-of-the-Art Features on Function: To verify the influence of state-of-the-art features presented in the research on brain tumor classification, the feature union was partitioned into two classes. The first class, called the benchmark feature, includes density, size, and area, whereas the second class, called the state-of-the-art class, includes cell count, Angle, density, perimeter, and center of mass. The all-around comparison of accuracy, recall rate and F-measure of

mathematical performance analysis is shown in Table III, which N represents the amount of cases in the training and test set, where A denotes the amount of attributes, N_{tree} indicates the amount of trees built via the random forest, M_{tree} represents the amount of attributes sampled by every node of the tree, and D represents the dimension of features demanded by naive Bayes. According to Table III, for $\Omega(O)$, the time complexity of some trees is lower than that of Random Tree, Rep Tree and Random Forest algorithms. Compared with partial trees, naive Bayes is more effective in computation costs than partial trees, but less accurate than partial trees, as shown in Table III and Table II, which is very significant for correct diagnosis, prevention and therapy of diseases. Experimental analysis is denoted in Table II, which shows that it takes about 0.03 s to build a model for some trees. This is less time than other struggling approaches like random trees, Rep trees, and random forests.

Naive Bayes takes less time than partial trees. However, it can be concluded from Table III that the amount of cases of
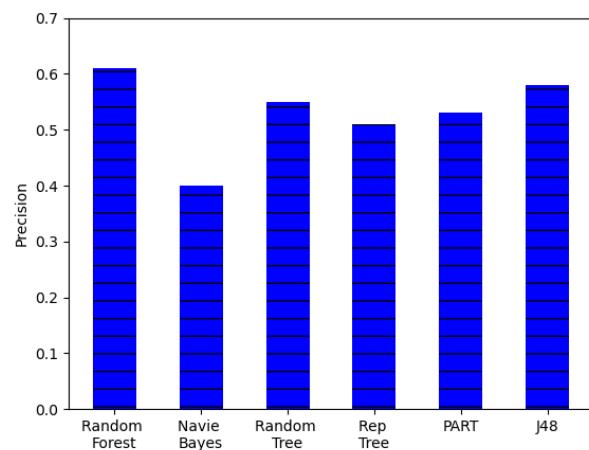

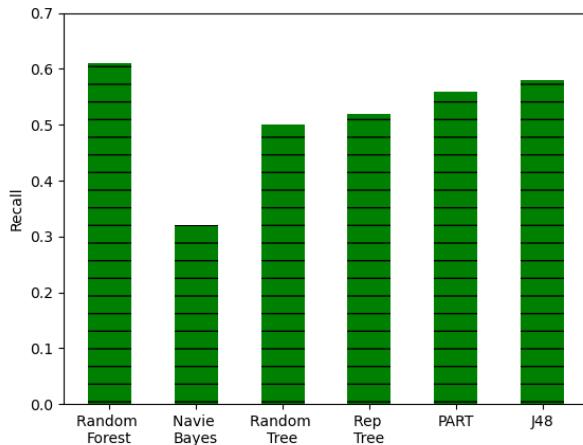Fig. 7. Accuracy between Algorithms based on Baseline Features.

Fig. 8. Various Recall Algorithms based on Baseline Features.
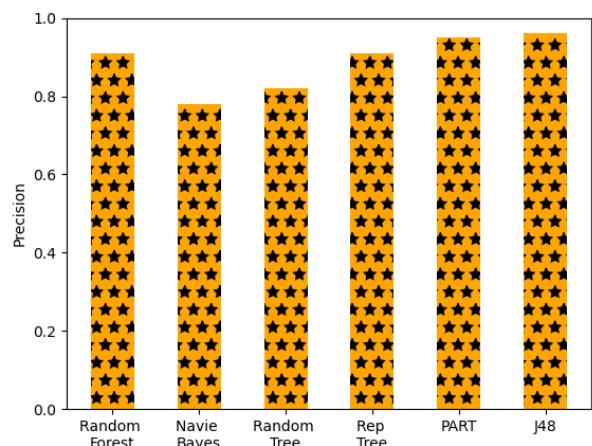

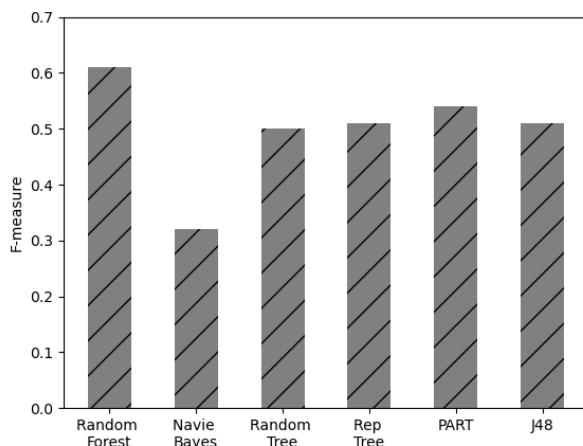Fig. 10. Accuracy of Various Algorithms based on Advanced Feature Sets.

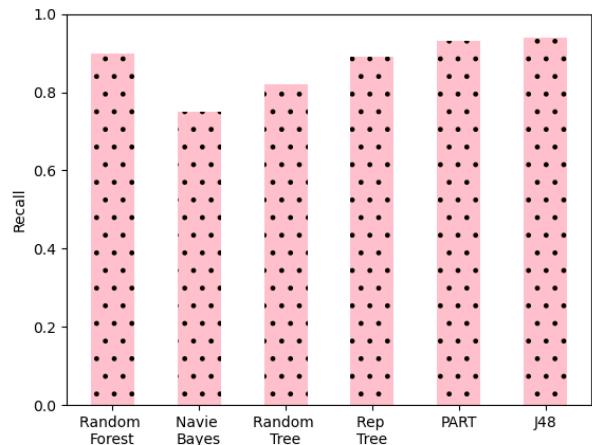Fig. 9. F-Measure in Different Algorithms based on Baseline Feature.

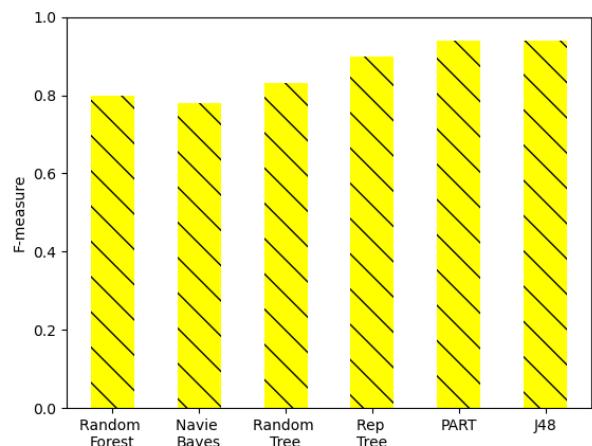Fig. 11. Recall of Various Algorithms based on Advanced Feature Sets.

Partial Tree, J48, Random Tree, Rep Tree, Random Forest and Naive Bayes is shown in **Fig. 7 to 9**, and baseline feature sets are used respectively. **Fig. 10 to 12** shows the comprehensive comparison of accuracy, recall rate and F-measure of Partial Tress, J48, Random Tree, Rep Tree, Random Forest and Naive Bayes, separately employing high-level function union features. It is important to note that the most state-of-the-art methods have baseline characteristics, accuracy, recall rates, and F-measures of less than 60%. For another, with the improvement of advanced feature sets, these methods increase significantly in accuracy, recall rate and F-measure. However, Partial Tress and J48 with 96% accuracy, recall and F-measure will show superior than other schemes. J48 has 60% F-Measure, but its performance is significantly improved through the advanced feature set, as shown in Fig. 10 to 12. Therefore, the function of distinct machine learning models should be better with advanced feature sets.

Fig. 12. F-Measure of Different Algorithms based on Advanced Feature Sets.

VI. Conclusion

With the emergence of the BDD_FFS system in the medical field, there have been many security risks in big data medical equipment. However, the most serious security threat facing the healthcare field is brain tumors. Brain tumors are irregular growths of cell tissue in the brain, which may lead to life-threatening. In a safe environment, the use of BDD_FFS-based system applications to detect early brain tumors is important to reduce mortality. The conventional techniques used to detect brain tumors are biopsy and MRI or CT scanning by human experts. Biopsies are very unbearable for patients, and a large number of MRI and CT scans is a complex task that is impractical for limited specialists.

Therefore, it is necessary to adopt safe and automatic technology to accurately detect brain tumors. In this work, firstly, a secure PART_T-based computational approach is employed to correctly identify the lesion grade of brain tumors. Secondly, this work introduces a high-ranking feature union not formerly involved for the proper recognition of brain tumors. Finally, The experimental results show that the designed PART_T technology with advanced feature group is superior to other subsistent technologies for instance Rep Tree, Random Tree, Random Forest and Naive Bayes in correctness and computational overhead.

The future work is as follows: expert automation technology system is very necessary to determine brain tumors in the early period, so that they can be more treated with drugs, so as to avoid a series of processes of surgical pain. Firstly, Applying techniques such as compounded machine learning models or neural networks to improve brain tumor diagnostic procedures is an inevitable need for active academic attention. Secondly,, some further modern functions can also be applied to make better medical effects. BDD_FFS combines active metadata, semantics, knowledge mapping, data virtualization, AI and other technologies to enable accurate, agile, and efficient matching between users and data to achieve optimization for specific medical scenarios. Finally, BDD_FFS is a technical architecture approach that addresses the complexity of data and metadata in an intelligent way and provides seamless access and sharing for all data consumers.

Acknowledgment

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