International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Interestingness Framework for Brain Tumor Classification Using Image Apriori and Shape Priori Segmentation Algorithm

Geeta Santhosh[1], Dr. R. Maruti[2]

Submitted: 25/06/2023 **Revised**: 07/08/2023 **Accepted**: 25/08/2023

Abstract: Data mining entails discovery of beneficial patterns from an extraordinary number of large patterns. The discovered patterns are categorized by applying appropriate metrics known as the interestingness measures. Data mining is a highly effective technique that finds extensive application in various domains, including healthcare. One of its significant uses cases in healthcare is the identification of health services sequences from massive medical datasets, facilitation of decision-making, and provide early-stage treatment to patients. In the field of medical imaging, a plethora of computer-aided diagnosis (CAD) systems have been introduced to aid radiologists in their patient utilized. A head tumour is a pathological condition characterized by the anomalous proliferation of brain cells, and is considered a significant contributor to mortality rates in the population. A computerized system for detecting brain tumours enables early stage diagnosis. The present study introduces an intelligent system designed for the purpose of diagnosing and classifying brain tumour disease, as well as providing the user with a comprehensive description of the disease and offering advice for maintaining a healthy lifestyle. The methodology employed involves the utilization of data mining techniques on a health care dataset. The focus of the proposed system is primarily on the diagnosis of tumours in the brain through the utilization of Computerised Tomography (CT) images of the brain. This study provides an additional approach for neuroradiologists to readily discern neoplastic cells from cerebral images. The proposed work incorporates a crucial data mining concept, namely, the pre-processing of CT scan brain images. The proposed system is composed of four distinct phases, namely pre-processing, segmentation, feature extraction, and classification. This paper presents a proposed algorithm for image segmentation utilising shape priors, and an association rule-based classification approach using interestingness measures utilizing the image apriori algorithm. The algorithm proposed was evaluated and attained a success rate of 99%. The outcome is evaluated in comparison to other extant mining algorithms.

Keyword: *Computerized Tomography (CT), neuroradiologist, brain tumor, data mining, Computer Aided Diagnosis (CAD).*

1. Introduction

The brain is a multifaceted organ located within the human body. Neurological disorders are prevalent in contemporary society. The proliferation of anomalous cells within the brain is commonly referred to as a brain tumour, which can manifest in a variety of forms. Tumours have the potential to manifest in various sizes and locations within the brain. The proliferation of anomalous cells within the brain results in elevated intracranial pressure, which can give rise to a host of deleterious physiological consequences. Benign tumours are neoplasms that lack the ability to metastasize and are considered non-malignant. However, certain tumours possess malignant characteristics and can present diagnostic challenges, ultimately resulting in a lower likelihood of survival [1]. The expense associated with the treatment of brain tumours is beyond the financial means of a significant proportion of patients.

The management of brain tumours is contingent upon several factors, including the dimensions of the tumour, the histological classification of the tumour, and the stage of tumour progression. The healthcare industry employs various medical imaging techniques, including MRI (Magnetic Resonance Imaging) and CT (Computed Tomography) scanning, to detect the presence of brain tumours. These methods are utilized by medical professionals to diagnose and identify such conditions. There is a need for increased attention to be given towards dealing with severe brain diseases. The medical industry has adopted methods based on data mining to enhance decision-making processes and identify the presence of various diseases. Medical professionals have the option to utilise a brain tumour detection method as a supplementary assessment tool for both the diagnosis and treatment of brain tumours [2].

The paper's primary contributions may be succinctly summarised as follows:

- As far as current knowledge permits or (In view of our literature survey,) this study represents the initial endeavour to execute a computer-aided design system for the categorization of brain tumours into four grades, in accordance with the World Health Organization's criteria for brain tumour classification.

[1]*Professor and Head, Dept of FCA, Acropolis Institute of Technology and Research, Indore, Madhya Pradesh*
[2]*Associate Professor, Hindustan Institute of Technology & Science, Padur, Chennai*

- The employed preprocessing technique involves the utilization of the histogram equalization method, while the segmentation process is executed through the implementation of the shape priori algorithm.
- The feature vector is utilized to extract features, to be stored subsequently, in the transactional database.
- Association rule mining is executed during the testing phase to enhance the required features produced by the feature vector.
- Ultimately, classification is achieved through the generation of keywords via the utilization of the image apriori algorithm. These keywords are subsequently compared with optimised features, culminating in the ultimate determination.
- The system has demonstrated superior accuracy in analyzing brain CT images in comparison to other contemporary techniques, despite the fact that certain systems have exhibited higher accuracy in processing pathological images.

2. Literature Survey

P. Rajendran and colleagues presented an enhanced image mining methodology for categorising brain tumours [3]. The pre-processing methodology incorporates the Shape Prior technique. Association rule mining was utilized for the purpose of feature selection from brain images. The regulations produced for extracted characteristics have been saved in a transactional database and subjected to classification through the data mining technique known as Decision Tree Classification. The proposed system achieves an impressive level of accuracy and efficiency through the utilization of both association rule mining and decision tree classification techniques.

Sajjad and colleagues have proposed [4] a classification method for multi-grade brain tumours using a deep convolutional neural network. The process of segmenting tumour locations from an MR image is accomplished through the utilization of a method based on deep learning. The proposed system utilizes extensive data augmentation to effectively address the issue of insufficient data when handling MRI for multi-grade brain tumour classification. Ultimately, a convolutional neural network model that has been pre-trained is subjected to fine-tuning through the utilization of augmented data, with the aim of facilitating the classification of brain tumour grade. The system under consideration is subjected to experimental utilized using augmented and original data. The findings indicate that the system exhibits a convincing performance when compared to existing methodologies.

The paper authored by Keerthana T K and Sobha Xavier presents [5] an intelligent system designed to diagnose and classify brain tumour disease. The system provides users with disease descriptions and healthy advice. The system utilises data mining techniques to analyze a medical image dataset. The system under consideration consists of four distinct phases, namely pre-processing, segmentation, feature extraction, and classification. The tumor's classification is determined by a Support Vector Machine algorithm within the system. The author employed a genetic algorithm to optimise the features and parameters of the support vector machine. The system operates by utilising brain MRI images, and the application of data mining methodologies in the tumour detection system is expected to yield a high rate of detection.

Chauhan et al. proposed [6] a method for pre-processing MRI brain images through the use of median filtering. In order to distinguish lesions from an image, the process of color-based classification and detection of edges is employed. The images are represented using various feature extraction techniques, including a histogram of gradient orientation and grey level co-occurrence matrix. In order to categorise the tumour as benign or malignant, the IBkLG classification (Instance based K-Nearest utilising Log and Gaussian weight Kernels) was used to all the retrieved characteristics that have been saved in a transactional database. The observed classification accuracy is 86.6%.

Khan et al. provide a comprehensive summary of the ongoing research utilising data mining methodologies for the purpose of brain tumour diagnosis. The objective of this research is to ascertain the optimal data mining algorithms utilized in the analysis of health care brain MRI and clinical variables for enhanced performance. The algorithms identified by the author include Decision Trees (DT), Support Vector Machine (SVM), Artificial Neural Networks (ANN), as well as their Multilayer Perceptron model, and Fuzzy C-Means. The authors conducted an analysis of the challenges associated with the data mining technique utilized for the classification of brain tumours. Occasionally, certain algorithms exhibit superior performance in comparison to others. However, there exist scenarios where the amalgamation of characteristics from aforementioned algorithms yields a favourable outcome. This study involves a thorough assessment of the reviewed literature [7].

3. Proposed Work

Feature extraction and training, testing, association rule mining, and classification are the four pillars of the proposed system. Figure 1 depicts the flow chart of image segmentation using shape prior method. Histogram equalization is used to pre-process obtained input CT scan images of the brain in the extraction of features and training phase to enhance picture quality. The shape prior approach was used for segmentation once the image was preprocessed [8]. The features were then retrieved from the segmented patches, and the feature vector defined. Finally, the whole set of features was commited in the operational database.

The feature vector is used to build an association rule, which is then saved in the transactional database. The Image Apriori technique is used to mine associations from this representation of the transaction. The extensive collection of rules has been constructed using the photos used for training. Pruning has been performed on the produced rules in order to reduce complexity.

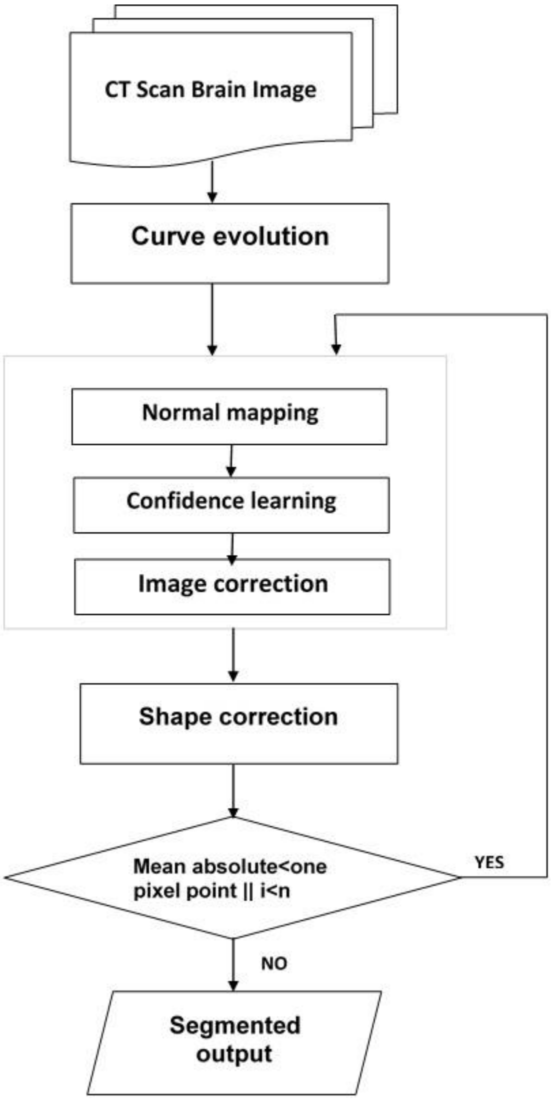


Fig 1: Flow chart of shape prior algorithm for segmentation

The testing phase allows for the execution of pre-processing, segmentation, feature extraction, and feature vector computation. Image Apriori may be used to mine the association rules between features without saving the features in a database.

During the classification stage, it is possible to compare the association rule of a given test image with the association rules present in the pre-trained database. Based on the quantity of matches, the test image will be categorized as either typical or atypical [9,10]. In instances where the number of supports values and keywords deviate from the usual range, CT scan brain images are termed as either benign, indicating the absence of a tumour meaning no cancerous tissues, or malignant, indicating the presence of a tumour with cancerous tissues.

3.1 Pre-processing

Pre-processing is a necessary step in CT scan image analysis due to the potential presence of noise, inconsistency, and incompleteness in the acquired images. The act of cropping can be executed to eliminate extraneous background elements, while image enhancement techniques may be employed to augment the dynamic flexibility of specific features, thereby facilitating their detection. The majority of soft tissues exhibit intersecting grey levels, and the illumination conditions during the period of CT scan acquisition are variable. Histogram equalization and hybrid median filtering techniques can be employed to respectively enhance the contrast within soft tissue of brain images and improve their overall quality. Texture characteristics are derived from the image that has undergone pre-processing [11].

3.2 Shape Prior method

The fundamental concept underlying this methodology is to iteratively transform a curve within the image to ultimately align with the shape segmentation prescribed by the algorithm. The evolution of the curve is influenced by two factors, one of which employs characteristics extracted from the image, whereas the other incorporates pre-existing knowledge regarding the curve's shape, thereby restricting the range of feasible solutions. Figure 1 illustrates the sequence of steps that comprise the implementation of the shape prior procedure.

The preliminary approximation is derived through a rough alignment of the average configuration of the geometric space, denoted as the shape space, that is delineated by a collection of sampled points referred to as control points, with the pre-processed image. The primary curve undergoes iterative deformation through a sequence of two consecutive procedures, namely image correction and shape correction. The initial stage pertains to the image, whereby the curve undergoes a transformation regarding the image data through the facilitation of pronounced local deformation. Therefore, the creation of a range of values around the initial estimate through coordinate transformation is known as normal mapping. The band imposes limitations on the utilization of image data within the specific regions of interest pertaining to this particular procedure. Subsequently, the control points pertaining to the present curve are displaced in the direction of the normal vector, with a magnitude contingent upon the characteristics of the image within the surrounding region [12]. The magnitude of this displacement is contingent upon the weighted mean of the properties of the pixels situated along the normal vector of the present curve.

The weight factor considers the existence of luminous areas that are approximately aligned with the present curve. The second stage pertains to the comprehension of the algorithm's shape. Having prior knowledge of the shape is crucial for interpolating the curve in areas where there is insufficient data. The process of obtaining shape correction involves the utilization of mean shape and statistical analysis. The algorithm employed is iterative in nature, with the cessation criterion contingent upon the trajectory of the curve throughout the course of its evolution. The test for the stop condition is executed subsequent to the completion of both the image and shape correction procedures. The algorithm's termination criterion is contingent upon two conditions: either the mean absolute variance between the points of control of the present curve and those of the earlier iteration is below one pixel per control point, or a predetermined number of iterations have occurred..

3.3 Curve utilized

Effective initialization is crucial for preventing the occurrence of local minima and achieving prompt convergence. This step involves the identification of the appropriate position, orientation, and scale of the shape within the algorithm. The first step involves the application of a Region of interest (ROI) to eliminate scanner artefacts, such as the date, scale, and time. Subsequently, an anisotropic diffusion filter is employed to eliminate speckle noise within the identified region of interest [13].

The curve evolution process has been executed using the subsequent procedures:

i. ROI

ii. Image quality enhancement

iii. Edge detection

Subsequently, a high-pass filter featuring an extremely low threshold frequency is employed to counterbalance the gradual fluctuations in luminosity present within the image. The output of the high-pass filtering process is subjected to binarization through utilization of a threshold value that is proportionate to the variance of the grey level within the region of interest, as described by Serhat and Yulmaz in 2005. A seed point is established within the expansive areas of the binarized image to specify the initial location of the curve. This is accomplished by identifying the initial high intensity pixel from the top, bottom, left, and right edges of the region of interest (ROI). The contour of a curve is defined by utilising the seed location and the average of the distances from the centres to the first bright location in all four directions. This process yields the first estimate of the shape.

3.4 Image Modification

3.4.1 Normal Mapping

Facilitating robust local distortions of the curve is imperative to effectively align it with the image data. A circumferential band is established to accommodate normal deformations along the curve. The configuration of this musical ensemble is analogous to the visual data utilized by professionals in the process of manually delineating the contours. Furthermore, it imposes limitations on the utilization of image data solely within the relevant area during this procedure. The process of forming a band is commonly referred to as Normal Mapping (Nm) and relies on a curve known as Cv. It is also referred to as a coordinate transformation. The proposed concept involves the process of unwinding the band along the curve, whereby the horizontal axis (i) represents the length of the arc of the curve, and the vertical axis (j) denotes the distance from the curve. In the context of normal mapping, a fixed point (m, n) within a band can be represented in terms of its normal mapping space coordinates (i, j), where the vertical position j denotes the distance of the point from the curve. The vertical points in Newton metres (Nm) correspond to the normal direction of the curve Cv depicted in the image [15].

The acquisition of contour regularity is achieved through the process of observing the grey level data in the surrounding vicinity along the manually examined curves. The process involves the application of the normal mapping technique to the manually marked curves on the CT scan image set. Subsequently, the set of images is subjected to a computation of the average at the pixel level, as well as the vertical gradients thereof. The terms "mean NM image" and "mean NM gradient image" are utilized to refer to these particular images. The interestingness measure weight function or weight measure is determined by utilizing the two aforementioned values, as per the subsequent equation (1)

$$W_{function} = N_f G_{\partial} * (\overline{I_{N_M}(J,0) + \sigma I_{N_M}(J,0)}) \quad (1)$$

Where,

N_f=Normalization factor

G_σ=Gaussian filter

J= length of the arc

I_{N_M}= normal mapping image

σI_{N_M}=Gradient mapping image

The above mentioned interestingness measure serves the purpose of modulating the level of confidence attributed to the image data in proximity to the contour.

3.4.2 Shape correction

The incorporation of prior knowledge regarding the curve's shape is a crucial aspect of the shape correction process, as it enables the interpolation of the curve in areas where data is insufficient. The present procedure involves the displacement of the existing curve following the geodesic trajectory towards the average configuration in the spatial domain of shapes. The formulation of the shape space involves the application of manual segmentation to multiple CT images. The present methodology involves regarding shape as a singular point within a designated manifold, whereby the distance among shapes is defined as the magnitude of the geodesic path linking the corresponding points within the aforementioned manifold. The shape prior refers to the average shape that is obtained as the Karcher mean of a subset of manually annotated data. The Karcher mean is a statistical method that seeks to minimize the total number of squared geodesic lengths between an average shape and each of the shapes in the shape space. The process of correcting shape is accomplished through the utilization of mean shape and statistical analysis. The process of shape correction involves utilising the mean shape to determine the shape depicting the present curve, followed by calculating the geodesic path linking the average shape and the current curve [16]. The shape segmentation on input image is shown in figure 2.

After aligning the image's form with the curve's control points, the new curve's size, orientation, and location are all corrected. After the images and shapes have been fixed, we do the final condition test. Each of the two following requirements must be met before the algorithm will exit:

- The overall difference between both control points of the current and the previous curve iteration has a mean value of less than one pixel per control point.
- Upon reaching a predetermined number of iterations

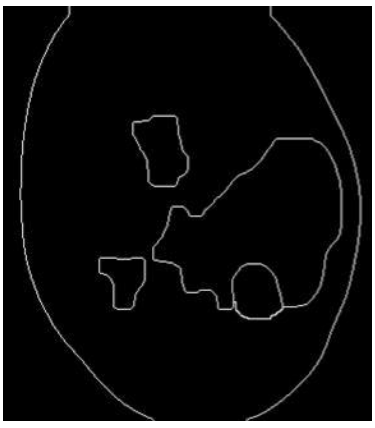


Fig 2: tumor segmentation using shape prior algorithm

3.5 Texture feature Extraction

In order to classify medical images, four texture characteristics have been applied. Mining based on Association rule is utilized to identify anomalies in medical images through the utilization of texture information. The spatial organisation of pixel intensities can serve as a basis for categorising this information. To effectively represent the spatial arrangement of grey levels in a given neighbourhood, the utilization of two-dimensional co-occurrence matrices is a viable approach for computing both global and pixel-level features.

The following descriptors or interestingness measure can be used for extracting texture features:

Feature	Definition	Formula
Contrast	The measure of intensity contrast among a pixel as well as its neighbour across the entire image is returned. When an image remains constant, its contrast is measured at 0.	$\sum_{x}^{a}\sum_{y}^{b}(x-y)^2 N(x,y)$
Correlation	The measure quantifies the degree of correlation between a pixel and its neighbouring pixels across the entire image.	$\sum_{x}^{a}\sum_{y}^{b}\frac{(x-\mu)(y-\mu)^2 N(x,y)}{\sigma^2}$
Energy	This function computes the summation of the squared elements present in the Grey-Level Co-occurrence Matrix (GLCM).	$\sum_{x}^{a}\sum_{y}^{b}P^2[x,y]$
Homogeneity	The function yields a metric that quantifies the proximity of the arrangement of constituents in the GLCM to the GLCM diagonal.	$\sum_{x}^{a}\sum_{y}^{b}\frac{P[x,y]}{1+\|x-y\|}$

3.6 Classifier Construction

The feature vectors extracted from the training set images have been stored in a transaction database for the purpose of classification. The utilization of novel data mining techniques, such as image mining, has the potential to extract association rules from test images through the extraction of feature vectors. The test set characteristic vector's mined rules were compared to the trained set feature vector's mined rules in the classification process.

3.6.1 Association Rule Mining

The task of identifying association rules in data mining entails the identification of rules that meet the user's predetermined minimum support and confidence thresholds. The proposed methodology involves the utilization of a modified image apriori algorithm to conduct association mining among the features present in a transactional database. The algorithm under consideration is referred to as Image Apriori.

3.6.2 Image Apriori Algorithm

The present study employs a modified version of the apriori algorithm to extract associations among characteristics from the training transactional a database of CT brain images. The primary objective of the Image Apriori algorithm is to produce a candidate item set and establish an association rule based on the transactional database of image feature vectors. The execution of mining association rules on the feature vector of an image can be accomplished through the utilization of the join and prune steps.

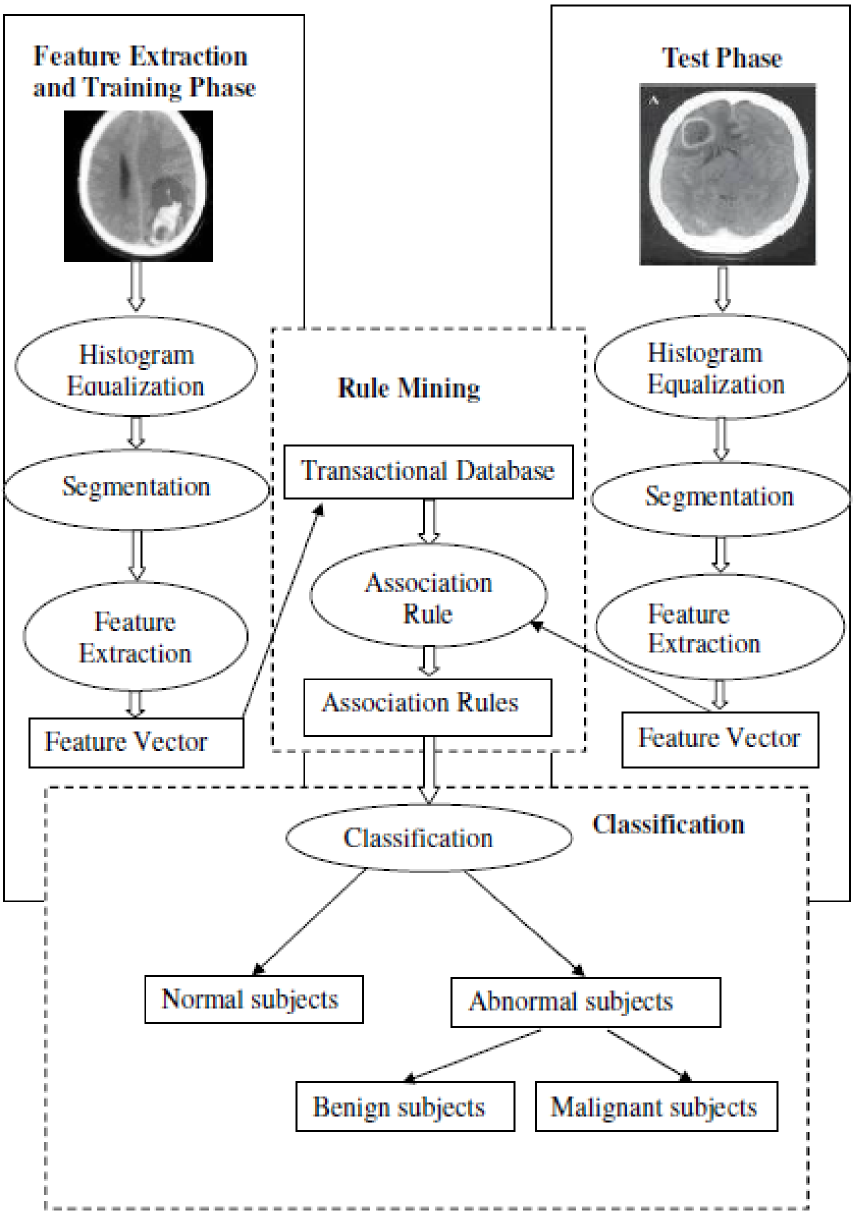


Fig 3: Flow diagram of proposed work

Join Step: Candidate sets of image feature vectors. The set Sm is produced through the concatenation of Mm-1 with itself, where each element in the set contains a label and a corresponding minimum support count value.

Prune Step: It can be inferred that a k-item set that is frequent must contain all of its (k-1)-item subsets. Conversely, any (m-1)-item set which is not frequent cannot be considered a subset of a common k-item set.

The algorithm that was developed is capable of identifying association rules within the learning vector of features set of a transactional database. The algorithm receives a collection of image patches (I1) in the format of Ii:{m1,m2……..mm, f1,f2……fn}, where mi represents a keyword associated with the patches and fj denotes the chosen feature vector for the patches. Additionally, the algorithm requires a minimal support threshold (th).

Algorithm

Obtain candidate set and their support and keywords (c_0)

Obtain frequent keywords and their support (f_0)

Find candidate keyword 1 item set and their support ($c_{1)}$

Find frequent 1 item set and their support (f_1)

Find candidate set c_2 from the candidate pairs (i,j), such that (i,j)€ P and i€ f_0 and j€f_1

for each patches p in p_1

for each keyword (kw)= (kw) in candidate set c_2

kw_support ← kw_support+count (kw,p)

End for

End for

f_2← {kw€ c_2|kw.support > th}

P_2←Pruning (p_1,$f_{2)}$

c_i←self_joining of (f_{i-1},$f_{2)}$

c_i←c_i-{kw|(i-1) item set of kw € $f_{i-1\}}$

P_i ← Pruning (p_{i-1}, f_{i-1})

for each Patches P in p_i

for each kw in c_i

kw.support ← kw.support+count(kw,p)

end for

end for

f_i ← {kw€ c_i|kw.support > th}

end for

sets ← U_i {kw€ f_i|i>1}

Rule ≠ th

for each item set I in sets

Rule ← Rule+{f → kw|f∪kw€I^f^kw€c_0

end for

End

The rules for association are subject to constraints that dictate that the precursor of the rules must consist of a conjunction of features extracted from the brain image, while the result of the rule is invariably the class label that corresponds to the brain image.

3.6.3 Classification of Test Image

Upon concluding the training phase, it is possible to construct an authentic classifier utilising a pruned collection of association rules to train brain images. A collection of keywords is linked to every training image. Keywords are selected by medical experts to aid in the utilized of medical images. It is imperative to take into account the expertise of professionals in the field when analysing medical images obtained through mining techniques, as this can serve to authenticate the outcomes. The features extracted from the test image and the resultant feature vector may be presented to the classification algorithm, which employs association rules to produce a collection of keywords for the purpose of constructing a diagnosis for the test image.

Algorithm

Input: Feature vector F of the test image, threshold (th)
Output: set of keywords W
Start
Obtain feature vector F of the test image and threshold value
for each rule r€R of the form body → head do
for each item set i € head
do
if(body matches feature vector)
then
body matches++
else
increase the no of non matches by 1
end if
end for
end for

Keyword Generation

For each rule r € R of the form body → head
do
for each item set i € R head
do
follow equation
if i € W
end if

end if

Return set of keywords W

End

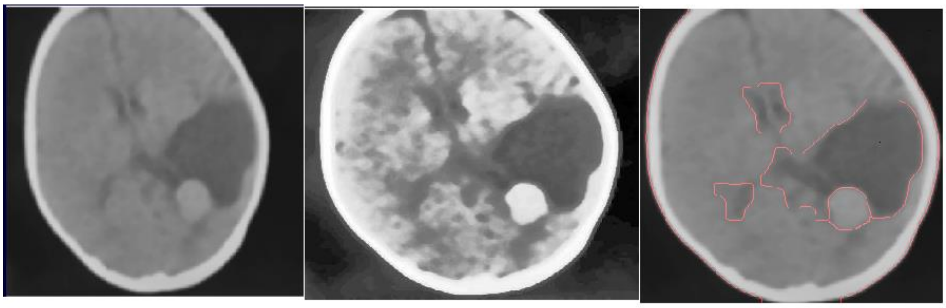
The aforementioned classifier is capable of producing multiple classifications upon analysing a given test image. The developed algorithm has been utilized to produce recommendations for the purpose of diagnosis. The data structure utilized by this algorithm is designed to store the item sets, specifically the set of keywords, that pertain to the head of the rules. The suggested diagnosis returns an item set h if the condition specified in Equation (2) is satisfied

$$\frac{n(M_I)}{n(M_I)+n(N_I)} \geq th \qquad (2)$$

The variable $n(M_I)$ represents the count of matches for the item set I, while $n(N_I)$ denotes the count of non-matches. The concept of threshold (th) is utilized to restrict the minimum number of matches that must be met in order to generate an item set within the proposed diagnosis. A match is established when the characteristics of the image meet the criteria for the corresponding body part as specified by the rule. The performance utilized of the proposed approach was conducted using a confusion matrix.

4. Result and Conclusion

The processing of brain images obtained from the CT scanner is conducted in accordance with the proposed flow diagram, as depicted in Figure 3. The image utilized as a sample input in this study is presented in Figure 4 a. The application of histogram equalisation technique has been employed to enhance the visual clarity of CT scan brain images. The application of the median filtering method is employed as a pre-processing step for CT scan images to reduce noise prior to executing advanced processing procedures, such as detection of edges. Figure 4 b and 4 c displays a pre-processed CT scan of the brain. The shape prior technique was utilized to perform an automated segmentation of a CT scan image of the brain.



4.a Input Image 4. b Preprocessed image 4.c Segmented image

The algorithm for mining association rules has been developed utilising the association rule derived from the feature vector that is stored within the transactional database. The transaction table has undergone six iterations of joining and pruning. Tables 2 and 3 demonstrate the presented information.

Table 2: Candidate set for Level 1

Range	'A1'	'A2'	'B1'	'B2'	'C1'	'C2'	'D1'	'D2'	'E1'	'E2'	'F1'	'F2'	'G1'	'G2'	'H1'
Support	6	4	5	5	4	6	4	6	2	8	2	8	2	8	3
Range	'I1'	'I2'	'J1'	'J2'	'K1'	'K2'	'L1'	'L2'	'M1'	'M2'	'N1'	'N2'	'O1'	'O2'	'P1'
Support	3	7	5	5	5	5	5	5	4	6	3	7	5	5	4

Table 3: Pruned set for Level 2

Range	'H2'	'A1'	'B1'	'B2'	'C2'	'D2'	'E2'	'F2'	'G2'	'H2'	'I2'	'J1'
Support	7	6	5	5	6	6	8	8	8	7	7	5
Range	'P2'	'J2'	'K1'	'K2'	'L1'	'L2'	'M2'	'N2'	'O1'	'O2'	'P2'	--
Support	6	5	5	5	5	5	6	7	5	5	6	--

Our algorithm generates candidate and pruned sets for up to six levels, as demonstrated in tables 2 and 3. During the testing phase, an image was captured and its associated feature vectors were computed. Table 4 presents the contrast, correlation, energy, and homogeneity feature vectors for the provided test image.

Table 4: Test image feature Values

Input Image	Contrast	Correlation	Energy	Homegenity
Img001	2.1250	0.9304	0.0598	0.7637
Img002	4.8299	0.8407	0.0488	0.6943
Img003	7.6575	0.7462	0.0431	0.6510
Img004	10.9510	0.6354	0.0382	0.6091

The association rule that was stored in the transactional database has been compared with the association rule of the test image. A comparison can be conducted through the utilization of a comparison algorithm. In the event that both the test and training images exhibit the highest count of matches, with a support value exceeding 5, the diagnostic report will indicate the presence of a malignant mass in the test image. An image is classified as benign if it has a minimal number of corresponds below the support threshold of 5. In the event that the test image does not correspond with the training image, it is determined that the test image is a normal image. Table 5 presents a comparative analysis between the current and proposed research efforts.

Table 5: Comparison of performance

Methodology Name	Type	No of Training image	No of testing image	No of images classified as correctly	Accuracy
Navie Bayes Classifier for brain tumor classification	Benign	200	75	52	69.3
	Malignant	200	75	53	70.6
Association Rule based Classification	Benign	200	75	69	89.3
	Malignant	200	75	70	93.3
Proposed Shape prior image priori algorithm for brain tumor classification	Benign	200	75	73	**97.3**
	Malignant	200	75	74	**98.6**

Table 6: Overall performance comparison of existing and proposed Method

Approach	Training time (CPU time in Sec)	Testing time (CPU time in Sec)	Sensitivity %	Specificity %	Accuracy %
Navie Bayes	41.9	7.03	75.3	63.4	73
Associaion Rule Based	11.05	4.31	94.9	83.9	93
Proposed Shape prior Image priori	4.5	1.08	97.5	91.3	99

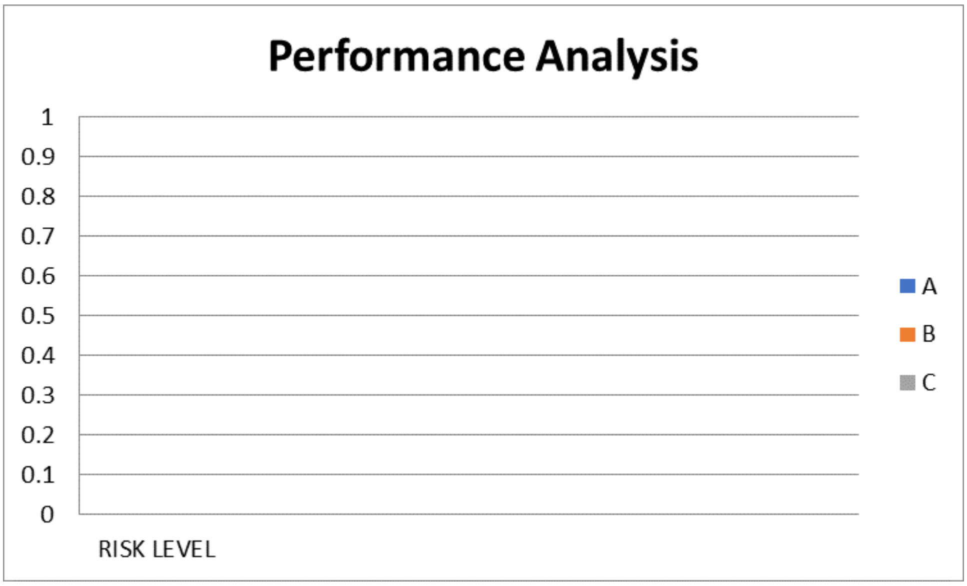


Fig 4: performance Comparison of Proposed and Existing

The complete outcome of the work is shown in Table 6 and Figure 4. This study utilized a dataset of 200 images for the purpose of training, and an additional 75 images for testing. The images were categorised as either benign or malignant. The images that underwent training and testing were subjected to classification using various classifiers, based on the resulting outcomes. The results indicate that the proposed system outperforms the existing classifiers in terms of accuracy.

5. Conclusion

For a more accurate categorization of brain images, the performance of the shape before segmentation technique and pruning association rule using ImageApriori algorithm was established. The results of the analysis indicate that the developed interestingness framework for brain tumour classification system has an estimated accuracy of 99%, sensitivity of 97.5%, and specificity of 91.3%. These findings suggest that the system could prove to be a valuable diagnostic support framework for physicians.

References

[1] P. Rajendran, M. Madheswaran and K. Naganandhini, “An Improved Pre-Processing Technique with Image Mining Approach for the Medical Image Classification”, 2010 Second International conference on Computing, Communication and Networking Technologies.

[2] Muhammad Sajjad, Salman Khan, Khan Muhammad, Wanqing Wu, Amin Ullah, Sung Wook Baik, “Multi-Grade Brain Tumor Classification using Deep CNN with Extensive Data Augmentation”, Journal of Computational Science (2018), https://doi.org/10.1016/j.jocs.2018.12.003.

[3] Keerthana T K, Sobha Xavier, “An Intelligent System for Early Assessment and Classification of Brain Tumor”, Proceedings of the 2nd International Conference on Inventive Communication and Computational Technologies (ICICCT 2018), IEEE Xplore Compliant - Part Number: CFP18BAC-ART; ISBN:978-1-5386-1974-2.

[4] Saumya Chauhan, Aayushi More, Ritumbhra Uikey, Pooja Malviya, Asmita Moghe, “Brain Tumor Detection and Classification in MRI Images using Image and Data Mining”, Proceeding International conference on Recent Innovations is Signal Processing and Embedded Systems (RISE-2017) 27-29 October,2017.

[5] Parveen Khan, Amritpal Singh, Saurabh Maheshwari, “Automated Brain Tumor Detection in Medical Brain Images and Clinical Parameters using Data Mining Techniques: A Review”, International Journal of Computer Applications (0975 – 8887), Volume 98 – No.21, July 2014.

[6] Gonzalez.R.C and Woods. R.E, Digital image processing (Pearson Education, Singapore, 2002).

[7] Zexuan Zhu, Yew-Soon Ong, Manoranjan Dash, “ Wrapper-filter feature selection algorithm using a memtic framework”, IEEE transactions on System, Man, and Cybernetics Part B, Cybernetics : a publication of the IEEE systems, man and cybernetics society 2007: 37(1)

[8] Pang-Ning Tan, Michael Steinbach, Vipin Kumar,“Introduction to data mining” Addison Wesley Longman, 2006.

[9] Jiawei Han, Micheline Kamber. Data Mining: Concepts and Techniques, Second Edition. Morgan Kaufmann, 2006.

[10] W. H. Pinaya, A. Gadelha, O. M. Doyle, C. Noto, A. Zugman, Q. Cordeiro, et al., "Using deep belief network modelling to characterize differences in brain morphometry in schizophrenia," Scientific reports, vol. 6, p. 38897, 2016.

[11] J. Barker, A. Hoogi, A. Depeursinge, and D. L. Rubin, "Automated classification of brain tumor type in whole-slide digital pathology images using local representative tiles," Medical image analysis, vol. 30, pp. 60-71, 2016.

[12] K. Muhammad, J. Ahmad, Z. Lv, P. Bellavista, P. Yang, and S. W. Baik, "Efficient Deep CNN-Based Fire Detection and Localization in Video Surveillance Applications," IEEE Transactions on Systems, Man, and Cybernetics: Systems, pp. 1-16, 2018.

[13] A. Ullah, J. Ahmad, K. Muhammad, M. Sajjad, and S. W. Baik, "Action recognition in video sequences using deep Bi-directional LSTM with CNN features," IEEE Access, vol. 6, pp. 1155-1166, 2018.

[14] [31] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," Neurocomputing, vol. 288, pp. 30-42, 2018.

[15] J. Ahmad, K. Muhammad, J. Lloret, and S. W. Baik, "Efficient Conversion of Deep Features to Compact Binary Codes Using Fourier Decomposition for Multimedia Big Data," IEEE Transactions on Industrial Informatics, vol. 14, pp. 3205-3215, 2018.

[16] J. Ahmad, K. Muhammad, and S. W. Baik, "Medical image retrieval with compact binary codes generated in frequency domain using highly reactive convolutional features," Journal of medical systems, vol. 42, p. 24, 2018

[17] Mehta, E. S. ., & Padhi, S. . (2023). Quality and Defect Prediction in Plastic Injection Molding using Machine Learning Algorithms based Gating Systems and Its Mathematical Models. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3s), 216–230. https://doi.org/10.17762/ijritcc.v11i3s.6183

[18] Pekka Koskinen, Pieter van der Meer, Michael Steiner, Thomas Keller, Marco Bianchi. Automated Feedback Systems for Programming Assignments using Machine Learning. Kuwait Journal of Machine Learning, 2(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/190

[19] Anand, R., Khan, B., Nassa, V. K., Pandey, D., Dhabliya, D., Pandey, B. K., & Dadheech, P. (2023). Hybrid convolutional neural network (CNN) for kennedy space center hyperspectral image. Aerospace Systems, 6(1), 71-78. doi:10.1007/s42401-022-00168-4