

Hybridization Techniques To Detect Brain Tumor

Asif Hussain¹, Muhammad Abrar², Roha Masroor¹, Ifra Masroor¹

Abstract:

Diagnosing brain tumor in the present era through digital techniques need serious attention as the number of patients is increasing in an awkward manner. Magnetic Resonance Imaging is a tool that is used for the detection of brain tumors. Deploying Machine learning models to detect the abnormality pattern of the brain on MRI scans is quite beneficial in this modern era. This paper deploys GLCM on MRI scans to extract 66 features. Then, Feature selection and classification are applied to the given data set. Classification on a given data set is done through K- Nearest Neighbor. The given article classifies scans, i.e., normal and abnormal brain images. In the given study, we have taken normal and abnormal samples from the MRI department, Nishtar Medical hospital, Multan under doctor supervision. The scans were T2 weighted and having 256*256 pixels. In order to classify brain images, first, it needs to pre-process by skull stripping technique then the proposed algorithm is followed. The algorithm involves feature extraction through GLCM and feature selection through ACO in order to reduce the dimensions for optimal features. Results have proved its efficiency level up-to 88% on testing data.

Keywords: Brain; classification; extraction; selection; Magnetic resonance imaging.

1. Introduction

The individual central nervous system is entirely commanded by means of the human brain. The brain feeds in from the sensory body organs along with directs information towards muscles. The normal human brain is composed of mainly three elements namely white matter, black matter, and also cerebrospinal fluid. The actual, white-colored matter is referred to as white matter for its bright appearance. It adds up pertaining to 60% to entire human brain volume. The particular white matter includes fiber content similar to the composition of the neuron identified as axon. The white-colored matter offers a mean of communication among various areas of the particular central nervous system such as greyish matter, spinal cord as well as other portions of the body. The gray

matter is the part of the human brain accountable for the whole processing of the nervous signals. It involves dendrites along with the neuron nucleus. It adds up forty percent to whole-brain volume. The entire control of the nervous alerts is done in the gray matter and the effect can result in transmitted to the human body through the extension associated with the white matter which usually is made up of axons. Cerebrospinal fluid is an actually colorless fluid that provides defense against physical shocks and in addition sends out some significant hormones in order to make the connection possible involving white matter, gray matter, and the spinal cord of the central nervous system. The white matter, greyish matter along cerebrospinal fluid associated with the human brain are mainly impacted by a variety of brain irregularities,

¹ National College of Business & Economics (NCBA&E), Multan, Pakistan

² Bahauddin Zakriya University, Multan Pakistan

therefore our attention concerning the intensities of numerous pixels addressing most of these sections will be typically considered. Generally, there are many varieties of brain problems that induce modifications in human brain distinct sections. A few of them particularly intense mental brain stroke, Huntington's disease, and brain tumor. Each one of these irregularities presents a new appearance towards the human brain that completely sets itself apart from an affected brain by an ordinary one.

Brain disorders now have considerable attention because of their harmful plus life taking characteristics. The conventional approach to recognition of numerous disorders within human brain images continues to be the particular manual evaluation which in turn is deficient in the attributes regarding reproducibility and may even bring in various results within diverse situations and may additionally present different analysis consequence done by several experts. In an effort to bring out the correct evaluation regardless of countless situations, there is a rigorous demand for automating this particular process. To carry out the diagnosis of different conditions in the human brain, a variety of illustrations or photos may possibly be kept under account however most appropriate and also aim to accomplish is MRI (Magnetic Resonance Imaging). The MRI [1] is useful for the automated human brain disorders recognition for the reason that it can record significantly quality information that happens to be overlooked simply by other sorts of images. In order to process MRI images with regard to automatic recognition associated with irregularities in them, we require the expertise of digital image digesting techniques. Prior to commencing information on processing the MRI images of the brain, we have to understand the design regarding the brain, a variety of brain conditions, in addition to different types of images which can be used as processing in order to identify diseases within the brain and will compare and contrast the feasibilities associated with other brain images together with MRI images pertaining to processing. The neurological system associated with humans involves a couple of sections namely CNS (Central Nervous

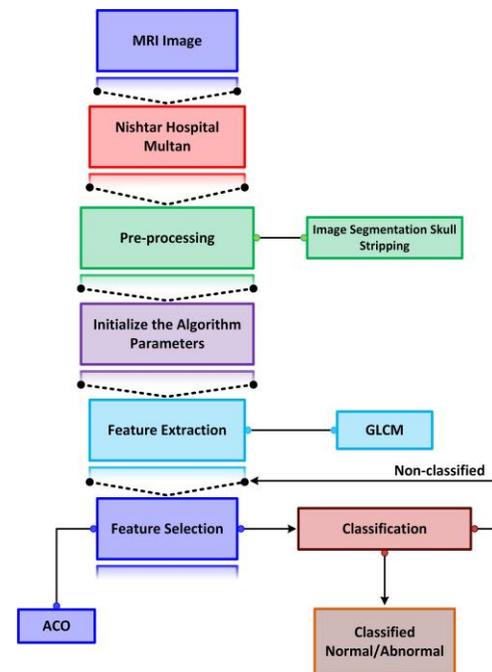
System) and peripheral nervous system. The Central Nervous System is additionally broken into two areas specifically the brain and spinal cord. There are plenty of compact portions of the brain however in terms of our region of attention is concerned, we are going to contemplate just three sections including white matter, bleak matter, and also cerebrospinal fluid. We are going to consider only abnormalities that may have an effect on these portions of the brain.

2. Literature Review

Current research has proved that classification involving the human brain within magnetic resonance (MR) images [2] are quite possible through supervised methods including artificial neural networks in addition to supporting vector machine (SVM), and unsupervised classification techniques unsupervised which include anomaly detection and additionally fuzzy c-means along with feature extraction techniques [3]. Some other supervised classification techniques, which include k-nearest neighbors (k-NN)[4] Moreover, group pixels depending on their own similarities within each feature image are useful to classify typically the normal and abnormal T2-weighted MRI images. We tend to put into use a supervised machine learning algorithm (k-NN) to achieve the classification regarding images placed under two classes, possibly normal or possibly abnormal. Wavelet transform is an effective technique intended for feature extraction; due to the fact they permit analysis regarding images at diverse degrees of resolution. This method demands considerable storage area as well as being computationally costlier [5]. Consequently, an alternative approach for the dimension diminishment method can be used. GLCM [6] is an effective technique for texture feature extraction. On the basis of the evaluation method, feature selection algorithms are of two types. **Filter approach (open loop approach)**, includes correlation coefficient residual mean square, mutual information [7], RELIEF [8], Focus [9], based on selecting feature applying between-class separability criterion and it performs feature selection independently of any learning algorithm. **Wrapper approach (closed-loop**

approach) which is based on searching through feature subset space implementing the estimated accuracy from an induction algorithm as a measure of subset suitability. These two are further classified into five main methods including forward selection, backward elimination, forward/backward combination, instance based and random choice method. Feature selection initiates with an initial subset that may consist of all features, no feature, selected features or random features. Features are removed (backward elimination), added (forward selection), repetitively added or removed or produced randomly. Features once selected/removed cannot be later discarded/re-selected urged many researchers to address this problem. Pudil et al. [10] proposed floating search method; to flexible add or remove features. Amongst several closed-loop approaches which have been proposed regarding Feature Selection, population-based optimization algorithms including Genetic Algorithm (GA)-based method and also Ant Colony Optimization (ACO) [11]-[15] based method have drawn plenty of attention. These methods aim to attain much better solutions by applying knowledge from prior iterations. Genetic algorithms (GA's) are optimization techniques depending on the mechanics associated with natural selection. They applied operations within natural genetics to guide by itself because of the paths in the search space [16]. Due to their benefits, recently, GA's have already been widely used as a tool regarding feature selection within pattern recognition. Meta-heuristic optimization algorithm depending on ant's actions (ACO) was represented during the early 1990s by M. Dorigo along with colleagues [17]. ACO is actually a part associated with newly developed type of artificial intelligence referred to as Swarm Intelligence. Swarm intelligence is an area which usually studies "the emergent group intelligence associated with sets of basic agents [16].

ACO algorithm is certainly impressed involved with ant's social behavior. Ants don't have any sight regardless of that they can handle locating the shortest path from a food source and their own nest simply by chemical



substance termed as pheromone which they leave whenever moving.

Fig. 1. Flow chart of Methodology

3. Methodology

The suggested algorithm is classified into two parts. First is feature selection then classification. At first skull stripping is done through histogram method then we have done feature extraction. It is done through Gray Level Co-occurrence (GLCM). Sixty-six features have been extracted then we have randomly selected three best features through ACO[11]. It is then passed through classification step through K-Nearest Neighbor Algorithm (KNN). This whole procedure is done under supervised learning. Fig. 1 is showing a pictorial view of whole paper.

4. Feature Extraction

Description of whole data set can be given by features. It differentiates abnormal image from normal image. Its basic function is to reduce original data sets by extracting certain features.

GLCM: Gray level co-occurrence matrix (GLCM) also renowned as gray level spatial dependence matrix is used in this paper. This method makes a difference between abnormal brain tumor and normal brain. Gray level image can be calculated from the equivalency of rows and columns. It is basically a two-dimensional (2D) histogram. A spatial connection between different gray level pixels is made. Then, it calculates distance d between two different pixels. Let l and m in given case with orientation θ . Hence, a co-occurrence matrix is made which is $Z(l, m, d, \theta)$. Since, l , m , d and θ are function of matrix. Mathematically, a co-occurrence matrix of $l*m$ can be written as (1).

$$C_{\Delta x, \Delta y}^{(l, m)} = \sum_{p=1}^l \sum_{q=1}^m \begin{cases} 1, & \text{if } Z(p, q) = 1 \\ 0, & \text{otherwise} \end{cases}$$

and $Z(p + \Delta x, q + \Delta y) = m$ (1)

Since, l and m are representing image intensity values, Δx and Δy are the offset values at angle θ . P and q are representing spatial position in image Z . This matrix can be calculated at four directions: 0, 45, 90, 135 degrees.

Following is a calculation of statistical texture feature.

Entropy: Texture of input image can be calculated through measurement of randomness. The result of entropy become 0 when all $p_{l,m} = 0$.

$$E_0 = \sum -p_{l,m} * \lambda_0 \gamma_2 p_{l,m} \quad (2)$$

Correlation: It shows correlation between a pixel to its neighbor pixel. Its range varies from 1 to -1 i.e. positively correlated to negative correlated. Mathematically, it can be written as;

$$X_0 = \sum_{l,m} \frac{(l-ul)(m-um)p_{l,m}}{\partial l \partial m} \quad (3)$$

Energy: It is actually return of square elements sum in GLCM. Its range varies from 0 to 1. When range is 1, image will be constant.

$$E = \sum_{l,m} (p_{l,m})^2 \quad (4)$$

Homogeneity: It measure spatial distance between GLCM and GLCM diagonal. Its range also varies from 0 to 1. Its value is 1 for diagonal GLCM. Mathematically, it can be written as,

$$H = \frac{\sum_{l,m} p_{l,m}}{1+(l-m)} \quad (5)$$

Contrast: It measure intensity between given pixel and the neighbor pixel. For constant image value is 0. It is written as;

$$X = \sum_{l,m} |l - m|^2 (p_{l,m}) \quad (6)$$

5. Feature Selection

Different type of feature selection methods is used. This paper is using Ant Colony Algorithm. Ant Colony Algorithm: Researchers named Dorigo and Gambardell was known to be father of Ant Colony Algorithm (ACO) [18],[19]. It was first introduced in ninety's as a multi-agent method to optimize problems such as challenges faced by travelling salesperson. Different researchers have already showed that ants are social insects. They focused to find food for their colonies than for individually oneself. Thought-provoking process of food searching makes ant different from other insects. Adding attributes to this, it makes a shortest distance between source and destination. These skills of food searching by ant is known as Mass Intelligence (MI). MI is description of random behavior of elements. It is an indirect type of communication in which ant communicate through stimuli. Ant left a footprint for other ants through a stimulus known as pheromone. It depends on quality of food and distance. Other ants got attracted by this pheromone and then came through this path. Suppose an ant gets shorter path to get their destination it will get more pheromone. Pheromone will get evaporated in short interval of time. Hence selection of path makes it probabilistic strategy rather than deterministic strategy. Leaving pheromone as footprint is basically instinctive behavior. Hence, here comes the importance of pheromone and probabilistic approach of ant. Time is making limitations on this strategy because as time passes pheromone get

evaporated and probabilistic selection of path will decrease.

Basically, ACO is a heuristic technique in which problem is solved through graph. A number of ants start to move on problem set and each ant add its contribution in solving problem. As it has already discussed that selection of direction by ants depends on quantity of pheromone. Let us consider L as path used by ant. Probability of 1th path when ant moves from n to j can be given by;

$$G_{nm}^l = \frac{[\tau_{nm}]^\alpha [\mu_{nm}]^\beta}{\sum_{k \in R_n^l} [\tau_{nk}]^\alpha [\mu_{nk}]^\beta}, \quad \forall \mu \in R_n^l \quad (7)$$

Where; $[\tau_{nm}]$ = pheromone stored between nodes n and m, R_n^l = Neighbor node for ant l in node n, α, β =Constraints controlling pheromone and heuristic technique. μ_{nm} = Heuristic value.

Completion of path will result in updating of data that is given by;

$$\tau_{nm}^{new} = \tau_{nm}^{current} + \sum_{l=1}^t \Delta \tau_{nm}^k \quad (8)$$

Since, $\Delta \tau_{nm}^k$ = Pheromone amount when l is added to travel from n to m. total number of ants is represented by t. Each addition of pheromone is given by;

$$\Delta \tau_{nm}^k = \begin{cases} \frac{1}{B^l} & \text{if arc is in the path of arc } l \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

Where, B^l = final cost of path crossed by ant l.

After completion of first iteration, pheromone evaporation will be applied on pheromone matrix using ϵ factor given by;

$$\tau_{nm} = (1 - \epsilon) \tau_{nm}, \quad 0 < \epsilon \leq 1 \quad (10)$$

6. Feature Classification:

In this process, set of samples are taken. They are assigned class on the basis of training done by the classifier. It helps in assigning input pattern to predefined classes. KNN: In this paper, classification is performed through K-Nearest Neighbor (KNN) method [20]. It was done by taking more discriminative

feature then end with ordinary discriminative features.

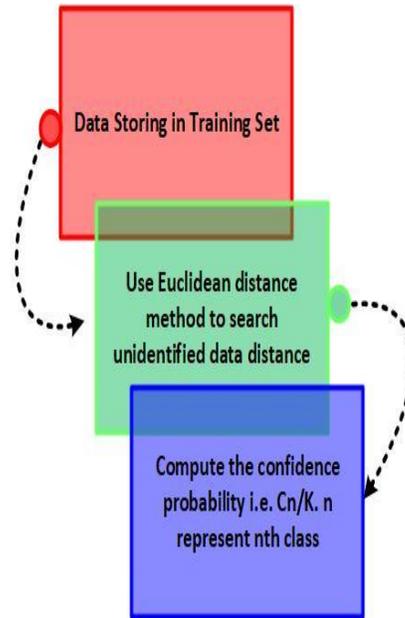


Fig.2. Rules of KNN Classifier

K-NN Classifier:

It is a non-parametric method in which any information about previous data is not required. One can add data at any stage of training to previous data set. Output of K depends on the probability on the pattern taken at input side. If the value of K increases the chances of getting close to discriminative result will increase. Fig. 2 is pictorial overview of K-NN classifier.

Binary Phase of KNN:

KNN classifier consists of two steps:
 Training Stage: In this step, data sets are assigned with their classes.
 Testing Stage: In this step, algorithm makes a set of data which have not assigned classes. They will give n class here.

Rules of KNN:

It follows three steps:
 i) It needs stored data sets.

- ii) It involves distance metric parameter in which distance between unidentified and identified data is measure.
- iii) Identification of undefined data is done. Then, label to them is given through majority voting.

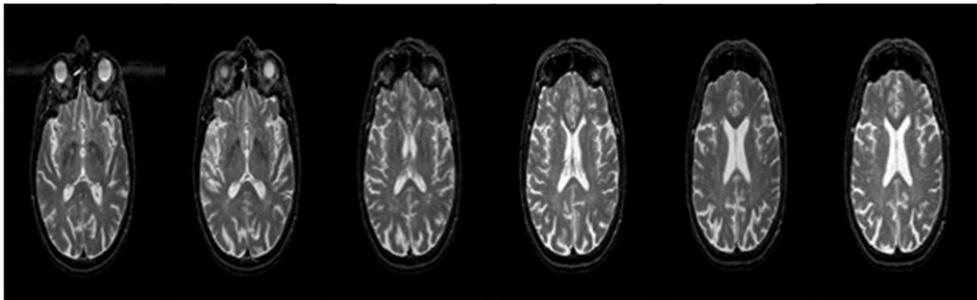


Fig.3. Normal brain images

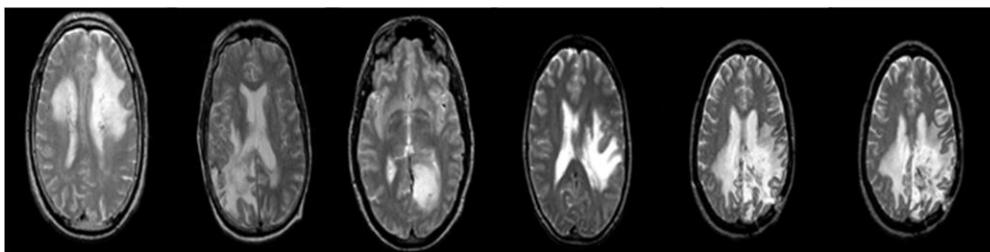


Fig.4. Abnormal brain images

7. Result and Discussion

Table 1 is showing different number of features for optimum results by using ACO and KNN, while doing this we achieved 88% as maximum accuracy for 3 features that are Homogeneity, Inverse Difference Moment Normalized and Difference Entropy. For four features, we achieved 86% accuracy. For all features, we have achieved 66% accuracy.

Graph of accuracy Fig.5 shows blue peak for selected feature and here number of selected features are “three” out of 66 extracted features while three other peaks are accuracy against different value of K, it is clearly presenting that for K=5 the model achieved its highest accuracy of 88%.

Confusion Matrix (Table 2) which evaluates the performance of classifier on a set of test data whose values are known.

- There are two possible predicted classes: "Normal" and "Abnormal". If we were predicting the presence of a disease, for example, "Abnormal" would mean they have the disease, and "Normal" would mean they don't have the disease.
- The classifier made a total of 50 predictions (e.g., 50 MRI scans were being tested for the presence of deformity).
 - In reality, 30 MRI scans in the sample are Normal, and 20 MRI scans are Abnormal.
 - Out of those 50 cases, the classifier predicted "Normal" 27 times, and "abnormal" 17 times.

TABLE I: Results for KNN (K=1, K=3, K=5) Nishtar Dataset

Accuracy	No. of Feature	Value of K	Sensitivity	Specificity	Selected Feature
80%	3	K=1	65%	90%	Difference Entropy(r), Inverse difference moment normalized(v), Homogeneity(j)
88%	3	K=5	85%	90%	Difference Entropy(r), Inverse difference moment normalized(v), Homogeneity(j)
76%	4	K=1	65%	83.3%	Difference Entropy(r), Inverse difference moment normalized(v), Homogeneity(j), 'Inverse difference normalized
76%	4	K=3	65%	83.3%	Difference Entropy(r), Inverse difference moment normalized(v), Homogeneity(j), 'Inverse difference normalized
86%	4	K=5	90%	83.3%	Difference Entropy(r), Inverse difference moment normalized(v), Homogeneity(j), 'Inverse difference normalized
68%	All extracted features	K=1	60%	73.3%	All GLCM Feature
68%	All extracted features	K=3	40%	83.3%	All GLCM Feature
66%	All extracted features	K=5	40%	83.3%	All GLCM Feature

Let's now define the most basic terms, which are whole numbers (not rates):

- True positives (TP): These are cases in which we predicted yes (Abnormal), and they are actually Abnormal.
- True negatives (TN): We predicted no (Normal), and they are actually Normal.
- False positives (FP): We predicted yes (Abnormal), but they are actually Normal.

- False negatives (FN): We predicted no (Normal), but they actually are Abnormal.

TABLE II. Confusion Matrix

N=50	Predicted no	Predicted yes	
Actual no	TN= 27	FP= 3	30
Actual yes	FN= 3	TP= 17	20
	30	20	

8. Comparison of Results

Different researchers have used different techniques in diagnosing brain tumors. Some researchers have used KNN, ACO, GLCM and many more. It depends on the type of results everyone wants to achieve. This paper is already detecting abnormal brain patterns through ACO, GLCM and KNN. Here is a short, reviewed comparison of different papers that why the suggested techniques are preferred. In [21] authors have used Wavelet transform (Feature Selection) and Support Vector Machine method (Classification).

TABLE III. Comparison with other Studies

Feature Extraction Technique	Feature Selection	Classification	Accuracy (%)
	Wavelet Transform	SVM [13]	65
LoG, GLCM, RILBP, IBF, DGIF, RIC GF [14]	PCA	PCA-ANN	85.5
GLCM [15]		KNN	86
GLCM	ACO	KNN	88

They have achieved 65% accuracy through assigning labels to set of data. Basically, SVM divides the set of data into training and testing phase and apply both phases to set of normal and abnormal images. To make results more productive researchers in the given table have provided a combination with digital image processing. Still, their efficiency is quite low i.e. 65%. Similarly, the researchers as mentioned in Table 3 have used a bunch of feature extraction, selection and classification techniques but the accuracy of result goes to 85.5% [22]. More or less the study done by [23] seems similar with a single method change with comparison to the given research in this paper. Survey on papers realized that

accuracy need more work to do that's why in current situation we suggested a combination of ACO, GLCM and KNN. Results goes to 88% which can be increased more in future work using different models.

9. Dataset

Fig.3 and Fig.4 are the sample images taken from Nishtar Medical Hospital data set as 'Normal Images' and "abnormal Images" respectively. These scans are collected under the supervision of medical officer at MRI department. These scans are of 256*256 pixel and are T2 weighted.

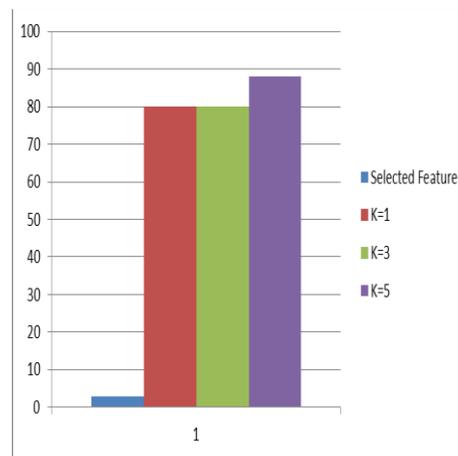


Fig. 5: Accuracy Graph

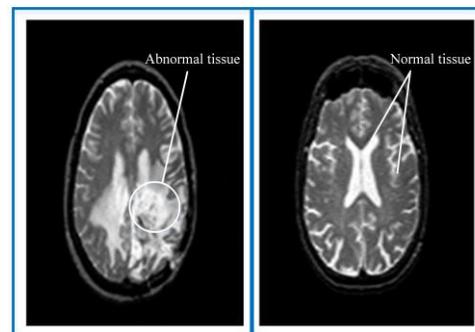


Fig.6. Normal and Abnormal brain tissues

Figure 6 depicts the major lesions and deformity in textural pattern of abnormal tissue, so we labeled it as abnormal scan while

the other which is quite normal and having a textural pattern is labeled as Normal scan.

10. Conclusion

Increased diseases of brain tumors need fast and accurate way to detect the problem. Currently, world is still lack of finding ways to these problems. In this paper, three popular methods are used to give an optimum solution. These are based on feature extraction, Selection and classification. GLCM is a feature extraction technique, ACO is feature selection which proved its result through decision making and finally classification is done through KNN. It has been observed that by reducing features, the classification and average hit time increases. The best accuracy results we obtained is 88% for three features i) (Difference Entropy(r), ii) Inverse difference moment normalized(v), iii) Homogeneity(j)) using KNN.

References

- [1] A. Kharrat, K. Gasmi, and M. B. E. N. Messaoud, "A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and Support Vector Machine," no. 17, pp. 71–82, 2010.
- [2] E. I. Zacharaki *et al.*, "Classification of Brain Tumor Type and Grade Using MRI Texture and Shape in a Machine Learning Scheme," vol. 1618, pp. 1609–1618, 2009.
- [3] C. Geetha and D. Pugazhenthii, "Classification of alzheimer ' s disease subjects from MRI using fuzzy neural network with feature extraction using discrete wavelet transform .," no. Mci, pp. 1–8, 2017.
- [4] P. A. Charde and S. D. Lokhande, "Classification Using K Nearest Neighbor for Brain Image Retrieval," vol. 4, no. 8, pp. 760–765, 2013.
- [5] R. S. Andersen, A. U. Eliassen, N. Pedersen, M. R. Andersen, S. T. Hansen, and L. K. Hansen, "Eeg Source Imaging Assists Decoding in a Face Recognition Task," pp. 939–943, 2017.
- [6] K. Hemalatha and K. U. Rani, "Data Engineering and Intelligent Computing," vol. 542, 2018.
- [7] H. J. Holz and M. H. Loew, *Relative feature importance: A classifier-independent approach to feature selection*, vol. 16, no. C. Elsevier B.V., 1994.
- [8] N. Kwak and C. H. Choi, "Input feature selection by mutual information based on Parzen window," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 12, pp. 1667–1671, 2002.
- [9] D. Hall, "From: AAAI - 91 Proceedings. Copyright © 1991 , AAAI (www.aaai.org). All rights reserved.," vol. 3, pp. 547–552, 1991.
- [10] P. Pudil, J. Novovičová, and J. Kittler, "Floating search methods in feature selection," *Pattern Recognit. Lett.*, vol. 15, no. 11, pp. 1119–1125, 1994.
- [11] P. Mohan, D. AL V, and B. Kavitha, "Intelligent based brain tumor detection using ACO," *Int J Innov. Res Comput Commun Eng*, pp. 2143–2150, 2013.
- [12] Q. Shen, "Combining rough and fuzzy sets for feature selection," *Proc. 2005 UK Work. Comput. Intell. UKCI 2005*, pp. 12–13, 2005.
- [13] S. Hodnefjell and I. Costa, "Classification rule discovery with ant colony optimization algorithm," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 7435 LNCS, no. January 2004, pp. 678–687, 2012.
- [14] A. Al-Ani, "Ant Colony Optimization for Feature Subset Selection," *Int. J. Comput. Electr. Autom. Control. Inf. Eng.*, vol. 1, no. April, pp. 999–1002, 2007.
- [15] H. H. Gao, H. H. Yang, and X. Y. Wang, "Ant colony optimization based network intrusion feature selection and detection," *2005 Int.*

- Conf. Mach. Learn. Cybern. ICMLC* 2005, no. August, pp. 3871–3875, 2005.
- [16] S. Mangaiarkarasi, “MEDICAL IMAGE SEGMENTATION USING ANT COLONY OPTIMIZATION ALGORITHM,” 2016.
- [17] M. Yeganeh, F. Mir, K. Mirnia, T. Branch, and T. Branch, “MRI medical images edge detection using ant colony optimization,” pp. 1193–1199, 2015.
- [18] G. Mohan and M. M. Subashini, “Biomedical Signal Processing and Control MRI based medical image analysis : Survey on brain tumor grade classification,” *Biomed. Signal Process. Control*, vol. 39, pp. 139–161, 2018.
- [19] S. Shah and N. C. Chauhan, “Techniques for Detection and Analysis of Tumours from Brain MRI Images : A Review,” no. January 2016.
- [20] S. Goyal, N. Johari, N. Singh, and A. Pal, “Survey on Different Brain Tumor Detection Methods or Algorithms,” no. 5, pp. 94–99, 2015.
- [21] N. Abdullah, U. K. Ngah, and S. A. Aziz, “Image Classification of Brain MRI Using Support Vector Machine,” *Imaging Syst. Tech. (IST), IEEE Int. Conf. on. IEEE*, pp. 242–247, 2011.
- [22] J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja, “Segmentation, feature extraction, and multiclass brain tumor classification,” *J. Digit. Imaging*, vol. 26, no. 6, pp. 1141–1150, 2013.
- [23] V. Wasule, “Classification of Brain MRI Using SVM and KNN Classifier,” pp. 218–223, 2017.