MRI Brain Scans Classification Using Extreme Learning Machine on LBP and GLCM

https://doi.org/10.3991/ijoe.v19i02.33987

Jhan Yahya Rbat Al-Awadi[1(✉)], Hadeel K. Aljobouri[2], Ali M. Hasan[3]
[1]Department of Biomedical Engineering, University of Technology, Baghdad, Iraq
[2]Department of Biomedical Engineering, College of Engineering, Al-Nahrain University, Baghdad, Iraq
[3]College of Medicine, Al-Nahrain University, Baghdad, Iraq
alawadijhan@yahoo.com

Abstract—The primary goal of this study is to predict the presence of a brain tumor using MRI brain images. These images are first pre-processed to remove the boundary borders and the undesired regions. Gray-Level Co-Occurrence Matrix (GLCM) and Local Binary Pattern method (LBP) approaches are mixed for extracting multiple local and global features. The best features are selected using the ANOVA statistical approach, which is based on the largest variance. Then, the selected features are applied to many state of arts classifiers as well as to Extreme Learning Machine (ELM) neural network model, where the weights are optimized via the regularization of RELM using a suitable ratio of Cross Validation (CV) for the images' classification into one of two classes, namely normal (benign) and abnormal (malignant). The proposed ELM algorithm was trained and tested with 800 images of BRATS 2015 datasets types, and the experimental results demonstrated that this approach has better performance on several evaluation criteria, including accuracy, stability, and speedup. It reaches to 98.87% accuracy with extremely low classification time. ELM can improve the classification performance by raising the accuracy more than 2% and reducing the number of processes needed by speeding up the algorithm by a factor of 10 for an average of 20 trials.

Keywords—brain tumor, MRI, ELM, classification, GLCM, LBP, ANOVA

1 Introduction

In terms of the health of patient as well as the planning of, a timely identification of a brain tumor is critical. Furthermore, analyzing the images of brain tumors is a process that consumes much time for the radiologists. As a result, the process of the planning of treatment is delayed, and the health of patient is jeopardized. The methods of machine learning have got progressively well-known in this area, and they are now being used to categorize the kinds of brain tumor. Algorithms of the robust machine learning improve the diagnostic accurateness [1], allowing clinicians to make more informed decisions [2, 3]. The images categorization depends totally on the precise choice of features as well as classifiers [4]. M. Eltoukh, et al. [2009] proposed a novel technique for the automated diagnosis and categorization of Magnetic Resonance (MR) human brain images. The suggested technique extracts features using discrete wavelets, selects features using PCA, and automatically classifies the brain MRI images using Back Propagation Neural (BPN) network and Radial Basis Function Neural (RBFN) network [5]. Shen, et al. [2009] employed Decision Tree Classifier, a prominent classification approach, because of its capacity to depict the non-linear correlations in data and its intuitive graphical representation of the learnt model (as opposed to, for example, SVM or ANN's models) [6]. Both [5] and [6] studies indicated that curvelet transform give reliable, effective and near-optimal representation of otherwise smooth objects containing discontinuities along smooth curves. By integrating the linear discriminant analysis (LDA) and the principal component analysis (PCA) for the feature reduction and SVM for the classification of MRI images, a new, better method was described in [7]. The presented findings demonstrate that the LDA-SVM or PCA-SVM approach's performance in medical data processing is both efficient and effective. In comparison to other works, high accuracy for feature selection and extraction was attained. Joshi et al. [2010] used the Neuro Fuzzy logic classifier to quickly identify and categorize the brain tumors. The artificial neural network (ANN) was created using texture features. The Gray Level Co-occurrence Matrix (GLCM) features were derived from the matrix after the co-occurrence matrices in various directions have been computed [8]. The technique may be constructed to classify other types of tumors as well with minor alterations, also it can expand the system's capabilities is to include other imaging modalities (such as PET, MRS, and CTS). Saraswathi, et al. [2019] collected the gray level co-occurrence matrix (GLCM) and the local binary pattern (LBP) features, and the PCA technique was then utilized to further reduce the dimensionality of the obtained feature vector. Three distinct Random Forest (RF) classification techniques were used using the gathered features. The accuracy for testing and validation was 88.72% and 85.56%, respectively [9]. It proved that RF-PCA random selection outperforms all other techniques presented in this study in terms of testing accuracy. Kaplan, et al. [2020] investigated two distinct LBP feature extraction algorithms (nLBP and αLBP) for identifying the highly prevalent kinds of the brain tumor: Glioma, meningioma, and the pituitary tumors of brain. This categorization was conducted using several machine learning classifiers, like Random Forest (RF), Linear Discriminant Analysis (LDA), and K-Nearest Neighbor (KNN) and Artificial Neural Networks (ANN). nLBPd feature extraction approach and KNN model had the greatest rate of success in the categorization of the tumors of brain at (95.56%) [10]. Combining many features using suitable fusion approach leads almost to improve the detection performance [11]. Both [10] and [11] are of low cost, simplicity, ease of application, and suitable for developing a decision assistance system for radiologists. The features of both Gray Level Co-occurrence Matrix (GLCM) as well as Local Binary Patterns (LBP) were utilized for the extraction of feature in the [12] approach. The 400 images in the actual brain database, whose ages range from (20 years) to (65 years), were collected at Jansons MRI Diagnostic Centre. The Neural Network classifier of the extreme learning machine (ELM) receives the statistically chosen features as inputs, and the weights being then tuned employing the technique of Krill Herd. The result when compared to other traditional procedures was 98.9% accuracy rate. Utilizing the Gaussian filter and morphological operations can reduce the noise and enhance the extracted features and hence maximize the accuracy. Convolution neural network (CNN) [13] and extreme learning machine (ELM) were utilized in [14] to categorize the tumors of brain and achieve a result of 93.68 percent accuracy rate when utilizing KE-CNN. ELM was used to classify the images to their corresponding extracted features.

The suggested categorization scheme of the MR-Brain image is divided into (3) stages:

- Preprocessing and Feature extraction: For every enhanced image, two methods of feature extraction, namely (GLCM) and (LBP) are employed to provide an overall of 22 feature vectors (12 features for GLCM and 10 features for LBP).
- Feature selection: Using statistical ANOVA to select the discriminative features based on covariance on P-factor, yielding 15 feature vectors or less.
- Classification: For testing the robustness of the resulting feature vectors, these features are submitted to ELM classifier and other state of the arts methods, such Decision Tree, LDA, LR, SVM, KNN and many other types.

2 Dataset and preprocessing

800 brain tumor MRI images (400 normal (benign) and 400 abnormal (malignant)) were collected from the public standard BRATS 2015 brain MRI database [15].

Input image: These 800 MRI images were used in the proposed algorithm. 70% of the data was used in training, and evaluating stage whereas 30% in testing stage.

Image pre-processing: It consists of the simple modules that perform color conversion to gray scale, cropping, image resizing to 2D with 256×256 and image de-noising with median filter, where each pixel is modified to the median of its neighbor pixels. Figure 1 shows a sample of this pre-processing on the MRI image.

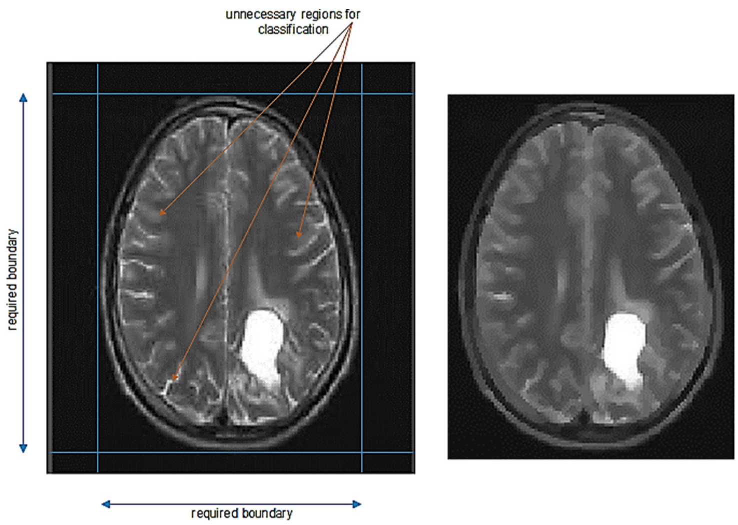

Fig. 1. A sample of pre-processing on the MRI image

3 Feature extraction methods

The feature extraction step is a critical step in machine learning algorithm. Obtaining a simplified and reduced representation of the images by retaining only the most important features can enhance the overall performance. It reduces the redundant and invariance information, time consuming, storage, outliers and noise. Here, two feature types were extracted, which are GLCM and LBP features.

3.1 Gray-level co-occurrence matrix (GLCM)

The GLCM [16, 17] is a statistical technique taking into account the spatial relation among the pixels. In other words, the texture characteristics are created using the statistical distribution of the observed combinations of intensities at given locations in the image relative to each other. The GLCM comprises information on the number of pairs of intensity values of pixels at various offset distances d (in nearly all instances d=1) with many different orientations (in almost cases=0^o, 45^o, 90^o and 135^o). Figure 2 shows the representation of the GLCM for d=1 and four orientations (0^o, 45^o, 90^o and 135^o).

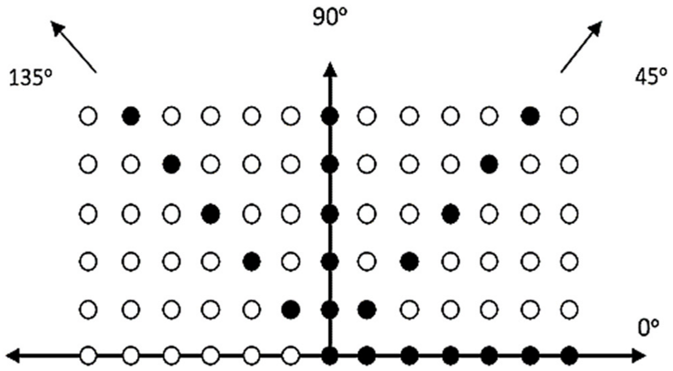

Fig. 2. Representation of GLCM

Statistics in GLCM are divided into three types: first-order, second-order, or higher-order. Many researches have approved that GLCM is a robust technique in extracting discriminative features for brain MRI and ultrasound images [18, 19]. Co-occurrence matrix is composed of twelve distinct texture features which are Mean, Variance, Standard Deviation, Root Mean Square (RMS), Energy, Entropy, Smoothness, Homogeneity, Contrast, Correlation, Kurtosis, and Skewness, as well as their mathematical expressions being referred in detail in reference [18].

3.2 Local binary pattern (LBP)

Local Binary Patterns (LBP) is a statistical method for extracting outstanding features from images that are extensively employed in the image processing and computer vision [20]. The LBP operator creates a local representation of textured images by computing the differences between adjacent pixels in spatial domain. The mathematical expression of LBP is given as:

$$LBP = \sum_{i=0}^{M-1} s\left(n_i - c\right).2^i \tag{1}$$

$$s\left(x\right) = \begin{cases} 1, & if\ x > 0 \\ 0, & otherwise \end{cases}$$

Where, M is the neighborhood pixels number (almost 8 bits), n_i represents the ith weight of neighboring pixel, and c refers to the central pixel.

The LBP operator sweeps a window over the image, identifying the central pixel via thresholding its neighbors with the central value as well as identifying the binary nos. for their neighbors. As illustrated in Figure 3, the LBP then computes the sum of the binary nos. multiplied via two powers. The histogram of (256) distinct labels is utilized to create a description of texture. The key benefits of LBP are its simplicity and insensitivity to continual fluctuations in image intensity. For each image, LBP features encoded the local texture information for 10 discriminative features.

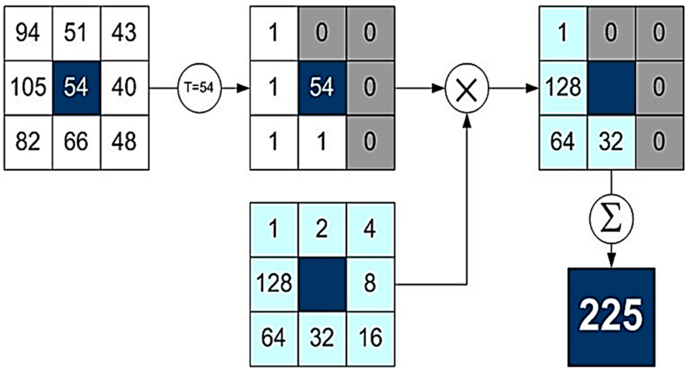

Fig. 3. Calculating the original LBP representation

4 Method of feature choice

The choice of feature is the procedure of selecting the most appropriate features from the extracted ones. Such choice decreases processing time as well as memory storage [21].

The statistical universal features being attained via computing the variance utilizing Analysis of Variance Approach (ANOVA) [22]. Features having the highest variance are selected. ANOVA includes several types, like one way ANOVA, two ways ANOVA, and multi-way ANOVA with many tests, such as t-test and f-test. Here, being based on ANOVA1 with f-test coefficients. Therefore, out of 22 features, 15 features or less are sub chosen as well as fed as input to the extreme learning machine (ELM) classifier.

5 ELM classifier method

The Extreme Learning Machine (ELM) is a single hidden layer feedforward neural network (SLFN) with a large adequate number of hidden neurons nodes to generically estimate any continuous function or compact input set with zero or very small error [23–24]. It can use almost any nonlinear activation function with arbitrary input weights and biases [25–26]. It has other advantages, such as low human innovation, high learning efficiency, and quick learning speed [27–29]. Unlike most practical ANN implementations, which require tuning all of the feedforward network parameters, ELM approaches do not require tuning the input weights and biases, and the output weights may be simply generated using least square optimization. The Regularized ELM (RELM) is a well-known version of ELM; it contains two critical factors that affect the performance, the number of hidden nodes (L) and the regularization value (λ). It allows for the addition of a small positive value known as the regularization parameter (λ) to the diagonal H^T H or HH^T to increase the stability, and generalization performance while avoiding model overfitting and enhancing the overall prediction accuracy. RELM allows for minimal training errors and tries to keep the network output weights' norm ‖β‖ as low as possible. It provides a compromise between maximizing marginal distance (reducing the norm of β) and minimizing least square error [30, 31].

$$Minimize_{\beta} : f_{ELM} = \frac{1}{2}\|\beta\|_2^2 + \frac{1}{2\lambda}\sum_{i=1}^{N}\|\xi_i\|_2^2$$

$$\text{Subject to: } H\beta = t_i^T - \xi_i^T ,\ \ \forall i \text{ ,i.e, } i = 1,\ldots,N \tag{2}$$

Where, λ is the regularization parameter.

By substituting $\xi = T - H\beta$ and taking $\frac{\partial f_{ELM}}{\partial \beta} = 0$, this leads to a unique closed form solution as in equations 2 and 3:

$$H^{\dagger} = (H^T H + \lambda I)^{-1} H^T \ldots \text{if } N \geq L \tag{3}$$

$$H^{\dagger} = H^T (HH^T + \lambda I)^{-1} \ldots \text{if } L > N \tag{4}$$

$$\text{Finally, } \beta = H^{\dagger} T \text{ and } f(x) = h(x).\ \beta \tag{5}$$

In RELM, *H^†* is formed depending on both *N* & *L* dimensions.

The flow chart of the proposed model is shown in Figure 4.

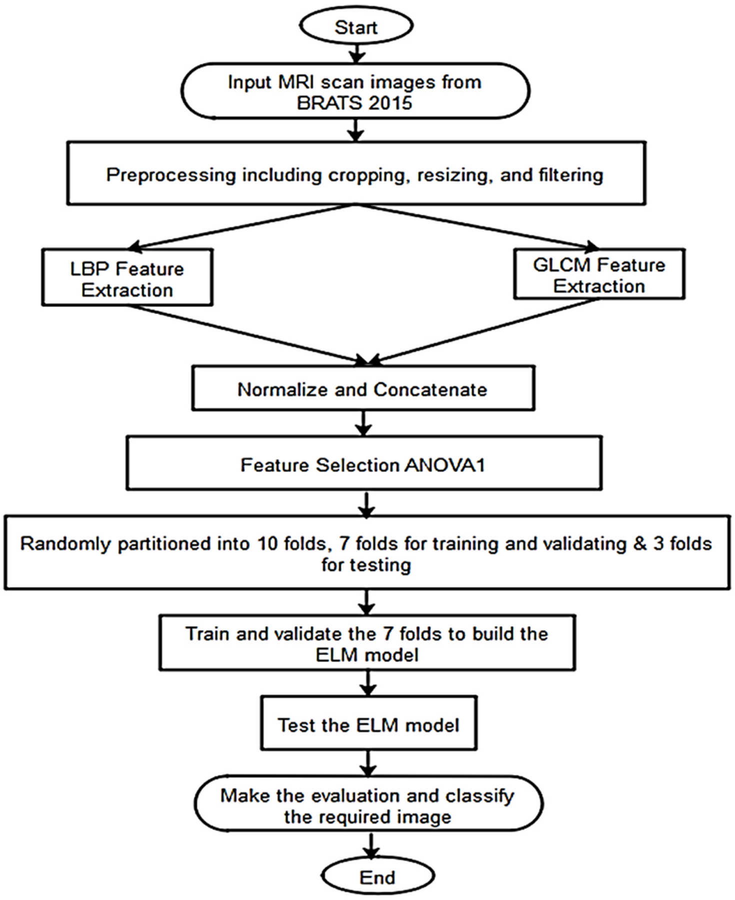

Fig. 4. The comprehensive proposed model

6 Experimental study

The experimental findings and runtime were based on the average of 10 separate trials for regular size datasets. All simulations were carried out using MATLAB 9.6 (R2019a) environment and performed on an (Intel Core i7, 2.4 GHz CPU, 8GB RAM) computer.

In this section, experiments are shared and presented on a prevalent benchmark MRI brain tumor dataset with BRATS 2015 in order to evaluate the proposed approaches in brain classification with tumor recognition.

6.1 Performance evaluation metrics

Five evaluation metrics are employed to test the proposed model: accuracy, precision, recall, specificity, and F-Measure [32].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} 100\% \tag{6}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} 100\% \tag{7}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} 100\% \tag{8}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} 100\% \tag{9}$$

$$\text{F} - \text{measure} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} 100\% \tag{10}$$

Where, TP, TN, FP and FN are demonstrated in Table 1. As a result, they can produce the confusion matrix that describes clearly the relationship between actual classes and predicated classes that can be estimated using suitable classifier approaches.

Table 1. Elements of the output confusion matrix

Actual Class	Predicated Class	
	Normal	Abnormal
Normal	TP	FN
Abnormal	FP	TN

The brain tumor dataset that includes the GLCM and LBP features was examined using different nature classifier types, like Decision Tree [33], Linear Discriminant Analysis (LDA) [34], Logistic Regression (LR) [35], Support Vector Machine (SVM) [36], and K-nearest neighbor (KNN) [37] besides to ELM approach with two hidden nodes numbers (80 and 90). Almost classifiers result in a high accuracy as in Figure 5, which approved the effectiveness of the GLCM and LBP approaches.

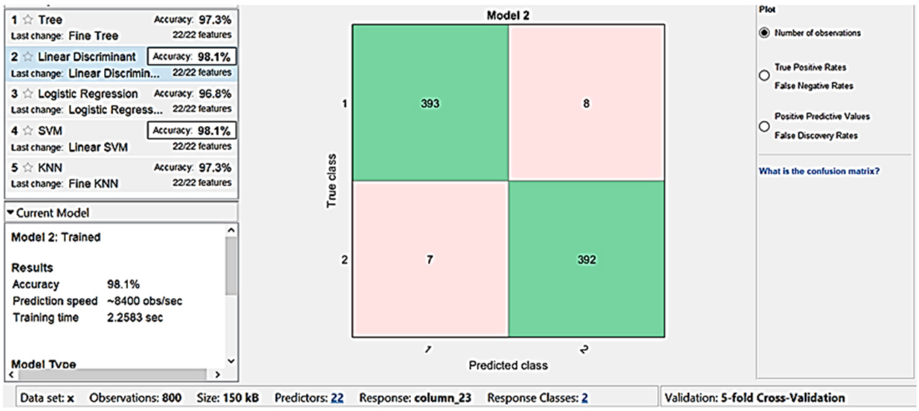

Fig. 5. The LDA confusion matrix with all state of the arts classification results

The confusion matrix of the ELM with L=NH=80 is elucidated in Figure 6.

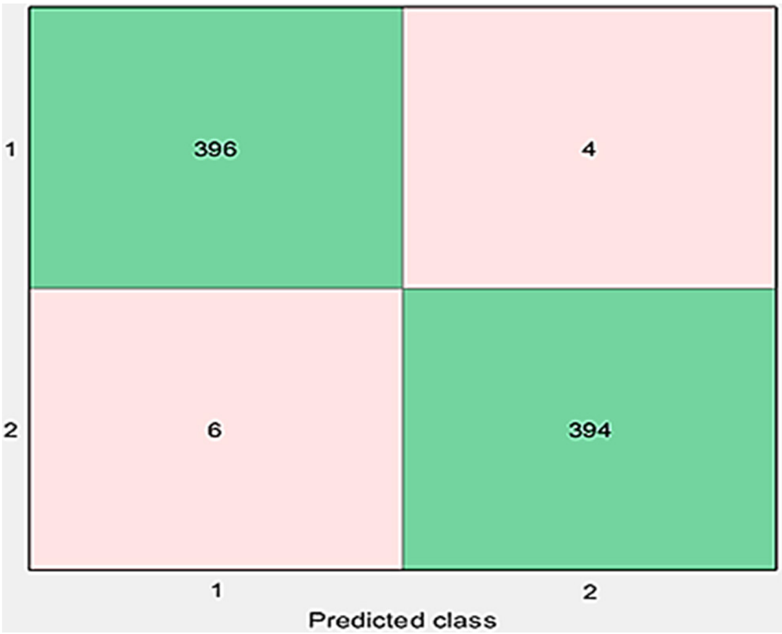

Fig. 6. The confusion matrix of the ELM classifier approach

Table 2 and Figure 7 present the evaluation metrics for the above six classifier approaches (Decision Tree, LDA, LR, SVM, KNN, and ELM with different hidden nodes). ELM achieves satisfactory performance in sufficient dimension cases, demonstrating the superiority and effectiveness of the proposed paradigm over other methods even for dataset under different conditions.

Table 2. Performance metrics for different state of the art classifiers

Metrics Methods	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F-Measure (%)
D-Tree	97.25	97.25	97.25	97.24	97.25
LDA	98.125	98.25	98	98.24	98.127
LR	96.7	96.9	96.5	96.9	96.75
SVM	98.125	98.25	98	98.245	98.127
KNN	97.25	97.25	97.25	97.24	97.25
ELM ($L=N_H=80$)	98.75	98.50	98.9	98.50	98.70
ELM ($L=N_H=90$)	98.875	99	98.75	98.99	98.87

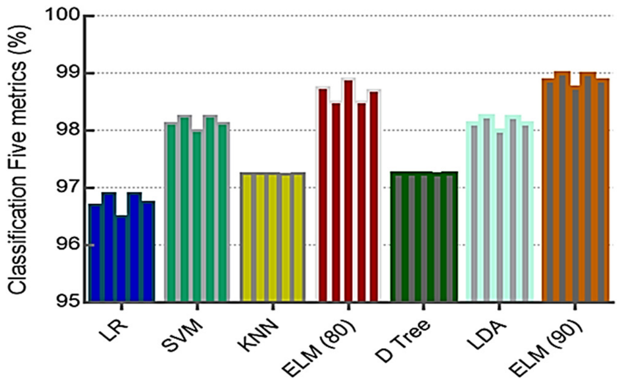

Fig. 7. Performance metrics for different state of the art classifiers

The ELM was trained and tested with two situations: Non-optimum and optimum hidden numbers. The performance (training accuracy and the computational time) of the primarily ELM learning algorithm was examined with respect to the hidden node numbers as manifested in Figures 8 and 9.

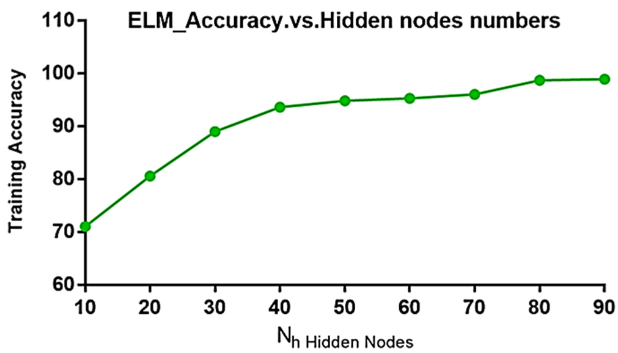

Fig. 8. Training accuracy for different hidden nodes

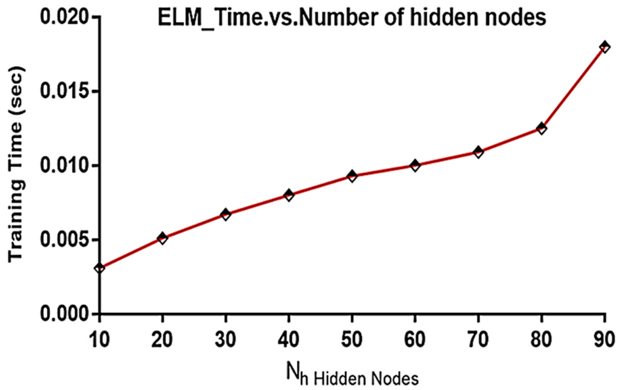

Fig. 9. Computational time for different hidden nodes

The above figures revealed that the accuracy of ELM with or without a slight increase in training time increases as the hidden nodes are increased.

The training time for the proposed ELM approach and the other classifiers methods is evinced in Figure 10. It is clear that the execution time of the (ELM) classifier was the least; i.e ELM has the highest training and predication speed with more than ten times than the other well-known classifiers.

Finally, to analyze the optimum number of features that are sufficient to the ELM approach, Figure 11 illustrates the accuracy against the number of features. Here, minimizing the features was done by removing the low variance feature utilizing the ANOVA approach.

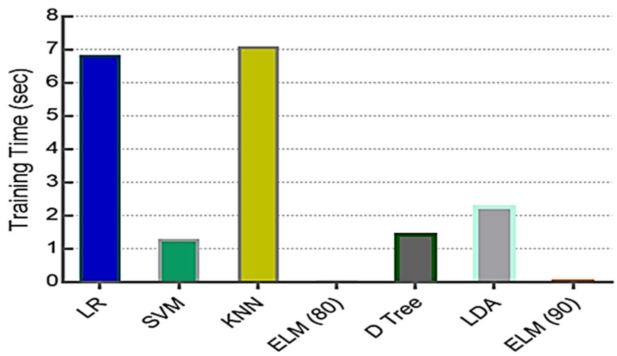

Fig. 10. Training time for all classifier approaches

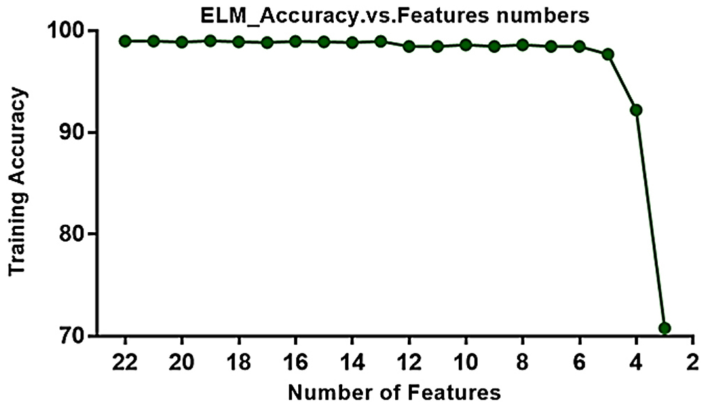

Fig. 11. The optimum number of features corresponding to training accuracy

Experimentally for brain tumor classification, ELM outperforms other state of the arts because it is more reliable, robust against variations, and has a good generalization performance, thus preventing the model overfitting and increasing the overall prediction accuracy.

In addition to better performance of ELM on different evaluation criteria, including efficiency, accuracy, and consumption time, ELM can be considered as a unified model that can achieve different ELM versions.

7 Conclusion

The goal of this study is to exploit the established and evaluated Magnetic Resonance Imaging (MRI) scanning technology for brain tumor classification using an Extreme Learning Machine (ELM). It can improve the performance by increasing the accuracy more than 2% and minimizing the required processing operations to more than ten times than the other predefined classifiers methods.

The existence of repetition or a lack of relevance to some features is the major cause that decreases the classification accuracy with overfitting; as a result, mixing the texture feature extracting techniques utilizing GLCM and LBP is efficient for extracting MRI discriminative features. For reducing the size of the non-useful feature vectors, ANOVA feature selection technique is employed to estimate the minimized highest variant features. It can conclude and provide some suggestions about this work:

The hidden node number (L) and the regularization parameter (λ) are two important performance factors in RELM. L does not require tuning as long as it is large enough, whereas λ is changeable and must be optimized. It is critical to include some processes to incorporate the feature selection inside the ELM technique in addition to its classification aims.

For simple 2D MRI images, the number of the hidden nodes in ELM is slightly low while for large data sets, ELM can achieve sparse advantages with a good generalization and performance. The structure of ELM classifiers is simple with extremely low processing time; it can employ the real time classification system with the availability of single chip MCU that supports the image processing toolboxes like Raspberry pi.

8 References

[1] N. N. Khamiss, "Unsupervised segmentation method for brain MRI based on fuzzy techniques," Nahrain University, College of Engineering Journal, vol. 13, no. 1, pp. 108–115, 2010.

[2] A. Tiwari, S. Srivastava, and M. Pant, Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019. Pattern Recognition Letter 2019. https://doi.org/10.1016/j.patrec.2019.11.020

[3] J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja, A package-SFERCB- "Segmentation, feature extraction, reduction and classification analysis by both SVM and ANN for brain tumors," Appl Soft Comput, vol. 47, pp. 151–672, 2016. https://doi.org/10.1016/j.asoc.2016.05.020

[4] G. Mohan and M. M. Subashini. "MRI based medical image analysis: Survey on brain tumor grade classification," Biomedical Signal Process Control, vol. 39, pp. 139–61, 2018. https://doi.org/10.1016/j.bspc.2017.07.007

[5] M. Eltoukhy, I. Faye, and B. Samir, "Using curvelet transform to detect breast cancer in digital mammogram," 5th International Colloquium on Signal Processing & Its Applications (CSPA), 2009. https://doi.org/10.1109/CSPA.2009.5069247

[6] Shen, Liran, and Qingbo Yin, "Texture classification using curvelet transform," Proceedings of the International Symposium on Information Processing. 2009.

[7] K. Deepa, K. S. Gokul, K. Hinduja, and R. Rajkumar, "An efficient approach to predict tumor in Brain image using classification techniques," Information Communication and Embedded Systems (ICICES), 2013 International Conference on, pp. 559,564, 21–22 Feb. 2013. https://doi.org/10.1109/ICICES.2013.6508256

[8] Joshi, M. Dipali, N. K. Rana, and V. M. Misra, "Classification of brain cancer using artificial neural network," Electronic Computer Technology (ICECT), 2010 International Conference on. IEEE, 2010. https://doi.org/10.1109/ICECTECH.2010.5479975

[9] Saraswathi, Vishlavath, and Deep Gupta, "Classification of brain tumor using PCA-RF in MR neurological images." 2019 11th International Conference on Communication Systems & Networks (COMSNETS). IEEE, 2019. https://doi.org/10.1109/COMSNETS.2019.8711010

[10] Kaplan, Kaplan, et al. "Brain tumor classification using modified local binary patterns (LBP) feature extraction methods," Medical Hypotheses 139 (2020): 109696. https://doi.org/10.1016/j.mehy.2020.109696

[11] A. Samreen, A. Taha, Y. Reddy, and P. Sathish, "Brain tumor detection by using convolution neural network," International Journal of Online & Biomedical Engineering: pp. 58–69, 2020. https://doi.org/10.3991/ijoe.v16i13.18545

[12] J. Preethi. "A bio inspired hybrid Krill Herd-extreme learning machine network based on LBP and GLCM for brain cancer tissue taxonomy." 2018 3rd International Conference on Computational Intelligence and Applications (ICCIA). IEEE, 2018. https://doi.org/10.1109/ICCIA.2018.00033

[13] SJ, Prashantha and H. N. Prakash. "A features fusion approach for neonatal and pediatrics brain tumor image analysis using genetic and deep learning techniques," International Journal of Online & Biomedical Engineering, vol. 17, no. 11, 2021. https://doi.org/10.3991/ijoe.v17i11.25193
[14] A. Pashaei, H. Sajedi, and N. Jazayeri, "Brain tumor classification via convolutional neural network and extreme learning machines," 2018 8th International Conference on Computer and Knowledge Engineering, ICCKE 2018, ICCKE, pp. 314–319, 2018. https://doi.org/10.1109/ICCKE.2018.8566571
[15] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, et al., "The multimodal brain tumor image segmentation benchmark (BRATS)," IEEE Transactions on Medical Imaging, vol. 34, no. 10, pp. 1993–2024, 2015. https://doi.org/10.1109/TMI.2014.2377694
[16] R. M. Haralick, K. Shanmugan, and I. Dinstein, "Textural features for image classification," IEEE Transactions on Systems: Man, and Cybernetics SMC, vol. 3, pp. 610–621, 1973. https://doi.org/10.1109/TSMC.1973.4309314
[17] A. Hasan and F. Meziane, "Automated screening of MRI brain scanning using grey level statistics," Computers & Electrical Engineering, vol. 53, pp. 276–291, 2016. https://doi.org/10.1016/j.compeleceng.2016.03.008
[18] A. M. Hasan, H. A. Jalab, R. W. Ibrahim, F. Meziane, A. a. R. AL-Shamasneh, and S. J. Obaiys, "MRI brain classification using the quantum entropy LBP and deep-learning-based features," Entropy, vol. 22, p. 1033, 2020. https://doi.org/10.3390/e22091033
[19] W. Gomez, W. Pereira, and A. Infantosi, "Analysis of Co-Occurrence texture statistics as a function of gray-level quantization for classifying breast ultrasound," IEEE Transactions on Medical Imaging, vol. 31, no. 10, pp. 1889–1899, 2012. https://doi.org/10.1109/TMI.2012.2206398
[20] A. M. Hasan, F. Meziane, and H. A. Jalab, "Performance of grey level statistic features versus gabor wavelet for screening MRI brain tumors: A comparative study," In International Conference on Information Communication and Management (ICICM), UK, pp. 136–140, 2016. https://doi.org/10.1109/INFOCOMAN.2016.7784230
[21] U. Stańczyk and L. Jain (Eds), "Feature selection for data and pattern recognition," Springer Series on Studies in Computational Intelligence, vol. 584, pp. 1–7, Berlin Heidelberg: Springer, 2015. https://doi.org/10.1007/978-3-662-45620-0
[22] K. J. Johnson and R. E. Synovec. "Pattern recognition of jet fuels: Comprehensive GC×GC with ANOVA-based feature selection and principal component analysis," Chemometrics and Intelligent Laboratory Systems, vol. 60, no.1–2, pp. 225–237, 2002. https://doi.org/10.1016/S0169-7439(01)00198-8
[23] G. B. Huang, Q. Y. Zhu, and C. K. Siew, "Extreme learning machine: A new learning scheme of feedforward neural networks." Proceedings of IEEE International Joint Conference on Neural Networks, vol. 2, pp. 985–990, 2004.
[24] G. B. Huang, Q. Y. Zhu, and C. K. Siew, "Extreme learning machine: Theory and applications." Neurocomputing, vol. 70, no. 1–3, pp. 489–501, 2006. https://doi.org/10.1016/j.neucom.2005.12.126
[25] M. A. Shehab and N. Kahraman, "Optimum, projected and regularized extreme learning machine methods with singular value decomposition and L2-Tikhonov regularization." Turk J Elec Eng & Comp Sci (2018), vol. 26, pp. 1685–1697, 2018. https://doi.org/10.3906/elk-1706-60

[26] M. A. Shehab and N. Kahraman, "A weighted voting ensemble of efficient regularized extreme learning machine." Computers & Electrical Engineering, vol. 85, p. 106639, 2020. https://doi.org/10.1016/j.compeleceng.2020.106639
[27] Y. Wang, F. Cao, and Y. Yuan, "A study on effectiveness of extreme learning machine." Neurocomputing, vol. 74, no. 16, pp. 2483–2490, 2011. https://doi.org/10.1016/j.neucom.2010.11.030
[28] M. Luo and K. Zhang, "A hybrid approach combining extreme learning machine and sparse representation for image classification," Engineering Applications of Artificial Intelligence, vol. 27, pp. 228–235, 2014. https://doi.org/10.1016/j.engappai.2013.05.012
[29] G. Huang, G. B. Huang, S. Song, and K. You, "Trends in extreme learning machines: A review." Neural Networks, vol. 61, pp. 32–48, 2015. https://doi.org/10.1016/j.neunet.2014.10.001
[30] E. Cambria, G. B. Huang, L. L. C. Kasun, H. Zhou, C. M. Vong, J. Lin, J. Yin, Z. Cai, Q. Liu, and K. Li, "Extreme learning machines [Trends & Controversies]." IEEE Intelligent Systems, vol. 28, no. 6, pp. 30–59, 2013. https://doi.org/10.1109/MIS.2013.140
[31] J. Chung, M. I. Español, and T. Nguyen, "Optimal Regularization Parameters for General-Form Tikhonov Regularization." pp. 1–21, 2014.
[32] D. M. Powers, "Evaluation: From precision, recall and f-measure to ROC, informedness, markedness, and correlation," arXiv preprint arXiv: 2010.16061, 2020.
[33] A. Magana-Mora and V. B. Bajic, "Omniga: Optimized omnivariate decision trees for generalizable classification models," Scientific Reports, vol. 7, no. 1, pp. 1–11, 2017. https://doi.org/10.1038/s41598-017-04281-9
[34] D. Cai, X. He, and J. Han, "SRDA: An efficient algorithm for large scale discriminant analysis." IEEE Transactions on Knowledge and Data Engineering, vol. 20, no. 1, pp. 1–12, 2008. https://doi.org/10.1109/TKDE.2007.190669
[35] J. Friedman, T. Hastie, and R. Tibshirani, "Additive logistic regression: A statistical view of boosting," The Annals of Statistics, vol. 28, no. 2, pp. 337–407, 2000. https://doi.org/10.1214/aos/1016218223
[36] S. Dutta, J. Vitay, and P. Ott, "Efficient learning of large Imbalanced training datasets for support vector machines," Technische Universität Chemnitz, thesis, MTR.-NO.: 334439, JANUARY 30, 2016.
[37] W. Zhang, X. Chen, Y. Liu, and Q. Xi. "A distributed storage and computation k-nearest neighbor algorithm based cloud-edge computing for cyber-physical-social systems," IEEE Access, vol. 8, pp. 50118–50130, 2020. https://doi.org/10.1109/ACCESS.2020.2974764

9 Authors

Jhan Yahya Rbat Al-Awadi obtained B.S. in Biomedical Engineering from Baghdad University on 2001, currently studying M.Sc. in Biomedical Engineering at Alnahrain University. Worked as a staff member at Biomedical Engineering department in University of Technology. My research interest involve biomedical image processing and applications of Artificial Intelligence in the medical field (email: alawadijhan@yahoo.com; https://orcid.org/0000-0001-9442-7379).

Hadeel K. Aljobouri received the B.S. degree in Biomedical Engineering from the University of Baghdad, Baghdad, Iraq, in 2000 the M.Sc. in Medical Engineering from Al-Nahrain University, Baghdad, Iraq, in 2004, and the Ph.D. at the Electrical and Electronics Engineering Department, Graduate School of Natural Science/ Ankara Yildirim Beyazit University in Turkey. She worked as an Assistant Professor at the Biomedical

Engineering Department at Al-Nahrain University in Iraq. Her research interests are biomedical signal processing, medical imaging, data mining, clustering techniques, and machine learning. She has many publications in the field of biomedical engineering (email: hadeel_bme77@yahoo.com).

Ali M. Hasan received the B.Sc. and M.Sc. degrees from the University of Technology, Iraq, in 2002 and 2004, respectively, and the Ph.D. degree from the University of Salford, U.K., in 2017. Since 2005, he has been an Assist. professor in College of Medicine, Al-Nahrain University, Iraq. His research interests include digital image processing and computer vision (a.hasan4@edu.salford.ac.uk; a.hasan4@colmed-alnahrain.edu.iq).

Article submitted 2022-07-13. Resubmitted 2022-08-12. Final acceptance 2022-08-12. Final version published as submitted by the authors.