Texture Based Feature Extraction on Brain Tumor Classification using Machine Learning

Chetana Patil [1], Dr. Sudhir Kumar Sharma[2]

[1]Research Scholar, Department of Electronics and Communication,JaipurNational University Jaipur,India.

email:chpn1122@gmail.com

[2]Professor,Department of Electronics and Communication,JaipurNational University Jaipur,India.

email:hodece_sadtm@jnujaipur.ac.in

Abstract

The success of brain tumor treatment depends on a prompt and precise detection of a tumor. The rate of success in neurosurgery is continually rising, thanks to the ongoing advancement of technology that reduce the risk of problems. Brain tumor are extremely difficult to identify because of numerous irregularities in tumor size and location. Magnetic resonance imaging (MRI) analysis also necessitates the expertise of a neurosurgeon. It might be difficult and time-consuming to identify tumor from MRI in developing countries due to a lack of skilled clinicians and understanding regarding tumor. The issue can be addressed by an automated approach. Brain tumor classification can be achieved by a variety of methods and algorithms. The primary goal of this research was to find the most effective feature extraction and Machine Learning (ML) model for classification, suggesting one that can learn automatically through training and then make a sound conclusion. To do this, we use a Grey Level Co-Occurrence Matrix (GLCM) and a Local Binary Pattern (LBP) as feature extraction methods. Next, an ML model, such as KNN (K Nearest Neighbor), SVM (Support Vector Machine), or NB (Naive Bayes), is selected. Several metrics were used to compare the effectiveness of different combination of two feature extraction methods and three ML models for tumor classification. The raw MRI data is used by the model during the classification procedure to determine the various tumor types. We examined the accuracy of 6 different combinations and discovered that GLCM plus NB algorithm yielded the highest accuracy (94.96%).

Keywords— *Brain Tumor, Resize, Image Enhancement, Feature Extraction, Evaluation Metrics*

DOI Number: 10.14704/nq.2022.20.9.NQ44772 **Neuro Quantology 2022; 20(9):6601-6609**

I. INTRODUCTION

The human brain serves as the body's command and control centre. It is in charge of executing actions over a huge network of neurons and connections. A brain tumor is a cancerous growth of abnormal cells in the brain or nervous system that impairs normal brain and nervous system functioning. It is one of the most lethal diseases. This disease affects both adults and children in the same way, according to cancer indicator reports [1]. In 2018, approximately 80k new cases of primary brain tumor were diagnosed [2]. When brain tissue is exposed to this form of tumor, it causes broad damage to the neural network, affecting brain function [3,4]. gliomas (26.5%), Meningiomas (36.3%), pituitary (16.2%), and other forms (7.3%) were the most common types of brain cancer. The major causes of this type of sickness are cancer-related illness and mortality. The ability to diagnose this illness quickly and accurately is crucial for effective treatment. The stage, pathology, and categorization of the tumor all have a role in selecting which treatment option is prioritized. The brain is the complex and crucial organ in the body, containing structures and nerve cells in charge of vital activities such as breathing, feeling, and movement. The capacities of a cell decide whether it develops normally or degenerates into an abnormal form that can no longer perform its functions, as some cells do.

Tumor tissue is formed when aberrant cells proliferate in huge quantities. Thus, brain tumor is distinguished by the uncontrolled proliferation of brain cells [5], and detecting tumor at an early stage provides patients with the best chance of survival and complete recovery, but this is only feasible with the doctor's competence [6].

An automated brain tumor classification system can greatly assist neurosurgeons in their search for the best feasible course of treatment. This disease continues to be a huge hazard to humanity. Early and precise diagnosis is critical for the successful treatment of a brain tumor. The success of the treatment and the speed with which the patient recovers are both contingent on the treating physician's expertise and skill. It may be difficult to identify the precise type of brain tumor early on, but it is critical so that doctors can deliver the best therapy possible [7]. Even though several illnesses have been overcome in recent times as a consequence of developments in physiology and human invention, cancer remains the biggest reason for death globally. The detection of human tumor is primarily reliant on the analysis of medical images. CT and MRI imaging techniques are widely used to analyse brain tissues for abnormalities in cell size, location, or structure, which can aid in the early diagnosis of tumor [8]. Robust ML techniques dramatically increase the identification accuracy that allows clinicians to treat patients. It is critical to utilize an efficient strategy with the appropriate characteristics and classifiers when classifying the tumor. Tumor categorization research utilizing ML and DL is mentioned briefly below.

The goal of the research [9], which utilizes a convolutional neural network (CNN) for the multi-classification of brain tumor. There are three classification tasks and three CNN frameworks were offered. Using a binary classification technique, the first CNN model successfully diagnoses a brain tumor. The second CNN model can discriminate between normal, glioma, meningioma, pituitary, and metastatic brain tumor. The third CNN model is capable of classifying brain tumor as intermediate (II and III) or severe (IV). We can automatically set values to all of the essential hyper-parameters in CNN models using a grid search optimization approach. Modern CNN models are compared to those produced in this study. Satisfactory categorization outcomes can be achieved on huge, freely accessible datasets.

For classifying MR images of brain tumor, researchers [10] suggest a neural dictionary learning with local constraint technique (CDLLC). To probe into information that might be used to differentiate between objects, we use a CNN framework that integrates multi-layer dictionary learning in our approach. To address the issue, an effective iterative optimization approach is created. The experiment generates two distinct multi-class classification tasks on standard datasets that can be used in clinical contexts. The comparison results reveal that our technique outperforms others when it comes to classifying MR images of brain tumor. The fundamental aim of the research [11] is to help researchers classify and categorize different forms of brain tumor. Deep learning (DL) based classification methods, such as CNN, offer the best results in medical image segmentation. In this article, we proposed a method for extracting the intrinsic features of MRI by training a specialized CNN and then analysing the outputs with an SVM (hybrid). We used the 2019 version of the Brain Tumor Image Segmentation (BraTS) dataset in this investigation. The investigational outcome supports the proposed method's efficacy.

Work [12] presents brain tumor classification algorithms based on ML and DL. The first proposed solution employs ML techniques and a total of 16 statistical characteristics. In the classification procedure, SVM and decision trees are also used. As a result, the second suggested method employs a DL network to categorize tumor, specifically the pre-trained VGG19 and ResNet152 CNN models. The figshare brain tumor, which contains 3064 images of three different types of brain tumor, is used to evaluate the efficacy of the aforementioned approaches. Our data suggest that the proposed CNN-based technique enhances classification accuracy. As a result, the proposed technique, which employs statistical characteristics and an SVM classifier, performs badly. The CNN-based methodology surpasses the state-of-the-art techniques regarding classification accuracy. The novel CNN-KNN architecture created in this study [13] can identify and categorize many types of tumors automatically. The images in the dataset are scaled during the pre-processing stage, and a Gray-scale transformation is conducted to convert the RGB to grayscale. CNN is utilized in the feature extraction phase to extract a range of intensity-based features. Finally, in the classifier step, we use two ML classifiers, SoftMax and KNN, to identify and classify the many types of brain tumor. The suggested CNN-KNN method accurately identifies and categorizes the numerous types of tumors. When the two classifiers were compared, KNN proved to be more effective.

II. RESEARCH METHODOLOGY

Brain tumor classification is necessary to reduce the physician's work burden and enhance the patient's survival rate. Figure 1 depicts the research-based brain tumor classification procedure. Kaggle will serve as the data source for the images of brain tumor. Image processing methods such as resizing, enhancement, and de-noising will be applied to the original brain scan. After the image has been processed, it is forwarded to the feature extraction methodology, where two approaches, including GLCM and LBP, are used to retrieve the salient features. The outcome of extracted feature approaches fed to the ML model for categorizing the various types of tumors. SVM, NB, and KNN are the ML algorithms employed. Once the ML model has been trained using the data, it will be put through its paces in a series of tests using the metrics used to evaluate the model's effectiveness.

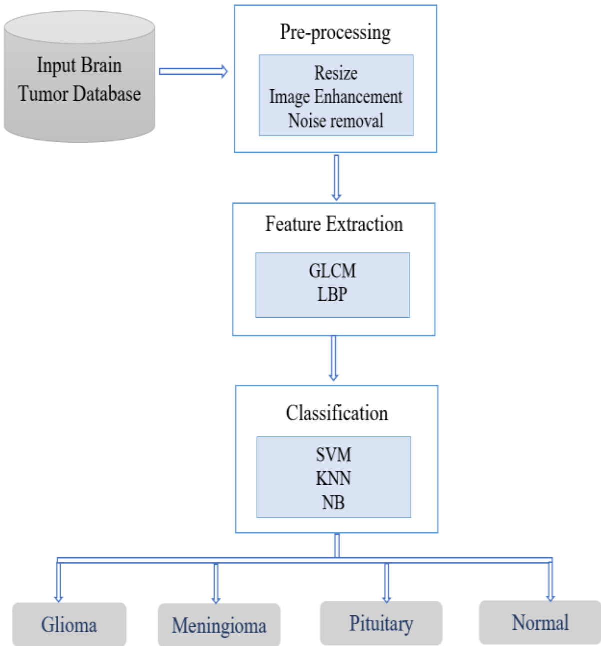
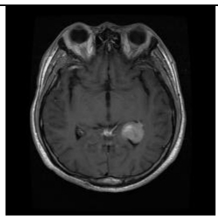
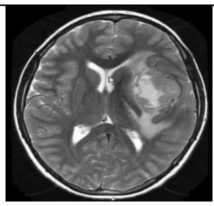


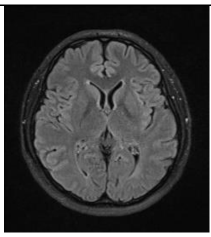
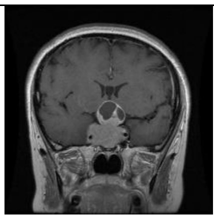
Fig. 1. Brain Tumor classification using ML

III. DATA COLLECTION AND PROCESS

The MRI images from the public database were used in this research [14]. The files include a normal image and ones labelled with a tumor type (glioma, meningioma, or pituitary). There is a record of 3,264 images available, but only 2,870 are being put to utilize during the training process. The remaining images are put to utilize during the testing process. The data distribution of the tumor type in the train and test phase and the sample images of tumor type is detailed in table 1. Figure 2 shows the tumor data distribution in the train and test stages.

TABLE I. BRAIN TUMOR DATA DISTRIBUTION

Tumor types	Sample image	Train data count	Test data count
Meningioma		822	115
Glioma		826	100

Normal		395	105
Pituitary		827	74

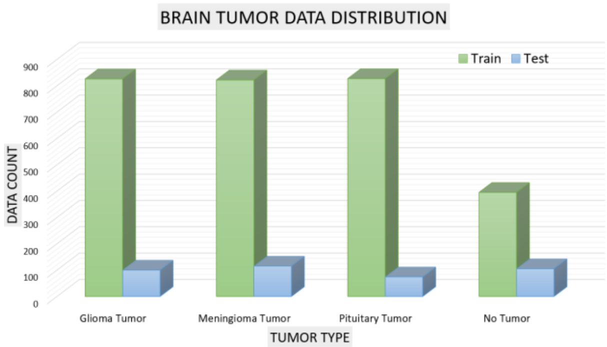


Fig. 2. Brain tumor data distribution

The image analysis process is rather complicated. Before working with an image, it is critical to remove any unnecessary information. After removing extraneous elements, the image can be altered efficiently. The fundamental breakthrough in image handling is image pre-processing [15]. Following the pre-processing stage, the MR images of brain images are of greater quality and more suited to further processing by clinical specialists or imaging modalities. It can also be used to optimize MR image images. The images menu has choices for improving visual MR images, reducing noise, and resizing. The following is a breakdown of the processing methods:

1. Image scaling, which includes adjusting the number of pixels used to represent an image, is a critical function in image processing. Image interpolation includes image down-sampling and up-sampling, which are both essential for data scaling [16]. Scaling image data appropriately is a critical step in the medical and scientific fields. The image has been reduced in size to fit a 256x256 grid.

2. There will always be some degree of noise or random variation in images of brightness or color information when a medical device or scanner makes an image. Image noise is usually seen as a detrimental consequence of the image processing process. Uncertainty in a signal caused by random oscillations in the signal is frequently referred to as "noise" [17]. These alterations have a variety of causes. All medical images contain visual noise. A noise-filled image will appear spotty, grainy, textured, or even snowy. To remove undesired noise, the median filter is utilized.

3. An image's contrast is equal to its maximum brightness minus its least brightness. The formula is used to extend the image's histogram to increase contrast.

$$g(x,y) = \frac{f(x,y) - f_{min}}{f_{max} - f_{min}} * 2^{bpp} \quad [1]$$

To use the formula, you'll need to determine the range of grayscale values between the lowest and highest intensities of individual pixels. As our image uses an 8 bpp channel, there are 256 shades of grey available. From 0 to 225, those are the range of possible values. In this instance, the formula would look like

$$g(x,y) = \frac{f(x,y) - 0}{255 - 0} * 255 \quad [2]$$

where the intensity of each pixel is represented by the function $f(x,y)$. The image's output is enhanced once the equations are applied.

IV. Feature Extraction

Dimensionality reduction can take many forms, and feature extraction is just one of them. The primary goal of this method is to retrieve important details from raw MRI and interpret them in a lower-dimensional space [18]. Both an LBP and GLCM were employed for feature extraction in this work. In the sections that follow, you'll get a summary of the above-mentioned approaches.

A. GLCM

The image's textural features can be analysed statistically using a technique called GLCM. This approach utilizes statistical data to build a protocol for determining an image's textural qualities. One possible representation of the image I is a 2D matrix with the dimensions R_n and C_n, where $R = \{1,2,\dots.R_n\}$ and $C = \{1,2,\dots.C_n\}$ correspond to rows and columns, respectively. The grayscale level varies from 0 to G_n, with 0 being completely black and 1 being completely white. The texture attributes of an image can be determined from the spatial distribution of the pixel repeats by distance and direction for neighbouring pixels, and this image I can be thought of as the function of spatial pixel relations represented by $I: R * C \rightarrow G$. The GLCM is a square matrix whose components can be represented by several parameters, such as the grey value of the pixel p at coordinates (x, y), and j, the grey level value of a neighbouring pixel in the direction of a parameter d distance by an angle θ. In sum, we can say that $p(i, j, d, \theta)$ is represented. Table 2 [19] shows that GLCM is employed twice in this paper: once for the RBO dominant characteristics, and once as a standalone third feature to be compared to other works based on its contrast, homogeneity, energy, and correlation.

TABLE II. GLCM FEATURES

Contrast	$\sum_{i,j} \lvert i-j \rvert^2 p(i,j)$
Homogeneity	$\sum_{i,j} \frac{p(i,j)}{1+\lvert(i-j)\rvert}$
Energy	$\sum_{i,j} p(i,j)^2$
Correlation	$\sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j}$
$p(i,j)$ represents the $(i,j)^{th}$ entry in the matrix	

B. LBP

The LBP feature extraction approach is a very useful technology that can survive variations in lighting. Simply put, LBP entails crossing the image using a window that has a specific neighbourhood value and labelling the pixel in the window's centre. The threshold is calculated by taking the values of the pixels surrounding the centre pixel into account. The LBP matrix is then computed by averaging the values of neighbouring neighbourhoods in either an anticlockwise or clockwise direction. As a result, the mathematical model of the statistical and structural features of the textural structure is computed [20]. The key advantages of the LBP method are its computational simplicity and resistance to grey-level variations, making it suited for use in real-time settings. Labels are assigned to pixels using equations 1 and 2.

$$LBP_{P,R} = \sum_{P=0}^{P-1} s(g_p - g_c)2^P \quad [3]$$

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad [4]$$

Where:

$g_c \rightarrow$ Grey level of the centre pixel,

$g_p \rightarrow$ Grey level of the neighbouring pixels.

$P \rightarrow$neighbours count

$R \rightarrow$ average distance between them.

In this research, the LBP method is used to generate feature matrices for each image, each of which has 10 image features. Classifiers are then taught to make use of these property matrices.

V. MACHINE LEARNING

The ML algorithm implemented in this work is detailed in this section

SVM

Data points are classified using the SVM [21] approach from statistical learning, which creates two equally-sized classes. In high-dimensional feature space, wherein multiple classes exist, SVM is an error-free technique for locating the hyperplane among 2 distinct categories. The two steps of the supervised learning process are training and testing. The SVM classifier uses a linear function for image categorization.

$$f(x) = W^T X + b \quad [5]$$

Where:

X → Input sample

W → Weight

b → Offset or bias.

Linear and non-linear type SVMs are the primary categories of classifiers. Compared to nonlinear, linear SVM classifiers are more desirable due to their ability to map the input parameter into a more generalized feature space. A hyperplane can be used to study data that can be partitioned along a linear axis, but a kernel function, such as a higher-order polynomial, can be used to examine data that cannot be partitioned along a linear axis. The SVM algorithm for data classification is based on several kernel techniques. The RBF kernel can be defined as follows: for two samples x and x', where x and $x'$are feature vectors in some input space.

$$K(x, x') = exp\frac{||x-x'||^2}{2\sigma^2} \quad [6]$$

Kernel functions have values between zero and one ($x = x'$), and these values decrease as the distance from the origin increases.

A. NB

The NB classification is a supervised classification method in ML that employs Bayes' theorem of probability. The NB algorithm is named after the assumption that feature occurrences are unrelated to one another. That is why our algorithm is so effective at recognizing brain tumor from various perspectives and with a wide range of features. Because the recovered qualities might occur independently of one another, probability considerations are a powerful tool in most fields dealing with unpredictability. The retrieved features matrix is fed into an NB classifier for training to identify whether a particular test image is healthy or malignant. The NB theorem relies on the Bayes formula, which is as follows [22]:

$$P\left(\frac{U}{V}\right) = \frac{P(U)P\left(\frac{V}{U}\right)}{P(V)} \quad [7]$$

Where:

V : Attributes

U : Class

$P\left(\frac{U}{V}\right)$: Probability of U given V occurred

$P\left(\frac{V}{U}\right)$: Probability of V given U occurred

$P(U)$: Probability of U

$P(V)$: Probability of V

B. KNN

For categorization, the KNN approach is dependable and simple to use. The testing feature vector is categorized according to its k closest training neighbours [23]. To calculate the distance between the training and test vectors, several distinct distance metric measuring methodologies are used. Euclidean metrics are used to calculate the distances between the train and test data vectors. The formula is used to determine the Euclidean distance between a training vector and a test vector.

$$d(a, b) = \sqrt{\sum_{i=1}^{n}(a_i - b_i)^2} \quad [8]$$

In this situation, the information corresponding to the feature vector with the least distance is labelled on the testing vector. As features are retrieved from training and testing sets of images, the values of these extracted features are used as observations for the related characteristics, resulting in a set of points in this space. The distance between two points in space can be regarded as a proxy for their similarity. The technique is built so that the k nearest data sample to the new sample is selected, and the class estimated for the given sample corresponds to the most frequent class amongst k data samples.

VI. RESULTS AND DISCUSSION

The brain tumor data of three tumor types and normal images are collected from Kaggle. The whole data is split into two phases training and testing. The images are cleaned based on the requirement using processing techniques. The processed image is given to the two feature extraction techniques. Then the extracted feature from LBP is given to the ML models. After training the ML model, the models are tested using the metrics like accuracy, precision, F1 score, True and False Positive Rate (TPR/FPR), True and False Negative Rate (TNR/FNR). The accuracy of the LBP with NB is the highest one and the achieved value is 93.19%, next the lowest value of 90.17% is achieved by KNN. The precision of the ML model in ascending order is 89.21%, 91.17%, and 92.64%, which is the result of KNN, SVM, and NB. Similarly, the F1 score is 90.32%, 91.85%, and 93.33% by KNN, SVM, and NB. The TPR and TNR achieved by NB are more when compared to the other two methods by the value of 94.02% and 92.34%. and the KNN is lowest by the value of 91.45% and 88.88%. Finally, the negative metrics of FNR and FPR are analysed. The lowest value of FPR and FNR is 7.6% and 5.97% by NB, highest value by KNN is 11.11% and 8.54%.

Next, the retrieved GLCM feature is fed into the ML models. The aforementioned metrics are used to evaluate the ML models after they have been trained. The GLCM with NB achieves the most accuracy, at 94.96%, followed by the KNN method, which achieves the lowest accuracy, at 91.43%. Precision measures for the ML model are 91.08% for KNN, 92.61% for SVM, and 94.11% for NB, in that order. The F1 scores for KNN, SVM and NB are 91.54%, 93.06%, and 95.04%, respectively. Compared to the other two approaches, NB yields higher TPR and TNR values (96% and 93.90%, respectively) and the KNN has the lowest values, with 92% and 90.86%, respectively. And finally, the negative metrics of FNR and FPR are examined. The maximum value of KNN's FPR and FNR is 9.13% and 8%, while the minimum value of NB's is 6.09% and 4%. Both the LBP and GLCM with three ML models are compared using the positive and negative metrics is tabulate in table 3. TABLE III. ML MODEL PERFORMANCE ANALYSIS USING ML ON GLCM AND LBP FEATURE EXTRACTION

FE	ML	ACCURACY	PRECISION	F1-SCORE	TPR	TNR	FPR	FNR
LBP	SVM	91.6877	91.1765	91.8519	92.5373	90.8163	9.18367	7.46269
	NB	93.199	92.6471	93.3333	94.0299	92.3469	7.65306	5.97015
	KNN	90.1763	89.2157	90.3226	91.4573	88.8889	11.1111	8.54271
	SVM	92.9471	92.6108	93.0693	93.5323	92.3469	7.65306	6.46766
	NB	94.9622	94.1176	95.0495	96	93.9086	6.09137	4
GLCM	KNN	91.4358	91.0891	91.5423	92	90.8629	9.13706	8

Figure 3 shows the performance analysis of the ML model followed by the LBP feature on brain tumor classification. The figure is drawn with the help of a bar graph. The LBP+SVM represents in the green bar, LBP+NB indicates by the blue bar, and lastly the LBP+KNN by the yellow color bar in figure 3. The graph helps to identify the best ML model in combination with LBP. The bar graph reaches maximum height by the NB model in positive metrics and minimal value by negative metrics. This shows the NB with LBP is better when compared with the other two.

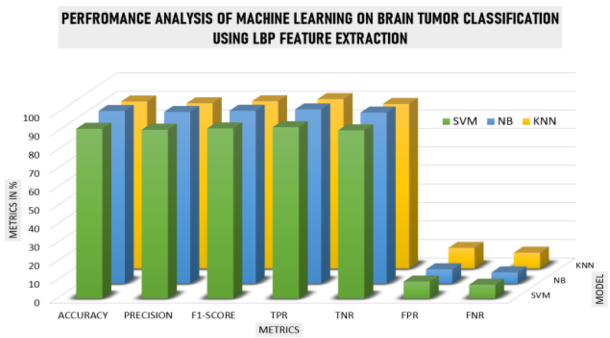


Fig. 3. Performance of LBP feature extraction + ML model on brain tumor classification In Figure 4, we see the results of a study assessing the effectiveness of an ML model followed by the GLCM feature in identifying brain tumor. A bar graph was used to create the illustration. Figure 4 depicts GLCM+SVM in the blue bar, GLCM+NB in the orange bar, and GLCM+KNN in the cement bar. The optimum ML model to use with GLCM can be found using the graph. Again, the NB model causes the bar graph's height to be maximum on positive metrics and minimum on negative metrics. This demonstrates that the NB with GLCM is superior to the other two.

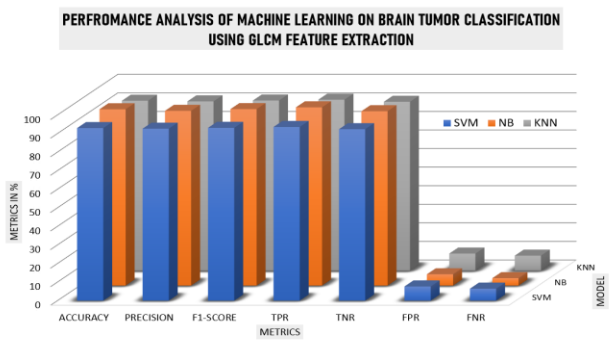


Fig. 4. Performance of GLCM feature extraction + ML model on brain tumor classification In both cases, the NB combination with feature extraction gives a satisfactory result. And

identifies the best combination among this two is done by metrics comparison. The accuracy of the NB+LBP is 93.199% and NB+GLCM is 94.9622%. This shows that the GLCM technique yields 1.76% higher correct prediction than LBP.

VII. CONCLUSION

Brain tumor are collections of defective cells found in the brain. Since there are numerous kinds of brain tumor, there is no uniform approach to treating them. The diagnosis of a specific form of brain tumor is therefore crucial for planning effective treatment. However, not everyone can get an appointment with a specialist, so it would be helpful if the process of diagnosing brain tumor could be automated. The brain tumor categorization by ML system involves genuine data. In this work first, the data will be acquired from Kaggle and processed to make it ready for the classification procedure. Second, the processed data is provided to the feature extraction algorithm. The results of feature extraction are sent through the three different ML models as a third step. The ML model helps to classify the three tumor types and normal MRI. The classification metrics are applied to validate the feature extraction and ML model. From the experimental data, it is identified as the GLCM with NB delivers the greatest score of accuracy, precision, F1, TPR, and TNR and the values are 94.96%, 94.11%, 95.04%, 96%, and 93.90%. Then the lowest score reached by the LBP with KNN combination and the values of the above-mentioned metrics is 90.17%, 89.21%, 90.32%, 91.45%, and 88.88%. In the future the optimum combination of GLCM+NB is planned to deploy in the mobile app, this would aid the patient to know their health state without delay.

REFERENCES

[1]. WHO Statistics on Brain Cancer. Available online: http://www.who.int/cancer/en/ (accessed on 1 July 2019).
[2]. International Agency for Research on Cancer. Available online: https://gco.iarc.fr/ (accessed on 1 July 2019)
[3]. Siegel RL, Miller KD, Jemal A, "Cancer Statistics", CA Cancer J Clin, vol. 67, no. 1, pp. 7-30, 2017, doi: 10.3322/caac.21387. Epub 2017 Jan 5. PMID: 28055103.
[4]. Brain Tumor Statistics, American Brain Tumor Association. Available online: http://abta.pub30.convio.net/ (accessed on Oct. 26, 2019.)
[5]. A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, ''A deep learning-based framework for automatic brain tumor classification using transfer learning,'' Circuits, Syst., Signal Process., vol. 39, no. 2, pp. 757–775, Sep. 2019, doi: 10.1007/s00034-019-01246-3.
[6]. E. Dandıl, M. Çakıroglu, and Z. Ekşi, ''Computer-aided diagnosis of ˇ malign and benign brain tumor on MR images,'' in ICT Innovations: Advances in Intelligent Systems and Computing, Cham, Switzerland: Springer, vol. 311. pp. 157–166, 2015, doi: 10.1007/978-3-319-09879-1_16
[7]. N. Sengupta, C. B. McNabb, N. Kasabov and B. R. Russell, "Integrating Space, Time, and Orientation in Spiking Neural Networks: A Case Study on Multimodal Brain Data Modeling," in IEEE Transactions on Neural Networks and Learning Systems, vol. 29, no. 11, pp. 5249-5263, Nov. 2018, doi: 10.1109/TNNLS.2018.2796023.
[8]. K. Salçin, "Detection and classification of brain tumor from MRI images using faster R-CNN," Tehniˇcki glasnik, vol. 13, no. 4, pp. 337–342, 2019, doi: 10.31803/tg-20190712095507
[9]. Irmak, E. "Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework", Iran J Sci Technol Trans Electr Eng, vol. 45, pp. 1015–1036, 2021, doi: 10.1007/s40998-021-00426-9
[10]. Gu X, Shen Z, Xue J, Fan Y, Ni T. "Brain Tumor MR Image Classification Using Convolutional Dictionary Learning With Local Constraint", Front Neurosci, vol. 5, pp. 679847, 2021, doi: 10.3389/fnins.2021.679847. PMID: 34122001; PMCID: PMC8193950.
[11]. S. Jain and V. Jain, "Novel Hybrid Boosted Ensemble Learning Framework for Brain Tumor Prediction," 2022 9th International Conference on Computing for Sustainable Global Development (INDIACom), 2022, pp. 866-869, doi: 10.23919/INDIACom54597.2022.9763105.
[12]. T. Arumaiththurai and B. Mayurathan, "The Effect of Deep Learning and Machine Learning Approaches for Brain Tumor Recognition," 2021 10th International

Conference on Information and Automation for Sustainability (ICIAfS), 2021, pp. 185-190, doi: 10.1109/ICIAfS52090.2021.9605909.

[13]. S. Shanjida, M. S. Islam and M. Mohiuddin, "MRI-Image based Brain Tumor Detection and Classification using CNN-KNN," 2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET), 2022, pp. 900-905, doi: 10.1109/GlobConET53749.2022.9872168.

[14]. https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri?select=Testing

[15]. X. -W. Chen, "Gene selection for cancer classification using bootstrapped genetic algorithms and support vector machines," Computational Systems Bioinformatics. CSB2003. Proceedings of the 2003 IEEE Bioinformatics Conference. CSB2003, 2003, pp. 504-505, doi: 10.1109/CSB.2003.1227389.

[16]. Schowengerdt, Robert.“A. Remote sensing: models and methods for image processing”. Academic press, 2006.

[17]. Kaur, Manpreet, and Sunny Behal. "Study of Image Denoising and Its Techniques". International Journal, vol .3, no. 1,2013.

[18]. Kamil M Y, “Computer-aided diagnosis system for breast cancer based on the Gabor filter technique”, International Journal of Electrical and Computer Engineering (IJECE), vol. 10, pp. 5235-42, 2020, doi: 10.11591/ijece.v10i5.pp5235-5242

[19]. R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural Features for Image Classification," in IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-3, no. 6, pp. 610-621, Nov. 1973, doi: 10.1109/TSMC.1973.4309314.

[20]. Heikkilä, M., Pietikäinen, M., &Schmid, C. “Description of interest regions with local binary patterns”, Pattern recognition, vol. 42, no. 3, pp. 425- 436, 2009,doi: 10.1016/j.patcog.2008.08.014

[21]. C. Cortes and V. Vapnik, “Support-vector networks,” Mach Learn, vol. 20, no. 3, pp.273–297, 1995, doi: 10.1007/%2FBF00994018

[22]. Han, J., Kamber, M., & Pei, J. “Data Mining Concepts and Techniques”, (3rd ed), USA: Elsevier Inc, 2012

[23]. S. M. Kumar. and G. Balakrishnan, "Classification of Microcalcification in Digital Mammogram using Stochastic Neighbor Embedding and KNN Classifier," in International Conference on Emerging Technology Trends on Advanced Engineering Research (ICETT’12), 2013.