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# Computer-Aided Diagnosis System for Automated Detection of Mri Brain Tumors

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***Abstract:** Detection and classification of brain tumors in manual or traditional way is an area which could be improved by having such automated detection and clarification system for brain tumors. In this paper, enhanced Computer-Aided Diagnosis CAD software system is introduced for brain tumor detection and classification. Total of 229 brain MRI images was taken as dataset for the purpose of this research; those dataset images include 105 normal brain MRI images, and 124 abnormal brain MRI images. Proposed CAD system is specialized for Meningioma brain tumor detection and classification, and the technique could be generalized and implemented for Glioma, and Pituitary brain tumors as well, and the whole system was implemented using MATLAB software. We started by cropping the region of interest (ROI) of dataset images. Then, feature extraction was implemented using first order statistical features, as well as using of some wavelets filters in combination with the former. T-test is used to exclude features of no statistical significance (p-value < 0.05). After that, different types of classifiers were used to separate the normal set from the abnormal one. Note that, we used an iterative approach to by changing features with many runs until we got best performance, where, best accuracy results were gotten with SVM-Kernel Function (Linear), KNN-1, KNN-3, and KNN-5 classifiers. Note also that, we used convolutional neural networks (CNN) from Deep Learning toolbox of MATLAB as a control method to compare, where the images were fed directly to the CNN. The results were evaluated using performance assessment techniques which are Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy, Error Rate, and Area Under the Curve (AUC) of Reciever Operator Characteristic (ROC). With SVM classifier, the best gotten accuracy results were 91 % with CNN classifier, 82% with SVM classifier, and 77 % with KNN classifier. Furthermore, it was very beneficial to find such feature extraction techniques which gave acceptable accuracy results with three different classifiers; this was the case two times as mentioned the study. All proposed CAD system areas was developed and implemented using MATLAB software.***

***Keywords:** CAD System, MATLAB, Automated Detection and Classification, MRI Brain Tumors, SVM Classifier, KNN Classifier, CNN, DCNN*

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## I. INTRODUCTION AND BACKGROUND

Generally, brain tumor could be seen as or defined as abnormal growth of brain cells in human beings' head, where the existing of these abnormal cells in the head could lead to death, if it is not diagnosed and treated properly. In fact, this growth of abnormal cells could damage the whole structure of the brain, causing such malignant brain cancer, and it should be mentioned that those tumors are not similar in shapes, types, or sizes [1] [2]. To go deeply, two types of brain tumors are there, which are primary and secondary brain tumors. Firstly, we have primary brain tumors which are started in brain or spinal cord, where, surprisingly, primary brain tumors are representing 85% up to 90% of all primary central nervous system (CNS) tumors [3]. Also, we have, secondary brain tumors, or, in other words, brain metastases, where those tumors are usually started somewhere else in the body and, then, spread to the brain [3]. Statistics always represent the fact, for example, according to statistics from American Society of Clinical Oncology (ASCO), associated with American Cancer Society Publication "Cancer facts and figures, 2021", brain tumor and other nervous systems cancer is the tenth leading death cause at the United States, where around 18280 adults deaths estimated to be happened in 2022 because of primary cancerous brain and CNS tumors [3] [4] [5]. Additionally, it is predicted that new cases of brain tumors in the US to be around 25050 adults deaths [4] [5]. Now, this article is focusing on one type of primary brain tumors which is "Meningioma". In fact, meningiomas and other mesenchymal tumors are representing 27% of primary brain tumors, and meningiomas are more common in women than men, and, meningiomas are most common in older patients, where highest rates in people with range between 70s and 80s [4] [5] [6]. Meningioma, according to American Cancer Society, exposure to radiation is the only known cause of brain and spinal cord tumors. So, prevention from Meningioma is only, as up to date knowledge, could be done by avoiding exposure to radiation. Other than that, there is no known to be protected from most of those tumors. Moving on to risk factors point, where risk factor could be any factor which could increase the potentiality of getting Meningioma. Risk factors, may include many other factors rather than radiation, meaning radiation treatment, like Obesity, where high body mass index (BMI) could be considered as risk factor for many types of cancers, including meningiomas, anyway, still the relationship between meningiomas and Obesity under investigation.

Also, since meningiomas are more common in women, as mentioned, some doctors, building on some studies think that female hormones may have a link with both breast cancer and meningioma. Some Syndromes like Gorlin syndrome (basal cell nevus syndrome), and Cowden syndrome as well as inherited nervous system disorder, which is rare disorder neurofibromatosis (Types 1 and 2) though to be a cause of increasing meningioma risk as well as other brain tumors.

To conclude, some controversial risk factors are still under investigations like the effect of using of cell phone, which include the existence of Radio Frequency (RF) rays. Also, in a way or another, the vinyl chloride exposure, which is a chemical used to manufacture plastics, as well as products including petroleum, and some other types of chemicals have been linked in a way or another with potentiality of increasing risk of brain tumors in some studies. Also, few studies have linked brain tumors with power lines, transformers, using of such sugar substitute called aspartame, and even with the infection with some viruses. Moving on to diagnostic part, meningioma could be detected by chance in many cases using techniques like Magnetic Resonance Imaging (MRI), by scanning the head or spinal cord. [5] [6] [7] [8].

As stated earlier, diagnosing of brain tumors generally including gliomas, metastases and meningiomas and, specifically, Meningiomas at early stages might help and lead to treat in better way. So the need for special techniques to help in early diagnosing of brain tumor would be very beneficial for the whole community. As a result, diagnosing and treating Meningiomas specifically and brain tumors generally using a Computer-Aided Diagnosis (CAD) system is very good choice with some challenges like detection accuracy. Now, as mentioned, many imaging techniques are available for detecting brain tumors, examples include using of contrast-enhanced computed tomography or (CT), as well as using of magnetic resonance imaging (MRI). In this paper, Meningiomas pictures database by using of MRI techniques will be the chosen one, since MRI has good point related to soft-tissue resolution. Additionally, MRI can detect, in better way, isodense lesions, tumor enhancements, along with other related findings. So, since, as stated above, different types brain tumors including Meningiomas may have different sizes, as well as irregular shapes. Also, knowing that manual diagnosis of brain tumors is not that efficient way since it has high percentage of error and it is time-consuming way for both the patient and the physician. Furthermore, knowing that different types of brain tumors may be in the patient years before detecting them, adding to the reality that detecting the tumor at early stages is much better in treatment process. As a result, there is strong need, globally, to use efficient and modern automated Computer-Aided Diagnosis (CAD) system which has promising high accuracy and minimize the effort done by the physician [1] [2] [4]. In this paper, Computer-Aided Diagnosis or CAD software system proposed for brain tumor, including tumor detection and classification will be proposed. At first, collecting of dataset will be done, which could be Magnetic Resonance (MR) brain images, which is, as mentioned, one of best imaging techniques available to detect the presence of brain tumor, or X-Ray images. Then, having such technique to cut the region of interest or ROI will be implemented. After that, the classification method should be activated and used. Finally, some assessments will be there to evaluate done work. Of course, the process is iterative, since finding a classification technique is iterative process which needs to be improved to reach best results. As mentioned earlier, manual detection and classification of brain tumor is the area of many possible errors, so, it is expected that the proposed system will help a lot in diagnosis. Another area of interest of this research is using of first order statistical spatial and frequency domain features to do feature extraction process, suggested software for feature extraction and classification is the MATLAB. In other words, at the end of this research, proposed CAD system or software will established to help the doctor detecting and classifying given brain tumors.

## II. LITERATURE REVIEW

According to Rezaei, Agahi et al (2020) [9], using of CAD systems as well as machine learning algorithms in given image analysis was very helpful and lead almost to results with zero percentage of error. Proposed approach by them was mainly for classification and segmentation of all brain tumors types taken from real MRI images. SVM or Support Vector Machine was used as a classifier to segment the given image. Then, extracting of 42 features was done. DE or Differential Evaluation was used then to choose the most practical features. The main point here was the using k-nearest neighbors or KNN, the weighted kernel width SVM (WSVM) and the histogram intersection kernel SVM (HIK-SVM) as classifiers to categorize tumor slices of selected features. According to them, given classifiers were combined using a way called, multi-objective differential evolution (MODE)-based ensemble way or technique. Results were acceptable, where classification accuracy has reached the percentage of 92.46%.

Deepak et al (2020) [10] Have also used an automated tumor characterization with the help of CAD system, where the interested area was also brain tumors. With the help of deep learning and machine learning algorithms in using of classification of given images, good results were achieved with accuracy reached to 95.82%. Because of small size of given image database, according to them, combination of convolutional neural network or (CNN) features along with SVM for medical images classification were used. Extracting features was done using designed CNN from selected MRI images. Then, along with the using of CNN features, multiclass SVM, proposed model or integrated system was tested and evaluated, followed by fivefold cross-validation procedure. Faleh Alanazi et al (2022) [11] Also applied machine learning to detect and diagnose brain tumor taken from such a dataset of MRI brain images. Proposed transfer-learned model here has reached high accuracy which was around 95.75% according to them. Proposed model, at this case was depending on transfer-learning concept. Now, according to them, proposed transfer deep-learning model was able to perform early diagnosis of all types of brain tumors. At first, isolated convolutional neural network (CNN) various layers were built.

Proposed model has helped specialists a lot, according to them, since given transfer-learned model has testing results, using another machine brain MRI images showed promising adaptability, and reliability with recording of high accuracy percentage reaching to 96.89% for those unnoticed brain MRI datasets. It should be noted here that, according to them, the technique named "isolated deep-learning network" means a network doing and learning a task from scratch without requiring previous knowledge. M. Sarhan et al (2020) [12] suggested that the conventional diagnosis of a brain tumors always done using MRI. They used CAD systems to help in classifying patient MRI image. In this given study, CNNs have been used. The resulted developed system can extract features from given MRI brain image by utilizing and getting the strong energy compactness property exhibited by the Discrete Wavelet transform (DWT). Then, Wavelet features were used and applied to such CNN in order to classify given MRI image. Proposed method had very high accuracy reached to 98.5%. So, proposed model was Wavelet-based CNN (WCNN) system specialized for detection and classification of brain tumors. Moreover, cascade functions were used by system to take the Wavelet decomposition of the given MRI image. Generally, implementing of CNN in proposed WCNN is done using Wavelet features as inputs to the CNN. Also, this study introduced a proposed system with the help of CAD systems, as well as Fighshare MRI medical images datasets. Now, CNNs, or convolutional neural networks have been implemented in given proposed system specialized for classification of medical images, in order for detection proposes of different brain tumors types existed in collected MRI images. Also, by using the property of utilizing the strong energy compactness with the help of using of the Discrete Wavelet Transform or DWT, the proposed system extracts features from the brain MRI images. Proposed system recorded 97.4% as sensitivity, specificity of 95.5 %, and accuracy of 99.3%. Guan et al (2021) [1] Emphasized the strong need for CAD system. Feature extraction is done by transferring image proposals enhanced input images to backbone architecture. To get high-quality image locations, refinement network was used to select most suitable images and discarded others. Next to that, refined or gotten proposals were aligned in same size. At the end, those images were transferred to the head network in order to reach desired or best classification task. Gotten results were acceptable and showed that proposed method got classification accuracy of 98.04%. According to [1] [5], intensity, diameter, position, and tumor type could be detected. Each tumor type has got an evaluation in terms of specificity, sensitivity, accuracy, as well as f1-score. Unlike previous presented examples, AlKubeyyer et al (2020) [13] is focusing on Meningioma, which is one type of brain tumors, and it is the most common primary brain tumors in the world. Also, here, MRI dataset was used also. Moreover, they used learning algorithms with typical descriptors in order to develop CAD tool specialized to be used for the Meningioma brain tumor firmness represented patient's taken MRI images. Now, to be clearer, LBP or Local Binary Patterns, as well as GLCM or Gray Level Co-occurrence Matrix and Discrete Wavelet Transform (DWT) were extracted from images dataset. SVM and KNN was used as classifiers. The Meningioma tumor firmness resulted balanced accuracy of 87%.

S. Musallam et al (2022) [2] also used CAD to help in accurate detection brain tumor using MRI images dataset. Preprocessing was depending on three steps used to improve MRI images quality. Deep Convolutional Neural Network (DCNN) architecture was used to diagnose as well as classification purposes. Proposed architecture used batch normalization for fast training with a higher learning rate and ease initialization of the layer weights. Also, proposed architecture, in a computational way, make things faster and easier for the model with a small number of convolutional, max-pooling layers and training iterations. Achieved accuracy reached 98.22%, based on 3394 MRI images dataset. Here, pre-processing method including three steps and proposed as the first step to enhance image quality, stretches histogram, and improves contrast. To assess the pre-processing phase, blind referenceless image spatial quality evaluator (BRISQUE) was performed. Then, mentioned DCNN was used to classify MRI images. To train model faster, Batch normalization technique was hired. It should be mentioned that proposed model, consisted from convolutional part, which includes ten convolutional layers, five batch normalization layers as well as four max-pooling layers, and the classifier one which has three dense layers and two dropout layers.P.M. et al (2019) [14] Used CAD to classify different types of brain tumors including glioma, meningioma and pituitary tumors, with the help of using deep CNN-SVM approach. Proposed classification model or system hires mentioned concept of deep transfer learning as well as using of a pre-trained GoogLeNet as feature extraction way from taken or gotten brain MRI images dataset. DCNN – KNN, and DCNN – SVM were used as classifiers. Resulted accuracy of proposed system reached 98%. Deep transfer learned CNN model was used for feature extraction from brain MRI images. Also, proposed system algorithm made the use of modified and fine-tuned GoogLeNet beneficial to learn and know the features of tumors existed in brain MRI images.

R. Ismael et al (2018) [16], introduced a CAD system built on MRI brain tumor database to design such an efficient framework for brain tumor classification. Proposed system combines neural network algorithms as well as statistical features and, where, mentioned algorithm mainly focuses on ROI or region of interest, in other words, segmentation of tumor, or tumor segment, which is identified manually via the specialist or via ROI segmentation techniques.

Feature selection is performed using a combination of the 2D Discrete Wavelet Transform (DWT) and 2D Gabor filter techniques. Using complete set of the transform domain statistical features, features set has been initiated. Most importantly, classification is done using back propagation neural network classifier, which has been selected to test the features selection impact. 3064 dataset MRI images was used including the three types of brain tumors. Gotten accuracy was 91.9%. Results showed predicted effectiveness of used features selection method and indicated that it could introduce effective feature set, which, then, could be used as a framework, and, that can be combined with other classifications techniques, to improve the performance.

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Sachdeva et al (2016) [17], proposed CAD system for brain tumor classification was based on the dataset of 688 MRI brain images containing different types of brain tumors. Segmented regions of interest (SROIs) are saved, then, texture feature set and intensity is extracted from those SROIs. Classification was done using (GA-SVM and GA-ANN).

Accuracy results have been improved with SVM to 91.7% and the accuracy of ANN has been improved to 94.1%. Better results were gotten with GA-ANN classifier in comparison with GA-SVM classifier. Speaking about the speed, GA-SVM provided the advantage. Generally, both classifiers results believed to be will beneficial for radiologists in classifying brain tumors. A. El-Dahshan et al (2014) [18] used (CAD) systems for proposing such system to help in diagnosing by reducing time for diagnostic and improving accuracy building on human brain MRI dataset. Simply, proposed system or technique used computational methods including feedback pulse-coupled neural network for image segmentation purposes. Moreover, proposed technique, at first, applied feedback pulse-coupled neural network as a front-end processor to do segmentation of the image as well as detecting the ROI or region of interest, wavelet transform then applied to extract features. Finally, they sent the reduced features to back-propagation neural network to classify given inputs as normal or abnormal images, which are MRI patient images, and resulted accuracy was 99%. Extracting features based on wavelet transform was the done here.

## III. OUR METHODOLOGY

To implement proposed CAD system, three main steps were done. In fact, figure (1) below shows the flowchart of proposed CAD system. At first, after getting brain images or the database, cutting the region of interest or ROI for every image, will be done using MATLAB. More about chosen database will be presented later. This step is done by loading every image and given fed to the MATLAB in order to cut the ROI. Now, continuing with showed flowchart, what is done until now including taken database pictures, containing normal and abnormal brain images, cutting ROIs for every image, for the abnormal picture, the tumor is considered as the ROI, while for normal one, any place in the image could be the ROI. Now, as the second main step in proposed CAD system, after dividing the database pictures into training and testing groups is done, where the training images represent around 70% of total normal or abnormal sets, while remaining percentage which represents around 30%, is reserved for testing. As represented in the flowchart, after dividing the database, second main step include feature extraction which is iterative step, and needs to be improved continuously until reaching acceptable performance, this step is done only for training group of images. Finally, as the third and final step, classification step, this is done using specialized classifiers. More about every step will be showed and presented in detailed way later in this report.

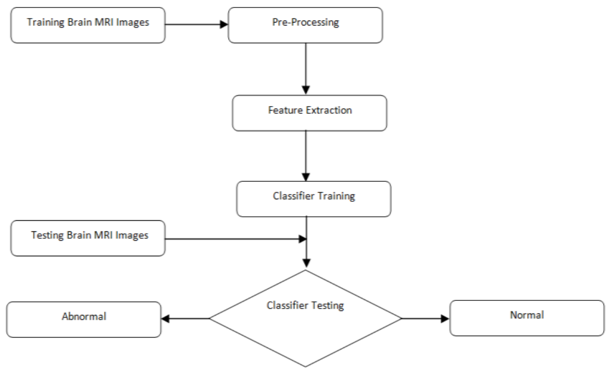


**Fig. 1: Proposed CAD System Flowchart for Detection and Classification of Brain Tumor**

## IV. DATABASE SOURCE

At first, database or dataset, was taken from (www.Kaggle.com), which contains huge different normal (no tumor) and abnormal (tumor) MRI brain images. In fact, selected dataset pictures were chosen from 3264 MRI brain images containing normal or no tumor MRI brain images, and abnormal or tumor images which include all types of brain tumors containing meningioma tumors, which was the main area of interest in this research, pituitary tumors, and glioma tumors [19]. Now, chosen dataset images for automated classification technique were 229 images, the normal ones were 105, while the abnormal ones were 124 ones. Figure (2) below shows samples of taken pictures to be used from the dataset. To be honest, taken dataset (229 MRI brain images) could be considered as enough ones for the purpose of this research, where those images, as mentioned, covered all types of brain tumors, where the MRI images are taken from different angles of the brain. Generally, taking around 30% of normal as well as abnormal images for testing and the remaining percentage for training purposes. So, the 105 normal brain MRI images were divided into 73 images for training, and 32 images for testing. On the other hand, the 124 abnormal brain MRI images were divided into 87 images for training, and 37 for testing goals. Furthermore, those images were fed to MATLAB code to cut the ROI as mentioned earlier.

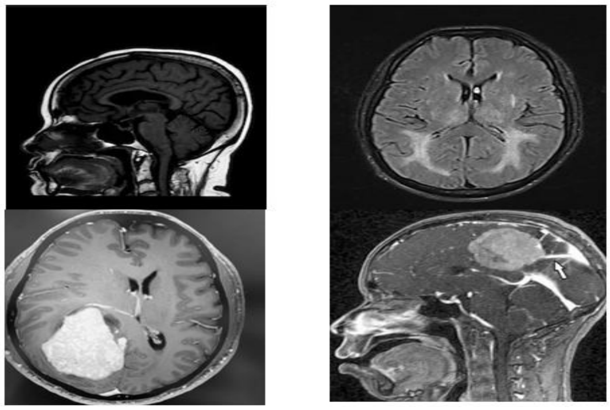

**Fig. 2: Samples of Taken Pictures for the Dataset (Top Normal, And Bottom Abnormal with Tumor)**

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## V. FEATURE EXTRACTION

Mainly, this the second main step in proposed CAD system, in fact, at this step, features of images ROIs are extracted and only the useful or significant ones are selected. Additionally, proposed CAD system tests only features which are statistically significant, the system can test only those statistically significant features out of all features, those statistically significant features could be seen after implementing the system using P-value figure, where this figure shows the number of useful features, and all features with P-value less than 0.05 could be considered as statistically significant features and tested and extracted by the system, while others which are not statistically significant ones are ignored by the system.

In proposed CAD system, 155 features were tested while selected features were ranging from 105 to 107 ones. Features selected and extracted by proposed system, using MATLAB, include 12 first order statistical features, containing, mean, standard deviation, mode, median, quantiles of different percentages. Additionally, 30 uniformity and entropy features from image histograms, and 30 uniformity and entropy features from gray-level co-occurance matrix (GLCM) of images. Those features were extracted from the spatial space of the ROIs as well as from the wavelet space, specifically the detailed coefficients of Discrete Wavelet Transform (DWT). To be clearer, the process is iterative, different types of wavelets were tested by the system, and given results performance parameters could be improved, since accuracy results were ranging under 70% as well as other parameters where those parameters gave results which could be better. So, after applying of first order statistical features as well as getting help of different types of DWT in feature extraction process, total applied features in features extraction process was 155, and accuracy of results has been improved along with sensitivity, specificity, PPV and NPV values, more about performance assessment will be presented later.

## VI. CLASSIFICATION

After implementation of first order statistical features as well as getting help of different of DWT in feature extraction process. Here comes the rule of classifiers as showed in the flowchart of proposed system as seen in figure (1) above, where every classifier has been applied for testing and learning groups. So, to get best performance, depending on results of performances assessments, which will be presented later, different types of classifiers were applied using MATLAB. Those applied classifiers are, Support Vector Machine or simply SVM classifiers with different kernels including radial basis function (RBF), polynomial, and Linear one. Then, we have k-voting nearest neighbor of simply KNN classifiers including KNN-1, KNN-2, KNN-3, KNN-4, KNN-5, KNN-7, KNN-9. Moreover, Convolutional Neural Networks (CNN) was used for comparison as a control method since it requires no feature extraction, where the ROIs are fed directly to CNN with each pixel considered as an input. So, total of tried classifiers were 11 classifier to get the best possible outcomes or results. It should be mentioned that, it was iterative way of classifier-implementing process along with implantation of different types of feature extraction techniques as mentioned, in order to reach best possible results depending on performance assessments. For instance, at first, talking especially about KNN classifiers, KNN-1, KNN-2, KNN-3, KNN-4, and KNN-5 classifiers were tried. However, to improve outcomes, KNN-1, KNN-3, KNN-5, KNN-7, and KNN-9 had been applied and results were better depending on performance assessments results. Speaking about them, performance assessments include, Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy, Error Rate, and Area Under the Curve (AUC) of Receiver Operating Characteristic (ROC). In fact, best classifiers, depending on results or performance assessments were SVM-Kernel Function (Linear), CNN, KNN-1, KNN-3, and KNN-5.

## VII. RESULTS AND DISCUSSION

As introduced, finding such acceptable outcomes or results depending on performance assessments could be reached via an iterative technique or way. As mentioned, at first, tried classifiers were SVM-Kernel Function (RBF), SVM-Kernel Function (Polynomial), and SVM-Kernel Function (Linear), KNN-1, KNN-2, KNN-3, KNN-4, KNN-5, and CNN. Actually, all of those classifiers were applied with First Order Statistical Features for features extraction purposes. In fact, since the accuracy, which is the most important performance assessment, as well as other performance assessments results were not acceptable with accuracy results ranging from 60% to 68%. To improve those results, secondly, applied classifiers were changed to include only odd numbers of KNN classifiers, so, second and new applied classifiers were SVM-Kernel Function (RBF), SVM-Kernel Function (Polynomial), and SVM-Kernel Function (Linear), KNN-1, KNN-3, KNN-5, KNN-7, KNN-9, and CNN. Anyway, resulted accuracy values were improved reaching around 71%. Final attempt to improve results of accuracy as well as other performance assessments was by trying different types of wavelets in feature extraction process, those tried DWT or Wfilters types were Bio-orthogonal (Bior 1.1, Bior 1.3, Bior 1.5, Bior 2.2, Bior 2.4, Bior 2.6, Bior 2.8, Bior 3.1, Bior 3.3, Bior 3.5, Bior 3.7, Bior 3.9, Bior 4.4, Bior 5.5, and Bior 6.8 all were tried), Coiflets ( Coif1, Coif2, Coif3, Coif4, and Coif5 all were tried), Daubechies (Db1, Db2, Db10, and Db45 all were tried), Discrete Meyer (dmey were tried), Fajer-Korovkin Filters (Fk4, Fk6, Fk8, Fk14, and Fk22 all were applied), Reverse Bio-orthogonal (Rbio 1.1, Rbio 1.3, Rbio 1.5, Rbio 2.2, Rbio 2.4, Rbio 2.6, Rbio 2.8, Rbio 3.1, Rbio 3.3, Rbio 3.5, Rbio 3.7, Rbio 3.9, Rbio 4.4, Rbio 5.5, and Rbio 6.8 all were tried), and Symlets (Sym2, and Sym8 were tried and applied). After implementation of all mentioned DWT or Wfilter along with First Order Statistical Features, as well as implantation of all of mentioned classifiers, best five gotten results are showed in table (1) below, along with results of performance assessments. It should be mentioned that in with the help of First Order Statistical Features and DWT (Reverse Bio-orthogonal, Rbio 3.3), three classifiers gave acceptable accuracy results which are KNN-3, KNN-5, and CNN, with accuracies 75%, 77%, and 88% respectively.

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The case is the same with help of using First Order Statistical Features and DWT (Reverse Bio-orthogonal, Rbio 3.7), where SVM-Kernel Function (Linear), KNN-5, and CNN classifiers resulted good accuracies which are 75%, 85%, and 85%. The idea of having such a technique for feature extraction which gave good performance results of three different classifiers is very beneficial. Additionally, as showed, First Order Statistical Features, and DWT (Symlets-Sym2) gave high accuracies with two different classifiers which are SVM-Kernel Function (Linear), and CNN with accuracies 78%, and 91% respectively. Also, using of First Order Statistical Features, and DWT (Coiflets - Coif 3) registered high accuracy reaching to 82% with SVM-Kernel Function (Linear) classifier, and 85% with CNN classifier.

Moreover, First Order Statistical Features, and DWT (Daubechies-Db45) has helped with recording of high accuracies of two different classifiers which are CNN, and KNN-1 classifiers reaching to 83% and 74% as accuracy results respectively. Table (1) below shows the best five classifiers performance assessments results, in numbers, as well as used techniques for feature extraction process of Proposed CAD System. In addition, table (2) represents simple comparison between previous systems' results along with results of proposed system. Furthermore, figures from (3) and (4) show sample of ROC curves results with different classifiers as well as different feature extraction tools or techniques. Also, sample of results of P-Value as showed in figure (5), where in this case, 106 out of 155 features were significant ones since they have P-value less than 0.05, in fact, as mentioned, those 106 features are considered as significant ones, while others are ignored. Other classifiers significant features numbers' were ranging from 105 to 107 significant features with P-value less than 0.05.

**Table - 1: Best Five Classifiers Performance Assessments Results and Used Techniques for Feature Extraction of Proposed CAD System**

| Used Classifier | Feature Extraction | Sensitivity | Specificity | PPV | NPV | Accuracy | Error Rate | AUC |
|---|---|---|---|---|---|---|---|---|
| -KNN-3<br>-KNN-5<br>-CNN | - First Order Statistical Features<br>-DWT (Reverse Bio-orthogonal Rbio 3.3) | - 73 %<br>- 72 %<br>- 90 % | - 78 %<br>- 82 %<br>- 87 % | - 75 %<br>- 81 %<br>- 84 % | - 76 %<br>- 73 %<br>- 92 % | - 75 %<br>- 77%<br>- 88 % | - 24 %<br>- 23 %<br>- 11 % | - 0.75<br>- 0.77<br>- 0.88 |
| - SVM-Kernel Function (Linear)<br>- KNN-5<br>- CNN | - First Order Statistical Features<br>-DWT (Reverse Bio-orthogonal Rbio 3.7) | - 74 %<br>- 70 %<br>- 82 % | -76 %<br>- 81 %<br>- 89 % | - 72 %<br>- 81 %<br>- 87 % | - 78 %<br>- 70 %<br>- 84 % | - 75 %<br>- 75 %<br>- 85 % | - 25 %<br>- 25 %<br>- 14 % | - 0.75<br>- 0.76<br>- 0.85 |
| -SVM-Kernel Function (Linear)<br>-CNN | - First Order Statistical Features<br>-DWT (Symlets-Sym2) | -77%<br>- 91 % | - 79 %<br>- 92 % | - 75 %<br>- 91 % | - 81 %<br>- 92 % | - 78 %<br>- 91 % | - 22 %<br>- 8 % | - 0.78<br>- 0.91 |
| -SVM-Kernel Function (Linear)<br>-CNN | - First Order Statistical Features<br>-DWT (Coiflets - Coif 3) | - 78 %<br>- 82 % | - 88 %<br>- 88 % | - 87 %<br>- 87 % | - 78 %<br>- 84 % | - 82 %<br>- 85 % | - 17 %<br>- 14 % | - 0.83<br>- 0.85 |
| - CNN<br>- KNN-1 | - First Order Statistical Features<br>-DWT (Daubechies-Db45) | - 74 %<br>- 70 % | - 96 %<br>- 77 % | - 97 %<br>- 75 % | - 70 %<br>- 73 % | - 83 %<br>- 74 % | - 17 %<br>- 26 % | - 0.83<br>- 0.73 |

**Table - 2: Comparison Between Previous Systems' Results Along with Results of Proposed System**

| Used System | Used Classifier | Feature Analysis | Resulted Accuracy |
|---|---|---|---|
| (Rezaei, Agahi and Mahmoodzadeh, 2020) [9] | -WSVM<br>-KNN<br>-HIK-SVM<br>- (MODE)-based ensemble technique | -wiener and median filters<br>-Differential Evaluation (DE) | 92.46% |
| (Deepak & Ameer, 2020) [10] | -CNN-SVM<br>-Soft Max | -CNN | 95.82% |
| (Faleh Alanazi et al., 2022) [11] | -transfer-learned model<br>-isolated deep-learning network | -CNN<br>-cropping method<br>-binary-classification | 95.75% |
| (M. Sarhan, 2020) [12] | -DWT (WCNN)<br>-SVM<br>-CNN | -CNN<br>-Wavelet features<br>-cascade functions | 98.5% |
| (Guan et al., 2021) [1] | -KELM network<br>-CNN | -backbone architecture<br>-refinement network<br>-CNN | 98.04% |
| (AlKubeyyer et al., 2020) [13] | -SVM<br>-KNN | -LBP<br>-GLCM<br>-DWT | 87% |
| (S. Musallam et al., 2022) [2] | - Blind reference less image spatial quality evaluator (BRISQUE)<br>-DCNN | -DCNN | 98.22% |
| (P.M. & S., 2019) [14] | - CNN-SVM<br>-CNN-KNN | - pre-trained GoogLeNet<br>- DCNN | 98% |
| (M. Sarhan, 2020) [15] | -WCNN<br>-SVM | -CNN<br>-DWT<br>-cascade functions | 99.3% |

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|---|---|---|---|
| (R. Ismael & Abdel-Qader, 2018) [16] | - back propagation neural network | -2D(DWT)<br>-2D Gabor filter techniques | 91.9% |
| (Sachdeva et al., 2016) [17] | -GA-SVM<br>-GA-ANN | - texture feature set and intensity<br>- Genetic Algorithm (GA) | 91.7% (SVM)<br>94.9% (ANN) |
| (A. El-Dahshan et al., 2014) [18] | -feedback pulse-coupled neural network<br>- back-propagation neural network | -Wavelet Transform or DWT | 99% |
| Proposed CAD system | -SVM<br>-KNN<br>-CNN | - first order statistical features<br>-DWT<br>-CNN | 82 % (SVM)<br>77 % (KNN)<br>91 % (CNN) |

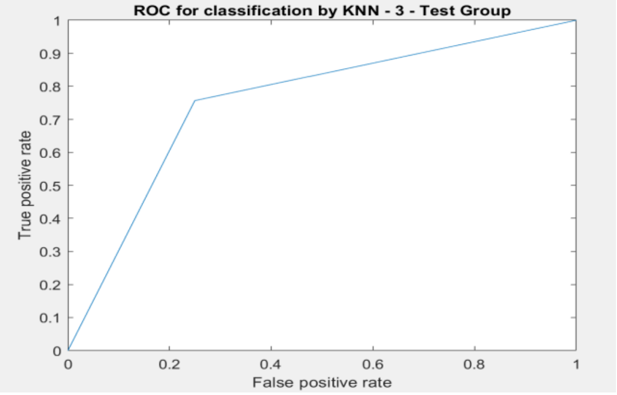


**Fig. 3: Sample of Resulted ROC Curve for used KNN-3 Classifier (Reverse Bio-orthogonal Rbio 3.3 is used as Wfilter)**

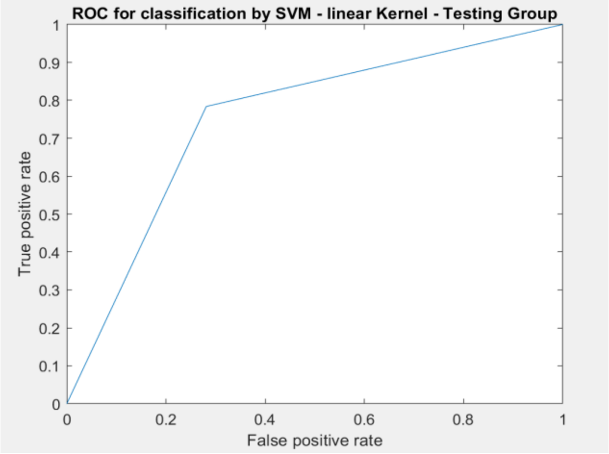


**Fig. 4: Sample of Resulted ROC Curve for used SVM-Kernel Function (Linear) Classifier (Reverse Bio-Orthogonal Rbio 3.7 is used as Wfilter)**

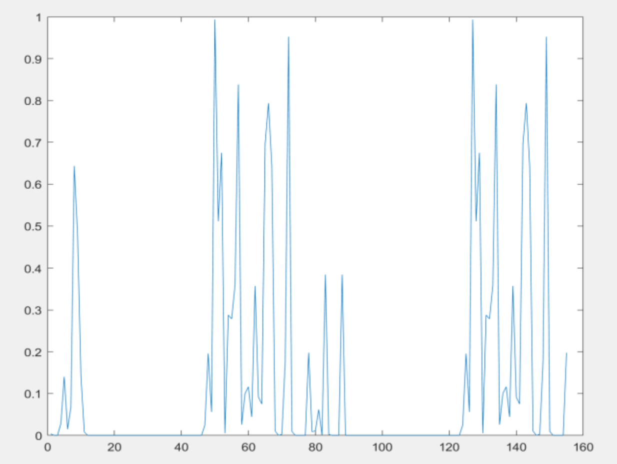

**Fig. 5: Sample of Results of P-Value (in This Case, 106 Out Of 155 Features Were Useful and Significant Features Since They Have P-value Less Than 0.05, Those 106 Features Are Considered as Significant Ones, While Others Are Ignored)**

## VIII. CONCLUSION AND FUTURE WORK

At the end, this paper presented enhanced Computer-Aided Diagnosis CAD software system proposed for brain tumor detection and classification. At first, collecting of dataset will be done from (www.kaggle.com) was done, so, 3264 MRI brain images containing normal and abnormal (MR) brain images. For the purposes of this study, 105 normal brain MRI images were taken and divided into 73 images for learning goals, and 32 images for testing. On the other hand, 124 abnormal brain MRI images were chosen and divided into 87 images for learning, and 37 for testing goals. Actually, proposed CAD system is specialized for meningioma brain tumor detection and classification, and the technique could be generalized for glioma, and pituitary brain tumors as well. After that, having such technique to cut the region of interest or ROI was implemented by using MATALB software. Next to that, feature extraction was done with the help of MATLAB software, to do that, First Order Statistical Features, as well as using of some Wfilters or DWT as feature extraction technique were done. Finally, and most importantly, classification was done, where SVM-Kernel Function (RBF), SVM-Kernel Function (Polynomial), and SVM-Kernel Function (Linear), KNN-1, KNN-2, KNN-3, KNN-4, KNN-5, KNN-7, and KNN-9. All of them have been tried as classifiers in iterative way to reach most acceptable results. Honestly, best accuracy results were gotten with SVM-Kernel Function (Linear), KNN-1, KNN-3, KNN-5, and CNN classifiers, those results were evaluated using performance assessment techniques which are Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy, Error Rate, and Area Under the Curve (AUC). To be honest, proposed system results were compared to other previous works' results. And, at the end, sample of plots of proposed CAD system results were showed. In fact, it was very beneficial to find such feature extraction techniques which gave acceptable accuracy results with three different classifiers; this was the case two times as mentioned in the study. All proposed CAD system areas was developed and implemented using MATLAB software. As mentioned, manual detection and classification of brain tumor is the area of many possible errors, so, it is expected that the proposed system will help a lot in diagnosis process accuracy and make the process faster. For future, it is better to improve such accuracy results by adding more features and trying to implement different transform techniques. Also, increasing number of dataset images as well as making less time-consuming processes would raise up the chance to the generalization of such system to the real world.

Additionally, having same technique for other types of tumors, especially for famous ones like breast cancer, is recommended also. At the end, the pumping of technology and Artificial Intelligence in biomedical field would help people and patients a lot, in different fields, and would improve the health services all around the world, by making them faster, easier, and more accurate ones.

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