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

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***Abstract:** The detection and classification of brain tumours manually or traditionally is an area that could be improved by having an automated detection and classification system for brain tumours. In this paper, an enhanced Computer-Aided Diagnosis CAD software system is introduced for brain tumour detection and classification. A total of 229 brain MRI images were taken as the dataset for this research; these dataset images include 105 normal brain MRI images and 124 abnormal brain MRI images. The proposed CAD system is specialised for the detection and classification of Meningioma brain tumours. The technique can be generalised and implemented for Glioma and Pituitary brain tumours as well. The entire system was implemented using MATLAB software. We began by cropping the region of interest (ROI) from the dataset images. Then, feature extraction was implemented using first-order statistical features, as well as the use of wavelet filters in combination with these features. The 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 standard set from the abnormal one. Note that we employed an iterative approach, changing features through multiple runs, until we achieved the best performance. The best accuracy results were obtained with the SVM-Kernel Function (Linear), KNN-1, KNN-3, and KNN-5 classifiers. Note also that we used convolutional neural networks (CNNs) from the Deep Learning toolbox of MATLAB as a control method to compare, where the images were fed directly into the CNN. The results were evaluated using performance assessment techniques, including Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy, Error Rate, and Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC). With the SVM classifier, the best accuracy results were 91%, followed by the CNN classifier at 82%, and the KNN classifier at 77%. Furthermore, it was beneficial to find such feature extraction techniques that yielded acceptable accuracy results with three different classifiers; this was the case twice, as mentioned in the study. All proposed CAD system areas were developed and implemented using MATLAB software.*

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

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I. INTRODUCTION AND BACKGROUND

Generally, a brain tumour can be defined as an abnormal growth of brain cells in the human brain, where the existence of these abnormal cells can lead to death if not diagnosed and treated correctly. 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 tumours are not similar in shapes, types, or sizes [1] [2]. To go deeply, two types of brain tumours, which are primary and secondary. Firstly, we have primary brain tumours which start in the brain or spinal cord, where, surprisingly, primary brain tumours represent 85% up to 90% of all primary central nervous system (CNS) tumours [3]. Also, we have secondary brain tumours, or, in other words, brain metastases, where those tumours usually start 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 tumours in the US will be around 25050 adult deaths [4] [5]. This article focuses on one type of primary brain tumour, specifically "Meningioma." Meningiomas and other mesenchymal tumours represent 27% of primary brain tumours, and meningiomas are more common in women than men, and meningiomas are most common in older patients, where the highest rates are in people aged between 70 and 80 [4] [5] [6]. Meningioma, according to the American Cancer Society, radiation exposure is the only known cause of brain and spinal cord tumours. So, prevention of meningioma is, as far as current knowledge allows, only possible by avoiding radiation exposure. Other than that, there is no known protection from most of those tumours. Moving on to the risk factors point, a risk factor is any factor that increases the potential for developing Meningioma. Risk factors may include many other factors, in addition to radiation, such as obesity, where a high body mass index (BMI) can be considered a risk factor for various types of cancers, including meningiomas. Nevertheless, the relationship between meningiomas and obesity is still 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, such as Gorlin syndrome (basal cell nevus syndrome) and Cowden syndrome, as well as inherited nervous system disorders like neurofibromatosis (Types 1 and 2), are thought to increase the risk of meningioma and other brain tumours.

To conclude, some controversial risk factors, such as the effect of using cell phones, which include the existence of Radio Frequency (RF) rays, are still under investigation. Additionally, in one way or another, vinyl chloride exposure, a chemical used in the manufacture of plastics, as well as products derived from petroleum, and some other types of chemicals, has been linked in some studies to the potential for increasing the risk of brain tumours. Additionally, several studies have linked brain tumours with power lines, transformers, the use of certain sugar substitutes, such as aspartame, and even with infections caused by certain viruses. Moving on to the diagnostic part, meningioma can often be detected by chance using techniques such as Magnetic Resonance Imaging (MRI), which scans the head or spinal cord. [5] [6] [7] [8].

As stated earlier, diagnosing brain tumours, including gliomas, metastases, and meningiomas, specifically at early stages, might help lead to better treatment. Therefore, the need for specialised techniques to aid in the early diagnosis of brain tumours would be highly beneficial for the entire community. As a result, diagnosing and treating Meningiomas specifically and brain tumours generally using a Computer-Aided Diagnosis (CAD) system is a perfect choice. However, it comes with some challenges, such as detection accuracy. Now, as mentioned, many imaging techniques are available for detecting brain tumours. Examples include the use of contrast-enhanced computed tomography (CT) and magnetic resonance imaging (MRI). In this paper, a meningioma picture database will be created using MRI techniques, as MRI has a distinct advantage in terms of soft-tissue resolution. Additionally, MRI can detect isodense lesions and tumour enhancements more effectively, along with other related findings. As stated above, different types of brain tumours, including Meningiomas, may have various sizes and irregular shapes. Additionally, manual diagnosis of brain tumours is not an efficient method, as it has a high error rate and is time-consuming for both the patient and the physician. Furthermore, knowing that different types of brain tumours may be present in patients years before detection, adds to the reality that detecting the tumour at early stages is much better in the treatment process. As a result, there is a strong need, globally, to use an 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, a Computer-Aided Diagnosis (CAD) software system for brain tumour detection and classification is proposed. Initially, the dataset will be collected, which may include Magnetic Resonance (MR) brain images, as mentioned, one of the most effective imaging techniques available for detecting the presence of a brain tumour, or X-ray images. Then, a technique for cutting the region of interest (ROI) will be implemented. After that, the classification method should be activated and used. Finally, some assessments will be in place to evaluate the completed work. Of course, the process is iterative, as finding a classification technique is an iterative process that requires improvement to achieve the best results. As mentioned earlier, the manual detection and classification of brain tumours are areas prone to numerous potential errors, so it is expected that the proposed system will significantly assist in diagnosis. Another area of interest in this research is the use of first-order statistical spatial and frequency domain features for feature extraction. The suggested software for feature extraction and classification is MATLAB. In other words, after this research, a proposed CAD system or software will be established to assist doctors in detecting and classifying specific brain tumours.

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. The proposed approach was mainly for the classification and segmentation of all brain tumour types derived from authentic MRI images. SVM or Support Vector Machine was used as a classifier to segment the given image. Then, 42 features were extracted. DE, or Differential Evaluation, was used then to select the most practical features. The main point here was the use of k-nearest neighbours (KNN), weighted kernel width SVM (WSVM), and histogram intersection kernel SVM (HIK-SVM) as classifiers to categorise tumour slices based on selected features. According to them, the given classifiers were combined using a method called multi-objective differential evolution (MODE)-based ensemble. Results were acceptable, with a classification accuracy 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 aid of deep learning and machine learning algorithms for image classification, satisfactory results were achieved, yielding an accuracy of 95.82%. Due to the small size of the given image database, a combination of convolutional neural network (CNN) features and SVM was used for medical image classification, according to them. Extracting features was performed using a designed CNN on selected MRI images. Then, along with the use of CNN features, the proposed model or integrated system was tested and evaluated using a multiclass SVM, followed by a 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. The proposed transfer-learned model achieved a high accuracy of approximately 95.75%, according to them. The proposed model, in this case, relied on the concept of transfer learning. According to them, the proposed deep-learning model was able to perform early diagnosis of all types of brain tumours. Initially, isolated convolutional neural network (CNN) layers were built.

The proposed model has significantly helped specialists, they say. The given transfer-learned model has yielded testing results, and using another machine's brain MRI images has shown promising adaptability and reliability, with a high accuracy percentage of 96.89% for those previously unnoticed brain MRI datasets. It should be noted here that,

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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 brain tumours is always done using MRI. They used CAD systems to help in classifying patient MRI images. In this study, CNNs have been used. The resulting developed system can extract features from a given MRI brain image by utilising the strong energy compactness property exhibited by the Discrete Wavelet Transform (DWT). Then, Wavelet features were used and applied to such a CNN to classify the given MRI image. The proposed method achieved an accuracy of 98.5%. The proposed model was a Wavelet-based CNN (WCNN) system specialised for the detection and classification of brain tumours. Moreover, the system used cascade functions to perform the Wavelet decomposition of the given MRI image. Generally, the implementation of CNN in the proposed WCNN utilises Wavelet features as inputs to the CNN. Additionally, this study introduced a proposed system utilising CAD systems, as well as Fighshare MRI medical image datasets. Now, CNNs, or convolutional neural networks, have been implemented in the proposed system, which is specialised for the classification of medical images. This aims to detect proposals for different types of brain tumours in collected MRI images. Additionally, by leveraging the property of strong energy compactness with the help of the Discrete Wavelet Transform (DWT), the proposed system extracts features from brain MRI images. The proposed system recorded a sensitivity of 97.4%, a specificity of 95.5%, and an accuracy of 99.3%. Guan et al. (2021) [1] emphasised the strong need for a CAD system. Feature extraction is performed by transferring image proposals and enhanced input images to the backbone architecture. To obtain high-quality image locations, a refinement network was used to select the most suitable images and discard others. Next to that, refined or gotten proposals were aligned in the same size. Ultimately, those images were transferred to the head network to achieve the desired or optimal classification task. The obtained results were acceptable and showed that the proposed method achieved a classification accuracy of 98.04%. According to [1] and [5], intensity, diameter, position, and tumour type can be detected. Each tumour type has an evaluation in terms of specificity, sensitivity, accuracy, as well as F1-score. Unlike the previously presented examples, AlKubeyyer et al. (2020) [13] focus on Meningioma, a type of brain tumour, which is the most common primary brain tumour in the world. Additionally, an MRI dataset was also used here. Moreover, they used learning algorithms with typical descriptors to develop a CAD tool specialised for the Meningioma brain tumour firmness, which was represented by patient MRI images. Now, to be clearer, LBP or Local Binary Patterns, as well as GLCM or Grey Level Co-occurrence Matrix and Discrete Wavelet Transform (DWT), were extracted from the image dataset. SVM and KNN were used as classifiers. The firmness of the meningioma tumour resulted in a 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 consisted of three steps aimed at improving MRI image quality. A Deep Convolutional Neural Network (DCNN) architecture was used for both diagnosis and classification purposes. The proposed architecture utilises batch normalisation for fast training with a higher learning rate and ease of initialisation of the layer weights. Additionally, the proposed architecture, in a computational sense, makes things quicker and easier for the model by utilising a small number of convolutional and max-pooling layers, as well as fewer training iterations. Achieved accuracy reached 98.22%, based on a 3394 MRI images dataset. Here, the pre-processing method comprises three steps and is proposed as the first step to enhance image quality, including stretching the histogram and improving contrast. To assess the pre-processing phase, a blind referenceless image spatial quality evaluator (BRISQUE) was performed. It was then mentioned that DCNN was used to classify MRI images. To train the model faster, the Batch Normalisation technique was employed. It should be noted that the proposed model comprises a convolutional part, consisting of ten convolutional layers, five batch normalisation layers, and four max-pooling layers, as well as a classifier comprising 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. The proposed classification model or system incorporates the concept of deep transfer learning, as well as the use of a pre-trained GoogLeNet as a feature extraction method from the brain MRI images dataset. DCNN, KNN, and DCNN–SVM were used as classifiers. The resulting accuracy of the proposed system reached 98%. A deep transfer learning CNN model was used for feature extraction from brain MRI images. Additionally, the proposed system algorithm utilised a modified and fine-tuned GoogLeNet, which proved beneficial in learning and recognising the features of tumours in brain MRI images.

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

Feature selection is performed using a combination of the 2D Discrete Wavelet Transform (DWT) and 2D Gabor filter techniques. Using a complete set of transform domain statistical features, a feature set has been initiated. Most importantly, classification is performed using a backpropagation neural network classifier, which has been selected to test the impact of feature selection. A dataset of 3064 MRI images was used, including the three types of brain tumours. The accuracy was 91.9%. The results demonstrated the predicted effectiveness of the feature selection method used. They indicated that it could introduce an effective feature set, which can then serve as a

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framework and be combined with other classification techniques to enhance performance.

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, and then texture feature sets and intensities are extracted from those SROIs. Classification was done using (GA-SVM and GA-ANN).

The accuracy results have been improved with SVM to 91.7%, and the accuracy of ANN has been improved to 94.1%. Better results were obtained with the GA-ANN classifier compared to the GA-SVM classifier. Regarding speed, GA-SVM provided an advantage. Generally, both classifier results are believed to be beneficial for radiologists in classifying brain tumours. 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, the proposed system or technique uses computational methods, including a feedback pulse-coupled neural network, for image segmentation purposes. Moreover, the proposed technique initially applied a feedback pulse-coupled neural network as a front-end processor to segment the image and detect the ROI (region of interest). Then it used a wavelet transform to extract features. Finally, they sent the reduced features to a back-propagation neural network to classify given inputs as normal or abnormal images, which were MRI patient images, and the resulting accuracy was 99%. Features were extracted based on the wavelet transform in this step.

III. OUR METHODOLOGY

To implement the proposed CAD system, three main steps were taken. Figure 1 below shows the flowchart of the proposed CAD system. Initially, after obtaining brain images or the database, the region of interest (ROI) for each image will be cut using MATLAB. More about the chosen database will be presented later. This step is performed by loading every image and feeding it to MATLAB to cut the ROI. Now, continuing with the shown flowchart, what has been done so far includes taking database pictures, containing both normal and abnormal brain images, and cutting ROIs for every image. For the abnormal picture, the tumour is considered the ROI, while for the normal one, any part of the image could be the ROI. Now, as the second primary step in the proposed CAD system, after dividing the database pictures into training and testing groups, the training images represent around 70% of the total normal or abnormal sets. The remaining percentage, which accounts for approximately 30%, is reserved for testing. As described in the flowchart, after dividing the database, the second primary step involves feature extraction, which is an iterative process that requires continuous improvement until an acceptable performance is achieved. This step is done only for the training group of images. Finally, as the third and final step, the classification step is performed using specialised classifiers. More information about every step will be presented in detail later in this report.

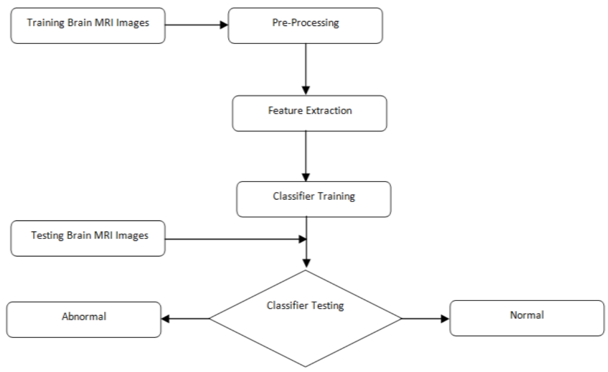

Fig. 1: Proposed CAD System Flowchart for Detection and Classification of Brain Tumour

IV. DATABASE SOURCE

At first, the database or dataset was taken from (www.Kaggle.com), which contains a large number of different typical (no tumour) and abnormal (tumour) MRI brain images. Selected dataset pictures were chosen from 3264 MRI brain images containing normal or no tumour MRI brain images, and abnormal or tumour images, which include all types of brain tumours, containing meningioma tumours, which was the central area of interest in this research, pituitary tumours, and glioma tumours [19]. The chosen dataset images for the automated classification technique consisted of 229 images, comprising 105 normal images and 124 abnormal images. Figure 2 below shows samples of pictures taken from the dataset. To be honest, the dataset (229 MRI brain images) can be considered sufficient for this research, as it encompasses all types of brain tumours and includes MRI images taken from various 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 split into 87 images for training and 37 for testing. Furthermore, those images were fed to MATLAB code to cut the ROI as mentioned earlier.

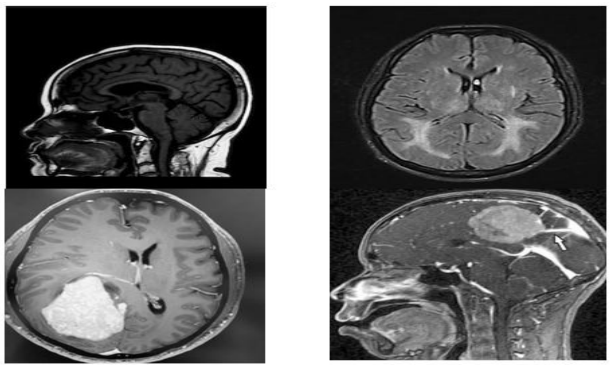

Fig. 2: Samples of Taken Pictures for the Dataset (Top Normal, And Bottom Abnormal with Tumour)

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V. FEATURE EXTRACTION

Mainly, this is the second primary step in the proposed CAD system. At this step, features of image ROIs are extracted, and only the useful or significant ones are selected. Additionally, proposed CAD system tests only statistically substantial features, the system can test only those statistically significant features out of all features, those statistically substantial features could be seen after implementing the system using P-value figure, where this figure shows the number of valuable 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 the system ignores others which are not statistically significant ones.

In the proposed CAD system, 155 features were tested, with selected features ranging from 10^5 to 10^7. Features selected and extracted by the proposed system, using MATLAB, include 12 first-order statistical features, comprising the mean, standard deviation, mode, median, and quantiles at different percentage levels. Additionally, 30 uniformity and entropy features from image histograms, and 30 uniformity and entropy features from the grey-level co-occurrence matrix (GLCM) of images. Those features were extracted from the spatial domain of the ROIs as well as from the wavelet domain, specifically the detailed coefficients of the Discrete Wavelet Transform (DWT). To clarify, the process is iterative; the system tested different types of wavelets, and based on the results, performance parameters could be improved, as accuracy results ranged below 70%, as well as other parameters, which yielded better results. 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 implementing first-order statistical features and utilising different DWTs in the feature extraction process. Here is the rule of classifiers, as shown in the flowchart of the proposed system, as depicted in Figure 1 above, where every classifier has been applied to both testing and learning groups. To achieve optimal performance, depending on the results of performance assessments, which will be presented later, various types of classifiers were applied using MATLAB. Those applied classifiers are Support Vector Machine (SVM) classifiers with different kernels, including radial basis function (RBF), polynomial, and linear ones. Then, we have k-voting nearest neighbour (kNN) classifiers, including KNN-1, KNN-2, KNN-3, KNN-4, KNN-5, KNN-7, and KNN-9. Moreover, Convolutional Neural Networks (CNNs) were used as a control method for comparison, as they require no feature extraction. In this case, the ROIs are fed directly to the CNN, with each pixel considered as an input. A total of 11 classifiers were tried to achieve the best possible outcomes. It should be noted that this was an iterative process of classifier implementation, along with the implementation of various feature extraction techniques, as mentioned, to achieve the best possible results based on performance assessments. For instance, initially, KNN classifiers, specifically KNN-1, KNN-2, KNN-3, KNN-4, and KNN-5, were tested. However, to improve outcomes, KNN-1, KNN-3, KNN-5, KNN-7, and KNN-9 were applied, and the results were better, as indicated by the performance assessment results. Speaking about them, performance assessments include Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy, Error Rate, and the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC). The best classifiers, depending on the results or performance assessments, were SVM-Kernel Function (Linear), CNN, KNN-1, KNN-3, and KNN-5.

VII. RESULTS AND DISCUSSION

As introduced, achieving such acceptable outcomes or results, depending on performance assessments, could be reached via an iterative technique. As mentioned, at first, the tried classifiers were SVM-Kernel Function (RBF), SVM-Kernel Function (Polynomial), SVM-Kernel Function (Linear), KNN-1, KNN-2, KNN-3, KNN-4, KNN-5, and CNN. All of those classifiers were applied with First Order Statistical Features for feature extraction purposes. Since the accuracy, which is the most critical performance assessment, as well as other performance assessment 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. The resulting accuracy values were improved, reaching around 71%. Final attempt to enhance 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 Wfilters along with First Order Statistical Features, as well as implementation of all of the mentioned classifiers, the best five results are shown in Table 1 below, along with the results of performance assessments. It should be noted that, with the help of First Order Statistical Features and DWT (Reverse Bio-orthogonal, Rbio 3.3), three classifiers yielded acceptable accuracy results: KNN-3, KNN-5, and CNN, with accuracies of 75%, 77%, and 88%, respectively.

The case is the same when using First Order Statistical Features and DWT (Reverse Bio-orthogonal, Rbio 3.7), where SVM-Kernel Function (Linear), KNN-5, and CNN classifiers yielded good accuracies of 75%, 85%, and 85%, respectively. The idea of having such a technique for feature extraction, which produces good performance results for three different classifiers, is very beneficial. Additionally, as shown, First Order Statistical Features and DWT (Symlets-Sym2) yielded high accuracies with two different classifiers: SVM-Kernel Function (Linear) and CNN, with accuracies of 78% and 91%, respectively. Additionally, the use of first-order statistical features and DWT (Coiflets - Coif 3) yielded high accuracy, reaching 82% with the SVM kernel function (linear) classifier and 85% with the CNN classifier.

Moreover, First Order Statistical Features and DWT (Daubechies-Db45) have helped achieve high accuracies with two different classifiers, namely CNN and KNN-1, reaching 83% and 74% accuracy, respectively. Table (1) below shows the best five classifiers' performance assessment results, in numbers, as well as the techniques used for the feature extraction process of the Proposed CAD System. Additionally, Table 2 presents a straightforward comparison between the results of the previous systems and those of the proposed system. Furthermore, figures from (3) and (4) show a sample of ROC curve results with different classifiers as well as different feature extraction tools or techniques. Additionally, a sample of results for P-value is shown in Figure 5, where 106 out of 155 features were significant, as indicated by a P-value less than 0.05. As mentioned, these 106 features are considered necessary, while the others are ignored. The considerable feature numbers of other classifiers ranged from 10^5 to 10^7, with a 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 -KNN-5 -CNN	- First Order Statistical Features -DWT (Reverse Bio-orthogonal Ribo 3.3)	- 73 % - 72 % - 90 %	- 78 % - 82 % - 87 %	- 75 % - 81 % - 84 %	- 76 % - 73 % - 92 %	- 75 % - 77% - 88 %	- 24 % - 23 % - 11 %	- 0.75 - 0.77 - 0.88
- SVM-Kernel Function (Linear) - KNN-5 - CNN	- First Order Statistical Features -DWT (Reverse Bio-orthogonal Ribo 3.7)	- 74 % - 70 % - 82 %	-76 % - 81 % - 89 %	- 72 % - 81 % - 87 %	- 78 % - 70 % - 84 %	- 75 % - 75 % - 85 %	- 25 % - 25 % - 14 %	- 0.75 - 0.76 - 0.85
-SVM-Kernel Function (Linear) -CNN	- First Order Statistical Features -DWT (Symlets-Sym2)	-77% - 91 %	- 79 % - 92 %	- 75 % - 91 %	- 81 % - 92 %	- 78 % - 91 %	- 22 % - 8 %	- 0.78 - 0.91
-SVM-Kernel Function (Linear) -CNN	- First Order Statistical Features -DWT (Coiflets - Coif 3)	- 78 % - 82 %	- 88 % - 88 %	- 87 % - 87 %	- 78 % - 84 %	- 82 % - 85 %	- 17 % - 14 %	- 0.83 - 0.85
- CNN - KNN-1	- First Order Statistical Features -DWT (Daubechies-Db45)	- 74 % - 70 %	- 96 % - 77 %	- 97 % - 75 %	- 70 % - 73 %	- 83 % - 74 %	- 17 % - 26 %	- 0.83 - 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 -KNN -HIK-SVM - (MODE)-based ensemble technique	-Wiener and median filters -Differential Evaluation (DE)	92.46%
(Deepak & Ameer, 2020) [10]	-CNN-SVM -Soft Max	-CNN	95.82%
(Faleh Alanazi et al., 2022) [11]	-transfer-learned model -isolated deep-learning network	-CNN -cropping method -binary-classification	95.75%
(M. Sarhan, 2020) [12]	-DWT (WCNN) -SVM -CNN	-CNN -Wavelet features -cascade functions	98.5%
(Guan et al., 2021) [1]	-KELM network -CNN	-backbone architecture -refinement network -CNN	98.04%
(AlKubeyyer et al., 2020) [13]	-SVM -KNN	-LBP -GLCM -DWT	87%
(S. Musallam et al., 2022) [2]	- Blind reference less image spatial quality evaluator (BRISQUE) -DCNN	-DCNN	98.22%
(P.M. & S., 2019) [14]	- CNN-SVM -CNN-KNN	- pre-trained GoogLeNet - DCNN	98%
(M. Sarhan, 2020) [15]	-WCNN -SVM	-CNN -DWT -cascade functions	99.3%
(R. Ismael & Abdel-Qader, 2018) [16]	- Back propagation neural network	-2D(DWT) -2D Gabor filter techniques	91.9%
(Sachdeva et al., 2016) [17]	-GA-SVM -GA-ANN	- texture feature set and intensity - Genetic Algorithm (GA)	91.7% (SVM) 94.9% (ANN)

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(A. El-Dahshan et al., 2014) [18]	-feedback pulse-coupled neural network - Back-propagation neural network	-Wavelet Transform or DWT	99%
Proposed CAD system	-SVM -KNN -CNN	- First-order statistical features -DWT -CNN	82 % (SVM) 77 % (KNN) 91 % (CNN)

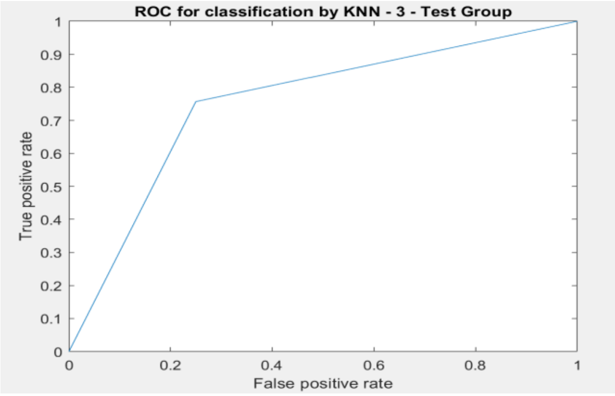

Fig. 3: Sample of Resulted ROC Curve for the used KNN-3 Classifier (Reverse Bio-orthogonal Rbio 3.3 is used as Wfilter)

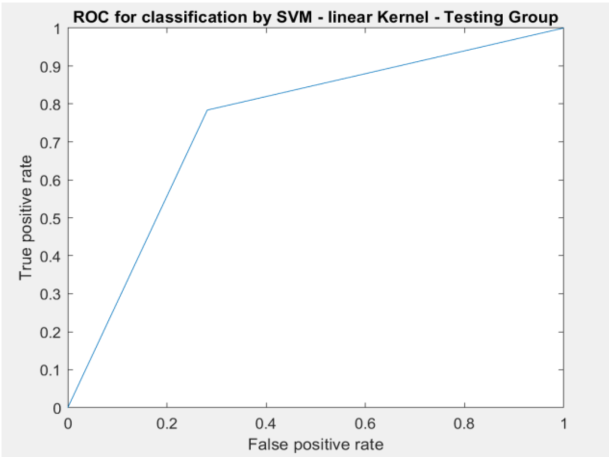

Fig. 4: Sample of Resulted ROC Curve for used SVM-Kernel Function (Linear) Classifier (Reverse Bio-Orthogonal Rbio 3.7 is used as Wfilter)

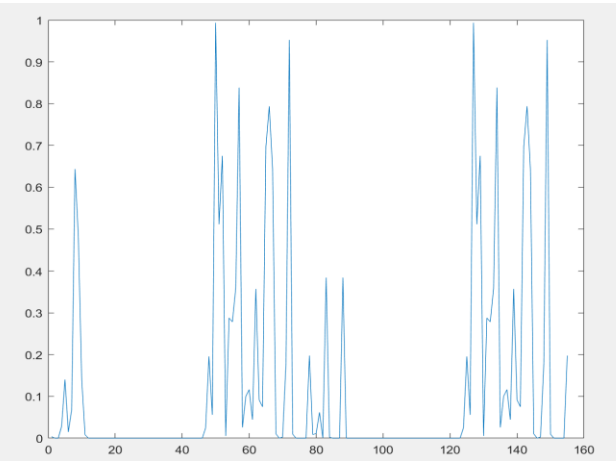

Fig. 5: Sample of Results of P-Value (in This Case, 106 Out Of 155 Features Were Useful and Significant Features Since They Have a P-value Less Than 0.05, Those 106 Features Are Considered as Significant Ones, While Others Are Ignored)

VIII. CONCLUSION AND FUTURE WORK

At the end, this paper presented an enhanced Computer-Aided Diagnosis CAD software system proposed for brain tumour detection and classification. At first, the collection of the dataset will be done from (www.kaggle.com), which includes 3264 MRI brain images containing normal and abnormal (MR) brain images. For this study, 105 normal brain MRI images were selected and divided into 73 images for training purposes and 32 images for testing. On the other hand, 124 abnormal brain MRI images were selected and divided into 87 images for training and 37 for testing purposes. The proposed CAD system is specialised for meningioma brain tumour detection and classification, and the technique could be generalised for glioma and pituitary brain tumours as well. After that, a method was implemented using MATLAB software to cut the region of interest (ROI). Additionally, feature extraction was performed using MATLAB software. To achieve this, first-order statistical features were utilised, along with the application of some Wfilters or DWT as feature extraction techniques. Finally, and most importantly, classification was performed using the following models: SVM-Kernel Function (RBF), SVM-Kernel Function (Polynomial), 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 an iterative way to reach the 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, the proposed system's results were compared to those of other previous works. Finally, samples of plots from the proposed CAD system results were shown. It was very beneficial to find such feature extraction techniques that yielded acceptable accuracy results with three different classifiers; this was the case twice, as mentioned in the study. All proposed CAD system areas were developed and implemented using MATLAB software. As mentioned, the manual detection and classification of brain tumours are areas prone to numerous potential errors. Therefore, it is expected that the proposed system will significantly enhance the accuracy and expedite the diagnosis process. For the future, it would be beneficial to enhance these accuracy results by adding more features and implementing different transformation techniques. Additionally, increasing the number of dataset images, as well as making processes less time-consuming, would raise the chance of generalisation for such a system in the real world.

Additionally, having the same technique for other types of tumours, especially for famous ones like breast cancer, is also recommended. Ultimately, the integration of technology and Artificial Intelligence in the biomedical field will greatly benefit people and patients across various fields, improving health services worldwide by making them faster, easier, and more accurate.

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