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Computer-Aided Detection System of MRI brain tumor images

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Abstract. Computer-Aided Detection (CAD) recognizes tumors or lesions in medical imaging or distinguishes between normal and abnormal images. The purpose of this paper is designing a CAD system that will automatically detect brain tumors and classify the brain images in terms of normality and abnormality. The proposed CAD system passed through seven essential processes which are data collection, preprocessing and enhancement, segmentation, feature extraction, feature selection, classification, and performance assessment, respectively. The database includes 280 normal and abnormal brain MRI images. Segmentation process in this paper was an independent process aims to aid in the extraction of the region of interest (ROI). ROIs were cropped from the original images around the center of the tumor region which was specified after segmentation. The overall results of the proposed CAD system depended on the performance of eight different types of SVM classifiers and KNN classifiers. SVM of radial basis function and linear types, as well as KNN of 3 and 5 neighbors, obtained perfect results with 100% in all performance assessment metrics. The remainder of the classifiers achieved high accuracy, where SVM of polynomial type with KNN of 1 and 2 neighbors achieved the same result with 97.62% a little less than KNN of 4 neighbors which achieved 98.81%. The proposed CAD system provided results more accurate and precise compared with other studies.

Keywords: *Brain tumor diagnosis; MRI images; Machine learning; CAD; Discrete Cosine Transform*

1. Introduction

Brain tumor is an abnormal growth in the brain cells that can occur in any part of the brain or skull. Brain tumors are classified into benign or malignant based on their growth pattern [1]. Benign and malignant tumors are starting in brain tissue, but rarely spread out of the nervous system tissues and they are called primary tumors. Metastasis or secondary

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cancer is spreading from another part of the body to the brain [2].

Magnetic resonance imaging (MRI) is the preferred scan device for diagnosing brain cancers. It gives high resolution with more information and details on tumor cellularity, metabolism, and angiogenesis, which aid in tumor grading, treatment, and diagnosis better than other medical scanner devices [3]. MRI still has problems with image quality with safety static magnetic field. Lower magnetic fields MRI is safe, but they have a lower signal-to-noise ratio (SNR) which affects the image quality [4].

Complexity and variances of brain tumor forms and problems of images quality made physicians have challenges in detecting, diagnosing, and analyzing brain tumor images taken from MRI. Also, conventional method of human diagnosing MRI brain tumor takes a lot of time and effort to reach final results and diagnoses, and it's not completely free from mistakes.

Computer-Aided Detection (CAD) is a famous and rapidly growing field for processing medical images that can aid physicians in the fast and accurate diagnosis and detection of brain tumors, where the CAD systems is used to determine the volume, diameter, and vasculature of a lesion or organ. Machine learning and deep learning algorithms help to design semi-automatic and fully automatic CAD system with more accuracy and take less time to process [5]. Machine learning allows computers to learn without having to be explicitly programmed and improves with training [6], but deep learning has many characteristics that make it perform better than machine learning [7].The CAD system depend on major stages which are data collection, preprocessing and enhancement, segmentation, feature extraction, feature selection, feature reduction, classification, and performance assessment.

Many studies presented techniques to increase the performance of MRI devices, while others designed systems that used artificial intelligence such as CAD models to enhance, process, and analyze MRI images. Although prior studies have shown reliable outcomes, still, additional studies and researches are needed to improve and develop CAD models for diagnosing and detecting brain tumors. The purpose of this paper is designing a CAD system that will automatically detect brain tumors and classify the brain images in terms of normality and abnormality as well as save time and effort.

2. Literature Review

The CAD system is an interesting study subject for researchers due to its broad usage to assist in diagnosing different cancers such as lung, breast, and brain cancers. Researchers place so much importance on developing a CAD system for brain tumors with high sensitivity and specificity due to the difficulties in detecting primary brain tumors in their early stages. Many researches presented CAD systems based on machine learning or deep learning algorithms to detect or diagnose MRI brain tumors were reported.

Johnpeter and Ponnuchamy presented brain tumors detection and segmentation approach, obtained an acceptable accuracy of more than 98%. The approach method first fused 160 brain MRI images (100 normal and 60 abnormal) using three-level dual-tree complex wavelet transform (DTCWT). Then the fused brain MRI image was utilized to extract statistical features, grey level co-occurrence matrix (GLCM) features, and local ternary pattern (LTP). Tumors were classified as normal or abnormal using the coactive adaptive neuro fuzzy inference system (CANFIS) classification approach. After distinguishing brain tumors from non-tumors, abnormal images are exposed to morphological opening and morphological closing functions, which are used to separate and detect tumors from other tissues [8].

Pushpa B R and F. Louies proposed an approach in which a framework is constructed to identify and detect tumors. Images are preprocessed using a median filter and a Gaussian high pass filter. Tumor was separated from normal tissues by using the morphological operation. Discrete wavelet transform (DWT)was used to extract features, and support vector machine (SVM) classified the tumor into benign, malignant, or normal with 99% accuracy. The training data in this study is smaller than the learning data since a total of 490 images from BraTS and around 1000 images from TCIA were gathered, but only 60 images were used for training [9].

Paul and Sivarani developed a CAD system to diagnose brain tumors using a database of 80 MR images. A novel automated method was used to determine if the tumor into benign or malignant. MR Images were converted to grayscale before being enhanced using a high pass filter and a filter mask. Threshold and Watershed transform are applied in post-processing to facilitate the feature extraction process. K-mean clustering using Bag of visual words (BOVW) and Morphological operation employed to segment tumor from the rest of brain image. GLCM features, statistical features, and Histogram features were extracted and then evaluated by the classifier BOVW and SVM classifier which had 96% and 95% accuracy, respectively [10]. The small size of the dataset is a weakness of this study, thus increasing the size of the dataset may have a large effect on the results.

Saleh et al. suggested a CAD system based on automatic segmentation for extracting ROIs from 170 brain MRI images by converting MRI images into binary images using the Otsu Binarization method with a predetermined threshold, and then adjusting the tumor area using the opening morphological operation. Statistical features such as Mode, Mean, Median, and Quantiles were extracted. After testing the features with K-NN and SVM classifiers, the system achieved the best performance during brain tumor classification by applying SVM classifier with polynomial kernel, which achieved 100 % accuracy[11].

Megha et al. presented a machine learning technique for detecting brain tumors. The image was enhanced in the preprocessing step, and then skull stripping was done to eliminate unnecessary skull tissues in images. The segmentation stage consisted of several processes, the first of which was determining the edges, followed by identifying the region of the tumor using region growing image segmentation based on the pixels. The threshold method separates the foreground and background of an image, which is next segmented using a clustering

algorithm. For binary images, morphological operations such as erosion dilation are employed to eliminate non-cerebral tissue from a brain image. GLCM and other useful features were extracted and selected. the SVM classifier predicted if the brain image was normal or abnormal with an accuracy of 83.3% [12].

Sabitha et al. developed a system to classify MRI brain tumors as benign, malignant, or normal. The proposed system used database of 100 MRI brain images and performed well, with an accuracy greater than 90%. First, unwanted noise and background were eliminated, then segmentation stages were done using the threshold method, while the feature extraction stage was implemented using (DWT) and (GLCM). During the feature reduction step, non-linear Principal Component Analysis (Kernal-PCA) was used to reduce image features to only those that were helpful since KPCA is more efficient when the number of samples is fewer than the size of the feature space. In the classification stage, the Kernal Support Vector Machine (KSVM) is preferred over conventional SVM because of its good accuracy, and precise mathematical characteristics [13].

Table (1): Classifiers Performance Results

Author	Year	Features Used	Transform	Classifier	Segmentation	Accuracy
Johnpeter et al	2019	Statistical, GLCM, (LTP)	DTCWT	CANFIS	yes	98%
Pushpa et al	2019	Statistical, GLCM	DWT	SVM	yes	99%
Paul et al	2021	Statistical, GLCM, Histogram	Watershed	BOVW, SVM	yes	96%,95%
Saleh et al	2020	Statistical	N/A	K-NN, SVM	yes	95%,100%
Megha et al	2019	GLCM	N/A	SVM	yes	83%
Sabitha et al	2021	GLCM	DWT	KSVM	yes	90%
Alam et al	2019	Statistical, IDM	DWT, Wavelength	IPOL- SVM, KSVM	no	98.5%
Proposed Method		Statistical, GLCM, Histogram	DCT	K-NN, SVM	yes	100%,100%

Alam et al. suggest a brain tumor detection model that combines DWT with PCA and K-SVM. A set of 200 Images (normal, benign, and malignant) were converted to a binary image and the blobs were removed. Intensity and texture features were extracted by DWT. Wavelength transform was used to transform the wavelength of images. PCA was used to eliminate redundant features. Inhomogeneous polynomial (IPOL) kernel SVM classifier recognized tumors and discriminated benign from malignant tumors. The combined model had an accuracy of 98.5% [14].

The previous studies produced novel methods for detecting and classifying brain tumors that include some techniques but lack others. They each have a set of strengths and weaknesses. Small database size, lacking processes such as segmentation or performance assessment, and low accuracy are some of the weaknesses. This paper' proposed method will present techniques that are unique and will address some of the weaknesses of previous studies. The paper will include all of the major stages in the CAD system, with more precise and accurate results.

3. Material and Methods

The proposed CAD system was built using machine-learning algorithms. The implementation was performed on a personal computer laptop (Toshiba-C805), with processor specifications (Intel(R) Core (TM) i5-3210M CPU @ 2.50GHz 2.50 GHz), and 8GB of RAM. The algorithms were coded by using MATLAB R2021b program. The CAD system as shown in figure (1) passed through seven essential stages which are data collection, preprocessing and enhancement, segmentation, feature extraction, feature selection, classification, and performance assessment respectively.

3.1 Database Source

This study's database was gathered from the Kaggle website [15]. The database was divided into two sets: learning and testing. The learning set was used to train the CAD system and represents 70% of the total database (196 images split into 98 normal and 98 abnormal). The testing set was used to test the CAD system and represents the remaining 30% of the total database (84 images are divided into 42 normal and 42 abnormal).

3.2 Image segmentation

Image segmentation is the process of dividing an image into objects based on the relationship between the pixels. The objects can be used to define a region of interest. In brain tumor detection and diagnosis, the segmentation process is used to separate the tumor from normal tissues. The segmentation process in this research was an independent process aims to aid in the extraction of the ROI by following the steps below.

1- Extracting tumor from abnormal images.
2- Determining the center of the tumor from the segmented image.
3- Cropping the region of interest from the original image around the center of the tumor.

After the segmentation process, an input image remained with only suspected lesions regions. Based on segmentation outcomes, tumor region was specified. A region of interest (ROI) of 32×32 size was cropped from the center of tumor region which was specified after segmentation. All ROIs were extracted from original images that have not been through imaging processing.

3.3 Preprocessing

Preprocessing was used to enhance image features, improve image quality, remove undesirable distortions, and increase the signal to noise ratio. The preprocessing process included image normalization and image enhancement to increase the image segmentation precision. Image normalization converted the database images to grayscale images in order to unite the range of pixel intensity values and remove any distracting elements from the images. Unsharp masking was used for enhancing image edges contrast, and Median filter was used to eliminate the noise, improve the resolution and contrast of images, and reduce blurring of the image. The new enhanced image obtained after the preprocessing was used as an input image in the next step.

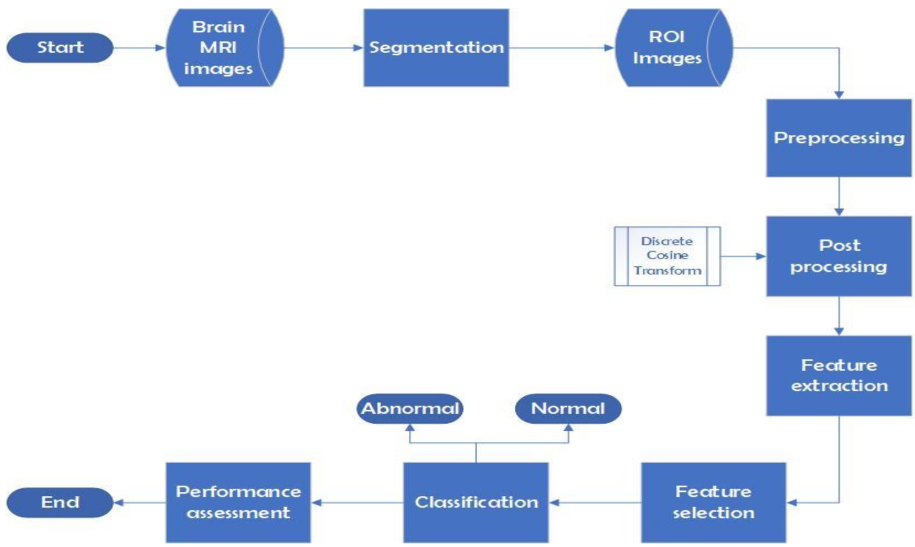

Figure (1): Proposed CAD Flowchart

3.4 Postprocessing

The ROIs were transformed into another domain by using the Discrete Cosine Transform in order to extract more useful features. DCT is useful for estimating brightness variation, enhancing contrast, and clarifying features. DCT converts an image from the spatial domain to the frequency domain by transforming the original image pixels to DCT coefficients with the same number of original image pixels. This technique leads to dividing the image into various frequencies based on rapidly changing of values. The DCT with high frequency components represent values that change rapidly on a short distance scale. The DCT with low frequency components describe values that do not change rapidly over a long-distance scale. For N-dimensional vectors, the one-dimensional DCT is defined by:

$$F(x) = \alpha(k) \sum_{n=1}^{N} f(n) \cos\left(\frac{\pi(2n+1)k}{2N}\right) \quad (1)$$

Where;

$$\alpha(k) = \begin{cases} \frac{1}{\sqrt{N}} & when\, k = 1, \\ \sqrt{\frac{2}{N}} & when\ 2 \le k \le N, \end{cases} \quad (2)$$

3.5 Feature Extraction and Selection

In imaging processing, features provide researchers with more information about targeted images, allowing them to analyze, categorize, and recognize image objects with the assistance of the computer. In this CAD system, spatial domain features such as statistical features were extracted to describe the texture based on pixel values or the gray-level distribution of ROI images. Statistical features which were used are lower order features and higher order features. Lower-order features are features determined by pixel values, and higher-order features are features determined based on pixel values and the spatial distribution of pixels. The features of mean, standard deviation, mode, median, median, minimum, maximum, and the quantile (0.1,0.2,0.3,0.4,0.6,0.7,0.8,0.9) were extracted as well as entropy, kurtosis, skewness, and GLCM.

The features that were extracted may not be useful for classifying MRI brain images. Feature selection process was followed after features were extracted to choose the best features to aid in the classification process. The P-value hypopaper test was applied for rejecting and reducing the insignificance features. Features were had P-value of 0.05 or less were significant and suitable.

3.6 Classification Process

The classification process is the process of classifying the MRI brain image database into different categories. Classification utilizes the selected optimum features and compare them with ground truth to predict normal from abnormal cases. In machine learning, there are many algorithms build the classification model.

Support Vector Machine (SVM) is a classification and regression analysis supervised learning model. The goal of the SVM algorithm is to find a hyperplane that optimally separates datasets of one class from those of another class. SVM can perform linear classification or nonlinear classification using kernel functions. SVM types of Gaussian or Radial Basis Function (RBF), Linear, and Polynomial were used for classify the ROIs data.

Nearest Neighbor algorithm (KNN) is a non-parametric, supervised learning classifier that classifies data based on its feature space by utilizing a majority vote approach to determine the neighbors surrounding a specific data point. The prediction and classification performance of KNN vary depending on the number of k-nearest neighbors. The k-nearest neighbors' algorithms of type 1,2,3,4,5 were utilized in this research.

For this CAD system, four types of SVM algorithm, and five types of KNN algorithm was applied.

3.7 Performance Assessment

Performance assessment is a crucial stage that offers a full picture of the performance of CAD system. Evaluation of the performance of CAD system in imaging processing is a measure of the ability of the system to distinguish and separate between the normal and abnormal cases in the data, in other words, to determine whether the system can with acceptable accuracy find the disease or not. Performance assessment was done in five metrics: sensitivity, specificity, positive predictive values (PPV), negative predictive values (NPV), and overall accuracy.

4. Results and Discussion

Based on segmentation outcomes, tumor region was specified such as shown in figure (2). After that, ROIs were cropped from the original images around the center of the tumor region.

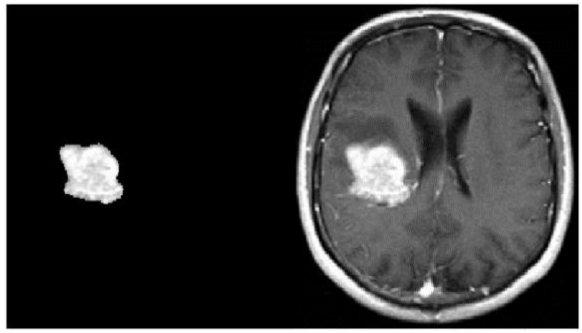

Figure (2): Example of the segmentation process

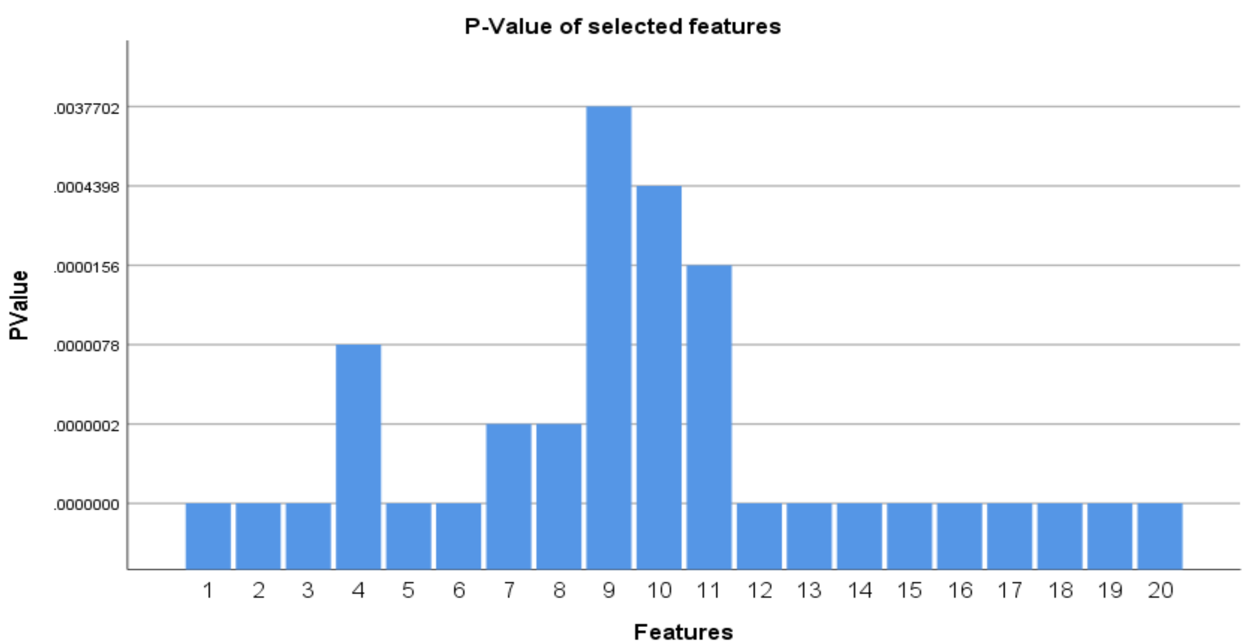

Figure (3): P-Value of selected features

The overall results of the proposed CAD system are the results depend on the performance of the classification process. This section will discuss the results of feature selection stage which affects classification, and the results of the performance assessment metrics of eight classifiers. The P-value hypopaper test presented the results of the feature selection process. Only four features were insignificant and were removed because they had a P-value of more than 0.05, whereas 20 features were significant and selected for classification. Figure (3) shows

the graph of P-value of the selected features.

Performance of eight classifiers was assessed according to five metrics: sensitivity, specificity, positive predictive values (PPV), negative predictive values (NPV), and overall accuracy.

Table (2) indicates to the performance assessment of eight classifiers: SVM of Gaussian or Radial Basis Function (RBF), Linear, and Polynomial types, and KNN of neighbors 1,2,3,4, and 5. Four classifiers, SVM_RBF, SVM_Linear, KNN_3, and KNN_5 achieved perfect results with 100% in all performance assessment metrics. For a more illustration of the CAD results, the Receiver Operator Characteristic (ROC) curve for each classifier was provided in figures (4,5, and 6) below.

Table (2): Classifiers Performance Results

Classifier	Sensitivity	Specificity	PPV	NPV	Accuracy
SVM_RBF	100 %	100 %	100 %	100 %	100 %
SVM_Polynomial	95.45%	100 %	100 %	95.24%	97.62%
SVM_Linear	100 %	100 %	100 %	100 %	100 %
KNN_1	97.62%	97.62%	97.62%	97.62%	97.62%
KNN_2	95.45%	100 %	100 %	95.24%	97.62%
KNN_3	100 %	100 %	100 %	100 %	100 %
KNN_4	97.67%	100 %	100 %	97.62%	98.81%
KNN_5	100 %	100 %	100 %	100 %	100 %

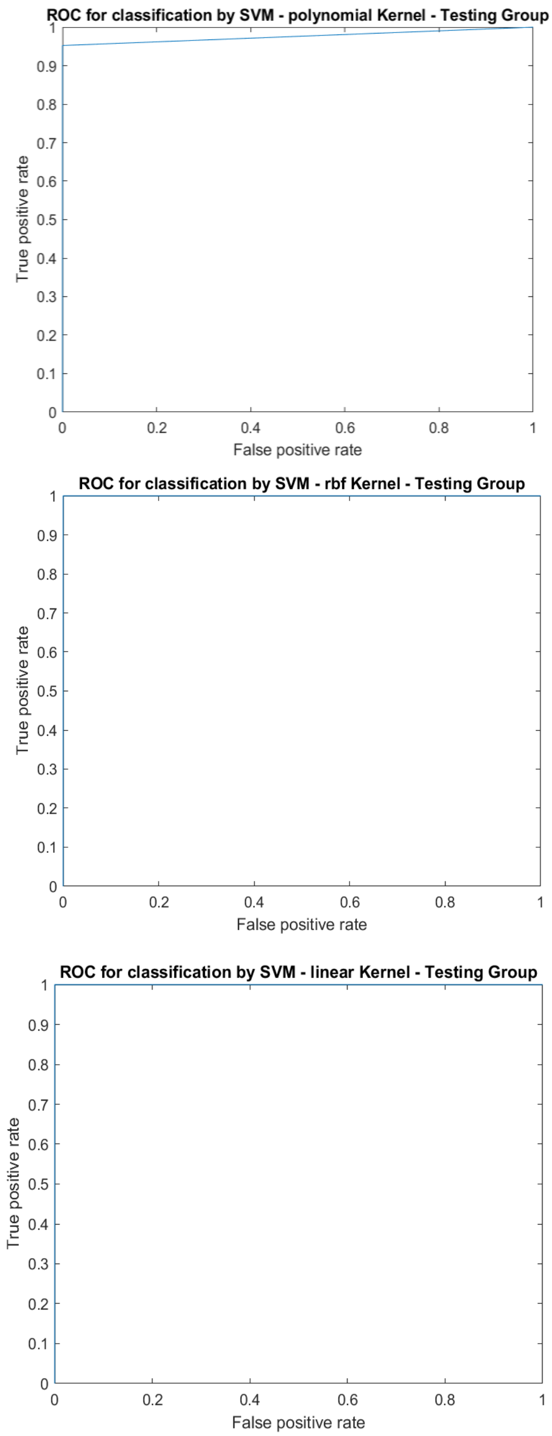

Figure (4): ROC of SVM- classifiers

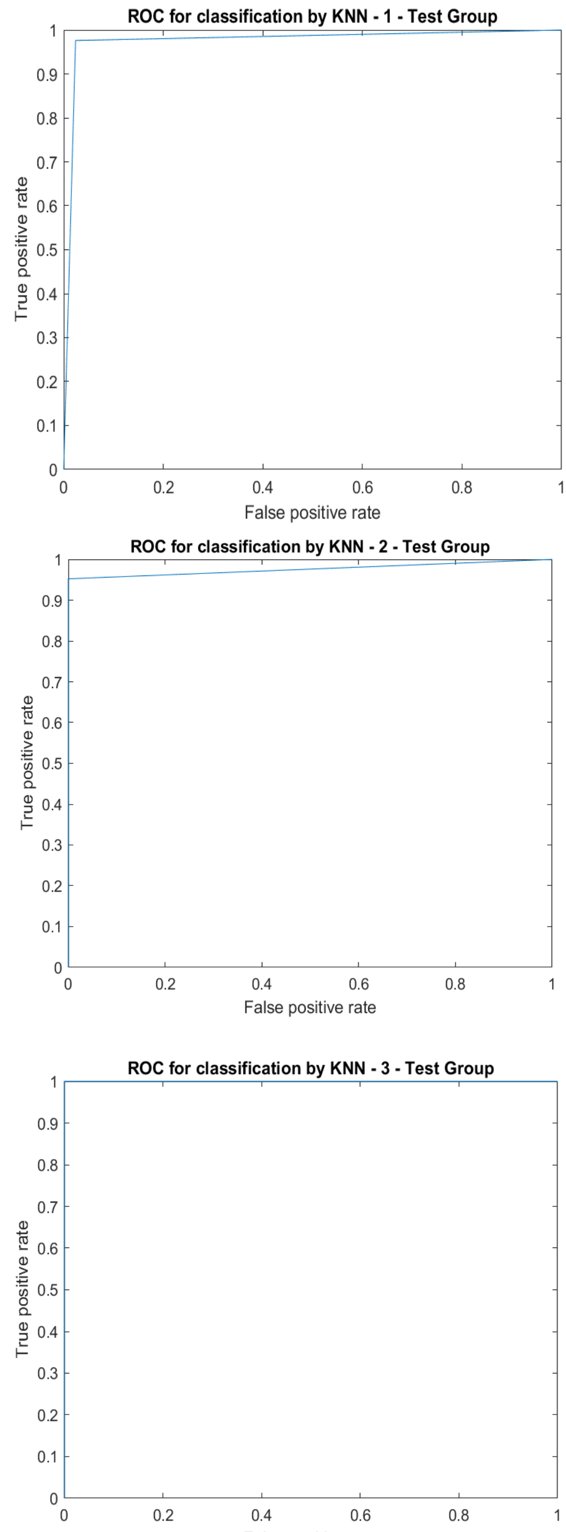

Figure (5): ROC of KNN-1,2, and 3 classifiers

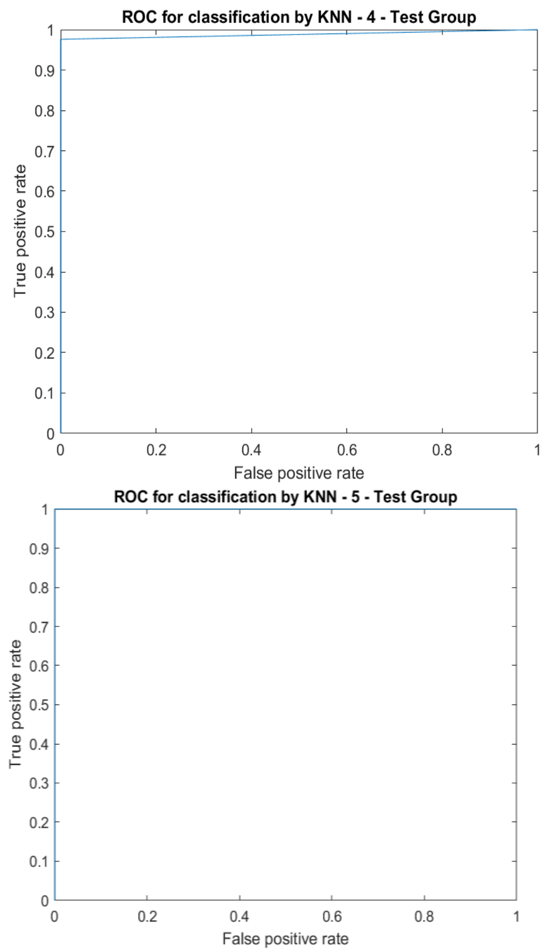

Figure (6): ROC of KNN-4 and 5 classifiers

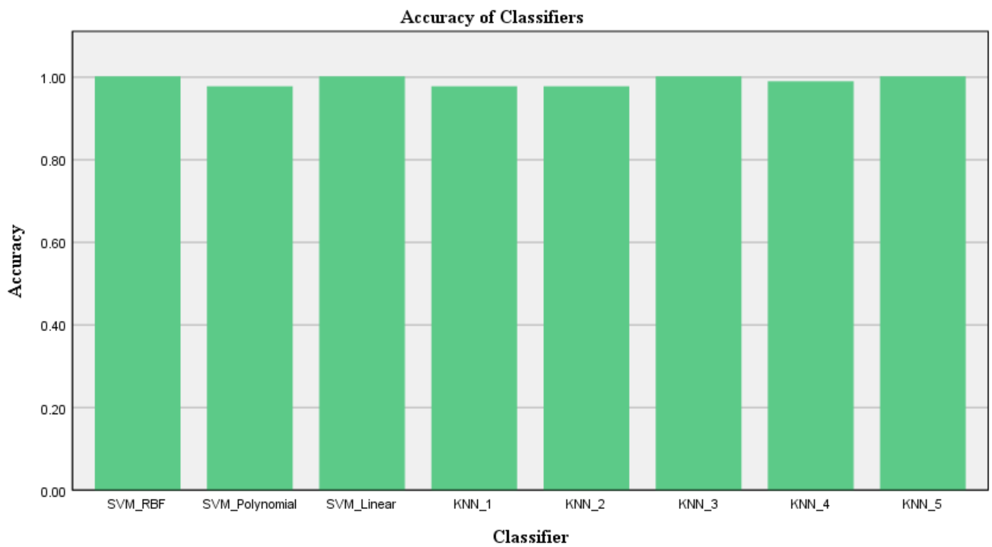

Figure (7): Overall results of the classifiers

Overall Accuracy of SVM and KNN classifiers was computed to assess the ability of the CAD system to detect the brain tumor. The accuracy results were close to the mean of the sensitivity and specificity results, or PPV and NPV according to the equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \dots (3)$$

The overall accuracy results are shown in figure (7) indicated that the SVM_RBF, SVM_Linear, KNN_3, and KNN_5 classifiers, all achieved 100% of accuracy, whereas SVM polynomial, KNN_1, and KNN_2 classifiers obtained the same result with 97.62% less than KNN_4 which achieved 98.81%.

In general, overall accuracy of all classifiers shows that the proposed CAD has a good performance in detecting brain tumors and ability to precisely distinguish between the normal and the abnormal of a tumor.

5. Conclusion

Complexity and variation of brain tumor forms, as well as image quality problems, presented physicians with obstacles in detecting, diagnosing, and analyzing brain tumor images obtained using MRI. This paper aimed to develop a CAD system that would automatically detect brain tumors and classify brain images in terms of normality and abnormality in order to serve as an assessment tool to assist physicians in the early detection of brain tumors. Based on a database of 98 without tumor and 98 with tumor of brain MRI images that were tested in the proposed CAD system, the proposed CAD system provided results more accurate and precise compared with other studies. Cropping the ROI from the center of the tumor region during the segmentation process helped to improve the system results. Another factor that contributed to good results was the use of the discrete cosine transform to convert the ROIs into another domain. The overall accuracy of the CAD system resulted that the SVM of radial basis function and linear types, as well as KNN of 3 and 5 neighbors, obtained perfect results with 100%, while the classifiers SVM of polynomial type with KNN of 1 and 2 neighbors achieved 97.62%, and KNN of 4 neighbors which achieved 98.81%. The proposed CAD system requires more testing with extra images or other databases, especially in the segmentation process. In general, the proposed CAD system presented techniques with good results that can aid physicians in the early detection of MRI brain tumors and can serve as a basis for future research.

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استخدام الكمبيوتر لتشخيص سرطان المخ عند التصوير بالرنين المغناطيسي

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مستخلص. سرطان المخ هو نمو غير طبيعي في خلايا المخ ينتج عنه ورم يمكن أن يحدث في أي جزء من المخ أو الجمجمة. تصنف أورام سرطان المخ إلى أورام حميدة أو خبيثة بناءً على نمط نموها. كل من الأورام الحميدة والخبيثة خطيرة، وتؤثر على وظائف المخ وتشكل تهديدًا لحياة الإنسان. يتعرف الاكتشاف بمساعدة الكمبيوتر (CAD)على الأورام أو الآفات في الصور الطبية أو يميز بين الصور المصابة بالورم وغير المصابة. الغرض من هذه الورقة هو تصميم نظام CAD يقوم تلقائيًا باكتشاف أورام المخ وتصنيف صور المخ من حيث مصابة أو غير مصابة. مر نظام CAD المقترح من خلال سبع عمليات أساسية وهي جمع البيانات والمعالجة المسبقة والتحسين والتجزئة واستخراج الميزات واختيار الميزات والتصنيف وتقييم الأداء. تتضمن قاعدة البيانات 280 صورة للمخ مصور باستخدام التصوير بالرنين المغناطيسي مقسمة بالتساوي بين صور لحالات مصابة بالمرض وأخرى سليمة. كانت عملية التجزئة في هذه الورقة عملية مستقلة تهدف إلى المساعدة في استخراج المنطقة المراد اكتشافها. تم اقتصاص منطقة الاهتمام من الصور الأصلية حول مركز منطقة الورم والتي تم تحديدها بعد التجزئة. اعتمدت النتائج الإجمالية لنظام CAD المقترح على أداء ثمانية أنواع مختلفة من مصنفات SVM ومصنفات KNN ، والتي تم تقييمها باستخدام خمسة مقاييس: الحساسية والنوعية والقيم التنبئية الإيجابية (PPV) والقيم التنبئية السلبية (NPV) والدقة الكلية. أثبتت أربعة مصنفات من أصل ثمانية القدرة على اكتشاف الورم بدقة 100%. حققت بقية المصنفات دقة عالية ، حيث حصل ثلاثة على دقة مقدرة ب 97.62% فيما المصنف الأخير حصل على دقة تقدر ب 98.81%. قدم نظام CADالمقترح نتائج أكثر دقة و موثوقية مقارنة بالدراسات الأخر ، وأظهر إمكانية استخدامه ليكون أداة تساعد الأطباء في الكشف المبكر عن أورام المخ لصور الرنين المغناطيسي.

الكلمات المفتاحية: *تشخيص سرطان المخ، التصوير بالرنين المغناطيسي، تعلم الآلة، الكشف بمساعدة الكمبيوتر ، تحويل جيب التمام.*

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