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Support Vector Machine (SVM) for Medical Image Classification of Tumorous

Reem Alrais[1]; Nazar Elfadil[2]
[1]College of Postgraduate Studies & Scientific Research, Fahad Bin Sultan University, Tabuk, KSA
[2]College of Computing, Fahad Bin Sultan University, Tabuk, KSA
nfadel@fbsu.edu.sa

Abstract— Cancer has become a leading cause of death worldwide. To deal with medical images to discover tumors and their types, Authors need a distinct experience in understanding medical images. Authors need machine learning techniques to reach great accuracy and speed to analyse these images to avoid a lack of experience or errors. In this paper, Authors will study a (SVM) of machine learning techniques used to classify brain images. SVM will be used in this paper to analyse brain images and discover Benign Tumor and Malignant tumor by using Matlab software. The results of the experiments conducted showed the accuracy of the system provided for the classification of tumor types (Benign, Malignant) found in medical brain images. Authors will adhere in this research that the images to be classified are limited by the presence of only two types of tumors. In the future, some pre-processing procedures will be added to the brain's medical images prior to the classification process.

Keywords— Tumor, Medical Image, Machine Learning, Support Vector Machine.

I. INTRODUCTION

The rapid growth of medical images and modalities requires extensive and exhaustive work on the part of medical professionals who are vulnerable to human error and may vary widely through experts (Ghesu et al., 2016). Alternate solution is to use machine learning techniques to automate the pre diagnosis process. Over recent years Machine Learning (ML) and Artificial Intelligence (AI) have made rapid progress. ML plays an important role in image analysis, it can be used to classify images and recognize objects in the image. Machine learning is also now used to infer information from images even if the data is difficult to derive and complex. It can be used to simulate the human brain to identify faces, analyse different types of medical images, and recognize the movement of people as explained in Fig. 1.

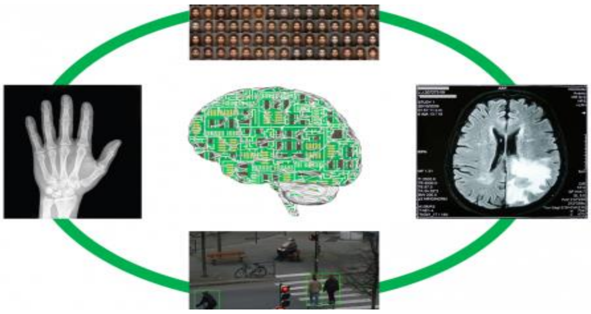

Fig. 1: Machine Learning in Image.

In medical fields such as digital image processing, computer-aided recognition, identity tracking, image retrieval, image interpretation, image segmentation, image-guided therapy, image rehabilitation and analysis, ML technology has played an important role in capturing image knowledge and viewing artefacts effectively and efficiently. ML and AI encourage, support physicians in the right and faster detection and analysis of disease risk, and in effect avoid it. Such methods improve the capacity of doctors and analysts to underline how to identify the common variants that will contribute to sickness. These approaches include standard non-learning algorithms such as Support Vector Machine (SVM), Neural Network (NN), K-nearest neighbours (KNN), etc., and fundamental learning algorithms such as Convolutionary Neural Network (CNN), Recurrent Neural Network (RNN), Deep Short-Term Memory (LSTM), Extreme Learning Model (ELM), and Generative Adversarial Networks (GANs).

Former algorithms are restricted to process the original, time-consuming natural pictures, based on expert knowledge, and require a great deal of time to change the features (Lai and Deng, 2018). The later algorithms come with raw data, automatic learner features and fast. These algorithms aim to automatically learn from large sets of images that show the required data behaviour multiple levels of abstraction, description, and information. The automated detection of disease by ML based on conventional medical imaging technology has been displaying considerable precision for decades.

Magnetic Resonance Imaging (MRI) is a good technique for taking images of many parts of the human body such as the brain. Many algorithms of machine learning have already been suggested to analyse this type of image (Alpaydin, 2009). These algorithms are divided into the supervised and unsupervised types of learning as illustrated in Fig. 2.

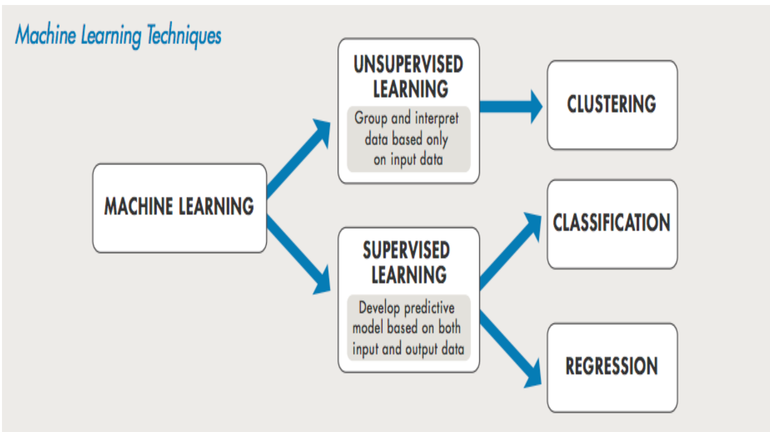

Fig. 2: Supervised and Unsupervised learning (Mathworks, n.d.).

In supervised algorithms, learning is done by having prior data on the correct answer. This type helps us predict non-existent data, as a large Labelled Data is passed to complete the learning process. For example, a various character images are entered to the system, identifying the name of each character on each image, after which the system will be able to analyse the pixels and the shapes in the images to recognize the character name in them. In contrast, unsupervised learning algorithms take unclassified data without actual output, and from which Authors get expected output based on the model designed. For example, this type can be used to bring website or newspaper news together to similar topics, primarily looking at similarities in data rather than distinguishing the data type. In light of the abovementioned, the proposed study aims to explore the impact of machine learning techniques in brain image classification.

II. LITERATURE REVIEW

Indeed, machine learning improves the possibility of developing intelligent systems, but, in spite of everything, a direct emulation of what AI programmers are trying to achieve. In its own way, it solves the previously discussed problem of trying to understand what consider people intelligent, and directly emulate the brains, it means for machines to be intelligent. The search of intelligent software is neither objectionable nor unethical (Chen et al., 2017).

In reality, many noticeable shortcomings in today's software come in part from the inability to program sufficiently intelligent programs. Machine learning are already being used successfully in many commercial applications ranging from document processing to the food industry. Machine learning systems are "especially good at pattern recognition, which has uses in odor analysis, handwriting recognition, credit analysis and many other tasks" (Alpaydin, 2009).

Computers that are able to do these tasks are useful for the reason that, even though people are very good at pattern recognition, they are not as good at the routine tasks that follow. It is easy, for example, for a computer to track and analyse credit card use for thousands of people 24 hours a day. Computers can constantly analyse food odors and aromas in cases where human sensation may become insensitive or in cases where the smell of bad food might make people sick.

Artificial intelligence is in itself a useful tool for helping mechanical systems reach their maximum capability. By working intelligently, computers can do more work in less time and even consume less power. However, there may be limits to the safety of intelligent systems. Some dystopian views of the future fear that intelligent machines will grow beyond the control and in due course take over the world. Apparently, these fears appear rooted in science fiction; however, their basis may not be wholly unsubstantiated.

Some prior modality classification research studies have used a variety of approaches that incorporate a wide range of image features that were extracted globally over the entire image as well as locally over several separate subpatches (Kitanovski, Dimitrovski and Loskovska, 2013). Such experiments all used variations of image attributes developed by humans to represent some of the basic image data properties, e.g. textures, colours, binary patterns and key point descriptors. Implicitly, the performance of these approaches was related to the accuracy of the images, which may allow domain experts to produce the image features for optimization. Many of these approaches also used manual data set expansion to increase the size of their training dataset, which in real world situations may not be possible.

Several methods of machine learning can be classified as Supervised Classification methods. This type of machine learning algorithm can be used to apply classification and regression processes. In machine learning the most widely supervised classification algorithms can be Naïve Bayes Classifiers, Decision Trees, Support Vector Machine and Neural Network, most of them are illustrated in Fig. 3.

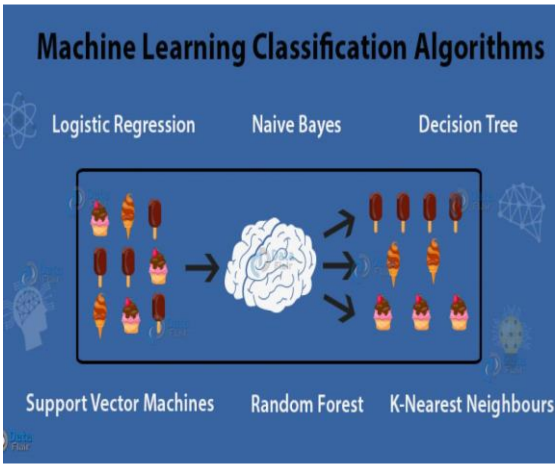

Fig. 3: Machine Learning (Data-Flair).

III. CLASSIFICATION ALGORITHMS

In (Wernick et al., 2010) some ideas were presented for using machine learning in medical image analysis. He gave an introduction to Supervised Learning and then explained how to use some of the supervised algorithms such as Support Vector Machine Classifier in Micro-calcification Detection.

The basic types of automated learning algorithms were presented in detail in (Erickson et al., 2017), Neural Networks, K-near Neighbors, Support Vector Machines, Native Bates Algorithm, and deep Learning. It is also explained how to analyze medical images, extract their features, and apply automated learning algorithms to extract and work with these features. Problems encountered in machine learning methods were addressed when analyzing medical images.

The Support Vector Machine (SVM) method has been applied in (Lo and Wang, 2012) to classify breast tissue in MR images according to tumor. The efficiency of this method (SVM) has been achieved in classifying MR images and extracting features from them in an efficiency manner.

The fundamental of machine learning techniques is illustrated in (Choy et al., 2018). Examples of current machine learning applications and AI techniques are displayed in diagnostic radiology.

Deep learning history, development, and applications discussed in (Lee et al., 2017). In addition, emphasis has been placed on using deep learning in analyzing medical images. He has concluded that deep learning need much data to produce accurate and efficient results.

Brain tumors are classified in (Ranjith et al., 2015) into two types, Benign and Malignant, depending on the features derived from MRI images. This research is using four machine learning algorithms: multilayer perceptron, support vector machine, random forest and locally weighted learning to diagnosis the tumor type.

IV. Research Methodology

To explore the adaptability of machine learning in brain image classification, a model based on Support Vector machines will be developed. In the first stage some preprocessing processes, feature extraction, and feature reduction are applied. In the second step, SVM will be trained; finally, Authors can pass a MRI image to the trained SVM to predict the type of tumor, benign or malignant. This framework can be explained in Fig. 4.

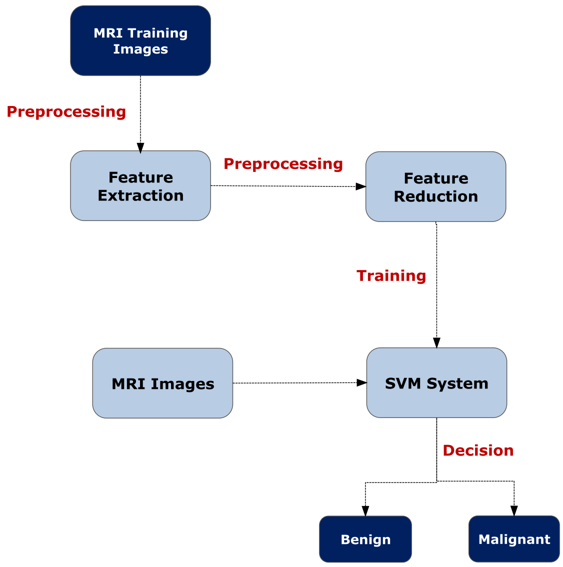

Fig. 4: Project Methodology.

Magnetic Resonance Imaging (MRI) is a technique that enables anatomical images of body organs (Scapaticci et al., 2012). It produces three dimensional detailed anatomical images to diagnosis and disease detection. in this project Authors apply a machine learning technique to classify brain tumor in MRI images. Support Vector Machine (SVM) is used as a machine learning technique to classify brain tumor into benign and malignant tumors.

A. Pre-processing

Firstly, some preprocessing processes is applied to the image data set before applying SVM. The Discrete Wavelet Transform (DWT) is used in the first step to remove noise from images. In the second step of preprocessing, the features have been reduced. Generally, images are made up of color dots (pixels), these dots increase with increasing image quality.

Authors need to store and process these images then Authors need a large volumes of storage units and complex computation. Here Authors need to reduce the features in the image while maintaining the underlying data. There are different techniques for feature reduction, Authors have been used PCA (principal component analysis) to reduce dimensionality in our project see Fig. 5. The data set is converted into a new group of data set, organized by its importance.

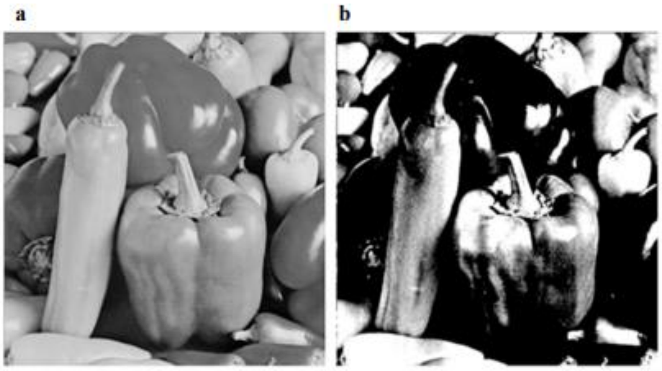

Fig. 5: (a) Original image; (b) feature-reduced image.

B. Feature Extraction

SVM is a supervised learning model used to solve a two-group classification problem. Learning in SVM Algorithm is done by giving a set of examples for each group (Ben et al., 2010). In SVM all data item can be considered as a point in N-dimensional space where n is the number of features Authors can get. So to apply the classification process Authors find Hyper-plane that distinguishes between the two groups as illustrated in Fig. 6. The line in 2-d that separate the hyper-plan can be called the classifier's decision boundary, which separate the two groups, where each group is located on a different side of it.

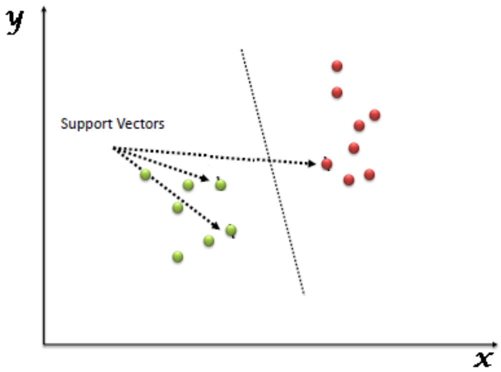

Fig. 6: A linear classifier. The hyper-plane (line in 2-d) is the classifier's decision boundary.

There are various hyperplanes, Authors need to obtain the best hyperplane. SVM make an efficient classification through maximum margin. i.e. the maximum distance between data points of both classes as illustrated in Fig. 7.

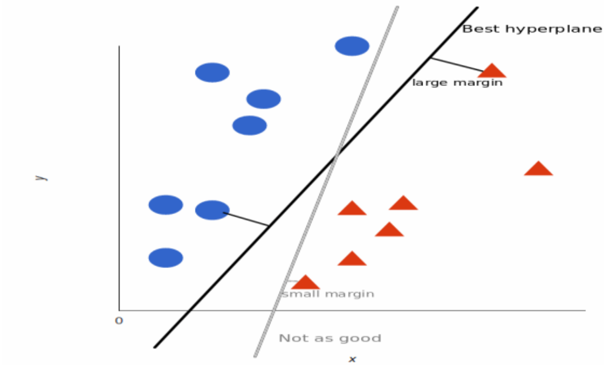

Fig. 7: The Best Hyperplane

SVM results are not affected by the small volume of training data, in this project SVM have been used to classify the two types of Benignant and Malignant tumors by training the system with pre-known data. The system will then be exposed to images that contain these two types of tumor to identify them. Authors use two groups of images, the first represents a brain with benign tumor and the second represents a brain with malignant tumor. Fig. 8 illustrates some images from our dataset of brain with benign tumor and Fig. 9 illustrates some images from our dataset of brain with malignant tumor.

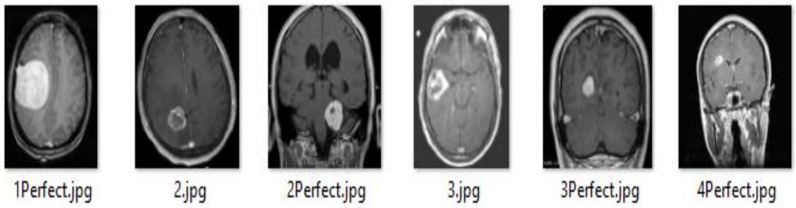

Fig. 8: Benign Tumors.

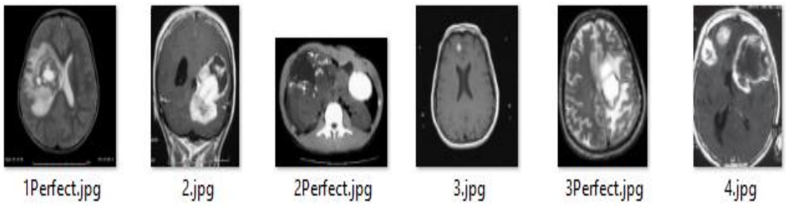

Fig. 9: Malignant Tumors.

V. RESULTS

The experiment is conducted on a computer with I7, 8 RAM hardware and Matlab software. The interface of the system is illustrated in Fig. 10. Authors can open MRI Image then the features are computed and illustrated in the interface, finally the tumor is segmented and recognized.

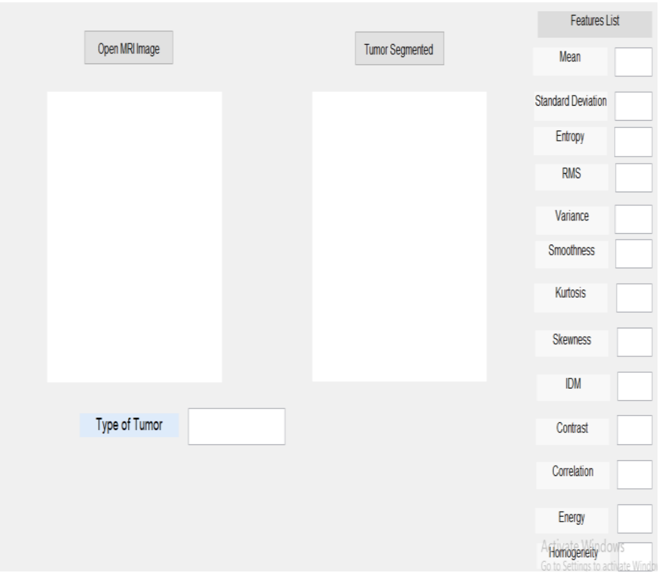

Fig. 10: Main Interface of the System.

The training process passes a group of MRI images to the system. Twenty MRI images are passed to the system, 11 have Benign Tumors and the others have Malignant Tumors. From each MRI image, 13 features are extracted. These features can be listed as follows: Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, and Homogeneity. The value for these features have been stored in the database for the 20 data set and can be illustrated in Fig. 11.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.2333	0.1284	0.7491	0.9308	0.0019	0.0898	2.6632	0.0898	0.0081	0.8778	7.2707	0.6117	-0.036
2	0.2717	0.0931	0.7686	0.9338	0.0024	0.0898	3.2698	0.0898	0.0081	0.8974	7.9567	0.8862	0.492
3	0.2272	0.1326	0.7439	0.9290	0.0043	0.0897	3.6046	0.0898	0.0080	0.9406	5.9972	0.5218	0.370
4	0.2442	0.1007	0.7409	0.9263	0.0032	0.0898	3.5797	0.0898	0.0080	0.9234	6.2735	0.6332	0.525
5	0.2033	0.1126	0.7554	0.9331	0.0019	0.0898	3.6549	0.0898	0.0080	0.8783	5.8117	0.3408	1.001
6	0.2558	0.0895	0.7557	0.9314	0.0025	0.0898	3.0756	0.0898	0.0081	0.9040	7.7971	0.5774	-0.260
7	0.2155	0.0951	0.7378	0.9274	0.0028	0.0898	3.6283	0.0898	0.0080	0.9132	5.3238	0.3230	1.041
8	0.2925	0.1584	0.7588	0.9330	0.0057	0.0896	2.6622	0.0898	0.0080	0.9551	13.0402	1.3124	1.277
9	0.2341	0.1321	0.7530	0.9315	0.0035	0.0897	3.1562	0.0898	0.0080	0.9291	7.4848	0.5212	-1.039
10	0.2689	0.0977	0.7861	0.9410	6.8659e-04	0.0898	2.7465	0.0898	0.0081	0.7186	10.9703	0.7365	0.119
11	0.2433	0.1294	0.7606	0.9344	0.0034	0.0897	2.9949	0.0898	0.0081	0.9270	7.6801	0.6318	0.381
12	0.2272	0.1326	0.7439	0.9290	0.0043	0.0897	3.6046	0.0898	0.0080	0.9406	5.9972	0.5218	0.370
13	0.2750	0.1180	0.7688	0.9346	0.0046	0.0897	3.0290	0.0898	0.0081	0.9453	13.1839	1.0085	0.286
14	0.2272	0.0908	0.7522	0.9308	0.0034	0.0897	3.6783	0.0898	0.0080	0.9270	5.5966	0.4004	1.046
15	0.2517	0.0734	0.7402	0.9267	0.0035	0.0897	3.5239	0.0898	0.0080	0.9284	6.5220	0.4979	1.652
16	0.2439	0.1072	0.7310	0.9246	0.0046	0.0897	3.5484	0.0898	0.0081	0.9446	6.5235	0.6204	0.503
17	0.2925	0.1584	0.7588	0.9330	0.0057	0.0896	2.6622	0.0898	0.0080	0.9551	13.0402	1.3124	1.277
18	0.2745	0.1095	0.7549	0.9308	0.0054	0.0897	3.1085	0.0898	0.0080	0.9523	11.1148	1.0231	-0.615
19	0.2161	0.1382	0.7548	0.9325	0.0025	0.0898	3.3156	0.0898	0.0081	0.9032	6.2320	0.3121	0.563
20	0.2786	0.1427	0.7604	0.9321	0.0053	0.0897	3.1943	0.0898	0.0081	0.9516	9.7318	0.9914	1.854

Fig. 11: Features Value for the 20 data sets

To test the system, Authors have been passed two images to the system. Firstly, Authors choose a MRI image with benign tumor to test the system. Fig. 12 illustrate the system results since it can recognize the correct type of tumor.

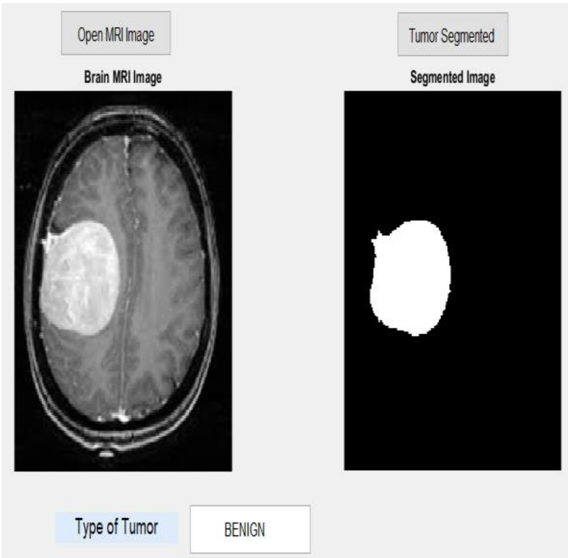

Fig. 12: Detect that the MRI Image has Benign Tumor.

The features are extracted first, then the system compare these features value with the features value that are stored in database to recognize the tumor type.

Secondly, also Authors choose another MRI image contains Malignant tumor, again, the system can recognize the correct type of tumor as in Fig. 13.

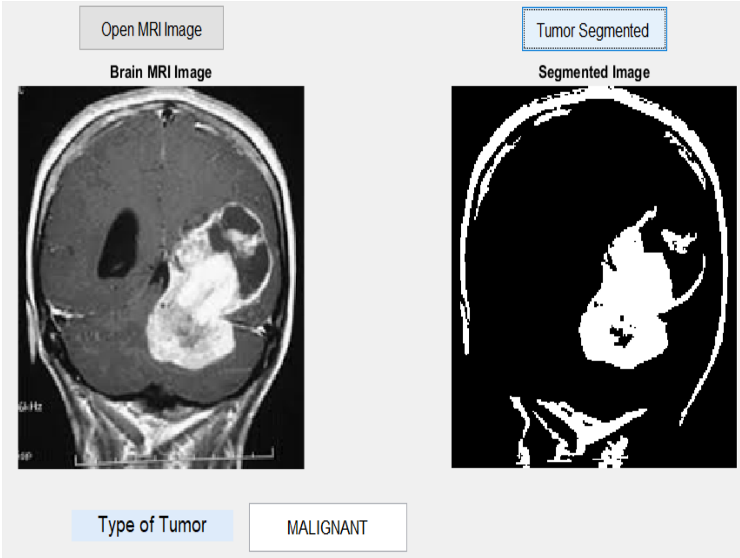

Fig. 13: Detect that the MRI Image has Malignant Tumor.

VI. CONCLUSION AND FUTURE WORK

In this project, how to apply machine-learning techniques in brain image analysis were studied. Authors focused on the detection and classification of two types of tumors Benign and Malignant. Previous literature work has been reviewed and clarified to be based on our project design. SVM method as a machine learning technique used in this project to complete the classification process. To prepare images before the classification was performed by SVM some preprocessing was performed on brain images. Discrete Wavelet transform (DWT) was used to remove noise from images to improve image quality. In addition, the Principal Component Analysis (PCA) is used to reduce the most features dimensional to reduce the required computation and storage space. Experiments were carried out by storing a group of brain images of two types of tumors, and based on the properties of these images, brain images were passed to identify the type of tumor in them. The results obtained from the system test procedure indicated its accuracy in the classification of the tumor types from brain images. Malignant and Benign tumor were successfully differentiated

There are different intelligent methods used to analyse medical brain images. Deep learning is one of the new ways to analyse medical images. Due to time constraints, we will work in the near future to apply deep learning in the analysis of medical brain images to detect the type of tumour. We will also make a comparison between the method presented in this search using the SVM and the new method using deep learning.

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