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RESEARCH PAPER

Brain Cancer Medical Diagnostic System Using Grey Scale Features and Support Vector Machine

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A B S T R A C T:

Automated segmentation and the classification of brain cancer based on Magnetic Resonance Imaging (MRI) is a significant medical development of the last twenty years. Based on computer systems, there are several techniques developed for diagnosis, but the automated diagnosis of cancer type is still a challenge. In this research, a cancer detection system has been proposed and tested to virtually segment the tumor and classify it based on the MRI images. To implement this, a k-mean clustering method is used in the segmentation step. In the features extraction step, each greyscale, symmetrical, and texture features are used. Then, a Principle Component Analysis (PCA) is used to minimize the number of features and Support Vector Machines (SVM) is applied to classify them. To implement the proposed methodology, a computer system was designed and simulated. A database of images was utilized to evaluate how the system is performing under testing. Finally, the test results of the experiments showed the effectiveness of the techniques used to segment and classify tumors.

KEY WORDS: Cancer detection ; Diagnostic System ; Morphological operators; Support vectors machine; Greyscale; K-mean clustering; Texture feature.
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1. INTRODUCTION:

With the development of information technology, techniques have evolved to segment and classify different types of cancer and provide significant information for treatment and surgery. Techniques such as Screening mammography(Yaba S. P.,2015) and Magnetic Resonance Imaging (MRI) are widely used. Nonetheless, segmentation and detection of cancer are difficult due to the complex properties of a tumor such as size, shape, and location. These properties are always unique for each patient.

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MRI is an important technique, used to study most cancer cases for many reasons.

One of these reasons is that the MRI images provide a lot of details about a tumor, and there are no significant medical side effects of this non-invasive imaging technique. The rapid development of technology led to the development of computer-aided imagery to support every medical department such as oncology, neurology, and gastroenterology (Abdulraqeb A. R. et al.,2018 and Peiet L. ,2015).

There are various kinds of techniques that can be used to extract exciting features in MRI images. A number of these techniques are simple; however, these simple techniques are not enough to give high recognition accuracy, but other methods such as grey-scale statistics give good results. A Grey-Level Co-occurrence Matrix (GLCM) is a feature extraction technique that is

widely used in medicine and other fields to process images digitally. The GLCM technique is based on statistical methods to extract textural features. Co-occurrence matrices give essential information about the textural features in an image (Bhima K. ,2016 and Akram M. U. , 2011) .

On the other hand, these diagnostic systems can improve their performance based on the system's experience; therefore, various types of machine learning methods are now applied, such as Support Vector Machine (SVM) and Artificial Neural Networks (ANN). SVM (Abdullah A. I., 2018) is a classifier that is used to solve this problem; it uses a small learning sample and provides an excellent generalization capability. SVM is already applied in several different digital image processing applications; therefore, SVM is described as being a widespread technique in the field of machine learning.

Different techniques, such as Principal Components Analysis (PCA), can be applied to reduce the data dimensionality without affecting the two quality of the image. (Arakeri M. P.,2015, Abd-Ellah M. K., 2016 and Zhang J., 2011).

In the last two decades, many of methodology have been developed to segment of the brain tumors. (Diaz I, Boulanger P, Greiner R, Hoehn B, Rowe L and Murtha A, 2013) have used four MRI modalities for segmenting Edema and Gross Tumor Volume by using automatic histogram multi-thresholding followed by morphological enhancement through geodesic dilation.(Ray N, Saha BN and Brown MR, 2007) proposed an algorithm for finding a bounding box which can enclose the abnormal brain region by symmetrical features in left and right brain structures. The algorithm works quite fast and in real time. It is also useful to provide initial estimate for other region growing algorithms(Selvakumar J, Lakshmi A and Arivoli T, 2012) implemented an algorithm using both K-Means and Fuzzy C-Means for segmenting brain tumor. Later the area and stage of tumor based on the measured area is also calculated by the algorithm. (George EB, Rosline GJ and Rajesh DG made use of optimization technique called the cuckoo search for detecting tumors and Markov Random Field for labeling the image pixels.

In (Yaba S.P. 2015), a system is proposed for detecting brain cancer using comprehensive wavelet features of mamorgram image and neural networks. In (Yaba S.P. 2015), they used an algorithm for classifying mammogram image into three categories (Norma, Benign, and Malignant). They used a test database consisting of 50 image (25 normal and 25 cancer patients).

The contribution of this research paper to the field of the brain cancer detection system is significant. The proposed methodology combines principal component analysis (PCA) and support vector machine (SVM) to obtain better results in cancer detection.

This paper is organized into the following sections: Section 2 describes the architecture of the proposed system. Section 3 introduces the results of the system experiments. The final section gives a conclusion to the presented work.

1.1 SYSTEM ARCHITECTURE

The architecture of the system consists of five steps which are applied to the MRI images to segment the tumor and classify it. Two pre-processing techniques are applied in the first step. These two techniques are histogram equalization and median filtering; both are used to enhance the quality of the images and reduce noise. Furthermore, K-mean algorithm is used for identifying different clusters to detect the tumor in the second step. To extract features of the image, each grey-level is applied to a co-occurrence matrix in the next step.

The ultimate step uses PCA to minimize the data size. Finally, in the last step, SVM is used to classify the kind of tumor in the image to either benign or malignant tumor.

Using the combination of these two methods is the focal point of the methodology used in this research paper. It combines the advantages of both methods to increase the accuracy of the system in detecting tumors.

Figure 1 shows the steps followed in the proposed system.

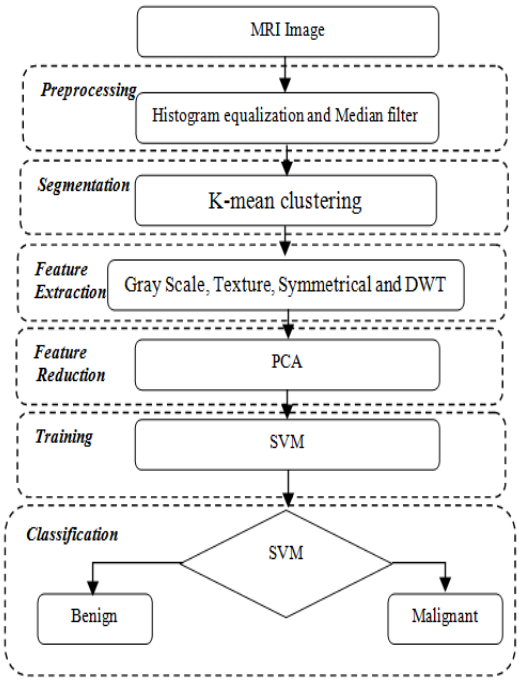


Figure (1): The steps of the System

Preprocessing

In this step, median filtering and then histogram equalization is applied to the input image to reduce the noise and improve the quality, to enhance the recognition rate.

- **Median filter**

The median filter provides excellent noise reduction capabilities. The outcome is significantly less blurry. The technique of this filter is to go over the pixels sequentially processing a small window of a fixed size. It compares the surrounding pixels to the central pixel within this window. During the scan, the surrounding pixel colors are changed with respect to the central pixel using the numerical median color value. This normalizes the image and reduces the number of sporadically colored pixels caused by noise in the imaging process. This type of filter does not affect the edge of the image, and it is possible to apply it many times (Maiti I. . 2012).

- **Histogram Equalization**

Histogram equalization is a technique, which is applied to adjust image contrast. The image intensity distribution is sometimes affected at the acquisition stage, causing poor contrast and image quality. For this reason, the image histogram is equalized to enhance the intensity of the image. The process of an equalized histogram generates an output greyscale from the input greyscale image. The equations applied to compute the histogram equalization are shown below (1):

$$k_0 = round\left(\frac{c_i(2^k - 1}{w.h}\right) \quad (1)$$

Whereby k_0 is the grey level histogram equalization value; ci is the cumulative distribution of ith greyscale in the original image; round defines a value rounding function to the nearest value; while w is the width and h is the height of the image (Natarajan P. .2011 and Gonzalez W. . 2008).

2. THEORETICAL BACKGRAOUND

2.1 SEGMENTATION

Generally segmentation techniques are used to divide an image into sections in order to detect boundries and objects for easier recognition. The segmentation step is one of the most crucial steps in the cancer detection system. This step aims to divide the image into several partitions for analysis. Initially, some basic image processing techniques are followed. Then the segmentation is done by the application of K-Means clustering" and morphological operators. K-Means clustering is applied to segment the tumor or abnormality. Morphological operators and basic image processing techniques are used to define the boundary between tumor and healthy cells further. Segmentation is implemented using the following steps:

2.1.1 Applying Threshold

The threshold technique is commonly used to determine contrast and highlight an area of the iamge. The idea of using threshold is to select a number that represents the level of greyness ina greyscale image and classify all the pixels according to that level. This uses a real number range between one and zero as a greyscale, whereby one is the darkest color and zero is the lightest. The complete image is defined as f(x, y) with x rows and y columns, a threshold grey value (T) is selected within the greyscale range, and pixels higher than this value is set to one; conversely, pixels less than this value are set to zero. (Natarajan P. , 2012) The mathematics of the operation defined below (2):

$$g(x,y) = \begin{cases} 1 & iff(X,Y)>T \\ 0 & iff(X,Y)<T \end{cases}$$

(2)

2.1.2 Watershed Transformation

Watershed transformation is another popular technique and one of the good tumor classification methods. The term watershed refers to a geological ridge between valleys, which alludes to explain this image transformation process. This technique segregates the image of different intensity portions then represents the greyscale image as a topographical map, with the lighter parts of the image being taller, and conversely, the darker elements being shorter. In a greyscale image, the intensity of the cell the tumor has contrasting intensity values, which directly relates to its topography. (Vincent L., 1999).

2.1.3 K-means Methodology

K-means algorithm is an efficient unsupervised methodology. It is applied in various computer applications. In this method; basically, the data is clustered into similar clusters based on the similar characteristics of the data points to discover patterns. In this algorithm, similar data points are grouped into clusters, so there are multiple clusters each representing data points with the same features. To explain this method, let's say that, X = {x1, x2,……,xN} is a group of data points and these must be split into a number of clusters C = {c1, c2,……,ck}. K-means method works by selecting several centroids and compute repetitively to optimize them. The center of all clusters is computed by using the equation below:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} ||X_N - C_K||^2 \qquad (3)$$

Where $||\boldsymbol{X_N} - \boldsymbol{C_K}||^2$ Indicates the distance between data point XN, which relates to the centroid of cluster CK. J is the distance of n points from their related centroid (Shanker R., 2017)

2.1.4 Morphological Operators

Morphological operations are tools applied to extract image features to determine region shape, such as boundaries. Some of the basic morphological techniques are erosion and dilation. These are done in both opening and closing operations. First, in the opening operation erosion is executed, to remove any undesirable pixels and then dilation is applied to concentrate on the required region. Secondly, in the closing operation, a dilation process is followed by an erosion process, in order to fill the gaps. The opening of image A by image B is denoted by $A \circ B$ and is defined as a composition of erosion and dilation. The dual operation to opening is closing, which is defined as a dilation followed by an erosion. The closing of A by B is denoted by $\cdot B$. The followings are the mathematical representations of closing and opening:

$$A \circ B = (A \ominus B) \oplus B$$

$$A \bullet B = (A \oplus B) \ominus B \qquad (4)$$

After these techniques are applied, clusters with high-intensity value pixels will form. The result of this is shown in Figure 2.

Input Image **After Segmentation**

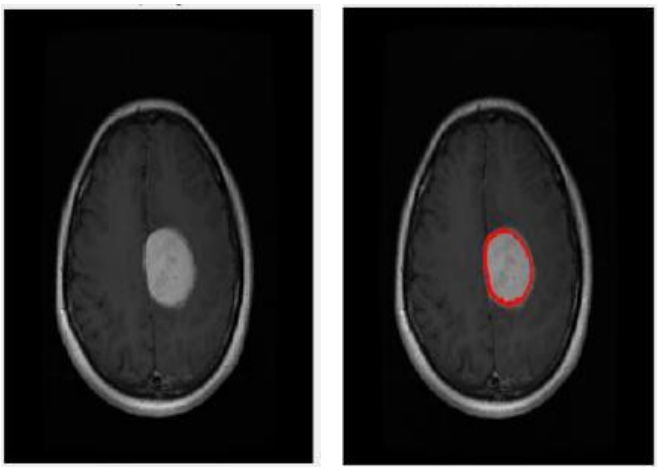


Figure (2): The segmentation stage output.

2.2 FEATURE EXTRACTION

Feature extraction represents one of the major parts of this system. It is used to obtain new sets of features from an image to apply in the following steps. The ultimate goal of this step is to define a wide range of data features as recognized features. Many methods can be used to extract these features. In this stage, greyscale, texture and symmetrical methods are used.

2.2.1 Grey Scale features

In this step, five types of features from a greyscale image are extracted including mean-variance, standard deviation, skew and kurtosis (Abo-Zahhad M. ,2015) These are explained as

follows:

Variance: defines the sum of the squared difference of pixels from the mean pixel value.

$$Variance = \frac{1}{N}\sum_{i=1}^{N}(|x_i - \mu|^2) \qquad (5)$$

Where x refers to the value of an individual grey pixel, $\boldsymbol{\mu}$ represents the grey pixel value, and N indicates the total number of pixels.

Standard Deviation: defines the square root of the variance.

$$SD = \sqrt{\text{Variance}} \qquad (6)$$

Skew: Is a measure of the symmetry in the grey level.

$$Skewness = Variance^{-3}\sum_{x=1}^{m}\sum_{y=1}^{n}(f(x,y) - \mu)^{-3} \qquad (7)$$

Kurtosis: is a measure of the flatness of the histogram grey level.

$$Kurtosis = (Variance^{-4})\sum_{x=1}^{m}\sum_{y=1}^{n}(f(x,y) - \mu)^{-4} \qquad (8)$$

2.2.2 Texture Features

The second type of feature extraction method is applied to the co-occurrence distribution matrix. Thirteen features are extracted for each input image which they are outlined in the equations below (Hossam M. M., 2010):

$$Entropy = -\sum_{s=1}^{n}\sum_{k=1}^{n} q(s,k)\, log(q(s,k)) \qquad (9)$$

$$Dissimalrity = \sum_{s=1}^{n}\sum_{k=1}^{n} q(s,k) * |(s-k)| \qquad (10)$$

$$Inverse = \sum_{s,k=1}^{n}\frac{q(s,k)}{(s-k)^2} \qquad (11)$$

$$Energy = \sum_{s=1}^{n}\sum_{k=1}^{n}(q(s,k))^2 \qquad (12)$$

$$Contrast = \sum_{s=1}^{n}\sum_{k=1}^{n} q(s,k) * (s-k)^2 \qquad (13)$$

$$IDM = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{q(s,k)}{1+(s-k)^2} \qquad (14)$$

Where IDM refers to Inverse Difference Moment.

2.2.3 Symmetrical feature

In images we can determine the symmetry between two regions. Symmetry is useful in detecting objects and boundries as it is known in human vision. Symmetry could be determined using:

$$Exterior\ Symmetry = \frac{\sum_{l=1}^{t}(s-s')^2}{t} \qquad (15)$$

Where s and s' represent the sample vectors

2.2.4 Feature Reduction

The ultimate goal of the feature reduction step is to reduce the computer processing time of mathematic operations by minimizing repeated operations on the dataset. For this reason, feature reduction is a significant step and Principal Component Analysis (PCA) aims to extract standard features, from high-dimensional feature space to a low-dimensional feature spac(Kaya I. E. ,2017).

3 TRAINING AND CLASSIFICATION

The goal of these stages is to classify the features extracted using an SVM method(ABDULLAH, A. I., 2019). SVM is a supervised learning binary classification method. It is applied to recognize a tumor and to classify its abnormality. The accuracy of the SVM classifier depends on its kernel functions. There are various kinds of functions that can be applied to calculate accuracy. The function types are linear, polynomial or radial functions (Abdul Qayyumet al., 2016 and Zhang Y., 2012).

A brief description of SVM is made here and more details can be found in [C. G. J. Schotten, W. W. L. Van Rooy, and L. L. F. Janssen,1995].

1- Linear case: We should now consider the case of two classes' problem with N training samples. Each samples are described by a Support Vector (SV) Xi composed by the different "band" with n dimensions. The label of a sample is Yi. For a two classes case we consider the label - 1 for the first class and +1 for the other. The SVM classifier consists in defining the function

$$f(x) = \text{sign}(\langle\omega, X\rangle + b) \qquad (16)$$

which finds the optimum separating hyperplane as presented in Figure below , where ω is normal to

the hyperplane, and $\frac{|b|}{\|w\|}\|$ is the perpendicular distance from hyperplane to the origin.
The sign of f(x) gives the label of the sample. The goal of the SVM is to maximize the margin between the optimal hyperplane and the support vector. So we search the min $\frac{\|w\|}{2}\|$.

To do this, it is easier to use the Lagrange multiplier. The problem comes to solve:

$$f(x) = \text{sign}\left(\sum_{i=1}^{N_S} y_i.\alpha_i\langle x.x_i\rangle + b\right) \quad (17)$$

where αi is the Lagrange multiplier.

2- Nonlinear case: If the case is nonlinear as the Figure 2 the first solution is to make soft margin that is particularly adapted to noised data. The second solution that is the particularity of SVM is to use a kernel. The kernel is a function that simulates the projection of the initial data in a feature space with higher dimension Φ: Kn → H. In this new space the data are considered as linearly separable. To apply this, the dot product ⟨xi , xj ⟩ is replaced by the function:

$$K(x, x_i) = \langle \emptyset(x), \emptyset(x_i)\rangle \quad (18)$$

Then the new function to classify the data are:

$$f(x) = \text{sign}\left(\sum_{i=1}^{N_S} y_i.\alpha_i.K\langle x, x_i\rangle + b\right) \quad (19)$$

Three kernels are commonly used:

The mathematical equations of these functions are shown below:

Linear kernel:

$$f_k = f(s, s') \quad (20)$$

Where s and s' represent the sample vectors and $\mathbf{f_k}$ is the linear kernel.

Polynomial kernel:

$$k(s, s') = (1 + s.s')^2 \quad (21)$$

RBF kernel

$$k(s, s') = e^{(-||s-s'||)^2} \quad (22)$$

3.1 System Performance Parameters

In order to evaluate the performance of the system we employeed three parameters (Sensitivity, Specificity, and Accuracy). The sensitivity parameter measured the percent of correct positive cases identified. The specificity parameter measured the percent of correct negative cases identified. The accuracy parameter is the percent of the true positives and true negatives. The followings are the parameter equations (Sumithra M. G., 2016).

$$Sensitivity = \frac{TP}{(TP + FN)} * 100\% \quad (23)$$

$$Specificity = \frac{TN}{(TN + FP)} * 100\% \quad (24)$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100\% \quad (25)$$

The database (Cheng. J., et al., 2015 and Cheng. J., et al., 2016) used to evaluate the performance of the system consists of 114 cases; 60 cases are benign cancers, and the others are malignant cancers

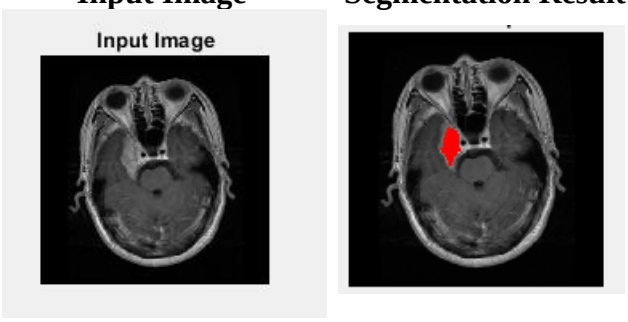
4 EXPERIMENTS AND RESULTS

The system discussed in this paper was implemented using MATLAB® 2018a software. The database used to evaluate the performance of the system contained images of 114 cases; 60 cases are benign cancers, and the others are malignant cancers.

The images were used as input to the system and all the steps were impelented on the data starting from preprocessing to prepare the data, then feature extraction, then an importan step was the segmentation and detection of the tumors in the images. Finally the most important step of classification of the brain tumors to benign or malignant.

Some of the results which it was obtained from the step of segmentation are shown in the figure 3.

Input Image **Segmentation Result**



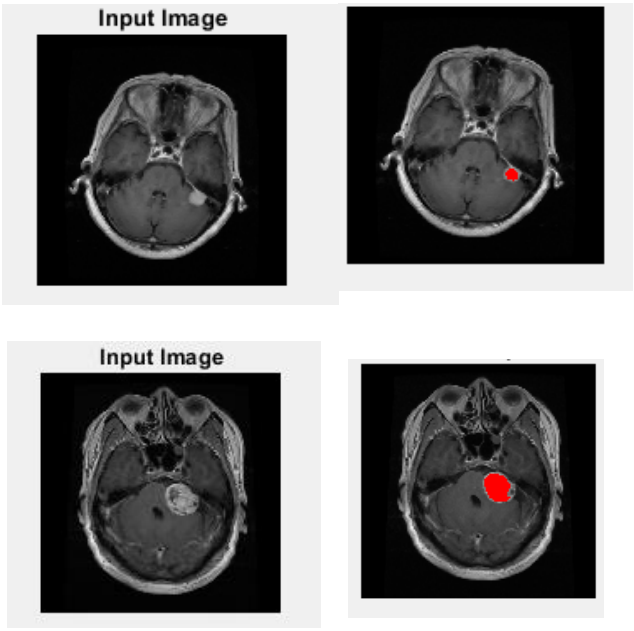


Figure (3): Segmentation Results.

After this step, the system carries out feature reduction and then classification. From this step all the results are recorded in terms of the accuracy, sensitivity, and specifity of the classification.

The performance of the system using parameters such as sensitivity, specificity, and accuracy are shown in table 1. As we see the system performed well considering all the parameters used to evaluate. The sensitivity parameter was at (%92.7), the specifity parameter was at (%99.7), and the accuracy was at (%99.6).

From this experimentation, it is noticed that a polynomial kernel function presents the best results from all the SVM methods used.

Table 1. The parameter results of the system.

Seq.	Parameters	Value
1	Sensitivity	%92.7190
2	Specificity	%99.7452
3	Accuracy	%99.6312

From the results obtained above we can analyze and say that the designed system can be a an accurate and very good tool for cancer detection that can be used by medical staff in determining the cancer cases. The system was able to carry out the process and all the required steps with a high percent of sensitivity, specifity, and accuracy. We can say that the system can be trusted in doing its function.

5 CONCLUSION

In this paper, a medical diagnostic system is designed to segment imaged brain tumors and then succefully classify it. The system contains five steps: pre-processing, segmentation, feature extraction, feature reduction, and classification. The segmentation step is executed by using each of k-mean clustering techniques and additionally uses morphological operator methods to successfully detect most tumors within a sample image database. The system database images came from 114 patients, 60 of these patients are diagnosed with benign tumors, while the other 54 are diagnosed with malignant tumors. Feature extraction methods such as "each of greyscale", texture and symmetry features, are applied. In the classification stage, the SVM method used four types of kernels for recognition; these are Linear, Quadratic, polynomial and RBF.

In conclusion, the system designed in this research work and its methodology proved to be succefull in carrying out a difficult process of identifying brain tumor. From the data used and its results we can say that the system was able to detect brain cancer with high level of sensitivity, specifity, and accuracy. Future work can include applying this system to detect breast cancer in women from mammogram images.

In order to determine the effectivitiy of the system by comparison, the system used in this research was compared to the system suggested by (Yaba S. P. 2015). In the system suggested by (Yaba S. P. 2015) they used the methodology of comprehensive wavelet features and neural netwroks. The test data used by (Yaba S. P. 2015) was 50 MRI images (25 for normal patients and 25 for cancer patients), while database images we used were from 114 patients, 60 of these patients are diagnosed with benign tumors, while the other 54 are diagnosed with malignant tumors. Higher level of the data will give the system and advantage in the results obtained.

In the performance evaluation of the system in (Yaba S. P. 2015), they used only two parameters (Specifity and Sensitivity) while in our study we used three parameters (Sensitivity, Specifity, and Accuracy). This is another advantage of the system of our study.

From the results obtained by the two systems we can determine that the system proposed by (Yaba S. P. 2015) was slightly more sensitive but it lacked in the specifity, and the data for accuracy were not available for comparison.

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