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FPGA Implementation for Automated Classification of Breast Cancer Using Support Vector Machines

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Abstract— This paper posits a conglomerated approach for the classification of mammogram images by employing colour converted hybrid clustering segmentation algorithm and utilizing wrapper based feature selection with binary-class support vector machine (SVM). The images are classified into normal or malignant mammograms by means of extracting the texture, colour and shape features. Image classification using SVM is carried out by various kernel functions and the performance with respect to each kernel is compared with the other. From the analysis and performance measures like classification accuracy, it is inferred that the mammogram classification is best done using SVM with Gaussian RBF kernel function than linear and polynomial kernel functions. The proposed system provides best classification performance with high accuracy and low error rate.
Keywords— Breast cancer, X-ray mammography, Computer Aided Diagnosis, feature extraction, SVM, LTP.

I. INTRODUCTION

The most prevalent type of cancer in women is Breast cancer and sadly the second leading cause of mortality in women due to cancer [1]. In mammograms, breast tumors and masses usually appear in the form of dense regions. A typical benign mass has a round, smooth and well curbed boundary; while, a malignant tumor usually has a speculated, rough, and blurry boundary [2], [3]. By spotting regions with high impressions of malignancy Computer aided detection (CAD) systems in screening mammography serve as a confirming factor for radiologists [4]. The ultimate goal of CAD is to spot such regions with a very high accuracy and reliability and most studies endorse that CAD technology for early breast cancer detection has a constructive influence [5], [6]. The literature on the development and evaluation of CAD systems in mammography is extensive and it follows a hierarchical approach. The CAD system initially prescreens a mammogram to detect malignant regions in the mammary gland parenchyma that are used as prime region for further analysis. SVM is a learning machine which serves to perform classification of data, approximation of function, etc, due to its generalization ability and has found success in many applications [7]. SVM minimize the upper bound of generalization error by maximizing the margin between separating hyper plane and dataset. The added advantage that SVM offers is automatic model selection. The SVM performance is highly dependent on the kernel [8], [9]. Recent work [10] has shown that classification of mammogram images by supervised techniques such as artificial neural networks and k-nearest neighbors (k-NN) [11], and unsupervised classification techniques. K-nearest neighbors (k-NN) group pixels based on their similarities in each feature image [12] to classify normal and malignant mammogram images. The classification method used in this proposed paper is supervised machine learning algorithm (SVM).

II. LITERATURE SURVEY

Jersy et al.[13] proposed a new approach to the problem of malignancy detection in digital mammograms using statistical sequential analysis theory. Statistical analysis is used to detect parameter changes of the stochastic process, which will indicate the presence of suspicious areas in the breast. Dong et al.[14] proposed three approach including feature selection using a clustering criterion, neural classifier and a combined scheme. Their performances are compared using quantitative evaluations. Ping et al. [15] proposed a novel hybrid feature extraction scheme for detection microcalcifications in the digital mammograms. The hybrid feature set is composed of the surrounding region dependence based features and wavelet-based fractal features.
Jeibo et al.[16] proposed a new fast fractal image coding method for the detection of microcalcification. Range blocks are classified into shade and non-shade blocks while contracted domain blocks are classified into shade, midrange and edge blocks. Songyang et al.[17] propose a development of CAD system for automatic identification of microcalcification clusters in digitized mammogram. In first step the potential microcalcification pixels are segmented out using mixed features obtained from wavelet transform and gray level statistical analysis and labeled into potential individual microcalcification objects. In the second step, these potential individual microcalcification objects are classified as true or false individual microcalcification

objects. Liyang et al.[18] proposed the use of SVM, KFD, RVM, and committee machines for classification of clustered MCs in digital mammograms. These different classifier models were trained through supervised learning to classify whether a cluster of MCs is malignant or benign, based on quantitative image features extracted from the MCs. Karnan et al.[19] proposed Ant Colony Optimization(ACO) algorithm with Markov Random Field(MRF) method to segment the microcalcifications. Kramer, D.[20] has compared the ability of three different types of image texture features to classify regions of interest (ROI) containing micro calcifications extracted from digitized mammograms.

Singh et al.[21] proposed SVM based computer-aided diagnosis (CAD) system for the characterization of clustered microcalcifications in digitized mammograms. First, the region of interest (ROI) in mammogram is enhanced using morphological enhancement (MORPHEN) method. Second, pixels in potential microcalcifications regions are segmented out by using edge detection and morphological operations. Third, features based on shape, texture and statistical properties are extracted from each region. Finally, these features are fed to a SVM based classifier for identifying the clusters as either benign or malignant.

Jong et al.[22] proposed a comparative study of texture-analysis method, performed for the surrounding region-dependence method. The textural features from each texture-analysis method are used to classify ROI's into positive ROI's containing clustered microcalcifications and negative ROI's containing normal tissues. Thangavel et al.[23] proposed a novel semi-supervised k-means clustering is proposed for outlier detection in mammogram classification. Initially the shape features are extracted from the digital mammograms, and k-means clustering is applied to cluster the features, the number of clusters is equal with the number of classes. The clusters are compared with original classes, the wrongly clustered instances are identified as outliers and they are removed from the feature space. Atam et al.[24] proposed a texture based classification approach of mammographic microcalcifications. The global texture based features are derived from a gray-level co-occurrence matrix and local texture features are computed from wavelet packets obtained by decomposing the regions at the first level of decomposition. Cho-Huak et al.[25] proposed a number of moments .and addresses some fundamental questions, such as image representation ability, noise sensitivity, and information redundancy. Moments considered here include regular moments, Legendre moments, Zemike moments, pseudo-Zemike moments, rotational moments and complex moments. Tamil Selvi et al.[26] proposed screening of digital mammograms for the presence of microcalcifications using support vector machine. It classifies mammogram into normal or abnormal. Tirtajaya et al.[27] proposed a methodology used in CAD system. Normally CAD consists of feature extraction and classification technique. Here, DT WT as feature extraction and SVM as classification technique are used. McLeod et al.[28] combined a self-organizing map(SOM) based clustering with modified gram Schmidt(MGS) method. To incorporate an unsupervised clustering algorithm such as self organizing map with a least square mechanism for determining clusters and weights of a multi-layer perception type neural network based classifier. The use of such a technique allows for the fast training of the classifier and overcomes the inherent problems of utilizing clustering algorithms like back propagation where a local minima or network paralysis could lead to less than optimal performance. Nakayama et al.[29] proposed a novel filter bank with three features 1) it allows enhancement of NC; 2) it allows enhancement of NLC; 3) its sub-images can be used to reconstruct the original image. Rezairad et al.[30] proposed an approach for detecting microcalcifications in digital mammograms in combination of Artificial Neural Network(ANN) and wavelet based sub-band image decomposition.

III. METHODOLOGY

The proposed approach is shown in fig1. The major steps in the proposed approach are mammogram image preprocessing which involves filtering for the removal of noise followed segmentation by means of k-means clustering. Next step is feature extraction based on kurtosis, variance, skewness, standard deviation and size features extracted from the segmented image and finally feature selection by means of support vector machine classifier which classifies and concludes whether the mammogram is normal or malignant.

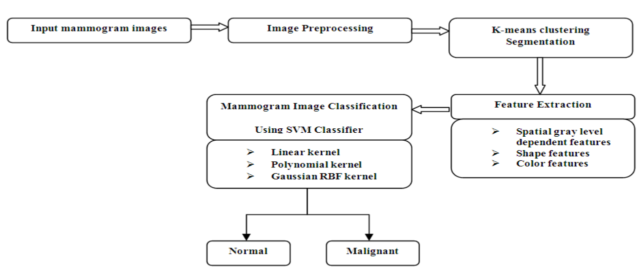

Fig. 1. Block Diagram of proposed methodology.

A. Preprocessing

Image de-noising is a common pre-processing step in image processing and analysis tasks, the goal of de-noising is to remove noise, which corrupts an image during its acquisition or transmission, while retaining its quality. In this paper Wiener filter and Wavelet filter have been used.

The Wiener filtering [31] executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework. Wiener method does a good job at de-blurring; however, it behaves very poorly in the presence of large noise.

To overcome the weakness of the Wiener filtering, Donoho and Johnstone proposed the wavelet based de-noising scheme in [32].

B. Segmentation

The partition of a digital image into similar regions simplifies image representation, is meaningful and easier to analyse [33]. Pixels in the similar region share similarities in characteristics like colour, intensity or texture.

K-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. It aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. Clustering is the process of partitioning a group of data points into a small number of clusters. In general, we have n data points x_i, i=1...n that have to be partitioned in k clusters. The goal is to assign a cluster to each data point. K-means is a clustering method that aims to find the positions μi=1, 1...k of the clusters that minimize the distance from the data points to the cluster.

It works with deciding the number of clusters k, followed by initializing the center of the clusters. The next step is to attribute the closest cluster to each data point and then set the position of each cluster to the mean of all data points belonging to that cluster and repeat it until convergence. The algorithm eventually converges to a point, and stops when the assignments do not change from one iteration to the next.

Given an initial set of *k* means $m_1^{(1)},\ldots,m_k^{(1)}$ (see below), the algorithm proceeds by alternating between two steps, the assignment step and the update step. The assignment step begins with assigning each observation to the cluster whose mean yields the least within-cluster sum of squares (WCSS). Since the sum of squares is the squared Euclidean distance, this is intuitively the "nearest" mean given in equation 1.[8] (Mathematically, this means partitioning the observations according to the Voronoi diagram generated by the means)

$$S_i^{(t)} = \{x_p : \|x_p - m_i^{(t)}\|^2 \le \|x_p - m_j^{(t)}\|^2 \forall_j, 1 \le j \le k\}, \quad (1)$$

where each x_p is assigned to exactly one $S^{(t)}$, even if it could be assigned to two or more of them.

The update step calculates the new means to be the centroids of the observations in the new clusters by equation 2,

$$M_i^{(t+1)} = (1/|\, S_i^{(t)}\, |) \sum x_j, \quad (2)$$

Since the arithmetic mean is a least-squares estimator, this also minimizes the within-cluster sum of squares (WCSS) objective. The algorithm has converged when the assignments no longer change. Since both steps optimize the WCSS objective, and there only exists a finite number of such partitioning, the algorithm must converge to a (local) optimum. The above algorithm is implemented on a FPGA i.e Spartan3E, and the output is the pixel values, which is converted back to the image on PC.

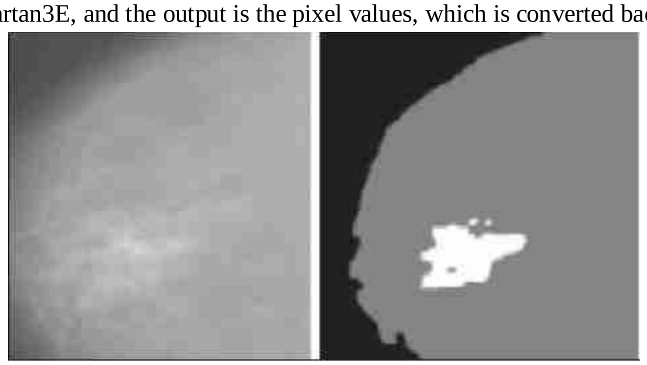

Fig.2. Mammogram original and segmented image.

C. Feature Extraction

After pre-processing we extract the features from global thresholding image. The features are kurtosis, variance, skewness, standard deviation and size. The term kurtosis is used in probability theory and statistics. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. For univariate data $Y_1, Y_2, \ldots, Y_N$, the formula for kurtosis is given by equation 3,

$$\text{kurtosis}=\{(\sum^{N}_{i=1}(Y_i-\bar{Y})^4/N)/ s^4\} \qquad (3)$$

where $\bar{Y}$ is the mean, s is the standard deviation, and N is the number of data points.

Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. It's calculated using equation 4. For univariate data $Y_1, Y_2, \ldots, Y_N$, the formula for skewness is:

$$g_1= \{(\sum^{N}_{i=1}(Y_i-\bar{Y})^3/N)/ s^3\} \qquad (4)$$

where $\bar{Y}$ is the mean, s is the standard deviation, and N is the number of data points. The above formula for skewness is referred to as the Fisher-Pearson coefficient of skewness. The histogram is an effective graphical technique for showing both the skewness and kurtosis of data set. In probability theory and statistics, variance measures how far a set of numbers is spread out. A variance of zero indicates that all the values are identical. Variance is always non-negative: a small variance indicates that the data points tend to be very close to the mean (expected value) and hence to each other, while a high variance indicates that the data points are very spread out around the mean and from each other. An equivalent measure is the square root of the variance, called the standard deviation. The standard deviation has the same dimension as the data, and hence is comparable to deviations from the mean.

D. Support Vector Machine Classifier

The classification technique that is widely used for the diagnosis of breast cancer is the Support Vector Machine (SVM). SVM is one of the shining peaks among the many learning algorithms deeply inspired by statistical learning theory and appeared in the machine learning community in the last decades. The theoretical advantage of SVMs is that by choosing a specific hyperplane among many that can separate the data in the feature space, the problem of over fitting the training data is reduced. They are often able to characterize a large training set with a small subset of the training points. Also, SVMs can work on features with arbitrary distributions, without the need to make any independence assumptions [34].

Mathematically, the purpose of SVM is to find the optimal values for the hyperplane parameters w (e.g. w_0) and b (e.g. b_0). After finding the optimal separating hyperplane, such as $w_0 \cdot x+b_0=0$, an unseen pattern, x_t, can be classified by the decision rule [35]: $f(x)=\text{sign}(w_0 \cdot x+b_0)$ (3-1) Where x is a vector of the dataset mapped to a high dimensional space. Each x_i, belonging as it does to one of two classes, has a corresponding value y_i, where $y_i \in \{1, -1\}$, while w and b are parameters of the hyperplane that the SVM will estimate. The nearest data points to the maximum margin hyperplane lie on the planes given by equations (5) and equation(6) below,

$$(w \cdot x) + b = +1 \text{ for } y = +1 \qquad (5)$$

$$(w \cdot x) + b = -1 \text{ for } y = -1 \qquad (6)$$

By rescaling w and b, with no loss of generality, and grouping the above constraints in a single equation (7) given as,

$$\forall_i,\ y_i f(x_i) \geq 1 \qquad (7)$$

Where $y = +1$ for class $w1$ and $y = -1$ for class $w2$. The optimal separating hyperplane is enforced to separate the two classes of examples with the largest margin because, intuitively, a classifier with a larger margin is more noise-resistant. SVMs identify the data points near the optimal separating hyperplane which are called support vectors. The distance between the separating hyperplane and the nearest of the positive and negative data points is called the margin of the SVM classifier [36].

IV. RESULTS

The mammogram images were obtained online from Mammographic Image Analysis Society (MIAS). Initially mammogram images are subjected to preprocessing using wiener filter and wavelet filter. Segmentation was implemented on FPGA using the

K-means clustering approach. Next the features were extracted and used for obtaining optimized feature set. The SVM algorithm with was used for classification to classify the input features into normal or malignant. In the classification step SVM with Gaussian RBF kernel is compared with linear and polynomial kernel functions. It can be concluded from the experimental results that Gaussian RBF kernel based SVM is a promising technique for mammogram image classification and give high classification accuracy with low error rate. The performance of the proposed method has been evaluated in terms of sensitivity, specificity and accuracy. Table 1 represents the performance comparison for classifier with different kernel functions. Here total 50 images are taken for training and testing. Among 50 images the normal category was 15 images and 35 malignant images were taken for training and testing which was classified using K-means and SVM with different kernel functions. The results show that the proposed system with Gaussian RBF give better percentage of classification while compared to SVM classifier with linear and polynomial kernel functions. Table 2 illustrates the classification accuracy, sensitivity, specificity, area under curve and standard error for performing the proposed approach by using the common kernel functions including linear, polynomial and Gaussian RBF. The experimental results have shown that the proposed method with Gaussian RBF achieves good classification accuracy and less standard error while compared to SVM classifier with linear and polynomial kernel functions. Therefore, it can be concluded that Gaussian RBF kernel based SVM is a promising technique for mammogram image classification. SVM classifier with linear, polynomial, Gaussian RBF kernel functions was implemented. It was seen that proposed method with Gaussian RBF has the highest sensitivity, specificity, accuracy value and the least error. Hence, proposed method provides a higher accuracy than other methods.

TABLE I. Classifier performance

		Number of correctly classified data			Percentage of correct classification		
Classes	No.of data for training/testing	Gaussian RBF	Polynomial	Linear	Gaussian RBF	Polynomial	Linear
Normal	15/15	14/15	13/15	13/15	93.33	86.66	86.66
Malignant	35/35	33/35	31/35		94.28	88.57	85.71
Average					93.805	87.615	86.185

TABLE II. kernel performance

Kernel used	Sensitivity %	Specificity %	Accuracy %	Standard error
Linear	90.12	80.54	89.17	0.04046
Polynomial	91.87	83.92	91.7	0.03924
Gaussian RBF	92.13	84.12	92.6	0.03340

V. CONCLUSION

An improved automated classification technique using FPGA implemented K-means clustering segmentation algorithm with SVM classifier with linear, polynomial, Gaussian RBF kernel functions for classifying mammogram as normal or abnormal (malignant tumor) has been proposed and the performance is evaluated. It is concluded from the analysis that the multiple features, K-means segmentation approach, the SVM with Gaussian RBF kernel function enhances the classification of mammogram image into normal and malignant classes' best. The proposed approach is efficient for classification of the mammogram as normal or abnormal (malignant tumor) with high sensitivity, specificity and accuracy rates.

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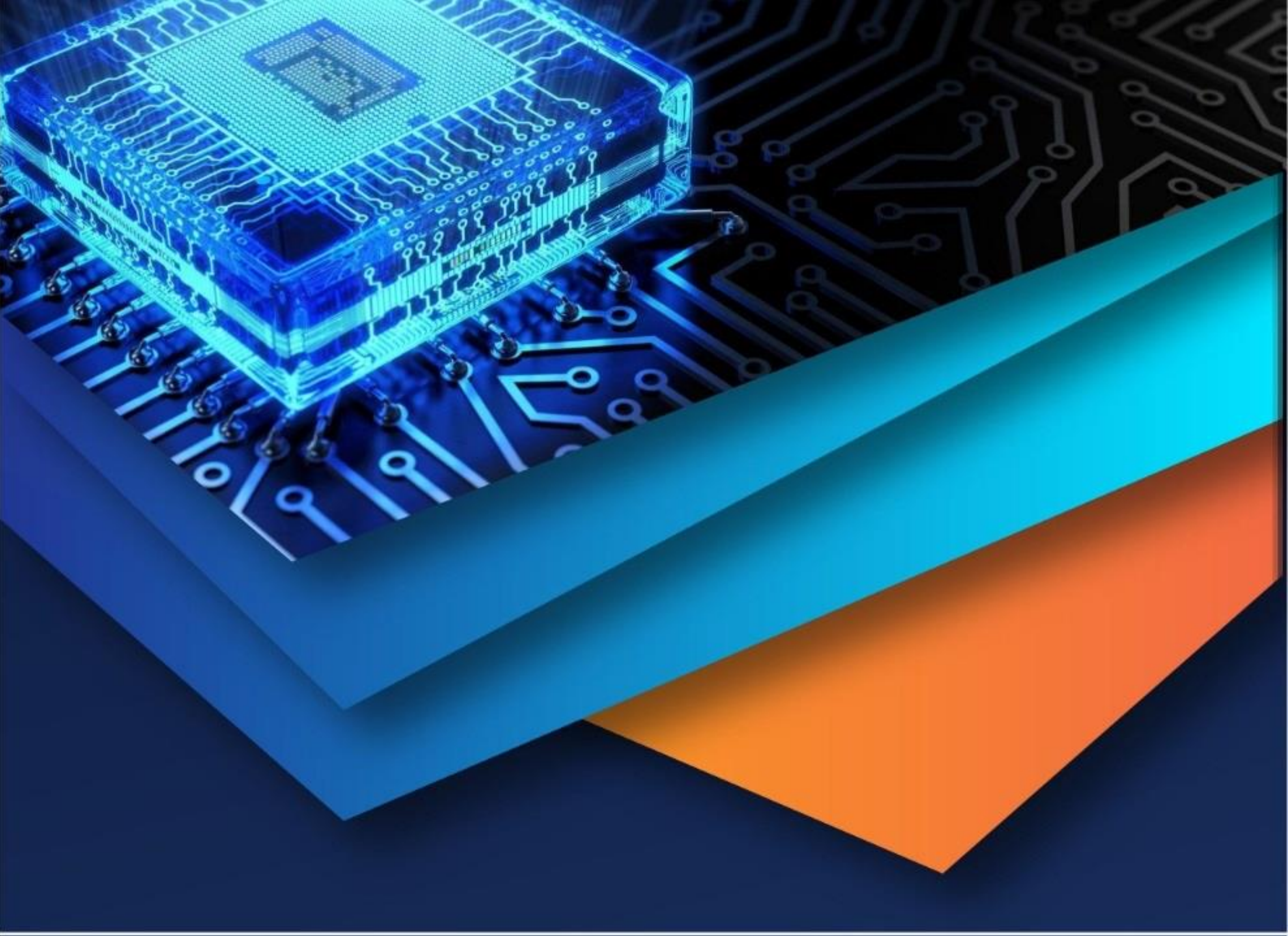

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