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Segmentation and Classification of Skin Lesions Based on Texture Features

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Abstract—
Skin cancer is the most common type of cancer and represents 50% all new cancers detected each year. The deadliest form of skin cancer is melanoma and its incidence has been rising at a rate of 3% per year. Due to the costs for dermatologists to monitor every patient, there is a need for an computerized system to evaluate a patient's risk of melanoma using images of their skin lesions captured using a standard digital camera. In Proposed method, a novel texture-based skin lesion segmentation algorithm is used and to classify the stages of skin cancer using probabilistic neural network. Probabilistic neural network will give better performance in this system to detect a lot of stages in skin lesion. To extract the characteristics from various skin lesions and its united features gives better classification with new approached probabilistic neural network. There are five different skin lesions commonly grouped as Actinic Keratosis (AK), Basal Cell Carcinoma (BCC), Melanocytic Nevus / Mole (ML), Squamous Cell Carcinoma (SCC), Seborrhoeic Keratosis (SK). The system will be used to classify the queried images automatically to decide the stages of abnormality. The lesion diagnosis system involves two stages of process such as training and classification. Feature selection is used in the classified framework that chooses the most relevant feature subsets at each node of the hierarchy. An automatic classifier will be used for classification based on learning with some training samples of each stage. The accuracy of the proposed neural scheme is higher in discriminating cancer and pre-malignant lesions from benign skin lesions, and it attains an total classification accuracy is high of skin lesions.

Keywords—Texture-based skin lesion segmentation, Feature selection, Probabilistic Neural Network (PNN).

I. INTRODUCTION

Skin is the most widely used primitive in human image processing research, with applications from face tracking, signal analysis, and subject based image retrieval systems to different human interactions. MELANOMA is the most deadly form of skin cancer, with an predictable 76 690 people being diagnosed with melanoma and 9480 people dead of melanoma in the United States in 2013 [7]. In the United States, the lifetime danger of getting melanoma is 1 in 49 [7]. Melanoma reasons for approximately 75% of deaths related with skin cancer [8].It is a malignant tumor of the melanocytes and commonly happens on the trunk or lower extremities [9].Different techniques for segmentation, classification and feature extraction methods related to the diagnosis of cutaneous malignancies. Numerous features have been extracted from skin images, including shape, color, and texture and border properties. Classification methods range from discriminant analysis to neural networks and support vector machines.

Maglogianetal is used for a review of the state of the art of computer vision system for skin lesion characterization. These methods are mainly developed for images acquired by epilumines cencemicroscopy (Dermoscopy) and they focus on differentiating reasons melanocytic nevi (moles) from melanoma. Examples of skin lesion images used in this work is undeniably important (as malignant melanoma is the form of skin cancer with the highest mortality),.In the "real-world" the majority of lesions presenting to dermatologists for assessment covered by this narrow domain. Most systems ignore other benign lesions and crucially the two most common type of skin cancer (Squamous Cell Carcinomas and Basal Cell Carcinomas).

The key contribution is to focus on 5 common classes of skin lesions: Actinic Keratosis (AK) , Basal Cell Carcinoma (BCC) , Melanocytic Nevus / Mole (ML) , Squamous Cell Carcinoma (SCC) , Seborrhoeic Keratosis (SK). Moreover, we use only high resolution color images acquired using standard camera (non-Dermoscopy).In the pre-processing stage canny edge detection is used to detect the edge regions in an image. It is employed to remove the unwanted pixels regions. Then the edge pixels are detected and further dilated using a dilation operation to get the optimal non smooth regions. The image pixel representations in a suitable color space are the primary step in skin segmentation methods. Skin appearance in color images can also be affected by illumination, background image, and camera characteristics. A large number of classifier combinations have been proposed the schemes for combining their architecture.

The individual classifiers in the hierarchical architecture are combined into a structure, which is similar to a decision tree classifier. The benefit of this architecture is the high efficiency and flexibility in exploiting the discriminant power of different types of features and therefore improving the recognition accuracy .The approach used in our research falls within the hierarchical model. Our approach divides the classification task into a set of smaller classification problems corresponding to the splits in the classification hierarchy. Each of these subtasks is significantly simpler than the unique task, since the node are classified in the hierarchy only distinguish between a smaller number of classes .Therefore, it may be possible to separate the smaller number of classes with higher accuracy.

The reduction in the feature space avoids many problems related to high dimensional feature spaces of measurement complexity .The main concept of feature selection is to choose a subset of input features by eliminating features with little or no predictive information. Each classifier uses a different set of features optimized for those images. This constrains the unique classifiers to contain potentially independent information. Hierarchical classifiers are well known and commonly used for document and text classification, including a hierarchical KNN classifier.

To smooth a noisy image, median filtering can be applied with a 3 × 3 pixel window. This means that the every pixel value in the noisy image is verified, along with the values of its adjacent eight neighbors. According to size these numbers are then controlled and the median is chosen as the value for the pixel in the new image. As the 3 × 3 window is moved one pixel at a time across the noisy image, and the filtered image is developed and Fig.1 illustrates the workflow of automatic detection of lesion is cancerous or normal .

In this paper we describe the system. Its general workflow of automatic system for skin lesions is shown in Fig.1.In Section II, we describe the image preprocessing, where shading areas are reduced. In Section III, we describe the Segmentation process, where image representation are produced and later used to separate between healthy and lesion areas. In section IV, we explain how to describe the features according to the skin lesions criteria, where computable illustration for the lesion areas gets created. The classifier is used in the features in Section V, where producing estimation if the lesion is normal or cancerous .The cancer skin lesions identified by using Probabilistic Neural Network classifier. In section VI, are explaining about the Experimental results and conclusion explained in Section VII.

Block Diagram:

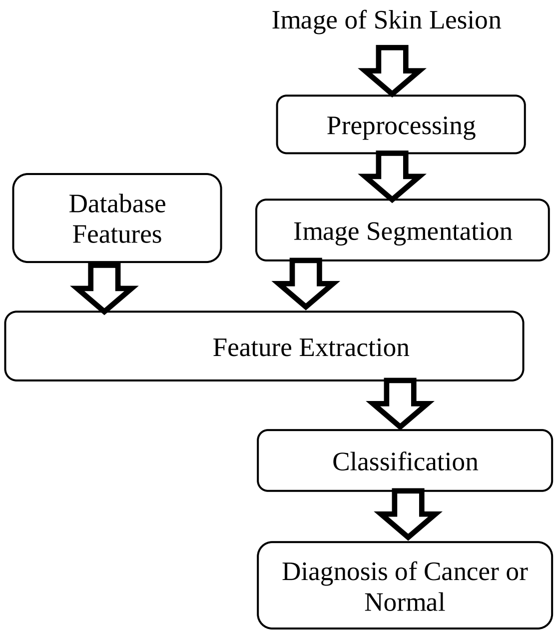

Fig. 1 workflow of automatic detection of skin lesions.

II. PREPROCESSING

An Introduction to Preprocessing

As mentioned before, the input image may be disturbed by illumination artifacts, and if used straight in the segmentation process, shading and lesion regions could be disordered. Therefore, shading is diminished in the input before image segmentation. Skin lesions often occur on curved surfaces (e.g. arms, hands, faces, etc.), and the illumination changes locally due to the surface curvature, generating shading effects. A smoothly darkening surface is presented as one that is turning away from the view direction, and we use shape from shading concepts [5,6] to relight the image (instead of determining the illumination variation by a morphological closing operation) [4]. In image processing, the Low level processes involve primitive operations decrease noise, contrast development, and illustration sharpening. The preprocessing includes two methods.

A. Dilation

Dilation is one of the two basic operators in the area of mathematical morphology. The fundamental outcome of the operative on a binary image is to gradually enlarge the boundaries of regions of foreground pixels. Thus areas of background pixels grow in size while holes within those regions become smaller. The dilation operator takes two parts of data as inputs. The initial is the image which is to be dilated. The next is a position of organize points known as a Structuring element. In this structuring element that determines the precise effects of the dilation on the input image, as seen in Fig. 2.

The dilation is applied on the binary image in a single pass. During the pass, If the pixels in hand is equivalent to binary 1,then apply the structuring component on the images by starting from that particular pixel as origin. In this case, only those pixels are compared with each other, where the structuring element contained.

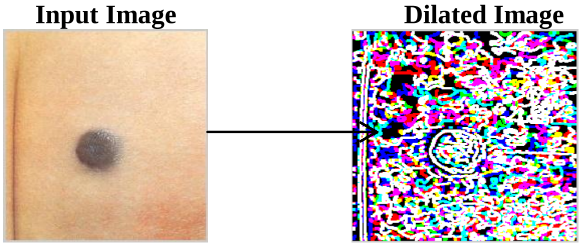

Fig. 2 Dilation applied in the given input image.

B. Canny Edge Detection

a) Edge

Edges are those paces in an image that corresponds to object borders. Edges are pixels where image clarity changes immediately. An edge is a property attached to a distinctive pixel and is calculated from the image function behavior in a neighborhood of the pixel.

b) Edge Detection

Edge information in an image is found by looking at the relationship a pixel has with its neighborhoods. If a pixels gray-level value is similar to those in the region of it, there is perhaps not an edge at that position. If pixels have neighbors with widely changeable gray levels, it may here an edge position.

c) Steps in Edge Detection

- Filtering-filter representation to get better performance of the edge detector
- Enhancement-Emphasize pixels having major change in local intensity
- Detection-Identify edges
- Localization-Locate edge perfectly, calculate approximately edge direction

d) Edge Detection operator (Canny edge detection)

It is optimal edge detection method. The Canny Edge Detection block finds edges by looking for the local maxima of the gradient of the image .It calculates the gradient using derivative of the gaussian filters. The canny method uses two thresholds to detect strong and weak edges. As a result, the method is to noise, and more likely to identify true inadequate edges. Noise is filtered out-usually a gaussian filter is used. Width is chosen carefully. Edge strength is found out by taking the gradient of the image, as seen in Fig .3.

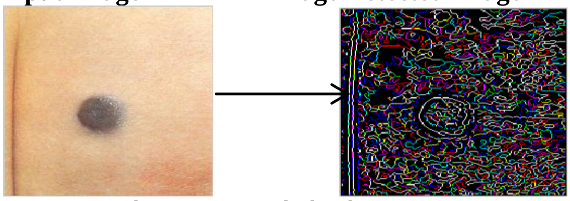

Fig. 3 Canny Edge Detection applied in the given input image.

III. IMAGE SEGMENTATION

An Introduction to Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments. The goal of the image segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to evaluate. It is characteristically used to find objects and image boundaries (lines, curves, etc.) in images and processed of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. It is states to the splitting of an image into separate regions that are identical with respect to chosen assets such as luminance, color, texture etc., and techniques can be categorized in to Histogram thresholding, clustering, Edge based detection, Region based detection, morphological detection, active contours etc., [2].A large of integration scale however results in large errors along in the texture boundaries due to the uncertainty introduced by the large windows. However, for arbitrary texture boundaries, the errors along boundaries can be large even when the overall segmentation performance is good. Texture based segmentation algorithms have been applied to dermoscopy images. Proposed textural lesion segmentation algorithms include using gray-level co-occurrence matrix [13], first-order region statistics [14], and Markov random field models [12].

The TDLS (Texture Distinctiveness Lesion Segmentation) algorithm involves of two main steps. First, a location of sparse texture distributions that characterize skin and lesion textures are well-read. A TD (Texture Distinctiveness) metric is computed to quantity the variation of a texture distribution from all other texture distributions. Second, the TD metric is operated to classify regions in the image as portion of the skin class or lesion class in the image [1]. To learn the characteristic texture distributions in image and planned the TD metric. Existing sparse texture algorithms apply sparse texture models for segmentation or classification of images with different texture pattern. Sparse texture models locate a tiny number of texture illustrations, such as texture patches, to distinguish an entire image [10].

There are many methods to absorb the model, including clustering or by expressing the difficult as an optimization problem [11].To build the fine probability model using given m pixels from each region and to capture the spatial association, it choose for each texture part a window as a template. For chosen m pixels, it defines their distance to a texture region as the minimum mean square distance between those pixels and the template. Using these distances of segmented regions, it build are fined probability model for each texture region as in the first step. These probability models are sensitive to alignments and thus should produce more accurate region boundaries than those based on the spectral histograms. The modified lesion image is separated into a large amount of regions. This early over segmentation step is unified to increase the TDLS algorithm's strength is to noise. Furthermore, it agrees for the use of an effective and fast classification algorithm to novelty which areas fit to the skin or lesion class. The early over segmentation algorithm is changed from the statistical region merging (SRM) [15] algorithm. The main variance is that the SRM algorithm utilizations the image in the RGB color space and the TDLS algorithm translates the photograph to the XYZ color space, as seen in Fig. 4.

Input Image **Segmented Image**

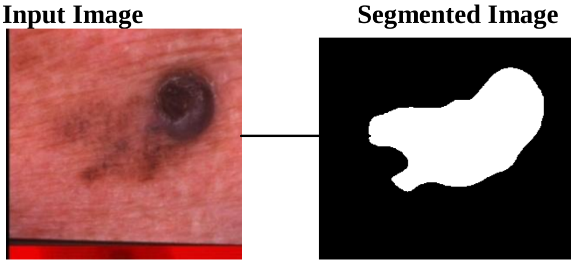

Fig. 4 Segmentation applied in the given input image.

IV .FEATURE EXTRACTION

Texture is that innate property of all surfaces that describes image patterns, each having property of homogeneity. It contains main information about the construct display of the plane. It also describes the connection of the surface to the surrounding environment. The texture properties include coarseness, Contrast, Directionality, Regularity and Roughness. Texture is characterized by the spatial distribution of gray levels in a neighborhood.For optimum classification purposes, what concern are the statistical techniques of description. This is because it is these techniques that result in computing texture characteristics. The most well-liked numerical representations of texture are:

- Co-occurrence Matrix
- Tamura Texture
- Wavelet Transform

6.3.3.1 Co-occurrence Matrix

These co-occurrence matrices represent the spatial distribution and the dependence of the gray levels within a local area.

Each (i, j) entry in the matrix, correspond to the possibility of available from one pixel with a grey level of '*i*' to another with a gray level of '*j*' under a predefined space and position. From this surrounding substance, sets of numerical measures are computed, called feature vectors. The co-occurrence matrix is created, based on the point of reference and space among image pixels. Then important information is taken out from the matrix as the texture representation. The texture features are:

- Energy
- Contrast
- Correlation
- Homogenity
- Entropy

Energy: It is a gray-scale image texture evaluate of homogeneity altering, reflecting the circulation of image gray-scale uniformity of manipulated and regularity.

$$E=\sum_{x,y} p(x, y)^2$$

P (x, y) is the GLCM (Gray Level Co-occurrence Matrix)

Contrast: Contrast is the main diagonal near the instant of inactivity, which computes the importance of the environment is spread and images of local alters in quantity, shiny the image clearness and consistency of shadow depth.

$$I=\sum\sum(x-y)^2 p(x, y)$$

Entropy: It actions image texture unpredictability, when the space co-occurrence matrix for all values is equal, it achieved the minimum value.

$$S= -\sum_{x,y} p(x, y) \log p(x, y)$$

Correlation Coefficient: Procedures the combined probability occurrence of the specified pixel pairs.

$$\text{Sum (sum } ((x- \mu x) (y-\mu y) p (x, y)/\sigma_x\sigma_y))$$

Homogeneity: Procedures the convenience of the circulation of elements in the GLCM to the GLCM diagonal.

$$\text{Sum (sum } (p (x, y) / (1 + [x-y])))$$

Here, skin lesions are characterized by their color and texture. Color features are represented by the mean color sk = (μR, μG, μB) of the lesion and their covariance matrices. Four normalization techniques were investigated to reduce the impact of lighting, which were applied before extracting color features.

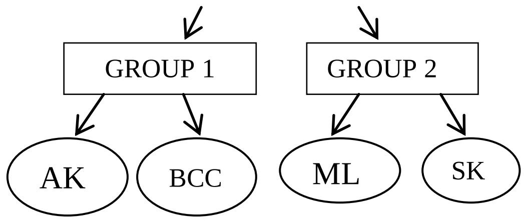

Fig. 5 Hierarchical organization of our skin lesion

Normalized each color component by dividing each color component by the average of the same component of the healthy skin of the same patient and it had best performance compared to the other normalization technique. Texture features are extracted from generalized co-occurrence matrices that are the extension of the co-occurrence matrix to multispectral images, as seen in Fig. 5.

V. CLASSIFICATION

The feature extraction step occasioned in 55 features, which are theoretically useful in selective a benign from a malignant lesion. Not all features are similarly valuable for this classification owing to, e. g., laying-off or inconsequence. [4]. Neural networks are predictive models loosely based on the action of biological neurons. Neural network is the best tool in recognition and discrimination between different sets of signals. Probabilistic Neural Network (PNN) and General Regression Neural Networks (GRNN) have similar architectures, but there is a fundamental difference: Probabilistic networks perform classification where the target variable is categorical, whereas general regression neural networks perform regression where the target variable is continuous. If select a PNN/GRNN network, it will automatically select the correct type of network based on the type of target variable.

All PNN networks have four layers. The first layer is input layer. It is one neuron in the input layer for each predictor variable. In the case of categorical variables, N-1 neurons are used where N is the number of categories. The input neurons (or processing before the input layer) standardize the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer. The second layer is hidden layer. It has one neuron for each case in the training data set. The neuron stores the values of the predictor variables for the case along with the target value.

When presented with the x vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the kernel function using the sigma value(s). The resulting value is passed to the neurons in the pattern layer. The third layer is pattern layer or summation layer. It is actual target category of each training case is stored with each hidden neuron. The weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category. The fourth layer is decision layer.

Although the implementation is very different, probabilistic neural networks are conceptually similar to K-Nearest Neighbor (KNN) models. The basic idea is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables. A probabilistic neural network builds on this foundation and generalizes it to consider all of the other points.

The distance is computed from the point being evaluated to each of the other points, and a Radial Basis Function (RBF) (also called a kernel function) is applied to the distance to compute the weight (influence) for each point. The PNN classifier presented good accuracy, very small training time, robustness to weight changes, and negligible retraining time. There are 6 stages involved in the proposed model which are starting from the data input to output. The proposed model requires converting the image into a format capable of being manipulated by the computer.

The images are converted into matrices form by using MATLAB. It is usually much faster and more accurate to train a PNN/GRNN network than a multilayer perceptron network. It is relatively insensitive to outliers (wild points) and generated accurate predicted target probability scores. It is similar to Bayes optimal classification.

VI. EXPERIMENTAL RESULTS

The TDLS algorithm is implemented in MATLAB on a computer with an Intel Core i5-2400s CPU (2.5 GHz, 6-GB RAM). To segment a skin lesion in a 1640 × 1043 image, the algorithm has an average runtime of 62.45 s. It applies the SRM algorithm in the normal skin color to find the regions corresponding to the lesion. The three other algorithms are proposed by Cavalcanti *et al.* and are designed specifically for lesion photographs. One algorithm (Otsu-R) finds the Otsu threshold using the red color channel. The second (Otsu-RGB) uses all three RGB color channels and finds Otsu thresholds for each channel. The final algorithm (Otsu-PCA) processes the RGB color channels to find three more efficient channels to threshold. A texture channel is obtained using Gaussian filtering, a color channel is obtained using the inverse of the red color channel, and the third channel is found using PCA. For simplicity, this algorithm is referred to as Otsu-PCA. All algorithms have additional postprocessing steps to clean up the contour, and these steps have been implemented as described in their publication.

A set of 126 images from the Dermquest database [16] are used to test the segmentation algorithms. There are 66 photographs with lesions diagnosed as melanoma and 60brk photographs with lesions diagnosed as nonmelanoma. These images are selected because they satisfy the stated assumptions and can be adequately corrected for illumination variation. All tested photographs were first corrected using the MSIM algorithm [19]. The segmentation algorithms are compared to manually segmented ground truth. The algorithms are compared visually and by calculating sensitivity, specificity, and accuracy of the algorithm to properly classify each pixel as normal skin or lesion. The metrics used to compare to the ground truth are sensitivity, specificity, and accuracy. Their formulas are given in [18], [19], and [20], where TP is the number of true positive pixels, FP is the number of false positive pixels, TF is the number of true negative pixels, and FN is the number of false negative pixels, as seen Region Of Curve (ROC) in Fig. 6.

Sensitivity = TP / (TP + FN) [18]

Specificity = TN / (TN + FP) [19]

Accuracy = (TP + TN) / (TP + FN + TN + FP) [20]

TABLE II

SEGMENTATION ACCURACY RESULTS FOR MELANOMA LESION PHOTOGRAPHS

Segmentation Algorithm	Sensitivity	Specificity	Accuracy
L-SRM [18]	90.0%	92.5%	92.1%
Otsu-R [20]	87.4%	91.5%	90.3%
Otsu-RGB [12]	**92.2%**	85.5%	85.0%
Otsu-PCA [21]	81.2%	**99.5%**	97.6%
TDLS	90.8%	98.8%	**97.9%**

TABLE III

SEGMENTATION ACCURACY RESULTS FOR NONMELANOMA
LESION PHOTOGRAPHS

Segmentation Algorithm	Sensitivity	Specificity	Accuracy
L-SRM [18]	88.7%	93.0%	92.6%
Otsu-R [20]	87.3%	78.7%	78.9%
Otsu-RGB [12]	**95.2%**	74.6%	75.0%
Otsu-PCA [21]	77.8%	**99.0%**	**98.7%**
TDLS	91.6%	99.1%	**98.7%**

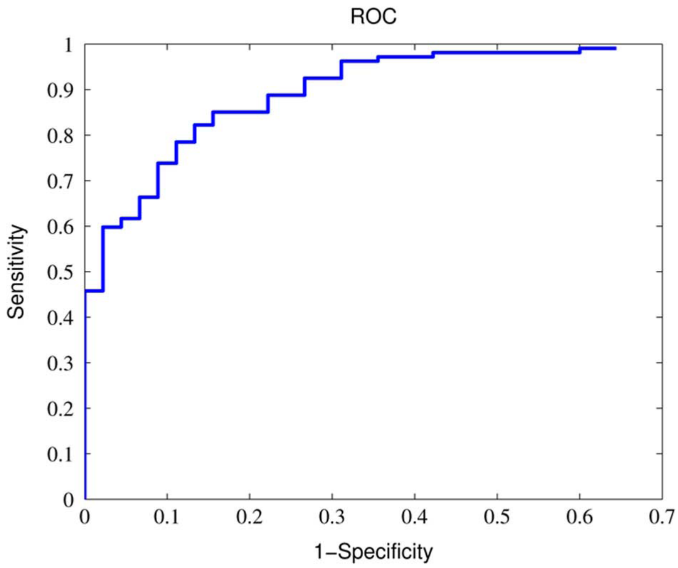

Fig. 6 ROC curve for the PNN classifier

VI. CONCLUSION

This paper presented several skin classifiers for detecting the human skin cancer. The preprocessing techniques are applied in skin lesion images to remove noise by using edge detection and dilation. In this approach, is influenced by biological vision and to overcome the border problem in segmentation. Dilation used to gradually enlarge the boundaries of region of pixels. The canny edge detection is performed to remove the non-smooth regions and to reduce computational complexity. Detection skin cancer accurately by texture based segmentation is used. In the proposed system, segmentation and classification of skin lesion as cancerous or normal based on the texture features. It will improve the efficiency of early detection for skin cancer. The segmentation error is reduced to 0.95%, and visually, the segmentation result is improved significantly and the wrongly segmented pixels of the refined segmentation. The proposed

Framework creates the highest segmentation accuracy using segmented images. A larger data collection and explanation of process, including added testing on extensive variety of images, will be agreed to as future work. While the experimental outcomes display that the planned method is able to segment the lesion in images of dissimilar scales and points of quality, it is value leading a more complete analysis on the influence of image quality and scale. We expect that the proposed system can aid as a source for an easy-to-access melanoma screening service, where the series of probable users includes dermatologists, overall practitioners, as well as laymen not exactly trained in the area. The system offers a chance for teledermatology, where the application can be prolonged to different forms of skin cancer and other skin diseases.

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