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Classification of Medical Plants Based on Hybridization of Machine Learning Algorithms

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***Abstract* - India is a nation where plants with significant medicinal value cover more than 37% of its land. Every plant is treated as having certain medicinal values, whether it be the roots, trunk, fruits, or leaves. Medical plants help in most of the treatments for human diseases if the plant species are identified more clearly. However, it is difficult for individuals to recognize the medical value of the plant accurately. In this work, we suggest a Hybrid model that overcomes this challenge by fusing together two types of classifiers to accurately identify medicinal plants. These classifiers include Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs). The proposed system has many advantages. The features are first extracted using a Convolutional Neural Network (CNN), and then the recognizer is a Support Vector Machine (SVM). It ensures that the proposed model automatically recognizes the features in the raw leaves and carries out classification using those features. The classifier has been applied to 72 different medical plant leaves and is above 97%. The results showcase that the proposed method is more advantageous than the single classifier for effectively recognizing medical plants.**
***Keywords:* Feature Extraction, Image Processing, Convolutional Neural Network (CNN), Performance Evaluation, Support Vector Machine (SVM)**

I. INTRODUCTION

Plants are essential to human life as they produce essential elements including oxygen, food, fiber, and fuel, apart from possessing medicinal values that help in many drug preparations. Numerous plants offer medicinal qualities and active ingredients that can be employed in medicines proposed in Kaur, S. *et al.,* (2019). In the recent generation, people had very little knowledge about medicinal plants and their medicinal values because of many significant factors like lack of interest, inadequate interest in continuing their hereditary profession, professional secrecy maintained by experts with knowledge, and sharing knowledge with the next generation. Therefore, this resulted in a situation where proper knowledge about the plants and their medicinal values became an extinct issue. Due to this lack of expertise, even though there are several plants surrounding us, their medicinal attributes are unknown. Therefore, only with the help of professional experts and traditional practitioners can medicinal plants be identified. As the numbers of medical cases increase along with the increase in population, sophisticated medicines are very much necessary for treating diseases caused by the environment, climate, and living situations. Thus, it is of primary importance to identify the medical plants appropriately so that they can be used in the preparation of effective drug samples.

As a result, the current circumstances require the development of a system that can assist in identifying medicinal plants and their medicinal worth even in the absence of a typical expert identifier in Singh, S. et al., (2017). In this direction, much work has been projected by many researchers using methodologies based on invariant features from Pavaloiu, I. *et al.,* (2017), artificial intelligence techniques from Mukherjee, G. *et al.,* (2017), Sabu, A. *et al.,* (2017), neural networks from Gogul, I. *et al.,* (2017); Amuthalingeswaran, C. *et al.,* (2019), multi-based feature extraction from Krisnawijaya, N. N. *et al.,* (2017), image processing techniques from Dileep, M. R. *et al.,* (2019); Sujith, A. *et al.,* (2020); Sarkar, A. *et al.,* (2020)., computer vision from Zhang, Y. *et al.,* (2020), Mohanty, S. P. *et al.,* (2016), texture-based approaches in Paulson, A. *et al.,* (2020); Hu, J., Chen, Z. *et al.,* (2018), etc. However, because of many issues, such as lightning, weather, and pesticides, identification of the leaves has become another challenging task.

This article offers a hybrid classification approach that combines a Neural Network classifier with a Support Vector Machine classifier to overcome these obstacles. Here's the rest of the article: section 2 of the article deals with the review of the literature in this area of work; the dataset is presented in section 3; and image processing techniques and their necessity are presented in section 4. Then, the hybrid classifier is presented in the section 5, the results derived are depicted in section 6, the performance accuracy metrics and the evaluation results are reported in section 7, and the article concludes with a summary in section 8.

II. REVIEW OF LITERATURE

Researchers use various approaches to determine the identity of potential medicinal plants. Most works use color and texture features from Amuthalingeswaran, C. *et al.,* (2019) and AI and machine learning-based techniques proposed in Muneer, A. *et al.,* (2020). One common approach is to analyze the plant's leaves for medicinal hints in order to identify the species; this, however, requires a reliable, accurate, and efficient procedure.

Malik, O. A. *et al.,* (2022) discusses the importance of automating plant species identification due to the laborious and time-consuming nature of manual identification processes. It suggests creating a system to identify plant species in real time for medicinal plants in the Borneo area. A mobile application, a knowledge base, and a computer vision system make up the entirety of the system. After training and testing, the deep learning model built with EfficientNet-B1 outperforms the reference model in terms of accuracy. Accuracy suffers marginally during real-world testing, perhaps because of differences between training data and test conditions. The study's other standout aspect is its innovative use of crowdsourcing for both feedback and species mapping. All in all, the proposed approach appears to have the potential for instantaneous plant species identification.

Automatic plant identification from leaf photos using computer vision techniques is surveyed in detail by Sachar, S. *et al.,* (2021). The purpose is to help botanists recognize plant species and make use of their useful qualities. Automatic plant identification can help with preservation initiatives. Even though it's possible to take pictures of leaves with a phone or digital camera, there are still obstacles to overcome, such as dust, shadows, and overlapping leaves. In this study, we explore the different classifiers used for plant identification and review state-of-the-art leaf extraction methods organized by leaf attributes. In the final analysis, we point out what needs fixing and where we should go from here in terms of research.

Leaf features derived from photographs of plants belonging to the Annonaceae, Euphorbiaceae, and Dipterocarpaceae families are the primary focus of Hussein, B. R. *et al.,* (2020), who want to automate the identification of plant species. Linear Discriminant Analysis (LDA), Random Forest (RF), and Support Vector Machine (SVM) are only a few of the machine learning approaches that were used for categorization. Classifier performance on unbalanced datasets was studied with the aim of enhancing it using the Synthetic Minority Over-sampling Technique (SMOTE).

In terms of accuracy, the results suggest that LDA performed best with SMOTE (56% for Annonaceae), SVM without SMOTE (79% for Euphorbiaceae), and inter-species classification (63%). LDA achieved 85% accuracy in classifying Dipterocarpaceae, whereas RF and SVM both reached 91% accuracy in classifying members of the Annonaceae and the Euphorbiaceae. According to the results, the retrieved features did well for the Dipterocarpaceae and Euphorbiaceae families but not for the Annonaceae. Furthermore, SMOTE was not able to significantly enhance the outcomes.

In order to speed up the laborious process of identifying medicinal plants, Azadnia R. *et al.,* (2022) propose a smart vision-based system. In this setup, a Convolutional Neural Network (CNN) is used for automatic herb identification. The DL model extracts features with a Convolutional Neural Network (CNN) block and classifies data with a separate classifier block. The classifier block incorporates multiple layers, such as the Global Average Pooling (GAP), dense, dropout, softmax, and the like. The system's leaf recognition accuracy was measured using images of 64x64, 128x128, and 256x256 resolutions taken from five distinct medicinal plants. The vision-based system achieved an accuracy of over 99.3 percent across all image resolutions, proving its efficacy in real-time identification and suggesting it may replace conventional methodologies.

Krisnawijaya, N. N. K. *et al.,* (2017), employed a different technique to identify medicinal plants based on flower species using color, texture, and shape. The textural properties of herbal plants were extracted and developed using a unique Local Binary Pattern model for efficient herbal identification. Feature selection and optimization were not carried out to improve the classification rate, but the multi-layer back propagation perceptron and the gray-level regression matrix were used to extract the features and categorize the plants in the study.

Multi-Channel Modified Local Gradient Model (MCMLGP) is a new structure-based feature descriptor introduced by Habiba, U. *et al.,* (2019). It employs several color channels in color images to extract essential features that help with classification performance. In this article, the authors have directly classified medicinal plants. Different kernels, including the author, used linear and multiple to train the suggested classification algorithm. In addition, the authors performed thorough experimentation using various MCMLGP experimental analysis instructions on the database of medicinal plants. As a result, the authors showcased that the proposed method is much more accurate (96.11%) than existing methods and helps explore and classify medicinal plants.

Sivaranjani, C. *et al.,* (2019) proposed system addresses the difficulty of segmenting leaves under complex background illumination conditions. It introduces an enhanced vegetation index known as ExG-ExR that captures more vegetative information from leaf images without requiring user-defined thresholds. The ExG-ExR index accurately distinguishes a binary plant region of interest, enabling the extraction of leaf sub-images using a color pixel mask. A Logistic Regression classifier is used to classify plant species based on the color and texture characteristics of the extracted leaves. The system identifies plant species with a 93.3% degree of accuracy, demonstrating its ability to compensate for variations in the illumination background.

Mepco Tropic Leaf is an open-access, annotated library of photographs of Indian medicinal plant leaves, and its introduction is highlighted in a paper by Ahila

Priyadharshini, R. *et al.,* (2021). The study reports initial findings on plant species recognition utilizing spatial, spectral, and machine-learned features from a subset of the database, consisting of 50 species. To extract machine-learned features, the authors propose a six-stage convolutional neural network (CNN), which has been shown to be effective in identifying plant species with an accuracy of 87.25 percent. This database and method are helpful for agronomists, ayurvedic doctors, and the ayurvedic medicine field as a whole.

Liu, J. *et al.,* (2018) proposed a novel classification scheme for plant leaves. The CNN algorithm is used in the feature extraction and classification steps of this technique. This CNN architecture is comprised of ten layers. In addition, this strategy used a leaf augment to increase the database size. Finally, to enhance categorization performance, the examination of the variables impacting accuracy was done using the visualization technique. On the Flavia dataset, this CNN approach was tested, and it produced an accuracy of 87.92%. Researchers have used a wide range of techniques, including feature extraction, image processing, and artificial intelligence, to correctly identify medicinal plants. However, it is necessary to propose algorithms to classify medical images even in light of illumination impacts, noise environments, color deformation, and more to have efficient recognition accuracy. Therefore, the present article attempts to move in this direction by proposing methodologies to overcome these challenges.

III. DATASET DESCRIPTION

On the list of medicinal plants maintained by the Department of Health are oregano, bayabas, yerba buena, ulasimang-bato, ampalaya, malunggay, sambong, lagundi, tsaang-gubat, and niyog-niyogan. Other plants on the list are yerba buena, ulasimang-bato, and ampalaya. This inquiry will concentrate on a list of medical applications that have been approved. Fig. 1 displays some of the photographs that were taken of the medicinal plant that served as the study's representative specimen. A total of 600 photographs were taken from Rao, M., *et al.,* (2023).

Fig. 1 Images from Flavia Dataset (Rao, M. *et al.,* 2023)

IV. IMAGE PROCESSING TECHNIQUES

The correct identification of medicinal plants requires the ability to recognize individual plants despite a variety of image quality challenges, including but not limited to variations in lighting, orientation, color, leaf breakage, leaf size, noise, and blur. In order to meet the above changes, each input image to be tested, whether it is a medicinal plant or not, is first subjected to the following enhancement levels:

A. Image Resizing: The input image should be normalized to a fixed size in order to minimize the size of the dataset and the time required to retrieve images from the dataset. It also helps to overcome orientation impacts. Therefore, in this work, we have normalized the input images to a size of 28 x 28.

B. Noise Filtering: Every image that is considered for testing consists of noise. In order to eliminate noise or blurring within the image, the input image must be processed using the Gaussian filtering formula.

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (1)$$

where (x, y) represent the pixel coordinates and 'σ' , is the standard deviation.

C. Feature Extraction: Information about the leaf's structure and pattern can be extracted with the aid of feature extraction. These features help in make the classification task easier. Every raw image needs to be processed before extracting features like shape, size, texture, etc. Fig.2 illustrates the structure of the proposed image enhancement techniques.

In this article, the histogram of oriented gradients (HOG) is considered for extracting features from the medical leaf image by proposing a histogram of the medical plant image. The main advantage of considering the HOG is that it helps to divide the image into gradients, which help to identify the features easily.

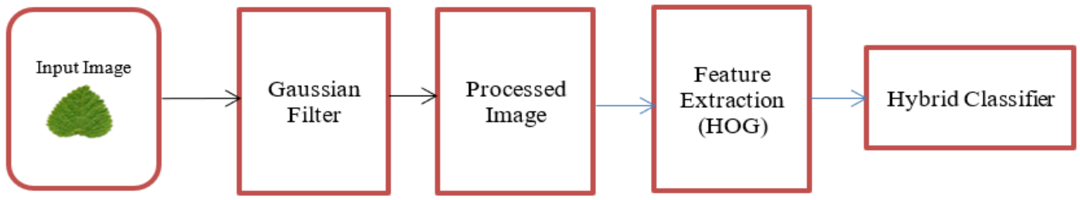

Fig. 2 Architecture of Proposed Image Enhancement

The connected regions inside each of the images are considered to be cells, and considering these cells, we construct the images. In our work, we have considered an 8x8 filter that is applied to a gradient of size 28x28. The filter is slided all through the image in order to identify the gradients within the medicinal leaves.

V. METHODOLOGY

To propose the current approach, the Gaussian filter was initially considered for noise elimination. HOG has been used to extract image features; this feature extraction method can extract image features from all image regions. As input to the classifier, HOG-extracted features are used.

A. Proposed Methodology

To detect the Ayurvedic medicinal leaf, we process the image of the medical leaf and derive the feature vectors. Next, we move on to the classifier, which pulls its model and weights from the database where they have already been trained. If the input image is similar to the image in the database depicted in Fig. 3, the model makes a prediction.

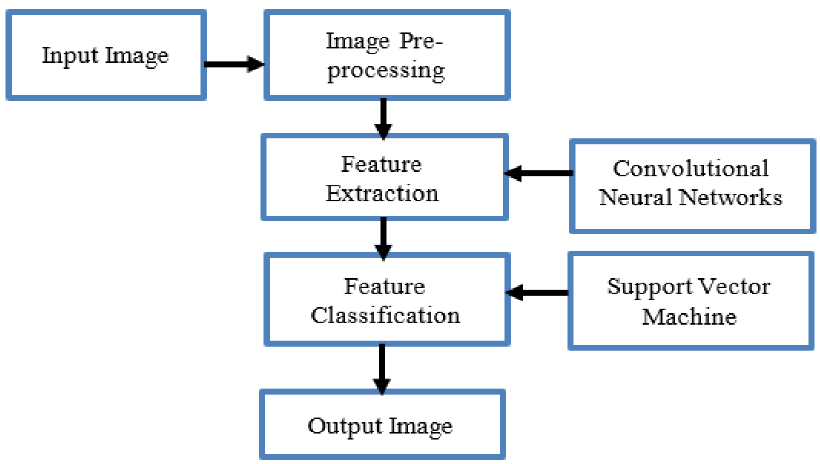

Fig. 3 Architecture of the Proposed Model

CNN is a hierarchical neural network that has the advantage of representing huge amounts of data and learning features at every layer. It has many advantages, in particular in recognizing the images more precisely. On the other hand, SVM is considered an approach for recognizing the multiple features inside the image regions. Therefore, the hybridization of these two models helps to recognize the medical leaves more precisely in spite of the illumination, color, shape, and size changes. Hence, in this work, we propose a novel model based on CNN and SVM for effective medical plant identification.

B. Hybrid Classifier Model

1. Loads and preprocesses the image data: The code loads images of each category from a specified directory and resizes them to a uniform size of 50x50 pixels. The images are converted to grayscale and normalized. Labels are assigned to each image based on the category it belongs to.
2. The medical data set should be divided into a training set and a testing set, with 80% of the data allocated to the training set and 20% to the testing set.
3. Describe the many parts that make up a CNN model. The CNN model's two convolutional layers feature 32 and 64 filters, respectively; following them are max-pooling layers and dropout regularization. After normalization, the data passes through a fully connected layer that produces probabilities for each category using a softmax activation function.
4. Defines a Support Vector Machine Model: An SVM model with a linear kernel is defined to combine it with the CNN model.
5. Each image in the training set has its CNN features retrieved and used to train the CNN model. Here, we use a technique that ties together the popular CNN and SVM models. The recovered features are then used to train a support vector machine (SVM) model to distinguish between the two classes.

6. Evaluates the model: To determine how well the trained model can categorize test images, it is put to the test on the testing set.

C. Training Phase

In the first stage, we considered the number of leaf samples with medicinal or non-medicinal values. These image samples are used as input in later processing steps. First, the pre-processing and feature extraction procedures are given the training and validated image set as input. As seen in Fig 4, the validation phase is in charge of correctly identifying the classifier trained during the training phase.

D. Testing Phase

After pre-processing and feature extraction, samples were split into training and validation sets. The training set trained the classifier, whereas the validation set validated its accuracy during training. The validation set enhances classifier precision by evaluating it. Both sets go to the classifier. Model parameters, including 0 and 1, and weights are saved to the database after training. During prediction testing, the classifier receives the trained model parameters and weights. We collected positive and negative samples, including photos of medicinal and non-medicinal leaves, during testing. Processing and feature extraction are the same, along with training and preparation. Based on the extracted attributes, the classifier predicted the outcome. “No medical leaf is present in the image” will result in an output of 0, and “one or more medical leaf images” will result in an output of 1. Figure 4 depicts the complete design of the workflow system. In the testing step, we determine whether an input image belongs to a set of medical images by classifying it. The procedure corresponds to the training procedure. The phases of testing and training are outlined below.

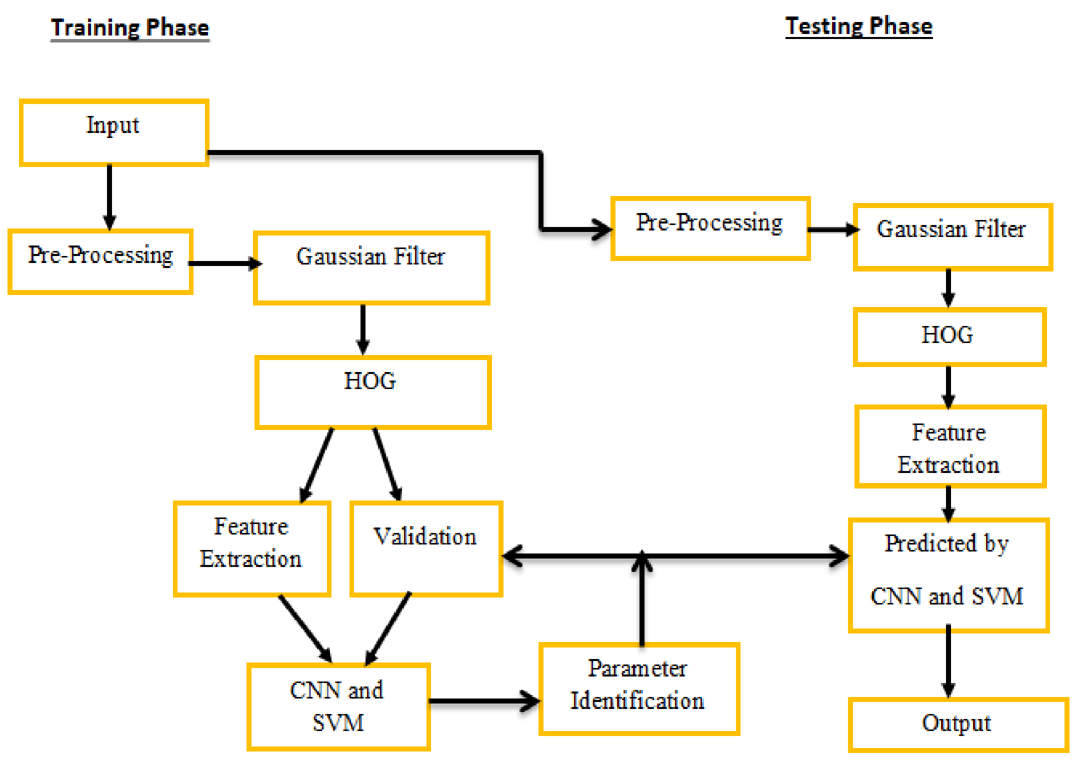

Fig. 4 Architecture of Training and Testing Phase

VI. RESULTS AND DISCUSSION

The hybrid model used in the leaf identification is two dimensional CNN+SVM as this is shown effective for image classification tasks. The CNN extracts high-level features from the images, which are then used as input to the SVM for classification. We have considered the data of two plants: Piper Betle (Betel leaf) and Mentha (mint leave).

Data contains,

1. Piper Betel (Betel leaf) - 48 images
2. Mentha (mint leave) - 98 images

A. Results Shown

For data of two plants Fig. 6 Piper Betle (Betel leaf) and Fig. 7 Mentha (mint leave). The model obtained 97% accuracy, as illustrated in Fig. 5.

```
report = classification_report(test_labels_1d, test_labels_predicted)
print(report)

              precision    recall  f1-score   support

           0       1.00      0.93      0.97        15
           1       0.93      1.00      0.97        14

    accuracy                           0.97        29
   macro avg       0.97      0.97      0.97        29
weighted avg       0.97      0.97      0.97        29
```

Fig. 5 Accuracy of Proposed Model

B. Test for Betel Leaf

```
img_path = '/content/drive/MyDrive/plantdata/Betel/PB-S-011.jpg'
img_size = 50
img_arr = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
resized_arr = cv2.resize(img_arr, (img_size, img_size))
input_data = np.array([resized_arr]) / 255.0
input_data = np.reshape(input_data, (1, img_size, img_size, 1))
features = cnn.predict(input_data)
label = svm_model.predict(features)

1/1 [==============================] - 0s 27ms/step

if label[0] == 0:
  print('Piper Betle(Betel leaf)')
else:
  print('Mentha(mint leave)')

Piper Betle(Betel leaf)
```

Fig. 6 Test for Betel Leaf

C. Test for Mint Leaf

```
img_path = '/content/drive/MyDrive/plantdata/Mint/M-S-006.jpg'
img_size = 50
img_arr = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
resized_arr = cv2.resize(img_arr, (img_size, img_size))
input_data = np.array([resized_arr]) / 255.0
input_data = np.reshape(input_data, (1, img_size, img_size, 1))
features = cnn.predict(input_data)
label = svm_model.predict(features)

1/1 [==============================] - 0s 21ms/step

if label[0] == 0:
  print('Piper Betle(Betel leaf)')
else:
  print('Mentha(mint leave)')

Mentha(mint leave)
```

Fig. 7 Test for Mint Leaf

VII. PERFORMANCE EVALUATION

A. Performance Evaluation Metrics

1. Accuracy: (It estimates the number of accurate results). The formula and the mixing of true and false values are as follows,

$$Accuacy = \frac{TP + TN}{TP + FP + TN + FN}$$

2. Error Rate: Calculate the number of incorrect answers.

$$Error\ \ Rate = \frac{FP + FN}{TP + FP + TN + FN}$$

3. Precision: (It is the ratio of right results to the total number of correctly recognized medicinal plants + non-medicinal plants identified.)

$$\Pr ecision = \frac{TP}{TP + FP}$$

4. Recall: (It denotes the ratio of number of positively detected leaves to the total number of medicinal leaves and non-medicinal leaves.)

$$\mathrm{Re}\, call = \frac{TP}{TP + FN}$$

TABLE I COMPARISON OF CURRENT AND SUGGESTED METHODS

Method	Accuracy	Precision	Recall	F-Score
SVM	93.3	89	92	88.4
Random forest	90.1	87.3	88	86.5
Multiclass SVM	93.26	92.17	90.5	90.26
CNN	96.6	92.5	93.2	90.2
Hybrid Model (CNN and SVM)	97.2	94	93.4	89.4

Traditional methods and the suggested model are compared in Table I. As compared to other methods, the proposed model is superior in its ability to recognize therapeutic plants. Traditional methods and the suggested model are compared in Table 1. Rao, Marada S. *et al.,* (2023) suggested CNN model they achieved an accuracy of 96.6%, the proposed hybrid model is superior in its ability to recognize therapeutic plants, it achieves an accuracy of 97.2%.

VIII. CONCLUSION

This article proposes a novel methodology based on the hybridization of CNN with SVM. The main advantage of this model is that it helps recognize the medicinal plant despite several deformities, lighting conditions, color pigmentation, size variation, and orientation. This methodology is tested against the data set using different medical leaves and could achieve a well-recognized accuracy above 97%. The results are tested using a model based on a single CNN, and it is seen that this developed model outperforms the existing model. The results are also evaluated using evaluation metrics like accuracy, precision, and recall. In all these measures, it is observed that the developed method signifies its noteworthiness. This methodology is very helpful for Ayurvedic medicinal practitioners to identify the medicinal leaves more accurately.

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