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Leaf Disease Detection using Ensemble

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ABSTRACT: Agriculture is critical now a days in India. India has gained the world's greatest producer of various crops, yet it continues to utilize archaic frame methods, resulting in lower agricultural yields. As a result of the introduction of improved seed types, new agricultural crop production technologies have increased. However, without utilizing more intelligent methods, the agricultural field would remain flawed, and a typical problem among Indian farmers is that they do not pick the correct crop for their soil needs. As a result, their productivity suffers significantly. Precision agriculture has addressed this issue for farmers. Precision agriculture is a sophisticated agricultural technology that analyses soil properties, soil types, and crop production data to recommend the best crop to farmers based on their site-specific criteria. This decreases crop failures and increases production. This research will examine techniques such as inception v3 and bespoke CNNs in event to improvise the accuracy of the system used in predict crop disease.

KEYWORDS: Crop disease detection, CNN, Ensemble Learning.

I. INTRODUCTION

Disease diagnosis in plants is critical part in field of agriculture, since most farmers must determine if the yield, they are harvesting is sufficient. It is critical to pay close attention to them as they can pose severe challenges in plants, affecting the quality, quantity, or profitability of specific items. From the very beginning of the crop's life cycle through the moment of collection, it should be inspected for disease. Initially, the approach for screening plants for illnesses was unsupported eye vision, which is a cumbersome operation that required foresight from professionals. Automatic categorization of plant diseases is critical during the early stages; this will aid in recognizing the disease's side effects when they manifest on plant leaves. As a result, this article will design an automated leaf disease classification system utilizing the CNN approach. Deep learning approaches have shown considerable classification results in recent years. The purpose of this article is to investigate a strategy for detecting leaf disease that is based on transfer learning.

II. LITERATURE SURVEY

In most agricultural systems, Ahmed, F., Al-Mamun, et al. [1] emphasize the need of weed control. Weed management in agricultural regions is often performed by the application of chemical herbicides, which have been proved to boost crop production and quality. Concerns about the environmental and economic effects of excessive pesticide usage, on the other hand, have stimulated interest in developing alternative weed management techniques. A cost-effective method of reducing pesticide misuse may be to develop an automated machine vision system capable of differentiating between crops and weeds in digital pictures. Rather of equally spraying herbicides throughout a field, real-time technology may be used to identify and spray just weeds. The goal of this article is to assess the efficacy of a machine-learning approach known as support vector machine (SVM) for categorising crops and weeds in digital pictures. The goal of this study is to test if an SVM-based classification model can achieve a high classification rate when used in an automated weed control system. The experiments analysed a total of fourteen parameters associated with crops and weeds in photographs in order to discover the optimal mix of traits associated with the highest classification rate. The study of the data indicates that SVM is more than 97 percent accurate throughout a collection of 224 test images. Notably, crops are never mistaken for weeds and vice versa.

According to Rothe, P. R., et al. [2], cotton leaf diseases must be recognised early and precisely, since they might be damaging to output. The proposed study establishes a pattern recognition system with the objective of recognising and categorising three cotton leaf diseases, namely Bacterial Blight, Myrothecium, and Alternaria. Photographs for this project were shot in Nagpur's Central Institute of Cotton Research and in cotton fields in the Buldana and Wardha

districts. An active contour model is used to segment the image, and Hu's moments are extracted as features for training an adaptive neuro-fuzzy inference system. The accuracy of categorization is judged to be 86 percent.

In A. Singh, B. Ganapathysubramanian, et al., [3]. Automation and high-throughput optical imaging have culminated in an outpouring of greater pictures of plants and sensor data. However, in order to extract patterns and features from this enormous data set, machine learning (ML) technologies must be used to ease data assimilation and feature identification for stress phenotyping. Different machine learning methods may be utilised at four stages of the selection cycle in plant stress profiling and reproductive activities: identification, classification, quantification, and prediction (ICQP). A simple taxonomy and complete review of machine learning technologies are provided here to aid the plant community in efficiently and effectively using the best machine learning techniques and best - practice for a variety of abiotic and biotic stresses conditions.

M. Islam, A. Dinh, K. Wahid, et al., [4]. Modern characteristic and disease detection technologies constitute a significant advancement in the effort to ensure food security and sustainable agriculture. Imaging and, more specifically, computer vision-based characterization enable the study of quantitative plant physiology. Manual interpretation, on the other hand, requires considerable work, expertise in plant diseases, and an abnormal amount of processing time. As demonstrated in this research, by combining image processing and machine learning, this technique enables the diagnosis of diseases using leaf pictures. Using photos from the publicly available 'Plant Village' plant image repository, this automated approach identifies diseases (or their absence) on potato plants. We exhibit sickness classification over 300 images with a 95 % confidence efficiency using a CNN segmentation approach and a support vector machine. As a result, the proposed approach enables massively automated plant disease diagnosis.

P. Srivastava, J. Shiney, et al., in Kumar Srivastava [5]. The diagnosis of plant diseases is crucial for minimising agricultural product productivity and quantity losses. The evaluation of visually visible patterns on the plant is necessary for the research of plant diseases. Plant health monitoring and disease detection are critical for sustainable agriculture. Monitoring plant diseases manually is fairly difficult. It requires a significant amount of labour, expertise in plant diseases, and an abnormally long processing time. As a consequence, image processing is used to determine the presence of plant diseases. Disease detection is a multi-stage procedure that involves picture acquisition, pre-processing, segmentation, feature extraction, and classification. The purpose of this article was to discuss methods for diagnosing plant diseases using pictures of their leaves. Additionally, this study discussed several segmentation and feature extraction techniques used in plant disease diagnosis. Maintaining the Integrity of the Specifications

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III. PROPOSED SYSTEM

Convolutional neural networks (CNNs) have excelled at picture classification. This research explores a unique strategy for constructing a model for diagnosing plant diseases based on leaf image categorization and leverages ensemble learning using Inception V3 as the basis convolutional neural network model. The new training process and methodology used enable a straightforward and speedy implementation of the system in practise. The created model is capable of distinguishing 13 distinct forms of plant illnesses from healthy leaves and distinguishing them from their surroundings. This approach for recognising plant diseases has been offered for the first time based on acquired information. The article covers in full all of the steps required to execute this sickness detection model, beginning with the gathering of photographs to create a database. For independent class examinations, the experimental findings on the created model attained an accuracy of between 91 and 98 percent, on average 96.3 percent.

IV. SYSTEM DESIGN AND ARCHITECTURE

Prediction process architecture is introduced in fig1 and interaction of users for the process was included. In fig2 the context diagram is shown the interaction of disease information and user's input. In fig3 the flow diagram show the workflow of app data from users registration to prediction. In fig4 the sequence diagram of disease prediction through neural network is shown.

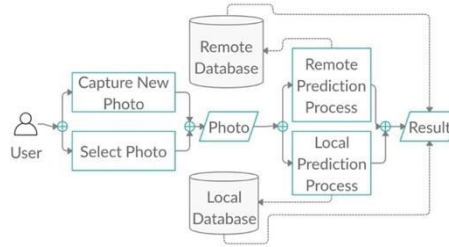


Fig. 1. Prediction process

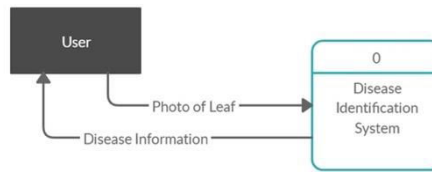


Fig. 2. Context Diagram

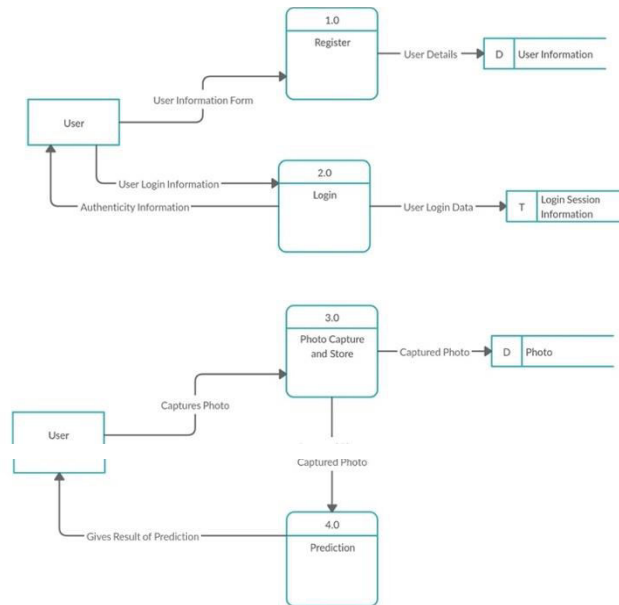


Fig. 3. Workflow of App Data

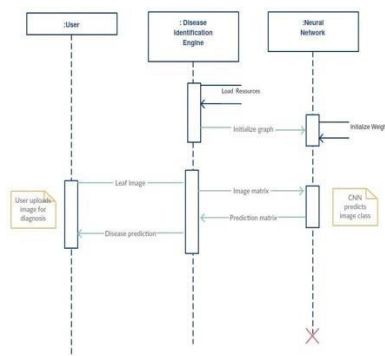


Fig. 4. Sequence Diagram of disease prediction



DATABASE DEVELOPMENT OF PLANT SPECIES AND RELATED DISEASES

Database development refers to the collection of detailed description about species and diseases to provide reliable information to the users after successful inference. Almost all of the data needed for the purpose were collected from the web. On the web, websites like Wikipedia, The Tree Geek, Tomato Disease Help, The Spruce, etc. provided very valuable as well as relevant information regarding the type of plant, scientific names of not only the plants but also the diseases that may attack them, causes of diseases, symptoms and preventive measures along with remedial solutions (if the disease was not preventable).

In order to have a clear vision of the information needed to properly describe and prevent plant diseases, with referring previously completed projects and applications regarding plant disease detection and identification. This projects primary initial collection only includes information about plants and fruits whose dataset we worked in plant village. Most of these species are commonly and abundantly available in South India like apple, tomato, paddy, corn, sunflower, oranges, peppers, potatoes, etc.

The following information was collected which are supposed to be provided for the user about the species and diseases:

- Short description about species of plant
- Cause of disease
- Symptoms of disease
- Mitigation and control measures

For each species of plant used for training the above information was collected. The following table1 shows an instance of the data.

TABLE 1. An Instance of Data in Dataset

Species name	Species scientific name	Disease common name	cause
Apple	Malus	Apple Scab	Ascomycete Fungus Venturia inaequalis

WORKFLOW OF DISEASE CLASSIFICATION SYSTEM

There are two phases in the lifecycle of the model for classification as shown in the fig 5. The training images i.e. well labelled dataset is first fed into the CNN model using machine learning algorithm where the feature vectors are used to train the model.

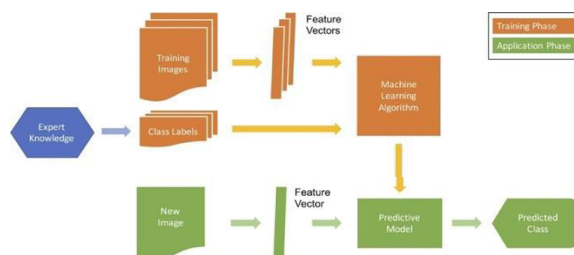


Fig 5. High level overview of image classification system

Training and preprocessing

Plant Village is a database consisting of crop health and crop diseases csv details. The dataset was worked on the standard data records of Plant Village containing 54,309 images collected and verified by expertise. The image is 3-channel (RGB) image with resolution of 256*256 taken in standard condition of lab in Plant Village with only one leaf in an image. The images span 14 crop species: Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, Tomato. It contains images of 17 fungal diseases, 4 bacterial diseases, 2 mold (oomycete) diseases, 2 viral disease, and 1 disease caused by a mite. 12 crop species also have images of healthy leaves that are not visibly affected by a disease[11].



To extend this project study from a standard dataset and test the robustness of image classifier we collected and verified hundreds of extra images of four more species by web scraping. The number of images is comparatively very less with that of plant village thus project study focuses mostly on the Plant Village dataset. The outline of the dataset is described in the below Table 2.

TABLE 2. Extended dataset for four additional species

Almond (Prunus dulcis)	Bacterial leaf (30) scorch	Healthy (21)	Total (51)
Rose (Rosa)	Anthraco-nose (32) Powdery Mildew (40) Rust (94) Leaf Spot (50)		Total (216)
Sunflower (Helianthus)	Leaf Blight (16) Powdery Mildew (34) Rust (18)		Total (68)
Paddy (Oryza sativa)	Bacterial-leaf-spot (40) Brown-spot (40) Leaf-smut (40)		Total (120)

Augmentation

Training CNNs takes a large amount of data. The more data that the CNNs learn, the more characteristics they may acquire. The original leaf image dataset used in this work is insufficient to ensure the robustness of the CNN classifier [18], such that minor distortions in the picture have no effect on the classification result. As a result, it is required to increase the dataset using various ways in order to differentiate the various illness types. A convolutional neural network is translationally invariant but not rotationally invariant. As a result, it may generate more training data by rotating the initial data. Similarly, other various techniques for augmentation have been developed and the transformations this project used is traditional augmentation techniques [12]. The aforementioned approaches augment the dataset, which aids in preventing over-fitting during the training stage.

Normalization

Prior to training the deep CNNs classifier, the pictures in the dataset are pre-processed to improve feature extraction and consistency. Normalization of picture size and format is a critical procedure. All photos in this research are downsized to 256x256 pixels using NumPy scripts during TensorFlow training. This scaling abolished the link between picture, allowing photos from disparate datasets to be combined while being obtained with disparate cameras at disparate heights.

Image Segmentation using watershed algorithm

The deep neural network was fed just raw pixel values, not feature descriptors, which implies that, unlike most standard shape-based classification systems, this network had no prior knowledge of what constitutes a plant and what constitutes a backdrop. This might potentially result in issues where the network learns to recognise the backdrop, resulting in the network being biased against certain classes. When it recognises particular backdrops, which is plainly unwanted [13]. Thus, the system performed an experiment by adding the segmented (background removed) to the training sets and found significant increase in validation accuracy indicating the reduction in biasness. The algorithm in this system is used for segmentation includes well known watershed cut for image segmentation as described below.

Results are more stable, detected boundaries are continuous in watershed algorithm thus its highly preferable technique for leaves image segmentation. In this project experiment more than 30% of images were successfully segmented using this algorithm which was significantly higher than of other techniques like canny edge detection, thresholding etc.

Segmentation of watersheds A watershed is a transformation defined on a grayscale picture in the field of image processing. The term is a metaphor for a geological watershed or drainage split that divides neighbouring drainage basins. The watershed transformation considers the image as a topographic map, with the brightness of each pixel reflecting its elevation, and locates the lines that run along the ridge tops [14].



Fig 6. Leaf images before and after successful segmentation



Fig 7. Leaf images before and after invalid segmentation

In fig 6 and fig 7 it show the leaf images before and after successful and unsuccessful segmentation done by watershed segmentation.

The image of leaf in the available dataset is segmented as shown above Table 2. and was added in the original dataset and the training set was increased by about 30%. The verification of successful segmentation was cumbersome for humans so it was again trained pretrained model of Nasnet Large with accuracy of 98% on the training set for automatic detection and removal of unsuccessful segmentation by taking small number of acceptable and unacceptable samples. In Fig. 8 it shows the mechanism of extraction of well segmented leaf [10].

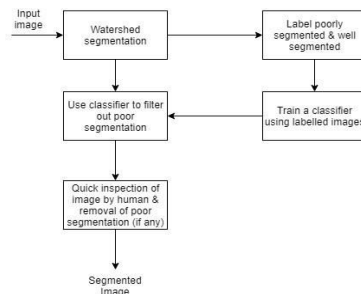


Fig 8. Segmentation flow diagram

CNN MODEL ARCHITECTURE DESIGN

The Inception design is founded on the principle of approximating and covering an ideal local sparse structure in a convolutional vision network with conveniently accessible dense components [16]. Extensive empirical data demonstrates that can gain accuracy when their depth is significantly raised. On the quest of lightweight CNN model for on-device inference various designs were experimented but the architecture consisting of two core concepts viz. Inception module of Googlenet and Resnet was found to perform well enough thus it propose thus designed model, Inception and performed training for each instance of dataset. The high-level architecture is as shown in fig9.

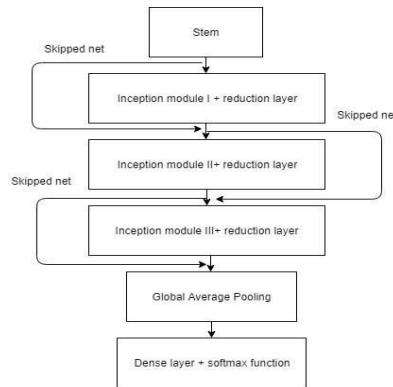


Fig 9. Inception architecture

Stem is composed of three 3*3 convolutional layer in stack thus has equivalent receptive field of that in 7*7 convolutional layer. The max pooling layer filters out the insignificant entities. The inception module first has stack of two 3*3 convolutional layer and the stack decreases subsequently while going deeper with module II and III. The stem layers incorporate the very basic features set like line and edge.

Transfer Learning

Transfer learning is, in simple words, the process wherein the model trained for a task is used again as an initial point to train another model. Transfer learning is an essential mechanism in machine learning to resolve the fundamental dilemma of inadequate practice data. It tries to shift the information from the origin domain to the destination domain by slackening the premise that the practice data and the test data need to be comparable. The problem of inadequate data is unavoidable in many circumstances. The whole process of data collection and refining is cumbersome and requires time and patience[17]. The Transfer learning process is illustrated in Fig 10.

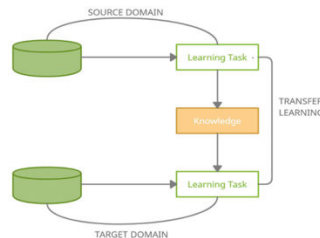


Fig 10. Transfer learning process.

The main aim of deep transfer learning is to utilize knowledge gained in some other domain. Here, the source domain and the target domain need not be identically equivalent. In this research, it has designed an ensemble of three deep learning models, each of which is built upon a pretrained base model and two custom CNN [17] shown in Fig 11

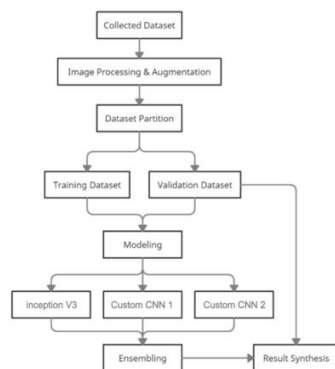


Fig 11 Ensembling three models

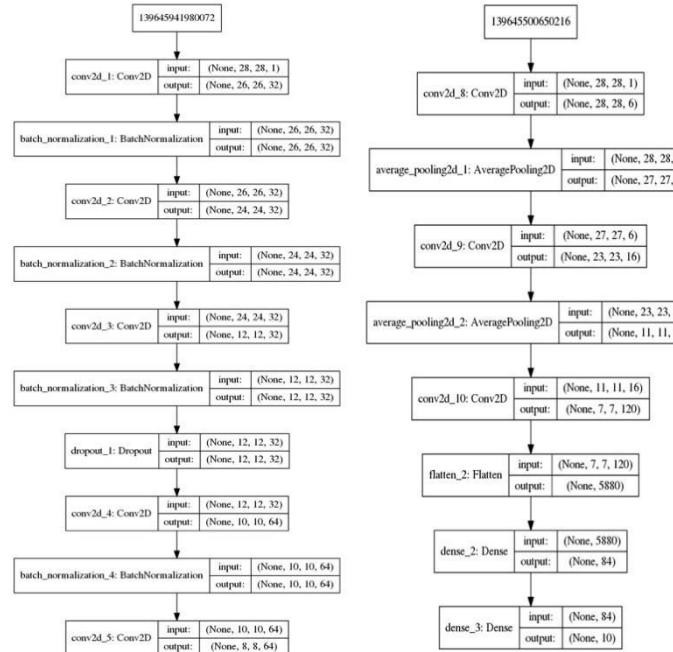


Fig 12 Custom CNN summary (a) and (b)

The model presented above is rather basic. It follows a standard structure of many convolutional layers followed by a pooling layer. Only the last levels of this model may be new to some. Rather of employing many completely linked layers, a global average pooling layer is employed.

The following is a high-level summary of how the global pooling layer works. Conv2D(10, (1, 1)) generates ten feature maps corresponding to ten output classes. The GlobalAveragePooling2D() layer then computes the spatial average of these ten feature maps, resulting in a vector with a length of 10. Following that, the vector is subjected to a softmax activation. As you can see, this strategy is equivalent to employing FC layers at the model's top.

Nota bene: no activation function is applied to the output of the final Conv2D(10, (1, 1)) layer, as this layer's output must first pass through GlobalAveragePooling2D()[9].

The custom CNN2 fig(b) model is quite similar to the preceding one. The only real distinction is that convolutional layers with a stride of two are utilised instead of max pooling layers. Again, no activation function is utilised immediately following the Conv2D(10, (1, 1)) layer. If a ReLU activation is applied directly after that layer, the model will fail to train.

Each of the three models (Inception V3, Custom CNN1, Custom CNN 2) is reinstated, and the best stored weights are loaded. The definition of an ensemble model is rather basic. It makes use of the same input layer as the preceding models. The ensemble computes the average of the outputs of three models in the top layer using the Average() merging layer.

After training the model, you may convert it to the Tensorflow Lite version. The TF lite model is a particular format model that is very accurate and also a light-weight version that gives up less-space; Fig 13 represents the tensor flow lite conversion process of a model by both the ends.



V. RESULTS

Table 4 summarises the classification accuracy and F1 score for each model for the two fundamental training/testing procedures for the 18 species categorization classes.

The fine-tuned Ensemble model achieves 99.73% of validation accuracy and nearly equal F1-score representing the balance in precision and recall. The mobilenetV3 on the other hand being extremely small CNN model could not depict enough information to classify large number of classes (18) and could gain accuracy of only 78.44%[8].

With training/testing in an 80/20 ratio and the segmented and original images in the first case, and with the original images in the second case the table also depicts the contribution of segmentation in increasing validation/training accuracy and even F1-score of the model. The top-1 training accuracy increased by 0.33% in training set and 0.13% in validation set for Ensemble model while the increment was 1.61% and 0.81% for Mobilenet V2. The accuracy of each species performed by MobilenetV2 and Ensemble model is shown in Fig 14.

TABLE 4. Performance of MobilenetV2 and Ensemble model architecture for the identification of 18 species classes on the training/testing dataset.

CNN Model	Segmented and Original dataset				Original dataset			
	Train		Test		Train		Test	
	Top-1 Accuracy	F1 Score	Top-1 Accuracy	F1 Score	Top-1 Accuracy	F1 Score	Top-1 Accuracy	F1 Score
Ensemble model	0.9873	0.9870	0.9973	0.9966	0.9840	0.9844	0.996	0.996
Mobilenet V3	0.7561	0.7547	0.7844	0.782	0.74	0.75	0.7763	0.7682

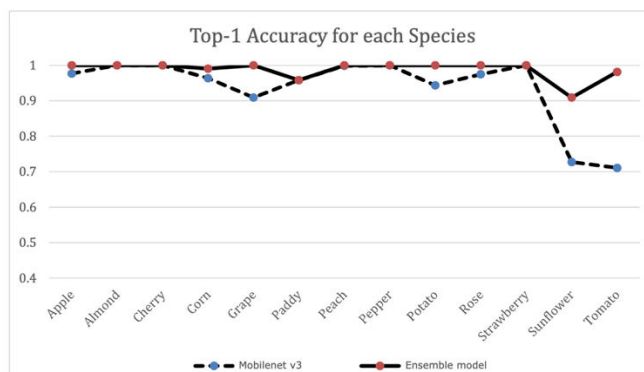


Fig 14. Accuracy of each species performed by MobilenetV2 and Ensemble model.

VI. CONCLUSION AND FUTURE WORK

An accurate and efficient image classification system has been developed which achieves comparable result with the existing state-of-art system. The project uses ensemble techniques in the field of neural networks. This application is very useful for the farmers to detect the disease within no time, such that the prevention of the disease from a wide spread can be stopped.

Still the concept of medication and details about those disease are yet to be included. Also, by the availability of a large dataset, and more number of classes that can built a more efficient model, hence this can know the ability of model working and its accuracy. In future, by using more efficient pre-model that can achieve much better accuracy.

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