Research Progress on Acquisition and Processing of Rice Disease Images Based on Computer Vision Technology

Hui Li
Department of Information Technology, Chengdu Agricultural College, Chengdu, Si Chuan,611130,China
Lhdxl2005@163.com

Abstract. Rice diseases are an essential factor that affects rice yield and quality, and carrying out researches on rice disease recognition and detection methods is of great significance to the promotion of green and high yield, stable yield, and high-quality and efficient development of rice. The recognition of crop diseases with computer vision technology is characterized by non-destruction, rapidity, real-timeness, and accuracy, etc, and has far-reaching influence on accelerating agricultural modernization and improving production efficiency. Recognition and detection of crop diseases have become a focus and front of research in the field of computer vision technology. The acquisition and processing techniques of rice disease images are researched in this paper, and the basic principles, key techniques, realization methods, and application effects of some typical methods are also analyzed, in the hope of providing reference for the researches on rice disease recognition. Prospect of future development trend and research direction in this field is also predicted.

1. Introduction
Rice has been the most widely planted grain variety in China, with the highest total yield and the highest yield per unit area, and also among the main grains for the Chinese. Nonetheless, many diseases often occur during the growing period of rice, such as rice blast, bacterial blight, and sheath blight, which may reduce the yield, pollute the environment, and also cause huge economic losses. Traditionally, rice disease judgment mainly relies on manual collection and classification of field samples based on human experience, and this method features shortcomings such as a low recognition speed, strong subjectivity, high misjudgment rate, and low efficiency, which has no longer met the needs in agricultural production. As precision agriculture and smart agriculture emerge, the application of computer vision technology into agricultural production as an aid has offered a fresh perspective for recognizing crop diseases. Crop disease recognition based on image processing technology can raise the accuracy, objectivity, and recognition efficiency of disease recognition, and provide technical support for automatic, intelligent, precise and scientific management of crop disease recognition; it is of great significance to timely and accurate determination of disease types, disease control, and reduction of farmers’ economic losses. So far, a large number of scholars in China and abroad have conducted deep researches into recognition and detection of rice disease images with computer vision technology, and most researches focus on four aspects: image acquisition, image processing, feature extraction, and classified recognition. In this paper, current researches on the two aspects of image acquisition and image processing in China and abroad are introduced to provide reference for follow-up researches.
2. Acquisition of rice disease images

In terms of acquisition devices for rice disease images, high-resolution digital cameras, digital video cameras, and digital scanners are predominantly adopted as image acquisition equipment. Literature[1] adopts a Nikon D80 digital camera, a metallic photography tripod and head, a SONY FCB-H111 high-resolution camera, a video server, and a constant-speed spherical head. The digital camera and the high-resolution camera can both rotate for 360 degrees, and, under the condition of natural lighting in the field, directly realize image acquisition from any angle of shot. The number of rice disease types acquired with this method is highly limited, and the research only includes image acquisition of leaf damage symptoms for six common typical rice diseases, and the disease image acquisition of different damaged positions of rice root, stem and ear requires further improvement. In Literature[2], for overcoming the shortcoming of digital cameras’ unsuitability for acquiring long and narrow rice leaf images, an EPSON scanner is adopted to acquire digital images of disease samples in vivo; sample image acquisition is conducted based on different resolutions, and different image processing methods are applied to images with different resolutions. Image acquisition with this method is done under a laboratory environment, unsuitable for rice image acquisition under real and natural field environments. Despite promotion of information technology into agricultural research and application, such methods can hardly be extensively applied and promoted in real production due to high costs, operational inconvenience, and lack of portability.

In recent years, as smart phones are increasingly available to all, their image processing ability and computing ability have been dramatically improved. Since rice disease images are acquired in the field, the light-weight, convenience and accuracy of smart phones can better satisfy the special requirement of field operation, offering a fresh solution and method for rapid recognition and processing of rice crop diseases. In Literature[3], a distributed mobile acquisition and diagnosis system for agricultural disease and pest images is designed, consisting of several portable image acquisition terminals and one image processing server; by installing a hand-held pole onto the front of camera, images of disease and pest areas inaccessible to hand or vision can be acquired; the HTTP protocol is adopted for data interaction between several acquisition terminals and the image processing server for cooperative, distributed computation, and the server end processes and diagnoses the disease images and feeds back the results to the smart phone. This system is appropriate for acquiring disease images at the middle and lower parts of rice; however, since rice stems and leaves are seriously covered and overlapped, the acquired image data information is not sufficiently objective and accurate, somewhat affecting the accuracy of disease image recognition. In Literature[4], common rice diseases are taken as the object of research, and Android cell phones are adopted to conduct acquisition, preprocessing, enhancement, segmentation, feature extraction and recognition of rice diseases images; moreover, a rice disease image recognition system is developed based on the Android cell phone client to realize diagnosis of rice disease images. However, in this method, square planks covered with black cotton cloth are adopted to clamp the blade for fixed shooting, and disease image acquisition is limited to uniform light and simple backgrounds, unsuitable for rice image acquisition and diagnosis under natural and complex backgrounds. Another method is put forward in Literature[5][6], in which a cell phone client acquires, compresses, and uploads disease images on a real-time basis and a remote server conducts recognition and returns the result; a Android-based smart diagnosis platform for rice disease is also built. This platform can effectively solve problems such as the low image processing ability of client, and slow image uploading, and it is thus rather practical. Nonetheless, its method of feature extraction from complex backgrounds needs improvement; the image diagnosis accuracy is not high; the effect of image compressions is not ideal enough; the classifier algorithm also needs improvement. A hand-held device for acquisition of rice plant hopper images is designed in literature[7], in which an Android cell phone controls the camera to acquire images of plant hoppers at the rice base and the images are uploaded via the HTTP protocol to the background server. The dynamic link library of recognition algorithms for main rice diseases and pests is called at the server end to accomplish rice recognition, and the result is fed back to the Android phone, realizing automatic recognition of rice pests. No research is conducted on the method of background removal in rice pest images in this literature, and
the acquisition and processing of complex rice disease images in real fields require improvement. Literature[8] adopts the open-source software LAMP and client development environment, and has proposed and developed an Android-based rice pest diagnosis system. Its system server end adopts an open design, and authorizes users to modify and update the rice pest data; the cell phone client may conduct classification according to the pest body size, damaged position, symptom, and characteristics, and then conduct real-time diagnosis based on text descriptions of pests and comparison with pictures. Disease and pest images are acquired through Android phones in literature[9], and the phones may also clip the acquired images to reduce the data transmission quantity. The to-be-recognized images are sent to the remote server through the HTTP protocol, and the server end receives the image data, calls the library of rice disease and pest algorithm recognition, accomplishes recognition of rice diseases and pests, and then returns the recognition result and diagnosis information to the client, realizing non-destructive, timely, and accurate recognition of rice diseases and pests. During this process, the Android phone may clip the acquired images, which, while reducing the data transmission quantity, facilitates subsequent image analysis and shortens the time of system operation.

With the development of the times and technological advancement, UAVs have been increasingly extensively applied into agricultural production. The UAVs used for field image acquisition may be small fixed-wing or multi-rotary-wing UAVs, carrying high-resolution digital cameras. In literature[10], a recognition method for the white panicle disease in the rice field was put forward. It utilizes small multi-rotary-wing UAVs to acquire rice field images and realizes rapid and accurate recognition of the white panicle disease in the rice field based on Haar-like features and Adaboost training algorithm. In literature[11], UAVs cruise at a low altitude, take photos of rice periodically during the cruising flight, and return the photos and position information of rice; the earth station processes the aerial rice images, selects the areas with suspect infection of Cnaphalocrocis medinalis, and finally conducts human field observation in the recognized suspect areas with diseases and pests.

To sum up, in terms of image acquisition devices and acquisition methods, the existing researches on image acquisition are mainly based on four methods:

Method 1: Samples of blades, etc, from to-be-detected crops are collected in the field and taken back to the laboratory; fixed devices for crop disease image acquisition are set up to accomplish detection of sample blades. In this method, detection hardware and photographing environments are relatively stable, and the acquired images are quite standardized and uniform, free from any influence of external environment changes such as weather or wind force or of any angle of shot; the image processing algorithm can be relatively easily realized. Nonetheless, a downside exists that blade samples of to-be-detected crops must be collected in the field; once separated from the plant itself, the collected sample may wither or be damaged, etc, due to storage or failure in timely transmission, so that the blade color or morph changes, affecting correct recognition of disease images. Moreover, image acquisition relies on specific laboratory acquisition devices, with high costs, lacking universality and versatility, difficult to be extensively applied into real agricultural production.

Method 2: Digital cameras or scanners are adopted to directly acquire and store image information, free from the inconvenience of setting up laboratory acquisition platforms, significantly reducing acquisition costs. However, for acquiring images, it remains necessary to photograph in the field and then take images back to the laboratory for computer equipment to read images, which is a complex procedure; besides, camera resolution, weather, and illumination influence may increase difficulty in the subsequent image processing algorithm.

Method 3: Mobile phones are used to photograph images and timely send them back to the image recognition system, which realizes real-time disease detection, features advantages such as easy operation, flexible use, universality and high practicality, and also raises higher requirements for the related image processing algorithms.

Method 4: Aerial photography of rice field is conducted based on the UAV technology to acquire sample information and return the data on a real-time basis; the earth station may conduct real-time recognition of disease type, disease area, and disease severity through the disease and pest recognition system and software. The technology of crop disease and pest image acquisition with UAV helps to
develop a more complete platform system of 3-dimensional spatial dimensions and with more layers; it is an essential supplement to the information acquisition technology of precision agriculture, and lays a foundation for low-cost, efficient, flexible, and real-time acquisition of crop information of large areas and high spatial resolution.

3. Processing of rice disease images

Image segmentation is an early step of image processing process. It segments the image into sub-regions or objects of features (i.e., image structure, color, grayscale, texture, etc), and is a qualitative conversion during image processing, which is the basis for both the extraction of feature value and the construction of classifier. Image segmentation has always been one of the most challenging tasks in image processing technology, and also a focus of research for Chinese and foreign scholars. The image segmentation technology can be mainly divided into two categories[12]: (1) The boundary methods utilizing the discontinuity of image grayscales: these methods are based on the discontinuity of grayscale usually existing on the boundary among the regions of different objects in the image, such as the edge detection method. The boundary segmentation methods consist of parallel boundary segmentation and serial boundary segmentation. In image processing with the serial boundary segmentation methods, the information of pixels processed one after another is considered together, and whether the current pixel is treated as a boundary point is related to the information acquired from previous processing of other points. (2) The region methods utilizing the similarity of image grayscales: these methods are based on the usual grayscale similarity in the regions of the same object in the image, such as thresholding segmentation, and region growing. The target of region segmentation is to, by using image features, map single pixels in the image into a pixel set. The effectiveness of region segmentation algorithm largely depends on the field of application and the input image. The region segmentation algorithms are further divided into parallel region segmentation and serial region segmentation, of which parallel region segmentation can be further divided into two categories (thresholding segmentation, and clustering)[13,14] and serial region segmentation can be divided into two categories (thresholding segmentation, and clustering)[13,14] and serial region segmentation can be divided into two categories (thresholding segmentation, and clustering)[13,14] and serial region segmentation can be divided into two categories (thresholding segmentation, and clustering)[13,14] and serial region segmentation can be divided into two categories (thresholding segmentation, and clustering)[13,14] and serial region segmentation can be divided into two categories (thresholding segmentation, and clustering)[13,14] and serial region segmentation can be divided into two categories (thresholding segmentation, and clustering)[13,14].

3.1. Edge detection method

The edge detection method is essentially to extract the boundary between the object and the background in the image; the gradient of image grayscale distribution is adopted to reflect the variations in image grayscales, so as to utilize the local image differential technique to acquire the edge detection operator. Common edge detection operators include the Roberts operator, the Sobel operator, the Prewitt operator, and the Laplacian operator[15,16]. In literature[17], the rice leaf blade image receives extraction of minimum bounding rectangle and denoising of median filtering; the Canny operator is adopted for edge detection, and opening operation and closing operation are adopted for stitching discontinuous edge points and removing non-boundary information, so as to put forward an algorithm for rice blade edge detection based on the multi-strategy integration technique. When this method is applied to images of blades with different features such as the background of whiteboard, soil or overlapping blades, relatively continuous and smooth edges of rice blades are acquired. This algorithm is characterized by high efficiency, accuracy, and robustness, providing technical support for non-destructive detection of images of rice blade edges. RGB images of rice leaf blast are taken as the object of research in literature[18] to calculate the $2R - G$ color difference component model. The Canny algorithm is adopted for edge detection, and the closed non-disease-spot boundaries are removed through edge repairing and filtering; repairing of edges of rice leaf blast spots can close some broken boundaries. The information of normal blade position extracted with the H component of HIS model and the repaired image are used for mask operation to acquire the result of disease spot boundary within the leaf blade, and DNGBI thresholding segmentation may be utilized to detect the common type of rice leaf blast.

With the edge detection method, the segmentation problem is solved through abrupt changes in the pixel grayscales at the edges between different regions; the abrupt change value of grayscale in the
crop disease region is great. Segmentation with the edge detection method is characterized by advantages such as simple and easy operation, and the disadvantage that the segmentation efficiency of edge detection algorithm relies on the edge detection operator, with poor robustness.

3.2. Thresholding segmentation method
Thresholding segmentation is a common, simple, and efficient image segmentation method. By setting one or several thresholds, it divides the grayscale of image into several parts, and compares the thresholds of pixels to divide pixels; the pixels of the same part constitute a whole[19]. Thresholding segmentation is the earliest applied method in researches on recognition of agricultural disease and pest images. The classical Otsu's thresholding method is adopted in literature[20]. The traverse method is applied to obtain the maximum value of intra-class variance between the object and the background so as to automatically research and determine the best threshold for image segmentation, without any need of human intervention. Images of Cnaphalocrocis medinalis spots are accurately extracted from original images. This method is with good adaptability, yet with random noise and even incorrect segmentation results. In Literature[21], canopy images are segmented by setting threshold values based on the magnitude and distribution of the green channel minus red channel (GMR) value, and then correlations are established between image feature parameters and the 3 plant indices (i.e., above-ground biomass, N content and leaf area index) before and after image segmentation. Results show significant exponential relationships between the image parameters and the plant indices. The edge method and the region method are adopted, respectively, in literature[22] to segment images of rice plants. The experimental results show that, due to the complexity of growing environment of rice plant, it remains difficult to apply the edge method to segmentation of rice plant; with the region method, since the grayscale of rice plant largely overlaps the surrounding environment, it is also difficult to segment rice plants directly through region segmentation based on the gray chart. In view of the characteristics that the R component of RGB color image of rice plant is smaller than that of the surrounding environment, the G component is close to that of the surrounding environment, and the difference between the rice plant and the surrounding environment in the ratio image of G component to R component is great, the iteration method is adopted to select thresholds during the extraction of rice plant in large quantities of images, and the thresholding segmentation method is adopted for segmenting the ratio image; the results of detected rice plants are relatively ideal.

The thresholding segmentation method is characterized by simplicity and high execution efficiency, and its difficulty lies in threshold selection. The disease region and non-disease region of crops often show dramatic differences in features such as color and texture; analyses of grayscale histograms of the two may vividly find the threshold and realize image segmentation.

3.3. Mathematical morphology method
Mathematical morphology adopts structural elements with certain morphs to process and extract the similar shapes of images so as to simplify the images and retain the needed basic information of shapes. As a discipline established on the basis of strict mathematical theory, mathematical morphology has significantly affected image processing and has been applied into digital image analysis and processing in many disciplines. Great progress has been achieved in the application of mathematical theory method into the field of agriculture, with priority given to the recognition of crop diseases. The researches on mathematical morphology are mainly divided into binary morphology, grayscale morphology, and color morphology. In literature[23-27], mathematical morphology is applied to segmentation of wheat leaf disease images, seedling stage blade images of Moth orchid, apple blade images, and cotton blade images acquired under complex backgrounds, with certain research progress. The mathematical morphology method is adopted in literature[28] to segment images of rice canopy, and, in combination with the grayscale median method, features such as height and area of rice canopy are extracted, with remarkable effect. In Literature[29], with the ellipse model, ellipse fitting is conducted to the biggest disease spot of individual rice plant with rice blast, and the length of principal axis of ellipse, i.e., the length of the biggest disease spot, is calculated to predict the
extent and grade of rice blast; ellipse fitting is conducted to the length of individual rice plant with sheath blight and the distance between the highest position of disease spot and the base, and the lengths of principal axes of both ellipses and the ratio of the two are calculated to predict the disease extent of rice sheath blight, resulting in good achievements.

The mathematical morphology method has effectively overcome low precision and poor effect of image segmentation. Morphological operation is essentially a two-dimensional convolution operation; the operational speed is slow when the number of image dimensions is great, so it is inappropriate for application in systems with real-time processing function[30]. The mathematical morphology method is sensitive to boundary noise, and its precision problem in segmentation of images under complex growing environments is rather obvious. The selection of structural elements is the key in morphological operation, but there has been no uniform selection standard yet; different structural elements exert different influence on the result of morphological operation, and the image processing method of morphological operation based on multiple structural elements is the key research direction in future.

3.4. Clustering method
The clustering analysis method, also known as cluster analysis, is a statistical analysis method for researching classifications (of samples or indicators) and also an important algorithm for data mining. Clustering analysis is based on similarity, and there are more similarities among the patterns in a cluster than those among patterns in different clusters. The clustering analysis method has abundant contents, including the hierarchical clustering method, the K-means method, the ordered sample clustering method, the dynamic clustering method, the fuzzy clustering method, the graph theory clustering method, and the clustering forecast method. Data of crop disease and pest images are characterized by fuzziness and uncertainty, and the membership function in fuzzy clustering just happens to realize modeling of fuzziness and uncertainty in images so as to be effectively applied into image segmentation. As early as in 1989, the fuzzy clustering method was adopted in literature[31] to conduct classified predication of occurrence extents of nine major rice diseases and pests and analysis of disease and pest occurrence trend; its accuracy totally depends on the reliability of analytical factors, i.e., the coincidence between the diseases and pests and the actual occurrences. Therefore, methods such as stepwise recursion, multiple regression, and fuzzy multi-level comprehensive evaluation are then required to conduct scientific statistical analyses of all forecast factors and identify the correlation factors for occurrence of each disease and pest. In Literature[32], artificial inoculation is conducted to detached leaves of 42 rice varieties, and systematic clustering analysis is applied to the virulence difference of 21 isolates of Magnaporthe grisea and the multiple indexes on rice blast resistance of 42 rice varieties, respectively; the rice varieties are divided into seven categories, and their strain virulence is significantly different; the pathogenic frequencies of strain are highly negatively correlated with the average virulence; the result is of certain practical significance to breeding of new blast resistant rice varieties, rational distribution of blast resistant rice in the area, and prevention and control of rice blast outbreak. In literature[33-35], clustering analysis is conducted to rice blast resistance, brown plant hopper resistance, and rice gall midge resistance, respectively, providing reference to the diagnosis and treatment of rice diseases and pests.

The advantages of clustering method are vividness and brief and clear conclusions. However, it is somewhat difficult to reach clustering conclusions for a big sample quantity; it is sensitive to image noise and initialization data; the amount of algorithm operation is rather big; it requires further improvement and optimization in its practical application in agricultural production.

3.5. Neural network
In the late 1980s, segmentation methods based on neural networks emerged from the influence of artificial intelligence development, and sample image data were used to train the multilayer perceptron to determine the connection and weight between nodes and finally to acquire the decision function, so that the acquired decision function and well-trained neural network may classify images to obtain
segmentation results. Depending on the categories of data processed by specific methods, there are the neural network segmentation algorithm based on image pixel data and the neural network segmentation algorithm based on image feature data. It is proposed in Literature[36] that the method of training BP neural network can be used to segment images of rice seedling blights; the RGB color component of image is taken as the sample for training, properly retaining the texture features of image, overcoming the restriction of color and surrounding influence in plant segmentation with traditional image segmentation methods, achieving satisfactory segmentation effect, and laying a preliminary foundation for further analysis of diseases and pests in plant images. BP neural network classifiers are designed for classifying the healthy and diseased parts of rice leaves in literature[37]. This paper selects rice brown spots as the object of research; the training and testing samples of the images are gathered from the northern part of Ningxia Hui Autonomous Region. The result shows that the scheme is feasible to identify rice brown spot using image analysis and BP neural network classifier.

Since the neural network is characterized by massive connectivity and easy introduction of spatial information, its application into image segmentation effectively overcomes noise and non-uniformity problems in images[38]. The selection of the type of network structure is the main issue to be addressed for applying the neural network method into image segmentation.

3.6. Deep learning
Deep learning has been a vital technical means in the field of image recognition in recent years, and it has achieved remarkable effects in many image segmentation tasks and in the field of computer vision. The introduction of convolutional neural network, in particular, has been highly effective in image segmentation and feature extraction and successfully applied into computer vision fields such as detection, segmentation, and object recognition. Deep learning has been used into numerous common datasets; it has been possible that, after a picture is input, the results of pixel-by-pixel segmentation can be output, without any pretreatment in between, and its precision far exceeds that of other algorithms. A model combining CNN and capsule network is proposed in literature[39] for recognition of crop disease and pest images, achieving an exceptionally high correctness of image recognition with the model and creating conditions for ongoing development of deep learning technology. In literature[40], based on the deep learning framework of Caffe, a fully convolutional neural network (FCN) is built to, with supervised learning methods, segment blade images through dataset annotation and dataset labeling. Based on the pest image database under light trapping and the field disease and pest image database, in Literature[41], frameworks for automatic feature learning, feature fusion, recognition and position regression calculation of disease and pest types are constructed based on deep learning methods, and a mobile intelligent pest sensing device and an automatic recognition system are also developed, realizing automation, smart operation and high efficiency of crop disease and pest recognition in the field. A deep convolutional neural network is adopted in Literature[42], and the data augmentation technique and the fine-tune method are used for tuning and building of the network; images of eight common rice diseases collected under natural scenes are input into the network model for training and testing, achieving high recognition precision under a limited image quantity; different from other methods which exclusively focus on rice leaves or panicles, the images recognized in that paper are scenes of multiple rice plants, which may provide critical technical support for automatic remote diagnosis of rice diseases. In view of problems such as strong dependence on specific image features and low recognition efficiency in traditional rice disease recognition technology, it is proposed in literature[43] that the deep learning theory should be applied into rice disease recognition in the hope of achieving satisfactory recognition effect. A rice disease recognition model is built through the use of deep convolutional neural network; data of three main rice diseases are normalized, and the deep learning framework Keras is used to perform deep CNN training. Through setting of different convolution kernel sizes and pooling functions, researches are made on classified recognition of three common rice diseases. This model is characterized by a strong generalization ability, high accuracy, good robustness, and small loss rate, providing reference for researches on plant disease...
recognition. A convolutional neural network is used in literature\cite{44} for recognition of rice sheath blight; comparison is also made with the recognition method based on support vector machine, with satisfactory recognition effect.

With the two characteristics of local connectivity and weight sharing, deep learning dramatically reduces the quantity of model parameters, so that the model can be built to a highly deep level, enjoying advantages such as rapid recognition and high accuracy. Nonetheless, problems such as big training samples, complex model structures, and low correctness of complex image recognition exist in the image recognition methods in the field of deep learning, requiring further researches and practice.

4. Conclusion and prospect
Relatively comprehensive review is made in this paper on methods of acquisition and segmentation of rice disease images based on computer vision technology. In terms of image acquisition, image acquisition equipment is constantly developing in an increasingly digitalized, networked, integrated, intelligent, high-resolution, and mobile manner; image acquisition methods are also shifting from information acquisition based on a small quantity of image samples in traditional laboratories to acquisition of sample information of massive data based on large-scale intelligent farmlands, meeting the needs of fine and intelligent agricultural production. In the field of image segmentation research, some noticeable research tendencies have also emerged: (1) As each method of disease spot image segmentation has some disadvantages, while some theories of emerging disciplines are introduced, appropriate segmentation algorithms are selected based on the object and scope of research, or alternatively, several segmentation algorithms are effectively combined and used, resulting in better segmentation effects. (2) As the types of rice diseases are numerous and the shapes, colors and textures of disease spots are characterized by great complexity, diversity, and irregularity, it is a main direction of current research to select appropriate segmentation algorithms based on a single feature of shape, color or texture, etc, of disease spot or a combination of multiple features. (3) Since acquisition and obtaining of rice disease images are affected by multiple factors of natural environment, such as wind force, illumination, temperature, humidity, and background, the segmentation of large-scale images under complex and real, natural scenes will still remain to be a focus and difficult point of research, and there is still huge potential for improvement in the research on rapidity, high-efficiency, and robustness of image segmentation algorithms.(4) With the rapid development of big data, IoT, and artificial intelligence technology, intelligent image segmentation and massive data processing will be of profound significance to recognition and processing of crop diseases.

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