Artificial Intelligence Enabled Internet of Things for Maize Plant Diseases Detection

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Abstract Diseases affect the quality of corn crops and reduce the efficiency of agriculture production, resulting in a significant loss to the farmers. Currently, Rwandan farmers utilize naked-eye observation to identify maize diseases, which necessitates being well trained and experienced, as some plant diseases are difficult to recognize. To overcome limitations presented by these techniques, Internet of Things (IoT) and Artificial (AI) technologies are great imperative technologies for making farming more efficient. In this research, for early maize plant disease detection, an AI-enabled IoT mobile application is proposed to help farmers accurately detect maize plant diseases earlier during growth stages. For detecting plant disease, a plant image is captured by the camera and transmitted to the local server running on raspberry pi with the help of an android application. Plant images are fed to the AI model which determines the types of disease and recommends further remedial steps to the farmer. Various performance indicators, such as classification accuracy and processing time, were used to evaluate our system. The model has an overall classification accuracy of 80%.

Keywords: Internet of Things, Artificial Intelligence, Mobile Application, Raspberry pi, Neural Network, Maize plant diseases detection

1. INTRODUCTION

The agricultural sector has a huge contribution to the Rwandan economy[1]. Agriculture provides the majority of the country's labor[2], where 79.5% of the population is directly dependent on this sector[3]. For small-scale farmers in the country, maize has become a major crop for food security and income-generating[4], [5]. Approximately, half of Rwanda's maize is grown in the East Province, and roughly 60% of it, is sold through Rwanda's manufacturing industry [6]. According to the Ministry of Commerce (MINICOM) report of 2014, informal commerce accounted for approximately 80% of the maize sold in the country.

Recently, the number of maize diseases increased, mainly due to the degradation of agricultural land, and climate changes, which in turn affect crop productivity[7]. Plants are not only affected by a lack of nutrients, but also by microbes such as fungi, bacteria, viruses, and mites [8]. These types of transmitted diseases are quite dangerous since they affect large farms. Precaution measures should be implemented to ensure that crop yields are maintained. Among the various diseases that affect maize plantations, leaf diseases are critical and lower the crop yield and food nutrition value[9].

Currently, the identification of plant diseases mostly depends on the naked eyes for small-scale farmers and this often brings issues, such as farmers misidentifying a disease by judging it from

their experience, resulting in the use of improper pesticides[10]. To address this, experts and pathologists are employed to help farmers with plant disease identification and their remedies[11]. However, due to the shortage of experts, they can't reach all farmers in real-time [12]. If the diseases are identified promptly, appropriate remedies can be applied and crop loss can be prevented[13]. For maize disease detection, regular inspection of cornfields is required.
In Comparison to human vision, computer image processing is a step forward since it can identify features like speediness of a large amount of data and distinguish even small diversity which human vision cannot[14], [15]. As a result, image processing can assist farmers in precisely identifying the condition and recommending the appropriate treatment.
According to existing research, different AI algorithms were used by previous researchers for plant diseases detection such as a K-Nearest Neighbors (KNN), Logistic Regression, Random Forest, Gradient Boosting, Support Vector Regression (SVR), Adaptive Neuro-Fuzzy inference, and Image classification using deep learning has proven to be helpful[16]–[21]. However, the previous researcher did not address how plant diseases can be controlled remotely. Existing solutions require that farmers be on the field to take the picture of a plant. This is time-consuming for farmers having a large plot of arable land.
In this study, researchers implemented a system based on TensorFlow Lite python running on Raspberry pi and controlled remotely through a mobile application to perform real-time image classification using image streaming from a pi-camera. By using deep learning technology, the system was able to classify the types of maize leaf diseases and monitor the farm remotely with the help of IoT technology.

2. METHODOLOGY

2.1. Dataset

For implementing this research study, the researcher has collected different types of data for creating an appropriate dataset for the classification of maize plant leaf diseases. The dataset images used are from corn plantations obtained from the plant village dataset originally hosted at the Kaggle dataset[22].

2.2. System architecture

The system architecture presented in Figure 1, shows how to use a Raspberry Pi to detect plant leaf diseases and display the results on an Android app using Wi-Fi technology.

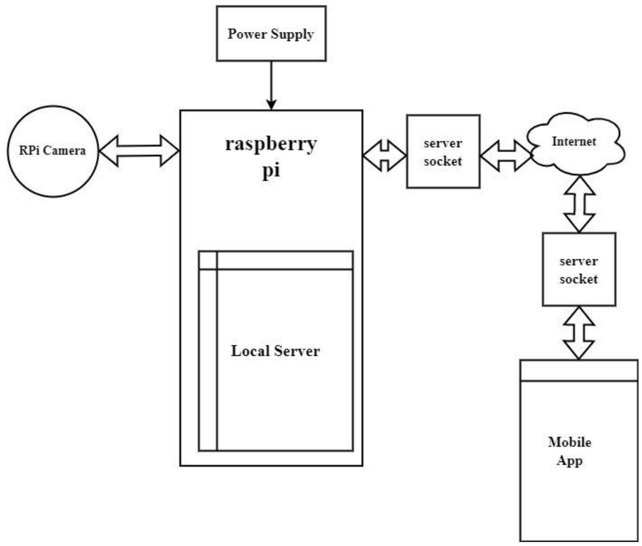


Figure 1. Block diagram

The Raspberry pi acts as the main controller. AI model is running on the server implemented in Raspberry pi this is used for processing the picture sent from the mobile app and sending back the result after analysis. A picture can be taken by using a raspberry pi camera module or smartphone camera. The Raspberry pi camera module is connected to Raspberry pi as shown in Figure 2 and is controlled by a mobile app. Socket allows communication between raspberry pi and mobile apps through internet connectivity.

Figure 2. RPi camera connected to raspberry pi

The mobile app is used to upload a picture to the local server running on raspberry pi either by taking a picture from an RPi camera, by using a phone camera, or by selecting a picture from Gallery as shown in Figure 3.

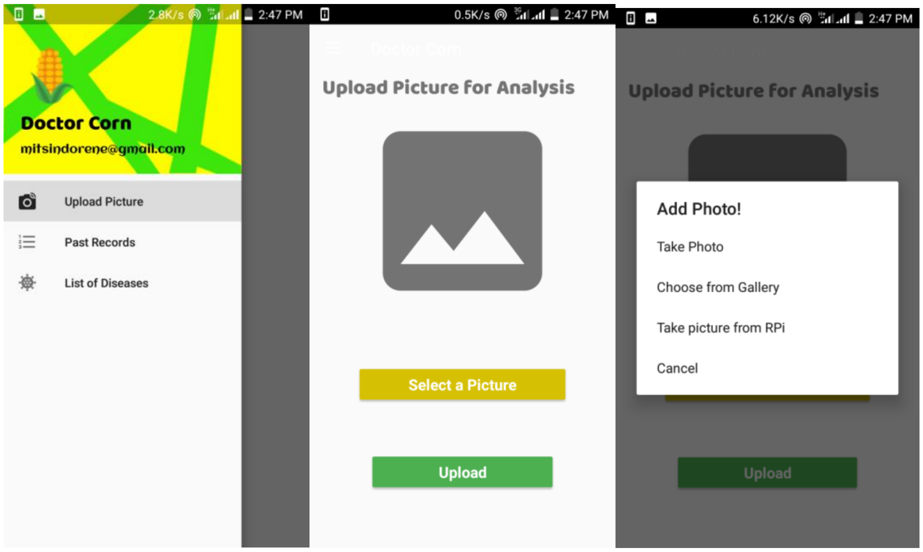


Figure 3. Steps for taking and uploading pictures using a mobile app

Figure 4, indicates the flow of information from sensing data in the farm up to the end-users through the display of information on the mobile application.

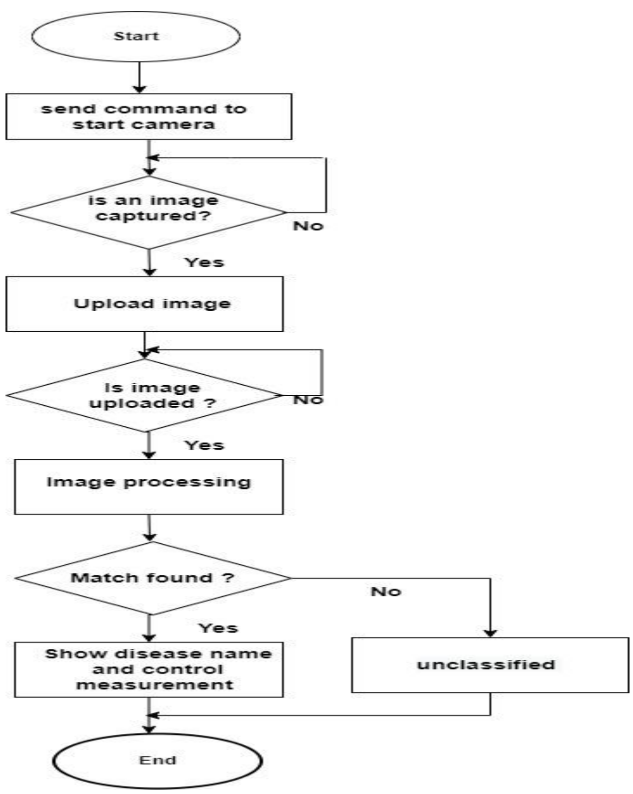


Figure 4. Steps for taking and uploading pictures using a mobile app

The model accepts an image of a maize leaf of the user's choice as input, classifies it by comparing it to the pre-saved characteristics of each of the four states (blight, common rust, gray leaf spot, and healthy) that the leaf might be in, and then returns an array of four probability values ranging from zero (0) to one (1), with the highest value among them representing the category that the leaf is most likely to be associated with.

This array will then be compared to a preset array of similar size that contains strings of the names of the classifications present in the model by grabbing the index of the highest probability value and associating it with the index of the string array, and then return the predicted state in the form of a single string. For example, let the resulting probability array be [0.1 0.05 0.09 0.76] and the preset string array be ['Blight','Common_Rust','Gray_Leaf_Spot','Healthy']. Since the fourth element of the probability array is the maximum value, its index value of '3' would then be carried over to the string array, which would result in the string array's fourth element of 'Healthy' being picked. This would mean that the model has determined to leaf in the photograph to be healthy.

Input Methods

To ensure a high level of flexibility of the system in terms of usability, 3 ways of choosing an image for the model to the process have been provided: taking a picture with the phone's camera, choosing a picture from the phone's gallery, and taking a picture with the Raspberry Pi by using the Pi's camera.

i) Using the phone's camera: Choosing this option in the mobile application will result in the camera process being run. The user will then take a picture which will then be sent to the Raspberry Pi for processing. This is a good method since smartphone cameras take photos that are generally better than the generic Raspberry Pi camera pictures.

ii) Picking a picture from the phone's gallery: Choosing this option in the mobile application will start the phone's gallery where the user can pick any picture of their choice that will then be processed by the Pi. This is very efficient as it will allow for the analysis of samples that the user doesn't have direct access to, such as past samples and samples that are too far for the user to reach. Associates of the user can even take pictures for them and send them to the user for analysis.

iii) Taking a picture from the Raspberry Pi's camera: This method will be helpful in case the Pi system and camera can be securely mounted on the field near the maize. This way, the user can carry out scans from wherever they may be remote.

3. RESULTS AND DISCUSSION

3.1. Machine Learning Model training and evaluation

For training and evaluating the model, a dataset was split into training, validation, and testing sets. 70% of the dataset was used as a training set for training the model, 20% of the dataset was used as a validation set for optimizing model parameters, and 10% of the dataset was used as a testing set for evaluating the final model performance. A data set of 4691 maize leaves images was divided into 4 different categories namely: healthy, Blight diseases, Common-Rust diseases, and Gray-Leaf-Spot diseases.

3.1.1. Model evaluation

Finally, the generated Machine Learning model has been evaluated for selecting the best predictive model using training and validation accuracy and with training and validation losses. The prediction accuracy is used to measure how well the generated predictive model is performing. In other words, it compares a predicted value and an observed or known value. The higher prediction accuracy value indicates that the model is performing better[23]. The number of epochs to train over can be used to set the length of training for a network[24]. The longer you train a model, the better it gets, but too many training epochs' increase the risk of overfitting[25]. Our epoch is 20 means that the model will go 20 times. Training accuracy and loss are graphically generated as shown in Figures 5.1-5.2. Over the twelve training epochs, the mean squared error loss reduces, while accuracy grows unevenly until it reaches 80% after twenty epochs.

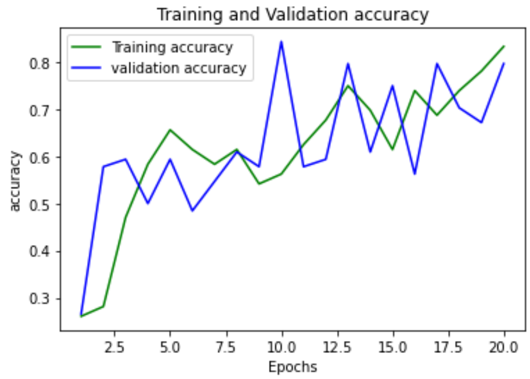


Figure 5.1. Training and validation accuracy CNN model

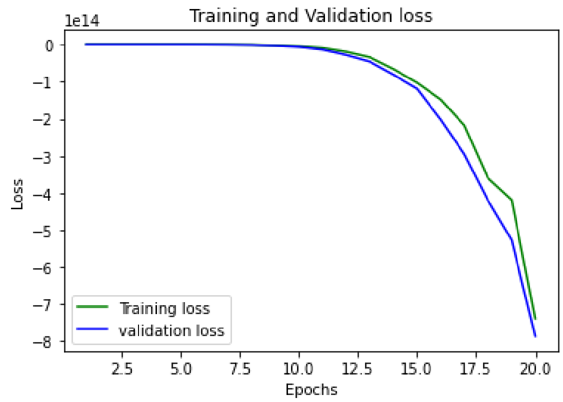


Figure 5.2. Training and validation loss of CNN model

3.1.2. Model evaluation

TensorFlow performance depends on time and memory allocation on the processors unit, in addition to accuracy, the model's training time was taken into account[26] . It has been observed that the Graphic Process Unit (GPU) reduces execution time compared to the central processing unit (CPU). The average model's training time using GPU was 3 to 4 faster compared to the average model's training time using CPU.

3.1.3. Performance evaluation of Convolution Neural Networks

The model has been tested by taking a test image from the test set and printing it with the help of the Matplotlib plotting library. The model process the selected image, then after processing, the model tells the name of the disease as shown in Figure 6.

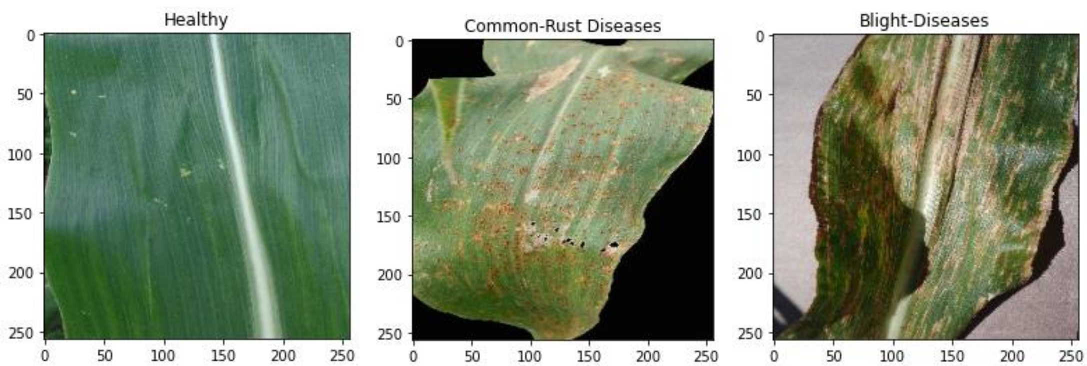
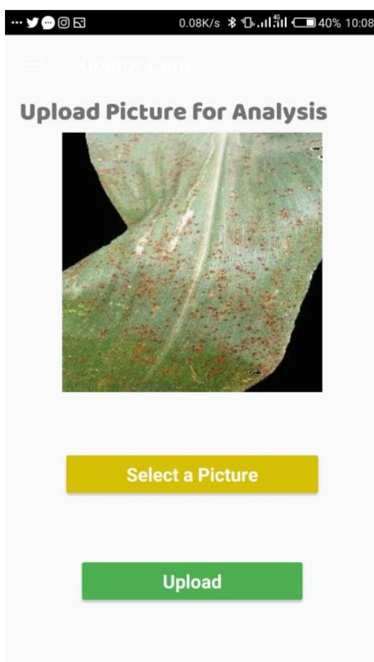
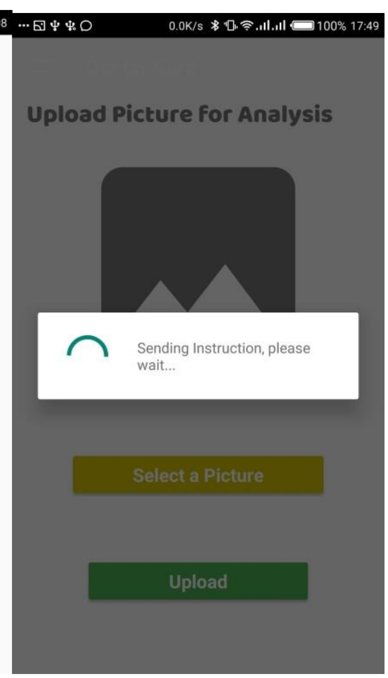


Figure 6. Maize leaf diseases and non-diseases images

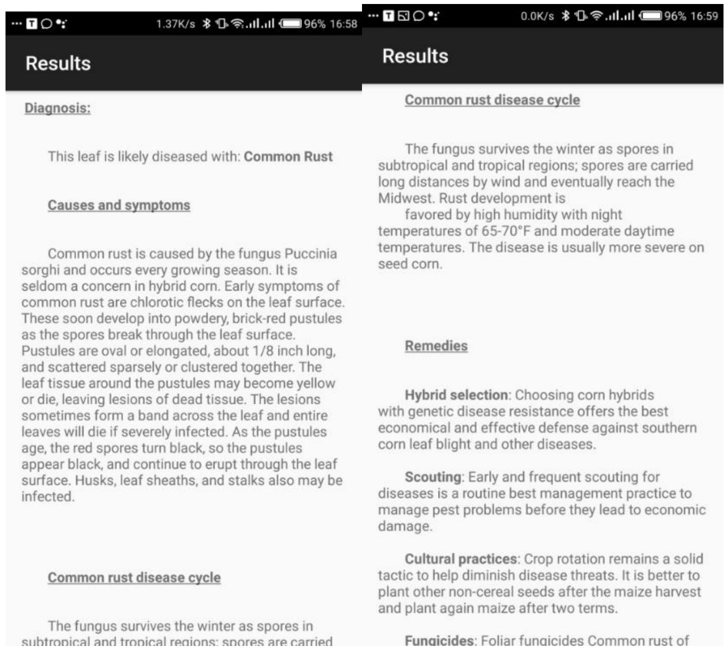
3.2. Integration of IoT system with Machine Learning predictive model evaluation

After training and evaluating the model, it has been deployed in the local server running on raspberry pi for edge computing. There are two approaches to programming communication between a local server operating on a Raspberry Pi and a smartphone. The server first checks to see if there is any connected client and if there is, a mutual data exchange would take place. This allows an application to send data through a socket to a hostname called raspberry pi and a port in the Transport Layer using the TCP protocol. As shown in Figures 7. a to 7. f, the system has a high classification accuracy for the majority of the classes in the testing dataset. However, due to a lack of sufficient training data, the system fails to attain high accuracy for Gray-Leaf-Spot Diseases.

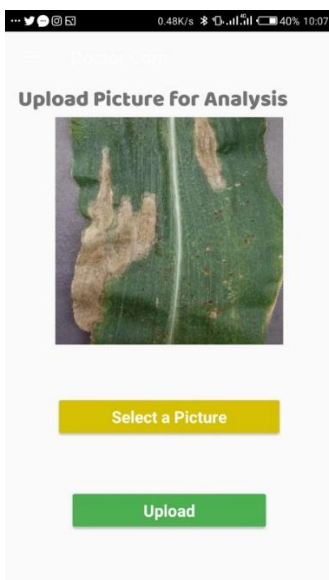


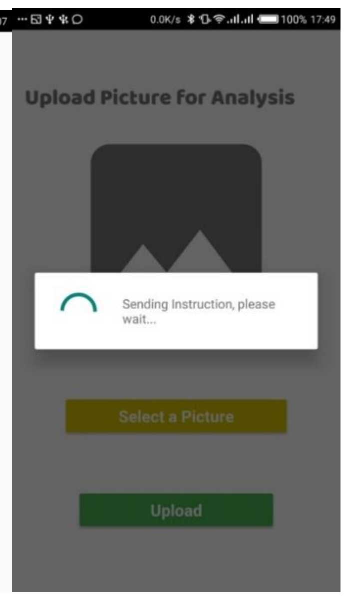


a) Image captured b) Image processing



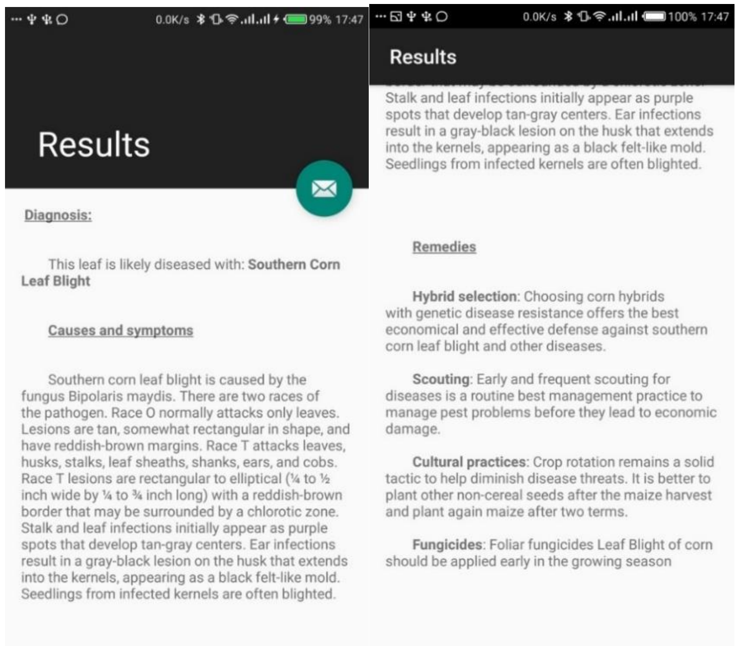
c) Image result





d) Image captured

e) Image processing



f) Image result

Figure 7a-f show the screenshots of the Mobile App for Detecting Plant Leaf Diseases and the remedies

The main objective was to implement a detection model that is efficient in the identification and classification of maize leaf disease. To understand the current limits and research gaps, a thorough literature review was conducted. These primarily highlighted the necessity for models that could predict well-unseen data remotely. A deep learning model using convolutional neural network algorithms is implemented on raspberry for such issues. The model was implemented by using maize leaf images containing healthy leaves and disease leaves. For building the model necessary pre-processing involving images resizing and converting them to NumPy arrays was done. Image Augmentation and validation were done for every epoch to ensure that the model is accurate. After training and testing the model, the results show an average accuracy of 80 % for detecting diseases in maize leaves.

In the previous research, the farmer takes the pictures physically in the field using a phone camera and should be connected to the internet. For detecting diseases remotely which is making this research different from the method used, a farmer can remotely take a picture through a mobile phone, by triggering the cameras mounted on the field using a developed mobile application. The camera directly takes a picture and loads it to the model deployed on raspberry pi for prediction, the model process the image and gives back the result to the farmer through a mobile app. Bidirectional communication between a mobile app and the model deployed on a raspberry pi camera is achieved by the implementation of a socket. In addition, when a farmer is offline can takes a picture and load them from Garelly when gets connected.

Based on the results obtained from the discussions held with farmers, the method used by a farmer for plant disease identification is visual observation and this method is prone to errors and inaccuracies. The approach implemented in this research can eliminate errors committed by farmers during the detection of plant disease based on the algorithms used and on the fact that it can be controlled remotely.

4. CONCLUSION

This research has successfully achieved objectives by detecting the maize leaf diseases with the help of CNN and open CV through a model deployed on raspberry pi and displaying the result on a mobile app. the model has an overall classification accuracy of 80% when it comes to distinguishing the three most common disease groups that damage maize leaves. This proves that the model is capable of detecting and classifying maize plant diseases early with good predictability and response time. The future work will consist of scaling the developed technology to further disease detection including mycotoxins. In addition to this, we will implement drone embeddable features that accomplish similar tasks at a large scale in a shorter time and with higher precision.

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