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Determination of the optimum ripeness of New Rice for Africa (NERICA) using Alexnet

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Abstract
The New Rice for Africa (NERICA) is a product of hybridizing African rice (Oryza glaberrima Stued) and Asian rice (Oryza sativa L.) in order to produce an improved variety of rice with very high yield, good resistance to draught, resistant to phosphorus deficiency and striga conditions. The research attempts to address the problem of food shortage as a result of increasing population and Draught in sub-Sahara Africa. The major two varieties of NERICA are Lowland and Upland varieties. One of the most acceptable varieties for uplands is NERICA-4, having delicious taste when compared to the other upland varieties. However, NERICA-4 suffers loss of grains during harvest, which leads to low productivity. In this paper, 75 images of different ripening stages were obtained from a cultivated farm land with NERICA-4 rice variety. The images were resized to a dimension of 277X277 with three channels to suit the input layer of Alexnet pre-trained network. The images are augmented for classification. The stochastic gradient descend with momentum training option is used with initial learning rate of 0.0001 for the settings. The training set achieved 100% classification accuracy from iteration 10 to 20 and zero loss at the 20th epoch. The test set obtained 87.9% classification accuracy which gave 15.46% improvement over an earlier classification accuracy using Alexnet for classifying maize comb images. The loss of grains can be reduced and yield increased when made operational.

Keywords: NERICA-4, Alexnet, Classification

1. Introduction
The increase in population worldwide requires a corresponding increase in the production of food to support the growing population. Several efforts have been put in place by agricultural research institutions, governmental organizations, nongovernmental organizations, etc. in improving the yield of agricultural produce. These was done by cultivating more land mass, controlling the problems of Insect pests, weeds, diseases, Vertebrate pests, Nematodes, etc. and equally improving on the soil fertility, reducing the acidity of the soil, mitigating the problems of soil erosion, etc. A more worrisome challenge is that of Drought. Draught is one of the main limitations in the farming of rice. Rice usually requires high amount of rainfall distributed uniformly throughout the growing period. This is not achievable in most parts of Sub-Sahara Africa, especially Nigeria. The impact of Draught is much felt in the uplands than lowlands. Rice varieties for uplands should possess the resistance for Draught. Efforts are being made by government at all level in fighting the menace of Draught by encouraging people to plant more trees. However, this is not sufficient as the rate of Draught supersedes the rate at which trees are planted and grow. Agricultural research organizations all over the world are making efforts in combating the effects of Draught on

agricultural produce by improving upon agricultural seedlings of several crops. They achieve this by producing draught resistant varieties. In Africa, one such effort is seen on a variety of rice called New Rice for Africa (NERICA) that can be grown on the uplands. NERICA variety is specially adapted to uplands with minimum period of maturity ranging from less than 90 to 100 days. Famers of most agricultural produce in Sub-Sahara Africa (SSA) usually allow their produce to reach biological maturity before harvesting. One of the challenges faced by farmers of NERICA rice variety is that of loss of the yield during harvest. This practice affects the quantity of crops that is usually obtained at harvest. Substantial amount of the yield from NERICA is lost at harvest. This amongst other reasons has also affected the recommendation to farmers in using the NERICA rice varieties in the uplands (Kamai, Omoigue, Kamara, & Ekeleme, 2020; Of, Mu, & Okeke, 2018). Though several famers have adopted the technique of early (before biological maturity) harvesting, this has resulted in the problem of harvesting premature grains with less weight and not easily threshed and sometimes remain on the panicle, thereby reducing the yield. In some cases, late harvesting is adopted by some farmers; this also results in the number of cracked grains being increased during milling, the problem of before harvest grain sprouting and birds' attacks on the rice also affects yield (Shinya, Kosaka, Inoue, Koimaru, & Sokei, 2011). The problem of human eye weariness, differences in sight, and differences in perception still affects the exact period that NERICA is harvested (Peter, Abdulkadir, & Abdulhamid, 2017). Determining the optimum maturity of NERICA-4 rice variety ranges from the end of the thirteen and fourteen weeks after sowing, which is usually experienced by change in color from yellow to golden (Shinya et al., 2011). In knowing the exact time for harvesting the grain by using human eyes is a herculean task due to the factors afore mention. In rice, the maturity varies from one variety to the other, especially when the numbers of days are used in the determination of each rice variety as temperature affects the maturity (Oli, 2018; Meena, Prasad, Dotaniya, & Meena, 2014). However, when visual characteristics are utilized, the husk color plays an important role in determining the optimum maturity of each variety (Kamai et al., 2020; Food and Agricultural Organization of the United Nations (FAO), 2017). The husk color in NERICA-4 rice variety at optimum ripeness is usually golden in color (Rodenburg et al., n.d.). In improving agricultural activities image processing (IP) techniques are utilized. The assessment of food value features is commonly done by IP methods that improve the independent and dependable measured outcomes. IP rely on the fact that the human spectrum receives visible light in the form of red, green, and blue (RGB) which are the color stimulus focal points. The classification of colors is commonly done using RGB and hue, saturated, and value (intensity) (HSV) color models. The RGB color model is represented by binary digits from 0 to 255, while the HSV color model ranges from 0 to 1. Millions of colors can be distinguished using RGB color model. ANNs are electrical analogue of the brain, as it mimics the brain activities in all respect. The ability of ANN to exhibit knowledge discovery and adapt to changes gives it the capability to classify objects more accurate than most techniques (Peter, Damuut, & Abdulkadir, 2020a). Convolutional Neural Networks (CNNs) are improvements upon the classical Artificial Neural Networks (ANNs) that are electrical analogue of the biological neuron with the capacity of imitating the characteristics of the biological neuron such as pattern recognition, motor control and perception (Peter, Damuut & Abdulkadir, 2020b). Yulcin and Razavi (2016) applied CNN in classifying 16 species of beans, pomegranates, cherries and apricot from 1,200 images obtained in a Turkey agricultural location and obtained 97.47% accuracy. Suma, Shetty,Tated, Rohan & Pujar (2019) used CNN in the identification and classification of leaf images from a simple environment and obtained 99.32% classification accuracy. Prashar & Kant (2019) reported the use of CNN model with the overlapping Pooling method and Multiple Layer Perceptron (MLP) technique to identify and classify healthy leaves, and obtained 96% identification accuracy in solving the problem of profit loss as a result of plant disease in cotton production. Boulent, Foucher, Theau, & St-Charles (2019) reported that CNN generates a better performance when images have complex situations. Images of plant crop infections are categorized into three sets. These images are classified based on conditions such as identical background, illumination, and unique plant organs. In an effort to enhance the potential of extracting features from images of Mosaic, Grey spot, Rust, Alternaria leaf spot and Brown spot of Apple leaf infections a deep CNN and GoogleNet were amalgamated to form an enhanced novel identification method. The model generated an average identification precision of 78.80% (Jiang, Chen, Liu, He, & Liang 2019). In addressing slope disappearance and overfitting of data in the training phase, a novel matrix-based CNN (M-bCNN) is propose in Lin et al. (2019) for the classification of 8 categories of 16652 experimental images that were augmented to 83260 images. The model gave 96.5% validation accuracy and 90.1% test accuracy outperforming VGG-16 and Alexnet pre-trained networks. Overlapping identification is an issue when classifying images. Li, Chen, Wang, & Xie (2019) combined Fergus and Zeiler networks to address overlapping identification problems. A mean of 88.5% identification precision was obtained from images of wheat infected by wheat mite. The health of crops is directly proportional to their yield. In identifying and classifying measles, black rot, and blight, three infections that affect grape, Inception version3, ResNet-50 version2, and Mobile-Net version2 on Adadetta, Adagrad, and Adam optimizers are used. Inception version3 generated the best performance of 99.9% classification accuracy followed by Mobile-Net with 99.3% classification accuracy as reported in (Suresh, Gnanaprakash, & Santhiya, 2019). Crops with high resistance to cold effects have more advantage in terms of cultivation as reported in (Yang, Yang, Hao, Xie, & Li, 2019). In estimating cold damages, Saleem, Potgieter, & Arif (2019) used ghostly features extracted under visible-close-infrared space from corn seeds using CNN. Cold damage levels of BxM as 25.6%, W22 as 41.8%, PH207 as 20%, B73 as 25.6% and Mo17 as 14% of corn seed species. There is a high coefficient of correlation of 0.8219 from chemical method. Resnet50 outperformed Mobile-Net version1 and ResNet101 with an average of 0.759 precision on a bench mark of 0.5 unification error in identification of blueberry images when trying to achieve mechanization in harvest management (Gonzalez, Arellano, &Tapia, 2019). A hybrid model of faster R-CNN fusion and K-Means Clustering algorithms are used in the identification of rice blast, sheath blight infection and bacterial blight of rice diseases from 3010 images of rice. Detection accuracies are 96.71% for rice blast, 98.26% for sheath blight infection and 97.55% for bacterial blight (Zhou, Zhou, Chen, & He, 2019). In identifying 10 types of Tomato leaf infections a Mobile-Net CNN is used and better identification accuracies were obtained (Elhassouny & Smarandache, 2019). Density estimation method and CNN technique are used in counting soya beans for improving crop breeding, the outcome show a potential for future breeding task as reported in (Li et al., 2019). An integrated approach of Gated Recurrent Unit Networks and CNN are used in the separation of indistinct crop differences of several temporal data. The results show an excellent performance on categories with similar phonological rules (Li, Chen, & Zhang, 2019). CNN was used in the prediction of maize yield with an average accuracy of 99.58% (Abdullahi, Sheriff, & Mahieddine, 2017). In classifying remote sensing scenes, the performance of CNN was enhanced by modifying the Pooling layers and Convolutional layers of AlexNet, VGG-16, and Caffe-Net pre-trained Networks (Li, Xia, Du, Lin, & Samat, 2017). The results obtained show a positive correlation between the number of layers and prediction accuracies as stated in (Sinha, Verma, & Haidar, 2017; Haryanto, Wasito, & Suhartanto, 2017). The accuracy and scalability of Tomato ripeness using Tomato maturity robot in the classification and prediction was determined using CNN. The result shows a 91.9% prediction (Zhang et al., 2018). In the segmentation and classification of several distinct organs in the medical discipline, Harouni, Karargyris, Negahdar, Beymer, & Syeda-Mahmood (2018) used Unet architecture in building a network that gave 99% classification accuracy with a mean dice score of 89% segmentation accuracy. Facial recognition and non-facial recognition classification task by CNN are reported in (Do, Kim, Yang, Lee, & Na, 2018). Alexnet, a pioneer pre-trained and deep CNN having more filters per layer that won the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) and reduced the top5 error rate from 26.5% to 15.9% is used. The images were augmented by cropping and modification of the pixel intensities within the images to reduce data overfitting during the training phase. This was achieved by randomly cropping the 227X227 dimensions of the input size of Alexnet to obtain different dimensions of 199X199 that increases the invariance in the data set (Zhang, Allen, Unger, & Cruz, 2018). To further reduce overfitting problem, the images are augmented by generating image translations and horizontal reflection that increased the training set by a factor of 1000. The remaining paper is organized as follows: Section 2 is the materials and methods, acquisition of images of NERICA-4 different stages of ripeness and subsequent classification are presented. Section 3 presents the results and discussions. In section 4, the paper is concluded with future research direction and recommendations.

2. Materials and Methods

In this work, NERICA-4 rice variety, site selection for farming, preparation of land for cultivation, a digital camera FINEPIX Z35 Full High Definition Charge Couple Device (CCD), NERICA-4 images are the materials. The methods deployed are presented in the system frame work of Figure 1.

NERICA-4 Rice Variety

Rice plant (Oryza sativa L.) is a member of the grass family which is an essential staple food in the world. NERICA-4 rice variety obtained from the success in crossing Oryza sativa L. (Asian rice) having high yield capability with Oryza glaberrima Stued. (African rice) by the Africa Rice

Center (AfricaRice) that is tolerant to Drought and phosphorus deficiency, resist pests and cultivated throughout the sub-Sahara Africa (SSA) ecological region (Oikeh et al., n. d.; Shinya et al., 2011) is cultivated on a farm land in Kujama for the research purpose.

Site Selection

The site cultivated for the NERICA-4 rice variety is located in Pamfura-Kujama in Chikun Local Government Area of Kaduna State. The land has good drainage, water retention potential, with very good clay and organic matter. The site has at least 12-25 mm of rainfall during the farming season.

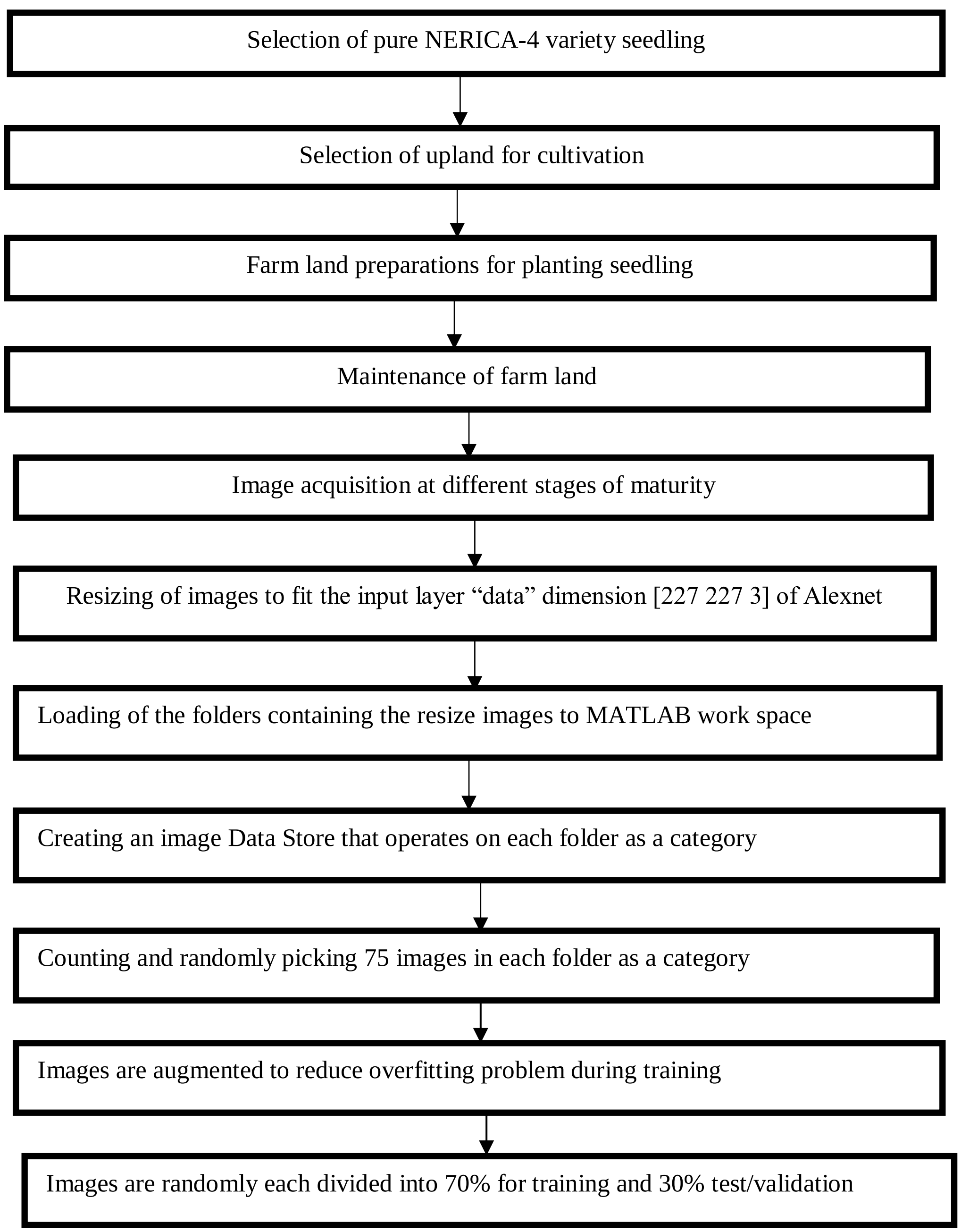

Figure 1: System frame work

Land Preparations

The land is cultivated manually by levelling it using hoe. The land was exposed to good amount of sunlight. The thick bushes were cleared and burnt, while the small debris and weeds were weeded and left to rot in the farmland as manure. The land is a size of about 750m2 area. The land preparation was done in February, 2020.

NERICA-4 variety seed preparation

Winnowing was used to separate between filled grains and empty grains. About 90 seeds were selected out of the filled grains to test the germination potency of the seedlings. It was observed that about 80 seeds germinated within 4 to 5 days.

Seed planting

When the rains became regular in the early month of June, 2020, the seeds were sown into a depth of 3- 4 cm using the drilling method (Shinya et al., 2011).

Initial Weeding

In an effort to reduce competition for nutrients and sunlight by weeds, regular inspections of the rice plantation are done and weeded before the application of the first fertilizer. This ensured a sanitized field and equally kept rodents away.

Basal Fertilizer

Fifteen kilograms (15kg) of N P K (15: 15: 15) was applied around the third leaf development to ensure that there is no loss of fertilizer due to heavy rainfall. This helps to increase the number of tillers.

Top Dressing

At the seventh week, which is about fourty-five (Panicle initiation stage) days after sowing (DAS), 7 kg of Urea fertilizer was applied to increase the yield of the NERICA-4 rice variety. When the rice was about ten weeks that is about seventy-five (Meiotic stage) DAS, the second application of 5kg Urea was done to increase the number of filled grains.

Image Acquisition

The Full High Definition CCD digital camera FINEPIX Z35 inclined at 90^0 and 5 inches from the NERICA-4 rice variety plant was used to capture hundred images each of the different ripening stages. The first stage of maturity was when the plant has attained the late dough stage around the end of eleventh weeks to the middle of twelve weeks after sowing. The second stage of maturity was when the plant is at the end of twelve weeks to the middle of thirteen weeks after sowing. The third stage, being the ripening stage was between the end of thirteen and fourteen weeks (Shinya et al., 2011). Figure 2 is the sample of the different maturity stages.

Experimental Setup

Image classifications are performed on a 64-bit Operating System Service Pack1 Windows 7 Ultimate. The processor is an Intel® Core (TM) i7, 2620M CPU @ 2.70 GHz. RAM size is 8.00GB with 500HDD. MATLAB2018Ra implemented the script.

Figure 2: Different Maturity Stages (Peter, 2021, p.505)

Image Processing

The images acquired were rescaled to 227X227X3 to suit the input layer of Alexnet pre-trained network. The images were augmented by cropping and modification of the pixel intensities within the images to reduce data overfitting during the training phase. This was achieved by randomly cropping the 227X227 dimensions of the input size of Alexnet to obtain different dimensions of 199X199 that increases the invariance in the data set.

Image Classification

The input layer of Alexnet pre-trained CNN accepted 75 random images of NERICA-4 varieties from three stages of maturity representing three categories. The setting used stochastic gradient with momentum. The numbers of epochs are set to 20 epochs with initial learning rate of 0.0001. In the classification of the images, Pool2 layers having a feature map of 256, size of 6X6X256, kernel size of 3X3, stride of 2 units and ReLU activation function is used to extract features for the classification.

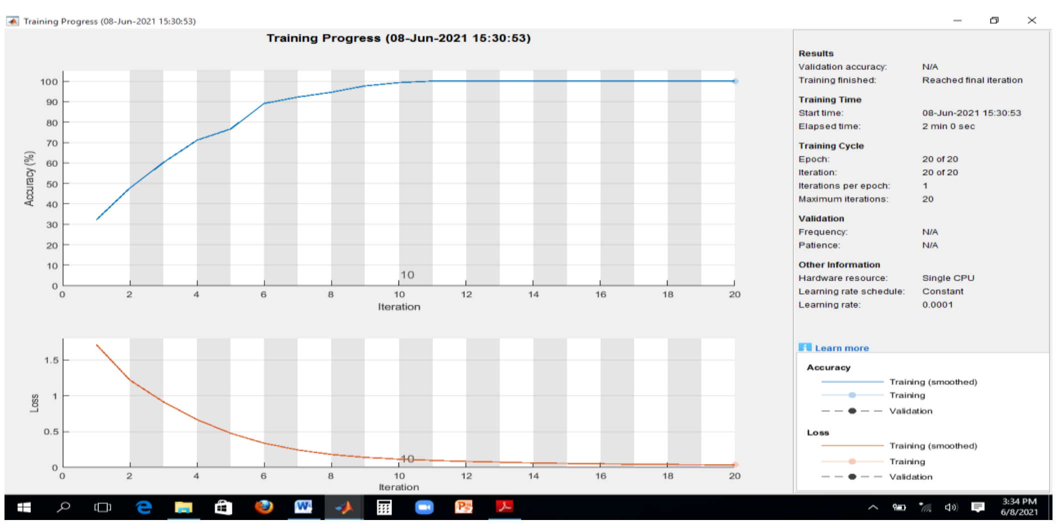

Figure 3: Training Progress of Alexnet

3. Results and Discussion

In this section, the results of classifications are presented in the form of confusion matrix as seen in Figure3 and Figure 4.

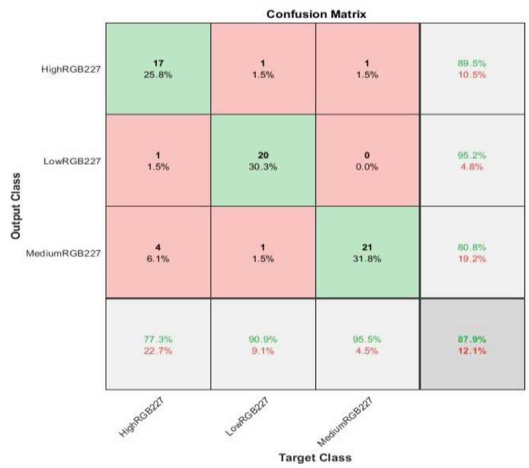

Figure 4: Confusion Matrix

In figure 3, the percentage training accuracy progress of the pre-trained Alexnet CNN starts at about 32.5% at the 1st iteration and at the 10th iteration reaches 100% up to the 20th iteration. The loss starts from about 1.8 and drops to as low as 0 with a very smooth curve depicting zero noise, which show that the network is able to adapt to the NERICA-4 images in the different categories. In figure 4, the confusion matrix of the target class verses the output class show that the high category (HighRGB227), representing the ripen NERICA-4 are corrected classified by 89.5% and wrongly classified as 10.5%. In the medium category (MediumRGB227), the hard dough stage the network classifies 80.8% correctly and misclassified 19.2%. While in the low category (LowRGB227), which is the soft dough stage, the network classifies 95.2% correctly and misclassified 4.8%. This shows that soft dough stage maturity level is more identifiable followed by the ripen stage of the NERICA-4 variety of rice. The average correctly classified accuracy is 87.9% with a misclassification of 12.1%. This is an acceptable performance as it is above the threshold of 70%.

4. Conclusion

In this research, NERICA-4 rice variety was cultivated on a piece of about 750m^2 land located at Kujama-Chikun Local Government Area of Kaduna State, Nigeria. The land was properly prepared for cultivation with good seeds at the early month of June, 2020. Proper weeding and right application of fertilizers were observed in order to obtain very good yield for the research. Sample images for classifications were obtained at different maturity periods labeled as late dough stage, yellowing stage, and ripening stage. The ripe stage represents the optimum maturity period. The images were augmented by cropping and modification of the pixel intensities within the images to reduce data overfitting during the training phase. This was achieved by randomly cropping the 227X227 dimensions to obtain a different dimension of 199X199 that increases the invariance in the data set. The result of the classification shows an overall performance of 87.9%

as seen in Figure 4 of the all confusion matrix which is higher than 72.44% of an earlier classification of maize using Alexnet as reported in (Peter et al., 2020b). This results when made operational would reduce losses encountered during harvest by local farmers and improve the use of NERICA-4 rice variety plantation in uplands ecological region of sub-Sahara Africa, as it is the most desirable variety due to its deliciousness. This will improve productivity and wealth for the local farmer.

Data Availability

The NERICA-4 rice variety images used for this research are available upon request.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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