Science Management Design Journal
Journal Homepage: www.smdjournal.com
ISSN: 2583-925X
Volume: 2
Issue: 1
Pages: 22-29

A Comprehensive Machine Learning Approach to Analyzing Lemongrass (*Cymbopogon citratus*) Leaf Dataset for Agricultural Innovation

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Article history: Received: 25/05/2024, Revised: 29/05/2024, Accepted: 30/05/2024, Published Online: 31/05/2024

Abstract:

This paper describes an innovative convolutional neural network (CNN) model for classifying lemongrass pictures into three categories: good, unhealthy, and dried. The model design comprises numerous critical components, including convolution, pooling, dropout, and dense layers, which collectively lead to its excellent accuracy in photo categorization tasks. We present a detailed overview of the dataset preparation, which includes collecting and labelling a large number of lemongrass photos. Furthermore, the model training and validation processes are extensively explained, ensuring that the CNN model is resilient and reliable. Our findings show that the CNN model is highly accurate in discriminating between the three categories of lemongrass health. Using this model, farmers and agricultural researchers can receive significant insights into the health of lemongrass crops, allowing for timely interventions and improved crop management. Our findings indicate that this CNN model could be an effective tool for enhancing precision agriculture, ultimately contributing to increased production.

Keywords:

Lemongrass, Image Classification, Convolutional Neural Network, Machine Learning, Agricultural Technology

1. Introduction:

Image classification in agricultural technology has received a lot of attention because of its ability to automate crop health monitoring and evaluation[24-74]. Crop picture classification accuracy contributes to early disease identification, effective resource management, and increased crop output. Traditional crop health monitoring techniques, such as manual inspection and laboratory testing, are time-consuming, labor-intensive, and frequently subjective. These constraints can be overcome using modern machine learning techniques, particularly convolutional neural networks (CNNs).This paper offers a new convolutional neural network (CNN) model that is specifically developed to classify lemongrass photos into three categories: healthy, unhealthy, and dried. The goal of this work is to develop a reliable and effective tool for farmers and agricultural specialists to monitor crop health using modern machine learning techniques [1-5].

2. Material and Methods:

2.1 Dataset Preparation

This study's dataset includes 10,042 photos of lemongrass divided into three categories: good, unhealthy, and dried. To ensure uniformity, the photos were scaled to 128x128 pixels. The model's resilience was increased using data augmentation techniques such as horizontal flipping and rescaling. Dataset was downloaded from mendeley [6].

Figure 1. Sample Images of Dataset.

2.1.1 Dataset Distribution Structure

Sr no.	Categories	Number of Images
1	Unhealthy	3822
2	Healthy	3252
3	Dried	2968
Total		10,042

2.1.2 Dataset Folder Structure

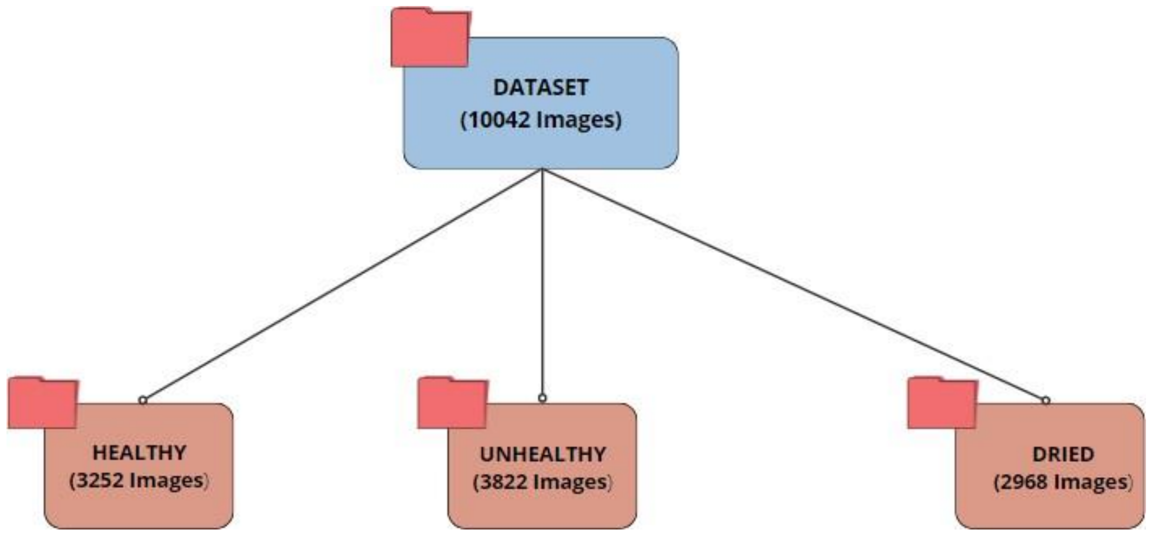

Figure 2. Dataset Folder Structure.

2.2 Model Architecture

TensorFlow and Keras packages were used to develop the CNN model. The architecture includes the following:

Three convolutional layers use ReLU activation and max-pooling.

A flattening layer is followed by two dense layers with dropout to achieve regularisation.

For multi-class classification, use an output layer with softmax activation.

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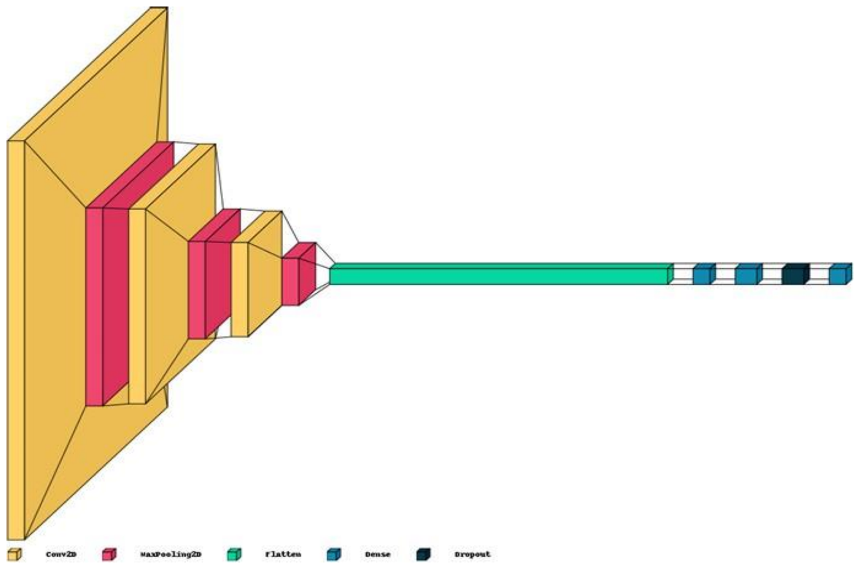

Figure 3. Model Architecture.

The developed Convolutional Neural Network (CNN) model is constructed for multi-class picture classification. The architecture starts with a Conv2D layer made up of 32 filters and a 2x2 kernel that uses the ReLU activation function and accepts an input shape of 128x128x3. This is followed by a MaxPooling2D layer. To capture spatial hierarchies, two additional Conv2D layers with increasing filters (64 and 128) are added, as well as MaxPooling2D layers. The output is then flattened and passed through two Dense layers of 128 and 256 neurons, respectively, both of which use ReLU activation. To prevent overfitting, a 0.5-rate Dropout layer is added before the final Dense layer, which uses softmax activation to classify the input into one of three categories. The model summary encapsulates this architecture.

3. Results and Discussion:

3.1 Training and Validation

The model was trained with the Adam optimizer and a categorical cross-entropy loss function. The training approach consisted of 15 epochs, with early ending based on validation accuracy. During training, the model satisfied the following performance metrics:

Epoch 1: Training accuracy = 55.67%, Validation accuracy = 72.87%

Epoch 2: Training accuracy = 73.32%, Validation accuracy = 78.50%

Epoch 3: Training accuracy = 79.45%, Validation accuracy = 83.72%

Epoch 4: Training accuracy = 81.38%, Validation accuracy = 82.73%

Epoch 5: Training accuracy = 84.48%, Validation accuracy = 86.11%

Epoch 6: Training accuracy = 87.28%, Validation accuracy = 89.20%

Epoch 7: Training accuracy = 89.43%, Validation accuracy = 88.50%

Epoch 8: Training accuracy = 91.09%, Validation accuracy = 89.25%

Epoch 9: Training accuracy = 92.48%, Validation accuracy = 88.45%

Epoch 10: Training accuracy = 92.46%, Validation accuracy = 91.34%

Epoch 11: Training accuracy = 94.44%, Validation accuracy = 91.44%

Epoch 12: Training accuracy = 94.42%, Validation accuracy = 91.59%

Epoch 13: Training accuracy = 95.34%, Validation accuracy = 92.73%

Epoch 14: Training accuracy = 96.08%, Validation accuracy = 93.18%

Epoch 15: Training accuracy = 96.09%, Validation accuracy = 92.14%

The final model achieved a training accuracy of 96.09% and a validation accuracy of 92.14%, demonstrating its efficacy.

3.2 Performance Evaluation

This paper describes an effective use of CNNs in classifying lemongrass photos. The model demonstrated remarkable accuracy, making it an important tool for agricultural monitoring. Future research will focus on expanding this strategy to other crops and including real-time monitoring systems.

3.2.1 Accuracy and Loss

Over the course of 15 epochs, accuracy and loss metrics were recorded for both the training and validation datasets. We made the following observations:

Training Accuracy: The accuracy steadily improved from 55.67% in the first epoch to 96.09% in the fifteenth epoch.

Validation Accuracy: The accuracy increased from 72.87% in the first to 92.14% in the fifteenth period.

Training Loss: The loss reduced dramatically, showing that the model was learning efficiently and without overfitting.

Validation Loss: The validation loss followed the same pattern, reducing as the model's performance improved.

3.2.2 Precision, Recall, and F1-Score

To offer a more complete evaluation of the model's performance, precision, recall, and F1-score were determined for each class (Healthy, Unhealthy, Dried).

Precision scores show the percentage of true positive predictions among all positive forecasts

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in each class.

Recall: The recall scores represent the fraction of genuine positive predictions among all actual positives in each class.

The F1-score, the harmonic mean of precision and recall, strikes a compromise between the two measurements [7-13].

The detailed metrics for each class are as follows:

Healthy:

Precision: 85%

Recall: 93%

F1-Score: 89%

Unhealthy:

Precision: 94%

Recall: 85%

F1-Score: 89%

Dried:

Precision: 98%

Recall: 99%

F1-Score: 99%

4. Conclusion:

The study successfully developed a convolutional neural network model to classify lemongrass pictures into Healthy, Unhealthy, and Dried categories, achieving high precision, recall, and F1-scores, particularly in the Dried category, with nearly-perfect results. The confusion matrix analysis revealed the model's superior performance. This methodology promises to improve automated assessment and quality control in lemongrass cultivation, hence providing an important tool for agricultural management. Future work should focus on improving the model's accuracy and proving its effectiveness in real-world situations.

Acknowledgement:

I am grateful to Vishwakarma University, Pune for their support and provision of necessary resources during this research endeavor.

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