Detection and Management of Water Stress at Plants by Deep Learning and Image processing Case-study of Tomato

Mohammed Guerbaoui[1], Ismail Ichou[2], Zakaria Bakziz[2], Abdelouahed Selmani[3], Samira El Faiz[1], Abdelali Ed-Dahhak[1], Bachir Benhala[4], and Abdeslam Lachhab[1]

[1]MMCS Team, EST Meknes, Moulay Ismail University, Meknes, Morocco
[2]Faculty of Sciences Meknes, Moulay Ismail University, Meknes, Morocco
[3]S.A.R.S Team, ENSA of Safi, UCA University, Marrakech, Morocco
[4]Faculty of science Dhar El Mahraz, Sidi Mohamed Ben Abdellah University, Fes Morocco

Abstract

This project aims to develop an innovative technique for detecting water stress in tomato plants using deep learning and image processing techniques, and to integrate it into a mobile application for real-time monitoring. The methodology adopted includes the acquisition and preprocessing of image data, the construction and training of a deep learning model, and the development of a user-friendly mobile application. The results show a promising performance of the model in the precise detection of water stress, confirming the usefulness and usability of the developed mobile application.

1 Introduction

Smart agriculture involves the use of technologies such as IoT, robotics, drones, and AI to manage farms, increase production, and reduce environmental impacts. The goal of smart agriculture is to increase the quality and quantity of agricultural products while optimizing human labor to achieve the best possible results. [1]

With the integration of IoT techniques, it is possible to optimize resources, reduce costs and improve agricultural yields. The collection of crucial data on soil moisture, weather conditions and crop health by IoT sensors is essential for making precise decisions, for example irrigation control, ensuring a specific climate for certain crops.[2]

Artificial intelligence (AI) is another pillar of smart agriculture. It analyzes massive volumes of data to predict yields, detect plant diseases and optimize irrigation. AI applications, such as machine learning and deep learning, which significantly increase the accuracy and efficiency of agricultural practices. However, integrating these systems with existing agricultural infrastructure and collecting high-quality data remain major challenges.[3]

Image processing is also a key technology in smart agriculture, used for crop monitoring and management. Early detection of diseases and pests, plant growth assessment, and soil quality analysis can be achieved through image-based systems. Farmers can make informed decisions and optimize field interventions with the help of detailed visual information provided by these tools. By using IoT systems and image processing techniques, farms can be managed more accurately and efficiently, which highlights the significance of device connectivity and sustainability.[4, 5]

Water stress is one of the main challenges of modern agriculture, which significantly affects crop yield and quality. This phenomenon is the result of an imbalance between the water needs of plants and available resources. While, it can be difficult to detect early in the absence of appropriate tools.

The main goal of our study is the development and validation of a method of detection of water stress in tomato plants, using deep learning techniques and image processing. More specifically, the objectives include the implementation of a mobile application that allows remote and real-time monitoring of the detection of signs of water stress on images of tomato plants. The study also aims to assess the accuracy of the model developed and its reliability compared to conventional methods of detection of water stress.

methodology used in this study integrates both quantitative and qualitative research methods. It includes collecting images of tomato plants under various water conditions, preprocessing image data, designing and training a Deep Learning model, and the development of a mobile application for the monitoring and analysis of results. The methodology ensures the generalizability and robustness of the model by including evaluation and validation phases.

This article is structured in different sections to present clearly and coherently the whole research project. After this introduction, the next section presents a state of the art on water stress in plants and similar studies. Then, the research methodology is detailed, followed by the results obtained and their discussion; data availability. Finally, the conclusion summarizes the main contributions of the study and suggests avenues for future research.

2 State of the art:

Development of an Automatic Irrigation Method Using an Image-Based Irrigation System for High-Quality Tomato Production [6]

The study presents an automatic irrigation method using an image-based irrigation system for the production of high-quality tomatoes in greenhouses. The main objective is to study the effects of a diurnal periodic irrigation cycle on photosynthesis, growth, yield and quality of tomato fruits.

Experimental site and materials: The experiment was conducted in a greenhouse on the Matsudo campus of Chiba University, Japan, with tomato plants grown under controlled conditions. Image-based irrigation system: Used to monitor the wilting conditions of tomatoes every minute and control wilting thresholds for irrigation. Experimental treatments: Two levels of wilting were tested: MR (Moderate Wilting - Full Recovery): Moderate wilting with an average threshold. SR (Severe Wilting - Full Recovery): Severe wilting with a high threshold.
Average daily wilt rate: 7.2% for RM and 11.3% for SR. Total irrigation quantity: Similar between MR and SR, but less than untreated control. Photosynthesis rate: Decreases under water stress, but MR values are higher than SR and recover quickly after irrigation. Growth and yield: Lower in MR and SR treatments compared to control. Fruit quality: Improved under water stress treatment, especially when started at anthesis stage or early fruit development. the study concludes that the total amount of irrigation is a more important parameter than the threshold value to control the growth, yield and quality of tomato fruits. Water stress treatment can improve fruit quality when well managed, especially in early fruit development.

Study on the detection of water status of tomato (Solanum lycopersicum L.) by multimodal deep learning [7]
This study, conducted by a team from the School of Agricultural Engineering at Jiangsu University, China, along with other collaborators, explored the detection of the water state of tomatoes (Solanum lycopersicum L.) using a RealSense D435i camera to capture RGB, NIR and depth images of tomato seedlings, with resolutions up to 1920x1080 for RGB images and 1280x720 for depth images. A total of 21,600 image sets were acquired after 7 days of water treatment of the plants, with 4,320 image sets for each water state (severe water deficit, light water deficit, moderate irrigation, mild over-irrigation, severe over-irrigation). The dataset was divided into 70% for training, 10% for validation and 20% for testing.

Two types of deep learning networks used in this study to detect the water status of tomatoes:
Unimodal deep learning:
Only one type of image (RGB, NIR or depth) to train the network for detecting the water state of tomatoes. The results showed that the accuracy of detection of tomato water status based on unimodal deep learning ranged from 88.97% to 93.09%.
Multimodal deep learning:
merges several types of images (RGB, NIR and depth) to train the network to detect the water state of tomatoes. The results showed that the accuracy of tomato water state detection based on multimodal deep learning ranged from 93.09% to 99.18%, significantly outpacing unimodal deep learning.

Use of CNN for Water Stress Identification in Rice Fields Using Thermal Imagery[8]

This study focuses on detecting water stress in rice fields, a critical issue due to climate change and drought. Using thermal images and convolutional neural networks (CNN), the researchers classified irrigation levels into 100%, 90%, and 80%. Experiments were conducted on three rice varieties in Taiwan, analyzing 403 images.

Leaf temperatures, captured via thermal cameras, were used to assess irrigation effects on stomatal behavior. Three CNN architectures—VGG16, ResNet34, and DenseNet121—were applied, achieving classification accuracies between 85% and 100%. Thermal images outperformed RGB in detecting water stress, and accuracy was further improved by combining temperature scores from different fusion branches.

Identification and Classification of Maize Drought Stress Using Deep Convolutional Neural Networks (DCNN)[9]

This study highlights the importance of deep convolutional neural networks (DCNN) in agriculture, focusing on the identification of drought stress in maize. A dataset of 3,641 images was collected and labeled according to three irrigation treatments (optimal, light, and moderate). The images were converted to grayscale.

Using Transfer Learning with ResNet50 and ResNet152 models showed better time efficiency and higher accuracy compared to models built from scratch. The DCNN model achieved outstanding performance, with an identification accuracy of 98.14% and a classification accuracy of 95.95%. Additionally, color images outperformed grayscale images in terms of accuracy.

3 Methodology

First, We collected the data as RGB images, constituting a set of 22,950 images divided into four classes. These classes are 25, 50, 75 and 100, each representing a specific amount of water given to the plant. Here is an example of images from this dataset:

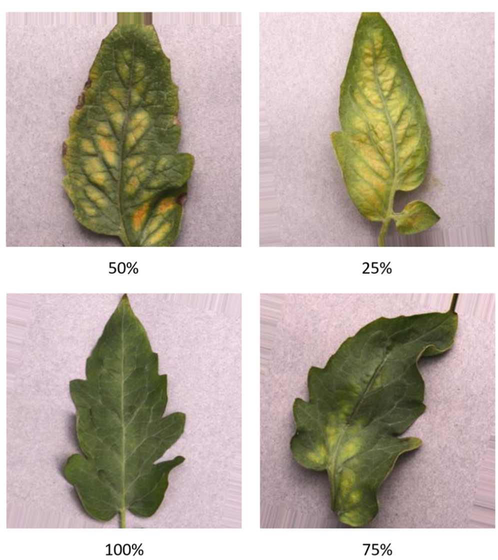


Figure 1: Examples of dataset(1)

However, before using these images, we found that some were misclassified and others were of poor quality, such as:

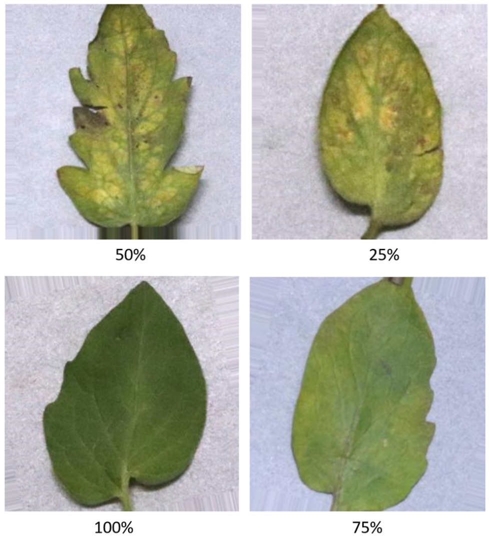


Figure 2: Examples of dataset(2)

After the initial preprocessing, we managed to collect 9600 images, with 2400 images for each class. Then we loaded the images and divided them into three sets: 80% for training, 10% for testing and 10% for validation. Our approach was to process the images to remove their background, enabling a visual comparison between the original and processed images. This was achieved by converting the images into pixel arrays, identifying and replacing the background with a solid color, and then resizing the images for a consistent presentation.

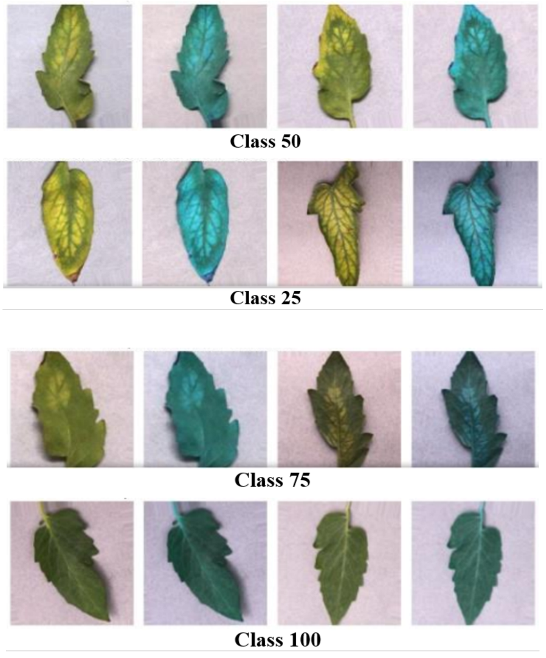


Figure 3: Examples of dataset before and after processing

After that, we built a neural network using TensorFlow, based on CNN with the following features:

- **Convolution Layers:** Three convolution layers are used with 32, 64 and 128 size filters respectively (3, 3).
- **Pooling Layers:** After each convolution layer, a pooling layer is applied with a window of (2, 2) to reduce dimensionality.
- **Fully connected layers:** Two fully connected layers are added after the last pooling layer. The first fully connected layer has 128 neurons, followed by an output layer with a number of neurons equal to the number of classes in the problem.

4 Results and Discussion

4.1 Context

This schema shows the different stages of water stress detection in the plant from mobile application to irrigation control:

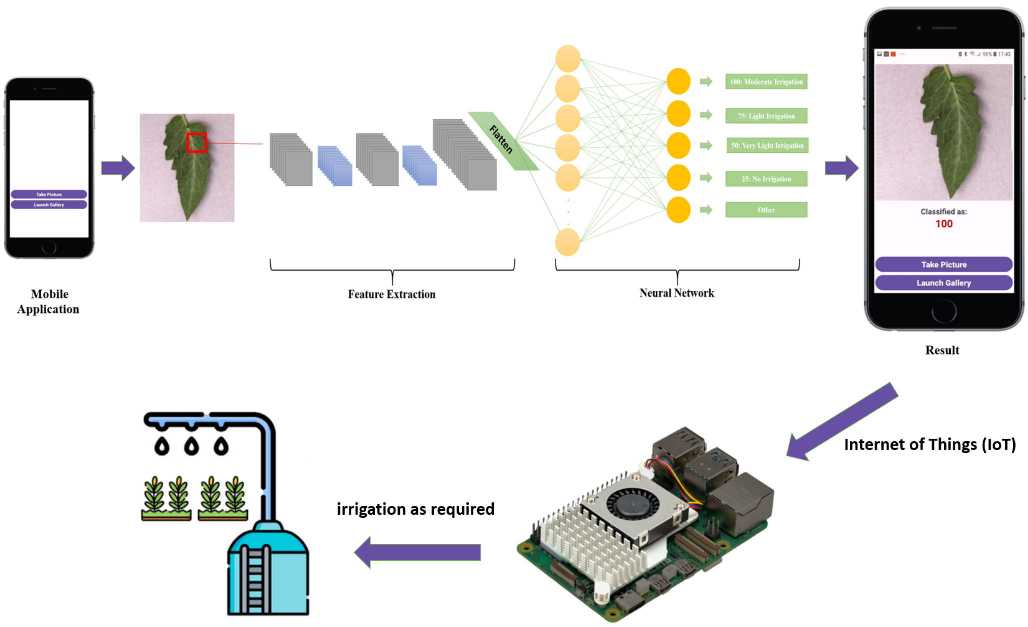


Figure 4: general scheme of the system

After capturing an image of the plant, it passes through convolutional neural networks to know the state of the plant: 100% (moderate irrigation), 75% (light irrigation), 50% (very light irrigation), 25% (no irrigation) or other. and according to the result obtained by sending a command to the raspberry pi 5 to trigger the water pump to give the plant the appropriate need for water.

This is an flowchart for the system:

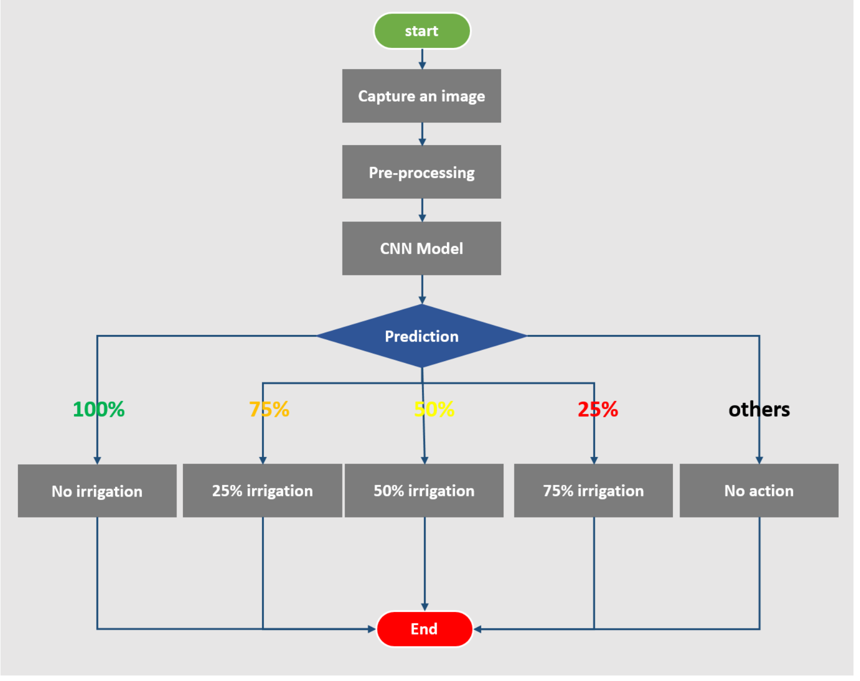


Figure 5: flowchart of system

4.2 First method

After training, we achieved 98.54% accuracy. When we tested the predictions on images the model had never seen, we obtained about 95% correct predictions. However, we realized that something was missing when testing the model with our own photo, it classified us in class **50!**. So we were forced to add another class called "other", which contains images of various categories such as humans, animals, plants, objects, etc., with a total of 3100 images. So we have a total of 12,700 images. After repeating the same previous steps, we got **96.81%** accuracy. This time, my photo was predicted to belong to the **"other"** class.

Here is a test on images the model has never seen:

- Of the 500 images in the class [class name], all images were predicted correctly.
- Of the 528 images in class 75, 516 were correctly predicted.
- Of the 120 images in class 50, 114 were correctly predicted.
- Of the 1,029 images in class 25, 889 were predicted correctly.
- Of the 70 images in the "other" class, all were correctly predicted.

accuracy: 0.9901 - loss: 0.0353 - val_accuracy: 0.9621 - val_loss: 0.1591

epoch20
prediction pour la classe 100

100	75	50	25	autre	original	erreur			
500	0	0	0	0	500	0	100%	0%	20%

epoch20
prediction pour la classe 75

100	75	50	25	autre	original	erreur			
5	516	5	0	2	528	12	97.72%	2.28%	19.54%

epoch20
prediction pour la classe 50

100	75	50	25	autre	original	erreur				Total
0	5	114	1	0	120	6	95.00%	5%	19%	95.81%

epoch20
prediction pour la classe 25

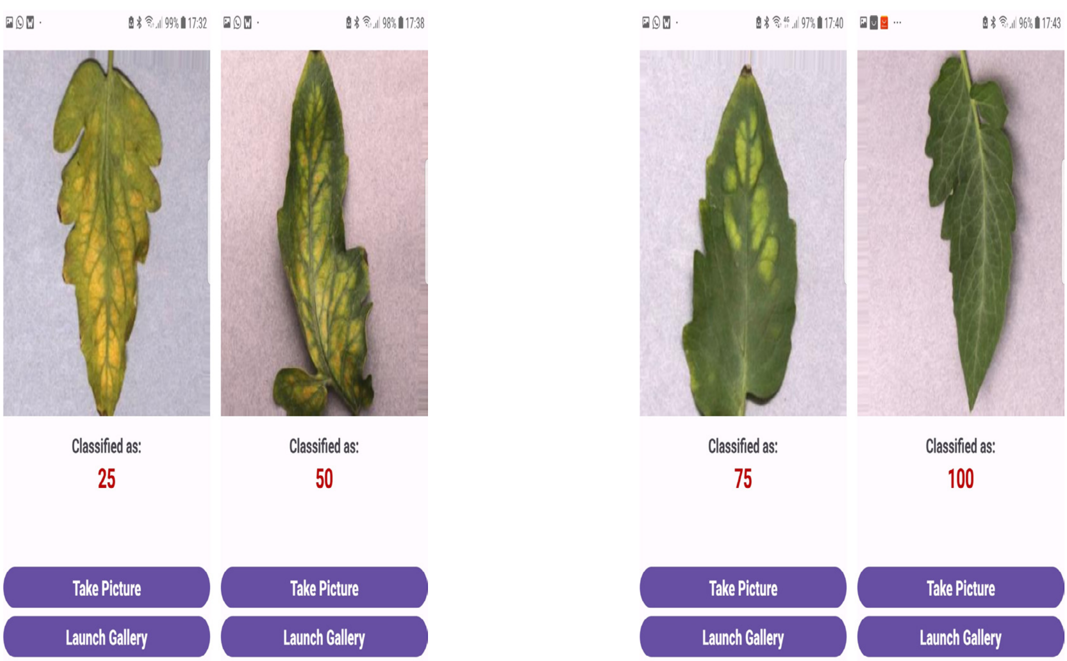
100	75	50	25	autre	original	erreur			
0	0	137	889	3	1029	140	86.39%	13.61%	17.27

epoch20
rediction pour la classe autr

100	75	50	25	autre	original	erreur			
0	0	0	0	70	70	0	100%	0%	20%

Figure 6: Test of prediction)

After that, we converted the model to TFLite format so that it could be used in Android Studio. We then developed a simple Android application using Java and XML. This application is able to load images from the gallery or take photos and then provides the result of the prediction:



(a) (b)

Figure 7: Images loaded from gallery

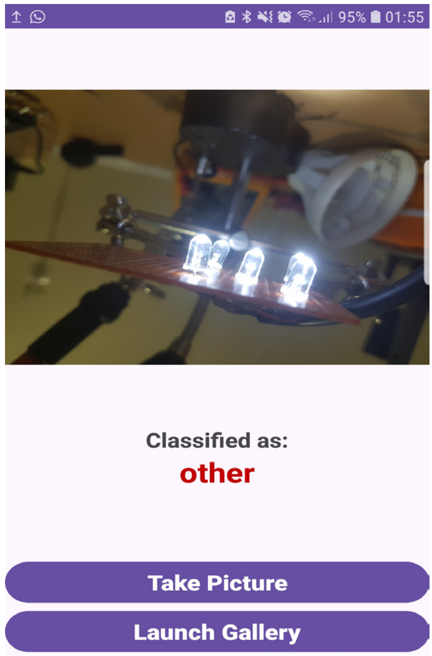


Figure 8: Image loaded from the camera

4.3 Second method

Next, we update and modify our model, like increasing number of neuron for all layers, and disabling some neuron randomly to avoid the overfitting, also updating number of epochs to 120... To fit the model we use in this time a computer with a high performances: Dell Precision 5820 Tower Xeon W-2104, RAM: 16Go, Hard Drive: 4TB - Graphics Card: NVIDIA Quadro P1000.

	100	75	50	25	other	Total
prediction %	100	90.97	84.02	91.67	99.30	**93.19**

Also we use a pre-trained models: VGG16, DenseNet, Iception and ResNet50. We obtained different results, summarized in these graphs:

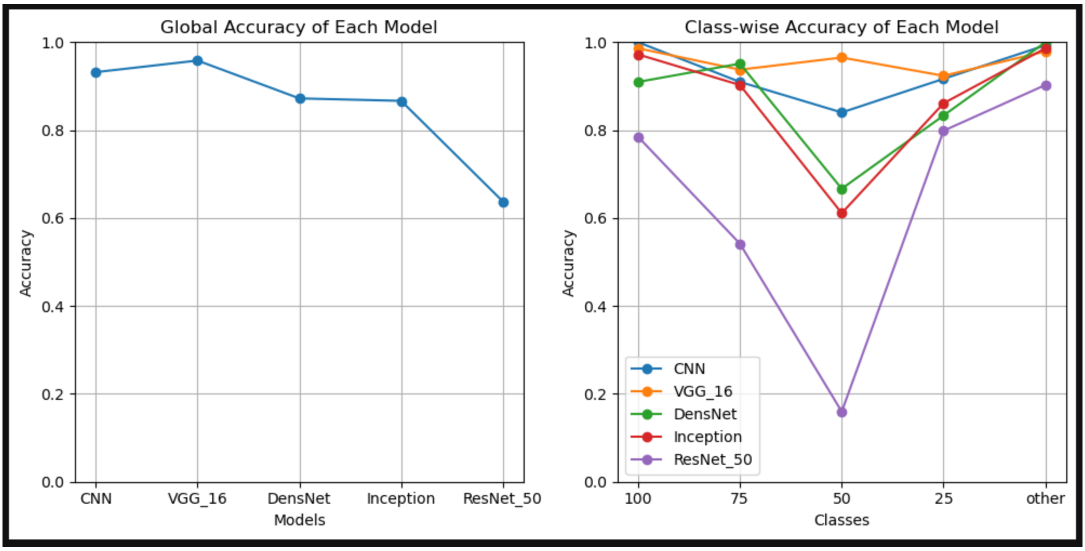


Figure 9: chart of accuracy and prediction of models)

Description and interpretation of results:

Left chart: "Global Accuracy of Each Model"

This graph shows the overall accuracy of each neural network model evaluated. The observations for each model are:

- **CNN**: About 0.95 precision.
- **VGG_16**: Highest accuracy, close to 1.0.
- **DenseNet**: Accuracy about 0.90.
- **Inception**: Accuracy slightly below 0.90.
- **ResNet_50**: Lowest accuracy, around 0.60.

Right chart: "Class-wise Accuracy of Each Model"

This graph shows the accuracy for each specific class for the different models. Classes are listed from 100 to "other". The observations are as follows:

- Classes 100, 75, 25, and "other": All models, except ResNet_50, have an accuracy close to 1.0.
- Class 50: Accuracy drops drastically for all models, with ResNet_50 having the lowest accuracy, close to 0.0.
- Class 75: ResNet_50 accuracy is also low but better than class 50.

Global Accuracy:

- VGG_16 stands out as the most successful model in terms of overall accuracy, indicating that it has learned the characteristics of the data very effectively.
- ResNet_50 has an overall lower performance compared to other models, with an accuracy of only 0.60. This could indicate problems adapting to specific data or suboptimal training parameters for this particular model.

Accuracy by Class:

- Model accuracy is generally high for classes 100, 75, 25, and "other", suggesting that these classes are well represented and easily distinguishable in the dataset.
- Class 50 seems to be a problem for all models, with a drastic drop in accuracy, especially for ResNet_50. This could indicate several possibilities:
  - Data imbalance: Class 50 could be under-represented in the dataset, resulting in poor performance.
  - Poorly discriminating characteristics: Class 50 characteristics can be difficult to distinguish from other classes, leading to inferior performance.

5 Data availability statement

The data is available at [10]

6 Conclusion

In conclusion, this work aims to contribute significantly to precision agriculture by providing an advanced technological solution for water stress management using advanced image processing techniques. Future prospects include improving the deep learning model, integrating multispectral data, and extending the application to other crop types and environmental conditions. Adaptive irrigation management strategies based on image data should be explored in future research to maximize water use efficiency and improve agricultural yields in a sustainable manner.

References

[1] what's smart agriculture url: https://safetyculture.com/fr/themes/smart-farming/ Accessed on: 2024-06-05

[2] Tace, Youness et al. *Smart irrigation system based on IoT and machine learning.* Energy Reports, vol. 8, pp. 1025-1036, Nov. 2022. doi: https://doi.org/10.1016/j.egyr.2022.07.088

[3] Nilakshi Devi et al. *Design of an intelligent bean cultivation approach using computer vision, IoT and spatio-temporal deep learning structures.* Ecological Informatics, vol. 75, p. 102044, 2023. doi: https://doi.org/10.1016/j.ecoinf.2023.102044

[4] Hasibur Rahman et al. *IoT enabled mushroom farm automation with Machine Learning to classify toxic mushrooms in Bangladesh.* Journal of Agriculture and Food Research, vol. 7, p. 100267, Jan. 2022. doi: https://doi.org/10.1016/j.jafr.2021.100267

[5] Natarajan, V. et al. *Detection of disease in tomato plant using Deep Learning Techniques.* Dec. 2020. url: https://www.researchgate.net/publication/349860175_Detection_of_disease_in_tomato_plant_using_Deep_Learning_Techniques

[6] Zhao, Fei et al. *Development of an Irrigation Method with a Cycle of Wilting–Partial Recovery Using an Image-Based Irrigation System for High-Quality Tomato Production.* Agronomy, vol. 12, p. 1410, Jun. 2022. doi: https://doi.org/10.3390/agronomy12061410

[7] Zuo, Zhiyu et al. *Study on the detection of water status of tomato (Solanum lycopersicum L.) by multimodal deep learning.* Frontiers in Plant Science, vol. 14, May 2023. doi: https://doi.org/10.3389/fpls.2023.1094142

[8] Mu-Wei Li, Yung-Kuan Chan, and Shyr-Shen Yu. *Use of CNN for Water Stress Identification in Rice Fields Using Thermal Imagery.* In: Applied Sciences 13 (Apr. 2023), p. 5423. doi: https://doi.org/10.3390/app13095423.

[9] Jiangyong An et al. *Identification and Classification of Maize Drought Stress Using Deep Convolutional Neural Network*. In: Symmetry 11 (Feb. 2019), p. 256. doi: https://doi.org/10.3390/sym11020256.

[10] Bhogendra Mishra et al. *Irrigation Management in Tomato Plants : A Precision Agriculture Approach*. Mar. 2023. doi: 10.6084/m9.figshare.22297915.v1. url: https://figshare.com/articles/figure/Irrigation_Management_in_Tomato_Plants_A_Precision_Agriculture_Approach/22297915.