LIDL4Oliv: A Lightweight Incremental Deep Learning Model for Classifying Olive Diseases in Images

Emna Guermazi[1,2,3], Afef Mdhaffar[1,3], Mohamed Jmaiel[1,3] and Bernd Freisleben[4]
[1]*ReDCAD Laboratory, ENIS, University of Sfax, B. P. 1173 Sfax, Tunisia*
[2]*National School of Electronics and Telecommunications of Sfax, University of Sfax, 3018 Sfax, Tunisia*
[3]*Digital Research Center of Sfax, 3021 Sfax, Tunisia*
[4]*Department of Mathematics and Computer Science, Philipps-Universität, Marburg, Germany*

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Abstract: We present LIDL4Oliv, a novel lightweight incremental deep learning model for classifying olive diseases in images. LIDL4Oliv is first trained on a novel annotated dataset of images with complex background. Then, it learns from a large-scale deep learning model, following a knowledge distillation approach. Finally, LIDL4Oliv is successfully deployed as a cross-platform application on resource-limited mobile devices, such as smartphones. The deployed deep learning can detect olive leaves in images and classify their states as healthy or unhealthy, i.e., affected by one of the two diseases "Aculus Olearius" and "Peacock Spot". Our mobile application supports the collection of real data during operation, i.e., the training dataset is continuously augmented by newly collected images of olive leaves. Furthermore, our deep learning model is retrained in a continuous manner, whenever a new set of data is collected. LIDL4Oliv follows an incremental update process. It does not ignore the knowledge of the previously deployed model, but it (1) incorporates the current weights of the deployed model and (2) employs fine-tuning and knowledge distillation to create an enhanced incremental lightweight deep learning model. Our conducted experiments show the impact of using our complex background dataset to improve the classification results. They demonstrate the effect of using knowledge distillation in enhancing the performance of the deployed model on resource-limited devices.

1 INTRODUCTION

Agricultural crops have a significant nutritional role in our lives. However, plant diseases threaten agricultural yields and pose a considerable risk to the production of food. Indeed, about 20% of global crop losses stem from plant diseases (Savary et al., 2012; Ney et al., 2013). This percentage has increased in the past decade due to the influence of pollution and shifts in climate patterns. To tackle this problem, researchers have made significant efforts to identify and detect plant disease at an early stage. The proliferation of smart farming technologies has fostered the development of innovative technologies to automatically detect plant diseases, such as smartphone-assisted plant disease diagnosis.

To build an effective mobile device solution for plant disease detection, several researchers have proposed to use appropriate deep learning models, either (a) by hosting a deep learning model on a cloud server and implementing a mobile application that interacts with the deep learning model using a communication protocol, or (2) by embedding the deep learning model directly into a mobile application running on a mobile device. The first approach supports the use of large-scale deep learning models running on a server with substantial storage capacity and extensive computational resources. Moreover, this approach is not suitable for real-time agricultural applications. The second approach supports real-time agricultural data analysis, but creating and deploying a lightweight high-quality neural network is not an easy task. Several researchers have created automated mobile solutions that leverage the power of deep learning across various plant types. Some of these solutions are specialized to detecting diseases in tomato leaves (Aishwarya et al., 2023; Chandan et al., 2022). Others identify diseases in corn plants (Hidayat et al., 2019). Additionally, there are efforts to detect terrestrial plants in the Philippines using similar techniques (Valdoria et al., 2019). Furthermore, some researchers proposed solutions for disease detection

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of a variety of plants (Ahmed and Reddy, 2021; Gurav et al., 2022). However, all these approaches do not take into account the need to adapt the deployed model to the changes seen in real-life images. Moreover, up to this point, a smart deep learning based mobile application specifically designed to detect olive leaf diseases is still absent. Detecting olive leaf diseases is particular relevant for the Mediterranean and Aegean regions that collectively contribute to about 95% of the world's olive production (Soyyigit and Yavuzaslan, 2018). This justifies the need for a smart deep learning-based mobile application dedicated to detecting olive diseases.

In this paper, we propose a novel lightweight incremental mobile deep learning model to detect and classify olive diseases in images. For classification, we use the object detection model YOLOv5-n to detect an olive leaf in an image and then proceed with disease classification. We also create and annotate a complex background dataset. This dataset improves the capabilities of the deep learning model to recognize diseases under various settings and in images with different realistic backgrounds. We use knowledge distillation (KD) for object detection to enhance the performance of YOLOv5-n. Next, we deploy our lightweight neural network in a mobile application dedicated to olive farm management and disease prediction. Our approach supports sustainable data collection and offers an incremental update process. This process enables the model to always be up-to-date to the features observed in real-life images.

This paper is structured as follows. Section 2 discusses related work. In Section 3, we present our approach, called LIDL4Oliv. Section 4 sketches implementation details. Section 5 presents the conducted experiments and discusses the obtained results. Section 5 concludes the paper and outlines some areas for future research.

2 RELATED WORK

Detecting plant diseases is among the primary applications of smart agriculture. Deep learning models are widely used for the detection and classification of plant leaf diseases.

Several studies have shown a dedicated interest in the development of deep learning models for the recognition of olive leaf diseases. (Alshammari et al., 2023) presented an approach to analyze olive leaves. The authors used the Whale Optimization Algorithm (WOA) to choose necessary features. Then, they classified the leaves using an optimized artificial neural network (ANN). (Alshammari and Alkhiri, 2023) presented an approach that combines a recurrent neural network architecture with an ant colony optimization algorithm. The ant colony optimization algorithm was used to extract relevant features. Then, disease classification was performed using RNN models. (Osco-Mamani and Chaparro-Cruz, 2023) employed a modified VGG16 architecture for the classification of olive leaf diseases in Tacna. (Mamdouh and Khattab, 2022) used a deep learning model based on the InceptionV3 architecture. (Ksibi et al., 2022) presented MobiRes-Net, a neural network that combines the architectures of ResNet50 and MobileNet. Although these methods propose efficient deep learning models to classify olive leaf diseases, the complexity of the developed deep learning models hinders their deployment on resource-limited mobile devices, such as smartphones. Moreover, none of these methods involves a mobile application-based approach to detect olive diseases automatically.

Research on mobile application approaches that offer automated deep learning-based detection of plant diseases can be classified into two categories. The first category uses cloud servers to host deep learning models (Ahmed and Reddy, 2021; Chandan et al., 2022; Hidayat et al., 2019), while the second category involves deploying a deep learning model within the mobile application itself (Aishwarya et al., 2023; Gurav et al., 2022; Valdoria et al., 2019). (Chandan et al., 2022) developed a plant disease detection system. This system integrated an Internet-of-Things (IoT) platform to collect various measurements, including humidity and temperature. Then, these measurements were uploaded to a cloud server for processing. Leaf images were also transmitted to the cloud platform for analysis. Then, the authors employed a mobile app to display measurement values, send SMS alerts, and provide notifications. (Hidayat et al., 2019) developed an Android application for diagnosing corn diseases using deep learning. Here, farmers select an image from their gallery, which is then sent to a cloud server for processing. A convolutional neural network (CNN) predicts the disease, and the diagnosis is subsequently displayed in the mobile application. (Ahmed and Reddy, 2021) proposed a cross-platform mobile application designed to detect infected plants. The mobile app enables taking a picture of the leaf via the camera or uploading an existing image from the smartphone. Then, a cloud server uses a CNN model for disease detection. Subsequently, the diagnosis of the disease is displayed in the app. The methods belonging to the first category successfully achieve automatic plant disease detection, but their approaches necessitate the availability of extensive computing resources and cannot be

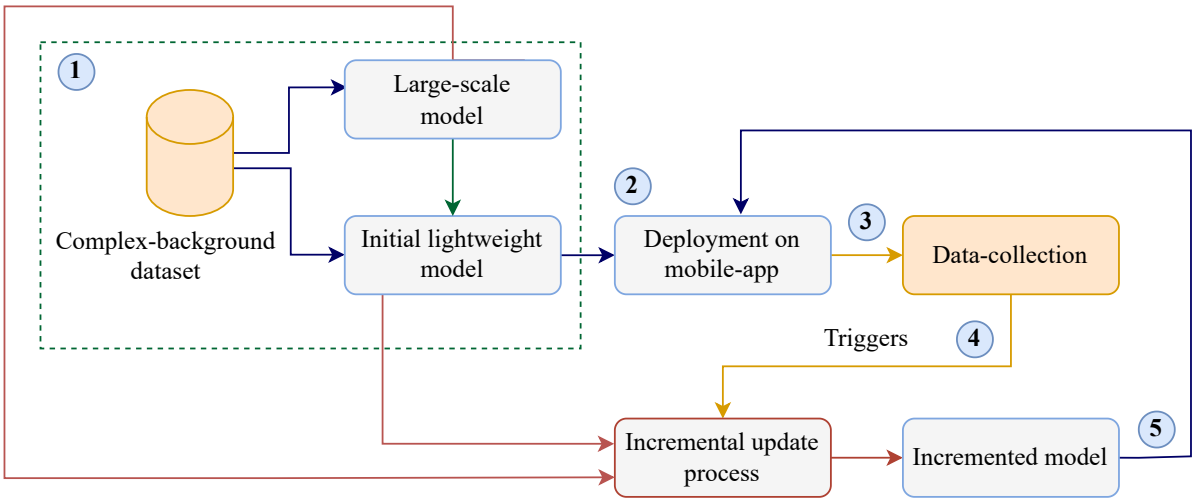


Figure 1: LIDL4Oliv.

easily deployed on resource-limited mobile devices.

The second category of approaches addresses this issue by developing a lightweight neural network and deploying it directly in a mobile application. (Valdoria et al., 2019) proposed a mobile application named "iDahon". This app aims to improve terrestrial disease classification and diagnosis in the Philippines using a deep learning model. (Aishwarya et al., 2023) suggested using a custom CNN model to classify tomato leaf diseases. The application uses a Flask API to establish communication between the user interface and the underlying model. (Gurav et al., 2022) presented an Android application that offers different functionalities. First, it enables farmers to buy and sell saplings. Moreover, it enables the plants' disease detection via employing a lightweight TensorFlow Lite based deep learning model. It also enables the farmers to establish an agricultural community. Additionally, it offers up-to-date weather forecasts for the duration of one week and delivers real-time GPS tracking by utilizing satellite information sourced from OpenWeatherMap. Although the methods in the second category effectively integrate lightweight neural network models into mobile applications, they fail to take into account the models' need to accommodate changes occurring in real-life images.

In contrast to the previously mentioned state-of-the-art methods, we present an incremental update process that allows us to maintain an updated deep learning model that is well-adapted to the features of real-life images. Furthermore, we ensure sustainable data collection, as opposed to other mobile disease diagnosis solutions.

3 LIDL4Oliv

Our approach, called LIDL4Oliv, is based on an incremental lightweight deep learning model that detects and classifies olive leaf diseases via a cross-platform mobile app. Figure 1 illustrates LIDL4Oliv (i.e., **L**ightweight **I**ncremental **D**eep **L**earning model for classifying **Oliv**e diseases). Our approach involves five phases. The first phase includes several steps: (i) Initially, we identify our deep learning model that will be used for deployment. (ii) Then, we create our complex background dataset. (iii) Next, we identify a large-scale deep learning model that is used as our teacher model. (iv) Subsequently, we use knowledge distillation to optimize the performance of our student model. In the second phase, we deploy our lightweight deep learning model as a cross-platform mobile application. The third phase consists of continuously enriching our original dataset by newly processed images. This ensures the creation of a sustainable dataset of olive leaf images. Upon accumulating 30% of new data relative to the original dataset, the fourth phase is initiated where the deep learning model undergoes an incremental update process to enhance its performance, guaranteeing that it is constantly adapted to the new features of the collected images. In the fifth phase, we deploy our incremented deep learning model in the mobile app. Each phase is further detailed in the following sections.

3.1 Deep Learning Model Identification

Classification of olive diseases in images is a challenging task. In this paper, we use olive leaves to detect and identify olive diseases. To solve this task,

(a) Aculus Olearius (b) Aculus Olearius (c) Aculus Olearius (d) Peacock Spot

(e) Peacock Spot (f) Peacock Spot (g) Healthy (h) Healthy

Figure 2: Different olive leaf states (Uguz,S., 2020).

we employ an object detection model instead of a classification model. This decision is motivated by three reasons. First, real-life images usually contain different backgrounds. Thus, it is more suitable to make a distinction between the background and the region of interest itself (i.e., the olive leaf) before identifying the disease. Object detection first localizes the object and then proceeds with classification. By following this process, we have a higher chance of classifying the disease. Second, deploying a single model and using it for both localization and classification is more practical and resource-conserving than deploying multiple models (initially a deep learning model to eliminate the background, followed by another model to classify the leaf disease). Third, an object detection model can detect multiple objects per image. However, in this case, we use it on images where each image includes only one leaf. This is due to the non-existence of an open real-life annotated olive leaf dataset containing multiple leaves per image. Thus, we decided to primarily create a dataset where each image includes a background and solely one leaf. This serves as the first set of training data to train our initial model. Then, after deploying the model as a mobile app, it is possible to collect realistic images and annotate them on the basis of experts' knowledge. Subsequently, we are able to adjust our model accordingly to localize and classify multiple leaves in an image.

We conducted a search for annotated olive leaf images and identified an open dataset established by (Uguz,S., 2020). This dataset was created for olive leaf disease classification. It involves olive leaf images that correspond to three states (i.e., 'Healthy" or affected with "Aculus Olearius" or "Peacock Spot"). However, it is composed of images having a simple and unrealistic background, as illustrated in Figure 2. Thus, relying on such a dataset would yield a deep learning model that is not suitable for real-life olive leaf disease detection. Given these circumstances, we used the Uguz dataset (Uguz,S., 2020) and generated a complex background dataset with bounding box annotations to localize a leaf and identify its state. The next section explains the process of generating the complex background dataset with bounding box annotations.

We use the YOLO architecture as our object detection model. Indeed, contrary to two-stage detectors like Faster R-CNN, YOLO's architecture enables us to detect multiple objects in a single pass through the neural network, making it faster. Additionally, YOLO achieves a good balance between speed and accuracy, qualifying it for usage scenarios requiring real-time processing. Moreover, YOLO is available in different lightweight architectures, such as YOLO-s and YOLO-n, which make it adequate for our use case. We identified YOLOv5-n, following the work of (Ye et al., 2023), as our model to use for deployment.

3.2 Generation of an Annotated Complex Background Dataset

To create a dataset including leaf images with a complex background, we followed two steps. First, we constructed a dataset with a white background and created the corresponding bounding box labels. Then,

we used an overlapping technique to generate images with complex background. These intricate backgrounds correspond to images captured in the garden, incorporating elements such as sand, hands, etc. Although these backgrounds may not perfectly match the context of photographing in the field, they allow the model to detect the leaf within images containing backgrounds. Thus, our model differentiates between the background and the leaf, and identifies the state of the leaf accurately. This dataset allows us to deploy an initial model in real life (i.e., ready to be used by farmers).

3.2.1 Generation of an Annotated White Background Dataset

Our newly produced white background dataset is based on Uguz's dataset (Uguz,S., 2020). It incorporates bounding box annotations to train deep learning models for object detection and classification, contrary to Uguz's dataset that is solely used for image classification. The original dataset is composed of two folders: one for training and the second one for testing. Within each folder, there are three subfolders. Each of these subfolders contains images that correspond to a specific class of an olive leaf. This class can be either "Healthy" or affected with either "Aculus Olearius" or "Peacock Spot". In the remainder of this paper, we refer to the "bounding box annotations" by "annotations", and to the true labels of each class by "ground truth labels".

To construct our dataset, we first applied data augmentation techniques to Uguz's dataset. This allowed us to introduce greater image variations.

Then, we used the Canny method (Canny, 1986) as a contour detection algorithm to annotate 31% (1,479 images) of our dataset. We also used several preprocessing techniques such as Gaussian blur, histogram equalization, and median filtering to create annotations. We developed a Tkinter (Steen Lumholt and Guido van Rossum, 2009) interface to support the selection of images with accurate bounding boxes, as shown in Figure 3.

The Tkinter interface is used for validating the annotation of each image. For the rest of the images that were not annotated, we used YOLOv5-m to complete the annotation process. We employed the annotated images, which represent 31% of the dataset, to train the model. Then, we used the trained model to produce the annotations of the remaining images. YOLO allowed us to annotate around 66% of the dataset, i.e., leaving 3% (i.e., 150 images) not annotated. The remaining images were manually annotated, via the use of LabelImg (Tzutalin, 2015), as shown in Figure 4. We selected LabelImg due to its user-friendly simplicity.

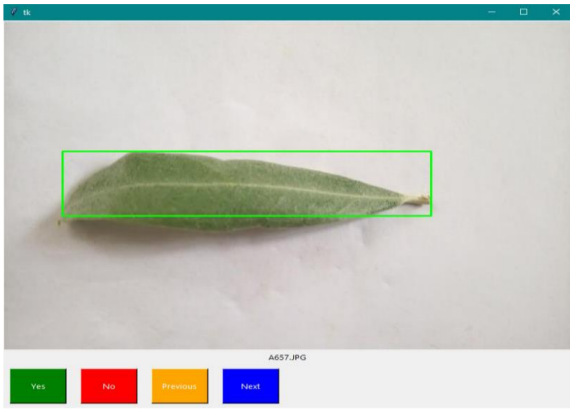


Figure 3: The Tkinter interface used to validate the bounding box annotations.

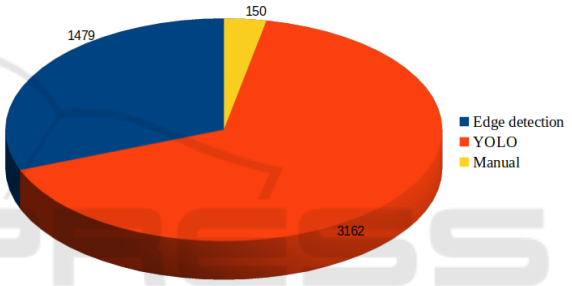
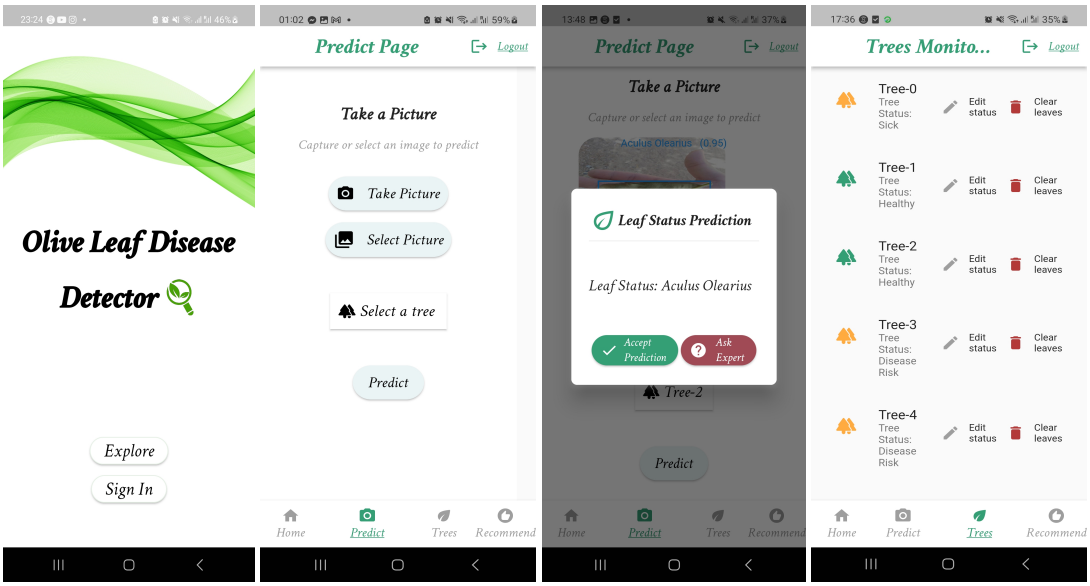


Figure 4: Number of images annotated using different methods.

3.2.2 Overlapping Process

The second step involves changing the white background of the dataset to a more complex one. To guarantee the retention of the established annotations, we undertook a meticulous overlapping process. This process involves two steps. The first one consists of generating masks from the white background dataset using a pre-trained U2-Net model (Qin et al., 2020). The generated masks are binary images where the background is represented by black pixels, and the region of interest, which is the leaf, is represented by white pixels. The employed U2-net model was pretrained on the DUTS dataset (Wang et al., 2017). After the masks' generation, we moved on to the second step. This step involved combining the generated masks with other images that represent a complex background. The resulting complex background dataset enables the YOLO model to accurately detect and classify the state of the olive leaves in intricate and varied settings, paving the way for improved classification performance in real-life situations.



(a) Splash screen (b) Prediction page (c) Prediction results (d) Trees' monitoring page

Figure 5: Selection of some pages of the mobile application.

3.3 Initial Training Process

To enhance the performance of our lightweight neural network, i.e., YOLOv5-n, we incorporated knowledge distillation into the training process. This technique is based on knowledge transfer from a large-scale neural network referred to as teacher to a lightweight neural network named student to boost its performance. Its initial application was in image classification tasks (Hinton et al., 2015; Gou et al., 2023; Tian et al., 2020), subsequently expanding to encompass object detection in images (Chen et al., 2017; Kruthiventi et al., 2017). The integration of knowledge distillation into object detection tasks significantly boosted the performance of the employed models (Li et al., 2023; Yadikar et al., 2023). However, it is still a challenging task.

Some approaches are based on global distillation where the student tries to mimic the whole feature maps extracted from the middle layers of the teacher. However, relying on all the feature maps might lead to learning irrelevant knowledge that would not help the student in its task. Therefore, some researchers showed interest in local feature distillation (Wang et al., 2019) to arrive at detector distillation, proposing the distillation of backbone features extracted from local regions surrounding objects. We use this approach to distill knowledge from YOLOv5-m to YOLOv5-n.

3.4 Cross-Platform Mobile Application

We deployed our model as a cross-platform mobile application (i.e., compatible with both Android and iOS). This application is designed to enable automatic olive leaf disease prediction while also establishing an olive farm management system. It is called "Olive Leaf Disease Detector", as illustrated in Figure 5a. The splash screen of the application allows users to either explore or sign in. It provides them with multiple functionalities based on their roles. A user can have the role of an admin, a farmer, or an expert. An admin assumes responsibility for managing other users and the existing trees on the property. Indeed, the admin adds trees to the system. Each added tree corresponds to an existing tree in the field. Our application enables the farmer to predict the state of an olive leaf based on the prediction of a deployed deep learning model. A farmer can either take a picture using the camera of his or her smartphone or import it from his or her gallery. Then, (s)he chooses the tree to which the leaf is associated. The prediction page is shown in Figure 5b. Subsequently, (s)he can either accept the model's prediction or seek an expert's evaluation, as illustrated in Figure 5c. Additionally, the farmer can recommend an expert to the admin through a provided form within the mobile application. The expert is responsible for answering the farmers' requests and giving his or her opinion regarding the condition of specific leaves. Furthermore, (s)he is able to go through all the leaves existing in the database via the mobile application, enabling him or her to offer insights on

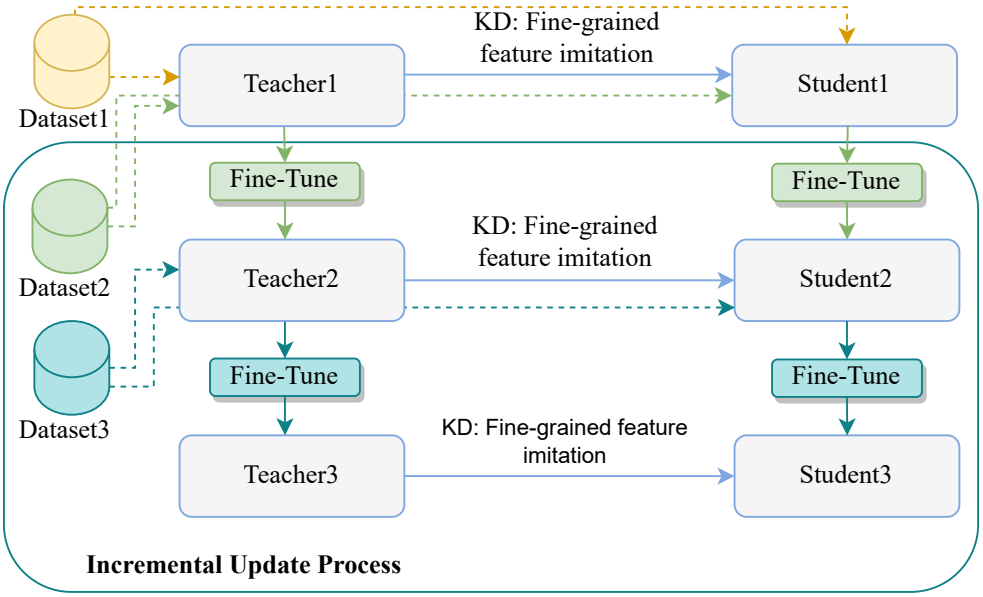


Figure 6: Incremental update process.

any leaf status. When a leaf has two predictions, one provided by the deep learning model and the other given by an expert, the status attributed to it will be based on the expert's opinion.

Furthermore, our application enables the monitoring of the health of the existing trees. By default, all trees are considered to be in a healthy state. However, when a leaf state is changed to "Aculus Olearius" or "Peacock Spot", the status of that corresponding tree changes to sick. After the identification of an unhealthy tree, it receives proper treatment. Then, a farmer can access the mobile application and change the status of the tree to healthy again. (S)he can also delete all its leaves since they hold no meaning after its status has changed. Furthermore, the farmer can also delete the leaves after the season changes. Figure 5d presents the trees' monitoring page. This application also ensures a sustainable data collection. Indeed, whenever a leaf status is predicted, the image is saved with its corresponding label and bounding box annotations in a remote server. Figure 7 illustrates the communication process between the mobile app screens (i.e., front-end) and the back-end, while also representing the data collection process.

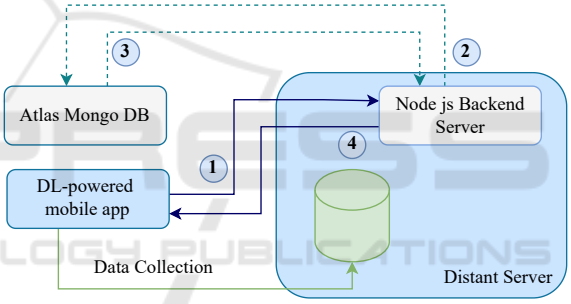


Figure 7: Global overview of the mobile application.

3.5 Incremental Update Process

To ensure the adaptability of our deployed model to the features of the real-life images, we propose to use an incremental update process. This process gives the model the ability to evolve after gathering new data. It involves a number of iterations as illustrated in Figure 6. Each iteration is initiated when the images of new data reach 30% of the initial data. We retrain the insights of the pre-trained teacher and the pre-trained student by incorporating their pertained weights into the update process. In each iteration, we fine-tune the pre-trained teacher on dataset$_{i+1}$, which represents the newly gathered dataset, at iteration$_i$. Thus, we obtain a fine-tuned teacher. This teacher is referred to as teacher$_{i+1}$. We also apply fine-tuning on the pre-trained student. The produced student is referred to as student$_{i+1}$. Then, we apply the same knowledge distillation method that we used in the initial step (Wang et al., 2019) (i.e., fine-grained feature imitation). This incremental update process reaches its end when a student$_{i+1}$ (i.e., produced in iteration$_i$) achieves good performance when evaluated on a dataset$_{i+2}$. It means that this student model is well adapted to the features of real-life images. This incremental process will be implemented and experimentally validated upon collecting real-life images through the mobile app and

Table 1: Performance of YOLOv5-m: ***Setting 1*** vs ***Setting 2***.

	Precision		Recall		mAP50-95	
	Setting1	Setting2	Setting1	Setting2	Setting1	Setting2
All	0.978	0.986	0.984	0.991	0.961	0.979
Healthy	0.988	0.987	0.989	0.994	0.955	0.972
Aculus Olearius	1	0.985	0.975	0.987	0.968	0.982
Peacock Spot	0.946	0.987	0.987	0.993	0.961	0.982

annotating them accordingly.

4 IMPLEMENTATION ISSUES

We implemented LIDL4Oliv using the SGD optimizer with a momentum value of 0.9. The initial learning rate, weight decay, and batch size were set to 0.01, 0.0005, and 16, respectively. The training and testing phases were conducted on an NVIDIA RTX3080 GPU. For a fair comparison, all models underwent training for 100 epochs.

5 EXPERIMENTAL EVALUATION

5.1 Experimental Settings

To evaluate our approach, we conducted a series of preliminary experiments allowing us to identify our experimental setting. These preliminary experiments consist of training and evaluating the performance of our teacher (i.e., YOLOv5-m) on the white background dataset, in two settings. ***Setting 1*** involves training the model from scratch, while in ***Setting 2*** we use pre-trained-model's weights as a starting point. These weights correspond to the YOLOv5-m model after being trained on the COCO dataset (Lin et al., 2014).

The main objective of this experiment is to identify the best setting to be used for the rest of the experiments.

Table 1 and Figure 8 show the obtained results when training YOLOv5-m in ***Setting 1*** and ***Setting 2***. Table 1 demonstrates that the overall precision, recall, and average mean precision (i.e., mAP50-90) are higher when using ***Setting 2***. These results also reveal that the recall and the mAP50-95 values of each class individually exhibit higher values in comparison to ***Setting 1***. However, the precision values of the "Healthy" and the "Aculus Olearius" classes are higher when using ***Setting 1***. Figure 8 presents the accuracy of predicting each class correctly. It shows that ***Setting 2*** shows a better classification accuracy for the "Healthy" and the "Aculus Olearius" classes,

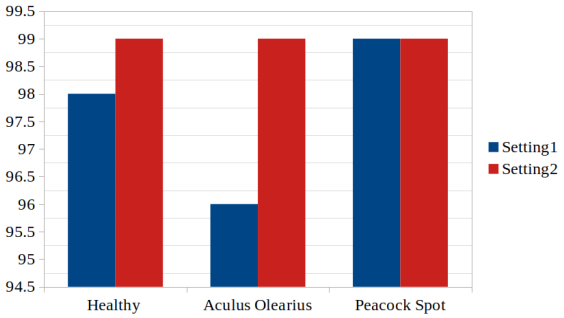


Figure 8: Classification accuracy of YOLOv5-m: ***Setting 1*** vs ***Setting 2***.

while, the accuracy of predicting the class "Peacock spot" is the same for both settings. Thus, we can conclude that ***Setting 2*** enables the model to achieve better results in most of the evaluation metrics.

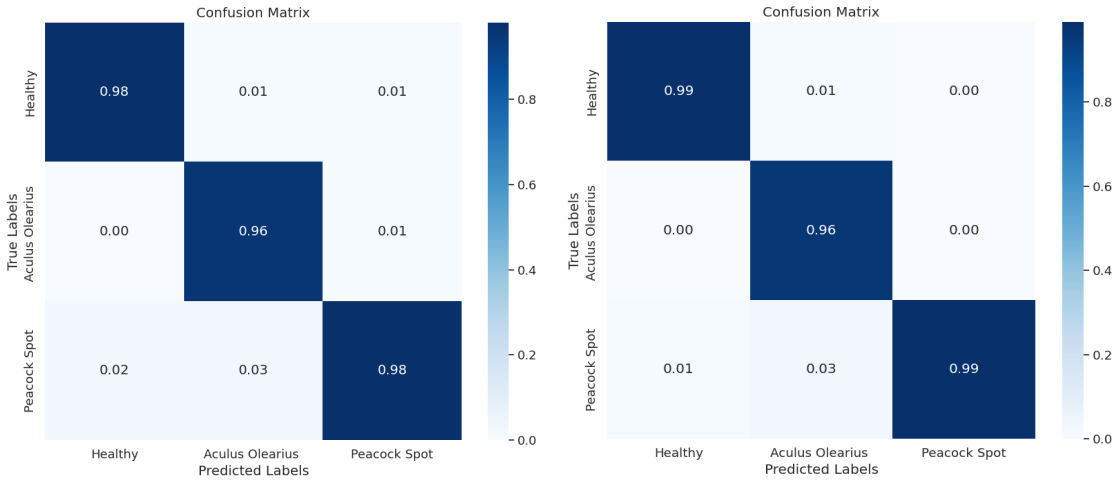
As a result, we work with ***Setting 2*** in the rest of this paper.

5.2 Evaluation of LIDL4Oliv

To evaluate the performance of LIDL4Oliv, we followed three steps. First, we assessed the performance of the pre-trained teacher model (i.e., trained on the white background dataset) on images with complex backgrounds. Second, we trained and evaluated the performance of a teacher model trained on our complex background dataset. Third, we evaluated the performance of the student model with and without knowledge distillation.

5.2.1 White Background Dataset

The results of the experiments conducted in the previous section show that YOLOv5-m, our teacher model, achieves good results when evaluated on white background images. However, when we evaluate its performance on images that have complex backgrounds, we notice that its performance decreases, as illustrated in Table 2. YOLOv5-m achieves an overall average mean precision of 0.298, demonstrating how inefficient the pre-trained model can be when faced with images containing complex backgrounds. Furthermore, we identify the limitation of using a white background dataset for training and also justify the



(a) Confusion matrix of YOLOv5-n (w/o) KD

(b) Confusion matrix of YOLOv5-n with KD

Figure 9: Confusion matrix of YOLOv5-n with and (w/o) KD.

Table 2: Results of YOLOv5-m trained on a white background dataset and tested on a complex background images.

	mAP50	mAP50-95
All	0.394	0.298
Healthy	0.347	0.266
Aculus Olearius	0.609	0.465
Peacock Spot	0.225	0.163

need to use a complex background.

5.2.2 Complex Background Dataset

Training on a dataset with a complex background is of high importance. This is because a real-life image usually includes a complex background. Thus, to ensure the performance of our deep learning network in the field, it is essential to train it on a similar dataset. We use the same images when testing both the teacher and the student. Samples of these images are presented in Figure 11. Table 3 presents the obtained results when training YOLOv5-m on our complex background dataset.

Table 3: Results of YOLOv5-m trained and tested on complex background dataset.

Class	Precision	Recall	mAP50	mAP50-95
All	0.992	0.988	0.993	0.969
Healthy	0.989	0.989	0.994	0.959
Aculus Olearius	1	0.983	0.995	0.974
Peacock Spot	0.987	0.993	0.991	0.975

It is plausible that the achieved outcomes exhibit remarkable performance in terms of precision, recall, and mAP50-90. Indeed, its precision and recall values are 0.992 and 0.988, respectively. Also, its mean average precision, mAP50-90, is equal to 0.969. Figure 10 presents the confusion matrix of YOLOv5-m. It demonstrates that our teacher model achieves reasonable classification results across all designated classes.

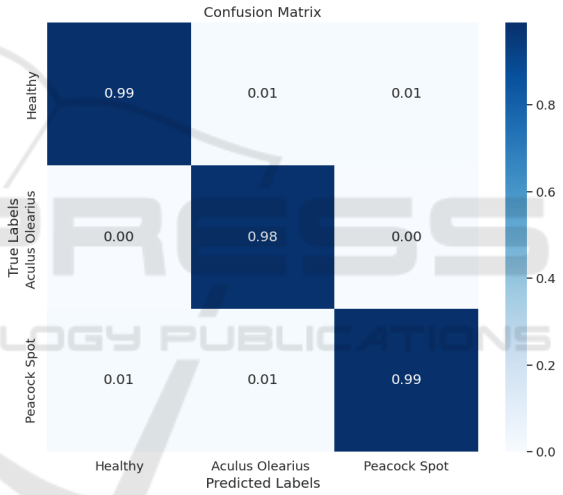


Figure 10: Confusion matrix of YOLOv5-m.

5.2.3 Comparative Performance Analysis of YOLOv5-n With and Without Knowledge Distillation

To evaluate the performance of our student model (YOLOv5-n) in detecting and classifying olive diseases, we compare its performance with and without using knowledge distillation.

We also present the performance of the teacher model (YOLOv5-m) for a meaningful comparison with the performance of the student model. Figure 9 presents the confusion matrix of our student model

Figure 11: Detection and classification results of YOLOv5-n trained with KD.

Table 4: Performance of YOLOv5-n: With KD vs. without KD.

	YOLOv5-m	YOLOv5-n (w/o KD)	YOLOv5-n (with KD)
Precision	0.992	0.987	0.989
Recall	0.988	0.976	0.98
mAP50	0.993	0.994	0.994
mAP50-95	0.969	0.954	0.951

with and without KD. It is clear that knowledge distillation has improved the performance of the student in classifying leaf diseases. Using KD enhanced the student's ability in classifying the "Healthy"and the "Peacock Spot" state by an additional 1% for each. The experimental results shown in Table 4 present the precision, the recall, and the mean average precision of the teacher (YOLOv5-m), and the student (YOLOv5-n trained with and without KD). It demonstrates that YOLOv5-n trained using KD outperforms YOLOv5-n trained without KD, in terms of precision and recall. Specifically, YOLOv5-n trained using KD obtains a precision value of 0.989 and a recall value of 0.980, while YOLOv5-n trained without KD achieves a precision value of 0.987 and a recall value of 0.976. We can also observe that the precision and the recall of YOLOv5-n trained using KD achieves comparable results when comparing it with the precision and the recall values of the teacher YOLOv5-m, showing the impact of fine-grained feature imitation knowledge distillation approach in enhancing the performance of the student's performance. However, we notice that the mean average precision, mAP50-90, achieved by YOLOv5-m trained without KD is slightly higher than that achieved by YOLOv5-m trained with KD. This is quite plausible and acceptable. Examples of detection and classification results of YOLOv5-n trained with KD are shown in Figure 11. The test images are part of our generated dataset.

6 CONCLUSION

In this paper, we presented a novel lightweight incremental deep learning model, called LIDL4Oliv, to detect and classify olive leaf diseases in images. It is based on YOLOv5-n for high-quality classification. We used knowledge distillation to achieve very good results and deployed our model as a cross-platform mobile application. This mobile application supports

automatic olive leaf detection and serves as a farm management system. Our mobile application enables a farmer to ask for an expert opinion if (s)he wants further evaluation of the leaf status. We established a sustainable data collection process by gathering processed images captured through the mobile application. We also introduced an incremental update process that ensures the adaptability of YOLOv5-n to real-life images collected through the mobile application. Our experimental results showed the performance of our deployed model in terms of classification accuracy, precision, recall, and mean average precision.

In the future, we intend to release our mobile application on the Play Store and make it available for free. This will allow us to collect annotated real-life data. The collected data will be used to improve the performance of our mobile application and effectively assess and validate our incremental update process. Moreover, the weights of our pre-trained YOLOv5-n model can serve as initial weights when we extend our task to include the detection of multiple leaves per image and identifying their status.

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