Artificial Intelligence Driven Vertical Farming Management System

Melis Siropyan, Ozan Celikel, Ozgun Pinarer

Abstract—**The change in the climate conditions and the increase of the consumption with the increased population, forced change in the agricultural field. This change brings a question of how to reach enough natural products even in small areas. Vertical farming option emerged as one of the sustainable options with the short supply chain processes. Besides, it helps to decrease the effects of climate change and improve the sustainability since it utilizes less water and avoids problems such as arid soil, soil infertility etc. Technological developments started to spread rapidly in the agricultural field and led to various digital transformations according to the needs. Recently, the new concept of smart agriculture makes agriculture more efficient and effective thanks to high-precision algorithms. The most significant farming applications are irrigation management, pest and disease control, greenhouse condition monitoring, soil and water quality monitoring, precision agriculture and dairy management. In this study, machine learning methods are applied such as CNN image processing model which can detect and identifying diseases on plants. In this research, AI based lettuce diseases detection system is proposed. An AI model is developed to identify different lettuce diseases. The model was built with ResNet50 and ImageNet on Tensorflow. Various over fitting prevention methods are also applied to the model to compensate for the limited training dataset and the results of the study are discussed. It will guide people towards enhancing awareness of the importance and necessity of using various machine learning techniques and various alternatives to traditional agriculture for the sustainability.**

Index Terms—**smart agriculture, vertical farming, machine learning, smart systems**

I. Introduction

Vertical agriculture is one of the valuable indoor methods to solve the food supply chain problem. This kind of agriculture is the method of growing crops in layers put together vertically. The main goal of these systems and the most important difference from other alternative systems is to produce more food per square meter of land, reducing the footprint. This innovative system consumes 95% less water than other systems and saves considerable space and soil [1].

Vertical farming is one of the valuable methods for food supply chain problem. Vertical farming is the practice of growing crops in vertically stacked layers. Major goal of such architecture is to produce more foods per square meter. This innovative system lowers the requirement of water to up to 70% and saves considerable space and soil. Nowadays, vertical farming is accepted as an attractive option for farmers. Due to its water and space requirements, it promises a much more sustainable way to produce foods. Since these systems are commonly constructed in indoor environments, a perfect combination of natural and artificial lights should be used to maintain the perfect light level in the room.

It has been an interesting agricultural approach in the world of agriculture as it saves water and requires less space. It is accepted as an attractive system for farmers thanks to these strengths. For the same reasons, it also provides the appropriate environment for sustainable agriculture. The most basic feature that distinguishes these systems from other competitors is the possibility of producing food in a closed area. The first requirement of growing food indoors is the proper adjustment of the light, humidity and temperature values in the indoor environment and following these settings optimally during food cultivation. Agriculture systems that require less soil and less water attract more attention and promise a much more sustainable way of producing food, as the land that can be cultivated in the world is decreasing day by day and the shortage of water worldwide is expected to start soon.

In conservative agriculture, the producer is dependent on many external factors, for example, unstable weather conditions, pests, diseases, infrastructure deficiencies, low rainfall, floods, etc. Many of these external factors are also dependent on to climate change. As climate change is real and could be seen by naked-eye, traditional agriculture has less advantage than vertical farming. In addition, air pollution that started to occur in rural areas also affects traditional agriculture significantly. The supply chain of conservative agriculture is long enough and polluting the air by swapping 3-4 different middlemen which causes climate change. By this swap, the prices rise and neither the farmer nor the consumer gains much. However, due to operational and investment costs, traditional farming has more advantages in prices than vertical farming.

Vertical farming can have many positive implications for the environment and climate change. Vertical farms tend to be more closed systems, the nutrients for the crops are re-circulated. As these nutrient solutions are valuable resources, they are not dispersed into the environment. With conventional farming when crops are fertilized, the fertilizer can run down into the environment where high concentrations can have a negative impact on the ecology. As fertilizers are in essential nutrients, many species can take advantage of this abundance and reproduce beyond the capacity of their local environment.

Another advantage of vertical farming is that it does not have to take up any land area which can be utilized to regrow forests which may help the current situation with climate change. Besides, climate change with weather instability

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has the potential to wreck crops with hurricanes or cause drought. Vertical farms have the possibility of completely being isolated from their environment. In fact, if other planets are to be colonized, it is our strong belief that it will involve vertical farming.

Considering traditional agriculture, efficient cultivation of the crops depends on many external factors. Many factors such as unstable weather conditions, plant insects, plant diseases, air pollution, precipitation and floods directly affect the efficient growth of food. For this reason, farming practices, such as vertical agriculture, which are well sheltered and away from external factors, become more attractive by farmers. In addition, traditional agriculture has a long supply chain in its internal functioning. Throughout this supply chain, the crop changes 3-4 different intermediaries until it reaches the end consumer and the price increases with each change. However, due to operational and investment costs, traditional agriculture is currently more financially competitive than vertical agriculture at the cost of environmental change. Another disadvantage with vertical farming is that it is more power-intensive than other farming methods as sunlight is not used or needs to be supplemented for the lower layers. In fully closed systems the day/night cycle of the plants does not need to be synchronized with the day/night cycles. Therefore, they can be used as a means of balancing the electrical grid. Vertical farming environments are in industrial buildings, container farms, in-store farms where the consumption or the purchase is high like supermarkets or restaurants, and appliance farm which targeted for in-house environments.

AI is an efficient computing tool trains the machines to learn from experiences, adapt to new data, and perform human-like tasks. In this study by using neural networks, the algorithm is trained to detect the diseases in plants by processing large amounts of images and recognizing patterns in the data.

Due to operating and investment costs, traditional farming is currently more financially competitive than vertical farming at the cost of environmental change. Another disadvantage of vertical farming is that it is more energy intensive than other farming methods because sunlight is not used or needs to be supplemented for the lower layers. In completely closed systems, the day/night cycle of the installations does not need to be synchronized with the day/night cycles. Therefore, they can be used as a means of balancing the power grid.

Today, in smart agriculture systems, one of the important problems is that the crops of the agricultural farmers are wasted due to various diseases. However, diseases of plants also have stages, and if the disease is diagnosed in the early period, the spread of the disease to other plants can be prevented and in a more optimistic scenario, the plant can be treated. For this purpose, in this paper a smart system is presented that detects diseases by looking at the leaves of plants based on supervised learning ML method.

The remainder of the paper is structured as follows: Section II discusses the theoretical background of the research. Section III presents the methods used and the work produced. Experiment setup and performed experiments are presented in Section IV. Finally, conclusion and discussion are given in Section V.

II. Related Work

Improving farm productivity is one of the main aims of farming applications and systems. Using machine learning (ML) techniques and improved artificial intelligence (AI) techniques may provide significant solutions to increase the productivity and crop harvest. In machine learning methodology, there are basic methods that can be applied on the acquired data (again basic data should be acquired from the environment): regression, clustering, Bayesian models, instance-based models etc. Besides, commonly a decision tree that is classification or regression models formulated in a tree-like architecture is constructed. With construction of such tree structure, the dataset can be progressively organized in smaller homogeneous subset.

In such ML applications support vector machine (SVM) and neural network (NN) are well known approaches. To separate two classes, support vectors define the discrimination function of linear SVM. In these approaches, k-mean is mostly preferred ML algorithm [2].

Moreover, artificial neural network (ANN) approaches can also be applicable on farming data. Basically, ANN emulates the human brain functionality and use pattern generation for complex functions [3].

With the gradual deepening and development of the machine learning methods, deep learning-based approaches are also involved in research. Especially deep learning methods are used for classification. Zhong et al. [4] propose a framework that covers multiple models to classify summer crops based on Long Short-Term Memory (LSTM), and one-dimensional convolutional layers. In the literature, these various machine learning models are applied in farming domain for crop and yield management, disease, weed, pest detection. Especially deep learning models bring high efficiency in plant classification, phenotyping, soil, and water management.

Disease detection has a critical effect on the crop production. Thus, much research are focused on the disease detection. etc [5], [6]. Authors proposes a monitoring system to detect the disease on the leaf and fruits. The study uses neural network and image processing to achieve a disease detection and to increase the harvest efficiency. As Jhuria et al., Bhange et al. [7], present that the uneven climatic conditions cause a decrease of agricultural yield. To avoid such effect, authors propose a web-based tool to identify fruit disease by image processing and feature extraction and several data analysis methods. Chung et al. [8] introduce a SVM classifiers and a genetic algorithm to detect bakanae disease in rice seedlings. Similarly, Ebrahimi et al. [9] propose using SVM classification methods and image processing for pest detection. Kim et al. [10] introduce cloud-based prediction system for disease detection on strawberries. With the proposed approach, several information such as weather, distribution, pricing etc are collected and analyzed in agricultural decision makers services. Ferentinos et al. [11] introduce CNN models to identify plant diseases through simple leaves images of healthy or diseased plants. al. [12] used SVM, RF and an ANN for pest and disease detection from the chili that features were extracted using a deep-learning-based approach and were compared with the traditional approach.

Plant stress and the detection of the health status are another critical challenge [13]. Plant stress means where a plant is growing in non-ideal growth conditions. It can be occurred by different outside parameters such as drought or wind, over irrigation or root disturbance. The proposed ML based system includes various optical sensor devices to identify biotic and abiotic stresses. The ML model uses LSSVM and the sensor fusion for the detection. Such models are summarized in Behmann et al. [2]. They introduce a brief summary of machine learning applications in the literature to improve crop yields.In the literature, there are many studies on machine learning based health conditions [14], corn grain yield health and prediction [15], [16], soil management [17]–[19]. On the other hand, IoT devices are highly easy to use in agriculture domain, researchers are motivated to integrate IoT solutions combined with ML based approaches [20], [21].

Thus, machine learning applications in farming require multidisciplinary approaches coming from IoT, big data and computation. A storage and real time data analyzing systems are highly crucial for these applications. Table I summarizes the existing machine learning applications in farming domain.

III. Proposed Approach

The concept of growing food in an indoor environment in a vertical manner creates several opportunities: handle future food demands, significantly less water, eliminate weather, crop effects, and diminish the diseases, less exposure to chemicals. On the other hand, the investment to build such a system can be costly. Pollination in such an environment is another problem to solve. Besides, these systems rely on technical infrastructure where any technical failure should be well considered [30]. Still, once more information are gathered and the workings of plants are discovered that need to be grown, the growing environment can be optimized to increase harvest size and reduce energy consumption.

The trend is that people want to eat healthier foods and lead healthier lives. This trend is leading people to look for alternatives to indoor farming. These types of agricultural alternatives are not affected by climate change or pests. Such approaches are used to develop a micro-based indoor system tool with AI function that detects diseases in vegetables. Artificial Intelligence (AI) is an effective computing tool that trains machines to learn from experiences, adapt to new data, and perform human tasks. In this study, using neural networks, the algorithm is trained to detect diseases in plants by processing large amounts of images and recognizing patterns in the data.

The objective of this project is to present an artificial intelligence system capable of detecting diseases on a closed vertical agricultural system. To accomplish this goal, things must be provided; on the one hand, a vertical farming system must be implemented, and on the other hand, an algorithm capable of detecting diseases.

Various techniques have been used to detect diseases in recent years. Studies by Jhuria et al. are a good example in this category, in this study, two apple diseases and three grapevine diseases are chosen to be detected and two image databases are used. One of the image datasets is used to detect for already stored diseases imaging and the other for query image implementation [22]. Another study on the same subject [7] uses image processing to detect diseases on pomegranates. Once the different features of the images have been extracted, the k-means algorithm is used to cluster the data. And SVM is used for classification.

Regarding these studies, a closed vertical agricultural system is proposed that will be monitored by an image capture system to detect diseases on plants. This system will allow users to develop their bodies wherever they want while detecting and fighting diseases they encounter in their bodies more quickly. Anticipate that an image processing must be used on a vertical farming system that is implemented.

The vertical farming model is an indoor farm, adopting a multi-level high-rise factory design [31], and by its nature, vertical farming gives us a very high yield without depending on external factors. However, building such a facility that can provide a system like this is more expensive compared to traditional [32] methods. Therefore, there are different variations of vertical farming models. Some of these models will be discussed in this part of the section.

One such model mentioned in the model proposed by Benke & Tomkins [31]. In this model the basics of vertical farming can be seen. A closed vertical farming system must be self-sufficient by relying on a renewable energy source, and the system must be completely independent. To provide this independence, they considered the use of artificial intelligence for system monitoring, resulting in minimal human interaction. In addition to this, they offer the use of LED lights instead of sunlight. This paves the way for production that is completely independent of weather conditions and the day/night cycle. Another important aspect of this study is the vertical placement of the body. By placement at several levels, it is possible to have a very favorable yield per use of space.

The system proposed in this study is a happy medium between these examples, a closed vertical agriculture with LED lights and various IoT components to monitor. And the management of the system will be done by an image processing algorithm. The concept of micro-scale vertical farming is illustrated in Figure 1.

For software purposes, Keras is used as a framework. Keras has many advantages that make it more attractive than its peers and the biggest of these advantages is its speed and accessibility. Keras minimizes the number of user actions needed for common use cases and provides clear, actionable feedback in case of user error. Keras is one of the most popular and successful deep learning frameworks.

Keras uses the TensorFlow machine learning platform, which allows its users to easily configure CPU and GPU configurations while training a model. Besides TensorFlow, there are various other options to choose from as a model. Despite PyTorch is one such model that is very popular, in our study TensorFlow was preferred over it due to its compatibility with Keras.

ImageNet is an image database platform. It is free for researchers and is one of the largest image databases for researchers. In ImageNet there are over 100,000 synsets. With ImageNet it is possible to identify many different objects without any prior training, making training much faster. There are other databases like ImageNet which are used in classification like MS-COCO or CIFAR-10. However

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TABLE I: Usage of Machine Learning Techniques in Vertical Farming

Study	Methodology	Application
Jhuria et al. (2013) [22], Moshou et al. (2014) [23], Bhange et al. (2015) [7], Chung et al. (2016) [8] , Ebrahimi et al. (2017) [9], Kim et al. (2018) [10]	prediction model, neural Network, SVM classifier and image processing	disease detection
Ahmad et al. (2020) [12]	SVM, RF and ANN	pest and disease detection
Geipel et al. (2014) [15]	image processing and regression	managing corn grain yield
Coopersmith et al. (2014) [24], Morellos et al. (2016) [18], Nahvi et al. (2016) [17]	multivariate regression models	soil management
Lottes et al. (2017) [19]	machine learning techniques	distribution of weeds and classification of crops
Rezk et al. (2021) [20]	WPART method	predict crop productivity and drought
Sa et al. (2017) [16]	CNN-based dense semantic classification	crop health
Grinblat et al. (2016) [21]	CNN	plant identification
Yadav et. al. (2021) [25]	CNN	disease detection
Maione et al. (2016) [26]	classification	geographic origin prediction
Pantazi et al. (2016, 2017) [14], [27], [28]	hyperspectral imaging	weed detection
Moshou et al. (2014) [29]	LSSVM	plant stress
Zhong et al. (2019) [4]	Deep learning based multi-temporal crop classification(Conv1D-LSTM-XGBoost RF and SVM)	classification of crops

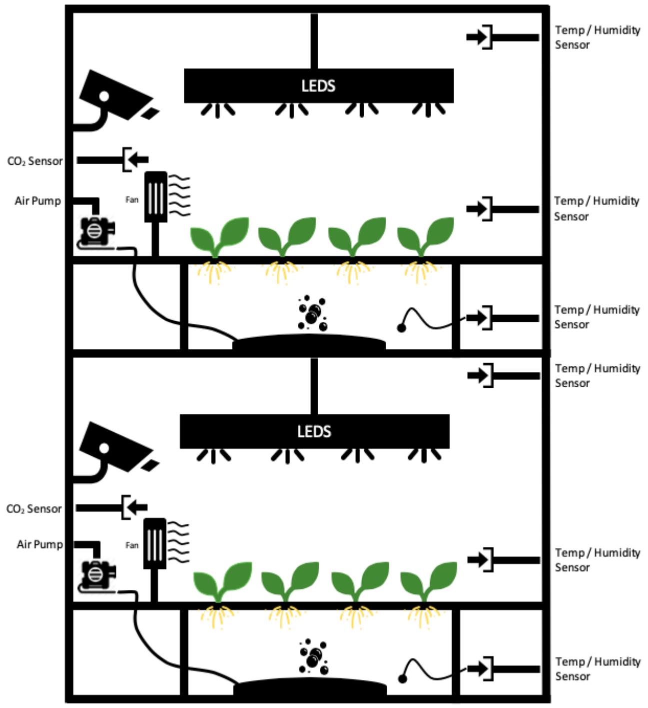

Fig. 1: Model flowchart

TABLE II: Environment Details

Specification	Value
Electrical Conductivity	1.4 mS/cm
pH	5.5-6.0
Daytime Temperature	22 C
Nighttime Temperature	18 C
Daily Light Integral	17 mol/m2d
Period	12-12 hours

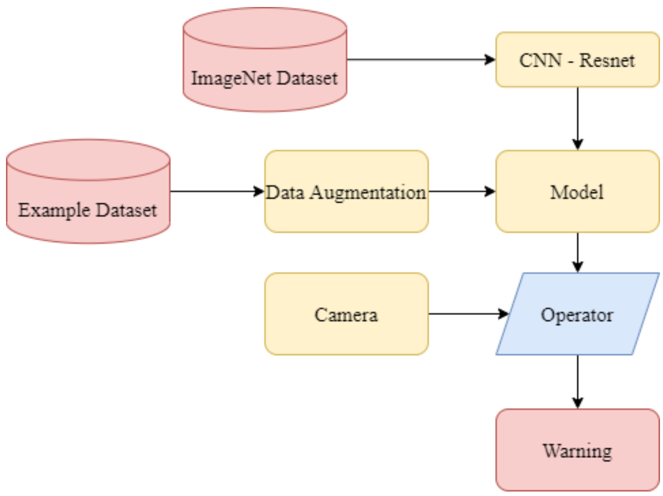

Fig. 2: Model flowchart

the size of these datasets is too small compared to ImageNet. The Open Images dataset is another dataset considered for the pre-training, however it was much larger in size [33] than ImageNet, which would be useless for this project.

In this study, Conventional Neural Networks (CNN) and ResNet sre preferred on the sample images. With Convnational Neural Networks and ResNet, the model will be trained on sample images and once the training is complete, the model will process the live data. With each of these elements decided, the final schematic of the system is shown in Figure 2. Setup details are given in Table II.

A small-scale vertical farm capable of growing 16 heads of lettuce was designed to study different growth parameters of lettuce. To accommodate the lettuce, black plastic pots 30cm deep are used, large enough to hold 4 heads of lettuce each. The solution must not see the light to prevent the growth of unwanted organisms. The bins were covered with expanded polyurethane with holes for the mesh pots. The lettuce was planted in rockwool to provide stability.

The 4 bins were stacked on 4 shelves on top of each other. For each level, the temperature and humidity of the top and bottom, the water temperature are monitored. The goal was also to monitor the pH and EC of each tank and the light level of each head of lettuce, however, this approach would have been prohibitively expensive for a larger system, these measures are measured manually. Besides, the light output is controlled for each lettuce, the airflow in each bin and the air ventilation for each head of lettuce. As the facility was in a temperature controlled indoor environment and there

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TABLE III: Dataset Details

Class	Number of images
Bacterial	21
Fungal	76
Healthy	20
Viral	17

were no major temperature fluctuations, the temperature is not controlled. Each level was equipped with a camera to monitor the progress of the 4 heads of lettuce and detect any problems.

IV. Experiment

In this study, we propose to train the model with a lettuce disease dataset [34]. Lettuce is a very common plant that can be found all over the world and diseases are very common on lettuces. Additionally, growing lettuce is easier than its peers, which is important for providing additional data to the model once the system is ready to be deployed on the closed vertical system.

The dataset consists of 134 lettuce images. These images are separated into 4 subclasses as follows: bacterial (21), viral (17), fungal (76) diseases and healthy (20) lettuces. The purpose of this subset is to familiarize the model to understand some of the common diseases encountered when growing lettuces. Fro the development, `tensorflow` framework and `keras` API are preferred. Dataset details are given in Table III.

One of the focal points of the project's software realization was data integrity. The first step to do this was to pre-process the image set. To do this, duplicate data and corrupted files are selected and removed from the image set. A part of the data preparation script is given in Example 1.

Listing 1: Data preparation

```
import tensorflow as tf

data_dir = 'dataset_lettuce'

train_ds = tf.keras.utils.
    image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="training",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)


val_ds = tf.keras.utils.
    image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="validation",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)

class_names = train_ds.class_names
```

One of the other problems with the database is its size, the number of images inside the database is not enough to feed the model. In this example, the training set has better accuracy scores and lower loss at each epoch, however, the same cannot be said for the validation set. This is the result of overfitting the model to the dataset. Because the example dataset is very small, the model tends to overfit the training data, making it sensitive to new data. To overcome this problem, randomly inverted, rotated, contrasted, and cropped the data is preferred. In this way, increase the amount of data illustrated in Example 2 can be managed.

Listing 2: Data augmentation

```
data_augmentation = tf.keras.Sequential
    ([
     tf.keras.layers.RandomFlip('
         horizontal'),
     tf.keras.layers.RandomFlip('vertical
         '),
     tf.keras.layers.RandomRotation(0.3),
     tf.keras.layers.RandomContrast(0.5),
     tf.keras.layers.RandomCrop(224,224)
])
```

The network learning rate is 0.001. Setting a low learning rate such as 0.0001 prevented the algorithm from adjusting to a lower number of epochs, after 50 epochs the model could only have an accuracy of 50%. And a high learning rate causes the model to be optimized too fast.

Due to these factors, the learning rate is reduced gradually, starting from a high value. Every 20 epochs, the model reduces the learning rate by 10%. This method gave better results compared to the other methods.

The dropout is given as 0.2 to avoid overfitting. With these values, after 15 epochs, the pre-trained ResNet50 model gave more accurate result in for the example dataset. Training accuracy is not significantly affected, training set accuracy remains relatively the same in each epoch. On the other hand, the accuracy of validation increases with epochs. However, both accuracy values remain below the desired margin which is greater than 90%.

After the base model is created, the model is trained with the sample dataset and trained for 125 epochs. After the training was done, the output layer is frozen to add another layer created by us for fine tuning. While the output layer was frozen, the ResNet50 model could not continue training, the added layer trained itself with the train dataset for 25 epochs. After applying all these methods, an accuracy of 0.869565 is acquired. With (learning rate = 0.001), 125 training epochs on ResNet50 and 25 additional training epochs on the new layer, the model gave an accuracy of about 86%.

V. Conclusion

In this study, we focus on one of the global problems: the limited resources such as land and food. Researchers on alternative methods for providing food to cities and growing plants in indoor environments.

The presented model has the potential to impact the agriculture industry, as it is possible to achieve reliable disease identification accuracy with a very limited data set. Applying various over-fitting prevention methods solved the problem of lack of variety and small size of the training dataset by .

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The field of AI is growing at a rapid pace, and it is obvious that many application areas arise every year. In its current form, our study may be a reliable starting point for other researchers interested in applying image processing or machine learning solutions to an agricultural problem. Currently, our model can detect the type of disease in the image, however, it is not able to further diagnose the given image. An important improvement that can be made to this project would be to fulfill its deployment goals, a self-feeding image recognition system would be a very important study point and help to provide new sets of images for studies later.

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