Visual sensor network based early onset disease detection for strawberry plants

Dar, Usman
School of CSEE
University of Essex
Colchester, U.K
ud21308@essex.ac.uk

Anisi, Hossein
School of CSEE
University of Essex
Colchester, U.K.
m.anisi@essex.ac.uk

Abolghasemi, Vahid
School of CSEE
University of Essex
Colchester, U.K.
v.abolghasemi@essex.ac.uk

Newenham, Chris
Managing Director
Wilkin & Sons
Tiptree, U.K.
cwn@tiptree.com

Ivanov, Andrey
Farm Manager
Wilkin & Sons
Tiptree, U.K.
ai@tiptree.com

***Abstract*—The ever increasing use of plant protection chemicals (PPCs) has been on the constant rise as the agriculture industry tries to keep up with growing demand. Excessive usage of PPCs leads to smaller profit margins for farmers as well as damage to ecosystems. An internet of things based visual sensor network was developed to feed data into a neural network classifier which would detect the early onset of plant disease. The sensor network was deployed at a farm owned and run by Wilkin & Sons, a soft fruit grower based in Essex, UK. A prototype convolutional neural network was developed with the purpose of classifying 3 types of images; healthy plants, powdery mildew affected plants and leaf scorch affected plants. The classifier was able to reach an accuracy of 95.48% for late stage disease detection through images alone.**

Keywords—Internet of Things, Deep Learning, Visual Sensor Network, Strawberry Diseases, Convolutional Neural Network

I. Introduction

Plant diseases have plagued the agriculture industry since its inception. The use of chemical agents (pesticides, fungicides, herbicides etc.) to protect plants has allowed the industry to progress by minimizing losses caused by infected plants with the global fungicide market worth a staggering £5.3 billion [1] as far back as 2010. In 2020, a decade later, The Food and Environment Research Agency (FERA) conducted a survey which found that over 66 tons of fungicides were used on strawberry plants in the UK alone, with over 87.23 % of plants being treated with fungicide more than 4 times in a given season. Sources from Wilkin & Sons, a UK based soft fruit grower, reports that this cost can exceed £2000 per acre per growing season, mainly used to combat Powdery Mildew epidemics at their farms which ruin the aesthetic and marketability of the fruit.

While effective, Plant Protection Chemicals (PPCs) must be used sparingly due to ever increasing costs and detrimental effects on biodiversity [2]. In order use fungicides as effectively as possible, detecting where and when diseases occur is of the utmost importance so that treatment can be focused on the most problematic crop areas. This has created a research opportunity for efficient and accurate plant disease detection methods.

This 2016 study [3] critically analyses several novel methods of plant disease detection including lateral flow microarrays, Volatile Organic Compound (VOC) profiling, bio sensing, nucleic acid assays, remote sensing and imaging spectroscopy. The study categorizes the methods based on how early in the disease progression, they are able to detect disease. Lateral flow microarrays, biosensing , image spectroscopy, and remote sensing were methods of that could detect diseases before the secondary infection. According to [4], primary infection is from the "*initial inoculum*" while secondary infection is from "*A direct transmission between plant tissue*." This means that methods of detection that are accurate before secondary infection are extremely valuable as they allows crop growers to target the disease before it becomes an epidemic. Of the pre-secondary infection detection methods described in [3], remote sensing and image spectroscopy are only non-invasive disease detection methods that have negligible ongoing running and labor cost.

Several computer vision based solutions have been developed based on deep Convolutional Neural Networks (CNNs) for the purpose of disease classification. One such study [5], that evaluated 3 popular CNN architectures; GoogleNet, VGG16 and ResNet-50 concluded that ResNet-50 was the highest performing architecture for standard image based disease classification. The datasets used in such studies contain images of plants with obviously visible symptoms of disease by which time the disease is in its advanced stages and the probability of secondary infection (and an oncoming epidemic) is extremely high. What these studies fail to consider are the environmental conditions surrounding the analysed images which can provide a complementary view on the progression of plant diseases. The significance of environmental factors is highlighted in [6], where the progression of *Sphaerotheca macularis*, a mildew causing pathogen, was analysed with respect to environmental conditions. The study found strong positive correlations to the progression and spread of mildew between 15 and 25 degrees Celsius temperatures and high relative humidity, while the reverse was true when it came to the presence of free water (due to rainfall).

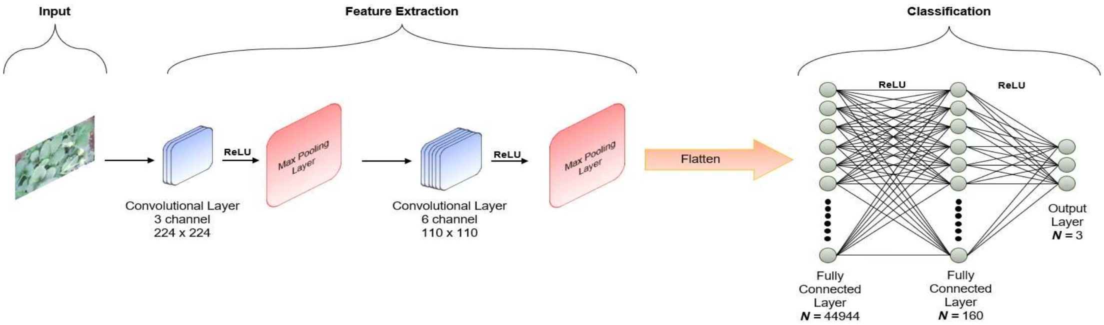

Figure 2a: *Convolutional Neural Network Classifier Architecture*

Cleary, the combined information from environmental and image data will allow the disease classifiers to make more informed classification decisions thereby improving the classification accuracy, especially if the plants were continuously monitored over a period of time. The main aim of this study is to develop such a system, where continuous crop monitoring is done via a visual sensor network that communicates with the neural network classifier using Internet of Things (IoT) approaches. With the primary objective being to target powdery mildew in strawberries, thereby allowing allow fruit growers to target fungicide usage effectively on affected crops before they are able to spread , thereby reducing the fungicide usage significantly.

II. METHODOLOGY

A. Data Aggregation

The visual sensor network consists of two subsystems; the imaging system that is responsible acquisition of visual data and the sensor network that is responsible for the acquisition of environmental data.

The imaging system is composed of four *Sonoff GK-200MP2-B* IP cameras , typically used in security applications, capable of capturing images at a 1080 x 1920 resolution. A *Raspberry Pi based camera controller* which is deployed on the same Wi-Fi Network as the cameras, requests images from each camera at fixed intervals during the day before uploading them via a Wi-Fi access point.

In contrast to the imaging, system, the sensor network has been custom designed to meet the needs of this particular application. The *ATMega644p* microcontroller is responsible for interfacing with 7 sensor modules; *temperature, pressure, humidity, ambient light, U.V light, soil moisture and leaf wetness*. The microcontroller samples the sensors roughly once every 30 minutes and uses a *Semtech SX1262 LoRa Transceiver* to transmit the data to a *Dragino LG01-N LoRa gateway* which pushes this data to a privately hosted server that is responsible for parsing the data and storing it in a database hosted on *Amazon Web Services*.

The sensor nodes and cameras were deployed within *Wilkin's New Growing System (NGS*), a polythene cover based growing setup with automatic humidity and temperature regulation. The cameras were positioned vertically above the rows of crops to survey an area of the canopy while the sensors nodes were placed closer to the stem of the plants. Each pair of cameras and sensor nodes were placed with approximately 25m of separation.

B. Analysis

As stated in the previous subsection, the data aggregation system is actively collecting data that will be labelled as the growing season progresses. In order to begin analytics early, the dataset from [7] was used which contained 2500 images of seven different strawberry plant diseases which was used to develop an image segmentation system (based on the ResNet architecture) that isolates symptomatic parts of the plant in the image.

Figure 2a showcases the structure of the Convolutional Neural Network (CNN) classifier with 5 hidden layers. The architecture is designed to take an RGB input image (of a strawberry plant) and then classify it into one of 3 categories;

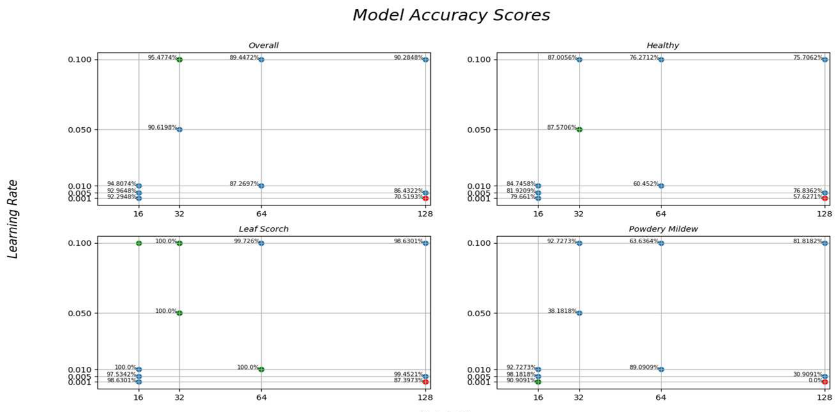

Figure 3a: *Model Accuracy Scores*

"Healthy" , "Leaf Scorch" and "Powdery Mildew". Input data was augmented with random rotations to balance the dataset.

The convolutional layers each have a kernel size of 5 with no padding, while the two identical Max Pooling Layers have a kernel size and stride of 2 respectively. During Training, the model was evaluated using Cross Entropy Loss and was optimized with stochastic gradient Descent. This particular architecture was designed with the convention of alternating convolutional and pooling layers in order to reduce the dimensionality and make training more efficient. While some of the hyperparameter tuning will be discussed in the subsequent section, the model architecture was not adjusted in this way due to a lack of graphical processing unit (GPU) at the time.

The classifier was developed and evaluated using the PyTorch framework in Python on a machine running *Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz with 32 GB of ram.*

III. Results and discussion

The model was evaluated under several combinations of batch size and learn rate in order to find the best performing hyperparameter combination. Ten combinations were chosen via a randomized grid search models were all trained over 10 epochs to get an early indication of the models that converge the fastest. From **figure 3a** it can be seen that the model with *batch size 16 and learning rate 0.01* converged the fastest during the training while the model with *batch size 128 and learn rate 0.001* did not converge at all due to how infrequently and insignificantly the model weights were adjusted.

The models were also evaluated on a test dataset. The results shown in **figure 3b** displays the performance of each model overall and by class where the percentages correspond to the fraction of labelled images correctly classified. It can be observed that the classifier performs consistently worse with large batch sizes and small learning rates. In contrast, small batch sizes with higher learning rates performed well on test data while being the quickest to converge during training as well. This is because over a relatively few number of epochs, weights are not updated frequently enough with larger batch sizes and smaller learning rates to converge to a steady loss.

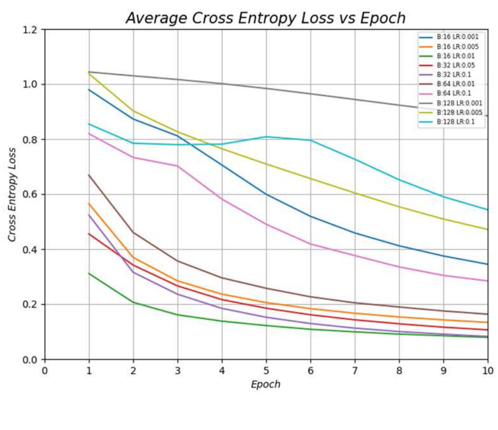

Figure 3b: *Average Cross Entropy Loss vs Epoch*

IV. Conclusion and future work

While the classifier evaluation is positive, the limitation of the works discussed above stem from the dataset that was used. It was comprised of singular images of plants in advance stages of diseases and not the data from Wilkin & Sons' farm that the previously alluded to. This is because the collection and labelling process is ongoing as of September 2022. Additionally, the overwhelmingly positive results in the "Leaf Scorch" category are caused due to an imbalance in the dataset with leaf scorch significantly outnumbering other categories.

The next step is to incorporate data from Wilkin & Sons and train the model on a machine with a GPU so that hyper parameters and CNN architecture can be fine-tuned faster, especially using a more intelligent approach such as Bayesian Optimization.

Furthermore, a Visible and Near Infrared (VNIR) image sensor will also be added to the data aggregation system as [8] has demonstrated that the most "spectral fingerprint features" of grey mould, another fungal disease in strawberries are found in this part of the spectrum with the main long term aim being to fuse image data with time series sensor data at the feature level by adding another feature extraction module before the classification module. This will allow the CNN is able to get a holistic understanding of the factors that indicate the early onset of plant disease before making the predictions.

References

[1] Cools, H.J. and Hammond-Kosack, K.E., 2013. Exploitation of genomics in fungicide research: current status and future perspectives. Molecular plant pathology, 14(2), pp.197-210.

[2] McMahon, T.A., Halstead, N.T., Johnson, S., Raffel, T.R., Romansic, J.M., Crumrine, P.W. and Rohr, J.R., 2012. Fungicide-induced declines of freshwater biodiversity modify ecosystem functions and services. Ecology Letters, 15(7), pp.714-722.

[3] Martinelli, F., Scalenghe, R., Davino, S., Panno, S., Scuderi, G., Ruisi, P., Villa, P., Stroppiana, D., Boschetti, M., Goulart, L.R. and Davis, C.E., 2015. Advanced methods of plant disease detection. A review. Agronomy for Sustainable Development, 35(1), pp.1-25.

[4] Gilligan, C.A. and Kleczkowski, A., 1997. Population dynamics of botanical epidemics involving primary and secondary infection. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 352(1353), pp.591-608.

[5] Xiao, J.R., Chung, P.C., Wu, H.Y., Phan, Q.H., Yeh, J.L.A. and Hou, M.T.K., 2020. Detection of strawberry diseases using a convolutional neural network. Plants, 10(1), p.31.

[6] Blanco, C., de Los Santos, B., Barrau, C., Arroyo, F.T., Porras, M. and Romero, F., 2004. Relationship among concentrations of Sphaerotheca macularis conidia in the air, environmental conditions, and the incidence of powdery mildew in strawberry. Plant disease, 88(8), pp.878-881.

[7] Afzaal, U., Bhattarai, B., Pandeya, Y.R. and Lee, J., 2021. An instance segmentation model for strawberry diseases based on mask R-CNN. Sensors, 21(19), p.6565.

[8] Jiang, Q., Wu, G., Tian, C., Li, N., Yang, H., Bai, Y. and Zhang, B., 2021. Hyperspectral imaging for early identification of strawberry leaves diseases with machine learning and spectral fingerprint features. Infrared Physics & Technology, 118, p.1038