The Use of Computer Vision to Combat Losses from Disease in Grapevines

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Abstract
The use of computer vision to support and automate agriculture and viticulture is increasing. Therefore, it is important to continuously test new technologies and equipment. Management of pests and diseases in viticulture is a labour-intensive task. This study aims to investigate current technologies in computer vision that could be applied to disease and pest detection in viticulture and the application of transfer learning on segmentation networks. This study also implements a case study and applies computer vision for disease and pest detection. Observation of limitations in the network's performance on testing images, after training on the limited data set, suggests that careful control is needed over lighting conditions in the image capture environment. Although initial results are positive, a larger training dataset is recommended to achieve a greater level of accuracy.
Keywords: Artificial Intelligence, Computer Visions, Viticulture, Sensors
DOI: 10.7176/CEIS/14-3-01
Publication date: August 31st 2023

1. Introduction
Grape harvest can be significantly negatively affected by diseases and pests. Identification of these diseases and pests is traditionally carried out manually, through visual inspection of the vines by trained staff (Hernández et al., 2021). There is a risk of human error in the process and trained personnel are currently in short supply (New Zealand Winegrowers Association, 2021). The combination of modern sensing technologies and computer vision has advanced to a point where classification and instance segmentation networks can operate on real-time video (Hossain & Deok-jin, 2019).

This research study will include an introduction to computer vision, and types of computer vision networks, before discussing the implications of transfer learning. The review will then be followed by a recent case study, implementing computer vision for crop disease detection. The case study aims to design and build a device capable of running live computer vision models, to test the device's performance, and build a segmentation model to detect and segment leaves and grapes.

2. Background and Justification for the Project
The value of exported wine to New Zealand's economy has greatly increased in recent years (Radio New Zealand, 2023), and is set to continue to grow. However, the industry is preparing for labour shortages over the coming years (New Zealand Winegrowers Association, 2021). Disease management in vineyards tends to be a labour-intensive task, requiring skilled staff to inspect rows visually for signs of disease. For example, the Winegrowers Association noted that 2017 saw an increased cost of identifying and treating botrytis and mealybug on member vineyards; conversely, the cost of treating sooty mould decreased during the same year.

Mealybugs live on plants that produce sap for them to consume. Their secretions stick to bunches of grapes, preventing proper drying post-harvest and encouraging the growth of sooty moulds. They can also transmit other diseases such as leaf roll, and large infestations may cause widespread crop failure (Australian Wine Research Institute, 2021, New Zealand Winegrowers Association, 2021). Sooty moulds grow on grape bunches and leaves. Although studies indicate that they do not affect wine quality directly, they are a major source of fruit rejection. This is because they tend to compromise the skin of the grape and allow it to be contaminated by other diseases as well as the elements.

Downy mildew's primary vine infection occurs when downy spores travel from infected soil to the vine. This produces an average of one to three "oil spots" in fifty meters of canopy. If such "oil spots" are not detected at an early stage, the spores will rapidly move from leaf to leaf and leaf to bunch, causing massive uncontrollable infection across the vineyard. The fungus Botrytis is responsible for some of the greatest losses from disease in vineyards (Bayer, 2023). Botrytis occurs in high humidity or prolonged rain and cool temperatures when moisture is allowed to collect on the surface of the grapes. The fungus produces an enzyme called Laccase which can be ruinous to the winemaking process, spoiling wine when exposed to oxygen.

Performing instance recognition and segmentation on images using neural networks is a computationally heavy task. Real-time image object detection on edge devices is possible through the use of devices such as the Raspberry Pi (Hinas et al., 2017) but real-time segmentation and instance recognition tasks prove too computationally heavy for the chipset. It is considerably more resource-intensive to process frames efficiently enough to perform object detection and segmentation on live video through such networks. Traditionally, in order to perform such a task, the video would be streamed over a network to a server that held the computing power for processing (Lee et al., 2021). However, with the release of GPU based embedded devices from Nvidia in the form of the Jetson range, and from Intel in the form of the Movidius, such live video recognition networks can be run in real time on the edge device (Cob-Parro et al., 2021; Hossain & Deok-jin, 2019).

Gathering and processing of imaging data at the edge node allows for tuning of the model without the network requirements or server processing load required from a centralised processing system. Edge-deployed neural networks can be re-tuned, before deployment, on training data gathered from the operating environment, allowing the network to be adjusted to the conditions in which the device will be operating. In an industry 5.0 use case (Fraga-Lamas et al., 2021) it was discovered that edge AI was likely to be a key enabler of digital transformation. Increased connectivity from fifth-generation networks allows many sensor devices to be interconnected through the internet. To facilitate this connection, and make use of the advantages provided, it is essential that computing resources are deployed at the network edge with sensor devices (Zhang et al., 2021). Deploying computing resources directly attached to the sensors allows a system access to a wealth of data for modelling (Zhou et al., 2019).

3. Literature Review and Related Studies

Computer vision is a subset of artificial intelligence which allows systems to extract and process information from images. Neural networks can be used to extrapolate low-level features, before systematically using them to identify higher-level features. The authors of a review: Knowledge based vision systems to cognitive vision systems (Souza Alves et al., 2018), note that the performance of current systems is entirely dependent on the quantity and quality of the data available to train the network. An ongoing significant challenge in computer vision is the creation of robust networks that can be retrained to identify complex classes. This will enable future networks to achieve better results on smaller, lower quality data sets.

Traditional machine learning computer vision systems are the forefather to modern AI-based systems. Traditional systems use neural networks to perform the classification of images, once expected features have been extracted manually and defined for the network. Modern computer vision systems utilise deep neural networks, using convolutional and pooling layers to learn and extract features that affect classification from images, before a fully connected dense neural network performs classification using those features (Shustanov & Yakimov, 2019). These convolutional-dense networks can be resource heavy compared to more traditional machine learning classification models.

Classification of an image or video frame refers to labelling the image with a series of concepts or labels, without displaying what in the image the label refers to. Object detection is the next step in the complexity of networks. In an object detection network, the system must be capable of identifying different distinct objects in an image or video frame (Shi et al., 2021). The network will output a label and boundaries for a bounding box containing the detected object.

Segmentation networks aim to classify each pixel in an image with a class label and can provide a pixel by pixel outline for each class in the image. Semantic segmentation networks can classify pixels into classes, but not separate instances of each class (Gupta et al., 2015). Deeper networks that can separate pixels both by class and occurrence of each object in the class are classified as object segmentation networks. Segmentation can only be undertaken after classification and object detection has been performed on an image. Segmentation networks are passed a region of interest defined by object detection algorithms and the major class contained within the region of interest. The segmentation network then allocates classes to pixels within the area of interest (Audebert et al., 2017).

Detect-net is a Google designed network optimised for object detection. It is constructed of two main sections: first, a fully convolutional network extracts all raw features from the image; next, a clustering dense neural network defines bounding box position and labelling (Zhang et al., 2020). Nvidia further optimised Detect-net and trained it on a series of public datasets, thus creating Detect-net V2 which is available from Nvidia and is optimised for use in transfer learning applications (Nvidia, 2021).

Deep neural networks suffer from degradation, with accuracy increasing with network depth to a point until a tipping point is reached after which accuracy rapidly decreases as the network grows deeper. To address this problem, ResNet or Residual network linking can be used as a backbone. The mechanism here is that links to residual data blocks are passed on to lower layers directly, giving classification networks insight into operations higher in the network than the output layer of the convolutional network (Long et al., 2020; Zhang et al., 2020).

Mask-region convolutional neural network (Mask R-Cnn) is a combined object detection and instance segmentation network. Its construction utilises a fully connected convolutional object detection network with an added branch, identifying and predicting segmentation masks on regions of interest defined by the object detection network. This more widely connected convolutional network is then passed, via a backbone, to a deep neural network for instance classification (Musyarofah et al., 2020; Wang et al., 2020).

Transfer learning refers to the method of utilising an existing network architecture that has been trained on a large diverse data series, such as the COCO dataset. These networks are quicker to retrain to a new task similar to their original role, as weights are already assigned to each node before training begins. These weights are then adjusted during training to achieve the best result. Once retraining is complete, and a sufficiently high level of accuracy attained, the network can be pruned to its lightest form (Han et al., 2020; Pérez-Pérez et al., 2021).

Transfer relies on the tasks being similar in nature, and the network's design and original training before transfer learning must allow for board identification. Models that are sufficiently fit for the task will not perform well when transfer learning is applied to train them to a task unsuited to their feature extraction weights.

Traditional computer vision applications for agriculture have required optical sensors to capture images and then have them processed on an external server. Fruit grading systems have achieved high accuracy in real-world situations (Wu et al., 2012). However, these systems require multiple servers to compute images fast enough to perform real-time grading. Computer vision is also used to perform recognition on video after the video has been captured. In the paper Ultra-scale aerial phenotyping and precision agriculture: A case study of lettuce production (Bauer et al., 2019) the authors suggest a model that successfully enabled farmers to make the best use of their available resources. This was achieved through processing drone footage and GPS data on a back-end server and providing farmers with insight into soil and growth data. This model, however, could not be run in real time, or be beneficial to run on an edge device. Similar systems have been suggested for weed identification and intelligent spray and feed controls (Kamath et al., 2020), although these systems also suggest processing images on a server rather than using edge computing devices to perform analysis directly.

A review of Applications of computer vision techniques in the agriculture and food industry (Gomes et al., 2012) found that the majority of applications for computer vision were in the form of automated inspection of products at various stages of the production process (Cubero et al., 2011). The remainder of the studies had applied computer vision to aid farmers with precision agriculture. The authors of the review noted several difficulties which were common to the studies reviewed: the lack of recognition of features, the lack of dedicated models for precise classification and the dependence upon strict control and repeatability of lighting in the image capture environment.

The authors of the study Real-Time Detection of Strawberry Powdery Mildew Disease Using a Mobile Machine Vision System (Md Sultan et al., 2020) suggest a laptop-based real-time system for detecting powdery mildew in strawberries. The authors implemented a combined convolutional neural network for feature extraction, using high saturation and value (HSV) data with the normal RGB data as an input and a dense neural network for classification. The system was retrained from existing weights, making use of transfer learning and so reducing the required training and pruning time (Han et al., 2020). To achieve the best outcome, the authors modified the camera hardware (Sultan Mahmud et al., 2019) by creating a cloud lighting container to carefully control the lighting conditions and camera position. This allowed the network to achieve over 99% accuracy in the real-world test case, when trained on images captured on the test site (Md Sultan et al., 2020).

The solution implemented in the study A Design Approach for Identifying, Diagnosing and Controlling Soybean Diseases using CNN Based Computer Vision of the Leaves for Optimizing the Production (Kamal et al., 2021) utilised multiple cameras to gather data from a variety of angles around the soybean leaf. The data was then transferred to an off-site server, where classification was performed. The neural network proposed by the study was built using LeNet and re-trained using transfer learning on a large dataset gathered in the test environment. The authors also note the need for correction for the lighting conditions in which the images were captured. There was also added complexity to the network by the addition of an edge server and cloud services. In their study, Praveen et al. (2023) indicate that R-CNN is one of the three deep learning models available with relatively accurate detection results for grape leaf disease detection.

In a laboratory environment, the authors of the paper Artificial Intelligence and Novel Sensing Technologies for Assessing Downy Mildew in Grapevine (Hernández et al., 2021) compared the performance of K-nearest neighbour (KNN) Convolutional Neural Network (CNN) and MultiLayer Perceptron (MLP) networks for identifying downy mildew in grapevine leaf images. It was found that only CNN and MLP networks were suitable for identification of the fungus, with both achieving over 80% accuracy for early detection. The strict

control of size and lighting conditions in the lab environment makes this an unsuitable candidate for transfer learning for real-world applications, as these conditions cannot be reliably replicated in the agricultural setting.
A common theme in disease classification problems is the lack of quality labelled data. Labelling data is time-consuming, and a high level of skill is required to correctly identify early signs of disease. Quality labelled data is key to successful training and high network accuracy (Sladojevic et al., 2016). A solution addressing the lack of quality training data of grape diseases is suggested by the authors of the paper Few-Shot Grape Leaf Diseases Classification Based on Generative Adversarial Network (Zeng et al., 2021). The study investigated the use of GANs to generate training data for leaf disease recognition. These networks are applied to small training datasets, and train themselves through re-enforcement learning, over time improving the quality of the data they generate.

4. Case Study: Training an Instance Segmentation Model to Deploy on Jetson Nano

To study the application of disease detection on an edge device, a smart camera has been built using an imaging sensor, GPS sensor and Jetson nano contained in a 3D-printed housing. Detect-net and Mask RCnn networks have been trained using transfer learning. Transfer learning has been selected to be applied for the case study as it reduces the computational requirements for training, and leads to greater network accuracy.

Hardware and toolkit selection

The Sony 12-megapixel IMX477 sensor was used as the imaging sensor for the smart camera, combined with a manual focus and zoom lens. This, along with a Ublox M8N GPS and Compass, were connected to a Jetson nano 2gb developer kit, powered by a lithium-ion battery and a power regulating board. A housing was designed using Fusion 360, and printed using PLA on a create-bot 3D printer.

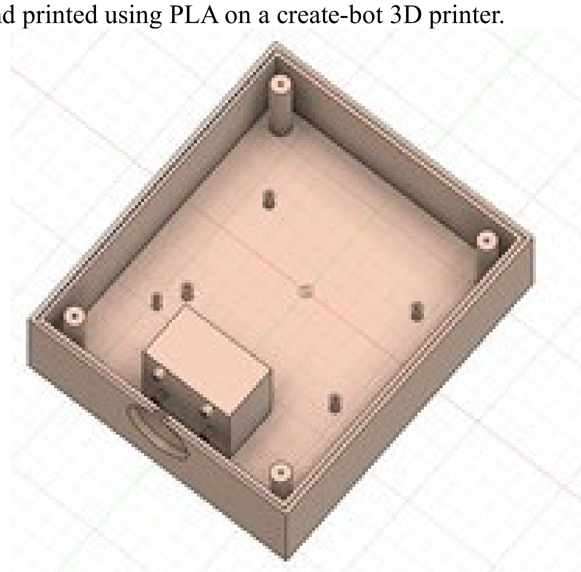

Fig.1 Smart Cam housing

Jetpack was installed on the Jetson nano, with TAO toolkit 3.0-21-11, TensorRT 8.0 and DeepStream 6.0 (Nvidia, 2021). Python3 was used with TAO, Keras, TensorFlow, GPSD, GPS, cuDNN and CUDA for transfer learning and training of the detect-net and Mask Rcnn networks. Intel has developed an open-source tool, known as CVAT, for image and video annotation (CVAT, 2023). CVAT allows users to label images with bounding boxes, as either rectangle or polygon. During the process of labelling the images for this case study, CVAT was hosted as a docker image on a system and accessed through the internet, allowing labelling to be undertaken remotely. 64 images were added to CVAT for labelling, 60 for training and 4 for validation. A total of 3,465 instances of grapes and 2,059 instances of leaves were labelled with polygon bounding boxes.

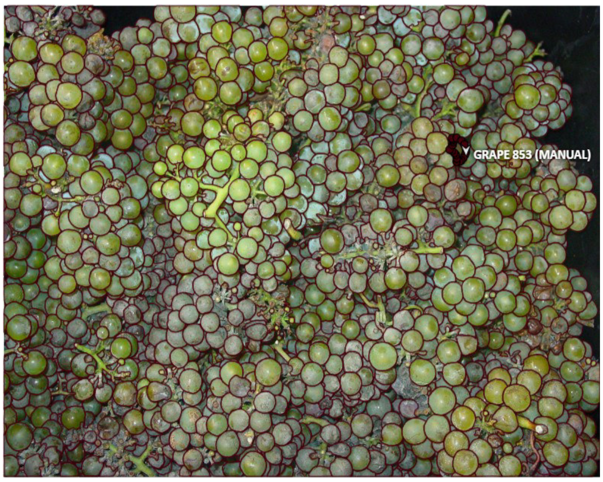

Fig.2 Labelled Grapes Fig.3 Labelled Grapes and Leaves on vine

A MaskRcnn implementation for Python3 was used with ResNet-101 as a backbone (AkTwelve, 2020). The model was compiled through Jupyter notebooks before being trained on the annotated images. The "Heads" or key layers were trained first, after which the entire network was tuned through transfer learning. The graphs below show the loss figures for both the head and full training runs.

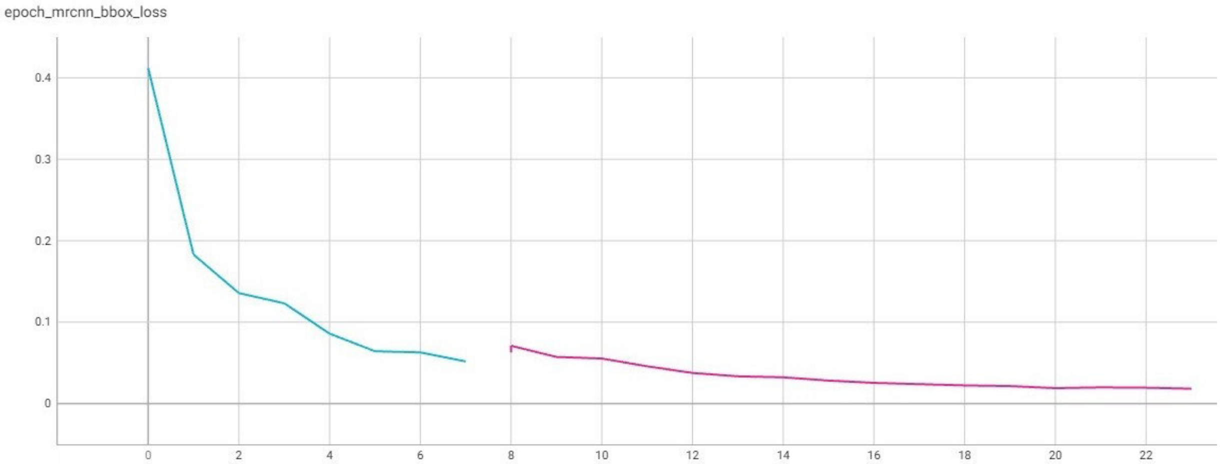

Fig.4 Bounding box loss during training

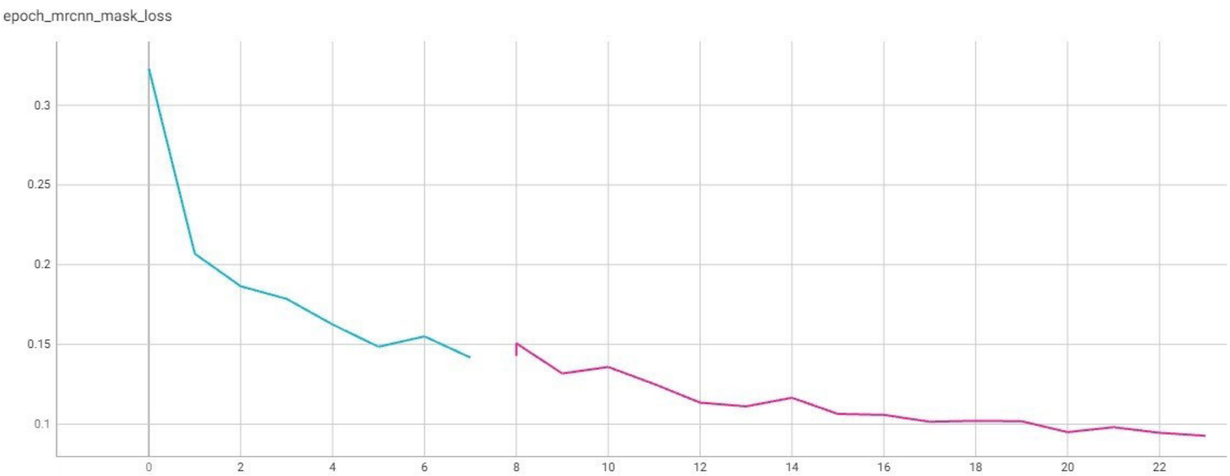

Fig.5 Segmentation mask loss during training

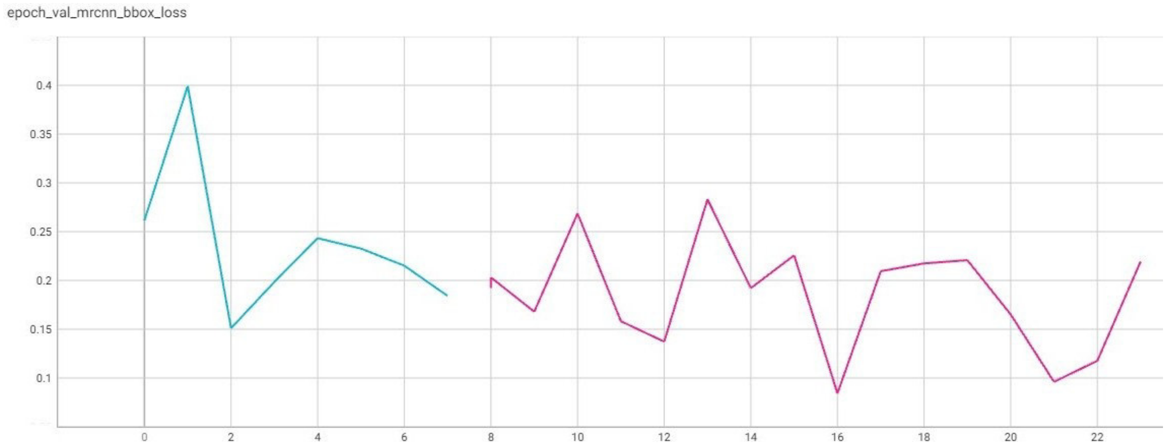

Fig.6 Bounding box loss on validation images

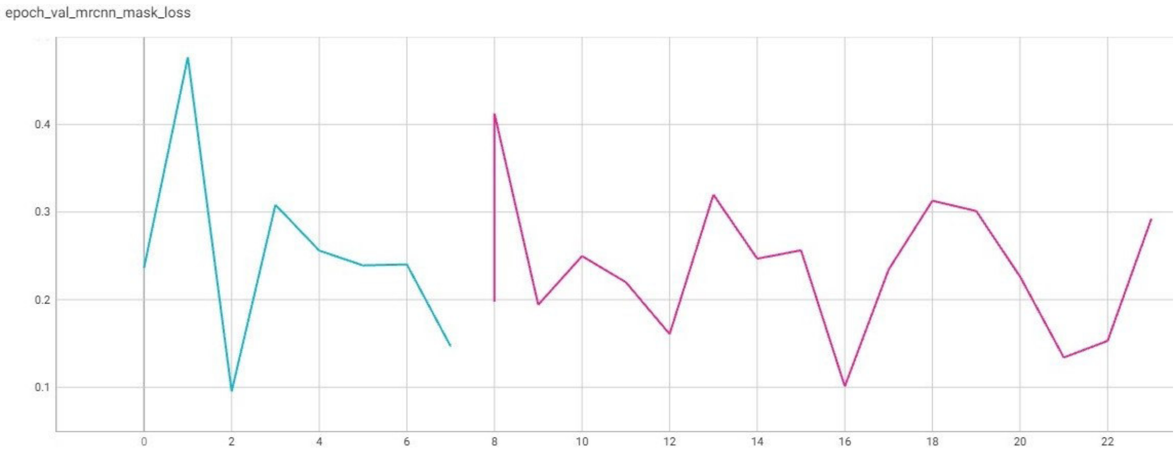

Fig.7 Segmentation mask loss on validation images

The loss figures for the training data were beginning to plateau towards the end of the full network tuning. However, there was still a clear downward trend during the training of the “head” layers. Further training of these key layers would help increase the effectiveness of the full network tuning. There is a general downward trend in the loss value on validation images during the full network training; it is likely that some further accuracy would be gained by increasing the training steps.

Sample inferences were made by the network for validation images. Validation images are not used for training the network directly, but included in the validation dataset measured at the end of each epoch and included annotation data. The network had modest success on these images, classifying the majority of the leaf in Fig.8, and all the foreground leaves and the majority of the grapes in Fig.9. It is presumed that lighting conditions in Fig.9 limited the network’s ability to understand the missing leaves.

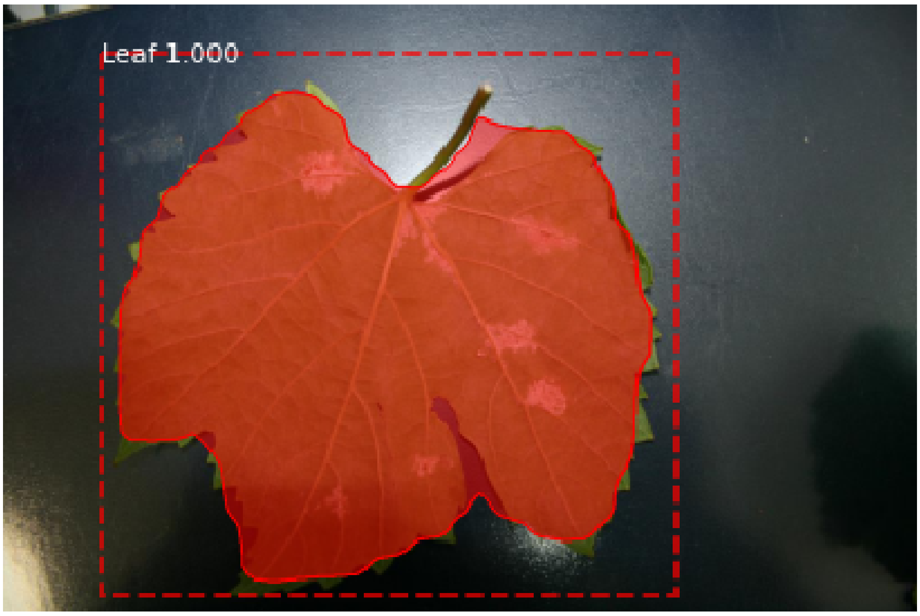

Fig.8 Sample image from validation

Fig.9 Sample image from validation

After training was complete, the network was given a series of test images that did not include annotation data. It performed with limited success on these testing images, identifying the majority of leaves and grapes in Fig.11, a single leaf and around half the grapes in Fig.12. The network was not able to classify any leaves or grapes in Fig.10, possibly as a result of the change of capture angle and lighting conditions when comparing the vine in this image to images in the training and validation sets.

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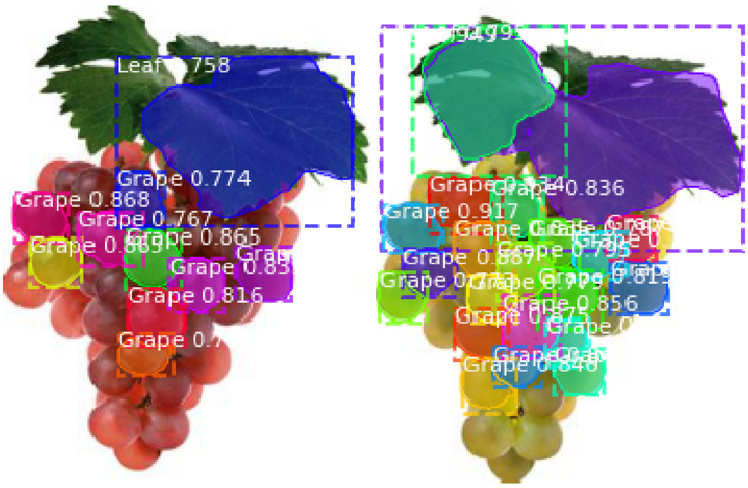
Fig.10 Image 1 from testing



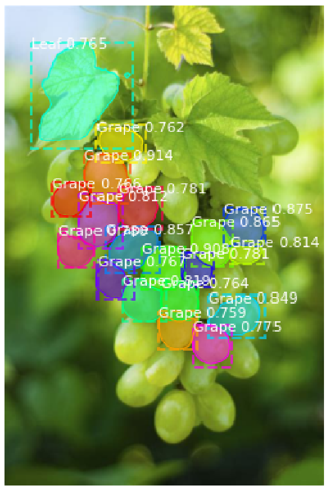


Fig.11 Image 2 from testing

Fig.12 Image 3 from testing

5. Conclusion and Recommendations for Future Research

The instance segmentation network performed with modest accuracy. The network did not perform well where lighting conditions were not optimal for detailed image capture. Successful deployment of networks in the field would require the careful control of lighting conditions through the use of a cloud lighting container as suggested by Md Sultan et al (2020). To better train the network to detect and classify diseases, quality labelled data of instances of the diseases and pests are needed. Such data is extremely hard to come by, as personnel with the specialised skill set needed for manual disease detection are in short supply. However, if a moderate amount of quality annotated disease data would be available, then a Generative Adversarial Network (GAN) could be used to generate further training data (Zeng et al., 2021) in order to supplement the available training dataset. This, combined with further image augmentation, may facilitate the training of a model that could be used for automated annotation of new images. Such a model might enable images captured in real-world conditions to be annotated automatically by CVAT and fine-tune the network for deployment using images that have been taken in conditions in which smart cameras will perform. Although accurate prediction seems to be the first priority, speed of processing should be another consideration for more future research as this factor is also important in industrial settings. Finally, another future research direction is to help improve, now only how accurately and fast, but also how early (during the grape growth process) disease detection can be conducted.

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