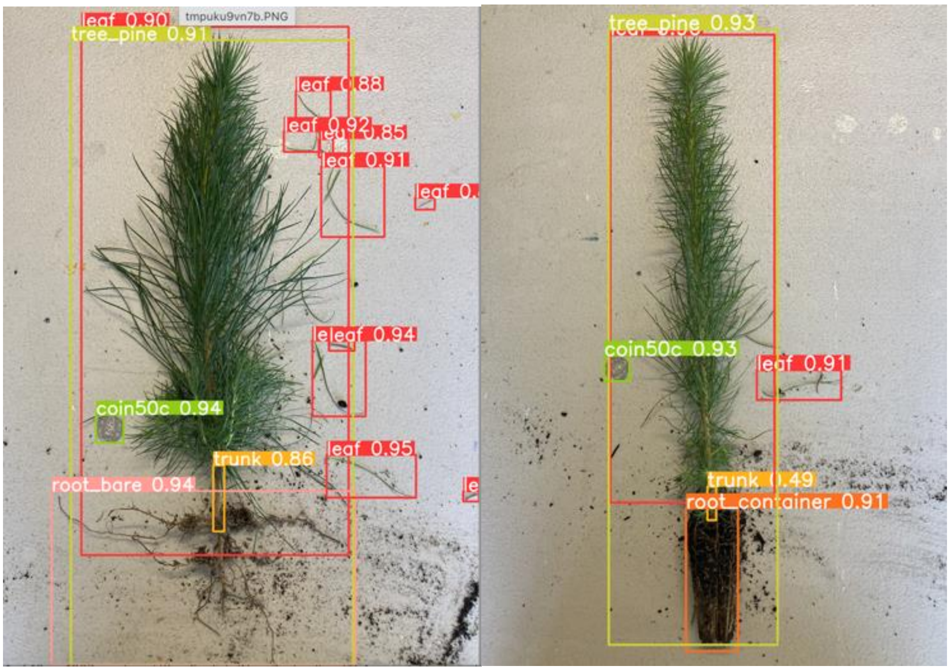
# Seedling Selection using Computer Vision
# Phase 2

Dr Brian Russell




Date: 20 Oct 2023

Report No: PSP-T010

# Table of Contents






Funded by:

Ministry for Primary Industries
Manatū Ahu Matua

supported by forestgrowers commodity levy

# EXECUTIVE SUMMARY

In productive forestry, seedlings, such as radiata pine, are grown for scaled forestry planting in nurseries using two planting methods: containerized and bare root. These seedlings are generally lifted and selected manually based on standard measurements. Machine based harvesting and selection is in development to scale beyond available labour and improve data collection for research outcomes. The lifting ‘machinery’ can be viewed as a combination of mechanical and computational systems.

The aim of the project is to investigate the feasibility of automating seedling selection using camera based computational approaches to accurately select seedlings in representative field environments such as variation in light, plant occlusion, background objects, and orientation. Phase 1 work showed that a hybrid approach using artificial intelligence, AI, and heuristics could detect different tree species, across orientation, backgrounds, and lighting.

Phase 2, this report, scaled the number of trees (n=68) with 4 orientations (0,90,180,270 degrees) this diversity showed that measurements could be taken and selection, based on a set of standard criteria is possible. There will always be some issues such as the trunk being occluded, which would have an impact on RCD measurement. It is possible more trees will need to be included in the dataset as more nurseries and seasonal conditions change.

# INTRODUCTION

## Background

Seedling trees are grown in nurseries either as containerised or bare root stock. Mechanisation of seedling lifting is under development to enable scale beyond available labour and also enhance longitudinal data analysis for crop optimisation through data collection. Manual lift requires a person to pick the seedlings into bundles then box them ready for short term storage prior to planting in forested areas. The person must physically pull the seedling and make an assessment of whether to keep the seedling based on grading rules [1] that can vary between nurseries, geographic location, season and market requirements.

**Previous work in phase 1** researched the development of an AI software pipeline detect various parts of a seedling, take measurements and perform and pass/fail test. This phase was successful.

In Phase 2, we aimed to significantly enhance the scope and accuracy of our image dataset while assessing measurement precision against manual techniques. We not only expanded the diversity of seedlings, including both successful and unsuccessful cases, but also increased the overall number of seedlings captured. Each seedling was intentionally photographed from five distinct angles, with additional emphasis on obtaining a top-down view. We also rotated each seedling a quarter turn to capture four different perspectives of the same plant. Furthermore, we implemented software updates to enable batch summary generation and comprehensive success reporting.

## Requirements

There are various requirements for the application deployment based a combination seedling selection rules and in-field practicalities, as shown in requirements table below.

| Requirement | Description | Value | Unit |
|---|---|---|---|
| Machinery operations | Should work on different sorting machines | >=2 | |
| Camera amount | Should use the minimum number of cameras, ideally 1. | <=1 | |
| Inference speed | Should process a minimum number of trees per second | 10 | per second |
| Lighting | Should work with different lighting | Sunlight, fluorescent | |
| Dirt and objects | Should work with dirt and random objects in camera view | Conveyor belt, dirt, loose leaves | |
| Obstacles | Should not have to correctly analyse tree if tree is obscured by a certain amount | 5<=% | |
| Calibration | The system should be capable of calibrating the camera to make measurements | | |
| Tree type | Should detect at least one tree type, Pine | pine | |
| Shoot Number | Should be capable of counting number of shoot | >=1 | |
| Shoot Height | Should be capable of measuring shoot height | Shoot height | mm |
| Disease/health | Assess brown needles in top ¼ of tree | Brown/green | % |
| Root type | Should detect two root types, containerised and bare. | Bare, Container | |
| Root Collar Diameter | Should measure RCD diameter | | |
| Root analysis | For containerised assess the percentage of root-with-soil relative to container shape. For bare root asses the quadrants ratio. | | |
| Mycorrhiza | Shall detect and count Mycorrhiza (note this is planned to be implemented at a later stage in the project) | | |

# METHODS

The methods for this study have been defined in three phases. Firstly, seedlings where selected to cover types and condition from pass to fail, these seedlings were photographed at 4 rotation angle and 5 different perspectives. The second phase labelled the images, improved the software to provide reporting on measurements and updated the algorithm. Phase three compared the manual and automatic measurements.

## Phase 1. Images

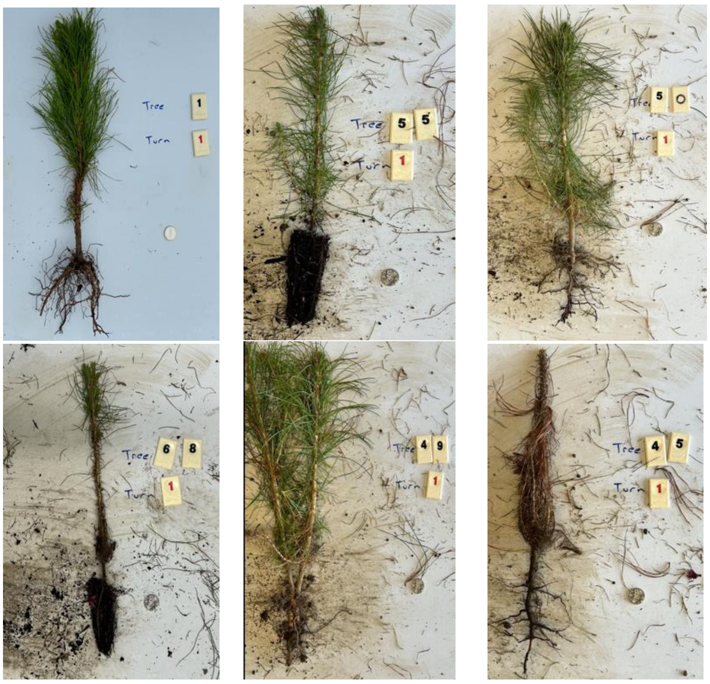


Figure 1 Example images with the top row pass and the bottom row fail.

Images were collected on 68 Radiata pines trees, 10 Redwoods and 10 Douglas Fir. Each seedling was rotated ¼ turn 4 times with 5 images taken each turn from above, to the side and end on. Initial analysis was with images from above, with other images kept in reserve based on results.

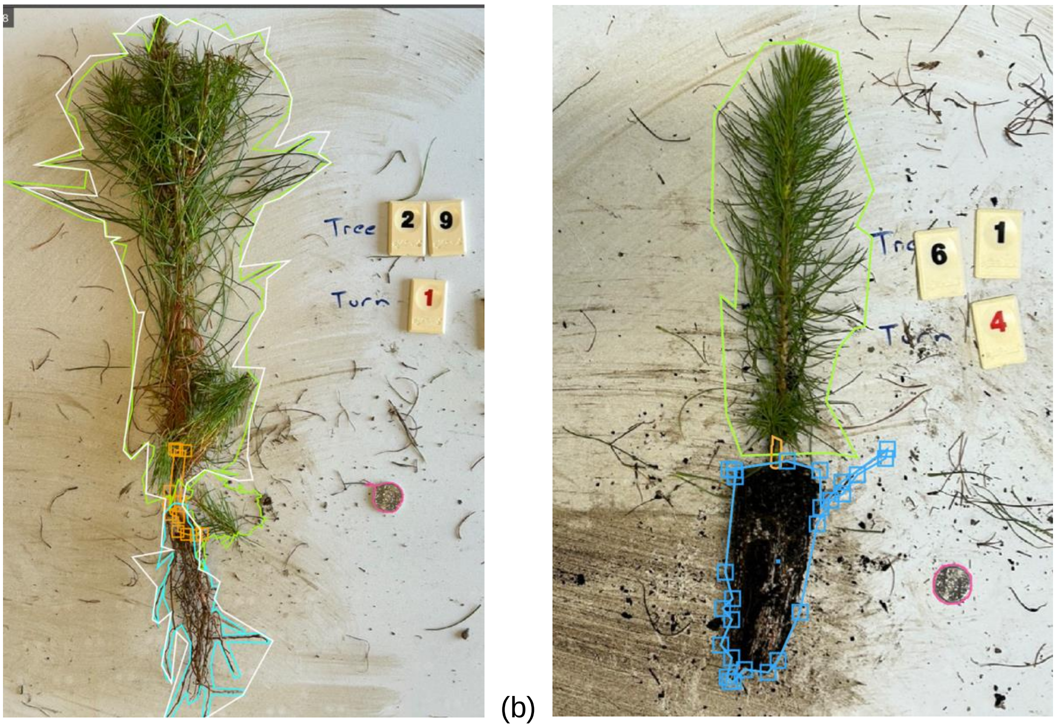
Manual measurements where taken for; species, seedling/cutting, container/bare root, shoot count, shoot height, brown/green ration, Root collar diameter (RCD), root ratio.

Manual measurements where repeated for RCD and height 10 times on three trees to calculate the manual measurement test-retest variation.

## Phase 2. Labelling, Training and Reporting

Labelling was performed on 68 radiata seedlings (50 bare root and 18 containerised) at 4 quarter turns resulting in 272 labelled images. The first rotation angle was used for training and other 3 for validation, note the rotation was done to generate more training images to test the AI, the end product will NOT require tree rotation. The training data used polygons, as boxes did not yield good results.

Labels included: tree_pine, tree_redwood, tree_douglasafir.  (the entire tree and root), leaf (the shoot above the RCD), trunk, root_container, root_bare and coin ( used to calibrate the image).




(b)

*Figure 2 Labelling with polygons for (a) radiata bareroot and (b) radiata containerised*

### Training

The model was trained with a custom dataset described above with 68+21 images for training and 205 for validation. The 21 images from the feasibility study were also used for training. Only pine were used for training and analysis.

Hyper parameters included: Epoch 2000, Batch size 16, learning rate 0.01, with early stopping if performance plateaued.

Previous work showed that the yolov5 small model performed well if trained for epochs > 2000.

### Reporting

The software was updated to output summary data that enabled comparison to manual measurements.

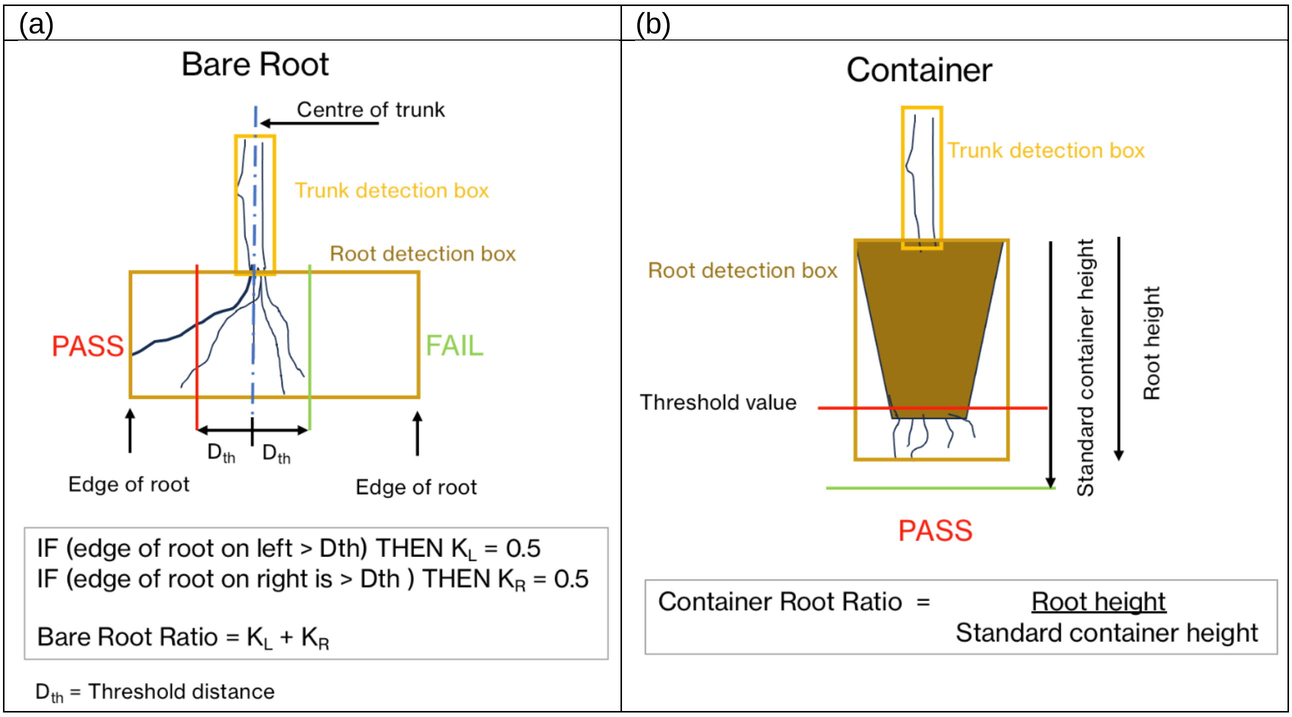


*Figure 3 Description of root ratio calculation for (a) bare root and (b) containerised.*

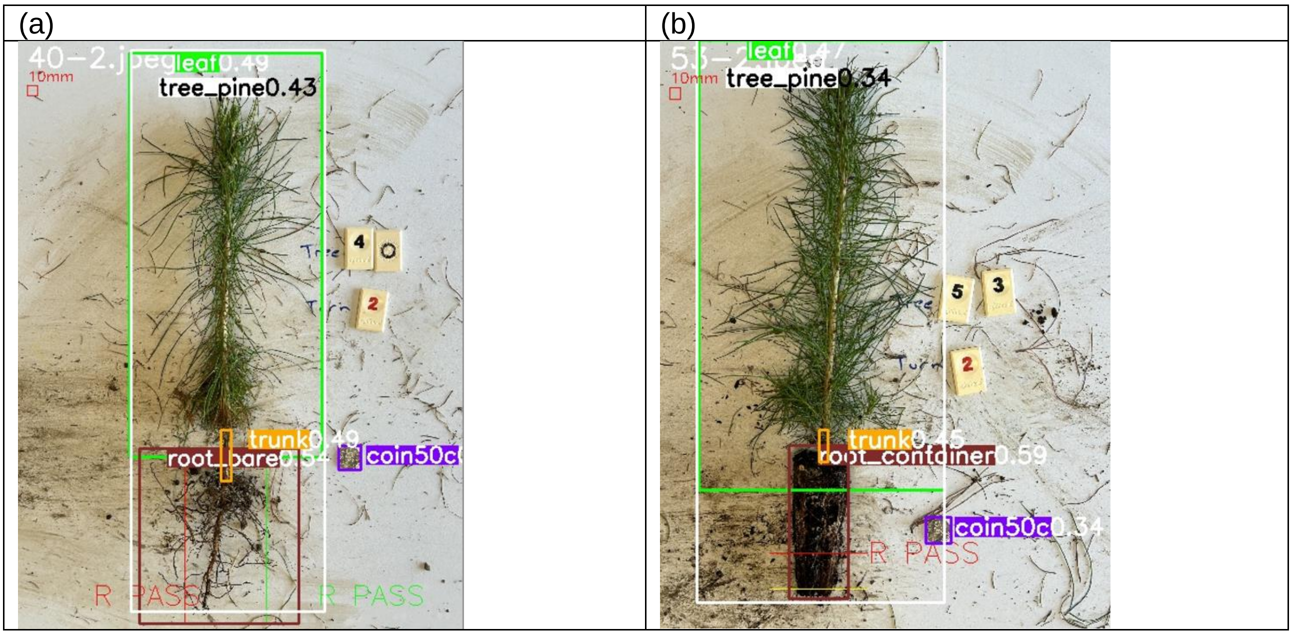


*Figure 4 AI analysed image showing features detected, the root quadrant thresholds for (a) bare root and (b) containerised roots.*

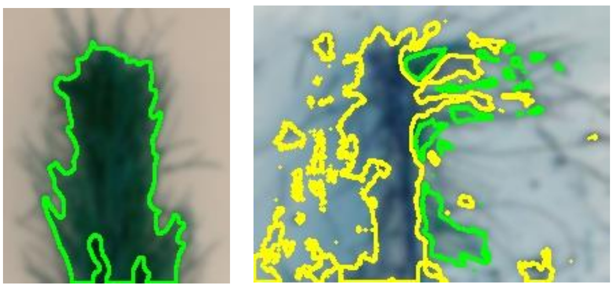


*Figure 5 Brown green pixel counting on top quarter of shoot*

## Phase 3. Analysis

The analysis method starts with detecting an individual tree and, using AI to detect different parts of the tree then using the dimensions of these object to make measurements in distance or colour. Then these values are compared to the rules to determine pass fail.

### Algorithm

1. Load image from directory
2. Object detection
    a. Calibrate pixel size
    b. Detect tree type
3. Count the number of trunks
    a. Measure tree angle
4. Measure tree height
    a. Measure RCD
5. Measure root ball ratio
    a. If container measure as a ratio of expected container height
    b. If bare root check left and right quadrant are wider than a set distance
6. Measure brown green ratio on top ¼ of shoot
7. Decision Engine
    a. Compare against rules
8. Go to step 1 for next image until the directory has been fully analysed.

### Rules

| Rules | Min | Max |
|---|---|---|
| Stem count | 0 | 1 |
| Shoot height | 150 | 600 |
| Brown leaf ratio | 0 | 0.1 |
| Root bare ratio | 0.75 | 1 |
| Root container ratio | 0.75 | 1.2 |
| RCD | 2.5 | 100 |

*Figure 6 Rules for seedling pass fail. All number can be modified.*

Tuning parameters that may need to be changed for different machinery, sheds and nurseries include:

| Parameter | Description |
|---|---|
| Confidence threshold | The AI uses this to detect objects. Anything below this value will not be included |
| Coin dimension | This is the calibration of the pixel size and will be set on install. It allows a object of known size to be used to calibrate for distance from the camera and resolution. |
| Bare root valid width | Distance from the trunk horizontally to the edge of detected roots. Pass if greater than this number. There is a trade-off to detect viable small roots close to trunk vs a bad root quadrant with one long leader. |
| Container root height | The container height is programmed in and a pass allows the root ball to be some fraction of the total length. Also, a pass is slightly larger to allow for lose roots. |
| Green and Brown definition | This is HSV (hue, saturation, value) set of three numbers and will likely change based on surroundings. It’s a trade-off for detecting too much brown or too much green.<br>Green min (25,50,50), max (100,255,255)<br>Brown min (5,50,50), max (20,255,200) |

*Figure 7 The configurable parameters in the software*

# RESULTS

Initial measurements were taken manually for (a) comparison to the automatic measurements and (b) understanding of what variation occurs in manual measurements so we can understand the definition of ‘good’ or ‘bad’.

## Manual Testing Variability

**RCD variation with measurement position** was measured on 3 trees along the trunk to determine what the measurement variation is. Measurements where at 1cm intervals from 0 to 5 cm above the root. Two types of measurement made at each height to account for nodules, Figure 8 (b). The overall variation in RCD was 1.7mm.

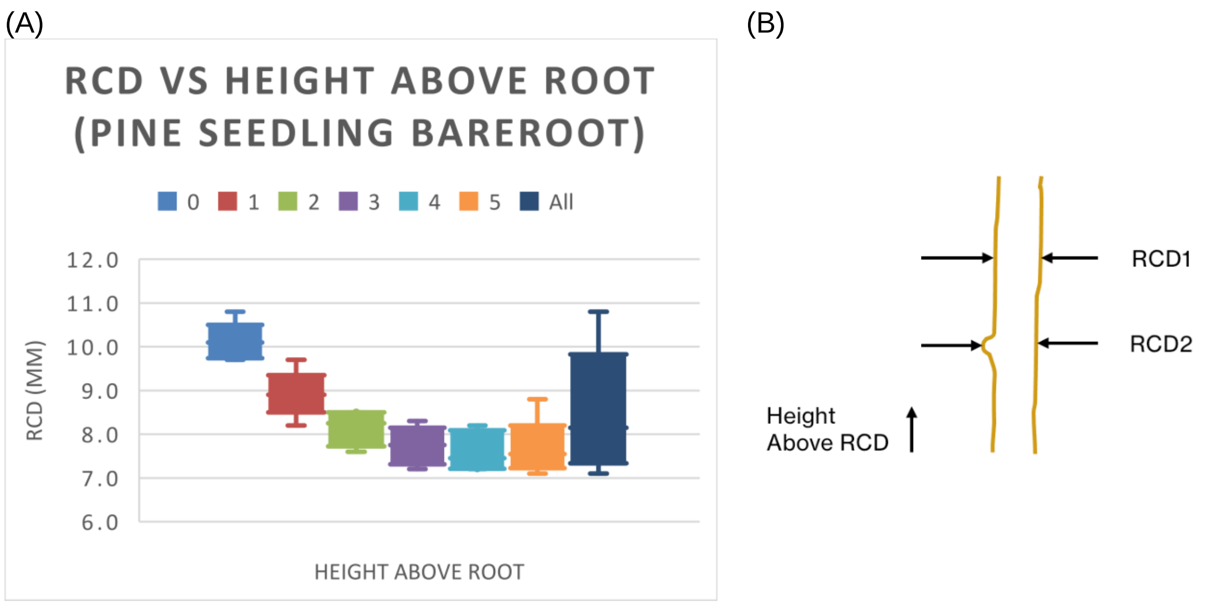



*Figure 8 RCD variation with trunk*

**RCD test-retest variation at the same position** was performed on two trees ((bare roto seedling and containerised cutting) with each tree being removed and replaced on the table. RCD range of 1.6mm between measurements was the largest range.

**Tree height** can be calculated based in 1/ top of the trunk or 2/ top of the highest needle. This changes for each tree based if the trunk can be seen or is occluded and also the needles directions can affect the measurement. Both methods shown in **Error! Reference source not found.** were performed on two tree types (bare roto seedling and containerised cutting). There range of measurements by tree type showed for 10 measurements on the same tree with the tree being removed and replaced for each measurement, H1 range (0.5mm, 0.6mm) and H2 range (3.8mm, 1.2mm).

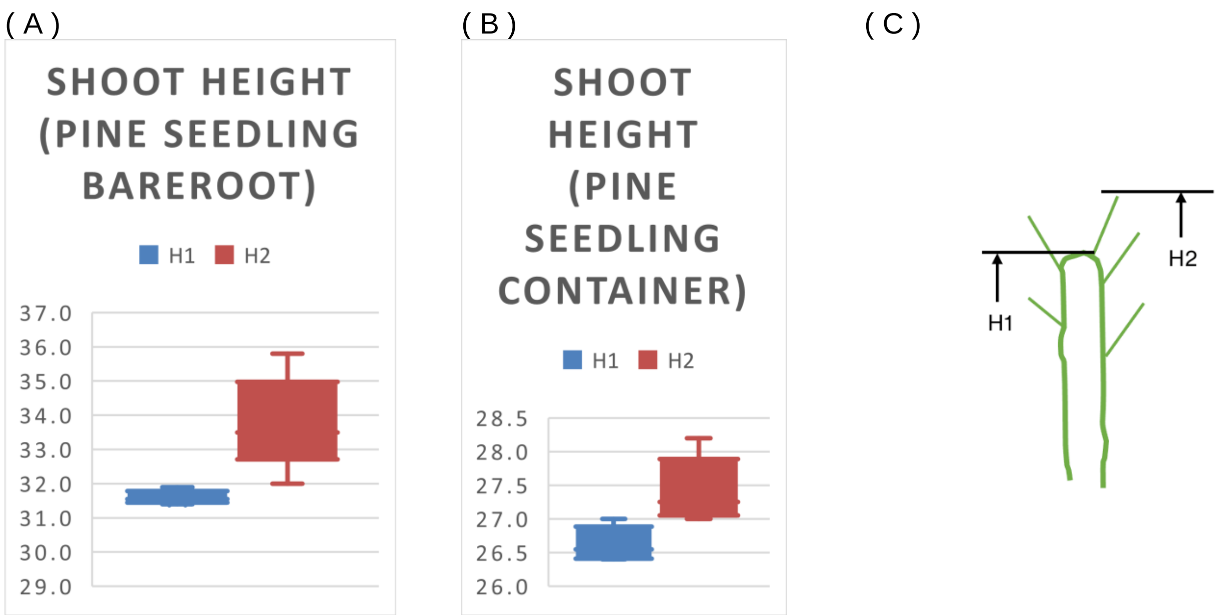



*Figure 9 Tree height variation for tree types (A) radiata seedling bareroot (B) radiata seedling container, and (C) tree height method of measurement*

## Automatic Testing

The automatic testing was focused on detection of parts of the seedling and then comparison.

## Detection

Object detection is important to enable measurements. This can be improved for more data and labelling. The results below are encouraging with 68+21 images used in training and 268 images used for detection. Additionally, half the images where examples of badly conditioned trees to make this a worst case scenario.

| *Total images* | *Tree Detected* | *Root Detected* | *Shoot Detected* | *Trunk Detected* | *Coin Detected* |
|---|---|---|---|---|---|
| 268 | 256 | 256 | 267 | 252 | 266 |
| | 96% | 96% | 100% | 94% | 99% |

**Two trunk detection** can be a challenge based on occlusion and rotation of the seedling. Figure 10 (A) shows an ideal view where the two trunks are detected and (B) a 90 degrees rotation occludes the second trunk such that it is not detected.

(A ) (B )

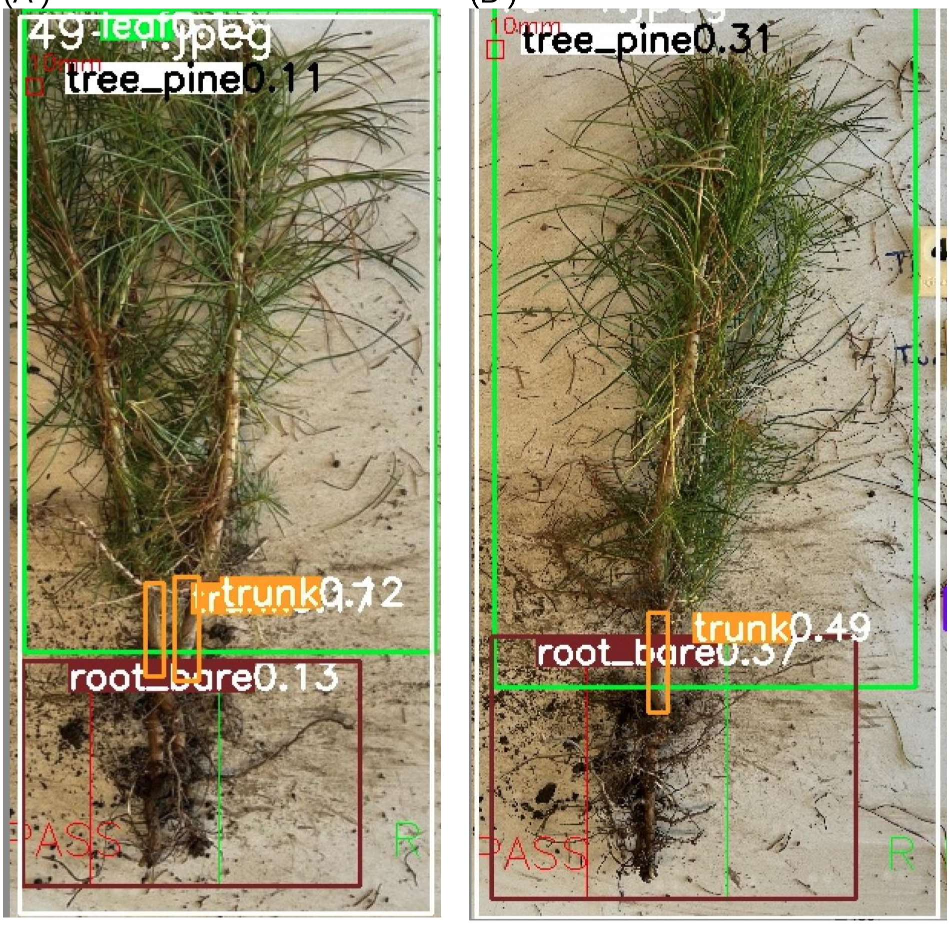



*Figure 10 Two trunk example with same seedling at different angles*

## Accuracy between Manual and Automatic Measurements

**Root Collar Diameter** depends on the detection of the trunk and can be affected by the angle of the trunk also, as the current AI draws a rectangle where the width of that rectangle is the RCD. Anomalies included, coin not detected image 47 where no coin was detected due to the root over hanging it Figure 11(A), image 57 dead tree an d no leaves detected (RCD 4.5 x , height 1.4 x), Figure 11(B).

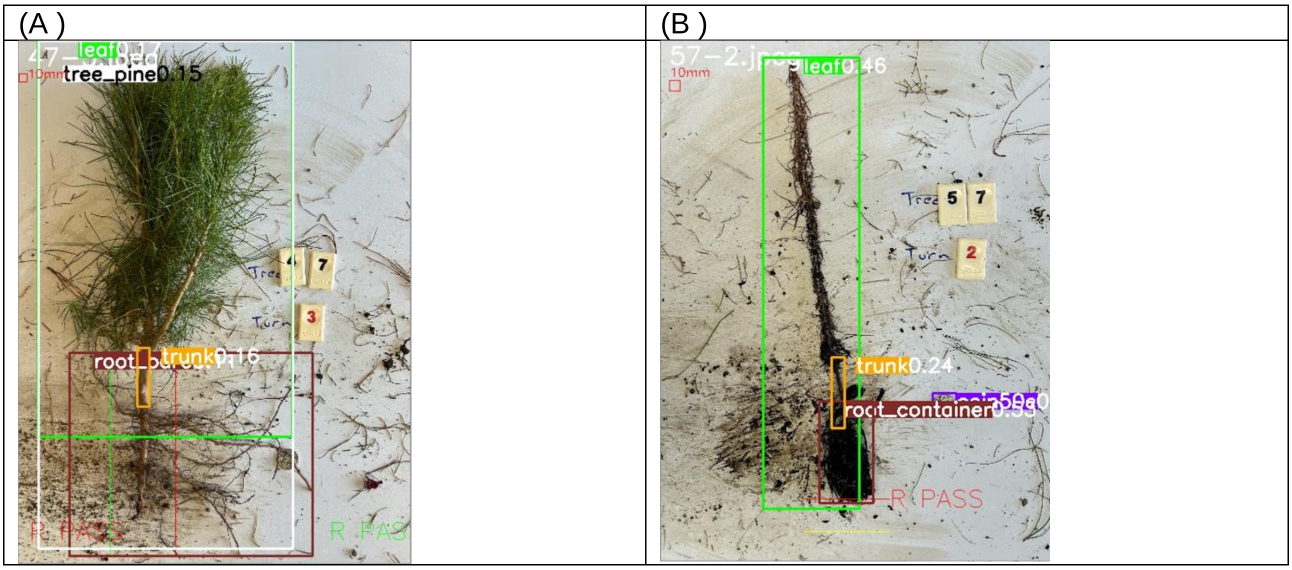



*Figure 11 Anomalies (A) coin not detected with root overlapping, (B) dead tree results in no shoot being detected and angle gives greater RCD.*

**Shoot height measurement comparison between manual and automatic measurements are** shown in Figure 12. The mean height was

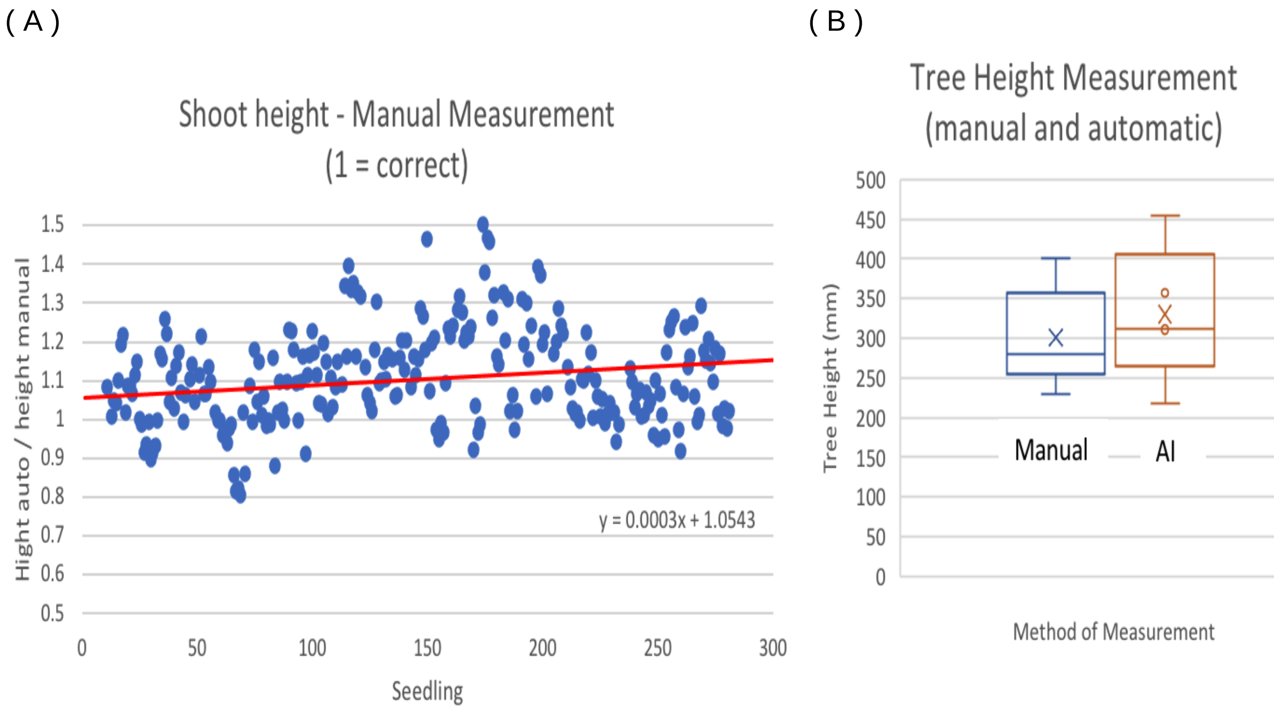



*Figure 12 Shoot height accuracy (A) each seedling automatic/manual measurement and (B) box plot of distribution*

| | Tree Height | | |
|---|---|---|---|
| | Manual | Automatic | Diff |
| Minimum | 230 | 218 | -12 |
| Maximum | 400 | 454 | 54 |
| Mean | 317 | 349 | 32 |
| Median | 313 | 357 | 45 |
| St.Dev | 35 | 46 | 11 |
| Range | 170 | 236 | 66 |

*Figure 13 Tree height measurement statistics*

**RCD measurement comparison** between manual and automatic measurements are shown in Figure 14

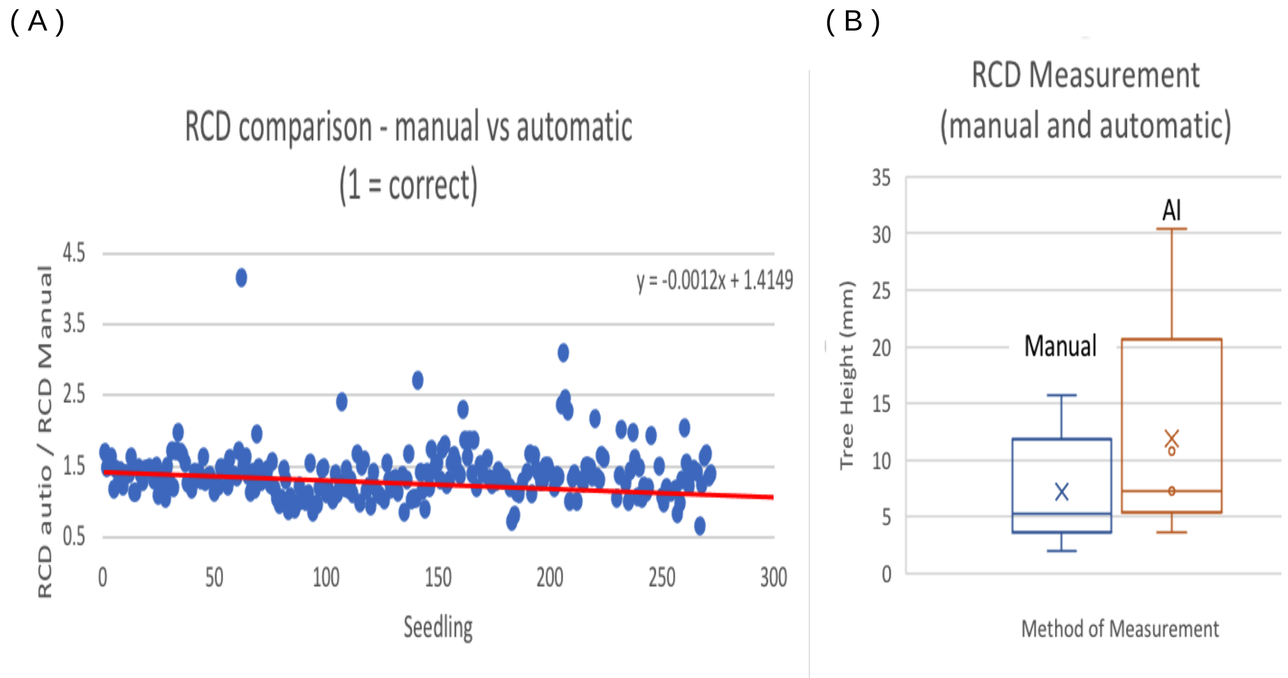



*Figure 14 Shoot height accuracy (A) each seedling automatic/manual measurement and (B) box plot of distribution*

| | RCD | | |
|---|---|---|---|
| | Manual | Automatic | Diff |
| Minimum | 2 | 3.6 | 2 |
| Maximum | 15.7 | 30.4 | 15 |
| Mean | 8 | 11 | 3 |
| Median | 8 | 10.8 | 3 |
| St.Dev | 3 | 4 | 1 |
| Range | 13.7 | 26.8 | 13 |

*Figure 15 RCD measurement statistics*

**Trunk Counting** has errors based on erroneous object detection of the trunk.

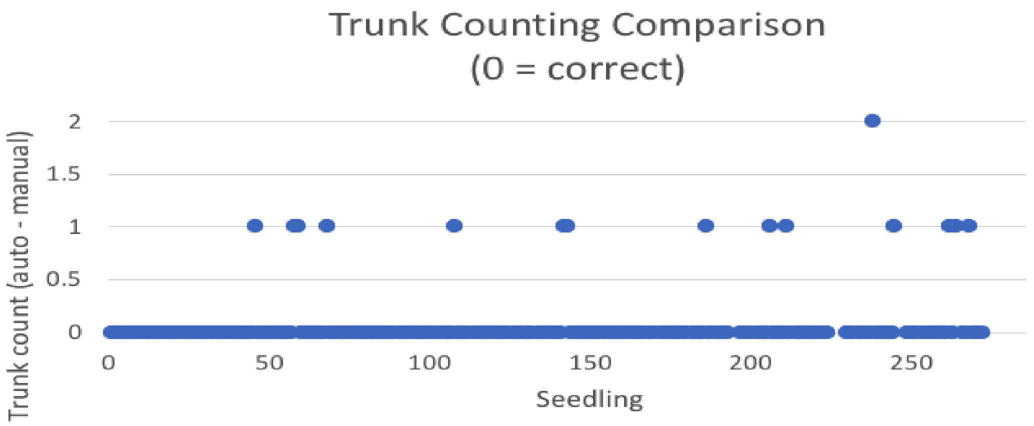



*Figure 16 Trunk counting*

**Root analysis** is calculated differently for bare root vs container. This shown below. The bare root is easily 0.5 or 2 as manual is measure in 0/4, ¼, 2/4, ¾ and 4/4, whereas the AI measure is 0/2, ½ or 2/2. This means if a manual quarter is missing, but this looks like half is missing on the camera then an error will occur.

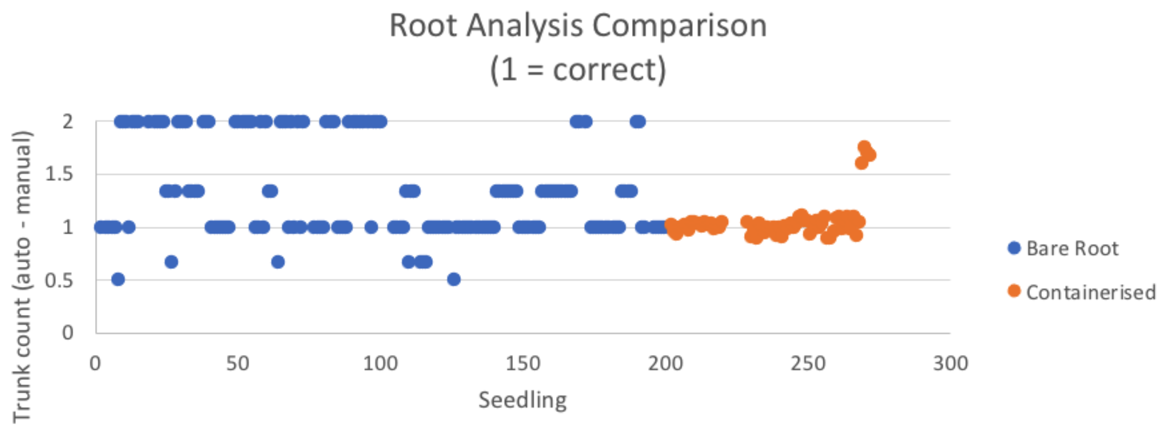



*Figure 17 Shoot height accuracy (A) each seedling automatic/manual measurement and (B) box plot of distribution*

# DISCUSSION

**Overall,** the approach from the feasibility study was consistent with more images and variation in seedlings. The comparison to manual measurements with a large number of seedlings required the software and AI to be updated. Some more logic was added, e.g., if no coin detected then don't measure anything.

**Green verses brown** uses computer vision after the AI object detection and this requires a definition of 'green 'vs 'brown' that will always need to be managed.

**Manual measurements** with a vernier scale showed smaller ranges than people would likely determine using their fingers as the callipers are narrow and find the thinnest part of the trunk for RCD. Mean RCD manual=8 and automatic=11 mm, with a +3mm offset for automatic. The range is also larger for automatic probably due the AI struggling at time to determine the edge of the trunk within a few pixels.  Height measurements need consultation with nurserymen to agree a best method for automation as the "top of the main trunk" seems like a good  place to measure compared to the "highest needle". Top of the main trunk is more difficult for a camera system as a human can brush the top of the tree to determine where the needles are compared to the trunk. Seedlings are less defined at the top of the tree compared to cuttings. The mean height measurements manual=317mm and automatic=349 are within 10%.

**Detection** of objects should be improved with more seedlings and labelling. This is time intensive and so should be considered with all the other trade-offs in the system design. Other considerations will need to be considered such as 100% trunk occlusion and what the pass/fail or selection criteria should be in these situations, i.e., if a trunk can't be seen, then RCD and root quadrant can be calculated, do you keep the seedling? These area will need clarification although it is important to note that thresholds could be tailored to nurseries specific requirements noting there are differences depending on contractual and seasonal factors.

## Future Work

There are likely some rules to be discussed for production if measurements can't be made (e.g., the trunk is visible and hence RCD is not calculated). Additionally, the RCD measurement range for automatic measurements may be give a undesirable yield for pass/fail and needs to be refined.

In upcoming work, we would seek to implement the capability to analyse multiple seedlings within a single frame, enabling the system to track and differentiate between individual seedlings. This multi-seedling "view" is important as will be likely in the real world scenario.

Additionally, there is the opportunity to work on establishing a communication link between the code and the mechanical selection mechanism of the machine. This communication will enable the code to convey the necessary information to the machine, allowing it to make real-time decisions regarding the pass or fail status of each seedling.

# CONCLUSION

In conclusion, this research demonstrates the feasibility of automating seedling identification and grading decisions through deep learning, even in scenarios with variable backgrounds. The system successfully detected shoots with an accuracy of 99.6% and managed to handle the more challenging objects like trunks at a rate of 94%. Tree height manual/automatic difference was with 32 mm. The RCD measurements had a 30% offset due to measurement technique differences between calliper and camera and a 2x range due to occluded trunks and excess dirt in the background.  We anticipate that further improvement in accuracy can be achieved with additional data labelling and lighting. However, addressing the challenge of occlusion, where the trunk is not visible, will be a critical aspect to consider. These results were intentionally worse case with 50% trees in bad condition with various failures and phenotypic anomalies and issues expected to cause issues for the automatic AI camera system.

For applications requiring bare root grading, it may be possible to rely on a single camera system, depending on specific grading requirements.

As the system moves closer to practical use, it will be essential to fine-tune accuracy-trade-offs and adapt to seasonal performance variations and market demands. A flexible system that can be easily reconfigured by end-users, possibly daily, will be crucial for meeting yield goals.

To facilitate user interaction and data collection, we recommend developing a graphical user interface (GUI) for operators, as well as data collection tools to support ongoing research. The graphical elements used in this stage, indicating detected objects and pass/fail thresholds, can serve as a valuable starting point. Moreover, it is important that parameters for customising the balance between pass and fail outcomes are readily accessible for users. These steps will contribute to the continued success and adaptability of the system in real-world applications.

# ACKNOWLEDGEMENTS

Thanks to the team that contributed to the definition of requirements and helped make trade-offs to reach an understanding of what mattered. This included Bruce Mennie and Kevin Haine. Also thanks to Kevin for the images of Redwoods and Robert Appleton for assisting with the Pine images.