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ORIGINAL ARTICLE

Machine learning based approach for wheat plant senescence quantification

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Abstract
Wheat plant senescence is the result of the natural ageing process but also due to unfavorable conditions such as water deficiency. Water deficiency induces senescence that directly relates to the yield as a cause to reduce fertile wheat ears and the number of grains per ear. For precision farming, it is highly desirable to develop genotypes tolerable to drought stress. For selecting the best genotypes tolerable to drought stress, there is a need to measure the senescence percentage. Traditionally measurement of senescence is manual and time-consuming. In this paper, image-based non-destructive approach is proposed for the quantification of senescence percentage. In this study, wheat plant image data was taken from Nanaji Deshmukh Plant Phenomics Centre ICAR-IARI and six machine learning algorithms, Naïve Bayes, KNN, Decision Tree, Random Forest, Gradient Boosting classifier, and Artificial Neural Network algorithms were trained. These algorithms are trained to segment the senescence portion from the wheat plant. All the algorithms performed well but ANN outperformed among the above trained algorithms with 97.28% testing accuracy. Machine learning-based proposed approach was compared with binary thresholding approach on wheat plant dataset and it was observed that machine learning based approach provided best results in the quantification of senescence. A desktop application, named as m-Senescencica, has been developed to facilitate senescence quantification using the traine machine learning algorithms and to visualize senescence across different plant growth stages.

Keywords Artificial neural network · Decision tree · Gradient boosting classifier · KNN · Machine learning · Naïve bayes · Random forest · Senescence

Introduction

Wheat is the major cereal crop grown in the larger part of India. Wheat is the staple food grain of India and is mainly grown in northern states in the Rabi season on irrigated lands. Already as a result of the Green Revolution, the water resources have been and continue to be overexploited, due to which there is water scarcity in northern states of India as groundwater table is diminishing every year. The Unavailability of irrigation at its critical stages may result in drought stress. Initially, drought stress results in a decrease of chlorophyll content in leaves (Nikolaeva et al., 2010) which results in visual symptoms with yellowing of leaves, i.e. the initiation of senescence. At later stages, drought-induced senescence results in a significant decrease in yield as fertile wheat ears as well as the number of grains per ear are reduced (Giunta et al., 1993).

Senescence is the final stage in the wheat crop cycle and the point when nutrients become remobilised from the plant into the developing grains. Yang et al. (2001) conducted an experiment and concluded that water deficiency accelerates wheat senescence. The first and most significant change in wheat senescence is the damaging of chloroplasts which result in the breakdown of photosynthetic pigments such as

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chlorophyll in leaf (Nikolaeva et al., 2010). Due to damage in chlorophyll, colour of the leaf changes from the usual deep green to yellow and finally brown.

Conventionally, senescence and green-ness are measured by visual scoring. Visual scoring is the inspection of plants to categorize them on a predefined scale. Visual scoring is a simple but subjective and time-consuming method (Rodriguez et al., 1979). In any particular agriculture research program, replicated trials in different multiple environments, are performed, which results in a large group of plant population. Therefore, visual scoring of senescence, for large plant populations is time-consuming and challenging.

This bottleneck in phenotyping leads to the new concept High-Throughput Phenotyping (HTP). HTP consists in using non-destructive image or sensor-based phenotyping in plants for a large number of traits including physiological, biotic (living organisms bacteria, fungi, virus, insects-pests, and weeds, etc.), and abiotic (includes non-living factors such as nutrient deficiency, flood, and drought) stress traits (White et al., 2012; Deery et al., 2014). A lot of research work is done on image based non-destructive plant phenotyping such as Leaf Image Analysis Interface (LIMANI) (Dhondt et al., 2012), High-Throughput Phenotyping Platform for plant growth modelling, and functional analysis (HPGA) (Tessmer et al., 2013), Integrated Analysis Platform (IAP) (Klukas et al., 2014), Easy Leaf Area (Easlon & Bloom, 2014), etc.

For image-based senescence quantification, segmentation of senescence portion from green and background portion is required. The literature is rich in traditional segmentation techniques, but segmentation techniques are totally dependent on the type of image data and other conditions such as noise and image illumination. Therefore a segmentation technique may be better for one set of images not for the other images (Pal & Pal, 1993). Thresholding, edge detection, and region growing are the three traditional classes of image segmentation techniques. The thresholding method is used for the quantification of wheat and chickpea senescence (Cai et al., 2016), extraction of brown and yellow pixels percentages in soybean (Naik et al., 2017). Thresholding is the most popular method for segmentation but it suffers from noise and illumination conditions (Gonzalez et al., 2002).

In the recent years, with the increase in computational power, nowadays focus has been shifted to the Machine Learning (ML) based phenotyping of plants. ML techniques are based on data driven approach and algorithms learns patterns from data, due to which they are more robust even when noise is present in digital images (Pal & Pal, 1993). Machine learning based techniques are used in other related phenotypic traits such as, spike segmentation in wheat plant (Misra et al., 2020), plant disease recognition (Sladojevic et al., 2016), weed detection (Gao et al., 2020) etc.

Most of the work done on senescence quantification is based on image processing techniques and the ML-based approach is least explored. Therefore, in this study machine learning-based approach is proposed for senescence segmentation and quantification. In this approach, machine learning based models are built for pixel-wise classification of plant into defined senescence and green-ness classes. After pixel classification, plant pixels are segmented into defined classes and for quantification, the total predicted pixels in each class are counted.

Senescence quantification results obtained using machine learning based approaches are compared with binary thresholding. It was observed that machine learning based approach provided the best results in comparison with binary thresholding.

Materials and methods

Image data acquisition

In this study, images of wheat plants were collected from LemnaTec imaging platform installed at Nanaji Deshmukh Plant Phenomics Centre (NDPPC), ICAR-IARI, New Delhi, India. Images of single wheat plants grown in pots under controlled conditions with white backgrounds were taken. RGB camera of spectral response 400 to 700 nm with sensor size 4384×6576 was used to capture visual (VIS) images (Fig. 1).

Senescence and green-ness classes

For senescence quantification purpose wheat plant is divided into five senescence and green classes by observing the wheat plant life cycle. In the initial stage of wheat plant and without senescence, leaves remain dark green. Due to senescence, leaf colour changes to pale yellow then yellow, and finally brown (for dry leaf). Based on this pattern five classes; brown, yellow, pale yellow, light green, and dark green are defined. Among the defined classes; brown, yellow, and pale yellow account for the senescence whereas light green and dark green comes under green-ness classes. For segmentation of plant from background, two additional classes, named as background classes, are also considered. Background classes consider the chamber portion, plant leaf shadow portion and the white pots turned yellow due to crop management practices like watering and soil filling in pots.

Sampling pixel values from image data

In this study, it is proposed to use machine learning based classifiers to learn the pattern of senescence from the pixel

Fig. 1 Imaging chamber and the captured image of wheat plant in NDPPC facility

values. The classifiers are trained on pixels values. Manual pixel sampling is done from each acquired image and sufficient numbers of pixel values are collected for the decided classes. GUI based ImageJ software (Schneider et al., 2012) is used to pick up pixel values. This tool provides a separate window to open an image file. ImageJ software has pixel inspector tool, which is used to copy pixel values by clicking at the desired location in image. Every image is opened in Image J software and pixels values is collected for every specified class. A CSV file (Fig. 2) is created, which contain four columns; R, G, B and class. R, G, B columns contain the red, green and blue pixel values respectively for each sampled pixel and the class column is the integer encoding of the decided training classes.

Around 1000 pixel values are sampled from each specified class. Table 1 below shows the number of sampled pixels values from each class.

Machine learning classifiers

In this study six machine learning based classifiers are trained. These classifiers are trained to classify each input

	A	B	C	D
1	B	G	R	Senescence Class
2	104	158	216	0
3	111	229	253	1
4	86	184	213	2
5	87	106	92	3
6	47	73	58	4
7	229	231	234	5
8	230	227	222	6
9	104	159	217	0
10	112	229	253	1
11	86	182	212	2
12	89	109	95	3
13	45	73	60	4
14	228	231	234	5
15	233	227	217	6
16	96	152	210	0

Fig. 2 Sample "pixel_data.csv" file. This file contains the sampled pixel values for each class. This file is used for the training of machine learning based classifiers

Table 1 Sampled pixel values from the image data

Class	Sampled pixel values
Brown (0)	999
Yellow (1)	999
Pale yellow (2)	999
Dark green (3)	999
Light green (4)	999
BG-1 (5)	995
BG-2 (6)	1225
Total	7215

pixel as yellow, pale yellow, green etc. After classification of each input pixels of image, quantification for senescence and green-ness is possible. Brief description of each classifier is given below.

GaussianNB

Gaussian naive Bayes is the simplest algorithms and based on bayes theorem (Bayes, 1763). This theorem assumes that all features are independent of each other. Gaussian naive Bayes classifier is more efficient as this classifier doesn't learn complex decision-making functions (Zhang, 2004). It learns parameters by looking at each feature individually and independently and collects simple statistics, mean and variances, for each feature, and from each class.

k-nearest neighbors (k-NN)

The k-NN algorithm is the simplest and easiest to train machine learning algorithm. This model stores the training dataset and for a given input point, prediction is made by finding the class of the data point nearest to the input data. The three algorithms used to find the k-closet data point are Brute Force, K-D Tree (Bentley, 1975) and Ball Tree (Omohundro, 1989).

Decision tree

Decision Tree (Breiman et al., 1984) learns a hierarchy of if/else questions from the input features called as test nodes and makes tree-like structure. At every step a test is used to partition the dataset in two half's. One half contains the dataset less than test values and other greater than test value. The test is chosen in such a way to generate the pure leafs. Pure leafs are those which share all the data points of the same class/target.

Random forest

A random forest (Breiman, 2001) is essentially an ensemble of decision trees, where each tree is built randomly. There are two ways by which distinct trees are built. In the first way, each tree is built on different data points and in the second way random features are selected. To select distinct data points, the bootstrap sample is used and instead of selecting the best features, random feature selection is done. For making a prediction, voting is done by each built classifier and the class with maximum votes is predicted.

Table 2 Confusion matrix

	Predicted positive (class 1)	Predicted negative (class2)
Actual positive (class 1)	True positive (TP)	False negative (FN)
Actual negative (class 2)	False positive (FP)	True negative (TN)

Gradient tree boosting

Gradient Tree Boosting (Friedman, 2001) is also an ensemble of decision trees. It builds trees one after another and each tree correct the mistakes made by the previous tree, by using greedy function approximation. There is no randomization of features or data in gradient-boosted regression trees as like in decision tree. Gradient-boosted trees are very shallow trees with maximum depth five which makes predictions faster.

Artificial neural network (ANN)

An artificial neural network (ANN) consists of multiple layers with Perceptron, they are also known as Multiple Layers Perceptron (MLP) (Hinton, 1990). ANN is used to detect nonlinear relationships in the data set. An ANN consists of 3 types of layers; input, hidden an output layer. Generally, there are more than one hidden layers. More the hidden layers, deeper is the model. A deeper model follows the training data more closely.

Performance measurement

Confusion matrix is a visualization tool used to evaluate the performance of trained classifiers. In a confusion matrix rows represents the actual classes and columns represents predicted classes. The correct prediction is shown by the main diagonal elements and off-diagonal elements represent the wrong predictions.

For binary classification problem Table 2 shows a confusion matrix.

Based on the confusion matrix following metrics are calculated for classification performance evaluation.

Accuracy

Accuracy quantifies the fraction of correct predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Precision

Precision is used to capture the percentages of samples that are predicted as positive are positive. Precision is calculated by the formula:

$$\text{Precision} = \frac{TP}{TP + FP} \times 100$$

Recall

Recall is used to measure the percentages of the positive samples which are captured by positive predictions i.e. among all the positive predictions, how many are positives. Recall is calculated by the formula.

$$\text{Recall} = \frac{TP}{TP + FN} \times 100$$

F1 score

This measure is used to summarize both precision and recall. The harmonic means of recall and precision is the F1 score. It is calculated by the formula.

$$\text{F1 score} = \frac{\text{Precision} - \text{Recall}}{\text{Precision} + \text{Recall}} \times 2$$

Approach for senescence quantification

After training of machine learning-based classifier, they are used to quantify the senescence percentage in the input image. The approach for senescence segmentation consists three steps:

Step 1 Select a machine learning-based classifier, input an image and predict the classes for all the pixels in the image.

Step 2 Count the total number of predictions made for all the classes. Senescence percentage and total plant pixels are calculated by using the following calculations.

$$\begin{aligned}
\text{Total}_{\text{plant pixels}} &= \text{Total}_{\text{brown}} + \text{Total}_{\text{yellow}} + \text{Total}_{\text{pale yellow}} \\
&\quad + \text{Total}_{\text{light green}} + \text{Total}_{\text{dark green}} \\
\text{Percentage}_{\text{brown pixels}} &= \text{Total}_{\text{brown}}/\text{Total}_{\text{plant pixels}} \times 100 \\
\text{Percentage}_{\text{yellow pixels}} &= \text{Total}_{\text{yellow}}/\text{Total}_{\text{plant pixels}} \times 100 \\
\text{Percentage}_{\text{pale yellow pixels}} &= \text{Total}_{\text{pale yellow}}/\text{Total}_{\text{plant pixel}} \times 100 \\
\text{Percentage}_{\text{light green pixels}} &= \text{Total}_{\text{light green}}/\text{Total}_{\text{plant pixels}} \times 100 \\
\text{Percentage}_{\text{dark green}} &= \text{Total}_{\text{dark green}}/\text{Total}_{\text{plant pixels}} \times 100
\end{aligned}$$

Step 3 Senescence percentage calculated by using this equation.

$$\begin{aligned}
\text{Senescence}_{\text{percentage}} &= \text{Percentage}_{\text{brown pixels}} + \text{Percentage}_{\text{yellow pixels}} \\
&\quad + \text{Percentage}_{\text{pale yellow pixels}}
\end{aligned}$$

Senescence segmentation approach

Segmentation consists of removing all the other objects in the digital image, and considering only the object of interest. Binary segmentation consists in the generation of binary masks (Fig. 3a). These masks are black and white. In binary masks, objects of interest are shown in and others in black. In this study there are a total of six classes, therefore, there are six binary masks for each input image.

Binary masks are difficult to visualize, as there are six masks for a single input image. To make visualization of segmentation easier, semantic segmentation is done (Fig. 3b). Semantic segmentation consists of the generation of a coloured mask. In coloured masks, different objects are shown by using different colours. A single coloured mask is sufficient to visualize the segmentation.

Algorithm for binary segmentation

This algorithm takes image as input and generates six 2-dimensional arrays, and each array is a binary mask. These are initialised with pixel values set to zero.

1. Take input an image of size w×h, where w and h denotes width and height of the input image.
2. Declare six 2-dimensional arrays of size w×h and initialise all w×h values to zero. Let brown[$]_{w\times h}$, yellow[$]_{w\times h}$, pale_yellow[$]_{w\times h}$, light_green[$]_{w\times h}$, dark_green[$]_{w\times h}$, background[$]_{w\times h}$ are the 2-D arrays for brown, yellow, pale yellow, light green, dark green and background portion respectively.
3. Repeat steps 4 to 7 for i = 0 to i = w − 1.
4. Repeat step 5 to 6 for j = 0 to j = h − 1.
5. Input the (i, j)th pixel to the trained machine learning classifier. The classifier predict whether the inputted pixels is brown, yellow pale yellow etc. If the predicted pixel is dry then set brown[$]_{i\times j}$ == 1, or if the predicted pixel is yellow then set yellow[$]_{i\times j}$ == 1, similarly for the other classes too. Here brown[$]_{i\times j}$ denotes the jth pixel value in ith row.
6. Set j = j + 1.
7. Set i = i + 1.
8. Save all binary masks to disk as an image using OpenCV library.
9. Repeat the steps 1 to 8 for all the input images.

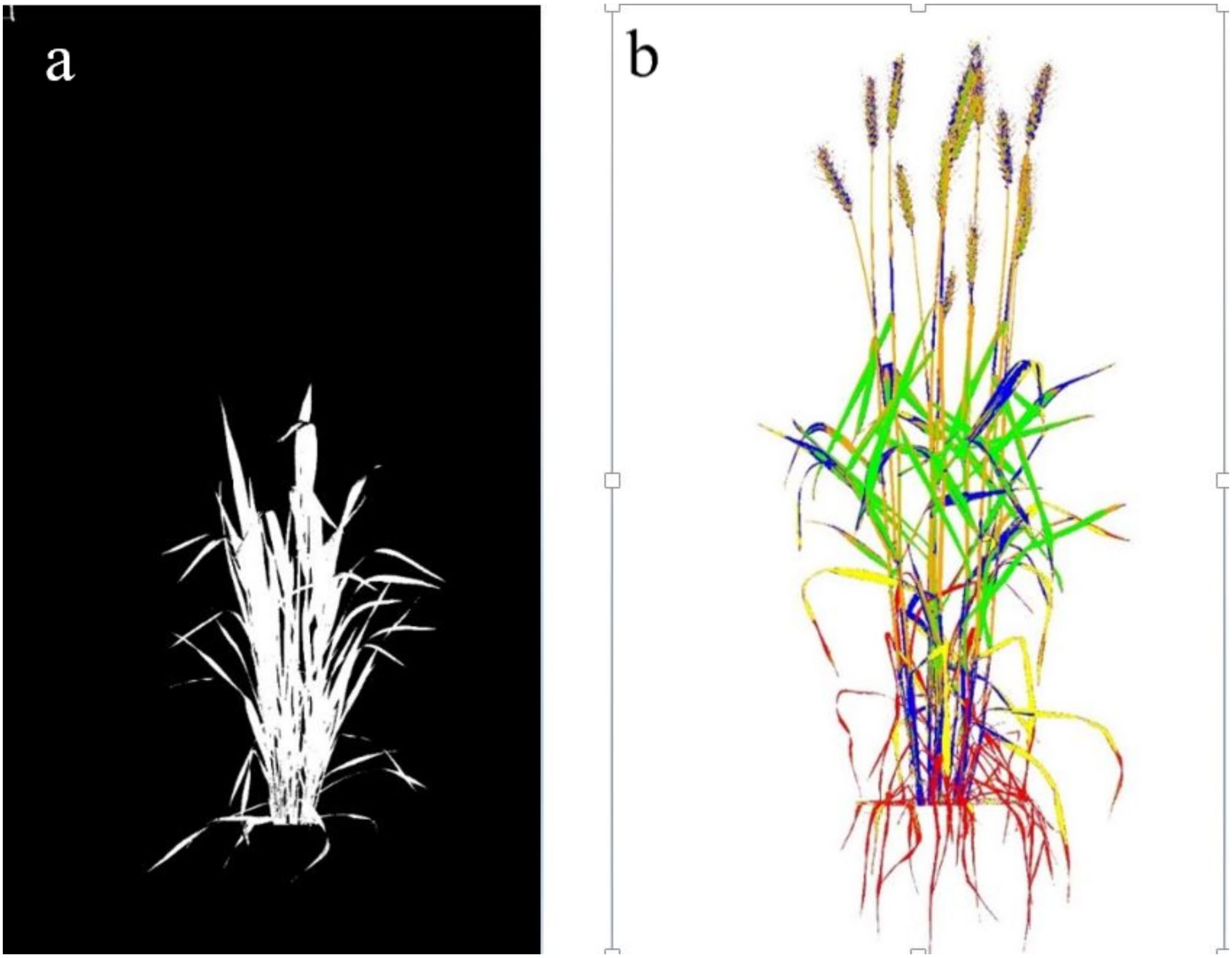


Fig. 3 Binary and semantic segmentation (**a**) Binary segmentation involves the partitioning of an image into two distinct regions: one representing objects of interest, displayed in white, and the other representing background, displayed in black. (**b**) Semantic segmentation where various objects within an image are distinguished by assigning them different colour schemes, enabling clear differentiation between them

Algorithm for semantic segmentation

1. Take input an image of size w×h, where w and h denotes width and height of input image.
2. Declare one 2-Dimensional array, C_MASK of size w×h and initialise all w×h values to zero. Set i = 0 and j = 0. Input (i, j)th pixel to trained classifier, and predict the class. Based on the condition matched below, change the (i, j)th pixel value of C_MASK:

    a. If predicted class is brown, set (i, j)th pixel to red colour.
    b. Elif predicted class is yellow, set (i, j)th pixel to yellow colour.
    c. Elif predicted class is pale yellow, set (i, j)th pixel to blue colour.
    d. Elif predicted class is light green, set (i, j)th pixel to orange colour.
    e. Elif predicted class is green, set (i, j)th pixel to green colour.
    f. Elif predicted class is background, set (i, j)th pixel to white colour.

3. Set j = j + 1, j < h, repeat step 2 for all values of j.
4. Set i = i + 1, i < w, repeat steps 2 and 3 for all values of i.
5. Save C_MASK as an image to the disk.
6. Repeat steps 1 to 5, for all input images.

Manual scoring of senescence

Senescence traditionally is measured by manual scoring, where a senescence scorer assigns the scores to the plants

Fig. 4 Scale used for the manual senescence rating

by visually observing the senescence percentage. The scales used for scoring are described below.

1 = less than or equal to 20% senescence.
2 = more than 20% and less than or equal to 40% senescence.
3 = more than 40% and less than or equal to 60% senescence.
4 = more than 60% and less than or equal to 80% senescence.
5 = more than 80% senescence.

Manual scoring is used to evaluate the senescence scores predicted by the trained classifiers. Senescence scores predicted by classifiers were converted to these 5 scales. Accuracy is calculated by taking manual scoring as ground truth. Higher the accuracy score for a classifier, better is the classifier learning (Fig. 4).

Results

Training dataset was created by sampling pixels values from the image data for three senescence, two green-ness and two background classes. This dataset has total 7215 labelled pixels values, approx. 1000 values for each class. Six machine learning-based classifiers were trained on this dataset.

Python's scikit-learn library (Pedregosa et al., 2011) was used to train the classifiers. 10-fold cross-validation was used to measure the performance evaluation metrics. All the classifiers performed extremely well where ANN outperformed with 97.23% 10-fold average accuracy (Table 3).

After training of machine learning based classifiers, they are used for senescence segmentation and quantification.

Table 3 10-fold performance measurements for classifiers

Algorithm	Precision	Recall	F1 score	Val. accuracy
Naïve bayes	0.88	0.87	0.87	0.87
k-NN	0.96	0.96	0.96	0.96
Decision tree	0.95	0.95	0.95	0.95
Random forest	0.96	0.96	0.96	0.96
Gradient boosting	0.96	0.96	0.96	0.96
ANN	0.97	0.97	0.97	0.97

For computation aspects, a desktop application named as m-Senescencica (Fig. 5), for senescence quantification was developed using Python. The application offers a user-friendly interface. The interface allows users to load images, select a trained classifier model, and choose input and output folders. After these selections, users can initiate image processing, which generates binary masks, semantic segmentation masks, and senescence quantification data, all saved automatically to the specified output folder. The application also includes features to visualize time-series plots comparing growth, senescence percentage, and total leaf area between control and drought-stress conditions.

Figure 6 shows the output of the semantic segmentation approach. For a given input image, output image contains the labelled pixels, where pixels are labelled according to the predicted classes. Pixels are labelled by using a specified colour scheme.

Senescence quantification algorithm was implemented using python programming language. This algorithm takes input image and returns the predicted percentage for each class and total plant pixels (Fig. 7).

To compare the results of machine learning based senescence quantification with binary Thresholding approach,

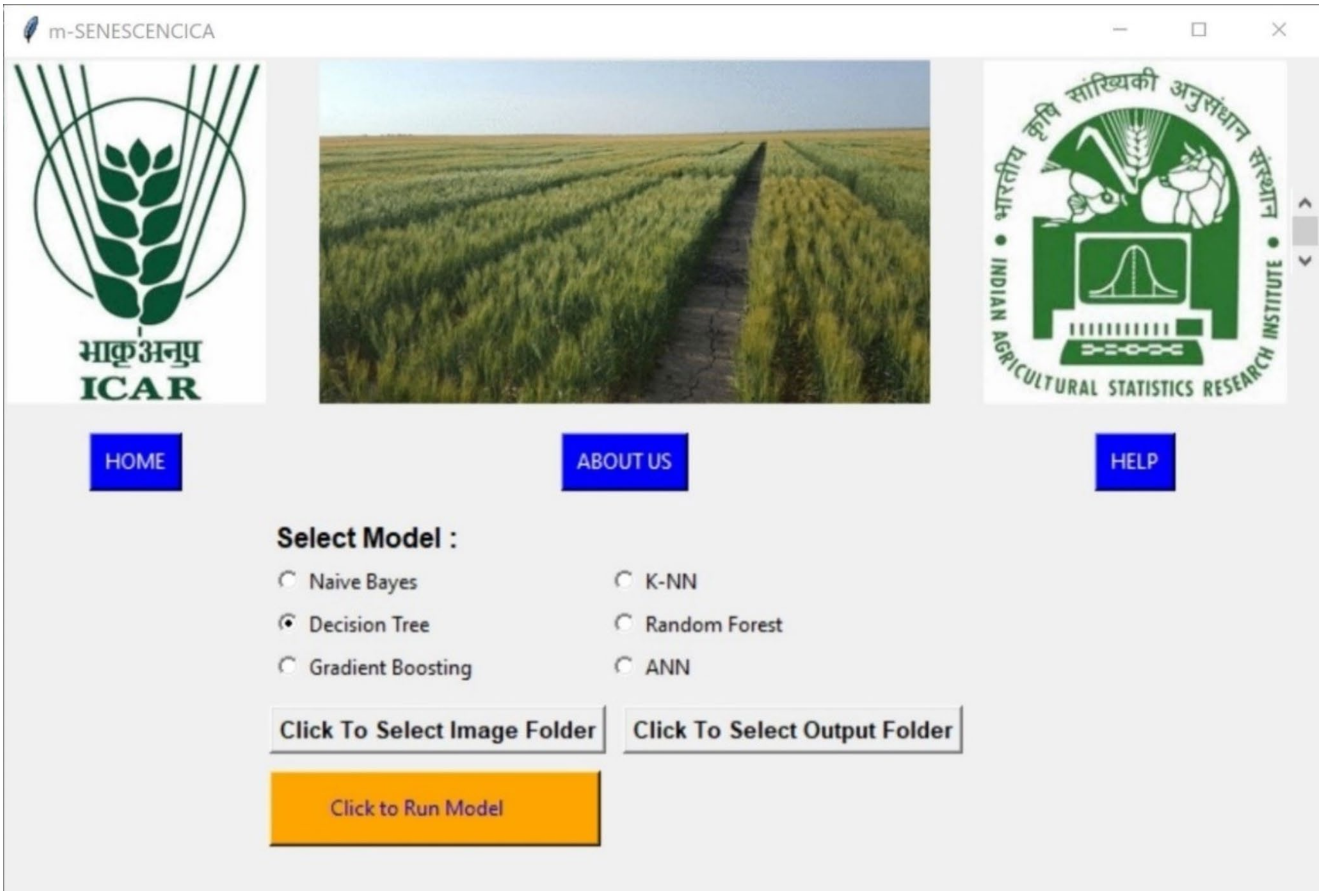


Fig. 5 User interface of the m-Senescencica software

for 1200 wheat plants, manual senescence scoring was performed at the maturity stage by the defined scales. Images for these plants were processed by using machine learning classifiers to get the senescence percentage. Binary threshoding based senescence percentage was obtained by finding the thresholding values to segment senescence portion. After segmentation, senescence percentage was obtained. Obtained senescence scores were converted to the scale 1 to 5, based on obtained senescence percentage. For example if senescence percentage is 57%, then scale is 3. This provided the predicted senescence scale.

To compare both the techniques, accuracy is calculated by taking manual scoring as ground truth. ANN achieved maximum 98.58% accuracy while Binary Thresholding based approach achieved 76.98% accuracy (Fig. 8).

The processing time for senescence quantification is a critical factor in selecting the appropriate algorithms. Therefore, it is important to compare the algorithms based on their time complexity. We assessed the time required to process a single image on a system with an Intel Core i5-4705 CPU, a 2.90 GHz processor, and 32 GB of RAM. The decision tree algorithm proved to be the fastest, processing an image in just 2.3 s, while Lemnagrid software was the slowest, taking 174.06 s.

Lemnagrid is a comprehensive software platform designed for HTP, enabling the analysis and management of plant image data. It provides workflows for image-based senescence quantification and various image processing and trait extraction tasks. However, Lemnagrid has some limitations: it is expensive, features complex workflows that require specialized training to operate, and lacks the open-source flexibility needed for customized solutions to specific problems. To quantify the percentage of senescence using Lemnagrid software, the workflows illustrated in supplementary file (Fig. S1–S7) was followed. The process begins with segmenting the foreground and background using a neural network. Next, two morphological operations were applied, and a colour classification system categorized the image into five classes: green, dark green, light green, senescent, and dead leaf. When compared with ground-truth senescence scores, Lemnagrid's senescence quantification achieved an accuracy of 92.1% (Fig. 8).

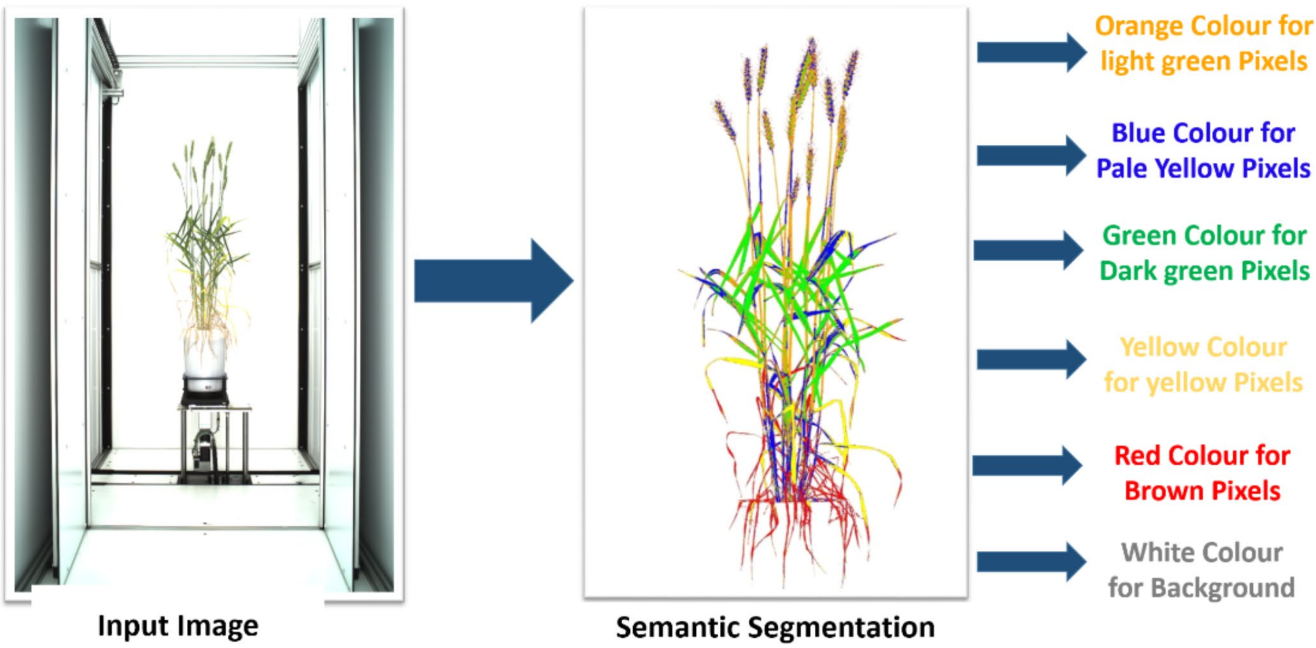
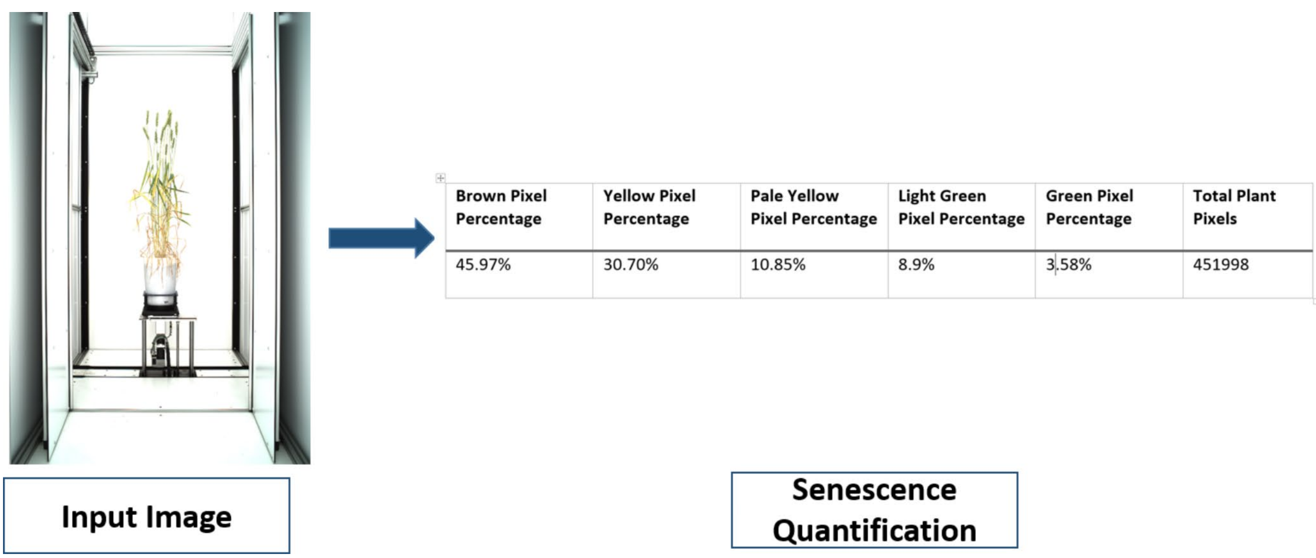


Fig. 6 This figure represents the semantic segmentation of an input wheat plant into different classes using a trained classifier and the colour scheme used to label the each pixel according to the predicted class. For example, red colour is used for all the pixels predicted as brown/dry



Brown Pixel Percentage	Yellow Pixel Percentage	Pale Yellow Pixel Percentage	Light Green Pixel Percentage	Green Pixel Percentage	Total Plant Pixels
45.97%	30.70%	10.85%	8.9%	3.58%	451998

Fig. 7 Senescence quantification output for an input wheat plant. For each class senescence percentage is computed using a classifiers and output is saved into a csv file

Discussion

Given the random and pattern-less nature of senescence in wheat plants, employing a deep learning-based object detection and segmentation approach is less suitable for accurately segmenting senescence. Therefore, machine learning-based approach is the ideal solution for senescence segmentation. Machine learning-based classifiers achieve more than 90% accuracy and (Naik et al., 2017) also reported the same results for iron induced stress in soybean crop.

Traditionally segmentation of senescence commonly relies on binary thresholding. Binary thresholding entail labour-intensive and intricate procedures for constructing image processing pipelines. These involve manual definition of texture and colour intensity ranges specific to a given scenario, aiming to detect and characterize segmentation issues (Gonzalez et al., 2002).

This method often encounters the issue of mistakenly categorizing background elements as part of the plant. In this study, it was noted that binary thresholding failed to

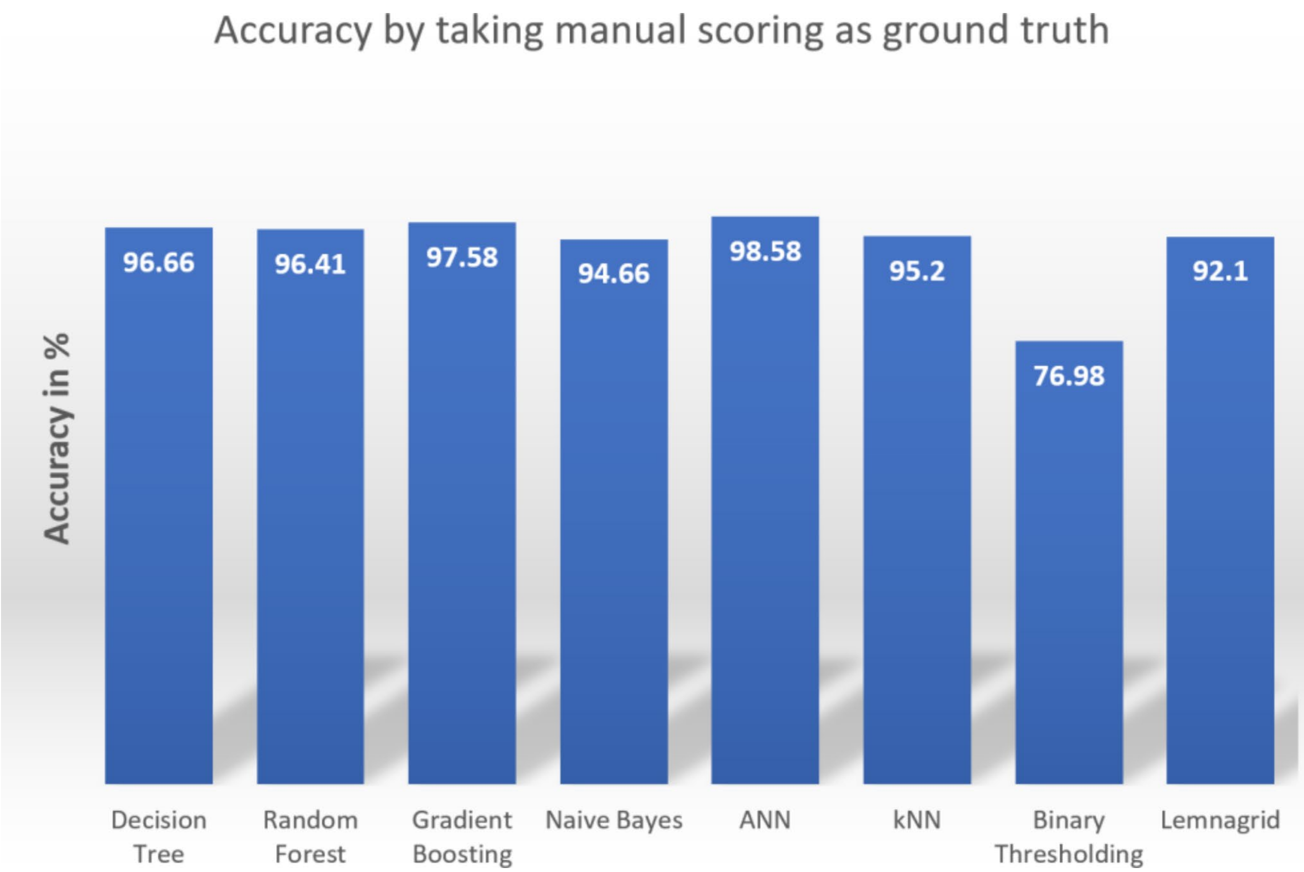


Fig. 8 Accuracy by taking manual scoring as ground truth. Binary thresholding, a conventional image processing technique, yielded an accuracy of 76.98%, whereas Artificial Neural Networks (ANN) achieved a significantly higher accuracy of 98.58%

effectively segment pots that had turned yellow as a result of agronomic management practices. As a result, binary thresholding achieved an accuracy of 76.98%, whereas the proposed machine learning-based classifiers achieved more than 90% accuracy.

One potential solution for dealing with the issue of yellow pots is to use a Region of Interest (ROI) approach. However, during senescence, lower leaves often turn yellow and fall onto the pot. Since senescence typically begins with the yellowing of these lower leaves, excluding them through an ROI can lead to an underestimation of senescence quantification. The Lemnagrid-based senescence quantification workflow uses an ROI-based approach, which fails to account for these fallen lower leaves. In contrast, the trained classifiers in our study analyse the entire image for senescence quantification, successfully segmenting the plant from the background. The data showed that the senescence scores obtained from Lemnagrid were slightly lower, likely due to the software misclassifying some senescent areas as background (Cai et al., 2016) and the use of an ROI that excludes fallen leaves.

Conclusions

Wheat plant senescence is a vital phenotypic parameter in breeding programs aimed at developing varieties tolerant to abiotic stresses like nutritional deficiencies and drought. Accurate and high-throughput measurement of senescence is essential for selecting superior varieties. In this study, we introduced a novel approach for segmenting and quantifying wheat plants into green and senescent portions. We trained six machine learning-based classifiers using pixel data sampled from images of wheat plants grown in controlled environments. Among the classifiers evaluated, the artificial neural network (ANN) demonstrated the highest performance on comparison with binary thresholding and Lemnagrid software. For high-throughput senescence quantification and visualization, we developed m-Senescencica desktop application for the users with minimal technical expertise to operate. The developed application takes less computation time than Lemnagrid software, offering a viable alternative to the time-consuming process of senescence quantification. Our study introduces a novel approach for senescence segmentation that specifically computes leaf area. This method not only segments senescent leaves from the rest of the plant but also isolates the plant from the background, a crucial step for accurate phenotypic analysis. By enabling precise measurement of leaf area and plant height, this approach directly supports the assessment of traits closely linked to yield, enhancing the ability to monitor plant health, manage agricultural practices effectively, and ultimately improve crop productivity. Looking ahead, we plan to test the trained classifier on other crops such as rice and maize, where senescence patterns exhibit similar characteristics to those observed in wheat. Given the resemblance in senescence patterns, we anticipate that the classifier will perform effectively in quantifying senescence in other crops.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Bayes, T. R. (1763). Essay towards solving a problem in the doctrine of changes. *Biometrika, 45*(1958), 243–315.

Bentley, J. L. (1975). Multidimensional binary search trees used for associative searching. *Communications of the ACM, 18*(9), 509–517.

Breiman, L. (2001). Random forests. *Machine Learning,45*(1), 5–32.

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). Classification and regression trees. Belmont, CA: Wadsworth. *International Group, 432*, 151–166.

Cai, J., Okamoto, M., Atieno, J., Sutton, T., Li, Y., & Miklavcic, S. J. (2016). Quantifying the onset and progression of plant senescence by color image analysis for high throughput applications. *PLoS ONE, 11*(6), e0157102.

de Rodriguez, S., Fehr, D. W., & Anderson, I. C. (1979). Genotypic evaluation for iron deficiency chlorosis in soybeans by visual scores and chlorophyll concentration. *Crop Science, 19*(5), 644–646.

Deery, D., Jimenez-Berni, J., Jones, H., Sirault, X., & Furbank, R. (2014). Proximal remote sensing buggies and potential applications for field based phenotyping. *Agronomy, 4*(3), 349–379.

Dhondt, S., Van Haerenborgh, D., Van Cauwenbergh, C., Merks, R. M., Philips, W., Beemster, G. T., & Inzé, D. (2012). Quantitative analysis of venation patterns of Arabidopsis leaves by supervised image analysis. *The Plant Journal, 69*(3), 553–563.

Easlon, H. M., & Bloom, A. J. (2014). Easy leaf area: Automated digital image analysis for rapid and accurate measurement of leaf area. *Applications in Plant Sciences, 2*(7), 1400033.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics, 29*, 1189–1232.

Gao, J., French, A. P., Pound, M. P., He, Y., Pridmore, T. P., & Pieters, J. G. (2020). Deep convolutional neural networks for image-based *Convolvulus sepium* detection in sugar beet fields. *Plant Methods, 16*(1), 1–12.

Giunta, F., Motzo, R., & Deidda, M. (1993). Effect of drought on yield and yield components of durum wheat and triticale in a Mediterranean environment. *Field Crops Research, 33*(4), 399–409.

Gonzalez, R. C., Woods, R. E., & Eddins, S. L. (2002). *Digital image processing*. Prentice Hall.

Hinton, G. E. (1990). Connectionist learning procedures. *Artificial Intelligence, 40*(1–3), 185234–181989. Reprinted in Carbonell, J. (Ed.), *Machine Learning: Paradigms and Methods*. MIT Press.

Klukas, C., Chen, D., & Pape, J. M. (2014). Integrated analysis platform: An open-source information system for high-throughput plant phenotyping. *Plant Physiology, 165*(2), 506–518.

Misra, T., Arora, A., Marwaha, S., Chinnusamy, V., Rao, A. R., Jain, R., Sahoo, R. N., Ray, M. N., Kumar, S., Raju, D., & Jha, R. R. (2020). SpikeSegNet-a deep learning approach utilizing encoder–decoder network with hourglass for spike segmentation and counting in wheat plant from visual imaging. *Plant Methods, 16*(1), 120.

Naik, H. S., Zhang, J., Lofquist, A., Assefa, T., Sarkar, S., Ackerman, D., Singh, A., Singh, A. K., & Ganapathysubramanian, B. (2017). A real-time phenotyping framework using machine learning for plant stress severity rating in soybean. *Plant Methods, 13*(1), 23.

Nikolaeva, M. K., Maevskaya, S. N., Shugaev, A. G., & Bukhov, N. G. (2010). Effect of drought on chlorophyll content and antioxidant enzyme activities in leaves of three wheat cultivars varying in productivity. *Russian Journal of Plant Physiology, 57*(1), 87–95.

Omohundro, S. M. (1989). *Five balltree construction algorithms* (pp. 1–22). International Computer Science Institute.

Pal, N. R., & Pal, S. K. (1993). A review on image segmentation techniques. *Pattern Recognition, 26*(9), 1277–1294.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Duborg, V., Vanderplas, J., Passos, A., & Cournapeau, D. (2011). Scikit-learn: Machine learning in Python. *The Journal of Machine Learning Research, 12*, 2825–2830.

Schneider, C. A., Rasband, W. S., & Eliceiri, K. W. (2012). NIH Image to ImageJ: 25 years of image analysis. *Nature Methods, 9*(7), 671–675.

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience, 2016*.

Tessmer, O. L., Jiao, Y., Cruz, J. A., Kramer, D. M., & Chen, J. (2013). Functional approach to high-throughput plant growth analysis. *BMC Systems Biology, 7*(6), S17.

White, J. W., et al. (2012). Field-based phenomics for plant geneticsresearch. *Field Crops Research, 133*, 101–112.

Yang, J., Zhang, J., Wang, Z., Zhu, Q., & Liu, L. (2001). Water deficit–induced senescence and its relationship to the remobilization of pre-stored carbon in wheat during grain filling. *Agronomy Journal, 93*(1), 196–206.

Zhang, H. (2004). The optimality of naive Bayes. *AA, 1*(2), 3.