Classifying Circumnutation in Pea Plants via Supervised Machine Learning

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Introduction

Circumnutation movement

Darwin was fascinated by the graceful movements of twining plants, revolving in large arcs, winding around a support, and forming a helical tube of tissue (1). He termed this movement circumnutation and described it as "a continuous self-bowing of the whole shoot, successively directed to all points of the compass".

Climbing plants need a support

Vines that find a suitable support to climb exhibit greater performance and fitness than those that remain prostrate. Therefore the detection of a suitable support is a key process in the life history of climbing plants.

Exploring circumnutation via machine learning

Numerous studies on climbing plants behavior have elucidated mechanistic details of support searching and attachment (e.g., 2). In this study, we explore the use of a range of machine learning tools to build predictive models for the individual and collective movement of pea plants based on kinematic data.

Figure 1. (A) an exemplar of pea plants grasping a support (left panel) and the circumnutation trajectories for each of the considered anatomical landmark (right panel).
(B) an exemplar of pea plants growing in the absence of the support and the trajectories for each of the considered anatomical landmarks.

Methods

Growth setup

Pea plants (*Pisum sativum* L.) were germinated under two conditions, a "support" condition (Fig. 2*A*), and a "no support" condition (Fig. 2*B*). Each pea plant was placed in an individual thermo-light controlled growth chamber. All plants exhibited evident circumnutation movement. The plants assigned to the support condition all grasped the support. In contrast the plants assigned to the no-support condition grew towards the light source and then fell to the ground.

3D trajectory reconstruction & Kinematics

By using the frames taken from two infrared cameras every three minutes, we reconstructed the plants' movement trajectories in 3D coordinates and extracted a set of kinematic features for machine learning classification (Fig. 2*C and D*).

Supervised machine learning

Three classifiers, random forest (RF), logistic regression (LR), and support vector classifier (SVC), were used as a cross-model validation. The classifiers generated models based on a binary labelled training set, learned to discriminate different growing conditions and formulated precise predictions based on an unlabelled test set. The performance is indicated as the accuracy of classification (i.e., the rate of discriminating plants growing in different conditions correctly on the test set).

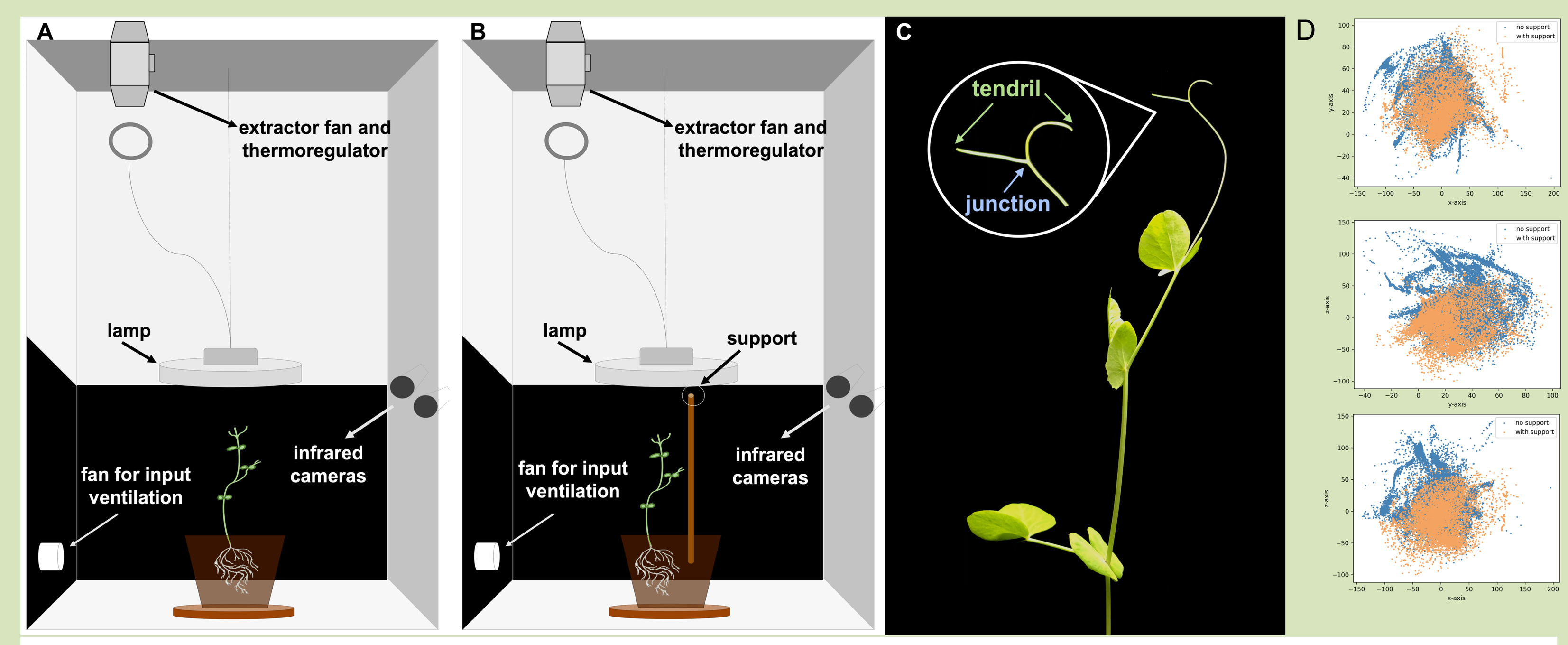


Figure 2. (A) The growth chamber of plant with no support. (B) The growth chamber of plant with a support. (C) The anatomical features (i.e., "tendrils" and "junction") used for classifications. (D) The 3D trajectories of plant grow with no support (blue) and plants grow with a support (orange).

Results

Classifiers are able to perform accurate predictions on the plants' growing conditions.
With a mean accuracy of 66.80 % (SD 15.39) for the "overall movement classification" task and a mean accuracy of 68.52% (SD 12.63) for the "circumnutation classification" task, the results demonstrate that the classifiers are capable of differentiating the growing conditions of the plants (presence/absence of the support) on the test set rather accurately above the chance level (> 50.00%). This shows that the presence of the support has an impact on how plants behave.

The considered kinematic features influence the accuracy of the classification.
We found that kinematic features characterizing the tendrils' movement, particularly the "tendril trajectories", the "tendril movement acceleration", and the "tendril aperture", performed worse for both classification tasks. The kinematic characteristics of the junctions, such as "junction trajectories" and "junction velocities", perform better. Movement time is the least relevant factor, nevertheless, for the "overall movement classification" and the accuracy for the Random Forest (RF) is below the chance level. Movement time for single circumnutations, on the other hand, is an indicative indicator of "circumnutation classification".

Table 1. Overall movement classification

	Accuracy % Mean (Standard deviation)			
	Random forest	*Logistic regression*	*SVC*	*Feature mean accuracy*
Junction trajectory	71.00 (18.30)	80.50 (13.54)	71.50 (9.89)	74.30 (14.80)
Junction velocity	78.50 (12.24)	78.00 (9.04)	75.50 (12.23)	77.30 (11.19)
Junction acceleration	66.50 (11.81)	72.00 (12.12)	71.00 (11.81)	69.80 (11.99)
Tendril trajectory	67.00 (16.49)	56.50 (14.93)	66.00 (11.13)	63.2 (14.95)
Tendril velocity	75.50 (10.51)	68.00 (15.34)	72.50 (10.21)	72.00 (12.47)
Tendril acceleration	51.00 (11.92)	57.00 (10.87)	63.50 (10.16)	57.20 (12.01)
Tendrils aperture	62.50 (15.73)	49.50 (12.23)	60.00 (6.25)	57.30 (13.17)
Movement duration	48.50 (17.43)	65.00 (16.54)	56.50 (10.90)	56.70 (16.48)
All features	76.50 (12.14)	71.00 (13.84)	72.00 (10.38)	73.20 (12.27)
Classifier's mean accuracy	66.30 (17.36)	66.40 (16.37)	67.60 (11.94)	66.80 (15.39)

Note. A string of accuracy for each classifier and feature is obtained after repeating the classification task 25 times.

Table 2. Circumnutation classification

	Accuracy % Mean (Standard deviation)			
	Random forest	*Logistic regression*	*SVC*	*Feature mean accuracy*
Junction trajectory	71.84 (10.71)	74.87 (12.14)	71.54 (14.03)	72.75 (12.29)
Junction velocity	65.09 (11.09)	71.01 (15.23)	70.42 (14.44)	68.84 (13.78)
Junction acceleration	67.12 (9.50)	70.27 (10.44)	69.33 (12.22)	68.91 (10.72)
Tendril trajectory	59.49 (9.10)	68.65 (14.56)	67.38 (12.01)	65.17 (12.61)
Tendril velocity	67.35 (11.39)	70.84 (15.23)	70.37 (14.28)	69.52 (13.63)
Tendril acceleration	62.87 (10.42)	65.62 (12.31)	66.20 (11.23)	64.90 (11.29)
Tendrils aperture	64.82 (11.28)	65.60 (11.80)	64.67 (12.79)	65.03 (11.82)
Circumnutation movement duration	63.24 (12.18)	72.98 (12.82)	69.92 (12.58)	68.71 (13.02)
All features	73.74 (12.91)	73.37 (10.35)	72.14 (11.54)	73.08 (11.51)
Classifier's mean accuracy	66.20 (11.60)	70.29 (12.98)	69.07 (12.96)	68.52 (12.63)

Note. A string of accuracy for each classifier and feature is obtained after repeating the classification task 25 times.

Overall movement classification task.
A whole plant with different features can have its growth conditions accurately predicted by the classifiers (Table 1). The SVC has a slightly higher average accuracy compared with the RF classifier and the LR classifier.
"Junction velocity", "junction trajectories", and "all features" show a better performance compared with the remaining features.
With a mean accuracy of 80.50% (SD 13.54) obtained with the LR classifier, "junction trajectories" seems to be the best indicator for distinguishing between the "support" and "no support" conditions.
Overall, this suggests that the plants exhibit generalized differences in behavioral patterns depending on the presence/absence of the support.

Circumnutation classification task.
With several features derived from a single circumnutation, the classifiers can reliably predict the growth conditions of plants (Table 2). When classifying circumnutation movements, the classifier performs marginally better than when classifying overall movements. In comparison to the RF and SVC, the LR has a little greater average accuracy
As for the features, " all features ", "junction trajectories", and "tendril velocities" exhibit generally better performance compared with the other features.
With a mean accuracy of 74.87% (SD 12.14) obtained with the logistic regression classifier, "junction trajectories" seems to be the best indicator for distinguishing between the "support" and "no support" conditions.
This is in accordance with the findings in "overall movement classification."

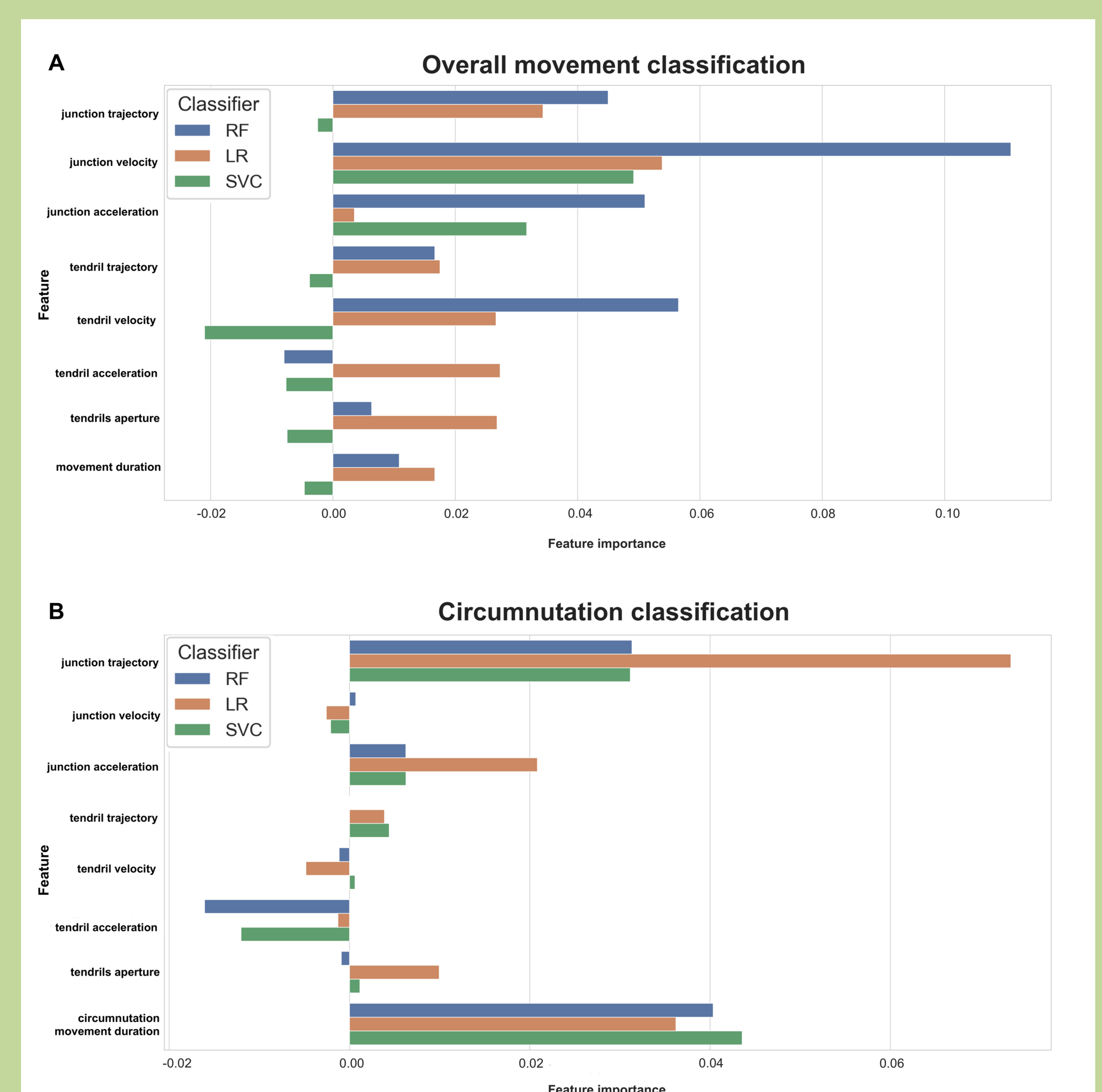
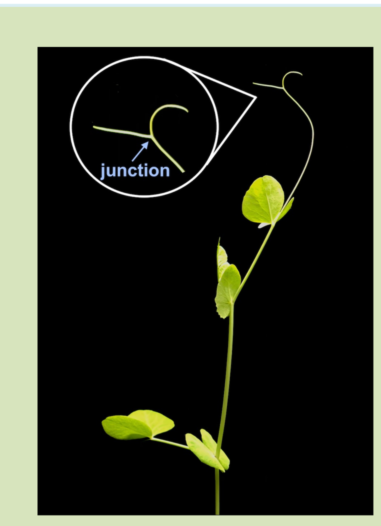


Figure 3. (A) Permutation feature importance in overall movement classification task. (B) Permutation feature importance in circumnutation classification task.

Having a complete kinematic profile is in favor of classification. When we combined all the extracted features for classifications, we were able to achieve both tasks' high accuracy with a rather consistent level across all classifiers (overall movement classification, see Fig. 3A; circumnutation classification, see Fig. 3B).
Feature importance in overall movement classification: "junction velocities", "junction trajectories", and "junction movement accelerations", for instance, are the most crucial classification characteristics.
Feature importance in circumnutation classification: "junction trajectories" and "junction movement accelerations" are also crucial. Movement duration is an important feature in classifying the circumnutation of plants when it comes to "circumnutation movement time," but not when it comes to "overall movement duration".

Discussion

- The results show that employing kinematic profiles to examine pea plant circumnutation movement can legitimate the use of machine learning.
- The movement pattern based on kinematics exhibited by plants is noticeably different for the support and the no-support condition. This implies that plants have a functional ability to interpret information from the environment, which is necessary to perform goal-directed movements. Classifiers can make accurate predictions for a single circumnutation movement revealing that the pea plant, at the time the circumnutation is initiated, is aware of its surroundings.
- Junction underneath the tendrils seems to be a superior indicator for discerning the presence/absence of the support by the plant.
- We contend that a similar machine learning approach could be used to better comprehend various plant behaviors, particularly their interactions with the environment (e.g., kin relationships, response to herbivores).



References

C. Darwin, *The power of movement in plants* (Appleton, 1897).
E. Gianoli, The behavioural ecology of climbing plants. *AoB Plants* **7** (2015).