Neural Computing and Applications
https://doi.org/10.1007/s00521-024-10502-w

S.I.: ADVANCES OF DEEP LEARNING FOR SMART FARMING

Temporal forecasting of plant height and canopy diameter from RGB images using a CNN-based regression model for ornamental pepper plants (*Capsicum* spp.) growing under high-temperature stress

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Received: 12 March 2024 / Accepted: 30 September 2024
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Abstract

Being capable of accurately predicting morphological parameters of the plant weeks before achieving fruit maturation is of great importance in the production and selection of suitable ornamental pepper plants. The objective of this article is evaluating the feasibility and assessing the performance of CNN-based models using RGB images as input to forecast two morphological parameters: plant height and canopy diameter. To this end, four CNN-based models are proposed to predict these morphological parameters in four different scenarios: first, using as input a single image of the plant; second, using as input several images from different viewpoints of the plant acquired on the same date; third, using as input two images from two consecutive weeks; and fourth, using as input a set of images consisting of one image from each week up to the current date. The results show that it is possible to accurately predict both plant height and canopy diameter. The RMSE for a forecast performed 6 weeks in advance to the actual measurements was below 4.5 cm and 4.2 cm, respectively. When information from previous weeks is added to the model, better results can be achieved and as the prediction date gets closer to the assessment date the accuracy improves as well.

Keywords Image-based temporal prediction · Morphological parameters · Ornamental potential · Precision agriculture · Solanaceae · Thermal stress

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1 Introduction

The sale of potted ornamental plants in self-service outlets (supermarkets and garden centers) and the trend toward urban areas with increasingly limited outdoor space have contributed to the popularization and growth of the potted ornamental plant trade throughout Brazil [1, 2]. Pepper plants of the genus *Capsicum* (Solanaceae) stand out in the ornamental plant market due to the wide diversity in colors and shapes of fruits and leaves [3]. However, most of the cultivars available on the market come from genetic breeding programs carried out outside the country [4, 5]. It is therefore necessary to develop and introduce new varieties of pepper plants and technologies that meet the demand of the ornamental plant sector and that are better adapted to Brazilian weather conditions [2, 6], especially in the face of the scenario of climate change.

Temperature fluctuations, triggered by climate change, harm plant development and represent a threat to the productive efficiency of crops [7]. The response to those fluctuations can usually change among species and genotypes, being those responses related to numerous alterations at morphological, physiological, biochemical and/or molecular level [8]. High-temperature stress is one of the most limiting abiotic stresses for the growth and development of pepper plants, resulting in less flowering, fruit drop and size reduction [9, 10].

The size of the pepper plant in the pot is one of the main quality attributes observed by the ornamental plant sector, and not every pepper plant can be considered ornamental. The desired ideotype includes, among other factors, the harmony between the plant and the pot given by the balance between plant height and canopy diameter in relation to the size of the pot used [11, 12]. Very tall plants with a wider crown do not adapt well to the pot, resulting mainly in the plants tipping over. Very small plants end up not standing out on the pot, directly compromising the aesthetics and visual balance [13]. Thus, it is required to develop strategies aimed at the assessment and selection of plants, within genetic breeding programs, in order to obtain plants with the desired morphological characteristics [14].

The evaluation of these parameters is traditionally carried out plant by plant when the first fruits ripen, using a ruler and caliper [15]. Despite the high precision provided by traditional methods, they are laborious and time-consuming, especially considering genetic breeding programs that evaluate numerous plants and progenies from many populations per year. For example, typically, a single germplasm collection of a genetic breeding program based on hybridization includes over 200 accessions in different breeding stages [16], where a single F_2 population usually evaluates from 90 to 730 plants in average [17, 18]. Driving each of these populations to the fruiting stage for subsequent selection of the best genetic materials requires a lot of financial resources and labor. Providing alternative methods, including artificial intelligence and computer vision, to predict morphological parameters of ornamental plants is a valuable tool for the industry in order to achieve faster, more faithful and reproducible results [19].

In this sense, artificial vision techniques can be useful tools within genetic breeding programs as they can enable the prediction of morphological parameters of plants in advance before the evaluation date. It has already been shown in the literature that RGB images can be used to accurately estimate several plant parameters, including those related to its growth rate and its morphological parameters [20]. For example, artificial intelligence techniques, including those associated with convolutional neural networks (CNNs), have been adopted for this kind of prediction in other species, such as Chinese mahogany [21], passion fruit [22], lettuce [23], among others. In the literature, some studies can be found using artificial neural networks for processing images in order to estimate the number of outdoor ornamental plants [24]. However, no studies can be found, to the best of the authors' knowledge, using convolutional neural networks with RGB images to estimate plant height and canopy diameter of ornamental pepper plants. Moreover, no other studies have been found trying to predict future values of these morphological parameters beforehand, just to estimate current values at the same present date in other species, but there is no work on estimating in advance future values of morphological parameters.

Based on the previous works, the work presented in this article has the goal of developing and assessing a method for accurately forecasting the plant height and canopy diameter of pepper plants using RGB images as input for the model. Furthermore, the influence of using several images and combining information from several dates is explored too. More importantly, this paper is the first to undertake the prediction based on images from previous dates instead of the estimation of current morphological parameters based on images from the current date.

2 Materials and methods

The methodological steps undertaken to conduct the research work described in this paper are summarized in Fig. 1. Each of those steps are further described in the subsequent subsections in greater detail.

2.1 Pepper plants seed selection

In this study, fifteen treatments of pepper plants (*Capsicum* spp.) with ornamental potential were used in the

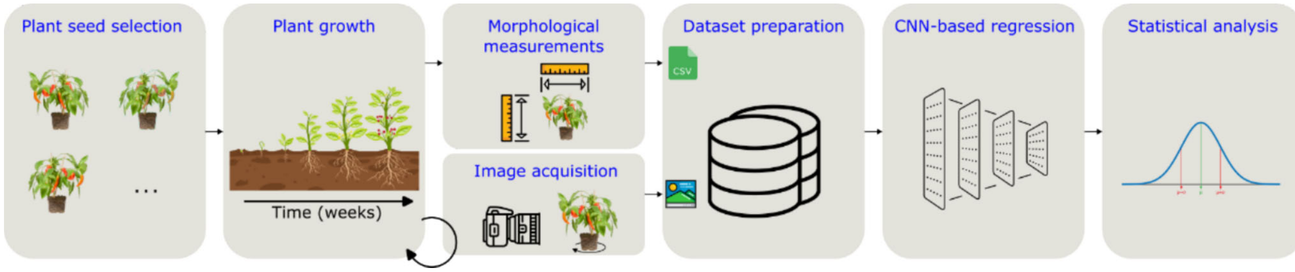


Fig. 1 Schematic diagram summarizing the proposed methodology for predicting the morphological parameters (plant height and canopy diameter) from RGB images

experiments. These different treatments were chosen in this work due to them being representative of the most widely commercialized ones in the southwest region of Piaui (Brazil). All of the seeds of those treatments are duly identified according to Table 1 and came from the Active Germplasm Bank of the Federal University of Piaui/Campus Professora Cinobelina Elvas (UFPI/CPCE).

2.2 Pepper plants growth conditions

The study was conducted under two experimental conditions: (*i*) a greenhouse with humidity and temperature control and (*ii*) a greenhouse without humidity and temperature control (Fig. 2). In this second experimental condition (uncontrolled greenhouse), the plants were kept under high-temperature stress due to the hot weather typical of the localization where the experiments were conducted. The facilities where the experiments took place are located in the experimental area of UFPI/CPCE in the city of Bom Jesus, Piaui (Brazil), corresponding to WGS84 coordinates latitude: 9°5′3″ S, longitude: 44°19′33″ W, and altitude: 290 m. Throughout the experiment, air temperature and relative humidity conditions in the greenhouses were monitored daily using a TH-50 digital thermo-hygrometer from Incoterm [25]. Measurements were taken every day at 3 pm local time (Brasília Time—BRT, UTC-3). In the greenhouse with uncontrolled conditions, 40.0 ± 2.6 °C for air temperature and $11.7 \pm 5.1\%$ for relative humidity were observed (mean value ± standard deviation). In contrast, in the greenhouse with controlled conditions, an average of 27.2 ± 1.6 °C for air temperature and $41.5 \pm 5.6\%$ for relative humidity was observed (mean value ± standard deviation).

Two seeds/cell from each of the 15 pepper accessions were used to set up the experiments, sown in 200-cell polyethylene trays with Terra Nova® (Flor da Serra do Sul/Paraná) commercial substrate. After germination and the development of two pairs of definitive leaves, the seedlings were transplanted into pots number 15 (height of 10.5 cm, upper diameter of 14.5 cm, lower diameter of 10 cm, and volume of 1.16 L) that were kept in greenhouses, one under uncontrolled conditions and the other under controlled conditions. Watering was carried out three times a day until the maximum retention capacity of the substrate was

Table 1 Identification of the pepper treatments/accessions coming from the Federal University of Piaui/Campus Professora Cinobelina Elvas (UFPI/CPCE) Active Germplasm Bank used in the experiments

Treatment number	Germplasm code	Common name	Scientific name
1	CPCE 008	Maya black blood	*Capsicum annuum*
2	CPCE 012	Masquerade	*Capsicum frutescens*
3	CPCE 003	Floribella	*Capsicum* sp.
4	CPCE 013	Bolivian rainbow	*Capsicum annuum*
5	CPCE 005	Calypso	*Capsicum annuum*
6	CPCE 006	Pyramid ornamental	*Capsicum frutescens*
7	CPCE 007	Black pyramid	*Capsicum frutescens*
8	CPCE 009	Black cuban	*Capsicum annuum*
9	CPCE 010	Black pearl	*Capsicum annuum*
10	CPCE 011	Purple tiger variegated	*Capsicum annuum*
11	CPCE 014	Medusa	*Capsicum annuum*
12	CPCE 017	Bird's eye baby ornamental	*Capsicum annuum*
13	CPCE 018	Not identified	*Capsicum* sp.
14	CPCE 019	Not identified	*Capsicum* sp.
15	CPCE 020	Not identified	*Capsicum* sp.

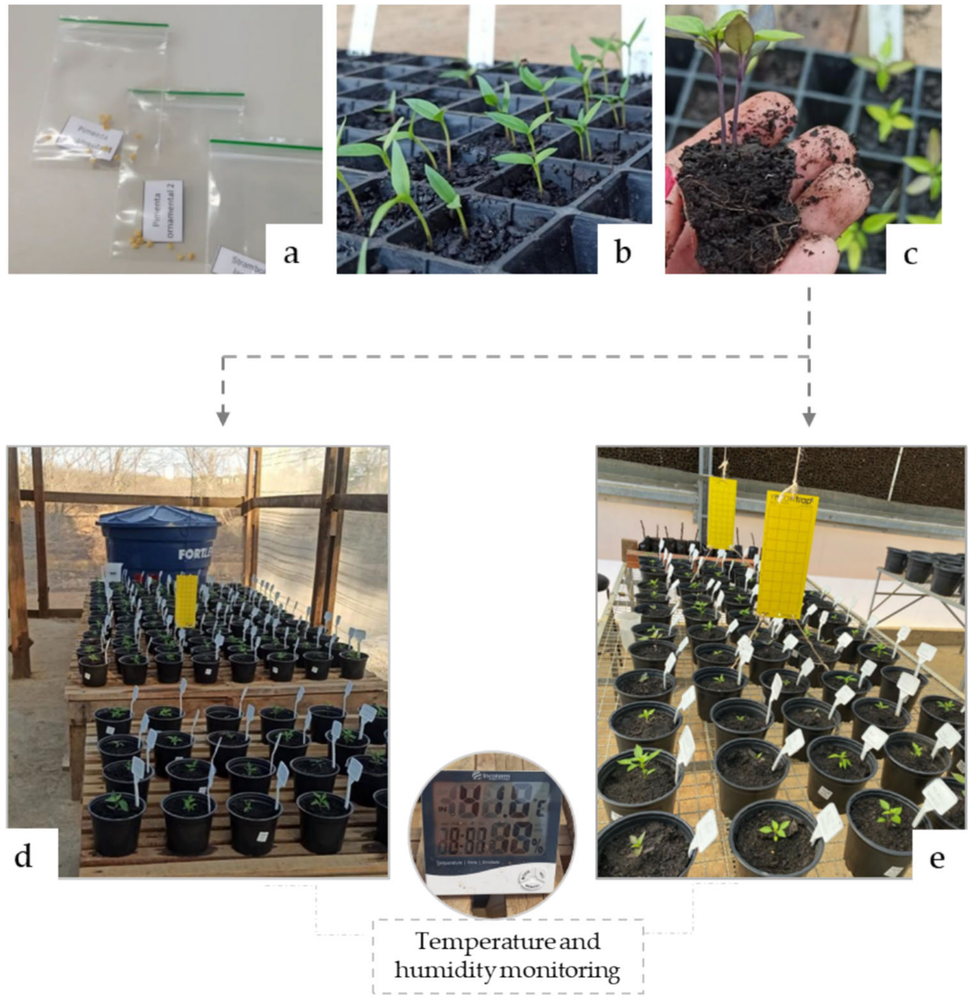


Fig. 2 Experimental conditions for pepper plants growth: **a** seeds coming from the active germplasm bank stored in plastic bags, **b** seedlings of pepper plants growing in 200-cell polyethylene trays, **c** a seedling and its substrate in the moment of being transplanted into a pot number 15, **d** pepper plants growing in a greenhouse with humidity and temperature control, and **e** pepper plants growing in a greenhouse without humidity and temperature control

reached. Once a week 10 g of Forth® Hortaliças fertilizer (Cerquilho Velho—Cerquilho/São Paulo, Brazil) was applied to each plant diluted in 200 mL of water.

In each of the experimental conditions, a randomized block design (RBD) was adopted, with 15 accessions and 4 replicates each, with each experimental unit consisting of a pot with one plant.

Fig. 3 Experimental setup employed to perform image acquisition: **a** zoom in the wooden booth with a rotating plate used to turn around the pot containing the plants; **b** whole setup showing lightning bulbs and camera position relative to the wooden booth; and **c** setup while the camera is taking a photo, with a pepper plant placed inside of the wooden booth

Table 2 Dates when images were acquired (mm/dd/yyyy) and the number of consecutive weeks after seeding the plants

Week number after seeding	Date when image acquisition took place
8	06/22/2023
9	06/29/2023
10	07/06/2023
11	07/13/2023
12	07/20/2023
13	07/27/2023
14	08/03/2023
15	08/10/2023

Fig. 4 Structure of the CSV file used for the morphological measurements from plant height and canopy diameter

Folder	Plant height (cm)	Canopy diameter (cm)
CG/B1/T1	23.5	23.85
...		
UG/B4/T15	33.7	31.05

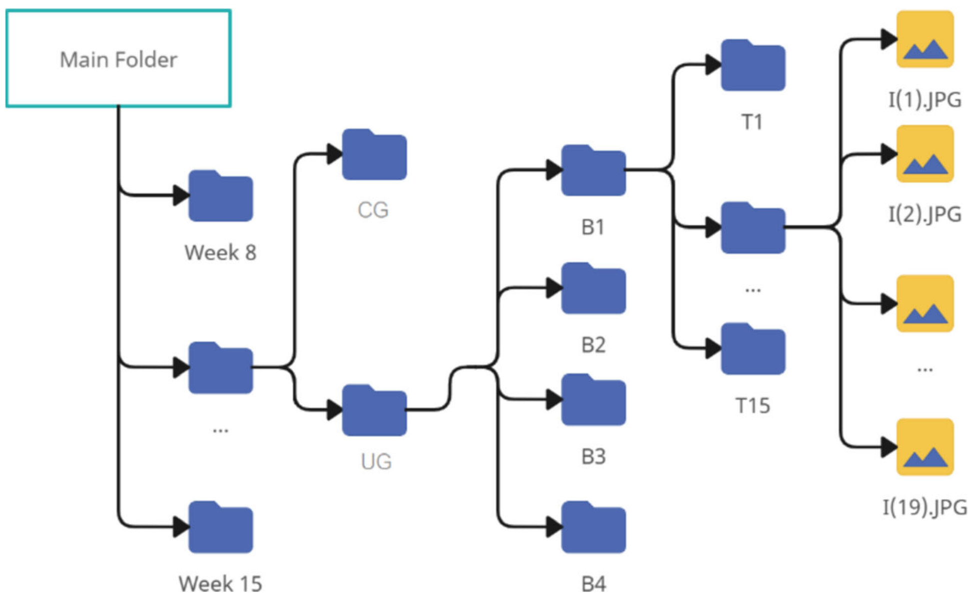


Fig. 5 Folder structure of the curated images dataset organization. First level of hierarchy was the date when the photos were taken (Week #). Second level of hierarchy was the growing conditions of the plants (CG stands for controlled greenhouse and UG stands for uncontrolled greenhouse). Third level of hierarchy was the block or repetition (B#). Fourth level of hierarchy was the treatment (T#). Finally, inside each treatment folder, nineteen images were placed, named as I(#).JPG, being the images rotations of the plant each 20° with the photos for 0° and 360° being taken and thus capturing the same viewpoint

2.3 Morphological measurements: plant height and canopy diameter

In the reproductive phase, all plants were evaluated for plant height and canopy diameter, according to the descriptors suggested by the IPGRI (International Plant Genetic Resources Institute) for pepper (*Capsicum* spp.) [15] and quality parameters for ornamental pepper plants suggested by Classification Criteria of the Veiling Holambra Cooperative [26]. Plant height was measured with a millimeter ruler considering the distance from the plant neck to the highest leaf/branch of the plant. The canopy diameter was measured with the aid of a horizontally positioned forest caliber, in which the diameter was taken in two different positions of the plant (longitudinal diameter and transverse diameter). These measurements were then used to calculate an average, aiming to obtain a more accurate representation of the plant's canopy. The measurements were recorded at the moment when 50% of the plants showed the maturation of their first fruits, which in this experiment corresponded to August 10, 2023, fifteen weeks after seeding took place. In order to reduce the chance of outliers appearing in the obtained data, all the measurements were taken from three different people. In addition, an exploratory data analysis was performed with the variables using both boxplot and histogram to spot anomalies with the data.

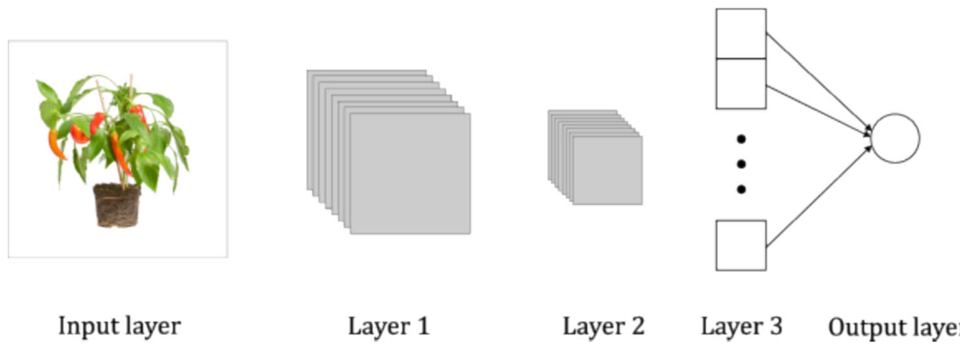


Fig. 6 Architecture of the CNN-based prediction model that uses just a single image from a specific date

Table 3 Specific parameters of each layer of the CNN architecture used for prediction using just a single image from a specific date

Layer		Input size	Kernel/pool size	Stride	Padding	Activation function
Number	Type					
Input	Image	300 × 200 × 3	–	–	–	–
1	2D Convolution	300 × 200 × 3	3 × 3	1	No	ReLU
2	Max Pooling	298 × 198 × 64	2 × 2	2 × 2	No	–
3	Flatten	149 × 99 × 64	–	–	–	–
Output	Dense	944,064	–	–	–	Linear

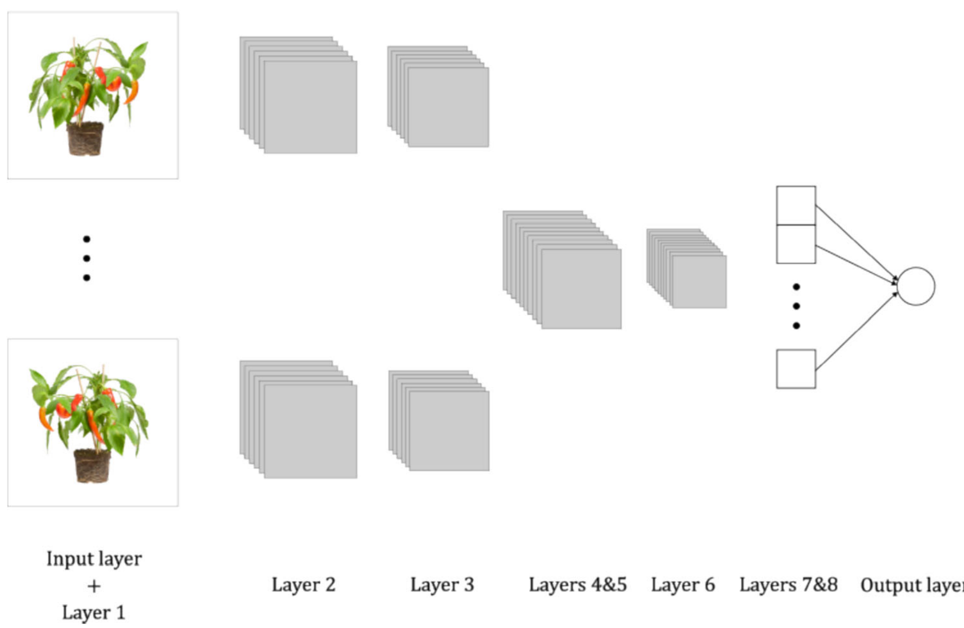


Fig. 7 Architecture of the CNN-based prediction model that uses several images from a specific date

2.4 Image acquisition of pepper plants during growth stages

After the plants reached the juvenile stage, marked by the bifurcation of the first branches, digital image acquisition began at the UFPI/CPCE Data Improvement and Analysis Laboratory. A wooden booth with a white background and dimensions 90 × 70 × 70 cm (height × width × depth) together with a softbox kit equipped with 20 W LED bulbs and 1800 lumens were used to acquire the images. A Canon® EOS digital camera (Rebel SL2 with lens EF-S 18–55 mm IS STM), positioned centrally at a distance of 46 cm from the photo booth, captured images of each vessel at a 20-degree interval, completing a 360-degree rotation. This method provided a comprehensive and detailed analysis of the morphological development of plants throughout the experiment.

The aforementioned setup that was used to acquire the photographs of the plants while growing is shown in Fig. 3. A total of 18 photos per plant were taken for each date, with photographs acquired every week (Table 2) for all treatments and repetitions. Taking into account (see

Table 4 Specific parameters of each layer of the CNN architecture used for prediction using several images from a specific date

Layer		Input size	Kernel/pool size	Stride	Padding	Activation function
Number	Type					
Input	Image	18 × 300 × 200 × 3	–	–	–	–
1a-1 s (18 replicates)	Slice	18 × 300 × 200 × 3	–	–	–	–
2a-2 s (18 replicates)	2D Convolution	300 × 200 × 3	3 × 3	1	No	ReLU
3a-3 s (18 replicates)	Max Pooling	298 × 198 × 3	2 × 2	2 × 2	No	–
4	Concatenate	18 × 149 × 99 × 16				ReLU
5	2D Convolution	149 × 99 × 288	4 × 4	1	No	ReLU
6	Max Pooling	146 × 96 × 32	2 × 2	2 × 2	No	–
7	Flatten	73 × 48 × 32	–	–	–	–
8	Dropout (p = 0.5)	112,128	–	–	–	–
Output	Dense	112,128	–	–	–	Linear

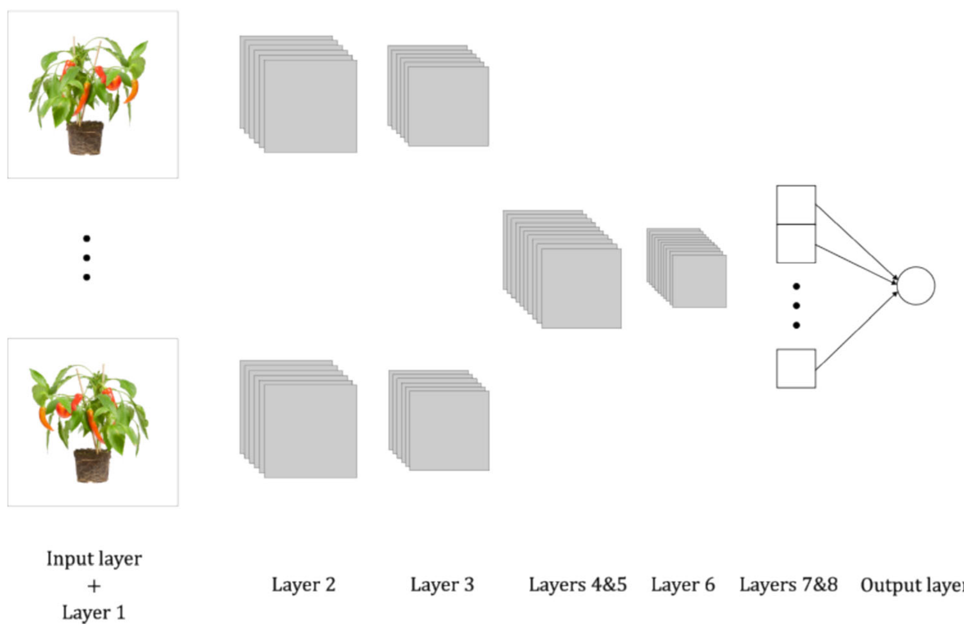


Fig. 8 Architecture of the CNN-based prediction model that uses one image from a specific date and another from the week before

subSect. 2.2) that 15 treatments with 4 repetitions for each greenhouse (controlled vs uncontrolled), a total of 15 × 4 × 2 × 18 = 2160 photos were taken for each date. The last week when photos were taken corresponds to the one in which the morphological assessment of plant height and canopy diameter was carried out. All photographs were saved as images both in JPEG and RAW formats with a resolution of 6000 × 4000 pixels.

2.5 Dataset preparation/curation

The morphological measurements from plant height and canopy diameter (subSect. 2.3) were placed into a spreadsheet using CSV format and following the structure depicted in Fig. 4.

In addition to those measurements, the dataset also consisted of all the images acquired for each plant every week. Additionally, the image size of each photo was downscaled from 6000 × 4000 px to 300 × 200 px. These images were organized in a folder structure as depicted in Fig. 5. The resulting dataset, already curated, has been made publicly available at Zenodo [27].

2.6 Image processing for forecasting using a CNN-based model

The aforementioned curated dataset was used for training the models and further testing the performance of those trained models. Firstly, this dataset was divided into three separate datasets: training (80%), evaluation (10%) and test

Table 5 Specific parameters of each layer of the CNN architecture used for prediction using one image from a specific date and another from the week before

Layer		Input size	Kernel/pool size	Stride	Padding	Activation function
Number	Type					
Input	Image	2 × 300 × 200 × 3	–	–	–	–
1a-1b (2 replicates)	Slice	2 × 300 × 200 × 3	–	–	–	–
2a-2b (2 replicates)	2D Convolution	300 × 200 × 3	3 × 3	1	No	ReLU
3a-3b (2 replicates)	Max Pooling	298 × 198 × 3	2 × 2	2 × 2	No	-
4	Concatenate	2 × 149 × 99 × 32				ReLU
5	2D Convolution	149 × 99 × 64	4 × 4	1	No	ReLU
6	Max Pooling	146 × 96 × 32	2 × 2	2 × 2	No	–
7	Flatten	73 × 48 × 32	–	–	–	–
8	Dropout (p = 0.5)	112,128	–	–	–	–
Output	Dense	112,128	–	–	–	Linear

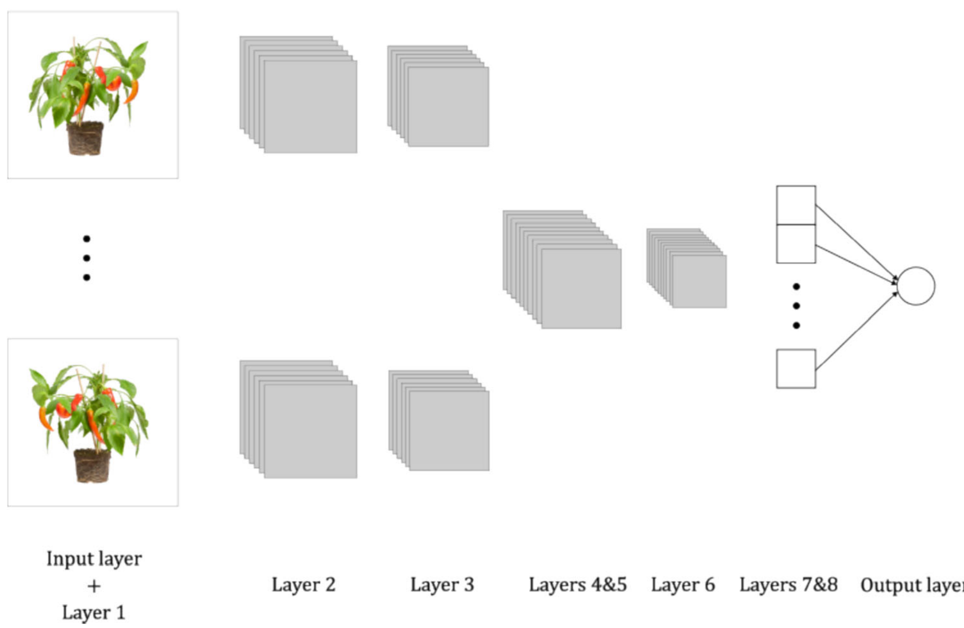


Fig. 9 Architecture of the CNN-based prediction model that uses one image from every week before a specific date

(10%). From all of the 19 photos for each treatment contained in the original dataset, either the initial (0°) or final photo (360°) was removed for being the same viewpoint of the plant. Thus, all the 18 photos corresponding to the same plant, i.e., those photos sharing the same treatment, block and greenhouse, were chosen for the same dataset in order to avoid dependence among all three datasets. Therefore, the division was randomly made at the level of treatment and block for each greenhouse, and all photos from this same combination of treatment, block and greenhouse were assigned to the same dataset accordingly. The same datasets were used for all the subsequent experiments in order to keep the comparison among scenarios as fair as possible.

Image data augmentation was also employed to artificially increase the number of instances fed to train the CNN model using just random flips both horizontally and/or vertically. Thus, the final number of training images was effectively multiplied by a factor of four.

All CNN models and architectures explained later in this subsection were coded in Python [28] language, version 3.10, using TensorFlow [29] library in version 2.15.

Training was performed 10 times, to minimize the influence of random weight initialization, for a maximum of 200 epochs each time. Early stopping and checkpointing were used in order to avoid overfitting and retain the weights that achieved the best evaluation results, respectively.

Table 6 Specific parameters of each layer of the CNN architecture used for prediction using one image from every week before a specific date

Layer		Input size	Kernel/pool size	Stride	Padding	Activation function
Number	Type					
Input	Image	$n \times 300 \times 200 \times 3$	–	–	–	–
1a-1x (n[a] replicates)	Slice	$n \times 300 \times 200 \times 3$	–	–	–	–
2a-2x (n[a] replicates)	2D Convolution	$300 \times 200 \times 3$	3×3	1	No	ReLU
3a-3x (n[a] replicates)	Max pooling	$298 \times 198 \times 3$	2×2	2×2	No	–
4	Concatenate	$n \times 149 \times 99 \times 32$				ReLU
5	2D Convolution	$149 \times 99 \times 32n$	4×4	1	No	ReLU
6	Max Pooling	$146 \times 96 \times 32$	2×2	2×2	No	–
7	Flatten	$73 \times 48 \times 32$	–	–	–	–
8	Dropout ($p = 0.5$)	112,128	–	–	–	–
Output	Dense	112,128	–	–	–	Linear

[a] $n$stands for the number of weeks used to perform the prediction, which can vary from 1 to 8

The performance of the trained models was evaluated, as later explained in subSect. 2.7, using the test dataset by inputting the images and obtaining predicted values and comparing them with actual values (ground truth) measured in subSect. 2.3.

Regarding the hardware environment where the software was run, all the aforementioned Python code scripts, both used for training the CNN model and for assessing its performance, were run on Google Colab platform [30] using a server with the following hardware specifications:

- Intel(R) Xeon(R) microprocessor at 2.20 GHz
- 12.7 GB of RAM
- NVIDIA Tesla T4 graphic card with 15 GB of memory

2.6.1 Forecasting using just a single image from a specific date

The CNN-based architecture shown in Fig. 6 was used for the prediction model used for forecasting both plant height and canopy diameter. Specifics of the parameters of each layer are shown in Table 3.

2.6.2 Forecasting using several images from a specific date

The CNN-based architecture shown in Fig. 7 was used for the prediction model used for forecasting both plant height and canopy diameter from 18 photos from different viewpoints of the same plant. Specifics of the parameters of each layer are shown in Table 4.

2.6.3 Forecasting using one image from a specific date and another from the week before

The CNN-based architecture shown in Fig. 8 was used for the prediction model used for forecasting both plant height and canopy diameter using as input one image from certain week and another from the next week. Specifics of the parameters of each layer are shown in Table 5.

2.6.4 Forecasting using one image from every week before a specific date

The CNN-based architecture shown in Fig. 9 was used for the prediction model used. Specifics of the parameters of each layer are shown in Table 6.

Table 7 Descriptive statistics for both morphological parameters, plant height (PH) and canopy diameter (CD), for the dataset employed in this article

	Mean	Max	Min	Standard deviation	Skewness	Kurtosis	Jarque–Bera score	Jarque–Bera *p-value*
PH[a]	32.0858	69.5	9.4	15.0536	0.76094	− 0.56356	13.24	0.001334
CD[b]	35.6054	55.85	23.7	6.6942	0.744753	0.435659	12.594	0.001842

[a]PH: plant height; [b]CD: canopy diameter

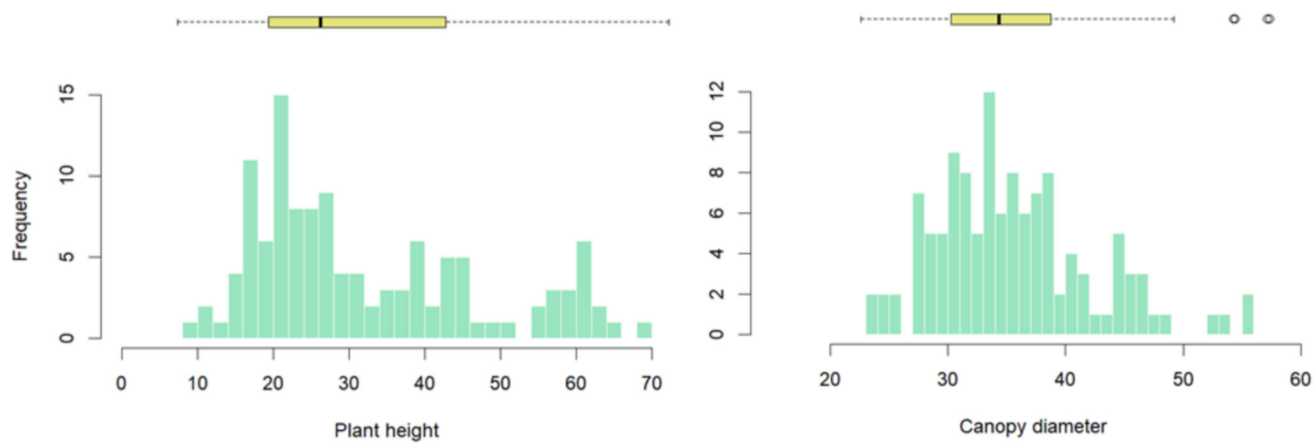


Fig. 10 Histogram and boxplot representing the distribution of the morphological parameters (plant height and canopy diameter) of pepper plants analyzed in these experiments

Table 8 Statistical accuracy metrics when predicting pepper plant height (PH) using only one image from a specific date

Week	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
15	4.7695	3.2925	11.3057	0.9546
14	5.2791	3.7279	13.8983	0.9435
13	3.8071	2.6264	9.1508	0.9640
12	4.4898	3.5373	16.2906	0.9384
11	4.8908	3.6589	14.3707	0.9207
10	9.1277	7.2531	26.8620	0.7144
9	8.2624	6.9598	23.9141	0.7358
8	10.1386	9.2179	34.7659	0.5924

RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; R^2: coefficient of determination

Table 9 Statistical accuracy metrics when predicting pepper canopy diameter (CD) using only one image from a specific date

Week	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
15	3.5152	2.8290	8.6821	0.7474
14	3.0840	2.5370	7.8156	0.7987
13	3.0641	2.6147	7.7594	0.7943
12	3.1459	2.4636	7.6421	0.7422
11	3.8287	3.1192	9.1574	0.6964
10	4.4141	3.6516	11.2662	0.5861
9	6.6464	5.4706	17.0908	0.0136
8	7.0289	6.1612	19.4125	0.0175

RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; R^2: coefficient of determination

2.7 Statistical analysis of the obtained results

The performance of each of the trained models (Sect. 2.6) was measured using the following metrics: RMSE (root mean square error), MAE (mean absolute error), MAPE (mean absolute percentage error), and R^2 (coefficient of determination). Mathematical equations to calculate all metrics are provided below (Eqs. (1)-(4)):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|x_i - \hat{x}_i| \tag{2}$$

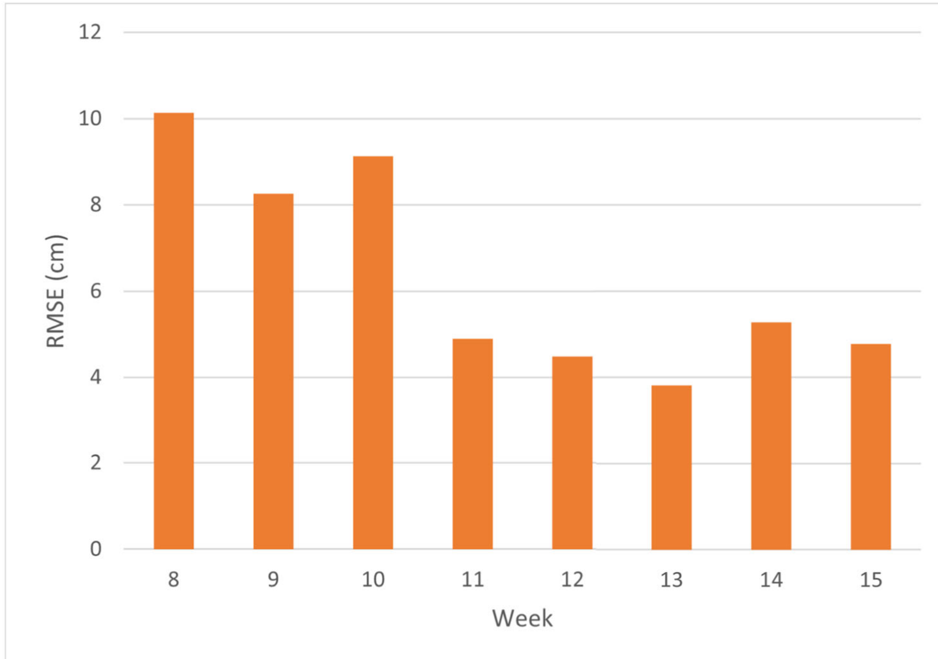
$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100 \tag{3}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{4}$$

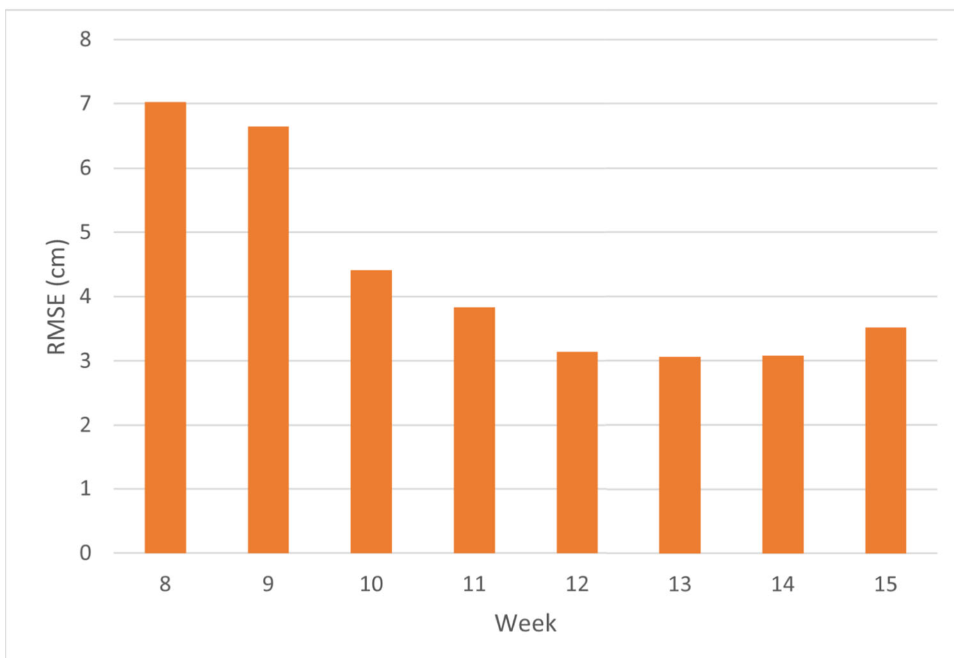
where x_i represents the actual or true value of each observation in the series, $\hat{x}_i$ represents the predicted value by the model, $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ is the mean value of the actual values in the series and N is the number of measurements of the analyzed variable.

Hyndman and Koehler [25] suggest using RMSE and MAE for testing accuracy of prediction models for time series with similar ranges. MAPE does not depend on the data range, being apt to be used for comparing errors for datasets with different ranges. The closer the values of RMSE, MAE and MAPE are to zero, the more accurate the predictions, while closer values to one of R^2 imply more accurate predictions [32–34].

All the calculations and visualizations were run using either Python [28] or R [35] programming languages. The



(a)



(b)

Fig. 11 Evolution for each week of the RMSE (cm) of the predictions when using only one image from a specific date. **a** RMSE for the plant height (PH), and **b** RMSE for the canopy diameter (CD)

scripts in *R* were programmed using version 4.0.3 and the `forecast` package was used.

2.8 Training and prediction times analysis

Finally, the times required to train each of the proposed models, for each model presented in each subsubsection of

Table 10 Statistical accuracy metrics when predicting pepper plant height (PH) using several images from a specific date

Week	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
15	3.5205	2.6913	8.6689	0.9534
14	3.5112	2.7088	8.7370	0.9600
13	4.3134	2.6925	7.9978	0.9516
12	4.4687	3.2937	10.5643	0.9551
11	5.5615	3.8007	12.2409	0.8908
10	6.9613	5.5864	17.9110	0.8549
9	9.7243	6.9184	18.9411	0.7279
8	8.7281	7.4250	25.9631	0.7073

RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; R^2: coefficient of determination

Table 11 Statistical accuracy metrics when predicting pepper canopy diameter (CD) using several images from a specific date

Week	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
15	3.2608	2.0600	5.5563	0.9169
14	2.5010	1.8908	5.1603	0.8812
13	2.4276	1.8009	5.1602	0.8684
12	3.0556	2.3609	6.4973	0.8222
11	3.0607	2.5525	7.3749	0.7781
10	3.6742	2.8124	8.3586	0.6871
9	5.5217	4.6606	14.5334	0.3193
8	6.2251	5.5077	15.7308	0.2191

subSect. 2.6, are calculated. These results are included in Appendix A instead of along the main results of the paper so as not to hinder the reading of the remaining of the article. It is worth reminding here that all training and prediction tasks were run on Google Colab platform [30] using a server with the following hardware specifications:

- Intel(R) Xeon(R) microprocessor at 2.20 GHz
- 12.7 GB of RAM
- NVIDIA Tesla T4 graphic card with 15 GB of memory

3 Results

This section is divided into five subsections: the first one showing the measurements that resulted from applying the methodology explained in Sect. 2.3 and the remaining dealing each with the results from applying the methodology explained in each scenario from Sect. 2.6.

3.1 Plant Height and Canopy Diameter: Morphological Measurements

The results presented in this subsection correspond to the morphological measurements of plant height and canopy diameter obtained following the methodology described in subSect. 2.3. In order to understand the main characteristics and provide descriptive statistics about the plants under study, Table 7 is shown. Moreover, to further help to visually grasp how these variables are distributed, a histogram for each variable is provided too in Fig. 10.

As it can be seen in Table 7, Jarque–Bera test shows that none of the two variables (PH and CD) followed a normal distribution. Intuitively, the shape of the histogram (Fig. 10) is in agreement with this result. Once again, according to Fig. 10, there were no outliers found in the boxplot for the plant height, whereas a few samples were deemed to be candidates for outliers in the case of the canopy diameter. However, these alleged outliers can be explained by the high genetic diversity inherent in the germplasm bank. Moreover, since all measurements were triple checked, none of the measurements was considered an outlier and thus no removing of any sample took place.

3.2 Forecasting using only one image from a specific date

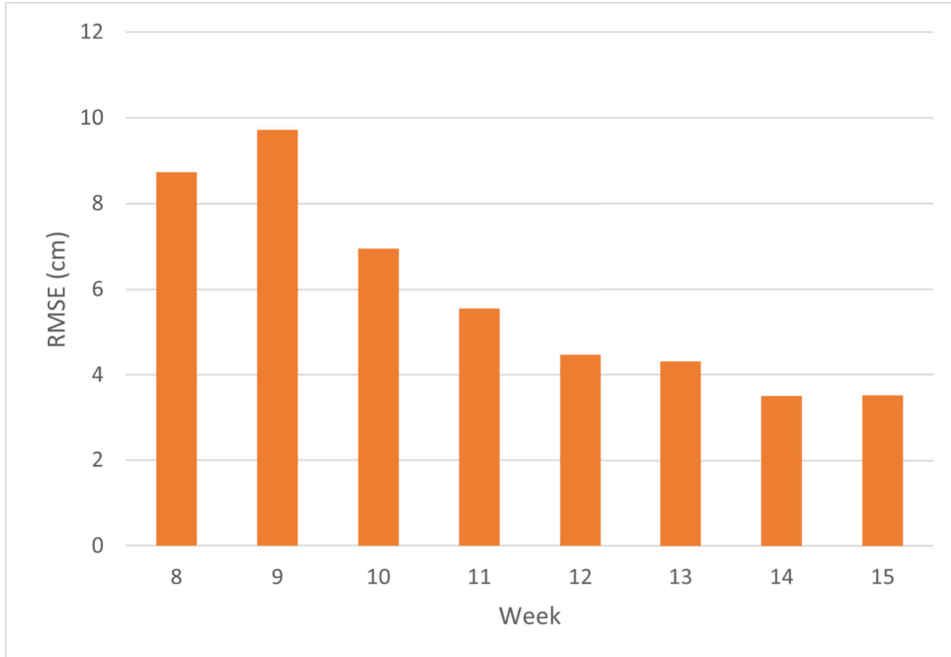
The results presented in this subsection correspond to the plant height and canopy diameter predictions obtained when only using one image from a specific date, following the methodology described in subSect. 2.6.1. Tables 8 and 9 show the different calculated metrics for plant height and canopy diameter, respectively.

Figure 11 shows the evolution of the RMSE when one photo from a specific date is used. It can be seen that, for both plant height (Fig. 11a) and canopy diameter (Fig. 11b), the error tends to be decreasing a the images from closer dates are used as input. Nevertheless, slight error increases can be observed in the latest dates due to some of the bigger plants not fitting completely in the wooden box used in the image acquisition setup because they grew more than expected.

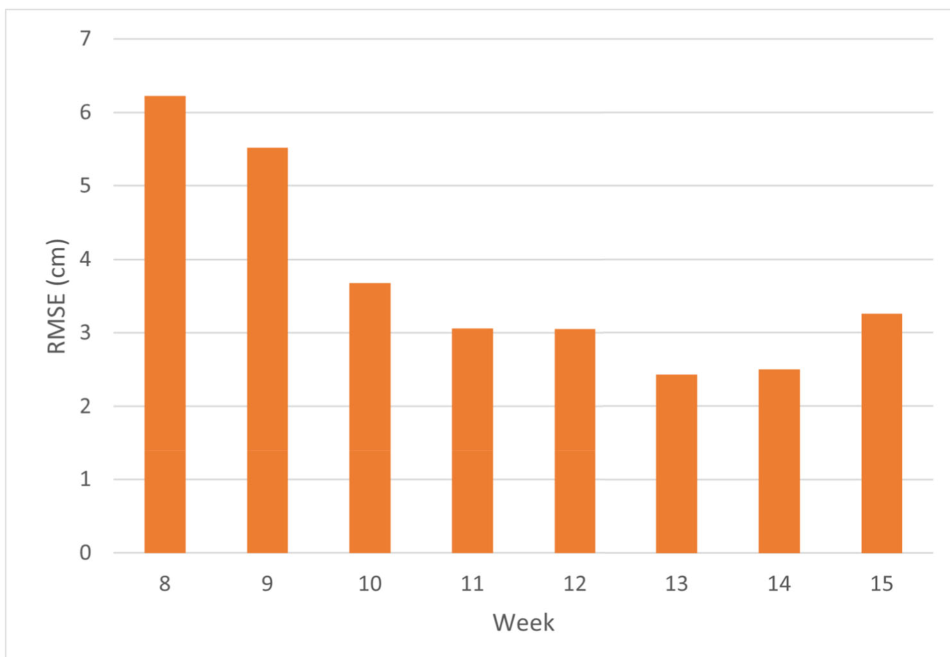
3.3 Forecasting using several images from a specific date

The results presented in this subsection correspond to the plant height and canopy diameter predictions obtained when using nineteen images from a specific date, following the methodology described in Sect. 2.6.2. Tables 10 and 11 show the different calculated metrics for plant height and canopy diameter, respectively. The results compared to

Fig. 12 Evolution for each week of the RMSE (cm) of the predictions when using several images from a specific date. **a** RMSE for the plant height (PH), and **b** RMSE for the canopy diameter (CD)



(a)



(b)

Tables 8 and 9, respectively, show a slight reduction in error due to using eighteen photos instead of just one. This fact reflects that some plants have asymmetries that are better captured when different viewpoints are used.

Figure 12 shows the evolution of the RMSE when all the eighteen photos from a specific date are used. It can be seen that, for both plant height (Fig. 12a) and canopy diameter (Fig. 12b), the error tends to decrease as the

Table 12 Statistical accuracy metrics when predicting pepper plant height (PH) using one image from a specific date and another from the week before

Weeks	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
14&15	3.1239	2.3686	8.4443	0.9564
13&14	3.7738	2.8418	9.2791	0.9343
12&13	3.1862	2.4299	8.1160	0.9571
11&12	3.4165	2.6151	8.7402	0.9560
10&11	4.4457	2.8394	8.3920	0.9217
9&10	4.3960	3.4280	11.8700	0.9097
8&9	4.4748	3.4484	12.5421	0.9093

RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; R^2: coefficient of determination

Table 13 Statistical accuracy metrics when predicting pepper canopy diameter (CD) using one image from a specific date and another from the week before

Weeks	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
14&15	3.2303	2.3443	6.7715	0.8497
13&14	2.8882	2.1233	6.1886	0.8642
12&13	3.4878	2.6071	7.4654	0.8455
11&12	3.3503	2.5976	7.1774	0.8605
10&11	4.2256	2.9863	8.3627	0.8355
9&10	3.3587	2.0506	5.9910	0.8090
8&9	3.6008	2.5442	7.2702	0.6786

RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; R^2: coefficient of determination

images from closer dates are used as input. Once again, slight error increases can be observed in the latest dates due to some of the bigger plants not fitting completely in the wooden box used in the image acquisition setup because they grew more than originally expected. In comparison to Fig. 11, RMSE is slightly smaller after incorporating more photos from different viewpoints.

3.4 Forecasting using one image from a specific date and another from the week before

The results presented in this subsection correspond to the plant height and canopy diameter predictions obtained when using one image from a specific date and another from the week before, following the methodology described in subSect. 2.6.3. Tables 12 and 13 show the different calculated metrics for plant height and canopy diameter, respectively. In contrast to the results shown in previous sections, the error is further reduced when information from two consecutive dates is incorporated. This is due to the additional information about the growth of each plant that each photo contributes from one week to the following one.

Figure 13 shows the evolution of the RMSE when a photo from a specific date and another from the week before are used. It can be seen that, for both plant height (Fig. 13a) and canopy diameter (Fig. 13b), the error tends to decrease as the images from closer dates are used as input. Nevertheless, in comparison to Figs. 11 and 12, RMSE error is slightly smaller after incorporating a photo from the week before and also small errors are kept when performing predictions from up to six weeks ahead in time.

3.5 Forecasting using an image from every week before a specific date

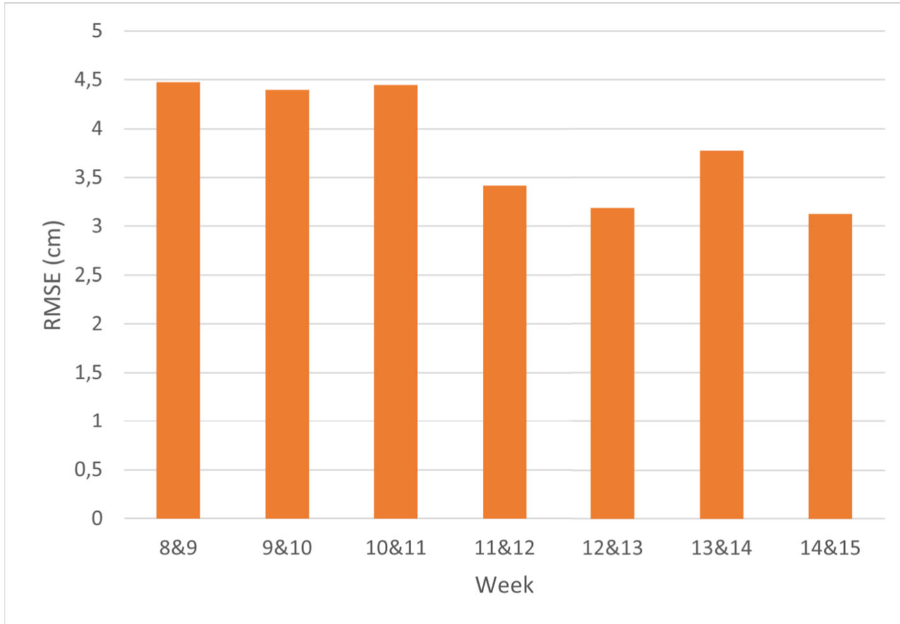
The results presented in this subsection correspond to the plant height and canopy diameter predictions obtained when using an image from every week before a particular date, following the methodology described in subSect. 2.6.4. Tables 14 and 15 show the different calculated metrics for plant height and canopy diameter, respectively. When compared to the results shown in previous sections, the error is reduced further beyond when information from all previous dates is incorporated. This is due to the additional information about the growth of each plant that each photo contributes.

Figure 14 shows the evolution of the RMSE when a photo from a specific date and another from the week before are used. It can be seen that, for both plant height (Fig. 14a) and canopy diameter (Fig. 14b), the error tends to decrease as the images from closer dates are used as input, but small and similar values are obtained up to six weeks ahead in time.

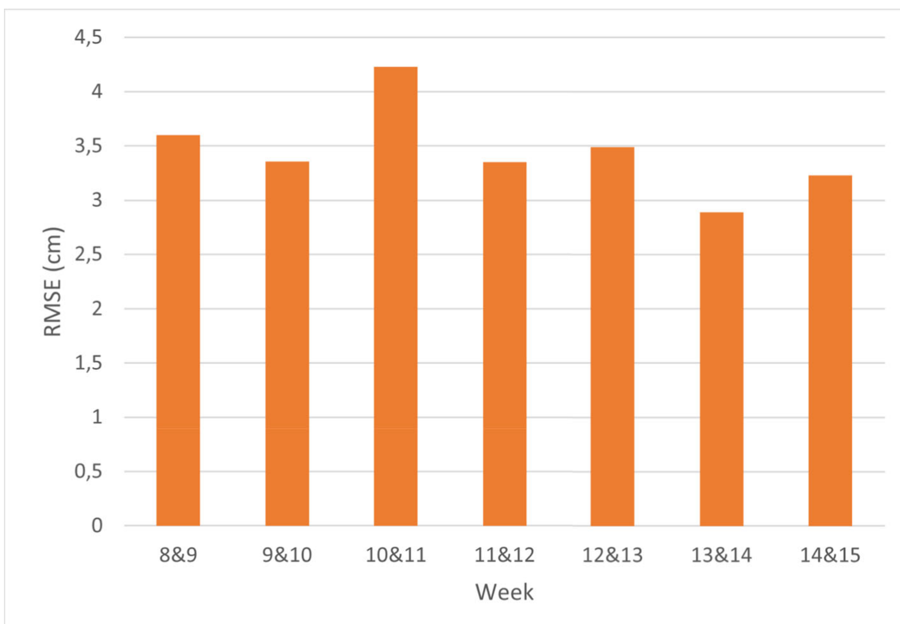
4 Discussion

Four main findings can be extracted from the work presented in this article. Firstly, and mainly, the capability of using CNN-based models for predicting both plant height and canopy diameter from RGB images has been shown, attaining feasible accuracy up to six weeks in advance. Second, when employing images from different weeks, instead of only one, smaller errors are obtained and the accuracy is improved, by incorporating additional information of the weekly plant growth. Third, using several images from the same date can improve the accuracy, reducing the error due to the asymmetries of the plants, that cannot be taken into account when using just a single image. Fourth, higher accuracy is obtained as the date when the images were taken gets closer to the

Fig. 13 Evolution for each week of the RMSE (cm) of the predictions when using one image from a specific date and another from the week before. **a** RMSE for the plant height (PH) and **b** RMSE for the canopy diameter (CD)



(a)



(b)

morphological assessment date, since there is less uncertainty about the plant development.

Based on the experience from the authors, errors below 5 cm for both plant height and canopy diameter, as observed in the results obtained in this article, are feasible and acceptable values when forecasting those morphological parameters in ornamental pepper plants. Measurements performed by hand, with a ruler and caliper, can be very time-consuming, exhibit low performance in terms of accuracy and can be subjected to human mistakes due to factors such as the position of the branches and the nastic movement of the leaves [36, 37]. Thus, the last scenarios ("forecasting using one image from a specific date and another from the week before" and "forecasting using an

Table 14 Statistical accuracy metrics when predicting pepper plant height (PH) using an image from every week before a specific date

Weeks	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
8–15	2.2612	1.7999	6.1223	0.9776
8–14	3.2666	2.6072	8.5794	0.9559
8–13	3.2358	2.5845	8.6255	0.9547
8–12	3.3289	2.5902	8.4851	0.9578
8–11	4.6261	3.0748	9.8359	0.9171
8–10	4.5651	3.5712	12.5572	0.9055
8–9	4.4748	3.4484	12.5421	0.9093
8	10.1386	9.2179	34.7659	0.5924

RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; R^2: coefficient of determination

Table 15 Statistical accuracy metrics when predicting pepper canopy diameter (CD) using an image from every week before a specific date

Weeks	RMSE (cm)	MAE (cm)	MAPE (%)	R^2
8–15	3.2375	2.0842	5.9785	0.8670
8–14	3.4705	2.1055	6.0394	0.8141
8–13	3.2952	2.0168	5.7714	0.8493
8–12	4.0008	2.1601	6.3966	0.7467
8–11	4.2232	2.5644	7.2621	0.7732
8–10	3.7951	2.1652	6.2823	0.7795
8–9	3.6008	2.5442	7.2702	0.6786
8	7.0289	6.1612	19.4125	0.0175

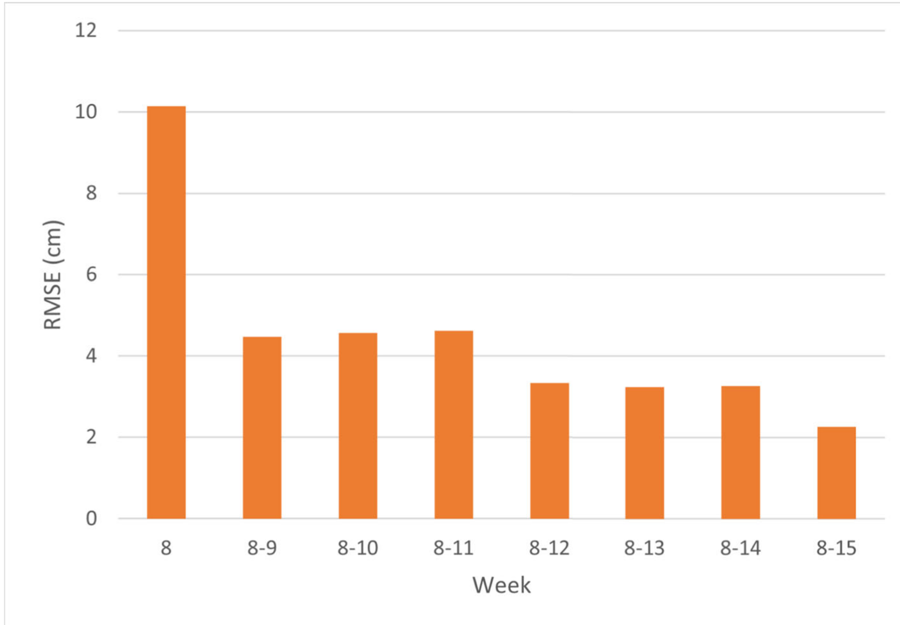
RMSE: root mean square error; MAE: mean absolute error; MAPE: mean absolute percentage error; R^2: coefficient of determination

image from every week before a specific date") can be considered suitable for the prediction of those parameters inside genetic breeding programs of pepper plants. The authors have anticipated that using only images from a single viewpoint can hinder the capabilities of image-based plant growth [20, 36]. In this paper it has been demonstrated that using only a single viewpoint, but in different dates, is effective in reducing the error and increasing the accuracy.

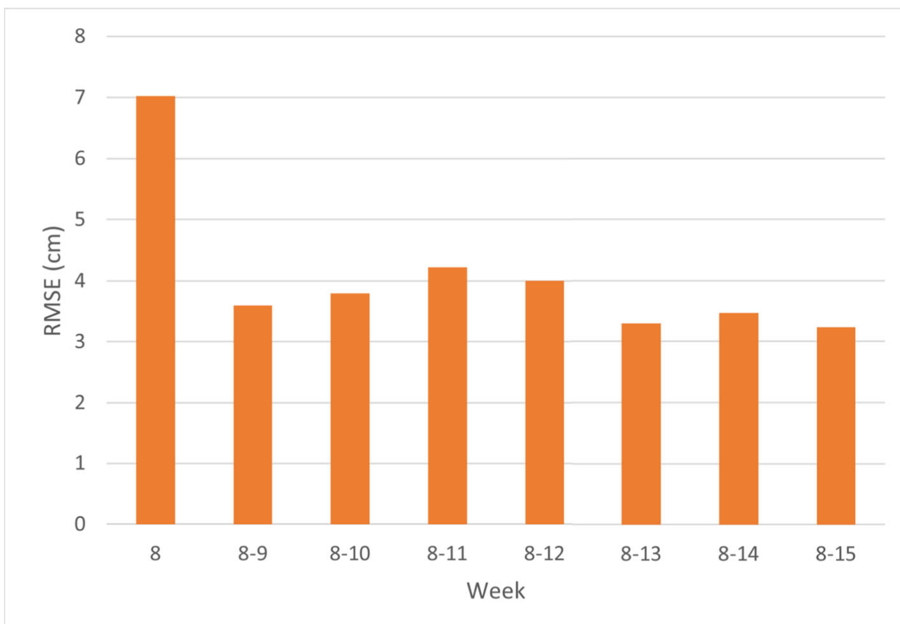
The aforementioned capabilities of the proposed method are of much interest in agronomy applications, as shown, for example, by a previous article for prediction of maize plant height and yield [38]. In particular, being able to accurately predict morphological parameters, such as the plant height and canopy diameter, of ornamental pepper plants is crucial for selecting seedlings and small plants beforehand in order to avoid growing them when their ornamental potential is predicted to be low [39].

To the best of the authors' knowledge, this article is the first one undertaking the prediction, several weeks ahead, of morphological parameters of pepper plants (*Capsicum* spp.). Nevertheless, there are other previous similar works that estimate morphological parameters of different species from images in the same date and their results can be somewhat comparable to this article's. Gupta et al. [32] proposed an image processing approach to measure the morphological parameters (plant height and width) of *Capsicum annuum* plants under field conditions, but in contrast to what was reported in this work, they did not acquire the images in different weeks and only estimation but not prediction was performed. This article's results for estimation (week 15), when compared to their reported results, are worse in terms of RMSE. Nevertheless, this can be explained by the fact that they only used a single accession of *Capsicum,* while in this article 15 different accessions were used in contrast, which adds more variability to the experiment. Moreover, it could also be due to some plants growing bigger than expected and not fitting completely into the wooden box, which is a drawback of this study that will be further explained in next paragraph. Similarly, Jayasuriya et al. [33] recently proposed a method to estimate plant height in *Capsicum annuum* by means of 3D clustering from RGB-D images, i.e., using depth information as well. They obtained good results, with similar determination coefficients to this paper, but once again they only undertook estimation and not prediction. Meiyan et al. [34] also developed a method for estimating plant height in crops using as input the multispectral images acquired from a UAV by constructing a 3D point cloud with a relative accuracy higher than the results obtained in this article. Nevertheless, once again, they only performed estimation in the current date and not prediction a few weeks in advance, unlike this article, and different plants are not straightforwardly comparable neither. Liu et al. [15], in Chinese mahogany (*Toona sinensis*), proposed a method to estimate the height of small seedlings, but once again no prediction ahead in time was undertaken. Obtained accuracy in their work was similar to the reported by this article, but it is worth noting that in this article grown plants were analyzed instead of seedlings. Oliveira et al. [35] estimated plant height for sugarcane (*Saccharum*) from UAV multispectral images with a RMSE of around 20 cm. This error is comparable to the one obtained in this article taking into account that sugarcane plant is about one order of magnitude taller than pepper plant. Herzig et al. [36] estimated canopy height in barley (*Hordeum vulgare* ssp. vulgare) with a coefficient of determination of 0.98 when using RGB and multispectral images coming from UAV. The accuracy of their estimation outperformed the one from this article, but no prediction ahead in time was undertaken and since plants'

Fig. 14 Evolution for each week of the RMSE (cm) of the predictions when using an image from every week before a specific date. **a** RMSE for the plant height (PH) and **b** RMSE for the canopy diameter (CD)



(a)



(b)

Table 16 Training and prediction times when predicting pepper plant height (PH) using only one image from a specific date (SubsubSect. 2.6.1)

Week	Training time (s)	Prediction time (ms)
15	120.35	2.86
14	151.15	2.96
13	266.78	3.07
12	242.63	2.85
11	194.42	2.94
10	176.01	3.02
9	101.61	2.87
8	206.91	3.00

Table 17 Training and prediction times when predicting pepper canopy diameter (CD) using only one image from a specific date (SubsubSect. 2.6.1)

Week	Training time (s)	Prediction time (ms)
15	228.52	2.91
14	161.38	3.07
13	157.98	2.96
12	234.84	2.97
11	251.64	2.86
10	249.85	2.96
9	135.66	3.03
8	159.37	2.99

Table 18 Training and prediction times when predicting pepper plant height (PH) using several images from a specific date (SubsubSect. 2.6.2)

Week	Training time (s)	Prediction time (ms)
15	3240.92	21.82
14	3660.28	22.75
13	3129.53	21.42
12	2713.67	22.39
11	3181.61	22.71
10	1519.33	23.02
9	3714.27	23.13
8	3116.09	22.21

Table 19 Training and prediction times when predicting pepper canopy diameter (CD) using several images from a specific date (SubsubSect. 2.6.2)

Week	Training time (s)	Prediction time (ms)
15	2549.12	21.20
14	2312.79	24.01
13	3001.34	22.45
12	3535.68	21.44
11	2082.37	22.43
10	2068.98	21.96
9	1634.69	22.08
8	1877.67	20.88

Table 20 Training and prediction times when predicting pepper plant height (PH) using one image from a specific date and another from the week before (SubsubSect. 2.6.3)

Week	Training time (s)	Prediction time (ms)
14&15	1248.83	3.67
13&14	1044.22	3.57
12&13	810.19	3.64
11&12	1275.69	3.60
10&11	632.98	3.73
9&10	1383.61	3.74
8&9	1326.98	3.62

Table 21 Training and prediction times when predicting pepper canopy diameter (CD) using one image from a specific date and another from the week before (SubsubSect. 2.6.3)

Week	Training time (s)	Prediction time (ms)
14&15	636.86	3.38
13&14	1280.76	3.67
12&13	1464.37	3.63
11&12	1087.27	3.72
10&11	763.51	3.37
9&10	1622.61	3.65
8&9	1649.30	3.49

genus differ it is difficult to extract conclusions from the observed differences. Matsuura et al. [37] proposed a method to estimate plant height with high resolution which required, apart from images captured by a UAV, an RTK-GNSS receiver for accurate positioning in order to perform a precise 3D reconstruction. Since they used positioning information, in contrast to this article, the results are not fairly comparable. Silva Andrea et al. [38] proposed a framework for estimating the plant height in cotton (*Gossypium hirsutum* L.), in this case based on indexes, variables and features derived from satellite multispectral images. Their results are outperformed by the ones from

Table 22 Training and prediction times when predicting pepper plant height (PH) using an image from every week before a specific date (SubsubSect. 2.6.4)

Week	Training time (s)	Prediction time (ms)
8–15	3729.35	9.70
8–14	4213.48	8.69
8–13	3322.96	7.78
8–12	2973.70	6.48
8–11	3164.46	5.76
8–10	2156.84	4.25
8–9	1326.98	3.62
8	206.91	3.00

Table 23 Training and prediction times when predicting pepper canopy diameter (CD) using an image from every week before a specific date (SubsubSect. 2.6.4)

Week	Training time (s)	Prediction time (ms)
8–15	4216.24	10.03
8–14	3860.13	8.90
8–13	2390.55	7.94
8–12	3105.41	6.49
8–11	2989.89	5.17
8–10	1804.70	4.53
8–9	1649.30	3.49
8	159.37	2.99

this article, but it should be taken into consideration that using frontal images of the plants, as used in this article, is hardly comparable to performing estimation from just satellite top view, as done by them. Tao et al. [39] employed a method to estimate the plant height in winter wheat (*Triticum aestivum*) extracted from UAV-based hyperspectral images. They observed that this parameter had a strong correlation (R^2 = 0.97) with the actual height of the wheat. This coefficient of determination is very similar to the value obtained in this article (R^2 = 0.95) when estimating based on images from week 15, but as previously stated the comparison is not straightforward because different viewpoint and kind of imagery was used in both articles.

The main drawback of this study is the issue that arose the last two weeks that image acquisition was performed, when some of the biggest plants did not fit completely in the box made for taking the photos, thus making errors grow artificially when predictions using data from this date would have been expected to report the best results. Another limitation from this article is the relatively small dataset used, which should be extended in future, especially if deep learning models are intended to be used. In addition, despite the CNN architectures proposed in this article having been chosen guided by previous works in the literature and its hyperparameters having been refined by trial and error, there is room for further research into optimizing these architectures or even proposing alternative ones. Moreover, the use of other state-of-the-art machine learning techniques that have shown promising results in similar areas, such as vision transformers (ViT), is encouraged too [48].

A future line of research could be exploring the capability of improving the predictions by including other sources of information such as forecasts of meteorological data and additional sensing of the plant growing conditions. Another line could explore making an experiment with a bigger dataset and exploring the chances of increasing the complexity of the CNN architectures. Another future line could be exploring how training different CNN weights for controlled and non-controlled greenhouses or different treatments could improve the results obtained in this paper. This could require having a bigger dataset to make this task feasible. Last, an additional future line could explore how the addition of more images increases accuracy, since in this paper it was only assessed when using a single photo versus using all 18 photos, but not any other number between those extreme values. It can be expected that just using a few photos could be enough to achieve accurate enough results. Moreover, other possible combinations of number of photos together with different combinations of dates can be explored too.

5 Conclusions

To the best of the authors' knowledge, this is the first paper proposing an accurate method to predict plant height and canopy diameter in *Capsicum* spp. based on RGB images. The results obtained in this paper have provided evidence that accurate prediction of both plant height and canopy diameter can be achieved based on images from previous dates. Up to six weeks ahead of the date of fruit maturation, the MAPE error remains below 12.6 and 7.3%, respectively. Moreover, the RMSE error is kept below 4.7 and 4.3 cm, respectively. In addition, using just one image can lead to feasible accuracy in the last stages of maturation, observing improvements when using several images from the same date, especially for canopy diameter, due to the asymmetry of some plants. Moreover, using images from all previous weeks, up to the day when forecasting is being made, reduces the error significantly compared to using only data from a single week, especially for those dates that are farther in time. Increasing the size of the dataset and including other sources of information, such as forecasts of meteorological data and additional environmental sensing of the plant growing conditions, would be interesting in order to improve the accuracy and robustness of the developed models.

Appendix A

This appendix contains the results, in the format of tables (Tables 16, 17, 18, 19, 20, 21, 22, 23), from both the training and prediction times for each of the experiments detailed in Sect. 2.6. Training times include the whole time required until the selected parameters of the model are calculated. It is worth noting that the training times are not straightforwardly comparable between scenarios due to the changing number of epochs, random weights initialization, different batch sizes, dataset size variable due to the specific model, etc. Thus, the authors of the paper encourage the reader to use prediction times instead when trying to fairly compare models. Prediction times are given for a single input to the neural network, which can be a single image or a group of images according to the model under assessment in each scenario.

Acknowledgements The authors would like to thank professor Guilherme Jose Bolzani de Campos Ferreira for his support in setting up the boxes to acquire the photos. The authors would also like to thank the Postgraduate Program in Agricultural Sciences at CPCE/UFPI for providing the controlled vegetation house used to conduct the experiments during plant growth. The participation of Marcos Bruno da Costa Santos and Rutten Kécio Soares de Brito Porto was made possible thanks to their respective scientific initiation scholarships granted by CNPq (National Council for Scientific and Technological Development) and UFPI (Federal University of Piauí).

Author contributions P.A.B., R.R.-G., A.M.M., A.M.M.N. and V.M.-M. contributed to conceptualization; P.A.B. and R.R.-G. contributed to methodology; R.R.-G. and F.S.S. contributed to software; P.A.B., R.R.-G. and V.M.-M. performed validation; P.A.B., R.R.-G., A.M.M. and A.M.M.N. carried out investigation; P.A.B. contributed to resources; M.B.C.S. and R.K.B.P. contributed to data and photos acquisition; R.R.-G., A.M.M.N. and V.M.-M. performed data curation; R.R.-G., A.M.M.N., P.A.B. and M.B.C.S. performed writing—original draft preparation; V.M.-M., A.M.M., F.S.S. and R.K.B.P. performed writing—review and editing; F.S.S. and R.R.-G. contributed to visualization; A.M.M.N. and V.M.-M. performed supervision; P.A.B. contributed to project administration and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding This research was funded by CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico), grant number 408444/2021–5.

Data availability The data presented in this study are openly available in Zenodo's repository at https://doi.org/https://doi.org/10.5281/zenodo.10619790.

Declarations

Conflict of interest The authors declare no conflict of interest.

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