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DOI

[10.3389/fpls.2023.1160645](https://doi.org/10.3389/fpls.2023.1160645)

Publication date

2023

Document Version

Other version

Published in

Frontiers in Plant Science

Citation (APA)

Wen, J., Abeel, T., & de Weerd, M. (2023). “How sweet are your strawberries?”: Predicting sugariness using non-destructive and affordable hardware. *Frontiers in Plant Science*, 14, Article 1160645. <https://doi.org/10.3389/fpls.2023.1160645>

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“How sweet are your strawberries?”: predicting sugariness using non-destructive and affordable hardware

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2 ABSTRACT

3 Global soft fruit supply chains rely on trustworthy descriptions of product quality. However, crucial
4 criteria such as sweetness and firmness cannot be accurately established without destroying the
5 fruit. Since traditional alternatives are subjective assessments by human experts, it is desirable to
6 obtain quality estimations in a consistent and non-destructive manner. The majority of research
7 on fruit quality measurements analyzed fruits in the lab with uniform data collection. However,
8 it is laborious and expensive to scale up to the level of the whole yield. The “harvest-first,
9 analysis-second” method also comes too late to decide to adjust harvesting schedules.

10 In this research, we validated our hypothesis of using in-field data acquirable via commodity
11 hardware to obtain acceptable accuracies. The primary instance that the research concerns is
12 the sugariness of strawberries, described by the juice’s total soluble solid (TSS) content (unit:
13 °Brix or Brix). We benchmarked the accuracy of strawberry Brix prediction using convolutional
14 neural networks (CNN), variational autoencoders (VAE), principal component analysis (PCA),
15 kernelized ridge regression (KRR), and support vector regression (SVR), based on fusions of
16 image data, environmental records, and plant load information, etc. Our results suggest that: (i)
17 models trained by environment and plant load data can perform reliable prediction of aggregated
18 Brix values, with the lowest RMSE at 0.59; (ii) using image data can further supplement the
19 Brix predictions of individual fruits from (i), from 1.27 to 1.10, but they by themselves are not
20 sufficiently reliable.

21 **Keywords:** Non-Destructive Analysis, In-Field Test, Machine Learning, Computer Vision, Data Fusion, Feature Selection, Total Soluble
22 Solid, Crop Management

1 INTRODUCTION

23 Soft fruits such as strawberries, raspberries, blueberries, etc. are popular and profitable fruit varieties. The
24 annual consumption of strawberries in Europe is estimated to be more than 1.2 million tonnes, which leads
25 the market share of horticultural crops (Ministry of Foreign Affairs (CBI), 2021a,b; Calleja et al., 2012).
26 Worldwide production of strawberries is stable with increasing demands and prices and is continuously
27 growing even through the COVID-19 pandemic (Chandler et al., 2012; Ministry of Foreign Affairs (CBI),
28 2021b; Simpson, 2018; Bos-Brouwers et al., 2015). However, without the protection of hard skins, soft
29 fruits are vulnerable during production and post-harvest activities. This results in significant food waste
30 and economic loss (Food and Agriculture Organization of the United Nations, 2011; Fruitteelt, 1991;
31 Stenmarck et al., 2016). The food loss and waste comprise up to 50% loss along the supply chain in some
32 countries (Kelly et al., 2019; Rees et al., 2012), among which the production loss is the majority, which
33 consists of up to 20% (Porat et al., 2018; Terry et al., 2011). It has been estimated that for every ton of food
34 waste, €1,900 of production and processing costs are lost. Moreover, it is argued that 50% of the waste
35 could be edible (Stenmarck et al., 2016).

36 The nutritional and economic value of crops is influenced by the harvesting strategy. However, subjective
37 assessments and inappropriate maintenance of fruit quality could bring conflicts in logistics planning
38 between suppliers and distributors, which results in even further post-harvest loss (Ramana et al., 1981;
39 Elik et al., 2019). Therefore, early decision-making supports both ecological and economic interests. To
40 make logistic and harvesting decisions as early as possible, it is highly desirable to predict the quality of
41 ready-to-harvest strawberries in the field (Lezoche et al., 2020; Abasi et al., 2018; Corallo et al., 2018;
42 Soosay and Kannusam, 2018).

43 Multiple variables determine the quality of a strawberry, including maturity, shape, sweetness, and
44 firmness (Liu et al., 2014; Xu and Zhao, 2010; Montero et al., 1996). As the majority of strawberry
45 products are consumed fresh, the taste is the highest priority for most European consumers of strawberries
46 (Chandler et al., 2012; Ministry of Foreign Affairs (CBI), 2021b). Therefore, we narrow our research scope
47 of this paper to concern the interior quality of the fruit, which is not directly told by their appearances: this
48 paper explores the assessment of the level of sweetness of strawberries, which is quantitatively described
49 by total soluble solid (TSS) content in the juice of freshly harvested fruits, using informatics and machine
50 learning (ML) approaches.

51 Traditionally, the TSS content is measured by a refractometer, quantified by the degree Brix ($^{\circ}$ Brix or
52 Brix) (Azodanlou et al., 2003). The measurement is expensive in both labor cost and capital because the
53 samples that are sent to destructive measurements can no longer be sold (Gómez et al., 2006; Agulheiro-
54 Santos et al., 2022). To reduce errors and optimize the supply chain, there is a desire for more accurate,
55 quantitative, and non-destructive tools to assess the quality of each fruit (Ventura et al., 1998; Mancini
56 et al., 2020). Therefore, we explore the feasibility of Brix prediction with easily-acquirable data, such that
57 the prediction can be carried out on-site without specific fruit preparation.

58 Related research has demonstrated the feasibility of applying computer vision (CV) in grading the quality
59 of fruits (Liu et al., 2017; Klinbumrung and Teerachaichayut, 2018; Munera et al., 2017; Zhang et al., 2016)
60 and in assessing specific quality attributes (Vandendriessche et al., 2013; Montero et al., 1996; Azodanlou
61 et al., 2003; Abeytilakarathna et al., 2013). CV and spectral analysis from hyperspectral imaging (HSI)
62 are popular techniques that have often been applied in investigating the intrinsic properties (Gao et al.,
63 2020; Liu et al., 2019; Amodio et al., 2019; Agulheiro-Santos et al., 2022). High prediction accuracy
64 could be achieved when fruit photos were acquired under a (mostly-)uniform experiment setup (Nandi

65 et al., 2016; Mancini et al., 2020; Shao et al., 2021; Weng et al., 2020; Xu and Zhao, 2010). Such setup
66 requires delicate devices which hinder the applications in a real-world setting and on an enormous number
67 of samples. Moreover, the "harvest first, analysis second" methodology limits the possibility of adjusting
68 the harvest strategy for supply chain optimizations because strawberries stop growing after being harvested.
69 Hence, our study concerns the implication of the fruit's intrinsic characteristics by its appearance under
70 natural light, when the fruit is still on the plant.

71 Meanwhile, the micro-climate in the greenhouse and the horticultural treatments strongly influence
72 the harvest quality and pace of growing (Choi et al., 2015; Díaz-Galián et al., 2021; Sim et al., 2020).
73 The temperature, humidity, CO₂ level, lighting conditions, and irrigation are proven to be crucial factors
74 (HIDAKA et al., 2016; Sim et al., 2020; Avsar et al., 2018; Corallo et al., 2018; Muangprathub et al., 2019).
75 The crop load is also argued to influence the quality of fruits (Verrelst et al., 2013; Belda et al., 2020;
76 Correia et al., 2011). In modern horticulture, environmental data is readily collected by field sensors or
77 climate computers in most greenhouses (Hayashi et al., 2013; Sim et al., 2020; Samykanno et al., 2013;
78 Muangprathub et al., 2019). Nevertheless, these point measurements cannot provide distinctive information
79 to specify the quality of individual fruits. Thus, our research introduces approaches to integrate in-the-wild
80 fruit images with environmental and plant-load data in predicting the Brix values of individual fruits.

81 By investigating the performances of Brix prediction models, we aim at providing insights in answering
82 two main questions: i) how accurately can the models estimate the Brix values by different sets of inputs?
83 and ii) which data are valuable for training the Brix prediction models? The research contributes from four
84 perspectives: i) we collected and labeled a dataset of strawberry images and quality measurements, using
85 commodity hardware; ii) we designed a conceptual methodology of non-destructive quality estimation; iii)
86 we shaped and implemented our methodology to predict the strawberry sugariness; iv) by comparing the
87 model performances, we suggest how to develop reliable prediction models by CV and ML techniques.

2 MATERIALS AND METHODS

88 2.1 Data collection

89 Data were collected from May 2021 to November 2021. This was carried out on overwintered trays of
90 *Favori* strawberry plants in a greenhouse at the Delphy Improvement Centre B.V. (Delphy) in Bleiswijk,
91 the Netherlands. Strawberries were cultivated in baskets that were hung from the ceiling in the greenhouse.
92 For the plants monitored by the cameras, the harvesting frequency is mostly once per week, or twice per
93 week when the strawberries grow faster in warmer periods. There is exactly one harvest round per day, so
94 we use "from a harvest" to describe the data collected from the same date.

95 The data collection setup consisted of the following parts: i) static cameras facing the planting baskets to
96 take periodic photos; ii) Brix measurements of the strawberries by the horticulturalists from Delphy; iii)
97 physical labels on the branches to identify the measurement results of a strawberry with its appearance in
98 images; iv) climate sensors to record the environment in the greenhouse and the outside weather; v) plant
99 loads, represented by the average number of *Favori* fruits and/or flowers per unit area; vi) other logs about
100 the plant cultivation.

101 Representations of individual strawberries were the major inputs to train the Brix prediction models. We
102 considered image data because they are objective and distinct. The images were collected hourly with
103 a time-lapse setting. The same sections of six example images are shown in Figure 1. As is shown in
104 the figures, we stuck a yellow label to indicate the ID of a strawberry a few hours before the harvest

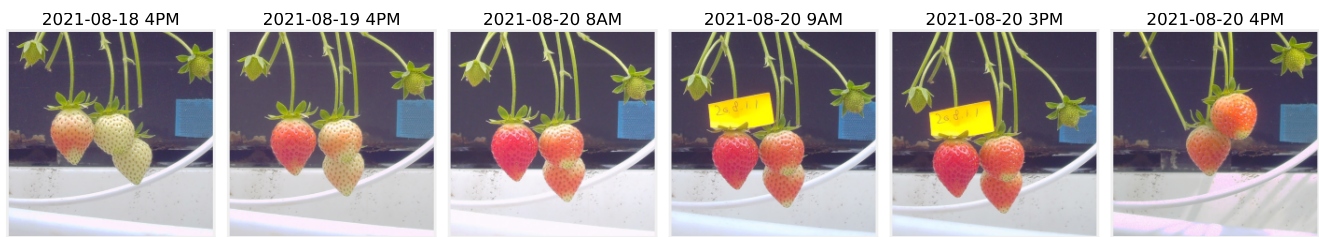


Figure 1. Illustration of the time-lapse images. The same parts of six images are selected. The time stamps of data collection are indicated above the images. According to the images, by 9 am on 2021-08-20, the yellow physical label is stuck onto the branch. The strawberry 20.8.1.1 was harvested between 3 pm and 4 pm of the same day, so the last time when it was observable on images was 3 pm, 2021-08-20.

105 (namely the “ID label”), such that the strawberry’s appearance in the images can be connected to the
 106 measurement results. The measurement data that are assigned to identified strawberries are called the
 107 “connected measurements” in the following text.

108 Based on previous research on influencing factors of strawberry qualities (Avsar et al., 2018; Chen et al.,
 109 2011; Correia et al., 2011) and the expertise of our collaborating horticulturalists, temperature, humidity,
 110 radiation level, CO₂ density, and relevant plant treatment records (additional lighting, watering were all
 111 considered as the environment data. The number of fruits and/or flowers per unit area was counted weekly
 112 and noted as the “plant load”. Both the environment and plant load data were collected by Delphy.

113 The strawberries with the ID labels were stored separately. On the same day of the harvest, researchers
 114 from Delphy measured the Brix value and the firmness of those strawberries, with a refractometer and a
 115 penetrometer respectively. The size category is defined by a ring test, and the ripeness level is evaluated
 116 according to the experience of the greenhouse researchers.

117 2.2 Methodology of experiment implementations

118 We segmented the strawberries from the in-field images, such that only the pixels that describe the
 119 sample strawberry were analyzed. We trained a Mask R-CNN model (He et al., 2017) with a ResNet101
 120 backbone for semantic segmentation. We used the Detectron2 platform (Wu et al., 2019) to build the model.
 121 The ResNet101 backbone was pre-trained on the *ImageNet* dataset. We resized the image segments to
 122 200*200*3 pixels. They were the raw inputs for Brix prediction and feature extraction in the *image-only*
 123 *experiment*, the *image-with-env experiment*, and the *image-with-Brix experiment*. We considered only
 124 the last available observations, e.g. the strawberry segment from the 5th image in Figure 1. In this way,
 125 we limited the quality changes between when it was in the image and when it was measured. We also
 126 normalized the colors of the images to reduce the distraction from the changing lighting conditions during
 127 the day by applying elastic-net regressions at the red, green, and blue channels respectively.

128 To analyze the images in the *image-only experiment*, we built Convolutional Neural Networks (CNNs)
 129 and Variational Auto-Encoders (VAEs) to analyze and encode the image segments of individual strawberries
 130 with Multi-Layer Perceptrons (MLPs). The models were either trained from scratch or with weights pre-
 131 trained by other popular datasets such as the ImageNet (Deng et al., 2009). Details of model architectures
 132 can be found in the supplementary materials. We also introduced principal component analysis (PCA) in
 133 the experiments for feature dimensionality reduction and model regularization (Shafizadeh-Moghadam,
 134 2021; Geladi et al., 1989). By taking the largest differences among the pixel data, PCA helps to exclude
 135 disturbance from the shared information of strawberry images to some extent. Hereafter, we use the word
 136 “encode” to represent the process of dimensionality reduction by the encoder parts of the VAEs and/or PCA.

137 We use “attribute” to describe the content of information that our model concerns. “Feature” or “input”
138 represents what goes directly to the models, such as information from the latent space of the VAEs and/or
139 after PCA.

140 We trained the CNNs, MLPs, the predictor part of the VAEs, and the PCA models by the strawberry
141 observations with connected measurements, which are 178 out of 304 Brix measurements. We trained the
142 encoder and decoder parts of the VAEs by all the segmentation outputs of the Mask R-CNN model. Hence,
143 this dataset includes images that were taken over the life cycles and of more strawberries. The *image-only*
144 *experiment* and the *image-with-env experiment* applied the same encoders.

145 We designed the *env-only experiment* to analyze the relationship between the environment data and
146 the Brix. We used rolling averages of the environment data over different periods. Since the environment
147 data does not include specific information about individual strawberries, we took all of the 304 Brix
148 measurements into account and grouped them by each harvest. They are called the “aggregated Brix”. The
149 reliability of the aggregated Brix could also be better ensured by introducing more sample measurements.
150 We not only trained machine learning models to predict the value expectation, but also the standard
151 deviation (std.) and the percentiles from 10% to 90% (with intervals of 10%). The representations of the
152 Brix distribution were considered in supporting further experiments of individual Brix prediction.

153 Since the amount of data points was reduced to the same as the days of harvests after the aggregation,
154 the volume of the dataset became too small to support the training of deep neural networks. Hence, we
155 applied linear regression (LR), support vector regression (SVR), and kernelized ridge regression (KRR)
156 models. In addition, leave-one-out experiments were considered to enlarge the training sets of the *env-only*
157 *experiment*. That means we split only one data point as the validation set in each experiment run, instead
158 of proportionally splitting. Under this setting, we ensured all the data was used once in performance
159 validation so that we could get a predicted value at every data point. The performance of individual Brix
160 prediction in the *env-only experiment* is discussed based on the results from the leave-one-out experiments,
161 by considering the predicted value expectation as the Brix predictions of all harvests on the same day.

162 In the *image-with-env experiment*, we stacked the features of images and the environment data according
163 to the object strawberries to train models. By the encoder parts of the VAEs and the PCAs fitting to the
164 training set, we encoded the images to image features. We trained the models of the *image-with-Brix*
165 *experiment* by the same image features but with the outputs from the *env-only experiment*– predictions of
166 the mean, std., and percentiles, etc. We established four neural network architectures to fit the various size
167 of features in both the *image-with-env experiment* and the *image-with-Brix experiment*, including three
168 three-layer MLPs and one four-layer MLP.

169 We used the Keras library (Chollet et al., 2015) to build and train the CNNs, VAEs, and MLPs in the
170 experiments. All model training used the Adam optimizer (beta1=0.9, beta2=0.999) and a learning rate of
171 0.0003. We considered random rotation, mirroring, and flipping to augment the image data. When training
172 the VAE, we also considered random scaling up to $\pm 10\%$. We used the Scikit-Learn library (Pedregosa et al.,
173 2011) to conduct PCA and to construct LR, SVR, and KRR models in the *env-only experiment*. The KRR
174 used polynomial kernels of degrees up to 3 and penalty terms of 1 and 10. These are all state-of-the-art
175 implementations in data analytics.

176 For all experiments except with specific definitions, we split the data into 7:1:2 for training: testing:
177 performance validation. We run each experiment 15 times with a fixed series of data splits. All the deep
178 learning models were trained on a Geforce GTX 1080 GPU under a maximum of 300 epochs.

3 RESULTS

179 This chapter describes our research findings in four steps: i) the exploration of the dataset that we collected;
 180 ii) our conceptual methodology of designing the experiments; iii) the model performance of each series of
 181 experiments respectively; iv) two influencing feature selections: whether to use the plant load data or not
 182 and which image encoder to choose. The last section gives a comparison among the experiment series and
 183 states our suggestions for developing a reliable Brix prediction model.

184 3.1 An integrated dataset describing the growth and harvest quality of strawberries

185 In order to predict Brix from non-destructive in-field data, we collected observations of the fruits and
 186 related environmental records in a greenhouse. The observations were in the form of images, and the
 187 environmental records are time-series and single-value measurements. All relevant data were linked with
 188 the observations of individual fruits. As such, we could implement machine learning techniques to discover
 189 the mapping from the collected data to the Brix values.

190 From April 2021 to November 2021, we recorded the growth of strawberries by 13,400 images from
 191 three RGB cameras and collected environmental records during this period. We measured the Brix of 304
 192 ready-to-harvest strawberries, which were selected from 28 harvests in 22 weeks. The overall statistics of
 193 the measurement data set are shown in Figure 2. According to the box plots and the line plot, the Brix at
 194 each harvest usually has a median value lower than the mean. It is implied that using the average sample
 195 measurements to estimate the Brix of every fruit has a higher probability to overestimate the quality.

196 The environmental records during the data collection period were archived hourly and were grouped by
 197 rolling averaging over periods. As a preliminary analysis, we computed the correlations of the environmental
 198 data under different averaging periods and the aggregated Brix values of each harvest. The results indicate
 199 a strong correlation between temperatures (measured on the leaves, plants, and in the air), radiation levels,
 200 watering, and cyclic lighting strengths with the mean Brix of each harvest. The correlations of the Brix
 201 with humidity and CO₂ density are weaker. Details are shown in Figure S2 in supplementary materials.

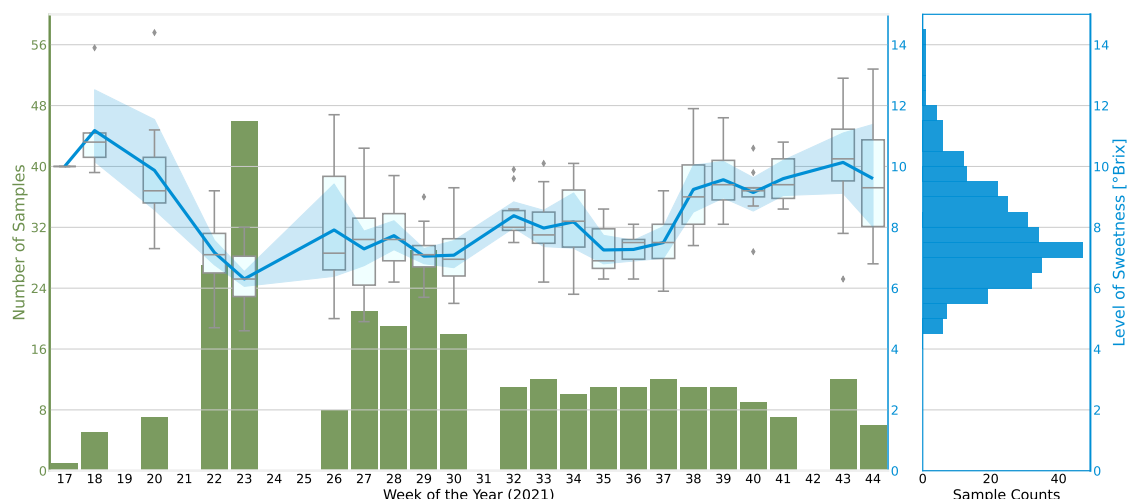


Figure 2. Statistics of the Brix measurements, grouped by harvests per week. On the left, the x-axis indicates the calendar week number of the harvests. The green y-axis presents the number of tested samples. The blue line and its contour indicate the averaged Brix value and the standard deviation (std.) of the measurements of the week respectively. The box plots illustrate the distribution of the measurement for the week. On the right, the histogram gives an overview of the distribution of all Brix measurements in 2021.

202 3.2 Conceptual Experiment Design

203 We designed four series of experiments to study the effectiveness of using these data, shown in Figure 3 :
 204 we first analyzed whether the images (section 3.3) or the environment data (section 3.4) could work alone
 205 in Brix prediction, and then we considered two ways of data fusion (section 3.5).

206 In the *image-only experiment*, the Brix prediction model was trained solely by the images of strawberries.
 207 We considered both supervised learning (SL) and semi-supervised (SSL) in training the models in this
 208 experiment series. A challenge in this experiment was that the inclusion of non-relevant pixel data lowered
 209 the learning process and even reduced the prediction accuracy. To reduce this effect, some of the models
 210 were accompanied by additional regularization procedures, such as conducting principal component
 211 analysis (PCA) on the training dataset and using the principal components as the features for learning.

212 We considered environmental records and/or plant loads as the input in the *env-only experiment*. Together
 213 we call these the environment data. In the primary step, we conducted correlation analysis to classify
 214 the importance of each sort of attribute and to define sets of features. Since the environment data cannot
 215 express information about individual strawberries, we trained regression models to predict the expectation
 216 and the distribution of Brix value aggregations of each harvest.

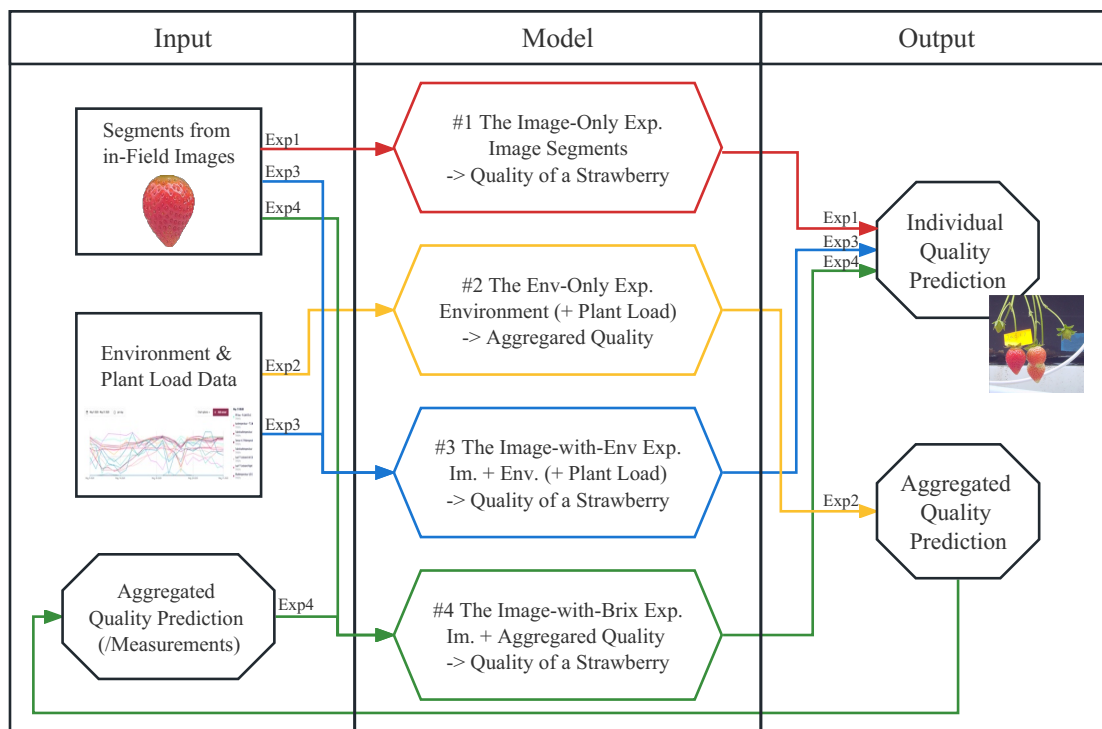


Figure 3. The methodology of the four experiment series in this research. They are described by the data flow, consisting of the input attributes, the output objects, and the models to map the corresponding inputs and outputs. The line colors and the short notes indicate different experiment series: red represents the *image-only experiment* (“Exp1”), yellow is for the *env-only experiment* (“Exp2”), blue is for the *image-with-env experiment* (“Exp3”), and green is for the *image-with-Brix experiment* (“Exp4”). All the models are evaluated by comparing the outputs with the ground truth.

217 We established the *image-with-env experiment* and the *image-with-Brix experiment* respectively as
 218 two ways of integrating the image data and environmental records in training. We encoded the image
 219 of each strawberry to comprise the image features. These features were combined directly with the

220 environmental records to train the neural networks in the *image-with-env experiment*. We considered the
221 image features and the aggregated Brix predictions from the *env-only experiment* as the inputs in the
222 *image-with-Brix experiment*. The setup was chosen based on two assumptions: i) the predictions from
223 the *env-only experiment* are good indications of the overall quality of harvests; ii) compared to predicting
224 the absolute Brix, the appearance information might be more helpful in terms of estimating the relative
225 position out of value distribution of Brix.

226 We set up two exam baselines to evaluate the experiment outcomes. Firstly, we used the average value
227 of all the Brix measurements as the expectation of the *Favori* species. It represents the empirical Brix
228 value that members of the soft fruit supply chain usually believe, so it is named the *empirical baseline*.
229 It is the baseline of this Brix prediction study. Secondly, we considered the average Brix of each harvest
230 as the expected value. As it represents the traditional way of sugariness assessment, which is anticipated
231 by sample measurements, it is called the *conventional baseline*. According to the experiment setup, the
232 *conventional baseline* is essentially the optimal situation of models from the *env-only experiment*.

233 We used root mean squared error (RMSE) and mean absolute error (MAE) to represent the model accuracy.
234 The RMSE is regarded as the main indicator of model performance. It gives increasingly more punishments
235 if the predicted value is further from the ground truth. After running the experiments over different dataset
236 splits, we used the standard deviation of the RMSEs (RMSE-std.) to indicate the robustness of model
237 performances. The coefficient of determination (also called the R² score) is considered a quantitative
238 assessment of the level of model fitting. It is the proportion of the variation in the dependent variable, i.e.
239 the individual or the aggregated Brix in this case, that is predictable from the input data. Higher R² scores
240 indicate better correlations between the inputs and outputs in the mapping.

241 3.3 Practical Brix prediction models cannot be trained with images alone

242 By the *image-only experiment*, we inspect the feasibility to train a Brix predictor with only images. We
243 trained CNNs from scratch, with transfer learning (TL), and with semi-supervised learning (SSL) methods.
244 The best-performing model of the entire experiment series has an averaged RMSE of ca. 1.33 over different
245 validation splits.

246 As the horizontal lines in Figure 4 indicate, the selected model outperforms *empirical baseline*, while it
247 is slightly worse than *conventional baseline*. It is implied that the appearances of strawberries provide hints
248 of the Brix to a limited extent, whereas the time of harvest has more predictive power. We hence conducted
249 further experiments to unravel the other attributes for Brix prediction.

250 Among the experiment results, we noticed that the involvement of feature dimensionality reduction
251 facilitates the model performance. A possible mechanism would be that a large proportion of overlapping
252 features were condensed in the latent space of VAEs or the orthonormal bases of PCA (Goharian et al.,
253 2007). As the pixel data from a fine image is likely to correlate with each other, PCA is a practical technique
254 to de-correlate the data and facilitate model-training. Meanwhile, the model fitting might also be regularized
255 with the help of PCA, particularly when the model was trained with a small data set in our situation (Geladi
256 et al., 1989; Delac et al., 2005). These findings also motivated us to encode the images in the data fusion
257 steps of further experiments.

258 3.4 Models reveal significant dependencies of aggregated Brix on environment data

259 The performance in predicting aggregated values

260 In the *env-only experiment*, we trained LR, SVR, and KRR models to assess how well the collective Brix
261 value can be predicted with only the environment data. When aggregating the data points, overfitting was
262 an indispensable issue. Particularly, when the data are very few whilst the inputs have a large dimension. To
263 assess the level of model-fitting, we calculated the R2 score of models using different subsets of features,
264 hyper-parameters, and train-test splits to predict the representations of value aggregations on the testing data
265 set. When we grouped the scores by the algorithms of models to evaluate the level of model determination,
266 we found more than half of the LR models have a negative R2 score, which indicates that simple linear
267 models cannot fit this mapping. With a stronger regularizer, or with higher outlier flexibility, the R2 scores
268 of KRR ($\alpha=10$) and SVR models are more condensed to 0.5-0.6. The generally higher R2 scores also
269 indicate they are more practical models in tackling this circumstance.

270 **The performance in predicting individual values**

271 To make the results comparable, the predictions of the averaged Brix were regarded as the estimation of
272 all the strawberry measurements at each harvest. The RMSEs were hence calculated on the same validation
273 splits as the other experiment sets take. Figure 4 compares the effectiveness of using various periods of
274 environment data with other experiments, of which the time spans are grouped by the ending time.

275 As the bars in Figure 4 demonstrate, when models use features from the periods closer to the harvest
276 time, they obtain lower and less diverged RMSEs in general. The RMSE-std of the models in the *env-only*
277 *experiment* is lower than the best-performing model from the *image-only experiment*. The result argues
278 that even using only the environment data in Brix prediction could train more reliable and stable models.
279 Hence, it is strongly suggested to involve the environment data in training further comprehensive models.

280 **3.5 Images give the power to perform individual prediction with environment data.**

281 Results from the *env-only experiment* indicate that we need specific information to distinguish fruit-to-
282 fruit differences from each harvest. Since the environment data are all point measurements, we encoded
283 the images into 200, 50, 10, and 5 features by four combinations of VAEs and PCA respectively to
284 fit the dimension differences between the two types of data. The *image-with-env experiment* and the
285 *image-with-Brix experiment* introduce two ways of fusing the image feature and environment data.

286 **Combining image features with direct environmental information**

287 The *image-with-env experiment* straightforwardly combined the two types of data to train the MLPs for
288 the individual Brix prediction. Unsurprisingly, the lowest RMSEs from all the groups outperformed the
289 best models from the *image-only experiment* and the *env-only experiment*, as is illustrated in Figure 4.

290 Curiously, the performance difference caused by the collection time span of environment data was
291 remarkably reduced in this experiment. A possible reason would be that the MLPs also learn the trend of
292 changes within the time-series data – such that the performance did not reduce as much as in the *env-only*
293 *experiment*. Meanwhile, the nonlinearity and regularization performed by the neural network also ensured
294 the robustness of the model performances.

295 **Combining image features with predicted Brix distribution of a harvest**

296 The fourth experiment, the *image-with-Brix experiment*, allows us to explore another way of integrating
297 the knowledge from the two sorts of data: to use the image features to predict the relative quality within
298 the distribution of Brix values. We used the predictions of Brix aggregations¹ from the leave-one-out

¹ To limit the variables, we took only results from the KRR model with $\alpha=10$ and polynomial degree=3.

299 experiments from the *env-only experiment*. Among all the experiment series, the models from the *image-*
 300 *with-Brix experiment* resulted in the lowest RMSEs, as illustrated in Figure 4. Among the different features
 301 of the aggregated Brix, models that were trained by Brix percentiles slightly outperform the models that
 302 assumed a Gaussian-distribution fit, i.e. using the mean and std. as inputs.

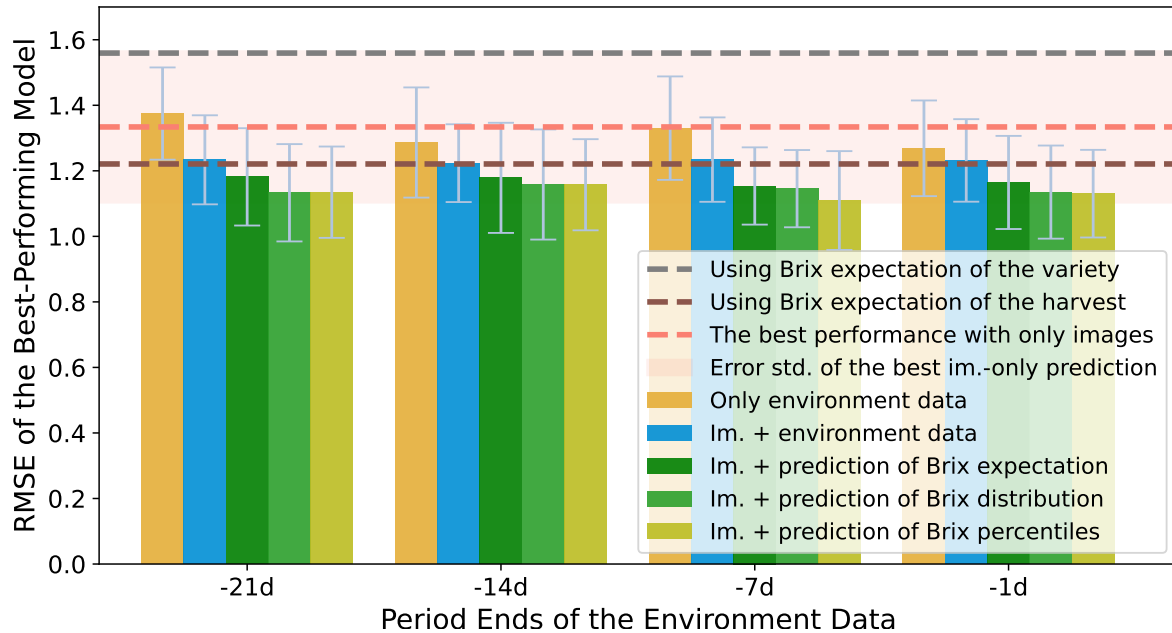


Figure 4. Performance comparison of Brix prediction accuracies among the four experiment sets, using RMSE as an indicator. The error bars indicate the standard deviation of RMSEs (RMSE-std) across different splits of validation sets. The models are grouped by the ending point of the periods of the environmental records. The y-axis shows the minimum RMSE of models from the same group. The colors indicate the input attributes of the experiment sets. The best performance of models using only image data is presented by a horizontal line. The contour around it indicates the corresponding RMSE-std. The horizontal line in gray and brown indicates the two benchmarks that are mentioned in the methodology section.

303 3.6 Plant load is crucial as part of the indirect environmental information

304 As is illustrated in Figure 5, introducing the plant load as part of the input attributes has a positive effect
 305 on the model performances, which is more outstanding on the models from the *env-only experiment*.
 306 In the *image-with-env experiment*, the upper limit of model accuracy was slightly improved. But more
 307 importantly, there were notable decreases in the std. of RMSEs over different data splits. Both changes
 308 were limited in the *image-with-Brix experiment*. In all, we suggest that plant load is a crucial feature when
 309 the raw environmental information comprises the input data.

310 Moreover, since our plant load data was averaged over different branches of strawberries, they did not
 311 directly reflect the division of nutrition on the camera-monitored plants as the literature suggests. Hence,
 312 we suppose that the data could reveal the general influence of the growing environment on strawberries in
 313 this greenhouse compartment in an indirect and deferred way.

314 3.7 Image encoders have a noteworthy influence on the model performances

315 The best-performing models of each family are considered in the previous result discussions. However,
 316 the number of image features also influenced the model accuracy. The information from different latent
 317 spaces is illustrated in Figure 6. Figure 7 discusses the effects when the image features are utilized with

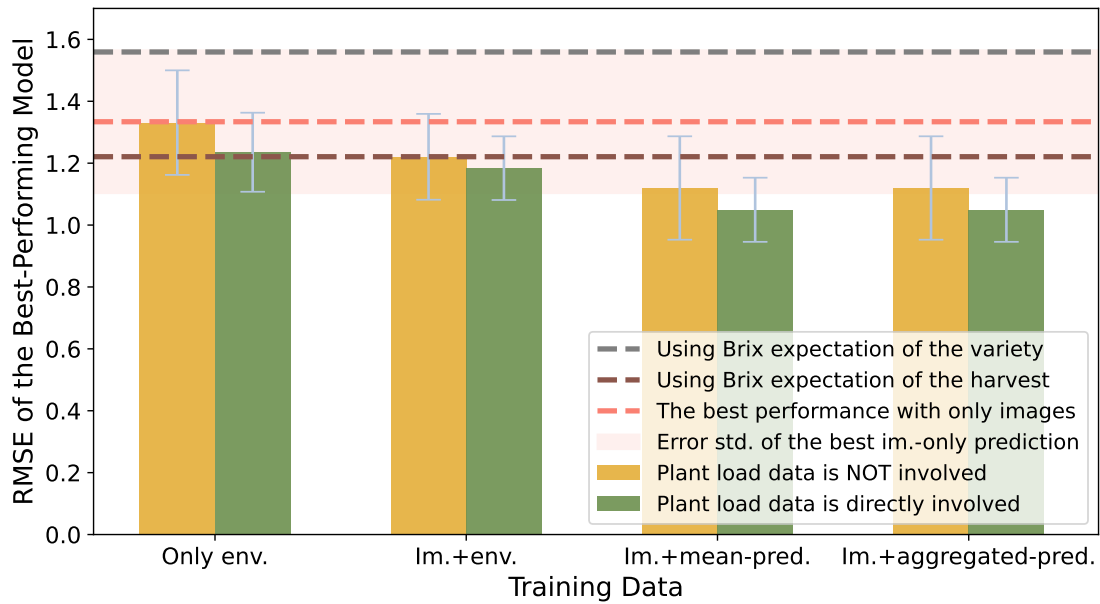


Figure 5. Performance comparison of Brix prediction using different attributes of environmental information, using RMSE as an accuracy indicator. The colors indicate the involvement of the plant load data. The y-values indicate the minimum RMSEs of models from the same group.

318 different representations of environment data. When we used only the images in the prediction, it is still
 319 important to keep as many features as possible. Referring to the illustrations in Figure 6, it is indicated that
 320 considering the texture and the shape of strawberries could have a positive influence on the intrinsic quality
 321 representation. When using image features together with the raw environment data, we cannot see much
 322 difference in the best performances. Nevertheless, we observe an increase in the RMSEs when using larger
 323 dimensions of image features with the aggregated Brix. Overall, it is suggested that similar dimensions of
 324 image features and the other source of data could generally achieve better RMSEs.

Table 1. Detailed accuracy indicators of the best-performing models using different sets of input attributes. The models are ranked according to the “RMSE” column, the *empirical baseline* is calculated by using the Brix expectation of the strawberry variety as all the predicted values, the *conventional baseline* is calculated by taking the average Brix of each harvest as the individual predictions. The MAE and RMSE of all models and benchmarks are calculated by averaging over 15 random validation splits. The std. of the RMSE on each validation split is presented in the “RMSE-std” column.

Image Feature	Env. Data	Plant Load	Brix Agg.	MAE	RMSE	RMSE-std.
Included	In Agg. Pred.	In Agg. Pred.	Percentiles	0.81	1.10	0.158
Included	In Agg. Pred.	In Agg. Pred.	Mean + std.	0.86	1.12	0.139
Included	In Agg. Pred.	In Agg. Pred.	Mean	0.90	1.15	0.118
Included	Included	Included	N/A	0.90	1.18	0.103
Included	Included	Not included	N/A	0.90	1.22	0.119
<i>the conventional baseline</i>				<i>0.91</i>	<i>1.22</i>	<i>0.151</i>
N/A	Included	Included	N/A	0.96	1.24	0.128
N/A	Included	Not included	N/A	1.00	1.27	0.146
Included	Included	Included	N/A	1.04	1.32	0.134
Included	Not included	Not included	N/A	1.00	1.33	0.189
<i>the empirical baseline</i>				<i>1.21</i>	<i>1.56</i>	<i>0.312</i>

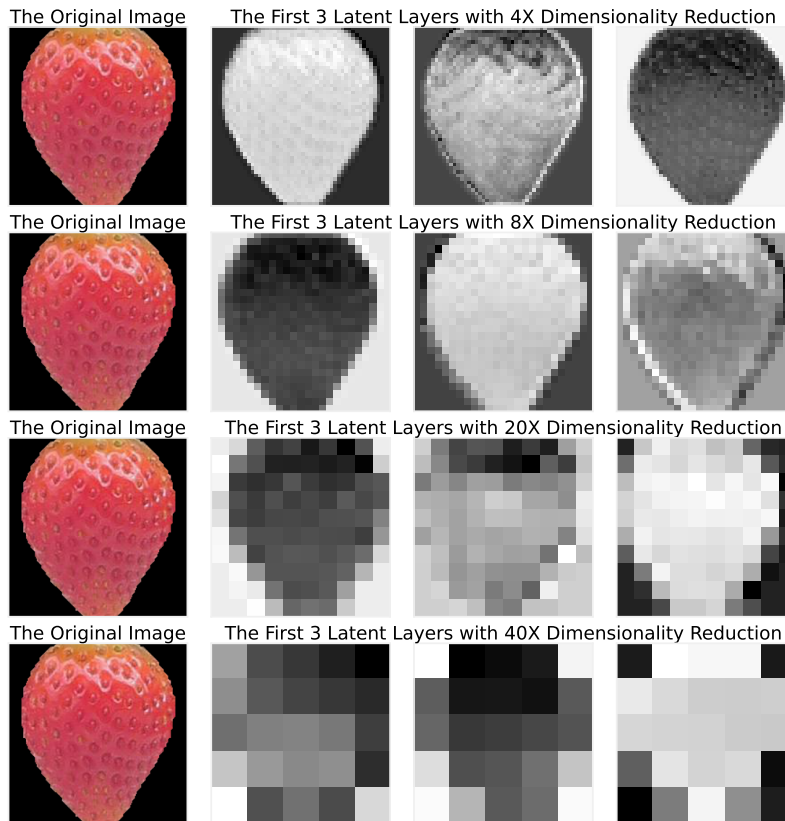


Figure 6. Examples of an image segment and its latent features from the four VAEs, plotted in a monologue style. The first column is the original image segment uniformed into a size of 200x200 pixels. The segment background is saved as black and transparent pixels. The level of dimensionality reduction from each encoder is shown on top of the latent space illustrations.

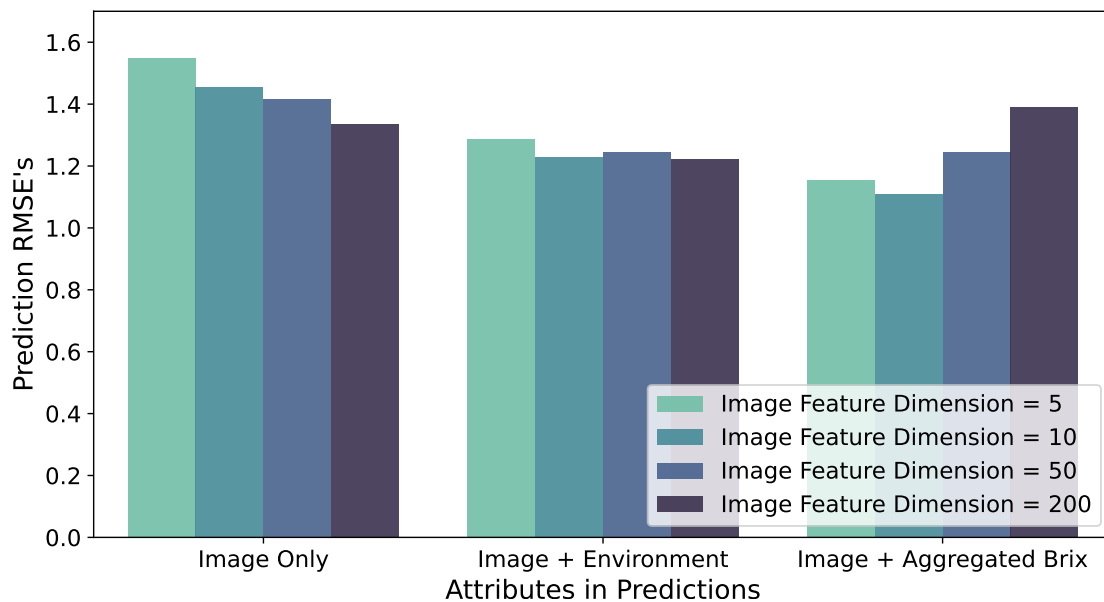


Figure 7. Performance comparison of Brix prediction using different image encoders, using RMSE as an accuracy indicator. The x-axis indicates the input attributes of the experiment sets. The colors indicate the dimensionality of the image features involved in the experiments. The y-values show the minimum RMSEs of all models from the same group.

4 DISCUSSION

325 With this paper, we propose and evaluate a practical methodology for estimating the sugariness of individual
326 strawberries, starting from planning the data collection setups. This approach uses affordable devices
327 to collect relevant observations in the field and does not require harvesting or destroying the fruit. The
328 experiment results demonstrate that it is feasible to anticipate the quality of strawberries when they are still
329 growing. Such information could support the decision-making of harvesting and supply-chain strategies of
330 greenhouse managers.

331 According to Figure 4 and Table 1, the models using image features with aggregated Brix information
332 are the optimal choices among all the attribute combinations. The models could reduce the RMSE by up to
333 28.8% and 18.9% from the *empirical baseline* and the *conventional baseline* respectively. Compared to the
334 image data, the environmental information has shown to be more relevant for the models to learn from,
335 yet they lack the capability to tell fruit-to-fruit variances. Compared to using data from a sole source, a
336 mixed-use of both could lead to an accuracy improvement of 10.0% and 6.2%, respectively.

337 Compared to other research in the field, we included multiple types of data to build machine-learning
338 models. Our models show competitive performances in the sweetness prediction of strawberries (RMSE 1.2
339 from Sun et al. (2017), RMSE 1.18 from Amoriello et al. (2022), MSE 0.95 from Cho et al. (2019)) while
340 using in-field data collected more easily-acquired devices. On top of that, the dataset that we collected for
341 pursuing this research is also useful for more research in this field.

342 In the above-mentioned experiments, we performed all the procedures step-by-step, yet we see the
343 possibility of exploiting higher levels of model integration. Nevertheless, as state-of-the-art computer
344 vision technologies allow detection models to be faster and more portable, expanding the capability of
345 real-time assessments of fruit quality could also be an interesting topic.

346 The research primarily studies in-field and non-destructive data that are worth to be considering in
347 training Brix prediction models. The images, which the prediction models were trained with, are essentially
348 a subset of the time-lapse image dataset. With the entire dataset, further research is suggested to include
349 temporal information for refining the quality prediction models. It is also an interesting topic to explore the
350 practicability of using earlier images in forecasting future Brix values.

351 Our results suggest that environmental information plays a vital role in training a reliable model.
352 Particularly, the environmental information from up to fourteen days before the harvest is crucial to
353 ensure the model's accuracy. Nevertheless, we did not discuss the detailed influence of specific sources of
354 climate data on our model accuracies. It is therefore recommended to conduct subsequent studies on the
355 effectiveness of learning with different environmental factors.

ACKNOWLEDGMENTS

356 The authors are grateful to Delphy Improvement Centre B.V. (Delphy) for providing strawberry plants to
357 be monitored and measured. We thank Lisanne Schuddebeurs, Stijn Jochems, Klaas Walraven, and Vera
358 Theelen from Delphy for their data collection advice. The environmental records, the plant load data, and
359 the destructive quality measurement tests that comprise the dataset are all provided by Delphy. We are also
360 thankful to Camiel R. Verschoor and Jan Erik van Woerden from Birds.ai B.V. for collecting, annotating,
361 and pre-processing the image data. Thanks to Lucas van Dijk from TU Delft, Erin Noel Jordan from TU
362 Dortmund, and Stijn Jochems from Delphy, for giving great and thorough suggestions on the paper.

CONFLICT OF INTEREST STATEMENT

363 The authors declare that the research was conducted in the absence of any commercial or financial
364 relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

365 Junhan Wen confirms her contribution to the paper as follows: research conception and design, data
366 (pre-)processing, analysis and interpretation of results, and manuscript preparation. All the work was
367 done under the supervision of Mathijs de Weerd and Thomas Abeel. All authors reviewed the results and
368 approved the final version of the manuscript. All authors agree to be accountable for all aspects of the work
369 in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately
370 investigated and resolved.

DATA AVAILABILITY STATEMENT

371 The datasets that are collected for this study can be found in the 4TU Data Repository: [https://](https://figshare.com/s/42593b2fd9549df8c1cb)
372 figshare.com/s/42593b2fd9549df8c1cb.

FUNDING

373 This project is fully funded by Topsector Tuinbouw & Uitgangsmaterialen, the Netherlands and
374 Innovatiefonds Hagelunie & Interpolis.

SUPPLEMENTARY MATERIALS

375 The Supplementary materials are collected in a separate document.

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