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RealTimeFruit: AN AI AND IoT-BASED DECISION-SUPPORT SYSTEM FOR PHENOLOGICAL MONITORING AND GROWTH-STAGE FORECASTING IN FRUIT ORCHARDS

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Abstract

Accurate, real-time monitoring of fruit-tree phenology underpins timely decisions on irrigation, frost protection, pollination, thinning, spraying, and harvest, yet conventional manual observation is labor-intensive, subjective, and hard to scale across many trees and species. This paper describes RealTimeFruit, an integrated artificial intelligence (AI) and Internet of Things (IoT) decision-support system (DSS) developed at USAMV Bucharest for automated phenological monitoring and growth-stage forecasting in experimental orchards of apple, pear, peach, nectarine, apricot, paw-paw, and jujube at two sites (Bucharest and Istrița). The system couples fixed RGB field cameras and Pessl iMetos 3.3 weather stations with automated AI-based BBCH classification of daily images (Anthropic Claude models) and with phenological models based on the Dynamic Model (Chill Portions), Chilling Hours, and Growing Degree Hours (GDH). AI-derived stages are validated against expert manual observations using a structured, tiered protocol, and forecasts are generated by a chilling-to-forcing model calibrated via leave-one-year-out (LOYO) cross-validation. Across species, full-bloom dates were predicted with a mean absolute error of about 2 to 8 days, and harvest/maturity with about 4 to 8 days; the largest errors reflected biologically diffuse flowering rather than model structure. All components converge on an operational web dashboard that displays parallel manual and camera-derived BBCH stages across multi-year datasets (2023-2026). The DSS provides a reproducible, extensible foundation for stage-targeted orchard management.

Key words: *artificial intelligence, BBCH classification, chilling portions, growing degree hours, orchard monitoring.*

INTRODUCTION

Phenology - the timing of recurring biological events such as bud-break, flowering, fruit development, and leaf senescence - governs almost every decision in modern orchard management. The date of full bloom conditions the risk of frost damage and the scheduling of pollination and thinning, whereas the progression of fruit growth and ripening determines the timing of plant protection, irrigation, and harvest. Because these events shift from year to year with weather and are strongly cultivar-dependent, growers and researchers need accurate, spatially explicit, and, ideally, forward-looking information on the developmental stage of each tree, all the more so as climate change is already shifting orchard phenology (Luedeling, 2012; Drepper et al., 2020; Reeves et al., 2022).

Traditionally, phenological stages are recorded by trained observers using the BBCH scale, a standardized two-digit code describing plant development from dormancy to senescence (Meier, 2001; Meier et al., 2009). Manual observation, however, is labor-intensive, inevitably subjective, difficult to scale across many trees, cultivars, and sites, and usually captures only a few dates per season. At the same time, forecasting the next stages requires

process-based models that translate temperature into physiological progress: chill accumulation during dormancy is commonly quantified with the Dynamic Model as Chill Portions (Fishman et al., 1987; Erez et al., 1990), while the subsequent heat requirement is expressed as Growing Degree Hours (Anderson et al., 1986). Combined chill-and-heat frameworks such as PhenoFlex (Luedeling et al., 2021) unify the two phases into a single calibrated predictor, building on earlier unified and sequential chilling-forcing formulations (Chuine, 2000; Cesaraccio et al., 2004); recent studies warn that unusually warm winters increasingly compromise the performance of models calibrated on historical data (Fernandez et al., 2022).

Advances in low-cost imaging and machine learning now make it feasible to automate stage recognition from field images and to integrate observation and prediction into a single operational tool (Kim et al., 2025). However, most reported systems address a single species or a single task, and few couple validated, camera-derived observations with weather-driven forecasting within a decision-support system (DSS) that a research team can actually operate day-to-day.

The present work describes RealTimeFruit, an integrated AI and IoT-based DSS developed at the University of Agronomic Sciences and Veterinary Medicine of Bucharest (USAMV). The system was conceived not as an algorithm for one crop but as a multi-species, multi-site platform that senses, ingests, classifies, validates, forecasts, and automates. It currently covers seven fruit species with contrasting phenological behavior - two pome fruits (apple, pear), three stone fruits (peach, nectarine, apricot), and two new species for Romania (paw-paw and jujube) - across two locations. The aims of this paper are: (i) to present the architecture and data flow of the DSS; (ii) to describe the AI-based BBCH classification and the structured validation protocol that make camera-derived stages trustworthy; and (iii) to report, across all seven species, the accuracy of the forecasting layer and the physiological findings that emerged from calibrating it. Species-specific analyses, treated only synthetically here, are the subject of companion papers.

MATERIALS AND METHODS

Experimental orchards and plant material

The study was carried out in the experimental orchards of USAMV Bucharest at two sites: Bucharest (the main site, 44.43° N, 26.07° E) and Istrița (45.13° N, 26.47° E), which experiences a slightly colder microclimate. Seven species were monitored: apple (*Malus domestica* Borkh.), pear (*Pyrus communis* L.), peach and nectarine (*Prunus persica* L. Batsch), apricot (*Prunus armeniaca* L.), paw-paw (*Asimina triloba* L. Dunal), and jujube (*Ziziphus jujuba* Mill.). Monitored cultivars, cultivation forms, rootstocks, and sites are summarised in Table 1. The two new species were included deliberately to test the AI classifier against atypical canopies and flowering habits, from the maroon, bell-shaped flowers of paw-paw to the small, inconspicuous, and very late flowers of jujube.

IoT sensing layer

Each monitored tree or plot was observed by a fixed Boly trail camera acquiring several time-stamped RGB images per day (with night infrared frames extending coverage), so that each image is a dated record of canopy state - bud, leaf, flower, and fruit development, color and density changes, and visible stress. Microclimatic data were provided by Pessl iMetos 3.3 stations installed within the orchards (Bucharest station 00215ABF; Istrița station 00215ADE), delivering high-frequency air temperature and humidity data via the FieldClimate API. Because the stations are co-located with the cameras, every image can be linked to the temperature history of the same tree.

Ingestion

Images are delivered automatically (by e-mail and cloud transfer) and organized by species, tree, and date into a machine-readable archive. One representative image per tree and day is selected and linked to the corresponding weather data and any manual records, yielding a dataset in which each observation includes a tree identity, a date, and its microclimate. A dedicated key (the message identifier rather than the recurring camera file name) is used to avoid

collapsing records, since camera file names are reused across years.

AI-based BBCH classification

Selected daily images are classified into BBCH stages by Anthropic Claude models, forming a tiered set that balances accuracy, speed, and cost across thousands of images: a high-capability model for demanding or ambiguous frames, a balanced model for routine daily classification, and a fast, lightweight model for high-volume clear cases. Each image yields a BBCH stage along with the model's stated reasoning, which is stored to ensure automated decisions remain traceable and reviewable. Two parallel tracks are scored per image - a floral track (BBCH_florifer) and a vegetative track (BBCH_vegetativ) - so that flowering and shoot growth are validated independently.

Validation protocol

Before automation, camera-derived stages were validated against expert manual observation using a structured, four-step protocol designed for demonstrable coverage rather than spot checks: (i) a logical and temporal pass cross-checking free-text notes and calendar consistency against the coded stage, which detects systematic errors regardless of the model's stated confidence; (ii) tiered visual re-verification of all flagged images through parallel image montages; (iii) a random control sample drawn from the unverified remainder to estimate the residual error rate with a Wilson confidence interval, followed by targeted sweeps where errors clustered into patterns; and (iv) a final developmental-monotonicity check, whereby a stage may not fall below a level already sustained in the season (the end-of-season reset excepted).

Forecasting models

Chill accumulation over winter was computed with the Dynamic Model as Chill Portions (CP) (Fishman et al., 1987; Erez et al., 1990) and, as a comparison, with Chilling Hours (0-7.2°C). Heat accumulation after dormancy was computed as Growing Degree Hours (GDH) following the Anderson et al. (1986) cosine formulation (base 4°C, optimum 25°C, critical 36°C). Rather than accumulating absolute GDH from 1 January, the DSS anchors each transition on the difference in GDH between successive principal stages, which proved more stable. A key physiological result, obtained during calibration and reported below, is that the heat required to reach bud-break is not fixed but decreases as winter chill increases; this chilling-to-forcing coupling is expressed as a linear relationship between accumulated CP and the GDH at bud-break, and it is used to correct the forecast. The integrated PhenoFlex model (Luedeling et al., 2021), which unifies chill and heat with a flexible transition function, was implemented as an experimental benchmark. Fruit development and maturity stages were anchored on the predicted full-bloom date plus a cultivar-specific offset expressed either in GDH from bloom or, for stone fruit, in days from full bloom.

Calibration and evaluation

Thresholds and coupling parameters were calibrated on the multi-year datasets (2023-2026) and evaluated by leave-one-year-out (LOYO) cross-validation, reporting the mean absolute error (MAE) and the root mean square error (RMSE) in days between predicted and observed stage dates. All components converge into an operational web dashboard that displays manual and camera-derived BBCH stages in parallel, projects upcoming stages, and is refreshed daily for both sites.

RESULTS AND DISCUSSIONS

The Decision Support System

RealTimeFruit turns daily images and microclimate data into validated, self-updating phenology through an integrated six-stage chain: sense, ingest, classify, validate, forecast, and automate (Figure 1). In its current state, the platform manages multi-year datasets (2023-2026) for the seven species of Table 1 at two sites. It presents them in an operational dashboard with a per-species tab, a chilling tab, an experimental PhenoFlex tab, and a farm-level 60-day outlook. For every monitored tree, it shows the manual and camera-derived BBCH stages side by side, with accumulated chill and heat and the projected date of the next stage, so records and forecasts are visible in one place.

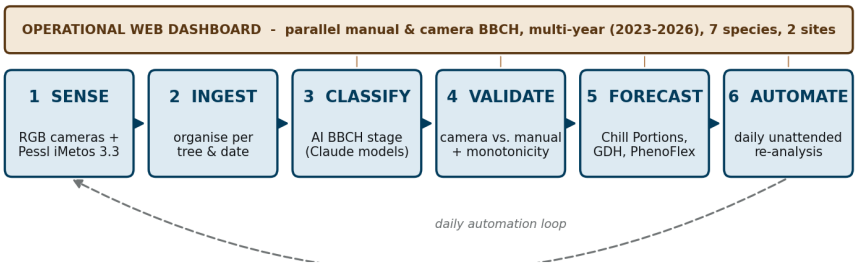

Figure 1. Architecture and six-stage data flow of the RealTimeFruit DSS, from sensing to daily automation, converging in the operational web dashboard

AI classification and the value of dual observation

Across all species, the camera reliably captured the phenological signal that matters most for decisions - the onset and progression of flowering and of vegetative growth - and the AI translated it into BBCH codes with reasoning stored for audit. Two limitations recurred and shaped the methodology. First, once fruit is set, it is frequently hidden by dense foliage, so the late fruit-growth and ripening stages (BBCH 71-89) are more reliably taken from manual records than from the camera in most species; the exception is jujube and the close-up cameras, where green and coloring fruit remain visible. Second, color is not a maturity signal in several cultivars (red pears, red-skin peaches), whose color is determined by fruit set as a varietal trait, so maturity must be assessed by final size, softening, and disappearance at harvest rather than by color. Conversely, the camera consistently added value that manual observation misses: it recorded the early sequence from bud swell to bud break, which is rarely captured by periodic manual visits, and in 2026, the camera-derived full-bloom dates matched the manual dates to within one day.

Table 1. Species, cultivars, sites, and cameras monitored by the RealTimeFruit DSS

Species (scientific name)	Type	Monitored cultivars	Rootstock/canopy	Site(s)	Cameras
Apple (*Malus domestica*)	Pome	Generos, Goldrush + 15 manual-only cultivars	M29/SJA; Vertical Axe	Buc, Istrița	4
Pear (*Pyrus communis*)	Pome	Euras, Williams, Red Williams + other cultivars	Franc/Quince/Own roots; Trident, Bi-baum	Buc	2+
Peach (*Prunus persica*)	Stone	Royal Summer, Filip	GF677/SJA; Trident, Bi-baum, Vertical Ax	Buc	3
Nectarine (*Prunus persica* var. *nucipersica*)	Stone	Big Top	GF677; Trident, Vertical Ax	Buc	2
Apricot (*Prunus armeniaca*)	Stone	Farbali, Farclo, Primaya + 26 manual cultivars	M29C/SJA; Trident	Buc	5
Paw-paw (*Asimina triloba)*	Berry	Sunflower, Simina, Pianu, Allegheny, Wilson	-	Buc, Istrița	5
Jujube (*Ziziphus jujuba*)	Stone	Dong Zao, Hupingzao, Xuan Chen, Ziprim	-	Buc, Istrița	5

Forecasting accuracy

The forecasting layer was evaluated by LOYO cross-validation for every species and cultivar (Table 2), reporting both mean absolute error (MAE) and root mean square error (RMSE). Full-bloom (BBCH 65) was predicted with a mean absolute error of about 2 to 8 days for the pome and stone fruits, and harvest or maturity with about 4 to 8 days. For pear, introducing the chilling-to-forcing correction reduced the LOYO error at bud-break from 16.6 to 3.5 days (RMSE 4.7), and the atypically cold winter of 2025-2026 - which the uncorrected model treated as an outlier - was predicted exactly once

winter chill was included as the missing factor. Anchoring fruit stages on an intermediate, robust reference (full bloom, or the half-size fruit stage BBCH 75 in stone fruit) rather than chaining heat units from bud-break markedly improved the late-stage forecasts, because it prevents thermal errors from accumulating across the long fruit-growth period.

Table 2. Forecasting accuracy (LOYO cross-validation) of the DSS, as mean absolute error (MAE) and root mean square error (RMSE) in days

Species	Cultivar/site	Full bloom (BBCH 65) MAE / RMSE (d)	Harvest (BBCH 87) MAE / RMSE (d)	Anchor
Pear	Euras	2.8 / 3.0	11.0 / 11.4	GDH, chill→forcing
Pear	Red Williams / Williams	3.5 / 4.7	5.7 / 6.6	GDH (BBCH65)
Apple	Goldrush, Bucharest	4.0 / 4.5	4.7 / 6.1	chill→forcing
Apple	Generos, Istrița	6.3 / 7.8	10.5 / 10.5	forcing (GDH)
Peach	Royal Summer (Trident)	1.7 / 2.1	4.9 / –	days-from-BBCH75
Peach	Filip	2.3 / 2.9	8.4 / –	days-from-bloom
Nectarine	Big Top (Trident / Ax)	0.3-2.3 / 0.6-2.4	8.4 / –	days-from-bloom
Apricot	Farbali/Farclo/Primaya	5.2-6.7 / 5.6-8.3	3.0-11.0 / 3.6-13.1	GDH-from-bloom
Jujube	Buc + Istrița cultivars	11.8 / –	7.2 / –	GDH (BBCH65/87)
Paw-paw	Bucharest cultivars	7-10 / –	–	GDH (BBCH65)

A physiological finding: chilling that is largely non-limiting. Calibration revealed that at both sites, winter chill accumulates well beyond the reported requirements of most cultivars (Table 3). Peak Chill Portions of about 100-119 exceed the roughly 44-64 CP reported for pear and apple (Ferlito et al., 2021; Fadón et al., 2023) and the ~75 CP reported for apricot in a comparably cold climate (Guo et al., 2015), and both jujube (whose flowering is facultative with respect to chill) and paw-paw are far above their needs. The practical consequence is that heat, not chill, is the limiting factor for spring development at Bucharest, which justifies anchoring the forecast on a forcing model. Chill nevertheless remains informative for the pome fruits, where the heat required for bud-break falls almost linearly as accumulated chill rises (r = -0.95 for pear and apple), whereas for apricot, peach, and the new species, the coupling is weak or absent, consistent with a non-limiting chill regime in which spring warmth dominates flowering time (Ruml et al., 2011; Fadón et al., 2020, 2023; Yang et al., 2025). This gradient across species is itself a useful output of the DSS.

Table 3. Winter chill accumulated at Bucharest versus the reported requirements, and the chill-forcing coupling

Species	Chill accumulated, Buc (CP)	Reported requirement (CP)	r (CP, GDH at bud-break/bloom)
Pear	~100-104 (peak)	~44-49	-0.95
Apple	~100-104 (peak)	50-64 (Golden Del.); 54 (Gold Rush)	-0.95 / -0.96
Apricot	~100-119	~75 (Beijing)	-0.05
Peach/Nectarine	~100-119	low (early-breaking)	-0.26
Jujube	~100-119	facultative	n.s.
Paw-paw	~100-124	~400 h	n.s.

Species contrasts

The pome and stone fruits behaved predictably and were forecast to within a few days. The two unconventional species stress-tested the system as intended. Jujube showed the largest bloom error (11.8 days), but this reflects biology rather than model failure: its flowering is extended over weeks, its flowers are only 2- 3 mm across and hard to resolve in a wide field of view, and its floral induction is partly photoperiodic (Yao, 2015; Zhang et al., 2016). An explicit photoperiod predictor showed no improvement

because jujube blooms in a narrow mid-summer window when day length is near-constant between years; the residual error is therefore observational, and harvest for the same species is predicted to be 7.2 days. Paw-paw, with its atypical maroon flowers borne on old wood, was classified successfully and its bloom predicted to 7-10 days, extending the standardized BBCH approach to species for which the scale has only recently been described - paw-paw by Ferrer-Blanco et al. (2022) and jujube by Hernández et al. (2015).

Relation to established models

Taken together, the DSS behaves as an interpretable, 'artisanal' version of PhenoFlex: it reproduces the same coupling of Dynamic-Model chill and GDH forcing, but with a transparent linear transition rather than a twelve-parameter fit. On the short series available (three to four years), this simplicity is an advantage - the flexible model tended to over-fit, and for pear and the stone fruits our specialized models matched or beat it; for apple, PhenoFlex held a small edge and is retained as a benchmark. The bloom errors reported here are close to the roughly four-day accuracy cited for PhenoFlex in the literature (Luedeling et al., 2021), and the sensitivity of all models to warm or atypical winters (Fernandez et al., 2022; González-García et al., 2025) reinforces the value of the DSS's explicit chill term and of its extrapolation warnings.

CONCLUSIONS

RealTimeFruit integrates fixed RGB cameras, an in-orchard weather station, AI-based BBCH classification, and weather-driven forecasting into a single operational decision-support system covering seven fruit species at two sites. A structured, tiered validation protocol - logical screening, visual re-verification, a control sample with a confidence interval, and a developmental-monotonicity check - makes camera-derived stages demonstrably trustworthy and exposed correctable, systematic faults in the automated classifier.

Calibrated by leave-one-year-out cross-validation, the forecasting layer predicted full bloom with a mean absolute error of about 2 to 8 days and harvest with about 4 to 8 days across the pome and stone fruits; the larger jujube bloom error is biological, since harvest for the same species is predicted to be about seven days. Winter chill at Bucharest is largely non-limiting, so heat is the main driver of spring development; nevertheless, the heat needed for bud-break in pome fruits falls almost linearly with accumulated chill ($r = -0.95$), and including this coupling cut the pear bud-break error from 16.6 to 3.5 days and captured an atypically cold winter exactly.

The system functions as an interpretable, low-parameter counterpart to integrated chill-heat models, providing a reproducible and extensible foundation for stage-targeted orchard management and species-specific analyses reported in companion papers.

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