EXTENDED ABSTRACT

Artificial intelligence-driven classification method of grapevine phenology using conventional RGB imaging

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ABSTRACT

The phenological stage of the grapevine (*Vitis vinifera* L.) represents a fundamental element in vineyard management, since it determines key practices such as fertilization, irrigation, phytosanitary interventions and optimal harvest time (Mullins et al., 1992). Phenology can be understood as the study of the phenological events, or the stages of plant development that occur during their active lifecycle, in response to climatic conditions. The phenological development of grapevines is mainly influenced by climatic elements, such as temperature, solar radiation, and precipitation, which also influence the production and the quality of grape berries. Temperature is the main forcing element in the phenology of grapevines, in this sense, the projected increases in temperature under future likely climate change scenarios may lead to the advancement of 6 to 25 days for different grapevine varieties in mediterranean climate regions (Reis et al., 2020).

To standardize the description of these stages, several phenological scales have been developed, including the Baggiolini scale, the Eichhorn-Lorenz (E-L) scale, and the extended BBCH scale. The Baggiolini scale, initially used for planning pesticide applications, was limited in scope as it only covered early development stages. In contrast, the E-L scale introduced 47 numerical codes describing 22 phenological stages from winter bud to leaf fall, providing greater detail and flexibility to incorporate sub-stages (Coombe, 1995). The extended BBCH scale increased precision by detailing phenological macro and micro-stages, facilitating its application across multiple crops and standardizing its use internationally (Lorenz et al., 1995).

Despite advances in these descriptive tools, phenological identification traditionally relies on manual observations by an experienced technical person. This method is time-intensive, subjective, and often unable to capture spatial variability within the vineyard, which can lead to suboptimal decisions (Verdugo-Vásquez et al., 2016). In addition, climatic variations, edaphic conditions and agronomic practices can further complicate correct identification (Altimiras et al., 2024).

In this context, emerging technologies, such as computer vision and deep learning, offer a promising solution. These tools provide a possibility to automatize the classification and monitoring of phenological stages by capturing and analysing large-scale images. Algorithms based on convolutional neural networks (CNNs) have proven to be effective for image classification techniques in agriculture, with accuracies exceeding 88% in applications such as grapevine phenological stage identification (Schieck et al., 2023). In addition, these technologies have also been successfully used in the detection of grape bunches under various occlusion conditions (Íñiguez et al., 2024) and in the assessment of diseases such as downy mildew (Hernández et al., 2021). Systems that integrate proximity sensors and IoT platforms are integrating the capacity for continuous and real-time monitoring in vineyards, reducing costs and improving decision making (Mendes et al., 2022).

RESEARCH OBJECTIVES

The objective of this study is to develop an Artificial Intelligence-driven classification method of grapevine phenology using conventional RGB imaging. The aim is to train an AI model capable of accurately identifying major grapevine phenological stages through image analysis under real field conditions. The practical objective is to implement a system that provides speed, objectivity, and scalability, addressing the limitations of traditional methods based on manual observations.

MATERIAL AND METHODS

Description of experimental sites

The experiment was conducted in two vineyards located in different countries and hemispheres: Spain (Site SP) and South Africa (Site SA).

SP: In Spain, the study was carried out at the University of La Rioja's experimental vineyard in Logroño (42° 27' 42.9" N; 2° 25' 40.2" W). Data was collected from Tempranillo vines trained to two systems: a Vertical Shoot Positioning (VSP) system with double cordon Royat and a free-cordon system with simple cordon Royat. The vineyard is situated at an elevation of 384 m above sea level, with a North-South row orientation and vine spacing of 2.8×1.1 m. Images were collected from 40 individual vines in each system during the 2024 growing season.

SA: In South Africa, the study was conducted at Stellenbosch University's Welgevallen Experimental Farm, Stellenbosch (33° 56' 26" S; 18° 51' 56" E). Data was collected from Cabernet Sauvignon and Chenin Blanc vines trained to a Vertical Shoot Positioning (VSP) system. The vineyard, established in 2000, is situated at 157 m above sea level with a North-South row orientation and vine spacing of 2.7×1.5 m. Images were collected from 120 individual vines per cultivar across three rows during the 2024–2025 growing season.

Image acquisition

Canopy images were captured using conventional digital cameras under natural lighting conditions, reflecting uncontrolled ambient environments. In SP site the images were taken with a Digital Single Lens Reflex (DSLR) RGB camera (Canon EOS 5D Mark IV, Canon Inc., Tokyo, Japan). The camera was mounted on a tripod, positioned 1.0 m from the row axis and elevated to 1.2 m above ground level. In SA site the images were captured using two compact digital cameras: a Sony Cyber-shot DSC-W800 (Sony Corporation, Tokyo, Japan) and a Canon PowerShot ELPH 160 (Canon Inc., Tokyo, Japan). These cameras feature 20-megapixel CCD sensors and optical zoom capabilities. Images were taken manually without a tripod, maintaining a consistent distance of 1.5 m from the canopy and an elevation of 1.3 m above ground level. No artificial lighting was applied in either location.

Reference dataset

The dataset was prepared by manually classifying canopy images based on the E-L major states described by Coombe (1995). Personnel with training in viticulture classified and organized the images into four phenological stages:

1. Shoot and Inflorescence Development (1_INF): Early growth stages such as shoot elongation and inflorescence development (2,099 images).
2. Flowering (2_FLO): Capturing the flowering phase (350 images).
3. Berry Formation (3_BER): Early berry development stages (503 images).
4. Berry Ripening (4_RIP): Depicting the ripening process of grape berries (238 images).

The fifth E-L state, Senescence, was excluded since no post-harvest images were taken. These abbreviations (*1_INF, 2_FLO, 3_BER, 4_RIP*) were used to name the image folders and are also reflected in the figures for consistency. This classification ensured the dataset was accurately labelled and suitable for training and validation.

Artificial intelligence algorithm

The AI classification model was developed using YOLOv11 (You Only Look Once, version 11), an advanced object detection algorithm optimized for real-time applications. YOLOv11 divides an image into a grid and predicts bounding boxes and class probabilities for objects in a single pass, making it efficient for processing large datasets. The algorithm was fine-tuned with labelled images to identify phenological stages, detecting subtle variations in canopy structure.

Training was conducted on a compute server equipped with an AMD Ryzen Threadripper 3970X 32-Core CPU, 32 GB of ECC DDR4 SDRAM, and an nVidia GeForce RTX 3090 24 GB GPU. The training process used a batch size of 32, an image input size of 640×640 pixels, and 60 epochs. To improve generalization and robustness, YOLOv11's built-in data augmentation techniques were applied during training, including transformations such as scaling, rotation, and colour jittering. A stratified dataset split was applied, allocating 80% of the images for training and 20% for validation to ensure balanced representation of all phenological stages.

Statistical analysis

Model performance was evaluated using Python. A normalized confusion matrix was generated during validation, providing a detailed summary of classification accuracy. The matrix compares predicted labels with true labels, highlighting correct predictions and misclassifications for each class. Representing data as percentages made the results easier to interpret, allowing identification of both strengths and areas for improvement in the model's performance. The confusion matrix forms the basis for analysing the model's ability to classify phenological stages accurately across different datasets.

RESULTS

Model validation: confusion matrix analysis

The normalized confusion matrix from the validation phase (Figure 1) provides an overview of the classification model's performance across the four phenological stages: Shoot and Inflorescence Development (1_INF), Flowering (2_FLO), Berry Formation (3_BER), and Berry Ripening (4_RIP). The matrix indicates the proportion of correctly predicted instances for each class, along with misclassifications.

–The model demonstrated strong performance in classifying 1_INF with 96% accuracy, although 9% of these images were misclassified as 2_FLO.

–For 2_FLO, the accuracy was 87%, with small overlaps where 4% were incorrectly labelled as 1_INF and 1% as 3_BER.

–The 3_BER stage showed an accuracy of 99%, with a minor misclassification of 4% as 2_FLO.

–The model achieved perfect classification (100%) for 4_RIP, with no misclassifications detected.

This matrix highlights that the model performs well overall, particularly for the 3_BER and 4_RIP stages. However, there is some confusion between adjacent stages, particularly between 1_INF and 2_FLO, which may indicate subtle visual similarities during transition phases.

Classification examples

Figure 2 showcases examples of the model's predictions for the validation dataset. The images illustrate the model's ability to classify phenological stages effectively under varying lighting and canopy conditions. Labels overlaid on each image indicate the predicted phenological stage, demonstrating the robustness of the model in distinguishing between stages even in challenging scenarios such as partial occlusion or diverse background elements.

Limitations and future work

While the model demonstrated strong overall performance, some limitations and areas for improvement were identified. One limitation lies in the imbalance of the dataset, particularly the underrepresentation of certain phenological stages, such as Flowering (2_FLO). Expanding the dataset to include more samples for these stages, as well as additional images of transition phases, could enhance the model's ability to distinguish subtle differences between closely related stages. For future work, it would be valuable to test the model on additional grape varieties and training systems to evaluate its generalizability across diverse vineyard setups. Moreover, assessing the model under different environmental conditions, such as varying climates, lighting, and soil types, could provide insights into its robustness. Another promising avenue would be to expand the classification framework to include more detailed phenological stages rather than limiting it to major stages. This approach would allow for finer-grained classifications but would require a significantly larger dataset to ensure adequate representation and accuracy.

CONCLUSION

The results of this study demonstrates the potential of using deep learning models for the automated classification of grapevine phenological stages under real field conditions. The model achieved high accuracy, particularly in advanced phenological stages, despite some misclassifications in early stages. Data augmentation and the application of AI techniques enhanced robustness, while insights into dataset limitations highlight opportunities for improvement. Future work should focus on expanding the dataset, testing the model on diverse cultivars and environments, and incorporating more detailed phenological stages to enhance precision and applicability in vineyard management.

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FIGURES

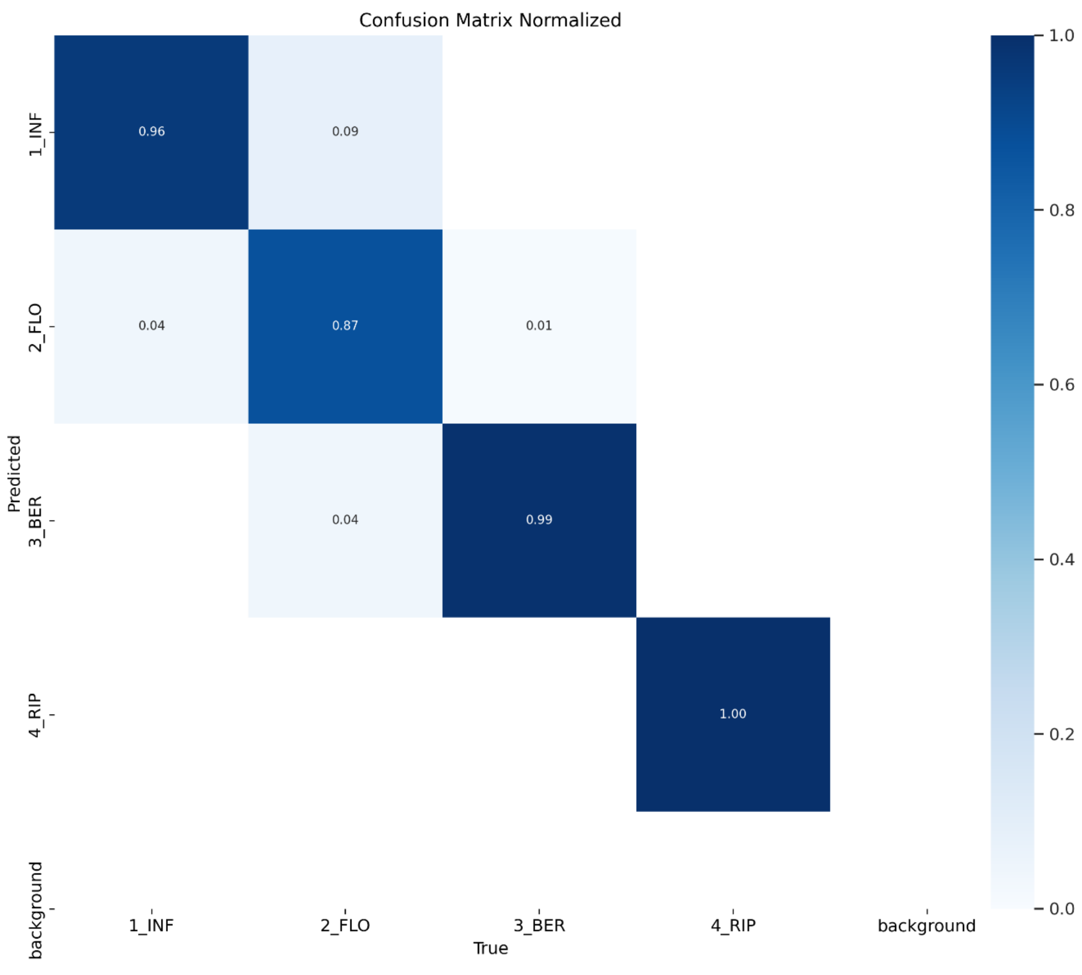

Figure 1. Normalized confusion matrix showing the classification accuracy of the model during validation across the four phenological stages: Shoot and Inflorescence Development (1_INF), Flowering (2_FLO), Berry Formation (3_BER), and Berry Ripening (4_RIP). Values represent the proportion of correct and incorrect predictions for each class.

Figure 2. Example of model predictions for the validation dataset. Each image is labelled with the predicted phenological stage: Shoot and Inflorescence Development (1_INF), Flowering (2_FLO), Berry Formation (3_BER), and Berry Ripening (4_RIP). The figure illustrates the model's ability to classify images under varying lighting, canopy conditions, and different cultivars.