segmentation, object detection, edge reconstruction, and geometric analysis to achieve automatic identification and parameter extraction of individual berries, including berry number, diameter, area, shape, spatial coordinates, and distribution density.

Early machine vision approaches mainly relied on two-dimensional image processing. For example, methods based on edge detection and geometric analysis can identify berry contours and estimate berry diameter, with an average error of approximately 2-3 mm and good stability across different grape types (Luo et al., 2021). Automated frameworks based on conditional random fields can classify approximately circular structures in images as “berries” or “non-berries,” with high correlation between image-derived and manually measured diameters ($\rho \approx 0.88$) (Roscher et al., 2017). In addition, field-scale berry size mapping systems can control diameter estimation errors within 6% and show strong correlations with berry weight ($R^2 \approx 0.96$), providing a foundation for automated evaluation of spatial variation and uniformity (Mirbod et al., 2016).

In recent years, deep learning models have further improved berry detection accuracy under complex backgrounds. The Segment Anything Model (SAM) enables high-precision segmentation of individual berries in large sets of 2D cluster images, showing strong agreement with manual annotations (Pearson correlation $r = 0.96$), and can generate over 150,000 berry masks with spatial coordinates for analyzing berry size distribution, cluster compactness, and spatial structure (Torres-Lomas et al., 2024). Moreover, instance segmentation models based on AS-SwinT and end-to-end berry counting algorithms can automatically detect and count berries before thinning, supporting intelligent thinning decisions in high-value table grapes such as ‘Shine Muscat’ (Du and Liu, 2023). Mobile vision systems integrating Mask R-CNN and calibration objects can achieve sub-millimeter accuracy in berry diameter measurement and dynamically track berry growth, providing a technical basis for temporal monitoring of berry uniformity (Upadhyaya et al., 2023).

6.2 Trait association analysis and predictive modeling based on big data

In the context of digitalization, research on grape berry uniformity is shifting from single-point measurements to multi-source data integration and large-scale modeling. By integrating phenotypic data across different cultivars, years, ecological regions, and cultivation conditions, it is possible to systematically analyze the relationships between berry uniformity and yield, fruit quality, stress resistance, and marketable fruit rate. For instance, questions such as whether lower berry CV corresponds to a higher proportion of marketable fruit, whether optimal cluster compactness reduces disease risk, or whether uniform berry size affects sugar and acid accumulation can be addressed through big data modeling.

High-throughput phenotyping platforms provide the foundation for such analyses. Automated berry imaging systems can extract over 100 traits per fruit within approximately one second, including size, shape, and color parameters, and store the data in standardized formats for subsequent genetic analysis and model training. When combined with genome-wide SNP data, these high-density phenotypic datasets can be used for GWAS, haplotype analysis, and multi-trait selection, enabling the dissection of the genetic basis of complex traits such as berry shape, sugar content, organic acids, and stress tolerance (Zhang et al., 2025).

At the vineyard scale, multimodal sensing and machine learning models can be used to establish predictive relationships among environment, plant status, yield, and fruit quality. By integrating hyperspectral vegetation indices, thermal infrared indices, photosynthetically active radiation interception, stem water potential, chlorophyll content, and gas exchange parameters, and applying algorithms such as random forest and gradient boosting, it is possible to accurately predict traits such as average berry weight, berry number per cluster, cluster weight, total yield, soluble solids content, pH, titratable acidity, and maturity index, with some models achieving R^2 values greater than 0.9 (Jewan et al., 2024). UAV-based multispectral and thermal remote sensing studies have also shown that vegetation indices are positively correlated with yield and berry weight, while canopy temperature is related to berry pH, polyphenol content, and anthocyanin levels, providing a basis for zone management and selective harvesting (Lee et al., 2024). In addition, artificial neural networks can use CIELab color parameters to accurately predict berry physicochemical properties, with correlation coefficients reaching $R \approx 0.98\text{-}0.99$, indicating that color information is also an important variable for modeling fruit maturity and quality.