of genetics, environment, and cultivation conditions, and can support decisions on harvesting time, irrigation, fertilization, and genotype selection (Roopashree et al., 2024). More generally, plant phenotyping research shows that machine learning can reduce the bottleneck created by large high-throughput datasets by linking extracted features to measurable phenotypes through classification, regression, and prediction.Model choice depends strongly on sample size, task complexity, and the need for interpretability. Traditional approaches such as PLSR, SVM, and decision-tree methods remain useful when training data are limited because they are interpretable and computationally modest, although they rely on manual feature engineering and capture nonlinear structure less effectively. By contrast, neural-network-based models and related modern phenomics frameworks have improved the precision of long-term forecasting and spatiotemporal pattern recognition in plant-growth prediction tasks (Debbagh et al., 2025).

Recent empirical studies confirm that nonlinear models can accurately estimate medicinal-plant growth indicators. In *Glycyrrhiza uralensis*, BP, SVM, and RF models were used to predict phenotypic indicators and yield, and integrated modeling with multiple indicators substantially improved performance (Zhang et al., 2025). Similar advantages appear in broader crop phenotyping, where deep learning models trained on time-series imagery have predicted future root and shoot growth with performance close to expert annotation and adaptability across plant species.Statistical and machine-learning models are also increasingly used to connect growth traits with metabolite accumulation.ANN-based and neurofuzzy approaches have been proposed as effective tools for modeling multifactorial processes that influence phenolic-compound production, while improving interpretability through rule-based simplification (García-Pérez et al., 2020). Reviews of genotype-to-phenotype prediction likewise argue that machine learning can outperform conventional statistical tools in high-dimensional settings because it can extract features from genetic, environmental, and image data more flexibly.

3.3 Artificial intelligence-based prediction and decision support systems

Artificial-intelligence-based prediction systems extend trait analysis into practical decision support by converting monitoring results into cultivation recommendations.In medicinal-plant production, this is especially valuable because AI can optimize not only biomass growth but also the accumulation of pharmacologically important secondary metabolites across variable conditions (Chen et al., 2026). Recent reviews of medicinal herb breeding therefore frame AI as a platform technology spanning multi-omics integration, trait optimization, intelligent monitoring, and genotype-environment-management interaction. At the farm-management level, decision support is moving from empirical adjustment toward real-time, demand-oriented control. UAV-guided monitoring in *Glycyrrhiza uralensis* was used to support variable irrigation and nitrogen topdressing, illustrating how integrated phenotyping can inform immediate water-nutrient management decisions (Zhang et al., 2025). Comparable work in plant-scale UAV monitoring has shown that logistic growth curves and dashboard-based reporting can project maturity before harvest and guide field interventions under heterogeneous conditions (Vigneault et al., 2023).

A second major application is predictive optimization of active-compound production.AI-based metabolite research shows that ANN models can learn nonlinear relationships among growth regulators, nutrient composition, light, elicitors, and metabolite accumulation, allowing prediction of optimal culture conditions without exhaustive experiments. This shift is important because conventional in vitro metabolite production is often irreproducible due to genetic variability, environmental fluctuation, and pathway regulation, all of which favor data-driven optimization (Srivastava and Bharadvaja, 2026). Future intelligent systems for Zhejiang medicinal plants will likely combine explainable prediction with broader biological and agronomic knowledge. Reviews of AI in medicinal-plant research emphasize not only phytochemical profiling and predictive modeling, but also the integration of AI with traditional ethnobotanical expertise to improve agricultural output and conservation. At the same time, future phenomics frameworks are expected to benefit from tighter integration of domain knowledge with data-driven methods and from more comprehensive standardized datasets, which should improve robustness in real cultivation settings (Debbagh et al., 2025).