supports the identification of efficacy-related marker components that can improve quality evaluation of complex herbal materials.Systems-level modeling is also becoming more predictive as it incorporates multi-omics and machine learning. Reviews of medicinal plant metabolic networks note that AI methods can extract key biological features from high-dimensional datasets and support the construction of digital-twin-like surrogate systems for optimizing elicitation, cultivation, and metabolic regulation (Chen et al., 2026). For Zhejiang medicinal plants, this suggests a future workflow in which transcriptomic, metabolomic, and phenotypic data are embedded in network models that can forecast how cultivation decisions alter both plant growth and secondary metabolite output (Chen et al., 2026).

5.3 Deep learning and predictive analytics in medicinal plant science

Deep learning and predictive analytics are extending medicinal plant research from description to high-dimensional inference.Recent reviews show that deep learning is particularly effective for analyzing complex data in bioactivity prediction and drug discovery, while medicinal-plant-specific assessments emphasize that deep models perform well on nonlinear multi-omics datasets and can reveal regulatory modules associated with secondary metabolite synthesis (Prajapati et al., 2025). This makes deep learning especially relevant for Zhejiang medicinal plants, where trait development and active-compound accumulation are shaped by interacting genetic, chemical, and environmental factors. One practical advantage of predictive analytics is automated feature discovery from heterogeneous data.Machine learning has been used to identify crucial metabolite features affecting phenolic synthesis, and in medicinal plant hyperspectral applications it can select characteristic wavelengths for accurate prediction of compounds such as tanshinones and for origin classification (Chen et al., 2026). Beyond spectroscopy, automated machine learning has also been used to predict precursors of specialized metabolites, with regularized linear classifiers outperforming prior methods while remaining interpretable, which is useful for accelerating pathway discovery in plant secondary metabolism.

Deep learning is also reshaping phenotyping and resource assessment through image-based prediction.In medicinal plant surveys, UAV imagery combined with deep learning has enabled high-accuracy instance segmentation of individual plants and improved yield estimation in complex field environments (Ding et al., 2023). In cultivation-oriented work, integrated UAV phenotyping has further supported real-time water-nutrient decision making, showing that predictive models can move beyond passive monitoring toward operational management support (Zhang et al., 2025). Despite these advances, predictive analytics in medicinal plant science still faces limits in interpretability, transferability, and data standardization. Deep learning models often act as black boxes and may not provide biologically verifiable mechanisms, while broader reviews of natural-compound modeling identify the need for benchmark datasets, interpretability tools, and stronger experimental validation (Prajapati et al., 2025). For Zhejiang medicinal plant research, the most promising direction is therefore not deep learning alone, but explainable predictive systems that combine remote sensing, multi-omics, and network knowledge into robust decision-support tools for cultivation and quality control (Prajapati et al., 2025; Chen et al., 2026).

6 Case Study: Computational Analysis of Growth Characteristics and Active Compound Accumulation in Zhejiang Medicinal Plants

6.1 Case selection and experimental dataset construction

A Zhejiang case study is best designed around representative medicinal species with clear economic value, measurable growth traits, and chemically defined active constituents. Case selection should also reflect the fact that medicinal plant quality depends on multi-component composition and varies across medicinal parts and environmental conditions, so dataset construction must capture both growth and compound heterogeneity rather than treating plants as uniform samples. This justifies choosing species for which phenotypic, ecological, and phytochemical data can be collected simultaneously, because multi-source data provide a more complete basis for quality evaluation than single analytical streams.

The experimental dataset should combine field observations, imaging, and chemical profiling in a unified sampling framework. A practical template comes from medicinal plant phenotyping studies that pair UAV or