# Developing a Quantitative Health Index for Ornamental and Bonsai Plants Using Sensors and Computer Vision: Proposal of the OPHI Score

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## Abstract

Ornamental and bonsai plants are typically assessed using subjective visual judgment of leaf color, soil moisture and pest damage, which can lead to misdiagnosis and inappropriate care, especially among novice growers. This study proposes a **quantitative set of criteria** and an integrated **Ornamental Plant Health Index (OPHI)** based on four measurable components: **(1) leaf color / chlorophyll, (2) root density and deformation, (3) soil moisture, and (4) pest and disease incidence and severity**. The criteria are derived from a literature review on the use of SPAD meters and CIE L*a*b* color values for chlorophyll estimation (Percival et al., 2008; Wei et al., 2024), root growth and deformation in container-grown plants (Judd et al., 2015; Ownley et al., 1990), soil moisture effects on plant performance (Odhiambo & Aguyoh, 2022; Zhang et al., 2002), and disease assessment methods for ornamentals (Hansen, 2009; Harmon, 2018).

To illustrate the proposed framework, we generated a **simulated dataset** of 120 container-grown ornamental and bonsai plants with values distributed according to thresholds reported in the literature. The OPHI score is normalized to a 0–100 scale and categorized into three health classes: **healthy (≥ 80), moderate (60–79), and poor (< 60)**. In the simulated dataset, 62.5% of plants were classified as healthy, 25.8% as moderate, and 11.7% as poor. The OPHI framework is designed for integration into smartphone applications and low-cost IoT systems, allowing growers to assess plant health from sensor data and images rather than relying solely on subjective judgment.

**Keywords:** ornamental plants, bonsai, plant health, SPAD, soil moisture, root deformation, plant disease, computer vision, IoT

# 1. Introduction

Ornamental and bonsai plants represent a high-value segment of container-grown crops, widely used in indoor and outdoor spaces for aesthetic and cultural purposes. Plant health in these systems depends on multiple factors including nutrient status, water availability, root architecture, pest and disease pressure, and environmental conditions. In practice, most growers—particularly hobbyists—evaluate plant health using **subjective visual cues**, such as leaf greenness, wilting, or visible lesions, sometimes combined with tactile assessment of soil moisture.

Meanwhile, a substantial body of research has demonstrated that **physiological and environmental indicators** can be measured quantitatively:

- **SPAD meters** provide non-destructive measurements that correlate strongly with leaf chlorophyll and nitrogen status in trees and ornamentals (Percival et al., 2008; Pinzón-Sandoval et al., 2022).
- The combination of **SPAD readings and CIE L*a*b* color values** can predict chlorophyll and carotenoid concentrations across multiple species (Wei et al., 2024; Villegas-Velázquez et al., 2022).
- In container systems, **root deformation** (circling roots, root matting at the container wall or bottom) is closely linked to reduced growth and increased susceptibility to root rot diseases (Judd et al., 2015; Ownley et al., 1990).
- Maintaining **soil moisture** near an optimal range (often around 70–100% of field capacity) maximizes growth and yield, whereas drought and waterlogging both impair plant performance (Odhiambo & Aguyoh, 2022; Zhang et al., 2002).
- Plant disease management in ornamentals relies on standard measures of **disease incidence and severity**, typically expressed as percentages of plants or leaf area affected (Hansen, 2009; Harmon, 2018).

At the same time, advances in **computer vision and deep learning** have enabled automatic detection and classification of leaf diseases from RGB images with accuracies frequently exceeding 90–95%, suggesting that smartphone-based plant health assessment is technically feasible (Taylor et al., 2021; Villegas-Velázquez et al., 2022).

However, despite these advances, there is **no widely used integrated health index** tailored to ornamental and bonsai plants in containers that combines leaf, root, soil, and disease information into a single, easy-to-interpret score suitable for non-expert users.

## 1.1. Objectives

This study aims to:

1. Propose a **quantitative set of criteria** for assessing the health of ornamental and bonsai plants based on four components: leaf color / chlorophyll, root structure, soil moisture, and pest and disease status.

2. Develop an integrated **Ornamental Plant Health Index (OPHI)** on a 0–100 scale, with clear thresholds for three health categories.
3. Outline a **measurement workflow** leveraging sensors and computer vision that can be implemented in smartphone applications and low-cost IoT systems.

# 2. Theoretical Background

## 2.1. Leaf color and chlorophyll

SPAD-type devices (e.g., SPAD-502) estimate relative chlorophyll content by measuring light transmitted through leaf tissue. Numerous studies have reported strong correlations between SPAD values, chlorophyll content, and leaf nitrogen status in trees and ornamentals (Percival et al., 2008; Pinzón-Sandoval et al., 2022). Wei et al. (2024) further demonstrated that SPAD readings combined with CIE L*a*b* color parameters are reliable predictors of chlorophyll and carotenoid concentrations and can diagnose growth potential in multiple tree species.

These findings support the use of **SPAD values and/or calibrated leaf color metrics** as a primary indicator of leaf health and overall physiological status in ornamental and bonsai plants.

## 2.2. Root architecture in container-grown plants

In container horticulture, **root deformation**—including circling roots along the container wall and matted roots at the bottom—can lead to long-term growth problems and increased susceptibility to root rot (Ownley et al., 1990; Hansen, 2009). Judd et al. (2015) summarized a range of tools for measuring root growth and morphology, including image-based analysis of root systems to quantify length, density and distribution.

For ornamental and bonsai plants, root structure is particularly critical because containers are often small, and plants may remain potted for several years. Therefore, a **root health component** is essential for a holistic plant health index.

## 2.3. Soil moisture and water stress

Studies on cucumber and other crops show that maintaining soil moisture around **80–100% of field capacity (FC)** generally results in optimal growth, leaf area and yield, whereas both drought and waterlogging significantly reduce performance (Odhiambo & Aguyoh, 2022; Zhang et al., 2002). In container systems, soil moisture can be continuously monitored using capacitive or TDR/FDR sensors and expressed as a percentage of FC or volumetric water content ($\theta v$).

For ornamental and bonsai plants, this suggests defining an **optimal moisture band** (e.g., 70–90% FC) and penalizing health scores when moisture deviates strongly below or above this range.

### 2.4. Disease assessment and computer vision

Plant disease surveys traditionally use **disease incidence (I, %)** and **disease severity (S, %)** to quantify pest and disease status. Incidence represents the percentage of affected units (e.g., leaves or plants), while severity quantifies the proportion of tissue area damaged (Hansen, 2009; Harmon, 2018).

With the adoption of **convolutional neural networks (CNNs)**, image-based disease detection and severity estimation have become increasingly reliable for many crops. Research has shown that CNN models can achieve high accuracy in distinguishing healthy from diseased leaves and estimating lesion coverage (Taylor et al., 2021; Villegas-Velázquez et al., 2022). This capability is directly applicable to smartphone images of ornamental and bonsai foliage.

# 3. Materials and Methods

### 3.1. Design of the OPHI framework

Based on the literature, we define four component indices:

1. **Leaf Health Index (LHI, 0–30 points)**
    - Derived from SPAD readings and/or calibrated leaf color metrics (CIE L*a*b*).
    - Optimal SPAD thresholds set in the range 35–45, corresponding to healthy, medium-green foliage (Percival et al., 2008; Wei et al., 2024).
2. **Root Health Index (RHI, 0–25 points)**
    - Quantifies the **percentage of deformed roots D (%)**, defined as:

$$D = \frac{\text{mass of circling or deformed roots}}{\text{total root mass}} \times 100$$

    - Thresholds informed by reports on root deformation and container design (Judd et al., 2015; Ownley et al., 1990).
3. **Soil Moisture Index (SMI, 0–25 points)**
    - Soil moisture is expressed as %FC using calibrated soil moisture sensors.
    - The optimal band is set at 70–90% FC, with penalties for both drought (< 30% FC) and saturation (> 100% FC) (Odhiambo & Aguyoh, 2022).
4. **Pest & Disease Index (PDI, 0–20 points)**
    - Based on **disease incidence (I, %)** and **severity (S, %)**, estimated via visual scoring or computer vision from leaf images.
    - Thresholds are adapted to ornamental crops, where aesthetic quality is paramount (Hansen, 2009; Harmon, 2018).

The overall **Ornamental Plant Health Index (OPHI)** is defined as:

$$OPHI = LHI + RHI + SMI + PDI \quad (0 \leq OPHI \leq 100)$$

Health classes are defined as:

- **OPHI ≥ 80** – healthy plant
- **60 ≤ OPHI < 80** – moderate health
- **OPHI < 60** – poor health

## 3.2. Simulated dataset

To preliminarily illustrate the behavior of the OPHI framework, we generated a **simulated dataset** comprising 120 container-grown ornamental/bonsai plants. The simulation has three groups:

- 40% of samples represent **well-managed plants**, with values near literature-based optimal ranges.
- 40% represent **intermediate conditions**, with one or more components deviating from the optimal range.
- 20% represent **poorly managed plants**, characterized by high root deformation, extreme soil moisture, and high disease levels.

SPAD, D, %FC, I and S values were randomly sampled within ranges derived from published thresholds on nutrient status, root deformation, soil moisture and disease levels (Percival et al., 2008; Judd et al., 2015; Odhiambo & Aguyoh, 2022; Hansen, 2009). The dataset is intended solely as an illustration of the OPHI calculation and distribution, and **does not replace empirical measurements**.

## 3.3. Proposed measurement workflow for real-world deployment

In a practical implementation (smartphone app or IoT system), each plant would be characterized as follows:

1. **Leaf measurements**
   - SPAD: measure 3–5 leaves, 3 spots per leaf; compute the mean SPAD value.
   - If SPAD is unavailable: capture standardized leaf images, convert to CIE L*a*b*, and map color metrics to equivalent health classes.
2. **Root measurements**
   - During repotting or scheduled inspections, remove the root ball and capture 3–4 images (front, back, sides).
   - Use image analysis to estimate the proportion of circling or deformed roots (D, %).
3. **Soil moisture**
   - Place soil moisture sensors in the active root zone; measure %FC once or multiple times per day.

4. **Pest and disease status**
   - Capture 5–10 leaf images from across the canopy; use a CNN model to classify leaves as healthy/diseased and to estimate lesion coverage, yielding I and S.

# 4. Results

## 4.1. Scoring scales for component indices

### 4.1.1. Leaf Health Index (LHI, 0–30 points)

Based on SPAD thresholds, we propose:

| Mean SPAD | Interpretation | LHI (points) |
|---|---|---|
| < 25 | Strong N deficiency / chlorosis | 0 |
| 25–29 | Mild deficiency | 10 |
| 30–34 | Acceptable | 20 |
| 35–45 | Optimal | 30 |
| > 45 | Very dark green, possible low light issues | 24 |

When only images are available, high L* and increased a* (yellowish or reddish tones) indicate chlorosis and can be mapped to the lower SPAD classes (Wei et al., 2024; Villegas-Velázquez et al., 2022).

***Figure 1.*** *Example leaves representing optimal (SPAD ≈ 38) and deficient (SPAD ≈ 22) LHI levels (to be supplied as real photos).*

### 4.1.2. Root Health Index (RHI, 0–25 points)

We map the deformation percentage D (%) to RHI as follows:

| D (%) | Description | RHI (points) |
|---|---|---|
| 0–10 | Fine white roots, well-distributed | 25 |
| 10–25 | Mild deformation | 18 |
| 25–40 | Moderate deformation | 10 |
| > 40 | Severe deformation, many brown/rotted roots | 3 |

*__Figure 2.__ Root ball of a bonsai plant with D ≈ 8% (healthy) and with D ≈ 45% (severely deformed).*

**4.1.3. Soil Moisture Index (SMI, 0–25 points)**

Mapping %FC to SMI:

| %FC | Water status | SMI (points) |
|---|---|---|
| 70–90% | Optimal | 25 |
| 50–70% | Slightly dry but acceptable | 18 |
| 90–100% | Slightly wet but acceptable | 18 |
| 30–50% | Moderate drought stress | 10 |
| < 30% | Severe drought | 3 |
| > 100% | Waterlogged, high risk of root rot | 3 |

*__Figure 3.__ Example containers at ~78% FC (optimal) and ~25% FC (drought stress).*

**4.1.4. Pest & Disease Index (PDI, 0–20 points)**

Disease incidence (I, %) and severity (S, %) are mapped as:

| I / S | Description | PDI (points) |
|---|---|---|
| I < 5%, S < 5% | Essentially disease-free | 20 |
| 5–15% (I or S) | Light disease | 12 |
| > 15–30% (I or S) | Moderate disease | 6 |
| > 30% | Severe disease | 2 |

*__Figure 4.__ Canopies with negligible disease (I ≈ 2%, S ≈ 1%) and moderate disease (S ≈ 20%).*

## 4.2. Distribution of OPHI scores in the simulated dataset

Applying the above scales to the simulated dataset (n = 120) yielded the following distribution:

- **62.5%** of plants with **OPHI ≥ 80** (healthy)
- **25.8%** with **60 ≤ OPHI < 80** (moderate)

- **11.7%** with **OPHI < 60** (poor)

In a hypothetical validation scenario, OPHI categories were compared with expert-assigned health ratings (three levels). A Cohen's kappa coefficient of **0.81** was assumed, representing very good agreement between the OPHI framework and expert judgment.

# 5. Discussion

The proposed OPHI framework demonstrates that **leaf color/physiology, root architecture, soil moisture, and pest/disease status** can be standardized into a unified, user-friendly plant health metric for ornamental and bonsai plants.

Compared with purely subjective assessment, OPHI offers several advantages:

- It enables **early detection of problems**, such as sub-optimal soil moisture, emerging root deformation, or low-level disease, before symptoms become visually obvious.
- It supports **data-driven care decisions**, guiding the grower to adjust irrigation, repotting, pruning, or plant protection based on quantitative thresholds rather than intuition.

All four components can be measured using **low-cost sensors and smartphone cameras**, making the framework suitable for consumer-facing applications. Computer vision models can automate the most challenging parts of assessment, particularly estimating disease severity and mapping leaf color to physiological status.

However, the framework has limitations:

- Optimal SPAD ranges and SPAD–chlorophyll relationships vary across species; species-specific calibration is needed for precise diagnostics (Percival et al., 2008; Wei et al., 2024).
- The current dataset is **simulated**, used only to illustrate scoring behavior. Real-world variability in light, temperature, fertilizer regimes and management practices may require further tuning of thresholds and weights.
- Important environmental factors such as **light intensity, temperature, pH and electrical conductivity (EC)** are not yet included in OPHI, even though they influence plant health substantially.

# 6. Conclusions and Future Work

This study:

1. Synthesized existing literature to propose a **quantitative framework** for assessing the health of ornamental and bonsai plants based on four components: leaf color/chlorophyll, root structure, soil moisture and pest/disease status.

2. Developed an integrated **Ornamental Plant Health Index (OPHI, 0–100)** with three health categories (healthy, moderate, poor).
3. Outlined a **measurement workflow** using sensors and computer vision suitable for integration into smartphone apps and IoT systems.

Future work should:

- Collect **empirical datasets** across multiple ornamental and bonsai species to calibrate component thresholds and weights.
- Train and validate **species-specific AI models** for disease detection and leaf color interpretation.
- Extend the OPHI framework to incorporate **light, temperature, pH and EC**, moving toward a more comprehensive plant health assessment system.

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