Monitoring Iron Stress in Tomato Plants Through Bioimpedance and Machine-Learning-Enhanced Classification Based on Circuit Component Analysis

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***Abstract*—Insufficient availability of essential nutrients, such as iron, can impede plant growth, decrease crop productivity, and even lead to plant death. This is why it is crucial to employ proximal monitoring techniques to detect early signs of nutrient stress and prevent yield loss. In this study, we continuously monitored the stem impedance of eight tomato plants every hour for 38 days. This was done to observe the effects of iron stress by comparing these plants with those not under stress. The normalized impedance magnitude at 10 kHz reveals a noticeable divergence in the trend of impedance magnitude shortly after the removal of iron from the nutrient solution, clearly indicating the effect of iron stress on plant bioimpedance. Additionally, the Cole equivalent circuit model was employed to evaluate the electrical parameters of the impedance spectra. The fitting results exhibit an average root-mean-square error of 466.3 Ω. Statistical analysis of the extracted circuit parameters shows significant differences between iron-stressed and control plants. Based on this hypothesis, the extracted circuit components have been used to train the machine learning classification model with several algorithms, to demonstrate that the multilayer perceptron is the best performing model, yielding 98% accuracy and 91% and 89% precision in identifying early and late stress, respectively. This research demonstrates the effectiveness of bioimpedance measurements in tracking iron stress in plants. Our findings highlight the usefulness of impedance measurements for monitoring iron stress in plants and provide insights into the physiological responses of tomato plants to nutrient deprivation by observing changes in bioimpedance circuit parameters over time.**

***Index Terms*—Electrical impedance spectroscopy, neural network, nutrient deficiency, smart agriculture.**

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I. Introduction

Tomato (*Solanum lycopersicum*) is a globally important crop, boasting a production surpassing 170 million tons, as reported by the Food and Agriculture Organization. Around 40% of harvested tomatoes are utilized in food processing, with Italy playing a major role in this industry [1]. Being a model organism, tomato plants are highly regarded in the scientific community for their well-known advantageous traits. These include a compact, fully sequenced genome, a relatively short life cycle with straightforward cultivation methods, the feasibility of horticultural interventions, as well as the availability of a wide range of mutant lines, advanced genomics tools, and established protocols for conducting controlled environmental experiments with tomato plants [2].

Tomato plants are continuously interacting with their surrounding environment, which has both positive and negative influences, contributing to the plant stress with a wide spectrum of abiotic and biotic stressors. Here, one of the main causes of stress is nutrient starvation, to which the plants respond with a series of well-studied physiological changes such as reduced photosynthetic activity and inadequate chlorophyll production leading to a clear impact on leaf greenness [3]. Among the most important nutrients for the plants correct physiological functioning, iron (Fe) plays an important role. In fact, despite its abundance in the soil, it results in an already low availability for the plant due to its low solubility [4]. Iron is, indeed, an essential micronutrient for plants contributing to several vital processes, including chlorophyll development and function. When plants lack sufficient iron, they experience reduced photosynthetic activity, resulting in yellowing and interveinal chlorosis in young leaves [5], leading to yield losses of up to 30% [6]. Such visible symptoms typically manifest several days or weeks after iron deprivation begins, varying with crop species, but typically when the plant is already in a late stress stage [5]. For this reason, tools allowing a precise characterization of the plant nutrient levels and needs assume a crucial importance to early detect any stress and allow thus a timely intervention thereby leading to higher yields. In this context, different proximal monitoring methods have been described in the literature [7], with increasing