Evaluation of Machine Learning Models for Water Stress Detection Using Stem Impedance

# Evaluation of Machine Learning Models for Water Stress Detection Using Stem Impedance

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***Abstract*—Food security, producing enough food for every person on the planet, is becoming a significant issue. Increasing world population and climate change are setting new challenges to food production. Water stress can cause severe damage to crops, and detecting and preventing this threat is crucial. Smart agriculture and the use of sensors directly on the field is a promising and rapidly evolving solution. Data collected by a large number of sensors must be analyzed and efficiently interpreted. In this context, machine learning is an effective solution. This article conducts a comparative analysis of several well-established machine learning models, all trained on a dataset enriched with a novel parameter for the assessment of plant health, the stem electrical impedance (modulus and phase). This feature gives promising results since it is a direct parameter of the plant itself. Moreover, the inclusion of the stem impedance parameter significantly boosted the model's performance, notably enhancing the effectiveness, particularly evident in the case of the top-performing model in this study, the random forest algorithm. When incorporating stem electrical impedance, this model achieved an impressive F1 score of 98%, markedly surpassing the 88% obtained in its absence. As a complementary analysis, a permutation feature performance analysis was conducted, highlighting the potential of stem impedance modulus as a promising feature for evaluating plant watering conditions. The removal of impedance modulus from the training model resulted in an average classification performance loss of 25% in terms of F1 score, suggesting how impedance monitoring is a promising approach for plant health management.**

***Index Terms*—Machine learning, plants monitoring, smart agriculture, stem impedance.**

## I. Introduction

IN RECENT years, the agricultural sector has experienced a transformative shift, driven by advancements in technology that aim to optimize farming practices and enhance crop yield. Moreover, the problem of desertification, caused by ongoing global warming, is challenging the world's agriculture, and a revolution in farming technology is imperative to achieve global food security. The recent advancements in machine learning technology have led to significant progress in the development of smart agriculture across various aspects, such as crop management, livestock management, and water and soil management [1]. Machine learning models can now be utilized in smart agriculture, particularly in conjunction with image processing, to detect diseases or make irrigation decisions. For what concerns disease detection, in their work Kerkech et al. [2] exploited images collected by an uncrewed aerial vehicle (UAV) and deep learning to detect vine diseases. Oppenheim and Shani [3] employed the commonly used convolutional neural networks to detect different diseases in potatoes. Sethy et al. [4] exploited a well-known algorithm, the support vector machine (SVM) to recognize diseases in rice leaf images. Many research works in literature use environmental monitoring for decision-making and detection of problems; however, a direct monitoring of the plant can also be a valuable source of information for agricultural practices. Bettelli et al. [5] monitored directly tomato plants using a biologic transistor called "bioristor" and employed those measurements to detect and forecast water stress conditions. Another example of direct plant monitoring is outlined in [6], where plant electrophysiology is used. The study employs an XGBoost [7] model to discern various abiotic and biotic stress conditions affecting plants. This highlights the significance of direct plant-focused approaches in providing valuable insights for agricultural management. A novel method for direct plant monitoring is introduced by Garlando et al. in [8] and [9], employing the analysis of stem electrical impedance. This approach aims to comprehend the correlation between stem impedance and daily cycles, as well as irrigation conditions, enabling an effective assessment of the overall health status of tobacco plants but also the possibility to use plants as a communication channel [10]. Stem impedance emerges as an interesting research focus with demonstrated efficacy. Calvo et al. [11] employed an indirect measurement of stem impedance through a relaxation oscillator acting as a wearable sensor. This methodology exhibited impressive capabilities in detecting watering events, noteworthy for its utilization of a device constructed with low-cost sensors. In the study conducted by Barezzi et al. [12], neural networks (NN) were employed using various sets of features, emphasizing the significance of impedance in detecting water stress.

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Building upon this foundation, the current research utilizes stem impedance measurements in conjunction with environmental data to develop binary classifiers. These classifiers are adept at identifying water stress situations in tobacco plants, employing diverse sets of features and employing various machine learning models. In this current study, our objective is to expand upon the research introduced in [13] by incorporating a variety of widely adopted machine learning models, namely, SVM, decision tree (DT), random forest (RF), and NN. This extension involves the integration of both environmental data and impedance measurements. The primary aim is to assess the effectiveness of binary classifiers in identifying water stress conditions. In addition, we seek to highlight the significance of stem impedance as a crucial measurement for effective irrigation management.

A deeper analysis of different feature sets is presented, including the case with only three key features used: impedance modulus, phase, and soil moisture. Furthermore, an in-depth examination of different models' hyperparameters is presented, leading to more accurate insights useful for optimizing design choices for future research developments and end node devices based on stem electrical impedance measurements. In addition, the feature permutation importance method [14] is employed to further confirm the results obtained in [13].

Fig. 1. On the left: plant labeled as water ok. On the right: plant under water stress.

## II. Methodology

The initial stage of this research involves gathering data from plants, in particular, tobacco plants grown in an indoor greenhouse will be used. Subsequently, it is essential to preprocess the collected data, employing operations, such as standardization, normalization, and division into training and testing sets. This preprocessing ensures that the measurements are suitable as input to the learning algorithm and facilitates the evaluation of the quality of the models. Different machine learning models are used to build binary classifiers able to distinguish a situation in which a plant is under water stress or is in normal watering conditions. In this research, Python 3.9.15 along with SciKitLearn [15] machine learning framework is employed. The training process takes place on a laptop mounting an Intel Core i7-8750H 8th generation processor, NVIDIA GeForce GTX 1050 GPU, 16 GB of RAM, and Microsoft Windows 11 as the operating system.

### A. Data Collection and Labeling

Models' performance is evaluated by splitting the dataset using a fivefold cross-validation technique. Three binary classification metrics are calculated: precision, recall and F1 score. Data analyzed in this article are obtained using the setup described in [8]. Impedance modulus and phase measurements are performed using a Keysight 4294A bench analyzer [16] with a four-point probe technique. Impedance modulus and phase spectra range from $100\ \mathrm{Hz}$ to $1\ \mathrm{MHz}$. As described in [8], data at $10.145\ \mathrm{kHz}$ show the best tradeoff between sensitivity and noise. Therefore, only the impedance values at that specific frequency are used in the models. Environmental measurements (temperature, air humidity, soil water potential, and ambient light) and impedance value (modulus and phase) are sampled every hour; moreover, a plant picture is taken to allow visual inspection and subsequent labeling of plant status. Up to four plants can be connected and monitored by the system simultaneously. Plants must be subjected to different conditions to create a meaningful dataset: initially, each plant is kept regularly watered, and then, drought stress is induced by water deprivation. Pictures taken at each measurement are analyzed, and a label "water stress" is assigned to a sample where the plant shows signs of drought (such as low leaves turgidity) and a label "water ok" when there are no visible signs of water stress. Overall data are collected from 24 March 2021 to 28 July 2021 for 6306 samples in total. Fig. 1 illustrates instances of plant labeling, depicting common stress symptoms arising from water deprivation, such as yellowing leaves and diminished turgidity.

Following the labeling process, 3323 samples (52.7%) have been identified as instances of water stress, whereas the remaining 2983 samples (47.3%) are designated as water okay. This distribution renders the dataset well balanced, offering a representative portrayal of both classes.

Subsequently, a diverse set of established machine learning algorithms is employed to train binary classifiers with the objective of effectively discerning between scenarios depicting plants under hydric stress and those characterized by adequate water conditions.

### B. Data Processing

Before feeding any data to a learning algorithm, it is mandatory to perform data preprocessing to ensure a correct and efficient training procedure. In this article, the technique used for data preprocessing is *standardization*. It is a technique that ensures that the input samples are elaborated in such a way to have zero mean and unit variance, according to the following formula:

$$x_{\text{scaled,stand}} = \frac{x - \mu_x}{\sigma_x}. \tag{1}$$

### C. Evaluation Metrics and Machine Learning Models

In this study, the examined models consist of SVM, DT, RF, and NN. Performance assessment is carried out through a five-fold cross-validation methodology, where the dataset undergoes division into five folds. Sequentially, four folds are utilized as the training set, with the remaining fold serving as the test set. This cycle repeats five times, each time modifying the composition of portions designated for training and testing. The ultimate metrics employed to evaluate the models are the averaged values computed across all fold combinations. The evaluation metrics under consideration include precision, recall, and F1 score [17], [18]. Precision is a metric useful to evaluate the correctness of positive predictions of a model and can be evaluated as follows:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

where "TP" represents the number of true positives whereas "FP" indicates the total number of false positives.

Recall, on the other hand, is a measure of how many positive samples are correctly predicted by the model, and it is evaluated using the following expression:

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{3}$$

The final considered metric is F1-score, which is a combination of precision and recall, and it is a good and state-of-the-art measure of classification performance. It is particularly helpful when the considered dataset is not fully balanced between positive and negative instances, a situation in which other metrics, such as accuracy, may fail in giving a right indication of models' classification performance

$$F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}. \tag{4}$$

*1) Support Vector Machine:* This is the first considered model and it is a supervised machine learning technique applicable to both regression and classification tasks. Considering classification, SVM aims at dividing the input samples in classes by finding a suitable hyperplane and also maximizing the margin between it and the closest data points for each class (the so-called support vectors). When dealing with data that cannot be effectively separated by a hyperplane in its original form, the kernel trick becomes a valuable technique. This involves utilizing kernel functions to map the input data to a higher dimensional space, where features can be linearly separated. In the context of this research, two specific kernel functions will be employed: the linear kernel and the radial basis function (RBF) kernel [19]. Another fundamental parameter for an SVM is the regularization parameter C, which tunes the margin: a small C implies a larger margin, enhancing the potential for better generalization to unseen samples but exposes to a potential underfit of the input data. A big value of C reduces the margin, improving the capability of the model of dividing input data but leading also to the risk of overfitting the training data.

*2) Decision Tree:* A DT classifier is a machine learning model that works by recursively dividing the input data into classes based on the available features, leading to the prediction of a target variable. At the beginning of the iteration the algorithm chooses the feature that is able to more effectively split data into distinct groups; this feature will become the root node of the tree. The algorithm uses a splitting criterion to decide the best way to divide data at each node. The final goal is to have pure resulting subsets where there is only one prediction outcome for each subset. In the context of this article, two different splitting criteria are used: gini impurity and entropy. The data are split into subsets based on the chosen feature and its values. Each subset forms a branch or child node of the tree. This process is applied recursively to each subset and a tree structure is formed. The process continues until a certain condition is met, such as the depth of the tree, the minimum number of samples in a node, or a target purity.

*3) RF Classifier:* In machine learning, the combination of different models to enhance the algorithm performance is called ensemble. This technique, when applied to DT, results in the creation of the RF, which is an ensemble of DT in which their predictions are combined together. The algorithm starts by creating multiple subset of the training dataset by randomly selecting samples with replacement, creating different datasets with the same size. Then, for each subset, a DT is created using a random subset of the available features at each node. This randomness helps to ensure the diversity between the DT. In the context of classification, each tree in the RF predicts a class for a give input and then a majority voting is performed to get the final prediction dataset.

*4) Neural Network:* NN are a powerful and versatile class of machine learning models that revolutionized different fields, from image and speech recognition to natural language processing and decision-making systems. They are inspired by the structure of the human brain and can learn complex patterns and relationships from input data enabling the possibility to classify information.

NN consist of interconnected nodes, called neurons, organized into different layers.

The first layer, called input layer, receives the input data and each node in this layer represents a feature, or input variable. Between input and output layers, there may be one or more hidden layers. Each node in a hidden layer receives inputs from the nodes in the previous layers, multiplies them by weights, sums them up, and applies an activation function, useful to introduce nonlinearity hence providing to the network the capability to learn more complex decision boundaries. The weights in each layer are the parameters that the NN learns during the training process through the backpropagation algorithm.

### D. Grid Search

In this study, various machine learning models are trained utilizing both environmental features and impedance values. Each

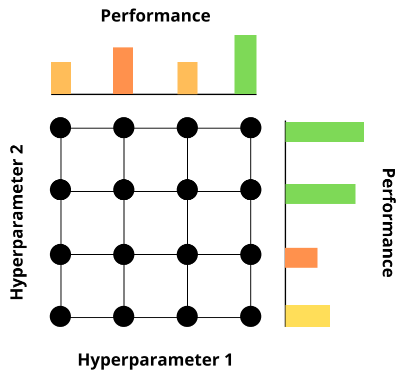


Fig. 2. Grid search process visual representation.

TABLE I
DIFFERENT FEATURE SETS

| Feature set name | Quantities |
|---|---|
| Set 0 | Impedance modulus($\Omega$), impedance phase($^\circ$), soil moisture(KPa), temperature($^\circ$C), air humidity(RH), ambient light(lux) |
| Set 1 | Impedance modulus($\Omega$), soil moisture(KPa), Temperature($^\circ$C), air humidity(RH), Ambient light(lux) |
| Set 2 | Impedance phase($^\circ$) soil moisture(KPa), Temperature($^\circ$C) air humidity(RH), Ambient light(lux) |
| Set 3 | Impedance modulus($\Omega$), impedance phase(deg), Soil moisture(KPa) |
| Set 4 | Soil moisture(KPa), temperature($^\circ$C), Air humidity(RH), Ambient light(lux) |

machine learning model is characterized by distinct hyperparameters that can significantly influence performance outcomes. To address this variability, we employ the grid search technique. For each model type, a range of models is trained, exploring various combinations of hyperparameters. A visual explanation of this process is presented in Fig. 2. Subsequently, the model demonstrating the highest performance is selected as the optimal choice. In this article, the F1 score is chosen to be the optimizing metric and the utility *GridSearchCV* [20] is utilized to efficiently combine a five fold cross-validation technique with the hyperparameter search. In addition to varying the hyperparameters, we explore different sets of features to assess their relevance. This exploration aims to identify configurations that achieve high classification accuracy while potentially reducing the number of input variables (sensors) required for the task. The different considered feature sets are reported in Table I.

### *E. Model Intepretability and Feature Importance*

To deepen our understanding of the models' behavior and evaluating the significance of each feature, we employed the permutation feature importance (PFI) technique [14] in the latter section of this article. Given the diverse nature of the compared models, we opted for this technique due to its model-agnostic characteristics and its ability to provide clear and intuitive results. The core concept of PFI is founded on shuffling a single feature's values within the dataset. This process effectively breaks the inherent relationship between the shuffled feature and the target variable. Subsequently, the model's predictions are evaluated on the data with the shuffled feature using an already fitted model. The core concept lies in comparing the model's performance, typically measured by a performance metric (in our case F1 score), before and after the feature shuffling. A significant drop in performance after shuffling a feature highlights its importance. Intuitively, this implies that the model heavily relied on the original, unshuffled feature for its predictions. By repeating this process for each feature and averaging the performance drops across multiple iterations, it is possible to obtain a relative importance score for each feature. Features that lead to higher performance degradation can be considered more relevant.

## III. RESULTS AND DISCUSSION

In this section, the results for the different learning algorithms are discussed.

### *A. SVM*

The analysis begins with exploring the SVM as the initial model. The key hyperparameters under consideration for optimization include the regularization parameter C and the selection of the kernel function. Within this study, we compare the performance of the linear kernel with the RBF to determine whether a linear kernel suffices or if a more complex kernel is essential for effectively capturing nonlinear relationships and improving the overall model performance. Simultaneously, we vary the value of the C parameter and evaluate the classification performance. Fig. 3 presents the F1 score of the classifier when varying the C parameter for both linear and RBF kernels.

Regarding the choice of the kernel function, it is evident that, in general, the linear kernel performs less effectively compared to the RBF kernel. This observation suggests that a nonlinear kernel function is more suitable for modeling the input data of the algorithm. Furthermore, in the case of the linear kernel, the algorithm demonstrates a weak dependence on the C parameter, exhibiting consistent performance across all tested C values (0.1, 0.5, 1, 3, 5, 10).

In the case of the RBF kernel, a more pronounced dependency on the regularization parameter C is evident, with higher C values corresponding to superior performance, peaking at C=10.

As we delve into different feature sets, Set 0 emerges as the most effective, obtaining an F1 score surpassing 90% for the RBF kernel function with C=10. This underlines the effectiveness of combining environmental and impedance values for assessing water stress. In Set 1, the removal of the impedance phase feature leads to a modest 2.5% performance decline. Conversely, in Set 2, retaining the impedance modulus results in a more substantial performance drop, indicating the greater relevance of the impedance modulus in evaluating water stress conditions compared to the phase.

Set 3, comprising only impedance features and soil moisture, achieves acceptable performance, even if numerous environmental sensors are not considered, with an F1 score around 82.5%. The last case, Set 4, where both impedance values (modulus and phase) are omitted, yields the poorest performance

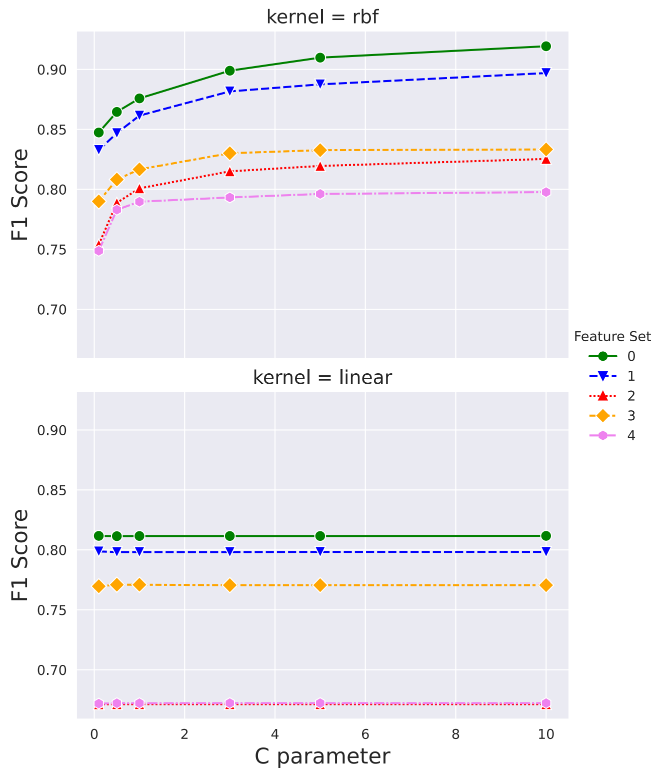


Fig. 3. SVM simulation results varying the regularization parameter C and the set of features.

among the considered scenarios, registering an F1 score of almost 80% for the RBF kernel. This underscores the key role of impedance features, alongside soil moisture, in effectively assessing water stress conditions in plants. Moreover, for the case of SVM, an RBF as kernel revealed to be a more suitable choice to achieve better water stress detection capabilities.

## *B. Decision Tree*

The second model under examination is the decision tree (DT). Within this analysis, we exclusively vary the hyperparameter associated with the splitting criterion, exploring different feature sets, as outlined in Table I. The outcomes are presented in Fig. 4. Notably, the DT model demonstrates superior performance compared to the previously explored SVM, consistently achieving notable results with F1 scores exceeding 88% across all considered feature sets.

Upon inspecting the histograms in Fig. 4, a noteworthy observation is the absence of significant variations in classification performance when altering the splitting criterion. In fact, the performance remains nearly constant for each pair of values considered separately.

When employing all the available features in Set 0, the achieved performance reaches an impressive F1 score of around 97%. A minimal performance decline is observed in Set 1, where the impedance phase is removed, suggesting the fact that it carries poor information about water stress conditions. In Set 2, removing the impedance modulus results in a more

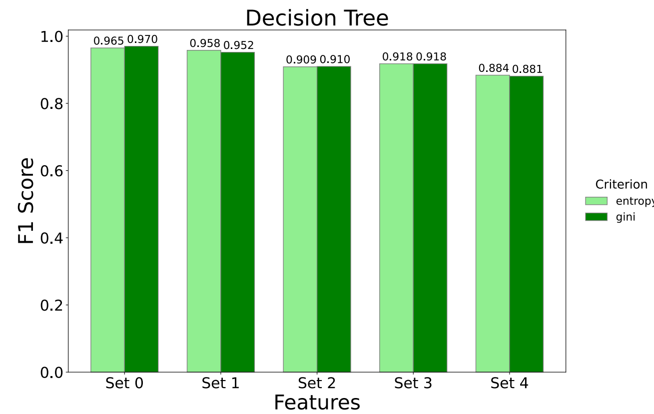


Fig. 4. DT results varying the splitting criterion for different set of features.

significant F1 score degradation of approximately 5% compared to the complete feature set, indicating the presence of valuable information within the impedance modulus as opposed to the impedance phase.

Set 3, involving only impedance values and soil moisture while excluding other environmental sensors, obtains a notable classification performance considering the limited number of sensors employed. The least favorable outcome for the DT classifier occurs in Set 4, where stem impedance is excluded, and only soil moisture and environmental sensors are considered. This underscores once again the pivotal role of impedance as an early indicator of impending water stress in plants.

## *C. Random Forest*

In this section, we assess the performance of the random forest (RF) classifier by varying the number of estimators in the model and exploring different sets of features introduced earlier. The visual representation of these results is presented in Fig. 5. The grid search involves varying the number of trees (estimators) in RF, ranging from 20 to 100, and considering different splitting criteria (gini or entropy). Similar to our observations with DT, since RF is an ensemble of DT, the classification performance remains relatively consistent across different splitting criteria. This is evident in the two graphs presented in Fig. 5, where minor differences exist between the upper and lower graphs. Notably, in both cases, the classification performance exceeds 90% in F1 score, with only slight variations observed when adjusting the number of estimators in RF. Considering the different feature sets, the Set 0 is the one performing better, with an excellent F1 score above 98%. The removal of the impedance phase smally affects the classification performance, reducing it by less than 1%. Sets numbers 2 and 3 show similar performance around 94% of F1 score; moreover, it is noticeable that set number 4 achieves this excellent performance considering only impedance and soil moisture. Interestingly, also in this case, the complete removal of impedance information from the features list caused the larger drop in performance, from 98% when all the features are employed, to 91%.

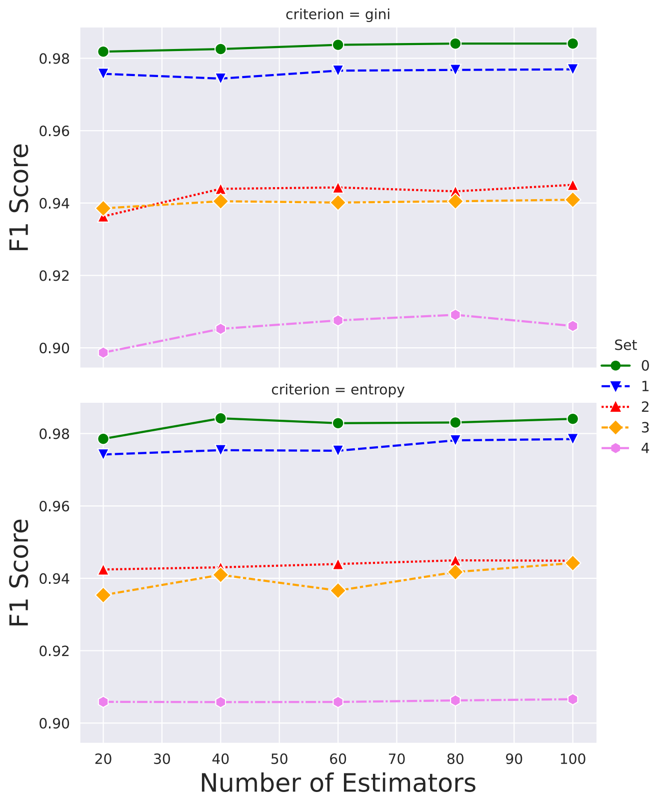


Fig. 5. RF algorithm results varying the number of estimators, splitting criterion and set of features.

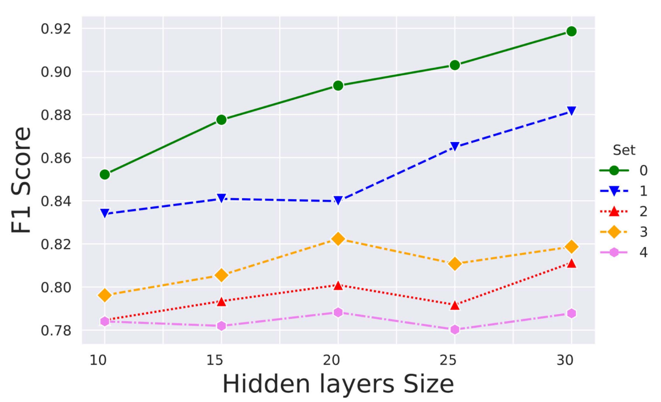


Fig. 6. NN results varying the number of neurons in each hidden layer and the set of input features.

TABLE II
TOP PERFORMING MODELS BY FEATURE AND TYPE

| Set | Model | Par. | Prec. | Rec. | F1 |
|---|---|---|---|---|---|
| 0 | SVM | C=10, rbf | 89.5 ±0.9 | 94.5 ±1.3 | 91.9 ±0.9 |
| 1 | SVM | C=10, rbf | 88.1 ±0.8 | 91.3 ±1.2 | 89.7 ±0.6 |
| 2 | SVM | C=10, rbf | 88.8 ±0.5 | 77.1 ±1.4 | 82.5 ±0.8 |
| 3 | SVM | C=10, rbf | 77.9 ±1.5 | 89.6 ±1.5 | 83.3 ±1.3 |
| 4 | SVM | C=10, rbf | 85.9 ±1.6 | 74.5 ±2.8 | 79.7 ±1.3 |
| 0 | DT | gini | 97.4 ±0.4 | 96.7 ±0.7 | 97.0 ±0.5 |
| 1 | DT | entropy | 95.9 ±0.6 | 95.6 ±1.1 | 95.8 ±0.6 |
| 2 | DT | gini | 90.9 ±1.0 | 91.2 ±1.1 | 91.0 ±0.9 |
| 3 | DT | entropy | 91.8 ±0.5 | 91.7 ±1.2 | 91.8 ±0.7 |
| 4 | DT | entropy | 88.6 ±1.2 | 88.1 ±1.7 | 88.4 ±1.2 |
| 0 | RF | entropy, N=40 | 98.6 ±0.2 | 98.2 ±0.4 | 98.4 ±0.1 |
| 1 | RF | entropy, N=100 | 98.2 ±0.3 | 97.5 ±0.5 | 97.8 ±0.2 |
| 2 | RF | gini, N=100 | 95.7 ±0.9 | 93.2 ±0.4 | 94.5 ±0.6 |
| 3 | RF | entropy, N=100 | 94.4±0.8 | 94.4 ±0.8 | 94.4 ±0.4 |
| 4 | RF | entropy, N=80 | 88.6 ±1.2 | 88.1 ±1.7 | 88.4 ±1.2 |
| 0 | NN | Neurons per hidden layer=30 | 91.4 ±2.9 | 92.3 ±3.9 | 91.8 ±3.3 |
| 1 | NN | Neurons per hidden layer=30 | 87.8 ±4.5 | 88.5 ±3.2 | 88.1 ±4.1 |
| 2 | NN | Neurons per hidden layer=20 | 86.4 ±4.8 | 76.5±3.6 | 81.1±2.1 |
| 3 | NN | Neurons per hidden layer=20 | 79.0 ±1.1 | 85.7 ±1.0 | 82.2 ±0.6 |
| 4 | NN | Neurons per hidden layer=30 | 84.5 ±1.6 | 73.9 ±2.5 | 78.8 ±1.1 |

## D. Neural Network

The final model under consideration is a simple feedforward NN. In this context, numerous hyperparameters need specification, and for this analysis, many were set to fixed values. Specifically, NN with two hidden layers, a rectified linear unit (ReLU) activation function, and a learning rate of 0.001 underwent training for 300 epochs with early stopping technique. The hyperparameter subject to tuning was the number of neurons in each hidden layer, ranging from 10 to 30 with increments of 5. The outcomes of this simulation are visually presented in the graph, as illustrated in Fig. 6. Upon evaluating various feature sets, it is evident that Set 0, comprising all available features, outperformed the others. The F1 score exhibits an increasing trend as the number of neurons per hidden layer increases, reaching an F1 score of 92% when employing two hidden layers with 30 neurons. Set number 1 exhibited a general performance decline with respect to set number 0 but a consistent trend of F1 score against the number of layers persists, reaching 88% when 30 neurons per hidden layer are used. Sets numbers 2–4 show a similar behavior reaching their top performance when 20 neurons are used.

Set number 3 stands out as particularly interesting, achieving an 82% F1 score when utilizing 20 neurons. This achievement is noteworthy as it exclusively relies on soil moisture measurements, with no other environmental factors taken into account. In contrast, the least favorable performances are observed in sets numbers 2 and 4.

Set number 2, specifically, exhibits a significant performance drop, recording the lowest F1 score of 81% when employing 30 neurons per hidden layer. Notably, this decline is attributed to the exclusion of only the impedance modulus from consideration suggesting the importance of this parameter. On the

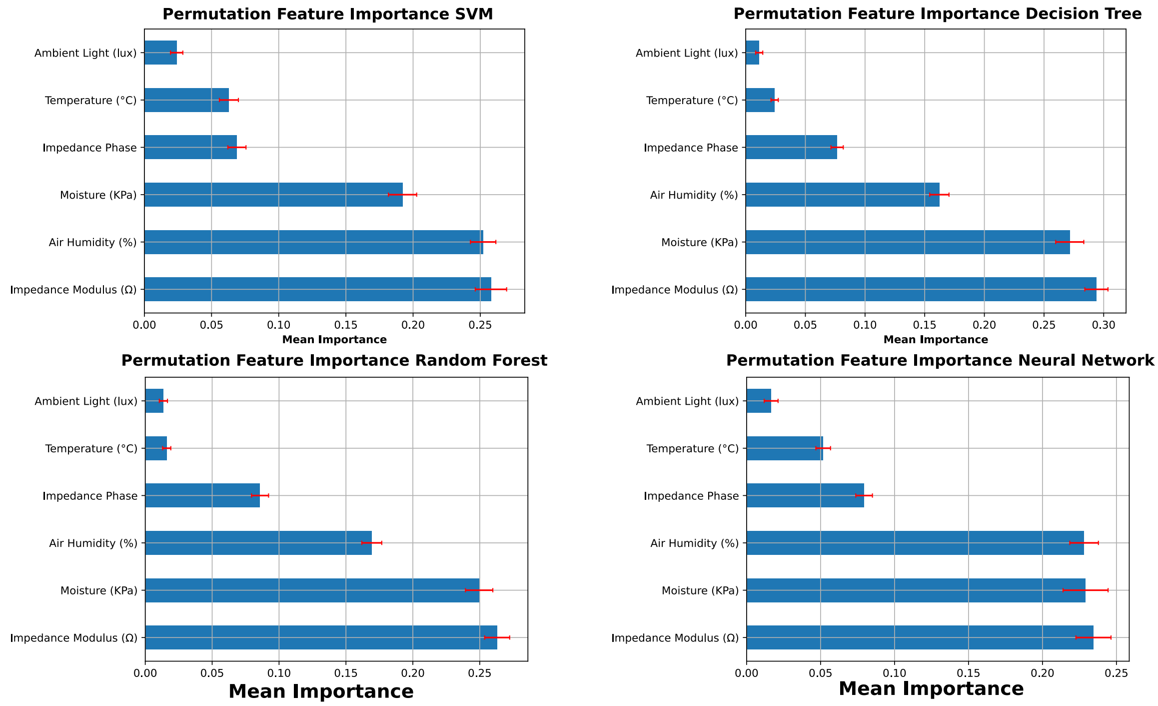


Fig. 7. Permutation feature importance for six variables (ambient light, temperature, impedance phase, air humidity, moisture, and impedance modulus) across four machine learning models: SVM, DT, RF, and NN.

other hand, set number 4, where no impedance features are considered, yields the overall lowest results. In the case of this NN configuration, the absence of these features severely impacts the model's classification capability, resulting in its poorest performance.

## *E. Models Comparison*

Various machine learning models were employed to detect water stress in tobacco plants, and the results are summarized in Table II. The table showcases precision, recall, and F1 scores for the best-performing model associated with each utilized feature set. Notably, the tree-like models, DT, and RF exhibited superior performance. Specifically, when all features were employed, the F1 scores for the DT and RF reached 97% and 98%, respectively. Similar high scores were consistently recorded for other feature sets.

SVM and NN delivered comparable results across all feature sets, yet their scores were consistently 5%–10% lower than those achieved by RF in various scenarios. It is noteworthy that notable classification performance was achieved with feature set 3, utilizing only impedance and soil moisture. Although not the top performer, this setup demonstrated the effectiveness of detecting water stress with a reduced sensor count, utilizing only three features, two of them resulted from a direct monitoring of the plant.

In addition, an interesting observation emerged when comparing feature sets with removed components. Set number 2, where impedance modulus was excluded, exhibited a greater performance loss compared to the case with all features, as opposed to set number 1, where impedance phase was omitted. This emphasizes the significant information contained in the impedance modulus compared to the phase.

Significantly, the feature set that consistently showed the lowest classification performance was set number 4, which excluded impedance information but included only soil moisture and environmental sensors. This underscores the importance of impedance measurements in effectively identifying water stress in plants.

As part of an extended analysis to underscore the significance of impedance features in determining the water condition of the plant, we employed the permutation feature importance technique. This method was applied to the top-performing models for each algorithm. Evaluating the importance of each feature aids in understanding their respective contributions to model predictions. It is imperative to apply the permutation importance technique to robust models, ensuring that the assessment of feature importance is reliable. Features that may appear insignificant in poorly performing models (as indicated by low cross-validation scores) might exhibit substantial importance in models with superior predictive capabilities. The findings of this analysis are presented in Fig. 7. The horizontal axis of the figure represents the average performance loss, measured by the mean F1 score reduction, when each feature is perturbed across multiple iterations (300). In addition, the red bars depicted on each bar indicate the standard deviation of performance loss associated with the respective feature across all training iterations. This approach not only enhances the understanding of feature importance but also ensures the validity and reliability of the insights gathered from the analysis. Observing Fig. 7, it is possible to notice how for all the employed models impedance modulus, soil moisture and air humidity revealed to be the most relevant features in the employed dataset. Soil moisture is notably important for the health condition of the plant, to provide water supply allowing the correct photosynthesis phase to the plant and nutrients uptake from the soil and this justifies the great importance of this feature for the employed classification models. Air humidity yielded on average above 15% of F1 score loss across all the analyzed models; this quantity is also notably relevant for plant health as it influences a wide range of physiological processes [21], [22]. Proper humidity levels help regulate water balance and transpiration rates, ensuring plants do not dehydrate. In addition, humidity helps moderate leaf temperature, preventing overheating. Maintaining optimal humidity reduces water stress, preventing wilting and promoting resilience against diseases. As mentioned above, stem impedance modulus proved to be a relevant feature in all the models considered in this article, resulting in an average F1 score decrease of 26%, 29%, 26%, and 24% for the SVM, DT, RF, and NN, respectively. This highlights the potential of stem impedance for drought stress detection. Moreover, as discussed in the previous sections, impedance phase was found to be less relevant in the context of drought stress, suggesting that it carries less information about water stress conditions.

## IV. Conclusion

In this study, we employed four distinct machine learning models to identify water stress conditions in tobacco plants. Our approach utilized diverse feature sets, comprising environmental measurements (such as soil moisture, temperature, relative air humidity, and ambient light) and impedance measurements (modulus and phase). While all models demonstrated strong classification results, the most effective performers were found to be RF and DT, followed by NN and SVM. The optimal classification performance was achieved when utilizing the entire feature set. However, promising results were also observed when restricting the feature set to only soil moisture and impedance. Notably, even without considering several environmental sensors, the combination of soil moisture and impedance proved effective. Furthermore, our analysis revealed that impedance modulus contained more informative insights than impedance phase for assessing water stress situations in tobacco plants, as evidenced by a performance drop when excluding impedance modulus. This study underscores the potential of integrating impedance measurements with environmental sensors to enhance the early detection of water drought in plants along with the use of modern machine learning techniques. Such insights can pave the way for optimized water usage strategies, ultimately leading to improved yields in agricultural settings.

Possible future research can explore more in depth the potential of stem electrical impedance as a robust indicator of plant health. Furthermore, while our current study primarily focused on assessing abiotic stressors, specifically drought, there exists the opportunity to expand our investigations to biotic stressors, such as bacterial or fungal infections. By leveraging stem electrical impedance as a diagnostic tool in detecting these biological threats, we can boost plant disease management strategies and enhance crop resilience. Moreover, given the relative simplicity of the analyzed models, future advancements could pave the way for the development of an autonomous, energy-efficient edge system capable of monitoring and making decisions about plant irrigation. Such a system would provide valuable support to farmers, enhancing irrigation efficiency and resource management.

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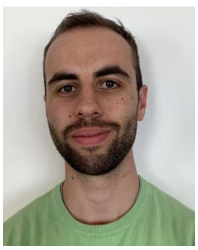

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