IoT-Driven Machine Learning for Precision Viticulture Optimization

Chiara Pero, *Member, IEEE*, Sambit Bakshi, *Senior Member, IEEE*, Michele Nappi, *Senior Member, IEEE*, and Genoveffa Tortora, *Senior Member, IEEE*

***Abstract*—Precision agriculture (PA), also known as smart farming, has emerged as an innovative solution to address contemporary challenges in agricultural sustainability. A particular sector within PA, precision viticulture (PV), is specifically tailored for vineyards. The advent of the Internet of Things (IoT) has facilitated the acquisition of higher resolution meteorological and soil data obtained through in situ sensing. The integration of machine learning (ML) with IoT-enabled farm machinery stands at the forefront of the forthcoming agricultural revolution. These data allow ML-based forecasting as an alternative to conventional approaches, providing agronomists with predictive tools essential for improved land productivity and crop quality. This study conducts a thorough examination of vineyards with a specific focus on three key aspects of PV: mitigating frost damage, analyzing soil moisture levels, and addressing grapevine diseases. In this context, several ML-based models are proposed in a real-world scenario involving a vineyard located in Southern Italy. The test results affirm the feasibility and efficacy of the ML models, demonstrating their potential to revolutionize vineyard management and contribute to sustainable agricultural practices.**

***Index Terms*—Artificial intelligence (AI), frost, grapevine diseases, Internet of Things (IoT), precision agriculture (PA), precision viticulture (PV), soil moisture.**

I. Introduction

In recent decades, modern agriculture has grappled with the need to balance the growing demand for high-quality food with the preservation of the environment and natural resources. A crucial step in this direction is represented by the adoption of new digital technologies, which serve as essential tools for addressing the challenges posed by this complex intersection of needs [1], [2]. The emergence of sensors and smart equipment has particularly revolutionized the agricultural sector, opening up new prospects for enhancing the sustainability of production processes and mitigating environmental impacts [3]. In this context, precision agriculture (PA) emerges as a fundamental pillar, offering innovative solutions to enhance agricultural production [4], [5], [6], [7]. PA aims to address the variability within cultivated fields with the goal of standardizing yields and maximizing overall efficiency [8]. This approach represents a synergistic integration of computer science and agronomic management, paving the way toward quality and sustainable production. The goal of PA is to become a decision-support tool for comprehensive and sustainable farm management [9]. Fig. 1 illustrates a typical PA scenario.

Within the realm of PA, precision viticulture (PV) is a specific application area in vineyards [10], [11]. Viticulture holds a significant position within both the agricultural and food industries due to its considerable economic impact. It stands out as one of the most extensively cultivated crops, spanning approximately 7.3 million hectares. This vast area is dedicated to cultivating various grape varieties, encompassing those specifically for wine production, table consumption, and raisin production. Addressing these challenges requires a profound recognition of the dynamic nature inherent in agricultural systems. This dynamism stems from substantial temporal and spatial variations in responses to various production factors. Consequently, implementing site-specific management strategies becomes essential. The progression of PV is intricately linked to technological advancements that have enabled tailored management practices for specific sites. Significant strides have been made in developing user-friendly software capable of handling spatial and geographic data. Furthermore, there has been a proliferation of remote sensing platforms boasting high spatial and temporal resolutions. The emergence of proximal sensors has further facilitated focused and continuous monitoring of crops within specific areas [12]. The objectives of PV encompass achieving finer control over crop yields, minimizing the occurrence and spread of grapevine diseases, and elevating the overall quality of produce. PV involves a cycle of activities that begins with the collection of accurate data related to vine cultivation, proceeds to the interpretation of such data, and culminates in the application of targeted agronomic techniques.

Incorporating wireless sensor networks and remote sensing technologies constitutes a crucial aspect of PA, leveraging the potential of data acquisition, analysis, global positioning systems, and the Internet of Things (IoT) for optimized solutions [13], [14], [15]. These methods enable remote monitoring

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Chiara Pero is with the Department of Management & Innovation Systems, University of Salerno, 84084 Fisciano, Italy (e-mail: cpero@unisa.it).

Sambit Bakshi is with the Department of Computer Science and Engineering, National Institute of Technology, Rourkela 769008, India (e-mail: bakshisambit@ieee.org).

Michele Nappi and Genoveffa Tortora are with the Department of Computer Science, University of Salerno, 84084 Fisciano, Italy (e-mail: mnappi@unisa.it; tortora@unisa.it).

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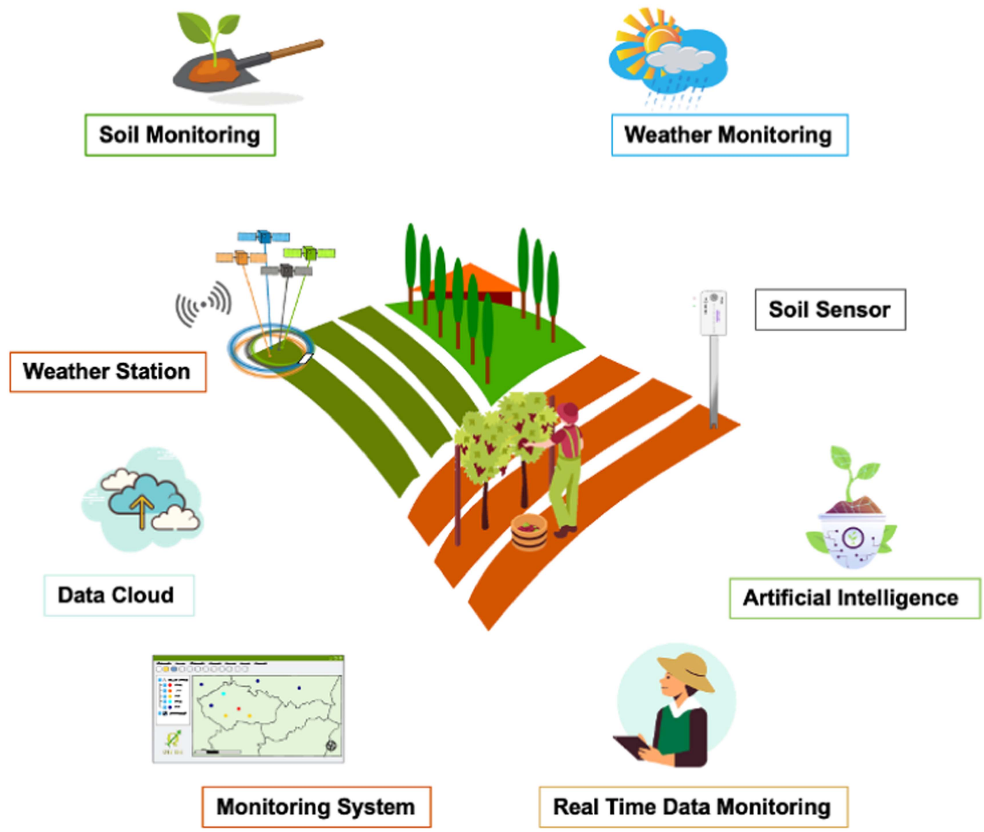

Fig. 1. PA ecosystem.

of production processes, providing a wide range of real-time information about the surrounding environment. The variety of available sensors is remarkable, ranging from measuring basic parameters, such as temperature and humidity, to more sophisticated elements, such as images, acoustic data, and microradars, among others. Variables, such as temperature, atmospheric humidity, and soil conditions, are aspects that PV particularly focuses on. This approach plays a central role in frost prevention thanks to continuous climate monitoring that allows for the anticipation of potential critical situations. At the same time, soil moisture analysis is fundamental to optimizing irrigation systems, enabling the delivery of the right amount of water in the most targeted manner possible. Another significant challenge is the prevention of grapevine diseases, where climatic factors exert a significant influence on the development of plant pathologies. As a result, anticipating the conditions of the vineyard and constant monitoring of every part of it are concrete tools to prevent the onset of pest infestations, or at least to intervene in the early stages [16].

In the abovementioned context, a significant point concerns the application of artificial intelligence (AI) [17], [18], [19]. The ability demonstrated by machine learning (ML) to solve a wide range of challenges, regardless of the context, has highlighted it as one of the most significant and promising research fields. When the problem can be adequately formulated as input, ML algorithms exhibit surprising flexibility in recognizing underlying rules and hidden connections among the provided information. This range of applications spans from categorizing data into specific classes (classification) to predicting numerical values (regression). Recently, even in the viticulture sector, the use of ML methodologies to address various challenges has been observed [20], [21], [22]. In many parts of the world, traditional farmers have historically relied on the experience and wisdom of industry professionals to make operational decisions. However, this method exposed them to the uncertainty of weather conditions, which have become increasingly unstable due to climate changes and variations in precipitation. Manual and indiscriminate pesticide use, for example, led to resource waste and environmental damage. The introduction of AI and IoT in agriculture has ushered in a new paradigm, eliminating the random factor. This new era provides farmers with tools to optimize every phase of the process, surpassing the randomness of a tradition-based approach. This lays the groundwork for more informed and targeted decisions.

Based on these premises, this study explores the use of a series of regression models capable of learning from historical data collected from weather stations. These datasets include various parameters, such as air temperature, relative humidity, wind speed, precipitation, and solar radiation. Information from time-domain reflectometry (TDR) probes, such as soil temperature and moisture, is also considered. The main goal is to generate valuable information and data to equip agronomists with predictive tools aimed at enhancing land yield and product quality. Therefore, the main contributions can be summarized as follows.

1) Mitigating potential frost damage by accurately predicting the minimum temperatures for the following day.
2) Optimizing irrigation scheduling through soil moisture forecasts, ensuring the efficient utilization of water resources for the highest crop yield.
3) Proactive grape disease management by developing a classification model that forecasts the onset of key factors contributing to the spread of major pathogens, including downy mildew and powdery mildew. This prediction considers current weather conditions.

The rest of this article is organized as follows. Section II provides a comprehensive review of the related literature, and Section III outlines the test vineyard area along with a comprehensive overview of the available data. Section IV details the experimental protocol employed for each forecasting module. Section V presents and analyzes the results obtained. Section VI critically examines the current limitations of this study, providing a foundation for future research directions. Finally, Section VII concludes this article.

II. Literature Review

This section provides an overview of the technologies and concepts relevant to frost prediction and protection systems. The concepts of soil moisture forecasting for smart irrigation (SI), along with an examination of current algorithms for predicting diseases in vineyards, are also discussed.

A. Frost Prediction

The crop damage caused by frost constitutes a significant economic challenge for farmers globally. In the viticulture industry, frosts introduce a significant threat, capable of causing extensive damage to wine production across expansive regions or entire territories in a single occurrence. Such damage can have adverse and long-lasting effects on plant growth and yields for multiple growing seasons. The severity of the damage is contingent upon the lowest temperature recorded and the duration of exposure to critical temperature thresholds. During winter, dormant plant buds can withstand temperatures as low as $-10°C$ (down to $-20°C$), but in spring, they can sustain damage even at temperatures slightly below $0°C$. Numerous studies have drawn attention to the role of climate change in altering the growth patterns of various plant species. For example, grapevines are exhibiting a propensity toward earlier spring budbreak due to milder winter temperatures. Common strategies to address frost-related issues include the use of wind turbines, fuel combustion, and heating enclosed environments, such as greenhouses. However, these methods come with a significant cost in terms of installation and management, potentially eroding the grower's profits. In addition, to avoid unnecessary expenses, it is essential for farmers to accurately recognize when a frost episode poses an actual threat. In this context, access to precise meteorological data and frost risk forecasts assumes an invaluable role [23].

Predicting the next day's minimum temperature based on key indicators, such as solar radiation, dew point, wind, rainfall, and humidity, could help mitigate frost damage [24]. However, it should be emphasized that climate prediction is a complex process due to its numerous dynamic and chaotic variables. Addressing this complexity requires the use of advanced computer models, field observations, and an understanding of meteorological patterns-aspects that have garnered the attention of researchers from a wide range of scientific disciplines [25], [26]. Most research regarding frost prediction relies on simulating partial differential equations or conventional statistical models to anticipate weather conditions. These methods are computationally intensive and necessitate constant theoretical refinement to incorporate meteorological and atmospheric assumptions. The use of ML models is now widely adopted for detecting frost episodes, as well as being applied in various other meteorological fields [27]. Employing ML techniques trained on specific data from a given area has enabled the creation of tailored models for local situations. In contexts, where factors, such as terrain complexity or other elements, could compromise the accuracy of existing meteorological models, these approaches prove particularly valuable. Previous studies have achieved encouraging results in complex scenarios, and further research has highlighted how integrating data from nearby weather stations can further improve the models' predictive capabilities. However, adopting such algorithms poses some challenges. For instance, variable local frost-related conditions make it difficult to obtain detailed information from weather stations. Furthermore, to obtain effective results, data must be collected over an extended period of time (greater than 7 years). In addition, the paucity of specific data on frost events makes modeling a challenging task. All these considerations have led to preferring the use of temperature regression-based models rather than those based on frost classification (frost/no frost) [28].

B. Soil Moisture Prediction

Soil moisture content plays a fundamental role in regulating water balances and ecological processes in various ecosystems [29]. These processes encompass phenomena, such as evaporation, transpiration, biological diversity, and rainfall runoff. Within the viticulture industry, soil moisture levels hold crucial importance in preventing water stress situations for crops and in monitoring drought conditions [16]. Insufficient moisture can impede plant growth, reduce production, intensify sugar content, and lead to an acidity deficiency in wines. Conversely, excessive moisture adversely affects grape growth, yield, and quality, heightening susceptibility to winter damage and diseases. Therefore, prudent irrigation management is essential for achieving high-quality grapes, underscoring the significance of continuous soil moisture monitoring and understanding the spatial and temporal patterns that underlie predictions.

In the past, onsite detection technologies were both expensive and unreliable. Consequently, this prompted the adoption of indirect methods, which estimated water consumption by considering plant evaporation and transpiration, with precipitation as the primary water source. However, with the emergence of the IoT, the era of SI began, allowing for more precise direct measurements and automated monitoring. SI systems utilize wireless sensor networks to precisely control irrigation operations. This emerging field employs data-intensive methodologies

Fig. 2. Example of powdery mildew (left-hand side) and downy mildew (right-hand side) infection.

to enhance agricultural productivity while simultaneously mitigating environmental impacts. Leveraging a variety of sensors, contemporary agricultural practices collect large amounts of data, providing meaningful information in operational contexts. As a result, this promotes more accurate and precise decision-making. Through the application of SI strategies in response to real-time soil and weather conditions, farmers can efficiently meet their water needs while preserving water consumption for the irrigation process [30]. SI has demonstrated its capacity to enhance water utilization, decrease energy consumption, and increase crop yield [31], [32]. These advancements have revolutionized the process of soil moisture monitoring and prediction, offering a viable alternative to indirect methods reliant on water balance. Moreover, given the various data sources available, the application of ML has emerged as a promising approach for soil moisture prediction [33], [34], [35], [36]. Over the years, various studies have compared conventional methodologies with ML techniques, including linear regression (LR), support vector machines (SVM), random forests (RF), and adaptive neuro-fuzzy inference systems. Despite the variances in applications across different investigations, accounting for factors, such as input data, locations, and specific crop types, the results presented in Section V align cohesively with the existing literature.

C. Grapevine Diseases Prediction

Downy mildew and powdery mildew represent the main microbial diseases that devastatingly affect grapevines (see Fig. 2). *Plasmopara viticola* is the pathogenic agent responsible for downy mildew in grapevines. This microorganism, native to the United States, causes a reduction in the photosynthetic efficiency of the affected green tissues, contributing to early leaf drop. At the same time, *Uncinula necator*, responsible for powdery mildew, also originates from North America and affects green tissues, including the berries, causing significant losses in yield and a decrease in the wine quality [37]. In Italy, the effects of downy mildew are becoming increasingly severe. Due to heavy spring rains that are affecting several Italian regions, the Italian Wine Union Observatory has anticipated losses in some areas of up to 40% in the upcoming imminent grape harvest season. According to [38], these infections can destroy 40% –90% of plants in the field at optimal humidity and temperature.

Downy mildew and powdery mildew can manifest severe symptoms in grapevines in the early stages of infection, prompting farmers to resort to fungicide treatments. However, concerns regarding the negative impacts of chemicals on the environment and human health have led to the implementation of restrictions to regulate the use of such fungicides. Weather conditions emerge as one of the main threats capable of triggering diseases in crops [39]. Adverse climatic conditions, such as frequent precipitation and high humidity levels, increase the risk of fungal disease development. In Table I, a summary of the main factors favoring the growth and spread of P. viticola and U. necator diseases in grapevines is provided, with particular attention to climatic conditions and the time interval necessary for the onset of infection. Therefore, continuous monitoring of weather conditions is of fundamental importance in detecting indicative signs of potential infections. In response to these challenges, various models, both empirical and based on climatic parameters, have been developed to predict grapevine diseases and assist farmers in making decisions regarding crop protection [40].

Expanding computing capacity is revolutionizing data collection and processing. By employing ML techniques, it becomes possible to investigate a wide range of factors, integrating different real-time data sources to evaluate interactions among the pathogen, host plant, and climatic variables, often before any visible signs of disease emerge [41], [42], [43], [44]. This in-depth analysis aims to guarantee the efficient and sustainable management of fungicidal treatments. Nevertheless, the efficacy of statistical models and ML algorithms in forecasting the onset of grapevine diseases has received limited attention in the current literature.

III. Materials and Methods

A. Data Acquisition and Overview

The test vineyard is located within the Taurasi DOCG area, in the province of Avellino (Campania, Italy), specifically in the municipality of Montemiletto, at the Donna Elvira Estate (Latitude: 41.0118, Longitude: 14.9323, Elevation: 328 m). The dataset employed in this research is categorized into two primary categories: meteorological data and soil moisture data. Data were collected over a span of approximately 2 years, from 2021 to 2023, with a frequency of 5 min. The professional Davis Vantage Pro2 Plus wired weather station is responsible for the collection of meteorological data, including key parameters, such as air temperature, air humidity, dew point, wind speed and direction, precipitation, and solar radiation. Three TDR probes (Acclima TDR-315H model) have been positioned at varying depths of 30, 60, and 90 cm, enabling precise data acquisition (soil temperature and moisture) at multiple levels. WeatherLink serves as the specialized software for managing data from Davis weather stations. One of WeatherLink's notable features is its capacity to present meteorological variables in standardized formats, facilitating data interpretation and thereby simplifying the comparison and analysis of information.

B. Data Processing

During the preprocessing phase, the data were grouped into daily 24-h intervals. Subsequently, it was necessary to perform certain statistical operations, including calculating the mean, maximum, and/or minimum of the climatic variables, along with

TABLE I
OVERVIEW OF THE KEY ELEMENTS THAT FAVOR THE PROLIFERATION AND DISPERSION OF P. VITICOLA AND U. NECATOR DISEASES IN GRAPEVINES, ALONG WITH THE TIMING OF INFECTION [37]

Grape disease	Precipitation (mm)	Temperature (°C)	Humidity (%)	Wind speed (km/h)	Time to Infection (Days)
Downy mildew	6–10	6–26	>90%	>9.0	7–18
Powdery mildew	2–10	15–25	>40%	>2.3	5–7

TABLE II
VARIABLES USED AS INPUT FEATURES IN ML MODELS FOR FROST PREDICTION

Variables	Abbreviation	Temporary aggregation
Temperature, °C	TAVG	Daily mean
Solar radiation, W/m^2	RAD14	Only 14:00 h
Dew point, °C	DP23	Only 23:00 h
Humidity, %	H23	Only 23:00 h
Wind speed, km/h	WSAVG	Daily mean
Wind run, km	WRAVG	Daily mean
Precipitation, mm	RSUM	Accumulated daily

TABLE III
VARIABLES USED AS INPUT FEATURES IN ML MODELS FOR SOIL MOISTURE PREDICTION

Variables	Abbreviation	Temporary aggregation
Temperature, °C	TAVG	Daily mean
Precipitation, mm	RSUM	Accumulated daily
Humidity, %	HAVG	Daily mean
Soil temperature, °C	STAVG	Overall daily mean averaged over three TDR probes
Soil moisture, %	SMAVG	Overall daily mean averaged over three TDR probes

TABLE IV
VARIABLES USED AS INPUT FEATURES IN ML MODELS FOR GRAPEVINE DISEASE PREDICTION

Variables	Abbreviation	Temporary aggregation
Temperature, °C	TMAX	Daily max
Solar radiation, W/m^2	RADMAX	Daily max
Wind speed, km/h	WSMAX	Daily max
Humidity, %	HMAX	Daily max
Precipitation, mm	RSUM	Accumulated daily

determining the total daily precipitation by summing the daily values. The soil moisture content was also adjusted to its daily average. In terms of data cleaning, NaN values were introduced to replace missing values, and outliers were removed. Additional details can be found in the following sections.

1) Frost Forecast: Due to the significant variability in minimum hourly temperature and the common practice of developing frost mitigation strategies in viticulture on a daily scale, a rolling 24-h window was introduced to forecast the minimum temperature for the next day. The meteorological variables included are temperature (°C), humidity (%), dew point (°C), solar radiation (W/m^2), wind speed (km/h), wind run (km), and precipitation (mm). Table II provides the complete list of parameters. The input data for each of the ML models are structured into an array featuring eight distinct columns. The first column indicates the daily mean temperature (TAVG), followed by parameters, such as solar radiation at 14:00 h (RAD14), dew point and humidity at 23:00 h (DP23 and H23, respectively), daily averages of wind speed and wind run (WSAVG and WRAVG), along with the accumulated daily precipitation (RSUM). Finally, the last column contains the minimum air temperature for the next day (TMIN). The rows of each array correspond to the daily temporal evolution from 2021 to 2023.

2) Soil Moisture Forecast: For effective predictive irrigation scheduling, a one-day-ahead (D + 1) forecast of soil moisture is essential [29]. In this context, the involved variables encompass the daily mean temperature (TAVG), accumulated daily precipitation (RSUM), daily average humidity (HAVG), the daily average of each sensor in relation to soil temperature and soil moisture (STAVG and SMAVG, respectively), and finally, the overall daily average for soil moisture of the next day. The parameters' details are presented in Table III.

3) Grapevine Diseases Forecast: Grapevine disease prediction plays a crucial role in promoting sustainable vineyard cultivation and the production of high-quality grapes. In the proposed model, data collected from sensors serve as input for ML algorithms, while the presence (or absence) of conditions that favor grapevine diseases acts as the target variable. Consequently, in the preprocessing phase of the time series, it was necessary to label the database. This process led to the creation of three columns, each with 24-h sliding windows, including meteorological factors contributing to the development of grape diseases, namely, precipitation, temperature, humidity, and wind speed. In accordance with the conditions outlined in Table I, two additional columns are introduced: "*DownyMildew*" and "*PowderyMildew*," respectively. The assigned value in these columns is 1 when the initial infection conditions are met; otherwise, it is 0. Variables involved include the highest daily temperature (TMAX), maximum solar radiation (RADMAX), highest wind speed (WSMAX), maximum humidity (HMAX), and cumulative daily precipitation (RSUM). For further details, refer to Table IV.

During database labeling, it is important to analyze the imbalance between the two classes. This imbalance can significantly impede model accuracy, increasing the chances of misclassifying an instance as part of the majority class. To mitigate this issue, utilizing data oversampling techniques, such as SMOTE [45], is fundamental, as it balances class distributions by oversampling minority-class data. This approach results in a significant enhancement of ML models performance, allowing them to adeptly handle the minority class with precision and dependability.

IV. EXPERIMENTAL SETUP

The experiments were conducted utilizing the free version of the PyCharm integrated development environment software on a MacBook Pro 2.6 GHz Intel Core i7 6 Core, 16 GB, 2667 MHz DDR4 Intel UHD Graphics 630, 1536 MB, with Python 3.7.6. The algorithms employed for model training were sourced from the scikit-learn repository, a Python module equipped with useful functions for ML. During the experimental phase, several well-known ML algorithms were applied to address regression and classification tasks. For regression, the algorithms included LR, RF regressor, XGBoost (XGB), support vector regression (SVR), and multilayer perceptron (MLP) regressor. In the domain of binary classification, the models considered were RF, SVM, and XGB. To enhance performance, the grid-search tuning technique was employed to identify the most effective hyperparameters for the considered models. For each database, a random dataset split was performed, allocating 80% for training and reserving the remaining 20% for constructing the test set.

A. Evaluation Metrics

To assess the performance of regression models, four performance measures are utilized, including the mean absolute error (MAE), root mean squared error (RMSE), mean squared deviation (MSE), and the coefficient of determination (R-squared, R^2), according to the following equations:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \tag{4}$$

In the given formulas, $\hat{y}_i$ denotes the forecasted value, y_i stands for the actual value, and $\bar{y}$ represents the mean of the observed value. The MAE evaluates the average of absolute prediction discrepancies, where lower values indicate superior model performance. The MSE measures the mean squared errors. Its square root, known as the RMSE, is particularly sensitive to outliers. A lower RMSE implies higher model accuracy. R^2 quantifies the proportion of total data variability attributable to the model. Values close to 1 suggest that the model adeptly accounts for observed data variations.

When dealing with classification tasks, the results are classified into four distinct groups: true positives (TP), true negatives (TN), false negatives (FN), and false positives (FP). Accordingly, each algorithm's performance was evaluated using different metrics, specifically accuracy, precision, recall, and F1-score. These metrics are defined mathematically as

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{5}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{6}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{7}$$

$$\text{F1-score} = \frac{2 \cdot \mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}. \tag{8}$$

TABLE V
ONE-DAY-AHEAD FORECAST MINIMUM TEMPERATURE: ML ALGORITHMS RESULTS

ML algorithms	MAE	MSE	RMSE	R^2
LR	**1.34**	**2.65**	**1.63**	**0.93**
RF	1.28	2.64	1.63	0.93
XGB	1.46	3.33	1.83	0.91
SVR	1.34	2.69	1.64	0.92
MLP	1.38	2.95	1.72	0.92

The bold values indicate the best results (in particular, for the Linear Regression model).

TABLE VI
ONE-DAY-AHEAD FORECAST MINIMUM TEMPERATURE: COMPARISONS OF ACTUAL AND PREDICTED VALUES—LR

Actual min. temperature	Predicted min. temperature
14.6	11.30
3.1	4.15
11.2	13.54
18.1	17.74
17.2	14.76
0.8	2.88

Accuracy quantifies the percentage of correct predictions among the entire prediction set. Precision evaluates the percentage of correctly predicted positive outcomes relative to all predicted positives. Recall computes the percentage of correctly predicted positive outcomes in comparison to the total instances within that class. The F1-score considers both precision and recall, enabling an analysis of FP and FN values.

V. RESULTS AND DISCUSSION

A. Results for Regression Problem

Frost: Table V provides the one-day-ahead forecast results for the minimum temperature. It can be observed that for all configurations, both MAE and RMSE are lower, at 1.28 °C and 1.72 °C, respectively. These values are clearly inconsequential when compared with the current thermal variability. Specifically, during the test phase, the LR and RF regression models yielded the most promising outcomes. The R^2 values indicate strong correlations between the models and observations (0.91–0.93), underscoring the effectiveness of the algorithms employed in capturing the variability of the minimum temperature. Importantly, the LR model excels in performance relative to more intricate algorithms, offering a distinct advantage in terms of model interpretability. Fig. 3 illustrates the prediction error plot, allowing for a visual comparison between the model's projected outcomes and the actual results; the closer the data points align with the regression line, the more accurate the model proves to be. Finally, Fig. 4 shows the LR model prediction results, while Table VI reports some forecasted minimum temperature values compared with the actual ones.

Table VII provides the evaluation metrics obtained from employing the LR model across different forecast lead-days. The D + 2 prediction horizon yielded a temperature forecast with an RMSE of 2.22°C, whereas the D + 3 time horizon produced an RMSE of 2.82°C. As expected, the model's performance

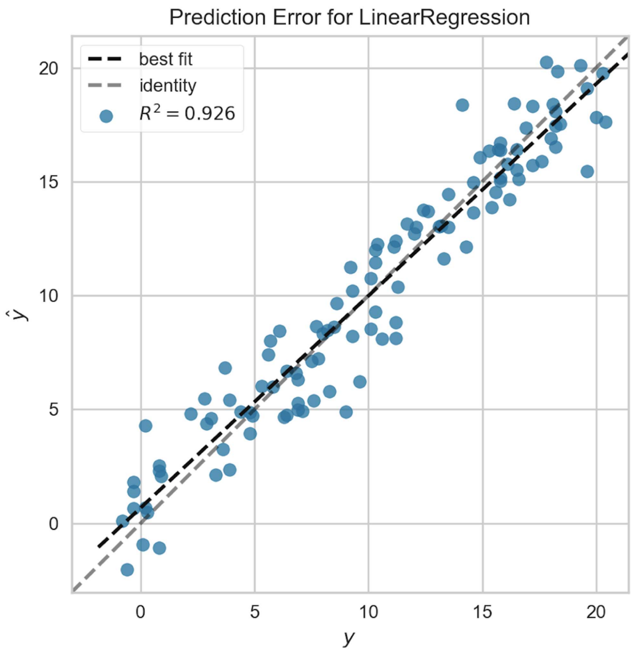

Fig. 3. One-day-ahead minimum temperature: Prediction error plot.

TABLE VII
MINIMUM TEMPERATURE: LR MODEL PREDICTION AT VARIOUS LEAD-DAYS

Time horizon	MAE	MSE	RMSE	R^2
D+2	1.78	4.92	2.22	0.85
D+3	2.4	7.93	2.82	0.77

TABLE VIII
ONE-DAY-AHEAD FORECAST SOIL MOISTURE: ML ALGORITHMS RESULTS

ML algorithms	MAE	MSE	RMSE	R^2
LR	0.4	0.74	0.86	0.98
RF	0.5	1.06	1.03	0.97
XGB	0.57	0.87	0.93	0.98
SVR	0.41	0.67	0.82	0.98
MLP	**0.39**	**0.65**	**0.81**	**0.98**

The bold values indicate the best results (in particular, for the Linear Regression model).

TABLE IX
ONE-DAY-AHEAD FORECAST SOIL MOISTURE: COMPARISONS OF ACTUAL AND PREDICTED VALUES—LR

Actual soil moisture	Predicted soil moisture
36.79	36.84
41.23	41.46
26.75	26.78
43.71	41.90
26.01	26.05
30.10	29.87

TABLE X
SOIL MOISTURE: LR MODEL PREDICTION AT VARIOUS LEAD-DAYS

Time horizon	MAE	MSE	RMSE	R^2
D+3	0.83	1.63	1.28	0.96
D+7	1.41	3.8	1.95	0.90

worsened as the prediction lead-time increased. When dealing with longer forecasting periods for minimum temperature, encountering a low R^2 value is not unusual. This can be attributed to multiple factors, including variability in weather patterns, the impact of seasonal shifts, and the potential for unforeseen events. Although the model may not explain as much of the variation, it can still provide valuable insights for planning and preparation.

The RF regression model assesses *feature importance* to identify the key parameters contributing to the frost forecast model's accuracy. Results reveal that predicting minimum temperatures greatly depends on the dew point (0.8), which represents the temperature at which air reaches saturation and water vapor condenses. When the minimum temperature aligns closely with or matches the dew point, it indicates nearing air saturation, paving the way for dew or fog formation. Hence, in weather forecasting, the dew point is pivotal for accurate predictions concerning temperature lows.

Soil moisture: The soil moisture prediction results presented in Table VIII are high across all models, with R^2 values surpassing 0.96. By incorporating precipitation, climatic factors, as well as current-day soil moisture and soil temperature as inputs, ML models can accurately foresee soil moisture average levels for the next day. Although MLP and SVR exhibit superior performance, the preference is for LR due to its interpretability and ease of explanation. This choice facilitates direct comparisons with more complex models and enables an evaluation of the model's complexity in relation to the inherent nature of the regression problem. Fig. 5 demonstrates the LR model's ability to capture soil moisture dynamics, with very few outliers in the predictions. The predicted soil moisture values compared with the actual target are shown in Fig. 6. Table IX reports some forecast soil moisture values and the effective observed measurements.

The results of the LR model for forecasting at D + 3 and D + 7 time horizons are also discussed. Predicting soil moisture beyond a single day in advance is essential for effectively implementing a precision irrigation system. A time frame exceeding one day enables more advanced and strategic planning of irrigation activities. In addition, accounting for the inertia of hydrological processes within the soil, these projections offer a more precise understanding of soil moisture variations over time. As reported in Table X, the results exhibit highly satisfactory performance, characterized by an average R^2 value of approximately 0.93.

Furthermore, an investigation comparing data utilization from one probe (TDR probes 1 and 2) to data from three probes was conducted. Excluding the deeper TDR probe 3, which could incur higher replacement costs, did not impact prediction accuracy. The R^2 values for TDR probes 1 and 2 are 0.96 and 0.95, respectively. While acknowledging the potential benefits of using more probes for better insights, the results emphasize that utilizing data from a single probe can yield exceptional predictions and potentially reduce maintenance expenses associated with additional probes.

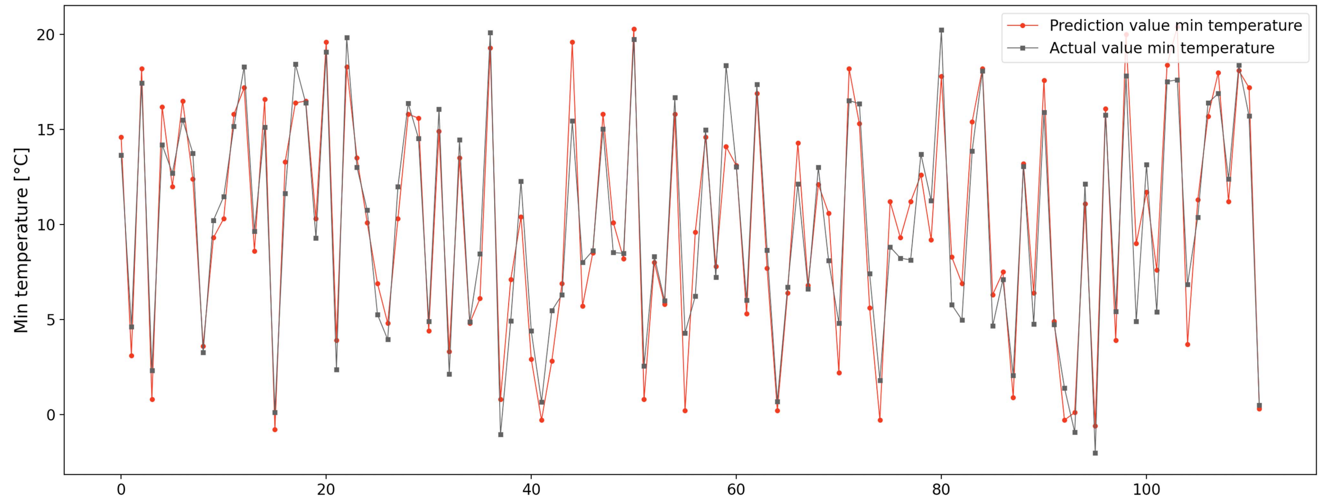

Fig. 4. One-day-ahead minimum temperature: Actual versus prediction values.

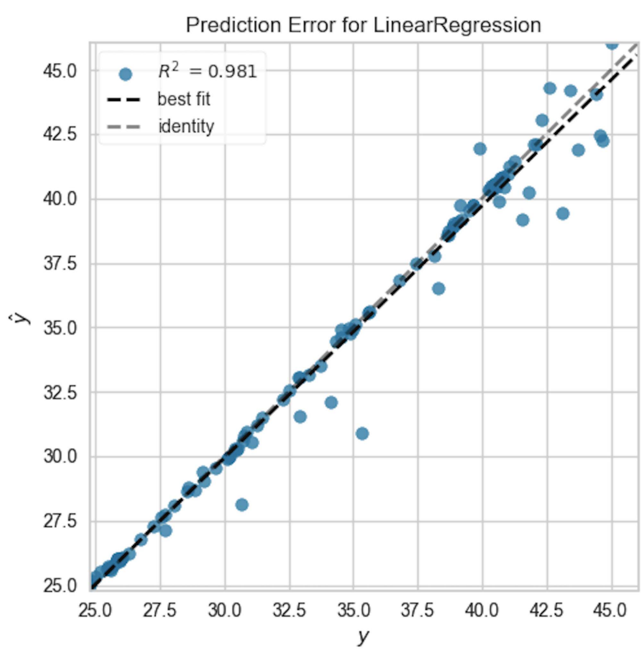

Fig. 5. One-day-ahead soil moisture: Prediction error plot.

TABLE XI
ONE-DAY-AHEAD FORECAST DOWNY MILDEW FAVORABLE CONDITIONS: ML ALGORITHMS RESULTS

Downy Mildew					
ML algorithms	Class	Precision	Recall	F1-score	Accuracy
RF	0	0.98	0.87	0.92	0.92
	1	0.86	0.98	0.92	
XGB	0	0.97	0.95	0.96	**0.96**
	1	0.95	0.97	0.96	
SVM	0	0.98	0.84	0.90	0.90
	1	0.83	0.98	0.90	

("1" indicates infectious initial conditions, "0" otherwise)
The bold values indicate the best results (in particular, for the Linear Regression model).

TABLE XII
ONE-DAY-AHEAD FORECAST POWDERY MILDEW FAVORABLE CONDITIONS: ML ALGORITHMS RESULTS

Powdery Mildew					
ML algorithms	Class	Precision	Recall	F1-score	Accuracy
RF	0	0.94	0.94	0.94	0.94
	1	0.94	0.94	0.94	
XGB	0	0.97	0.97	0.97	**0.97**
	1	0.97	0.97	0.97	
SVM	0	0.94	0.88	0.91	0.91
	1	0.89	0.94	0.92	

("1" indicates infectious initial conditions, "0" otherwise)
The bold values indicate the best results (in particular, for the Linear Regression model).

TABLE XIII
DOWNY MILDEW: XGB MODEL PREDICTION AT VARIOUS LEAD-DAYS

Downy Mildew					
Time horizon	Class	Precision	Recall	F1-score	Accuracy
D+3	0	0.93	0.89	0.91	0.91
	1	0.88	0.92	0.90	
D+5	0	0.90	0.90	0.90	0.90
	1	0.90	0.90	0.90	

B. Results for Classification Problem

Grapevine diseases: Tables XI and XII give the performance metrics (accuracy, precision, recall, and F1 score) obtained during the testing phase for each algorithm utilized in the downy and powdery mildew grapevine disease prediction. Specifically, the XGB algorithm accurately anticipated the initiation of downy and powdery mildew infection cycles (D + 1 time frame) with an accuracy of 96% and 97%, respectively. Further experiments were performed to assess potential infectious initial conditions using various prediction time horizons, i.e., D + 3 and D + 5. Tables XIII and XIV provide the results achieved using the XGB algorithm.

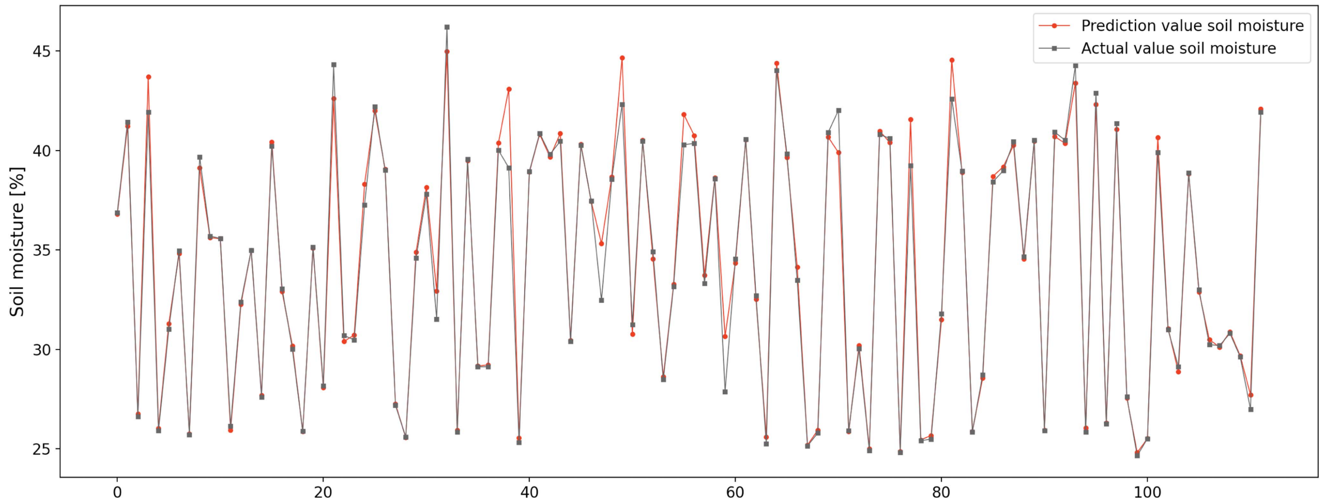

Fig. 6. One-day-ahead soil moisture: Actual versus prediction values.

TABLE XIV
POWDERY MILDEW: XGB MODEL PREDICTION AT VARIOUS LEAD-DAYS

Powdery Mildew					
Time horizon	Class	Precision	Recall	F1-score	Accuracy
D+3	0	0.91	0.94	0.93	0.92
	1	0.94	0.90	0.92	
D+5	0	1.00	0.94	0.97	0.97
	1	0.94	1.00	0.97	

VI. LIMITATIONS

AI and IoT-driven PA have introduced a level of precision that allows modern farmers to optimize every aspect of the agricultural process. Among these technologies, wireless sensor networks play a vital role in collecting data, including parameters, such as temperature and humidity. These variables are essential for predicting soil properties, meteorological conditions, crop yields, and diseases. However, traditional ML models encounter some challenges in estimating soil parameters and weather data across different ecosystems. They may also be influenced by historical trends, which makes forecasting extreme weather events more complex.

Advances in image processing and the rise of AI, particularly in the field of deep learning (DL), have revolutionized the analysis of complex scenarios and the automation of specific tasks [46], [47]. Compared with conventional remote sensing tools, unmanned aerial vehicles (UAVs) enable near-real-time field monitoring. The development of remote sensing technology has also improved the use of multispectral imagery, which has become an effective tool for assessing and monitoring crop health, crop stress, and making yield predictions. Looking to the future, further advances in remote sensing technology and the application of DL algorithms are expected to continue to revolutionize the field of PA [48], [49], [50]. This could lead to even more effective management of agricultural resources, enabling a more sustainable and efficient food production process.

VII. CONCLUSION

As the agricultural landscape undergoes rapid transformation, the integration of IoT and ML in PA emerges as a promising avenue for the future of smart and sustainable farming. This study exemplifies the potential of merging IoT-generated data with ML techniques to revolutionize agricultural practices, particularly in vineyards. This wealth of information empowers us to rely on ML-driven forecasts for frost damage and soil moisture, surpassing conventional methods for weather monitoring and irrigation planning. To mitigate economic losses and reduce environmental impacts, this research also incorporates a predictive model for the onset of grapevine diseases. This enables accurate and confident forecasts of the initial stages of infections, facilitating timely and effective interventions. Despite the data being collected over a limited time period, the results are highly promising. In the future, we plan to change the time measurements, analyzing hourly rather than daily intervals. The goal is to determine whether this leads to advantages, especially for crops that will benefit from a continuous irrigation method. Forecast models should be extended to also include rainfall. This will ensure that irrigation practices are meticulously adjusted to yield even greater water savings, maximizing the efficient utilization of anticipated rainfall volumes. The proposed approach has the potential to be seamlessly integrated into an IoT sensor network or a localized alarm system. In addition, we intend to incorporate UAVs for near-real-time field monitoring, alongside advanced DL algorithms, to further improve efficiency and diversify data sources.

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Chiara Pero (Member, IEEE) received the B.S. and M.S. degrees (cum laude) in computer science from the University of Salerno, Fisciano, Italy, in 2016 and 2018, respectively, and the Ph.D. degree in computer science and information technology from the Biometric and Image Processing Laboratory, University of Salerno, in 2023.

She is currently a Researcher with the Department of Management & Innovation Systems, University of Salerno. Her research interests include machine learning techniques in facial recognition, pattern recognition, image processing, biometrics, and behavioral profiling.

Dr. Pero is a Member of CVPL.

Sambit Bakshi (Senior Member, IEEE) was the Head of the Centre of Automation Technology, National Institute of Technology Rourkela, Rourkela, India. He is currently with the Department of Computer Science and Engineering, National Institute of Technology Rourkela. His research interests include surveillance, biometric security, and digital forensics. He has authored or coauthored widely in more than 100 journals and conferences.

He is currently an Associate Editor for the IEEE Transactions on Technology and Society, IEEE TRANSACTIONS ON EDUCATION, IEEE SYSTEMS JOURNAL, *IEEE IT Professional Magazine*, *Innovations in Systems and Software Engineering* Springer: A NASA Journal, *Expert Systems with Applications*, *Engineering Applications of Artificial Intelligence*, *Image and Vision Computing*, *Multimedia Systems*, *Multimedia Tools and Applications*, and *Neural Processing Letters*, and previously an Associate Editor for IEEE ACCESS, *PLOS One*, and Expert Systems in the past. He is a Founding Chair of IEEE Rourkela Subsection and IEEE Kolkata Section Biometrics Council Chapter. He is a distinguished Lecturer of IEEE Systems Council for 2023–2025.

Michele Nappi (Senior Member, IEEE) received the Laurea degree (cum laude) in computer science from the University of Salerno, Fisciano, Italy, in 1991, the M.Sc. degree in information and communication technology from I.I.A.S.S. “E.R. Caianiello,” Salerno, Italy, in 1997, and the Ph.D. degree in applied mathematics and computer science from the University of Padova, Padua, Italy, in 1997.

He is currently a Full Professor of computer science with the University of Salerno. He is a Team Leader of the Biometric and Image Processing Lab. He is the Author of more than 200 papers in peer review international journals, international conferences, and book chapters. He is Co-Editor of several international books. His research interests include pattern recognition, image processing, image compression and indexing, multimedia databases and biometrics, human–computer interaction, and VR/AR.

Dr. Nappi is currently an Associate Editor and Managing Guest Editor for several international journals. He is also a Member of TPC of international conferences. He was the recipient of several international awards for scientific and research activities. He is a GIRPR/IAPR Member. He has been the President of the Italian Chapter of the IEEE Biometrics Council. In 2014, he was one of the founders of the spin off biometric system for security and safety. He is a Deputy Rector for the University of Salerno Reputation and International Ranking, and Co-EiC of (Elsevier) *Image and Vision Computing Journal*.

Genoveffa Tortora (Senior Member, IEEE) was the Dean of the Faculty of Mathematical, Natural, and Physical Sciences, University of Salerno, Fisciano, Italy, from 2000 to 2008. Since 1990, he has been a Full Professor of computer science. She is the Scientific Director of the Laboratory on context-aware intelligent systems, Department of Computer Science. She is the author and coauthor of more than 290 papers published in scientific journals or proceedings of refereed conferences and is Co-Editor of three books. Her research interests include software engineering, visual languages and human–machine interaction, image processing and biometric systems, Big Data, data warehouses, data mining, and geographic information systems.

Ms. Tortora is currently an Editorial Board Member of high-quality international journals, Steering Committee Member of the International Working Conference on Advanced Visual Interfaces held in cooperation with ACM, and Program Chair and Program Committee Member of several relevant international conferences. She is an ACM Member, European Association of Theoretical Computer Science Member, International Association of Pattern Recognition Reviewer for several international scientific journals, Evaluator of research projects for Italian Ministries, Regions, Universities, and European Commission Member of the Board of Examiners for several Researcher, Associate Professor, and Full Professor positions both at a national and an international level.