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Lands DSS:
A Decision Support System for Forecasting Crop Disease in Southern Sardinia

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ABSTRACT

Decision support systems (DSSs) are used in precision farming to address climate and environmental changes due to human action. However, increments in the amount of data produced continuously by the latest sensor and satellite technologies have recently incentivized the integration of artificial intelligence (AI). A review of research dedicated to the application of DSSs and AI in forecasting crop disease is proposed. In this paper, the authors describe the DSS LANDS developed for monitoring the main crop productions in Sardinia and the case study conducted to forecast potato late blight. A feed-forward neural network was implemented to investigate if weather data provided by regional stations could be used to predict a disease risk index using an AI technique. The test performed by stratified k-fold cross validation achieved an accuracy of 96%.

KEYWORDS

Artificial Intelligence, Crop Disease, Decision Support Systems, Late Blight, Neural Network, Precision Farming

1. INTRODUCTION

Today's challenge in the agriculture sector is to address the continuous climate changes that are undermining food security and are driving economic, social and livelihood impacts. The Food and Agriculture Organization (FAO) outlines in (Steduto et al., 2012) that the climate changes are expected to cause serious declines yield of the most important crops in developing countries. Furthermore, it is estimated that agriculture will have to produce 70% more food by 2050 to feed the world's population which is expected to be 34% larger than today. Since most land suitable for farming is already farmed, this growth must come from higher yields thought the use of more sustainable practices.

The intensive and unsustainable agriculture adopted to date, have exposed the ecosystem to the risk of a progressive deterioration of their production capacity. Indeed, 25% of the world's agricultural land is already degraded (FAO, 2011). This challenge requires a radical change in the paradigm that governs the agricultural and food sector. The request translates into virtuous management of natural resources in which the concepts of territorial protection, environmental sustainability, and food safety are the key elements for the new agriculture model. In response to this emergency, Precision Farming was born, able to maximize productivity through a more complex vision of a production system.

In the literature, it is described as a data-based approach to agriculture (Ruß, 2010). It operates in areas that need treatment using the latest sensor and satellite technologies that continuously monitor the environment by producing a large amount of data at an unprecedented rate. The analysis of this Big Data through Artificial Intelligence (AI) techniques allows to better understand the interaction

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between the physical (soil, atmosphere, water) and biological elements (plants and parasites) that exist in the production process. These agricultural data can be collected, organized, analyzed and integrated automatically into Decision Support Systems. Decision support systems represent the brain of Precision Farming (Tan,2016). They can process these agricultural data with specific algorithms to suggest the actions to be used in the fields promptly. The integration of forecasting models which use AI techniques into DSS let farmers to be provided: (i) a holistic view of problem (ii) possibility to exploring from different points of view all the variables necessary to make timely decisions (iii) possibility to predict and evaluate several scenarios (iv) possibility to create a historical database. In this context, Artificial Intelligence and Decision Support Systems are emerging as an indispensable operating node for performing predictive analyses that take into account temporal, spatial, cultural, inter and intra-field variability to recommend strategic and eco-sustainable actions.

In this paper, we describe the system and the test conducted through the prototype DSS LANDS (*Laore Architecture Network Development for Sardinia)* developed to study artificial intelligence methods and models which can be used to know, understand and evaluate the relationship, patterns, and trends from data to simplify the agricultural decision-making process. The DSS has been developed in collaboration with the LAORE Sardinia Agency. LAORE Sardinia Agency deals with providing advisory, education, training and assistance services in the regional agricultural sector. The described system allows farmers and LAORE workers to upload monitoring data, use different and several analysis models and view the results as guidelines to be adopted in crop management. As many other existing Decision Support Systems, we aim DSS LANDS to be a tool that can improve business by optimizing the use of resources and preventing crop risk situations, thus saving unnecessary and unproductive interventions. The test conducted describes an application of artificial neural network to forecast a disease risk index for the potato crop.

The paper is structured as follows. In Section 2, we present a literary review of how the Decision Support Systems have been used in agriculture. In Section 3, we describe the DSS LANDS components. In Section 4, we illustrate the case study conducted to forecast potato late blight disease. In Section 5, we present the experimental framework. We end up in Section 6, with a discussion of our main findings and future lines of research.

2. AGRICULTURAL DECISION SUPPORT SYSTEMS

The application domain for Decision Support Systems in the agricultural sector has evolved significantly in the past decade. A decade ago, DSSs have mainly been introduced in agriculture for improving on-farm crop productivity. At that time, the earliest decision support systems were DSSAT (Jones et al., 2003), APSIM (Keating et al., 2003), CROPSyst (Stöckle et al., 2003), EPIC (Izaurralde et al., 2006) and STICS (Brisson et al., 2003).

In recent years, the application of DSSs does not focus only on improving productivity but has expanded its scopes in a range of applications: food security, risks of pest and disease losses, livestock production, climate change mitigation and adaptation, policy assessment, farmer advice.

Manos et al. (2004) have categorized the field applications, in the following five categories: Diagnostic-Forecasting DSSs, Advisory DSSs, Control DSSs, Educational – Informational DSSs, Operational DSSs. This expanding application domain is caused by the need to conduct more sustainable agriculture damaged by continuous human activities and climate changes.

Advances in technologies such as Global Positioning Systems (GPS), Geographic Information Systems (GIS) and remote sensing have increased the interest in developing Decision Support Systems that integrate new data analysis techniques like Artificial Intelligence (AI) and Machine Learning (ML). New Decision Support Systems have been developed to address different aspects of these purposes.

Soyemi et al. (2018) proposed a web-based decision support system to suggest sustainable agricultural practices that serves better both the communities and the Nigeria nation. In satisfying this need, the application uses Short Message Service (SMS) Technology to disseminate weather forecasting to farmers according to their eWarning setup.

Udias et al. (2018) designed a DSS to enhance agricultural growth in the Mékrou river basin, a place where conduct more efficient agricultural techniques are vital to enhance prosperity and alleviate poverty, especially in rural areas. The system was developed and applied to assess the Water Energy Food Ecosystem nexus, offering optimal management solutions at river basin level, in a context of food insecurity and increasing competition with other competing sectors. Specifically, they focused on the identification of optimal agricultural strategies for nutrient fertilizer and irrigation management, as well as on the optimal handling of modified cropland allocation and land use. Rupnik et al. (2018) described a novel decision support system for agriculture and farming, called AgroDSS. The system is based on data mining approaches, which can extract useful information from large volumes of data to predict future scenarios, a better understanding of the submitted data and an explanation of the dependencies (interactions) within the data.

2.1 Decision Support Systems for Monitoring Potato Late Blight Disease

Potato late blight, caused by the oomycete *Phytophthora infestans*, is considered one of the most serious diseases that afflict the potato production leading to great economic and yield losses. It is caused by three components known as disease triangle which are, a susceptible host, a pathogen, and a favorable environment. The epidemiology of late blight depends mainly on temperature, relative humidity, and rainfall and it occurs during cool and wet weather. Control of potato late blight relies heavily on the use of fungicides, which if applied in the wrong quantity and time can lead to large production losses and food safety problems. This practice, in addition to having an unsustainable environmental impact, it has a high financial cost. The continuous climates changes make it increasingly difficult for farmers to conduct a monitoring and prevention program that can be effective in the long term. The several environmental and cultural variables affect production increasing the problem complexity, which cannot be effectively solved by adopting agricultural practices based on experience and intuitions. Decision support systems are the tool able to meet the needs emerged in the last decade. Through the integration of predictive models, they give additional assistance and information, capable of supporting and simplifying the decision-making process that farmers must face every day. At a global level, in the agricultural sector, several DSSs have been developed to predict and suggest treatment programs against potato late blight using various disease forecasting systems and models. Among them, the most known systems in the literature are SimCast, BliteCast, ProPhy, SimPhyt, Plant-Plus, MILEOS, Guntz-Divoux and China-blight (Wander et al., 2006; Small et al., 2013; Hu et al.,2014). Recently, from two thousand to today, new decision support systems have been introduced.

Jörg et al. (2003) developed a DSS to aid control of potato late blight in German growing regions. It consists of three modules that use temperature and relative humidity as meteorological inputs. The first called SIMPHYT 1, predicts the date of the first appearance of late blight for eight crop emergences. The second SIMPHYT 2, simulates late blight epidemics on a plot-specific scale taking into consideration weather, crop data and fungicide properties. The third SIMPHYT 3, is an infection pressure model that is used to calculate the length of spraying intervals on a regional level.

Eremeev et al. (2006) developed the DSS NegFry. It is based on two existing models retrieved from the literature, the Negative Prognosis model, for forecasting the risk of primary attacks, and the Fry model for timing subsequent fungicide applications during the season. The main objective of DSS NegFry was to get high yield and quality with minimum use of fungicides. During the testing conducted in the season 2003-2004 has given a positive result by timing the first spraying for the anticipation of the infection and by optimizing the number of treatments for late blight control.

Forrer et al. (2006) proposed the PhytoPRE DSS to optimize the input of both copper fungicides and copper-free preparations.

Manorama et al. (2015) developed a decision support tool for recommending information on the optimum time of planting and the likely consequences of early or late planting of potato in about 173 locations of Nilgiris region of Tamil Nadu state in India.

Nielsen (2015) described Blight Management developed in collaboration between AU, SEGES, KMC, and AKV for control of late blight and early blight.

Small et al. (2015) proposed a web-based decision support system BlightPro for potato and tomato late blight management which links several models into a system that enables prediction of disease dynamics based on weather conditions, crop information, and management tactics. An integrated alert system allows users to receive notification of upcoming critical thresholds via e-mail or text message.

Filippo et al. (2017) designed the Vniifblight DSS which uses combined information about the local climatic conditions, weather forecast, plant growth stage, disease resistance of potato cultivars, and fungicide characteristics. Depending on the combination of all these factors, it suggests three possible recommendations to apply fungicide treatments.

Founghali et al. (2018) proposed a Cloud-IOT DSS for late blight enabling the use of location-specific weather data to drive disease forecasters and a mechanistic model of the late blight disease, to make real-time (in-season) support for late blight management. The farmers are notified by SMS when the first attack of disease “Late Blight” could take place.

3. THE PROPOSED DSS LANDS PROJECT

The DSS LANDS is a prototype agricultural DSS developed in collaboration with *LAORE Sardinia Agency*. LAORE Sardinia Agency is a regional government body that deals with providing advisory, education, training and assistance services in the regional agricultural sector.

It is responsible for the publication of phytosanitary reports aimed at reporting the main crop adversities and adopting the most suitable defense strategies.

The phytosanitary reports addressed to the agricultural operators of the regional territory, are drawn up based on specific monitoring programs and agrometeorological surveys carried out in the field, in the main areas of the region.

LANDS has been developed to assist LAORE workers in their monitoring program and help them in the decision-making process. It is a decision support service available in real-time on the web platform, tablet and smartphone via an internet connection and a couple of access credentials.

LANDS involves three steps: (i) it collects, organizes and integrates a large amount of data from different sources; (ii) it analyzes and interprets the information; and (iii) it uses the analysis to recommend the best action to adopt.

The starting point of the entire system is the monitoring of the plot. During the field survey, LAORE workers upload the retrieved data to the LANDS system using a mobile device. The uploaded data are stored and analyzed by different forecasting algorithms that deal with translating the data acquired into operational and management terms. The results of the analysis are available to the user through specific interactive dashboards that indicate the strategy to be adopted for crop management.

LANDS suggests the guidelines based on the following purposes: (i) optimize the resources management through reduction of certain inputs (e.g., chemicals and naturals resources, etc.) (ii) predict crop risk situations (e.g., diseases, weather alerts, etc.) (iii) increase the quality of decisions for field management (iv) reduce environmental impact and production cost.

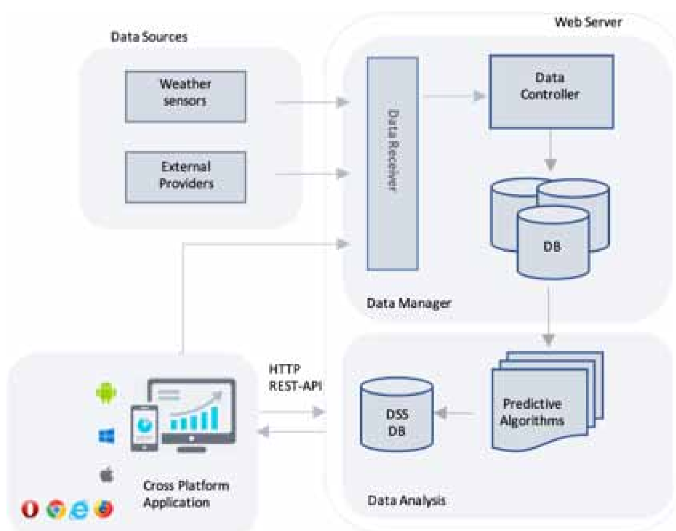
We structured the DSS LANDS into three components:

- An *integrated system* for monitoring the crop components and store their data; These sources include external providers and weather stations. The system is configured to acquire weather data from ARPAS (*Regional Agency for the Protection of the Sardinian Environment*) weather stations agree with specific procedures and intervals of time. The stations monitor several meteorological variables including: temperature (C), relative humidity (%), wind speed (km/h) and direction, precipitation accumulation (mm) and solar radiation (W/m2).

- A *data analysis module system* that performs through several mathematical and forecasting models a cross and dynamic analysis of different types of data. It discovers and evaluates the relationship, patterns, and trends from data originated from the *integrated system.* Their elaboration and interpretation allow us to recommend the best strategies to be applied in the field in order to forecast possible risk event situations which can damage the agriculture production.
- A *cross-platform application* used by farmers to upload crop data collected during the field survey and to visualize the up-to-date information for managing the cultivation. All information is in a graphic format that uses symbols and colors to advise and inform in an immediate, effective and unambiguous way the status of each crop management component. The platform is available by several devices: smartphone, tablet, and desktop. This feature simplifies and enhances the agricultural management process during the monitoring survey since the farmers through a connectivity internet can upload immediately the data identified during the supervised operations.

The architecture of the DSS LANDS is illustrated in Figure 1.

Figure 1. DSS LANDS Architecture



The data are collected at fixed intervals from different sources: weather stations, external providers and data uploaded to the cross-platform by LAORE technical during the field survey. The data received are managed from *Data Receiver* which controls the quality of data and then it stores them into different *DBs*. After that, the data are analyzed through several agricultural mathematical models. The output is stored and sent to the cross-platform application for the interpretation by the decision-maker. The output is visualized in the application as graphs and guidelines through different and specific dashboards. Each dashboard is a collection of widgets that gives to the farmer an overview of the metrics and let them monitor many metrics at once, so they can quickly check the health of their cultivation.

We developed the DSS LANDS using a RESTful architecture. The data processing infrastructure was implemented using the Python programming language. For the visualization of the guidelines and the integrated loading of cultural data, a graphic interface was developed using HTML and Javascript.

The LANDS architecture described is structured to manage the main crop productions in Sardinia: citrus, artichoke, wheat, corn, olive, potato, peach, tomato, rice, vine. Currently, the system provides specific modules for monitoring crops mentioned above. For each crop, we prepared an automatic data loading module, a manual data loading module (using by farmers during the monitoring survey) and a module for integrating forecasting models. To date, LANDS integrates all functionalities designed and geared for monitoring the potatoes crop.

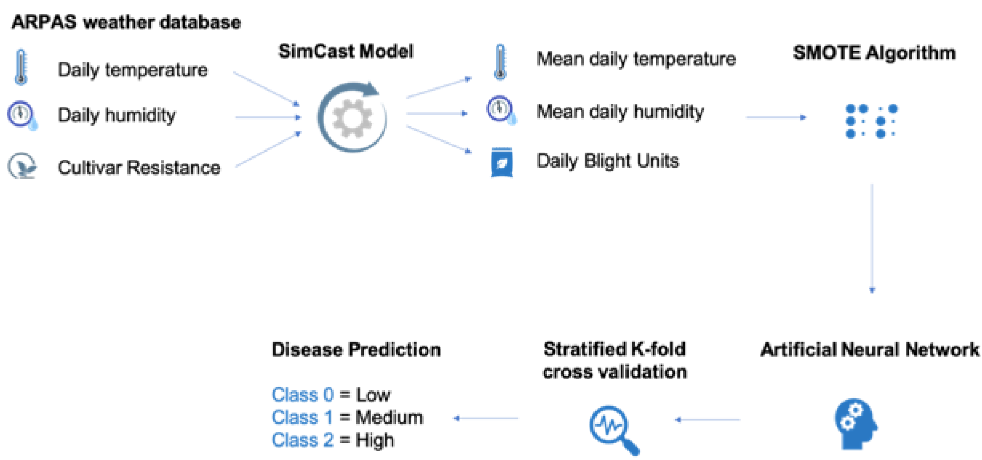
4. CASE STUDY

4.1 Methodology

In the present paragraph, we describe the short case study conducted to forecast the onset of potato crop disease. The object of the study was the development of a potato late blight forecasting model using an Artificial Intelligence technique based on regional weather data and investigates if these variables can be used to predict a crop disease risk index. In designing the potato late blight prediction model, hourly historical weather data, cultivar resistance, and blight units were used to build a feed-forward neural network. The historical weather data were provided by the ARPAS Agency database. The weather data were collected from Cagliari location over the 3 years (2016 – 2018). The risk occurrence of potato late blight expressed as blight units have been calculated using a mathematical model known in the literature as SimCast (Fry et al., 1983), developed in a previous study in (Fenu & Malloci,2019).

Figure 2 describes the entire work-flow of the proposed method.

Figure 2. Work-flow of the proposed method



Historical weather data recovered from ARPAS stations located in the monitored fields were used. Hourly data as temperature and humidity are previously used to calculate the blight units using the SimCast model. In the literature, it is a common approach to use the blight units as indicators for disease (Hijmans Hijmans et al., 2000; Eremeev et al., 2016; Gu et al., 2016;). The blight units are expressed on a scale of 0 to 7. This range is scaled into three classes (0,1,2) where the class 0 encodes the range [0-2], class 1 encodes the range [3-4] and class 2 encodes the range [5-7]. The output of the proposed method represents the dataset to be supplied as input to the artificial neural network. However, the dataset obtained presents an imbalance in the distribution of classes. This is due to the fact that potato late blight occurred with a certain intensity in the analyzed three-year period.

This imbalance could also occur even in the analysis of more than three years. To avoid overfitting situation, we used the SMOTE algorithm to balance the dataset before giving it to the artificial neural network. Subsequently, using the stratified k-cross-validation, we have evaluated the model. The final elaboration of the neural network estimates the severity of potato late blight infection through three classes (0,1,2) representing low, medium and high culture risk, respectively.

In the following paragraphs, the configuration and techniques adopted are illustrated.

4.2 SimCast Forecasting Model

The SimCast model formulated by Fry et al. (1983) predicts the occurrence of late blight for susceptible, moderately susceptible and resistant cultivar, but only predictions for resistant cultivars were used in this study. The model forecasts the disease stress to the plant using Blight Units (BUs) or Fungicide Units (FUs). The BUs indicate if there are favorable conditions for the disease onset on a given date. They are calculated according to the number of consecutive hours that relative humidity is greater than or equal to 90%, and the average temperature falls within any of six ranges (< 3, 3-7, 8- 12, 13-22, 23-27 and >27 C) as illustrated in Table 1. FUs are determined considering daily precipitation (mm) and time elapsed since the last application of the product.

Table 1. Blight units determined by temperature and periods of high relative humidity for SimCast model (Excerpted from Fry et al. 1983)

Average Temperature	Cultivar Resistance	Consecutive Hours of Relative Humidity >=90% That Should Result in Blight Units Of							
(C)		0	1	2	3	4	5	6	7
>27	MR	24							
23-27	MR	15	16-24						
13-22	MR	6	7	8	9	10-12	13-24		
8-12	MR	9	10-12	13-15	16-24				
3-7	MR	18	19-24						
< 3	MR	24							

MR = moderately resistant cultivars

4.3 Artificial Neural Network

Artificial Neural Network (ANN) is a model that can learn patterns from data by simulating the structure of the human brain. Typically, the ANN architecture is composed of three types of layers: one input layer, one output layer, and at least one hidden layer. Each layer represents an aggregation of neurons. The input and output layer contain nodes that correspond to input and output variables, respectively. The number of hidden nodes depends on the specific problem to solve. Data move between layers across weighted connections called edges. The weights are adjusted as learning proceeds. A node accepts data from the previous layer and calculates a weighted sum of all its net inputs (Khairunniza-Bejo et al., 2014):

$$t_i = \sum_{j=1}^{n} \left(w_{ij} x_j + b_i \right) \tag{1}$$

where n is the number of inputs, w is the weight of connection between node i and j, x is the input from node j, and b_i is a bias. The output node o_i is calculated applying a transfer function f_i to the weighted value:

$$o_i = f_i(t_i) \tag{2}$$

Different activation functions are available like Identity function, Binary Step Function, Sigmoid function, Linear function, Tanh Function, Relu Function, and Radial Basis Function.

A feed-forward neural network was developed to achieve the purpose of the study.

Three variables, mean daily temperature, mean daily humidity and daily blight units, were used as input parameters. The values that were used in the prediction were based on the scaled values using the min-max scaler algorithm defined as follows:

$$x_{sc} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

where X_{sc} refers to the value of either temperature or humidity factor after normalized, between 0 and 1; X refers to the original value of either temperature or humidity; and X_{min} and X_{max} refer to the minimum and maximum values of temperature and humidity factor respectively.

Two hidden-layers were constructed to ensure better results. Each hidden layer was constituted of eight hidden nodes. A sigmoid activation function was used. The sigmoid function is a non-linear function that maps all the inputs between [0,1] irrespective of the input value. It is defined as follows:

$$f\left(x\right) = \frac{1}{1 + e^{-x}} \tag{4}$$

The output layer was comprised of three neurons that express the intensity of blight units as low, medium and high identified respectively with the values from 0 to 2. More specifically, the 3-ordinal variable were encoded as follows: the vector [1,0,0] denotes the class 0, the vector [0,1,0] denotes the class 1, and the vector [0,0,1] denotes the class 2. A softmax output activation function and Cross-Entropy loss function were set.

4.4 Synthetic Minority Over-Sampling Technique (SMOTE)

Several classifier learning methods are designed to work with reasonably balanced datasets, but many real-world applications have to face imbalanced data (Sáez et al.,2016). Using an imbalanced dataset, the training of the model and its results may be biased by the most frequent class in the dataset (majority class). The literature suggests different techniques for the class-imbalance problem. The first technique consists of a data level solution by performing a sampling. The second consists to work at the algorithm level that includes several solutions as adjusting the costs of the various classes. Due to its effectiveness, we performed the data sampling approach. Data sampling aims to adjust the class in an equal distribution in the training set applying over-sampling or under-sampling methods.

Oversampling balances class distribution through the random replication of minority class. Contrariwise, Under-sampling balances class distribution through the random elimination of the majority class.

In our case study, the dataset constructed through the approach described in paragraph 4.1 is composed of 1074 instances where 950 instances belonging to low severity class, 75 instances belonging to medium severity class and 49 instances belonging to high severity class. To balance our dataset, we considered the oversampling method, since it proved to be more effective for small dimension datasets (Sáez et al., 2016). Specifically, Synthetic Minority Over-Sampling Technique (SMOTE) was performed.

SMOTE algorithm was introduced by Chawla et al. (2002). It is an oversampling technique in which the minority class is oversampled by creating "synthetic" examples rather than by oversampling with replacement (Pelayo et al.,2007). To create a synthetic example, SMOTE searches for the nearest neighbors (having the same class label) of a minority-class example. The new synthetic data is generated based on feature space likeliness that prevails between existing samples of the minority class.

The algorithm is described in table 2.

Table 2. The Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al., 2002; Jeatrakul et al., 2010)

O is the original data set P is the set of positive instances (minority class instances) For each instance x in P Find the k-nearest neighbors (minority class instances) to x in P Obtain y by randomizing one from k instances $difference = x - y$ gap = random number between 0 and 1 $n = x + difference * gap$ Add n to O End for

5. EXPERIMENTAL FRAMEWORK

In this section, we first introduce the evaluation measures used in our study and then describe the datasets. After that, we report the experimental results.

5.1 Metrics

To prove the effectiveness of the proposed crop disease prediction method we had to choose metrics that are most appropriate for multi-class problems. In the literature are present several measures that are successfully applied for solving multi-class problems are: Accuracy, Precision, Recall, and F1-Score. An experimental test was carried out using those metrics because they give us relevant information about our classifier.

Accuracy is defined as (TP + TN)/(P+N) and it represents the ratio of the number of correct predictions to the total number of input samples. TP denotes the true positives (i.e., instances of the positive class that are correctly labeled as positive by a classifier), TN denotes the true negatives (i.e., instances of the negative class that are correctly labeled as negative by a classifier), P represents positively labeled instances, and N represent negatively labeled instances.

Precision is defined as TP/(TP+FP) and it measures the exactness of a classifier.

Recall is defined as TP/P and it calculates the completeness, or sensitivity, of a classifier.

F1-Score is the Harmonic Mean between precision and recall. It is defined as:

$$2* \frac{TP}{2*TP+FP+FN} \tag{5}$$

5.2 Experimental Results

The proposed method is analyzed through different metrics explained in paragraphs 5.2. A feed-forward neural network was trained using back-propagation algorithm and was performed for a total of 2500 learning epochs. A split ratio of 80:20 was applied to segregate the normalized data into a training data set and validation set. The test set was used to validate if the model produced the desired output. Stratified k-fold cross-validation was performed with k = 10 to test the model's ability to predict new data that was not used in estimating it. After the learning phase, the feed-forward neural achieved an accuracy of 96%.

Table 2 reports the precision, the recall and the f1-score obtained for each class.

From the results obtained, we can observe that the model has a good level of prediction for the class that represents a low and medium risk index. However, the high-risk class achieved a high precision of 1.00 and a low recall of 0.67. This means that, in most cases, the model is not able to predict this class with the same ability it uses for the others.

Table 3. Results obtained using stratified k-fold cross-validation using the balanced dataset

Class	Precision	Recall	F1-score
Low	1.00	1.00	1.00
Medium	0.64	0.99	0.78
High	1.00	0.67	0.52

6. DISCUSSION AND CONCLUSION

In recent years, we are witnessing continuous climate changes that combined with excessive demographic pressure and unsustainable agricultural practices, have exposed the ecosystems to the risk of a progressive deterioration of their production capacity. To date, 25% of the world's agricultural land is already degraded. The Food and Agriculture Organization (FAO) report outlines that climate changes are expected to cause serious declines yield of the most important crops in developing countries.

In the present paper, the surveyed work demonstrates that Decision Support Systems are increasingly playing a key role in the agricultural world and there is a growing interest from researchers in exploring new forecasting algorithms and analysis approaches that aim to find those patterns in the data that are essential for crop management. The artificial intelligence adoption is becoming increasingly important in decision support toolbox used at different agricultural levels, from the prevention levels to tactical and operational levels. At the moment, in the literature, there are few cases of study concerning the application of artificial intelligence techniques for the prediction of potato late blight. Many approaches regard individual approaches that are not directly connected to decision support systems. However, these related works show an increasing demand for integrating data recording and generalizable artificial intelligence approaches for obtaining forecasts and classifications in line with emerging agricultural challenges, which motivates us to develop the proposed DSS LANDS and implement an AI-based predictive model able to predict potato late blight.

The study conducted focused on investigating whether regional meteorological data could be used to predict the late blight epidemic with an artificial intelligence technique. The experiments were conducted using historical weather data provided by ARPAS Agency from Cagliari location over the 3 years (2016 – 2018). We performed a feed-forward neural network using Stratified k-fold cross-validation. An accuracy of 96% was achieved. The result obtained proves that the model developed could be useful in predicting crop disease in Southern Sardinia. However, the model is limited to potato production and it doesn't take into account the treatments which are performed during culture monitoring. For this reason, we reserve for future development to exceed the shortfalls found and generalizable them in preventing the management of tomato and vine disease.

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