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Grape Plant Disease Classification by Analyzing Efficient Machine Learning Algorithm

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ABSTRACT

India is a social and economic country that values grape growth. Many factors have contributed to the decline in grape quality over the past few years. The diseases that affect grapes are one of the major culprits. In traditional farming, specialists are hired to do a meticulous, labor-intensive, lengthy, and potentially error-prone physical inspection of each plant line by line for host disease. Nowadays, diseases of cropscan be predicted using computers. To diagnose crop illnesses quickly and precisely and to stop them in their early stages, climate conditions might be evaluated. In this paper, we are analyzing the weather dataset provided by the National Research Centre for Grapes. The dataset used in this experiment was labeled into two categories, known as powdery mildew disease or no powdery mildew disease. The solution to this problem relies on supervised learning techniques because the labels were predetermined. During the experiment we trained and tested our model on four algorithms; support vector machine (SVM), random forest regression (RF), Naive Bayes (NB), and ZeroR algorithm. This work selects an efficient algorithm for the classification of grape plant diseases specifically, Powdery Mildew and Bacterial Leaf Spot.Naïve Bayes algorithm achieved highest accuracy compared with other algorithms and was found to be the best algorithm in order to classify grape diseases using weather datasets.

KEYWORDS:IoT, disease prediction, Support vector machine, Random forest, Powdery mildew, Downy mildew.

1. INTRODUCTION:

The most well-established occupation in the history of humanity is probably agriculture. There are greater difficulties facing farmers today than ever before because of the push to produce more food due to the growing global population and ongoing climate change. Plant pests and diseases do, in fact, pose a risk to food security because they destroy crops, which lower access to and availability of food while also driving up food prices [16]. Agriculture productivity suffers a severe loss as a result of crop disease attacks [2]. Any diagnostic inaccuracy has the potential to result in improper management and excessive pesticide application. In order to make the best decisions for optimum agricultural productivity, farmers could collect data utilizing information technology. To protect crop yield, early disease prediction and detection are crucial. [3].Machine learning can accurately forecast crop field environmental variables based on the Internet of Things (IoT) to anticipate the onset of plant diseases.

In many regions of the world, Downy and Powdery Mildew are two serious diseases of grapes that harm both leaves and grapefruits. In India, Powdery Mildew is a serious grape disease. Farmers must exercise discretion when deciding fungicides should be used to treat Powdery Mildew, keeping in mind that doing so raises crop residue levels as well as costs. Another illness that has economic significance is Bacterial Leaf Spot. This disease recurs in grape farms in India, where humid conditions (such as high relativehumidity) favor the disease's growth.

In this paper, we are analyzing the weather dataset provided by the National Research Centre for Grapes. NRCG provides us with the factors that cause diseases to spread. The next step is to analyze that data for the classification of diseases. For the classification of diseases from NRCG data, this work employs some machine learning approaches like RF, SVM, NB, and ZeroR and also compares algorithm results with each other. This work selects an efficient algorithm for the classification of grape plant diseases specifically, Powdery Mildew and Bacterial Leaf Spot.

STRUCTURE OF PAPER

The paper is organized as follows: In Section 1, the introduction of the paper is provided. In Section 2 we discuss related work. In Section 3 we haveinformation about machine learning classifier. Section 4 shares material and methods. Section 5discusses result. Section 6 concludes the paper with references.

2. RELATED WORK

An IoT monitoring systemwas developed by the authors that utilize a wireless sensor network to gather data on the environment and the soil [4]. Using the information gathered, a number of illnesses affecting tomatoes and potatoes have been identified early. In [5] authors created a technique for monitoring and forecasting mildew in a vineyard was devised. Machine learning algorithms can be employed instead of conventional approaches to construct successful prediction models since they are better at spotting diseases.

The Hidden Markov Model is introduced for developing an observance [6] that is able to determine diseases in grape crops in their early stages. Hidden Markov Models analyse a variety of environmental variables, such as temperature, humidity, leaf condition, etc., to forecast diseases in grape plants. A server was accessed by ZigBee for the purpose of transferring the data. The National Centre for Research on Grapevines (NCRG) functioned in the classification process by creating favourable conditions for those accountable for the development of grapevine diseases, shown in Table 1. On the basis of environmental and soil data gathered via an IoT monitoring system, a naïve Bayes kernel model was employed to forecast disease[7]. For the early diagnosis of agricultural illnesses, a KNN model was used [8].Multiparameter extracted from the field were used in the prediction, namely temperature, humidity, CO_2 concentration, soil moisture, soil temperature, and leaf wetness. Results showed that the environmental data were valid, demonstrating the truth of the model for early disease detection. To anticipate the health status of tomato plants, the authors also suggested a technique [9]. Abiotic elements like temperature, soil moisture, and humidity are taken into account in order to ascertain whether a plant is developing in healthy settings. The system may measure soil moisture and soil humidity using a soil moisture sensor and a temperature/humidity sensor. Authors evaluated the supervised learning algorithms SVM and Random Forest as well as the unsupervised learning method K-means clustering. The accuracy of 99.3% for SVM, 99.6% for Random Forest, and 99.5% for K-means were found. The Random Forest Machine Learning technique was proposed by the authors as a way to predict mango plant ailments based on the weather[10]. In predicting mango disease, the suggested method is quite precise. Rice blast disease detection method [11] offered by authors with the use of the Internet of Things (IoT) and machine learning. In order to train a machine learning model to detect rice blast disease, data from photographs of rice fields are transformed into hyperspectral data.

Author suggested an Internet of Things (IoT)-based disease detection system [12] integrating in-person observations of the crop field and machine learning to provide an early warning system. The author recommended detecting fungal diseases [13] utilisingIoT and machine learning skills. The Internet of Things is being used to monitor crop field environmental conditions. The directly observed environmental parameters of fungal illness are used to forecast the incidence of a disease. The researcher suggested a regression model and an association between disease population and atmospheric conditions in maize harvests [14]. The proposed method assists in determining the incidence of sickness at a specific time.

3. MACHINE LEARNING CLASSIFIERS

With the quick development of artificial intelligence and machine learning, ML has been implemented in various pieces of the farming sector[16]. From the section II, it is seen that to check accuracy or performance many researchers utilized tools for the execution of machine learning classifiers, e.g., Weka, R studio, RapidMiner, Orange, Knime, PySpyder, and Matlab. These programmes have performed key tasks such as dividing data sets into training and testing, parameter optimization, and model validation using cross-validation or K-fold validation. Weka or R's key tasks include data clustering, determining the associativity of data properties, regression analysis, and data categorization. According to the literature review, SVM can be used for early diagnosis of cotton leaf disease by picking the collection of factors that produces the best categorization of an individual's pathogen records [17]. SVM accuracy can be measured using the WEKA tools. The Bayes rule is used to the data based on the presence of co-morbidities, and this helps to discover the expected chance of detecting pest diseases. An adaptation of the Bayes classifier called Naive Bayes (NB) makes the assumption that each feature is conditionally independent of the others. In light of this supposition, the Bayes theorem can be used to determine the posterior likelihood of data being assigned to a class label by merely multiplying the conditional probabilities for each attribute. A decision tree is created using data samples via the Random Forest, or RF algorithm, and predictions are then obtained from each one for the best option through a majority vote. Overfitting is minimized by averaging the outcomes. The ZeroR classifier only predicts the prevailing class (category). ZeroR is used to set a baseline performance as a benchmark for other classification methods.

Table 1. Environment Parameters

Disease Name	Sensors	Measurement Range
Powdery Mildew	Temp (°C)	21-27
	RH (%)	More than 48
	Leaf Wetness	-
Bacterial Leaf Spot	Temp (°C)	25-30
	RH (%)	>80 &<90
	Leaf Wetness	-

4. MATERIALS AND METHODS

The proper machine-learning architecture is shown in the section that follows to categorize grape diseases, particularly powdery mildew. In two steps, the classification uses supervised learning techniques to map data to specified class labels.

A. For certain labeled data, a classification model is created during the training phase.

B. Data classification is carried out using the trained classification model created in phase one.

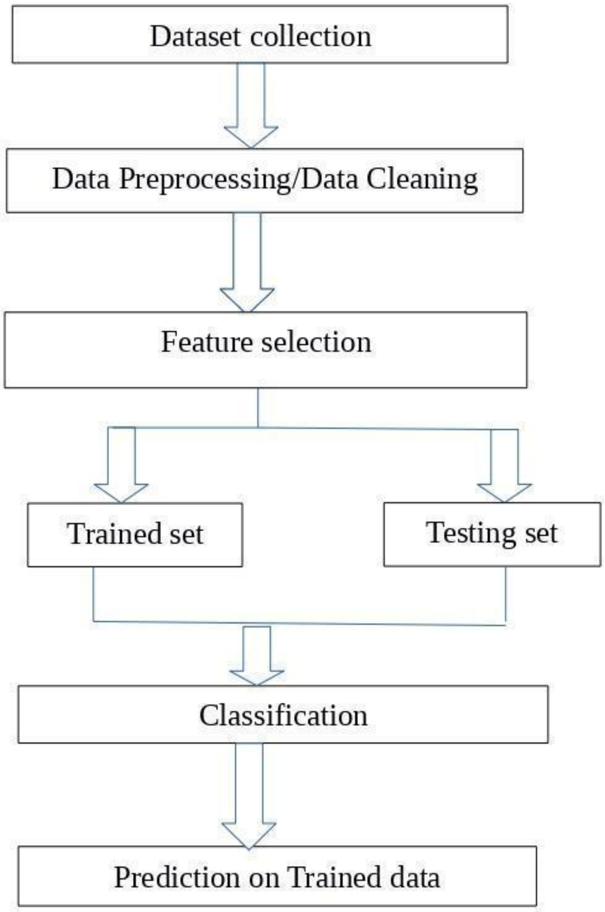

Fig.1. Grape disease classification system

In order to create predictions on new datasets for which the label is unknown, machine learning has the capacity to learn the relationships between the attributes automatically. The decoding of natural patterns and behaviors in modern agriculture is done using artificial intelligence applications with sophisticated algorithms, which also aid farmers in making adjustment for future results.

Table 2. Daily Weather dataset of NRC Grapes Pune

Sr no	Time	Date	Location	Air Temp	Leaf Wetness	Humidity
1	00:00:15	Apr 01 2017	Manjari	29.41	0	53.49
2	00:30:11	Apr 01 2017	Manjari	29.15	0	54.16
3	01:00:15	Apr 01 2017	Manjari	28.95	0	55.28
4	01:30:12	Apr 01 2017	Manjari	28.55	0	56.58
5	02:00:15	Apr 01 2017	Manjari	28.16	0	57.36
6	02:30:11	Apr 01 2017	Manjari	27.94	0	56.51
7	03:00:14	Apr 01 2017	Manjari	27.81	0	56.65
8	03:30:11	Apr 01 2017	Manjari	27.75	0	56.17
9	04:00:15	Apr 01 2017	Manjari	27.84	0	52.72
10	04:30:14	Apr 01 2017	Manjari	27.65	0	52.33
11	05:00:13	Apr 01 2017	Manjari	27.37	0	52.23
12	05:30:11	Apr 01 2017	Manjari	26.9	0	51.18
13	06:00:15	Apr 01 2017	Manjari	26.7	0	49.87
14	06:30:11	Apr 01 2017	Manjari	26.17	0	50.23

Following performance parameters were used for the comparison.

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F-Score = 2* ((P*R)/(P+R))

5. RESULTS

On the grape weather dataset, the output of various classification algorithms like RF, SVM, NB, and ZeroR algorithms are checked in detail and it was discovered that compared to other algorithms, RF classification techniques perform better. The weather dataset for grapes is split into 2 parts: training data (66 percent) and testing data (34 percent). Table 2 shows the performance metrics for powdery mildew disease and table 3 shows for bacterial leaf spot disease.

Table 3. Performance metrics for Powdery Mildew

Class	Precision	Recall	F-Score
no	0.90	0.95	0.92
yes	0.93	0.85	0.89

Table 4. Performance metrics for Bacterial LeafSpot

Class	Precision	Recall	F-Score
no	0.99	0.97	0.98
yes	0.65	0.86	0.74

The dataset used in this experiment is divided into two classifier, known as powdery mildew disease or no powdery mildew disease. The solution to this problem relies on supervised learning techniques because the labels were predetermined.

Table 5. Accuracy comparison for Powdery Mildew

Algorithm	Accuracy
SVM	83
NB	91
ZeroR	57.43
RF	90

Table 5. Accuracy comparison for Bacterial Leaf Spot

Algorithm	Accuracy
SVM	81.37
NB	97.41
ZeroR	95.63
RF	95.90

We trained and evaluated our model on four algorithms during the experiment; support vector machine (SVM), random forest regression (RF), Naive Bayes (NB), and

ZeroR algorithm. We first labeled the data into yes and no, where yes = powdery and no= no powdery, then parting the dataset into two sets: training set (66%) and a testing set (34%). Similar process is implemented for bacterial leaf spot. The testing accuracy is a more accurate measure of out-of-sample performance than the training accuracy. Table 4 and Table 5 show accuracy comparison using different algorithm for powdery and bacterial leaf spot respectively. The categorization accuracy of the machine learning techniques under consideration, and can clearly see Naïve Bayes algorithm have achieved better results compared to others.

6. CONCLUSION

The purpose of this study is to analyze and find an efficient supervised machine learning classification algorithm among RF, SVM, NB, and ZeroR to classify grape disease. Only three sensed characteristics are reflected in this work; more sensors, such as those that provide weather data, may be added for future development purposes. The dataset contains data like time, date, location, wind speed, air temperature, rainfall, leaf wetness, and humidity. Naïve Bayes algorithm achieved highest accuracy compared with other algorithms and was found to be the best algorithm in order to classify grape diseases using weather datasets.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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