Model for Training and Predicting the Occurrence of Potato Late Blight Based on an Analysis of Future Weather Conditions

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***Abstract*—Plant diseases pose a significant challenge to agriculture, leading to serious economic losses and a risk to food security. Predicting and managing diseases such as potato blight requires an analysis of key environmental factors, including temperature, dew point, and humidity, that influence the development of pathogens. The current study uses machine learning to integrate this data for the purpose of early detection of diseases. The use of local weather data from sensors, combined with forecast data from public weather API servers, is a prerequisite for accurate short-term forecasting of adverse events. The results highlight the potential of predictive models to optimize prevention strategies, reduce losses and support sustainable crop management. Machine learning provides powerful tools for analyzing and predicting data related to plant diseases. Combining different approaches allows the creation of more precise and adaptive models for disease management.**

Keywords—Machine learning; potato late blight; data analysis; forecast; prediction models

I. Introduction

Vegetable diseases represent one of the most serious challenges facing modern agriculture. They affect yields, production quality and economic sustainability of farms [21]. Caused by various pathogens, such as fungi, bacteria, viruses and nematodes, these diseases not only reduce the amount of food produced but also increase the cost of its production due to the need for treatment, prevention and control [1].

A. Economic Importance

Vegetable diseases lead to significant financial losses for both small producers and large agricultural companies [19]. They can:

- reduce yields by up to 30-50% in serious epidemics.
- oblige farmers to use expensive fungicides and pesticides, which increases production costs.
- reduce the quality of production, making it unfit for sale or export.

B. Agriculture Importance

From a business management perspective, vegetable diseases can lead to:

- Loss of competitiveness in the market due to a decline in the quality of production.
- Increased demand for resistant vegetable varieties, which are often more expensive to grow.
- Growing needs for the implementation of modern technologies for disease monitoring and control.

An example of a disease of high economic and agriculture importance is potato blight, which affects both tomatoes and potatoes [16]. In the absence of appropriate measures, it can destroy entire crops in a short time, leading to serious socio-economic consequences.

The development of effective disease management strategies, including risk forecasting through meteorological and agrotechnical data, is essential to ensure a sustainable and productive vegetable growing system. So, the purpose of this study is to improve contemporary models by adding hourly monitoring of the parameters which are important for the development of late blight and to issue timely warnings on this basis.

II. Methodology

A. Objectives of the Current Work

The current study uses environmental and meteorological data to create predictive models for the occurrence of plant diseases, with an emphasis on potato blight in tomatoes. Many models do not consider changes in real-time weather and early warning of disease occurrence but mainly use historical data [18]. Others analyze already appeared plant diseases based on machine learning from photos [11]. Thus, these models may not respond to short-term changes in conditions that can affect the development of the disease and will not trigger the preventive measures that can be taken to minimize losses.

The aim of the current work is to create a dynamic model that is constantly updated with new meteorological data (such as temperature, humidity, wind, etc.) in order to give forecasts for a short-term interval and to predict possible dangerous agronomic events.

Many of the existing models do not include the effects of carrying pathogens over distances, which can be important for widespread diseases such as potato late blight. In addition to basic data, it must take into account winds and other factors that contribute to the spread of spores over certain distances. This approach can combine weather data with diffusion patterns to predict the risk of new infections in different parts of the region or even on neighboring farms. The model should be able to predict the development of blight in the short term, for example, in the next 24-48 hours, using different sensors for a specific location, rather than global weather data.

The methodology includes the following stages:

- **Data collection**: Collection of historical meteorological data (temperature, humidity, dew point, precipitation) and disease records from open and controlled farms.
- **Preliminary data preprocessing**: Filling in missing values, normalization and identification of critical variables for disease development.
- **Modeling**: Using machine learning algorithms, such as logistic regression, decision trees, and neural networks, to predict favorable conditions for infection.
- **Model Evaluation**: The accuracy and performance of models are evaluated through metrics such as accuracy, sensitivity, and Area Under the Curve (AUC).
- **Validation and deployment**: The results are validated on field data, then the models are integrated into practical tools for agricultural applications.

This methodology aims at early warning and effective management of risks associated with plant diseases.

B. Potato Late Blight

Potato late blight (Phytophthora infestans) is one of the most significant diseases of tomatoes and potatoes, which annually causes serious damage to agriculture. There are many scientific studies in the field of agriculture that describe in detail the situations of the onset of the disease [10]. Favorable conditions are temperatures in the range of 10℃ to about 22℃, humidity above 75%, cloudy and/or rainy, foggy weather [24]. Also, there are side factors that have no less influence on development: light, dew point, wind speed, sunshine, etc., having a strong direct relationship with the pathogen of potato late blight and its development [6], [7].

1) Temperature conditions for occurrence: The temperature ranges in which the appearance of sporangia is favored are between 12-15°C, and for the growth and spread of infection – 20-22°C. At lower temperatures (about 5-6°C), zoospores remain mobile for up to 22 hours, which increases the time for possible infection. Conversely, at higher temperatures (e.g. 15-16°C), the period of mobility is significantly shorter, since accelerated metabolic activity leads to faster germination or depletion of energy, while high temperature, i.e. 24-25℃, reduces their mobility [12]. The optimum temperature for the development of sporangia is 16-24℃. For the reproduction of sporangia, a temperature of 19-22℃ is required. At temperatures above 26℃, the disease stops its development.

Sporangia are formed at high humidity and dispersed at high temperature and low relative humidity. The release of spores is mainly due to changes in humidity. Epidemic conditions are favored mainly by humidity, that is, the prolonged survival of sporangia requires high relative humidity. The development of the disease also depends on the presence of drops of water on the surface of the leaves. Retention of water droplets on the leaves for several hours [23]. In the absence of water vapor, air spores lose their viability. At higher air speeds, multiple spores are formed at 100% relative humidity [7]. Sporulation is also increased by high humidity associated with the dew point [15]. Sporulation in the presence of strong daylight is inhibited during the day. Spores are formed only at night, when temperature and humidity favor sporulation. Sporangia germinate by releasing zoospores at a low temperature, i.e. 12-14℃, while at high temperature (20-26℃) direct germination takes place. Sporulation is stimulated by high humidity near the leaves, which is also associated with surface soil moisture.

C. Analysis Models

There are many well-studied models for predicting the occurrence of potato late blight. They are mainly divided into two groups: empirical and analytical. Of the empirical ones, the most famous are that of Van Everdingen or the so-called "Dutch rules" – based on a quantitative assessment of temperature and humidity to predict initial infections, Wallin's model focuses on the degree of danger through daylight hours during which humidity remains high. Boork's system or also known as "Irish Rules" (IR) considers the duration of humid conditions and the presence of free water in the air to be decisive factors for the development of the pathogen [3]. On the analytical side are those of Fry's model [5] – analyzes critical temperatures and moisture conditions, including an assessment of the genetic resistance of plants, Hartill-Young [8] – it is based on mathematical dependencies that assess the development of the pathogen under specific weather conditions, Baker-Lake [2] – uses modern statistical techniques to determine the time for maximum risk, taking into account historical and current weather data, etc.

One of the important aspects of using machine learning is its ability to adapt to different real-world conditions. For example, models can adapt to changing weather conditions and the specific needs of different regions, considering local climatic differences. In addition, machine learning can combine various data sources, such as satellite imagery, weather forecasts, and agricultural sensor data, allowing for a more comprehensive and accurate assessment of potato blight development conditions.

Most models include an assessment of factors such as relative humidity, length of period of high humidity, temperatures and the likelihood of rain. For example, SimCast is another established model that includes weather data such as temperature, humidity, and genetic resistance of the host to assess the risk of infection [9].

The advantage of empirical models is that they are easily understandable, applicable and require a small amount of data. They are practice-oriented. Analytical ones can be said to be highly accurate, adaptable and predictive. The negatives, on the other hand, in the former are limited precision, lack of universality, sensitivity to local data, empirical models often do not include the biological aspects of infection, such as the latent periods of the pathogen, while in the analytical ones are complexity of algorithms, large volume of data, over-calibration. A third conclusion can be drawn, which applies to both approaches to data analysis, namely: neither category sufficiently integrates economic or environmental aspects that are important for sustainable disease management, many of the models do not take into account climate changes that can affect the prevalence and intensity of potato late blight.

D. Data Collection and Analysis

For the purposes of the ongoing development, data were collected from a local station made with Arduino architecture and temperature and humidity sensors DHT22, barometric pressure sensor BMP280**,** precipitation sensor, wind force and wind direction sensor Wind Speed Sensor RS485. Data collection, hardware architecture is borrowed from [20]. The data were collected for four months from the beginning of May to September 2024, and were collected every hour, and the placement of the sensors was in Central Northern Bulgaria, as vegetables that are susceptible to potato blight were also grown there. The goal is to track all the data and based on the selected prediction algorithm, to give an immediate signal of potential danger. The collected data is summarized in a file and distributed by columns, which are presented in Fig. 1.

date	temp	dew	humidity	precip	windspeed	winddir	pressure	cloudcover	results
2024-05-01 00:00:00	10	10.3	92.41	0	3.9	27	1025	72.4	0
2024-05-01 01:00:00	11	9.9	86.98	0	5	42.8	1024	93.2	0
2024-05-01 02:00:00	11.7	10	89.31	0	3.2	7.4	1024	96.3	0
2024-05-01 03:00:00	11.5	10.6	94.2	0	2.2	18.7	1024	93.1	0
2024-05-01 04:00:00	11.2	10.8	97.38	0	2.5	355.9	1023	95.2	0
2024-05-01 05:00:00	10.9	10.8	99.34	0	2.2	347.5	1023	94.1	0
2024-05-01 06:00:00	10.8	10.8	100	0	2.5	354.4	1022	90.7	0
2024-05-01 07:00:00	10.8	10.8	100	0	1.1	300.4	1022	85	0
2024-05-01 08:00:00	12.1	12	99.34	0	2.2	292.1	1022	83	1

Fig. 1. Collected data.

The last column, results, reflects the different states of development or stagnation of the sporangia. The calculations in it are made with logical checks according to the most described meteorological prerequisites for the development of potato late blight. They are divided into four categories:

- 0 – No blight conditions exist.
- 1 – Appearance of blight (favorable conditions). It is assumed that the temperature for the development of sporangia is between 12-15℃, the relative humidity is about 90%, the retention of water droplets on the plants is at least one hour or more, and this is monitored by dew. The formula by which the dew point is calculated is:

$$T_{dew} = T - \left(\frac{100 - RH}{5}\right) \tag{1}$$

where T_{dew} is the dew point in degrees Celsius.

T is the current air temperature (in degrees Celsius).

RH is the relative humidity of the air in percentage (from 0% to 100%). Another important condition is that these parameters are meaningful during the dark part of the day between 10 p.m. and 6 a.m.

Case favorable disease conditions:

$$FDC(t) = \begin{cases} 1, \ \sum_{i=n-10}^{n} a_i \ IF(IF\ (temp \geq 12\ AND \\ \quad temp \leq 15\ AND \\ \quad humidity \geq 85 \\ \quad AND\ temp - dev < 2 \\ \quad AND\ date \geq 20 \\ \quad AND\ date \leq 7)) \geq 2\ OR\ \leq 10 \\ 0, \ else \end{cases} \tag{2}$$

- 2 – Late blight development (development conditions are met). The air temperature should be between 15-20°C, high relative humidity above 80% and a difference between humidity and dew point less than 4 and the higher the relative humidity, the higher the dew point – hence we have water vapor condensation [14].

Case develops disease conditions:

$$DDC(t) = \begin{cases} 1, \ IF(temp \geq 15\ AND \\ \quad temp \leq 20\ AND \\ \quad humidity \geq 80 \\ \quad AND\ temp - dew \leq 4) \\ 0, \ else \end{cases} \tag{3}$$

- 3 – Stopping development (temperature >26°C or low humidity).

Case block disease conditions:

$$\text{BDC(t)} = \begin{cases} 1, \ IF(temp \geq\ 26\ OR\ humidity \leq\ 60) \\ 0, \ else \end{cases} \tag{4}$$

E. Model for Analysis and Learning

The considered way of analyzing input data and predicting future data involves several points. As it is known from the pathology of diseases, data are needed for appropriate temperature range, development time and moment of day, but also very important are the wind and moisture retention on the plants, combined with high humidity for the spread of spores. Chosen machine learning method is LightGBM [4] which is optimized to be very fast when processing large amounts of data. It uses a unique Leaf-wise tree growth technique, which allows it to achieve high accuracy and quickly process data, even with millions of samples. Although standard Gradient Boosting can be slow and resource-intensive, LightGBM is much more efficient and economical. The model includes multiple iterations, in which decision trees are built sequentially to improve prediction accuracy. LightGBM uses a gradient-boosting framework that combines weak learners (usually decision trees) into one strong predictive model. The basic concept relies on minimizing the loss function, which quantifies the error in the predictions.

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{j=1}^{K} \Omega(f_j) \tag{5}$$

L(θ) is the total loss, $l(y_i, \hat{y}_i)$ is the loss incurred by forecasting instead of the true value y_i, n is the number of samples, K is the number of trees, and Ωf_j is a normalization term that penalizes the complexity of the model to avoid refitting [13]. In each iteration, LightGBM creates a new tree based on the negative gradient of the loss function, which shows how to adjust the predictions to minimize error. The gradient g_i for each i is calculated as

$$g_i = \frac{\partial l(y_i, \hat{y}_i)}{\partial \hat{y}_i} \tag{6}$$

The new tree is trained on these gradients. This allows the model to focus on the areas where the most significant mistakes are made. LightGBM is a new way of innovative approach mostly known as leaf-wise tree growth. This way contrasts with the traditional level-wise growth of decision trees. Leaf-wise approach algorithm increases the tree by selecting the leaf with the maximum delta loss and expanding that leaf, which approach allows deeper and more informative trees [13].

Many of the models for predicting plant diseases, such as potato late blight, include various weather and environmental factors (temperature, humidity, wind, dew point, etc.). Using LightGBM in current development has the following advantages:

- It can handle high-dimensional and unstructured data well.
- It provides high-precision forecasts that can help farmers make informed decisions about plant protection methods.
- It processes large amounts of data for different weather conditions, such as those from sensors or weather forecasts.

The initial setup used the Macro Accuracy approach for evaluating the performance of multiclass classification models [22] and Area Under the Curve [17]. They assume that the closer the learning outcome is to 1, the more accurate predictive results the model will give us. If the results are below 0.5, it means that the training does not have the ability to correctly predict and analyze the input-output data.

The rows analysis is done over the column “results” considering “date”, “temp”, “dew”, “humidity”, “precip”, “windspeed”, “cloudcover”. The duration of the training, which is set, is five minutes, and can be changed depending on the results achieved. After training the model, a result of 0.9873 success rate was achieved, which is an excellent result.

III. RESULTS

On using machine learning models (such as LightGBM and other classification algorithms), the results show high accuracy in predicting the risk of occurrence and development of late blight. After training the model and submitting sample input data for analysis, the model proposed here generates the results shown in Fig. 2. Working on the sample input data from Fig. 2, the model shows a 74% probability of situation 1 to occur – prerequisites for the development of late blight, which is a reliable result from the initial conditions for development. Thus, the data with which the model was tested can be replaced with the current input data from the sensors and those from an external API that provides information about the development of the weather conditions in the next hour. Input data can be very easily summarized and analyzed, returning the final information about the development of late blight.

```
Date: 2024-05-01 01:00:00
Temp: 15
Dew: 14
Humidity: 90
Precip: 0
Preciptype:
Windspeed: 5
Winddir: 42,8
Sealevelpressure: 1024
Cloudcover: 93,2
Results: 0
Class                                   Score
-----                                   -----
1                                       0,74
0                                       0,26
3                                       0,00
2                                       0,01
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Fig. 2. Model results.

These models can process large volumes of data, including data on temperature, humidity, dew point, wind, and other weather conditions. By analyzing these factors, machine learning models are able to identify complex dependencies and predict with high accuracy when potato late blight is most likely to occur or develop. With the subsequent integration of the model, real-time data will be taken from the weather sensors, and an analysis will be made according to the current data, as well as those from the external API for forecast values in the coming hours. The collection of data from local measuring sensors will be monitored in the last hours to see if there are conditions for the development of the disease, as well as from the expected next few hours for the development of weather conditions. When collecting and summarizing all this data, the system will automatically make a guess and issue a warning about a possible occurrence. The created analytical model from the data with which it is trained will have to make the most accurate assumption about whether there are prerequisites for the development of the pathogen.

In order to check the effectiveness, during the construction of the model, an experimental field was planted in April 2024, divided into two groups – experimental and control. The experimental group consists of tomato plantations, on which agronomic measures will be applied in case of alarm from the model – spraying with a copper-based fungicide – "Carial Star" – Syngenta. The choice of such a fungicide is justified by the desire to minimize the harmful impact of modern fungicides on the environment, as well as on plants and human health, especially those with systemic and translaminar action. The second group includes the control plants, on which no treatment will be applied. For even more precise results, several varieties of tomatoes have been used. In both groups, tomatoes of the variety "Ideal", "Pink Magic", "Rugby" were planted, 10 of each variety. The aim is to check how different varieties react to environmental changes and whether there is a difference between them. The planting of both groups is done at a distance of 3 meters, in order not to transfer the aerosol from the fungicide to the border plants of the control group, and at the same time to keep the development conditions of both groups as similar as possible. The treatment strategy is to take measures only if an alarm is received. The tomatoes were planted on April 29, and they were not treated until a signal appeared. The first alarm was received on 2024-05-02 between 4 and 8 a.m. The conditions were suitable, with an average temperature of 13.1℃ and humidity of 90.4%. Before treatment, the plants are in good condition, no changes, necrosis or plaques are noticeable on the leaves. According to the manufacturer's recommendations, the treatment interval is between 7-10 days, and we decided that the next spraying should be on the seventh day, if the weather forecasts remain unfavorable. On May 9, the code "1" for favorable development is again received, and treatment with the same fungicide is applied again. In the control group, it was noticed that a coating appeared on the leaves of several tomato roots (of all types). After two days, necrotic brown spots were noticeable on the petioles of the leaves on the plants of the control group. Several of the plants have watery spots on the leaves themselves, and several others on the stems themselves. In the next week, the weather conditions remain unfavorable, and there is precipitation, which further complicates the situation. On May 17, 8 plants from the control group are visibly sick, with a lot of necrosis in all parts, the flower that has sprouted falls off. In the plants treated, weak concentric spots have appeared on several of them, and this is probably due to the poor coating with the contact fungicide. On May 25, these spots were visibly calcified, and the spread was limited only to the original area. In the control group, things continue to develop in an unfavorable direction. There are apparently plants that are not alive, and this implies their removal, in others the development of the pathogen has continued. Of all the plants of each variety, there are 3-4 that do not have very serious damage. It is impossible to say whether there is a variety that is more tolerant of potato blight, but certainly the damage from lack of treatment in the risk periods has drastically changed the situation in both groups.

IV. Discussion

Despite significant progress in the development of models for predicting plant diseases, such as potato late blight, there are still many uncertainties and challenges related to the accuracy and adaptability of these models to different agronomic conditions. The models commonly used to predict the development of potato late blight can be categorized as empirical and analytical. While they provide useful information, there are also some limitations that need to be considered when developing new and improved forecasts.

Empirical models, such as those of Van Everdingen, Wallin and Boork, rely on pre-accumulated observations and are mainly based on specific climatic and agronomic conditions related to temperature, humidity and wind. They provide quick and easy-to-use forecasts, but their main weakness is that they do not sufficiently take into account the differences in the microclimate of different regions. For example, area-specific conditions (such as wind, latitude, moisture levels and other factors) can affect the results of forecasts, making them less accurate in extreme weather conditions. Such models also cannot easily adapt to changes in climatic conditions or to emerging pathogens that have not been predicted in historical data.

Analytical models such as Fry, Hartill-Young, and Baker-Lake are based on mathematical and statistical approaches that allow for more accurate forecasts when new climate data is added. These models try to simulate the mechanism of disease development based on a deeper understanding of the biology of the pathogen and its interaction with the environment. While these models provide better accuracy, they require significantly more input and complex computational time, which can be a barrier to their mass deployment and practical application.

Some of the main challenges in predicting diseases such as potato late blight include dynamic microclimate conditions, frequently changing weather conditions, and interactions between various factors, such as temperature, humidity, wind, and precipitation. In addition, the dew point, which is essential for the development of late blight, is not always correctly calculated in existing models, which can lead to errors in forecasts.

Using machine learning (ML) offers new opportunities to address these challenges. With its adaptive learning and ability to train with large volumes of data involving multiple parameters, machine learning can extract data dependencies that traditional models cannot capture. The ability to analyze historical data as well as real-time weather forecasts gives machine learning models a significant advantage over traditional forecasting methods. Predictions that are based on such algorithms can be more accurate and adaptable, being able to take into account multiple external factors simultaneously and be updated in real time.

V. Conclusion

Predicting the development of potato late blight is crucial for sustainable agriculture, as it allows farmers to make informed decisions about disease prevention and treatment. Existing models, including empirical and analytical, have provided valuable guidance for determining the conditions under which the disease can occur or develop. However, these models often have limitations in terms of accuracy and adaptability to changing climatic and agronomic conditions.

Machine learning models that use large volumes of data and can adapt to different conditions offer new opportunities to improve predictions of the development of potato late blight. They provide more accurate and dynamic forecasts while taking into account multiple factors such as temperature, humidity, wind, and dew point. However, the success of these models depends on the quality and reliability of the data used, as well as on their proper integration into agronomic practice.

Despite these advantages, it is important to note that the use of machine learning requires a high degree of trust in the quality and accuracy of the data. Incorrect or incomplete data can lead to errors in forecasts and reduce the effectiveness of models. Therefore, for the successful application of machine learning in potato late blight forecasting, it is necessary to work with reliable and diverse data sources and ensure continuous updating and updating of models.

Existing models for predicting potato late blight have their advantages, but they are also limited in their accuracy and adaptability to changing conditions. Machine learning offers significant opportunities to improve these predictions, allowing for more accurate prediction of the conditions for the onset and development of the disease. However, to achieve reliable and practical results, it is important to combine different approaches and technologies and to ensure the quality of the data used to train the models.

In the future, in order to achieve better accuracy and efficiency, different approaches must be combined, including traditional models and machine learning technologies. This will allow farmers not only to predict the development of late blight, but also to optimize their efforts to prevent and control the disease, which will ultimately lead to better results in agricultural production and a reduction in disease losses.

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