

## ADVANCED MACHINE LEARNING-BASED ECO-INTEGRATED MODEL FOR PREDICTING LATE BLIGHT IN MULTIPLE CULTIVATION SYSTEMS

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**Abstract.** *This paper presents a machine learning-driven framework for analyzing and predicting potato late blight (caused by *Phytophthora infestans*) across two distinct cultivation systems—ecological and integrated—using six potato varieties. Traditional statistical methods, including a two-factor Analysis of Variance (ANOVA) and Tukey’s Honest Significant Difference (HSD) test, were applied to assess the effects of cultivation systems, potato varieties, and year. To enhance predictive accuracy and model interpretability, an advanced machine learning pipeline, termed the Eco-Integrated Model, was developed. This model integrates SMOTE (Synthetic Minority Oversampling Technique) for handling class imbalance, SHAP (SHapley Additive xPlanations) for interpretability and feature importance analysis, and the CatBoost classifier for robust, high-performance prediction. The dataset, collected over three years (2018–2020), includes multi-varietal and system-specific records of late blight incidence for both ecological integrated-based data, serving as input for model training and evaluation. The*

Received June 04, 2025; revised September 17, 2025; accepted October 07, 2025

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*proposed Eco-Integrated Model demonstrated high predictive capability, revealing that integrated cultivation systems are generally more effective at suppressing disease progression. Moreover, substantial varietal differences were identified in late blight susceptibility, as highlighted by both statistical and machine learning analyses. These findings underline the value of incorporating explainable, data-driven approaches into plant disease forecasting. The Eco-Integrated Model offers a scalable, interpretable, and accurate predictive solution, contributing to precision agriculture practices and supporting evidence-based decision-making for sustainable potato production and disease management strategies.*

**Key words:** *Potato Late Blight, Cultivation Systems, Disease Prediction, ANOVA, CatBoost, SHAP Analysis, Sustainable Agriculture*

## 1. INTRODUCTION

### 1.1. Agriculture systems

Sustainable farming systems play a crucial role in producing high-quality crops while minimizing their negative environmental impact. Among the available strategies, ecological and integrated production systems that combine modern technologies with environmentally friendly practices are becoming increasingly important [1-5].

Potato cultivation (*Solanum tuberosum* L.) is an essential element of agricultural production in the world, and its efficiency depends on the proper management of agrotechnics, plant protection, and fertilization. The ecological system is based on natural cultivation methods, excluding synthetic plant protection products and mineral fertilizers, which contribute to the protection of biodiversity and soil health [3]. However, the integrated farming system combines conventional and ecological approaches, optimizing the use of resources and reducing chemical pressure on the environment [3, 5].

In potato cultivation, selecting appropriate varieties, optimizing crop rotation, and using biological plant protection methods are essential. Studies indicate that integrated systems can increase tuber yield and quality while reducing the negative impact on the ecosystem [2, 6]. This paper analyzes the effectiveness of ecological and integrated management systems in potato cultivation, highlighting their advantages and potential challenges.

In ecological potato cultivation, synthetic pesticides and herbicides are not used, and plant protection is provided only by natural methods, such as copper preparations, biological protection agents, and crop rotation. In the integrated system, however, limited use of chemical agents is allowed, but they are used only when biological and agrotechnical methods prove insufficient. Fertilization in the ecological system is based exclusively on ecological fertilizers, such as compost, manure, or green fertilizers. In the integrated system, it is possible to use mineral fertilizers, but their use is rational and adjusted to the soil's macro and micronutrient content. In ecological cultivation, plant varieties (e.g., potatoes) resistant to diseases and pests are preferred, which minimizes the need for protective interventions. The integrated system allows for a greater variety of varieties, but choosing those with increased disease resistance is still recommended. Soil protection in the ecological system is crucial, which is why crop rotation, catch crops, and cover crops are used. These methods are also used in the integrated system, but to a lesser extent. In terms of yield, ecological crops are characterized by lower efficiency, but the obtained crops have a higher nutritional value and do not contain pesticide residues. In the integrated

system, yields are higher than in ecological agriculture, although lower than in intensive conventional agriculture. Ecological cultivation requires obtaining appropriate certification following ecological farming standards. In the case of the integrated system, certification can be voluntary, including, for example, Global GAP or Integrated Production [2, 6-11]. In summary, ecological farming is a more restrictive system that relies on natural methods, while integrated farming combines ecological farming methods with limited chemicals.

## 1.2. *Phytophthora infestans*

One of the unresolved, unsolved issues of contemporary agricultural sciences of measurable practical importance is the problem of modeling the development of plant diseases. These processes are so complex that their theoretical foundations have not yet been developed sufficiently. Also, the available empirical data is not always sufficient to create a model based on the “black box” principle. This paper’s objectives are precisely formulated in subsection 1.2.1, and the case of the potato blight epidemic (*Phytophthora infestans* Mont. De Bary) was addressed. It is described in detail in subsection 1.3. Based on the concepts in Section 2.3, a technique for modeling phenomena in which the output signal is not directly measurable (its aggregated values for the sequence of inputs can only be estimated) was proposed. This allowed the creation of a model for predicting the date of the outbreak of the potato blight epidemic based on the data presented in the model [12, 15]. The results description, discussion, and conclusions can be found in the following sections of the paper.

### 1.2.1. *Practical issues*

One of the most important crops in Poland is the potato, which currently covers over 600 thousand ha [13]. This is determined by its versatility of use, low soil and climate conditions, and the amount of dry matter and starch yields. Since about 65% of arable land in Poland is light soils, where the selection of plants is limited, the role of the potato in crop rotation is also essential as a plant that enriches soil fertility. Unfortunately, potato yields are lower than those obtained in the European Union by about 40% and differ from the potential potato yields in domestic climatic conditions, which, according to Mazureczyk et al. [14], may range from 60 to 90  $\text{t ha}^{-1}$  and, in the opinion of Sawicka et al. [12], 70-90  $\text{t ha}^{-1}$ . One of the reasons for this state of affairs is the insufficient protection of plantations against potato blight caused by oomycetes (*P. infestans* Mont. De Bary) due to the high susceptibility of genetically homogeneous potato varieties to pathogens.

Average losses caused by this disease amount to 8-10% worldwide and 20-30% in Poland [15]. There are two phases in developing this disease: early (latent) and epidemic. During the first, *P. infestans* spores multiply, leading to local infections and the growth of primary infection foci. Typically, 3 to 5 generations of this pathogen result in an epidemic outbreak of the disease. The periods of disease transition from the latent to the epidemic phase depend on many factors, such as the density and location of primary infection foci, susceptibility of varieties to potato blight, their share in the structure of crops, the physiological condition of plants, meteorological conditions, and changes in macro and microclimate. In Polish climatic conditions, the date of the outbreak of the potato blight epidemic falls in June or July, as indicated by many years of observations [7], which depends on the temperature and rainfall distribution during the growing season. The date of the outbreak of the epidemic and the pace of its development determine the potential

yields of potatoes. The development of the epidemic is usually rapid, and after a few to a dozen or so days, almost all destruction of plant leaves is caused by potato blight. In the absence of protection against *P. infestans*, the losses amount to about 10-50% in central and northern European countries due to premature leaf destruction and 0-40% due to tuber infection [1, 7, 15, 16, 17]. The population of *P. infestans* in Poland was characterized by low aggressiveness until 1988, when the occurrence of the second sexual type (A2) was first noted, which had previously been recorded only in Mexico. This has created the possibility of generative reproduction, causing greater genotypic and phenotypic diversity in the population, with more remarkable adaptation to environmental conditions and the control methods used. A significant increase in the threat to potato crops from *P. infestans* has recently been observed. There are many methods for detecting diseases, including the use of gas sensors and other techniques such as biomarker analysis, medical imaging, and molecular testing.

#### **Molecular methods include:**

PCR (Polymerase Chain Reaction) and Real-time PCR are some of the most commonly used methods, allowing for rapid and sensitive detection of pathogen DNA in plant or soil samples. Modern variants, such as real-time PCR, enable quantitative assessment of the presence of the pathogen [18].

**LAMP (Loop-mediated Isothermal Amplification):** This isothermal DNA amplification method is faster and easier to use than traditional PCR, often not requiring advanced equipment. It can be used for rapid detection of *P. infestans* in the field.

**Nested PCR:** Increases detection sensitivity through two amplification steps with nested primer pairs.

**Droplet Digital PCR (ddPCR)** enables the precise quantification of pathogen DNA by dividing the sample into thousands of separate micro-reactions.

**CRISPR-Cas:** Modern gene editing techniques such as CRISPR-Cas12a are being adapted to create highly specific and sensitive biosensors for detecting plant pathogens, including *P. infestans* [19].

**Biosensors:**

**Electrochemical biosensors:** Use electrodes modified with specific biomolecules (e.g., antibodies, aptamers, DNA) to detect a pathogen's presence via electrical signal changes.

**Optical biosensors** (e.g., fluorescent, photoelectrochemical): Use optical phenomena to detect interactions between a pathogen and a recognition element on the sensor surface. Nanomaterials can be used to increase the sensitivity of these sensors.

**Microfluidic biosensors:** Integrate microfluidic systems with recognition and detection elements, enabling rapid and automated analysis of small samples. Zoospore chemotaxis can be used to increase detection efficiency.

**Immunosensors:** Use specific antibodies to bind pathogen antigens, leading to a signal detectable by electrochemical or optical methods [19].

**Visual and imaging methods:**

**Rapid immunochromatographic tests** (lateral flow assays): Similar to pregnancy tests, they allow rapid detection of pathogen antigens without the need for sophisticated equipment [1].

**Hyperspectral imaging:** Analysis of the spectrum of light reflected from plants can reveal early physiological changes associated with *P. infestans* infection, often before visible

symptoms appear. The use of machine learning can improve the accuracy of this method [20].

Fluorescence imaging using molecular probes: Specific dyes or molecular probes can bind to specific pathogen structures or respond to changes in plant cells induced by infection, allowing them to be visualized under a fluorescence microscope [19].

**Other methods:**

Volatile ecological compound (VOC) analysis: *P. infestans* infection can lead to changes in the VOC profile emitted by plants. Analysis of these compounds using gas chromatography-mass spectrometry (GC-MS) or electronic noses can facilitate the early detection of infection.

**RNAi-based methods:** Detection of specific dsRNA (double-stranded RNA) sequences characteristic of *P. infestans* can be used to identify the pathogen. Nanotechnology can support the delivery of dsRNA to plants for protection, as well as in detection systems [19]. The choice of the appropriate method depends on the specific needs, such as sensitivity, speed, cost, feasibility in the field, and the stage of disease development that we want to detect. Often, different methods are combined to obtain more reliable and comprehensive results. However, none of these methods guarantees a complete prediction of the *P. infestans* epidemic.

New, more aggressive genotypes of this pathogen have appeared, infecting leaves and stems [16, 21]. If only one mating type occurs, *P. infestans* reproduces exclusively vegetatively, and the source of infection is only tubers. During generative reproduction, resting spores (oospores) appear, which can survive for up to 2 years in crop residues in the soil. They constitute an additional source of infection and a threat to potato plantations, resulting in the earlier appearance of potato blight by up to one month in practice [10, 15, 17]. Since the date of the potato blight outbreak is not known a priori, the classic solution to the problem is to perform protective treatments cyclically "just in case". Unfortunately, due to the costs, many medicines cause a decrease in crop profitability. As a result, they are performed in Polish conditions instead of the necessary 5-8 treatments [9, 15, 16, 17]. Air, soil, and water are polluted [21].

### 1.2.2. Related works on model implementation for the prediction of potato blight

In this category of related works, we shall compare the latest works on model implementation that were used to predict potato blight infection, which have been performed using machine learning techniques. Upon surveying this fact, we concluded that very few works utilize an extensive, improved ecological and integrated dataset, as we have in this work, and even fewer employ advanced machine learning models. Li et al. [22] and Larson et al. [23] implemented the PLB-SI-XGBoost model for enhanced detection of potato blight using Sentinel-2, UAV, and Ground Data. Sentinel-2 data obtained an average accuracy of 70% in this case. Also, the authors investigated the early warning of crop diseases using Random Forest, Balanced Random Forest, XGBoost, and CatBoost models, and obtained a mean AUC of 0.9912 for classes 'pest' and 'no pests'. The dataset used in this work was released by the National Agricultural Innovation Project (NAIP) of the Indian Council of Agricultural Research (ICAR). Ahmed et al. [24] also investigated the extent of damage caused to potato blight plants using random forests, and the model achieved an accuracy of 97%. The dataset was gathered across diverse plants in many regions of Pakistan, and the authors implemented many machine learning methods like K-

Nearest Neighbors (KNN), Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR). Zhou et al. [25] address the process of carbohydrate metabolism in potato tubers during tuber germination. The authors, focusing on “overexpression of protein kinase”, traced the pathways and mechanisms of starch degradation and modification during tuber germination. The improvements should significantly improve the quality and readability of the manuscript, which is not discussed here. Over the past three decades, an increase in the infectivity of *P. infestans* has been observed, which is associated with changes in the population of this pathogen [22]. Potato blight caused by *P. infestans* is the most serious potato problem worldwide. In [22], Li et al. revealed significant changes in mating types, with A1 dominating before 2012 and A2, A1A2, and self-fertile types becoming common later. Most isolates showed the Medina haplotype Ia, and only two showed the haplotype Idia. Pathogenicity studies of *P. infestans* identified 67 distinct pathotypes, while metalaxyl resistance increased from 32.7% (2010–2014) to 78.3% (2016–2021). Fourteen multilocus genotypes (MLG) were identified, with UPGMA clustering revealing five major clades (YN\_1 to YN\_5), including genotype EU\_13\_A2 in YN\_1. Thus, clonal propagation, tuber migration, fungicide pressure, host selection, and limited sexual reproduction have driven the genetic diversity and population dynamics of *P. infestans* in recent years. These changes lead to earlier outbreaks, faster disease development, increased pathogenicity of the fungus, and the breakdown of genetic resistance in many potato varieties, making traditional protection methods less effective [11, 21, 23, 24].

The increase in the severity of potato blight and the associated losses justify the need for effective disease control. Currently, advanced decision support systems play an essential role, such as:

- BLITECAST: A system forecasting the risk of potato blight based on weather conditions [23].
- SIMPHYT: A simulation model assessing the development of the disease depending on environmental factors [26].
- PhytoPRE: A computer information and decision support system for potato blight used in Switzerland [27].
- NEGFY: A decision support system implemented in Poland, adapted to local climatic conditions [28].

Many of these programs were developed based on Western European observations, which may limit their effectiveness in other climatic conditions. Therefore, further research aims to assess the efficacy of various potato protection strategies against *P. infestans* in central-eastern Poland and to develop methods for monitoring and forecasting the epidemic based on meteorological data and the development stages of potatoes. The latest works discussed have one significant gap, which we have addressed here. All the above existing works have mainly focused on ‘pests’ and ‘no-pests’ diseases, which could suggest an affordable way of categorizing plants. However, in this work, our primary objective is to develop a predictive model by refining and enhancing a model termed ‘Eco Integrated’, which has been initialized with the latest varieties of potato blight infections for both ‘ecological’ and ‘integrated’ categories.

Now, let us discuss a few machine learning models based on recent models used to predict potato blight infection rate. Gerakari et al. [29] formulated a critical review on potato blight infection levels, and here several potato infection diseases were discussed. Joshi et al. [30] employed AI-based classification approaches and applied them to the potato dataset. In this work, a total of 56 weighted indices were utilized, and simulation models using SVM and hybrid models were developed by the authors. Dolatabadian et al. [31] worked on a review paper using existing literature on image-based crop detection using AI. Here, different machine learning based classifiers and multiple works based on classifying plant diseases have been discussed. Dey et al. [32] used an optimized CNN that reduces the number of trainable parameters and achieved a test accuracy of 98.6%. The model predicted high accuracy, specifically 99% for early blight, 98% for late blight, and 100% for healthy potatoes. A comparative analysis with VGG-16, AlexNet, and ResNet-50 estimates the superiority of the present approach. AL Zakari et al. [33] used an LSTM-RNN model for predicting potato blight images. The model was more efficient than all other models and rendered an  $R^2$  value of 0.98. Zhu et al. [34] proposed a multimodal AI model, achieving an accuracy rate of 92.15% on the test set, which yielded the best evaluation compared to other models. The multimodal AI model proposed by the authors achieved a test accuracy of 98.43%. Joshi et al. [35] attempted to use YOLOv8n, a deep convolutional neural network, to categorize potato blight infection, thereby achieving a 96.5% mAP. The model proposed by the authors will help to detect and classify plant diseases or pests across different crops.

Previous studies have provided a wide range of methods for the diagnosis of *P. infestans*, including molecular techniques (such as PCR and LAMP), advanced biosensors (electrochemical, optical), visual methods (immunochromatographic tests, hyperspectral imaging), and analysis of volatile ecological compounds [21,22]. However, a fundamental limitation of all these approaches is their reactive nature, i.e., they identify the presence of the pathogen or traces of infection after its occurrence [1, 11, 21, 23, 24]. Consequently, none of the available methods offers the possibility of proactively predicting the moment of the *P. infestans* outbreak, which is crucial for early, effective preventive measures and minimizing crop losses. This critical gap in predictive capacity is the central justification for our research. Our work aims to fill this important void by predicting epidemics, including developing a predictive model to analyze specific environmental biomarkers and early plant physiological signals. We believe our innovative approach will contribute to the transition from reactive detection to proactive risk management of potato blight epidemics, offering farmers the tools for early intervention and increased food security. None of the methods can predict the favorable conditions for outbreaks (e.g., ideal weather for developing *P. infestans*). For this purpose, predictive models based on meteorological and biological data are used.

Table 1 illustrates the significant research conducted over the past five years on the application of AI and Machine Learning tools in agriculture.

**Table 1** Machine Learning in Potato Disease Detection

Reference/Year	Datasets Used	Technique Used	Performance/Accuracy
Gerakari et al. [29], 2025	Review paper on different potato-level infections.		
Joshi et al. [30], 2024	56 simple and weighted indices used for simulation	LASSO, SVM, multiple linear regression, and two hybrid models, namely LASSO-SVM and SMLR-SVM, were used.	In terms of performance, the SMLR model rendered the best results.
Walid et al [36], 2023	Images of potato leaves	CNN model	99.22%
Aldhyani et al [37], 2022	Plant village dataset	Support Vector Machine (SVM), K-Nearest Neighborhood (K-NN), Random Forest, Decision Tree	91.28%
Sinshaw et al. [38], 2021	Plant leaf images from the Holeta potato farm	InceptionV3, VGG16, and VGG19 pretrained models were used	InceptionV3 rendered an 87% score.

### 1.3 Main Contributions of the Present Work

This study aims to develop and evaluate a predictive model for the occurrence of potato late blight (*P. infestans*) across two cultivation systems—ecological and integrated—using six different potato varieties. The analysis focuses on assessing the impact of cultivation practices and varietal characteristics on the risk of infection as well as the effectiveness of plant protection strategies. The findings are expected to support the optimization of potato management practices by enabling better alignment of protection measures and informed selection of suitable varieties under specific cultivation conditions.

- **Null Hypothesis (H<sub>0</sub>):** The cultivation system (ecological vs. integrated) and potato variety do not significantly affect the risk of potato late blight (*P. infestans*) or the effectiveness of plant protection methods.
- **Alternative Hypothesis (H<sub>1</sub>):** The cultivation system (ecological vs. integrated) and potato variety significantly affect the risk of potato late blight (*P. infestans*) and the effectiveness of plant protection methods.

Additionally, to justify the above, we have used the CatBoost classification method to determine which cultivation method is more fruitful, Ecological or Integrated. This work provides insight into which form of cultivation method must be used to combat the spread of *P. infestans*.

## 2. MATERIALS AND METHODS

### 2.1. Field experiment

Field research was conducted in 2016-2018 at the experimental station in Parczew on light soil and clay sands of a good rye complex with a slightly acidic pH (pH 5.5 in KCl) [39]. The experiment included two potato cultivation systems, integrated and ecological, and six potato varieties:

- medium early: Irga, Jagna, and Mila, medium late: Arkadia, Salto, late: Ania.

This experiment was conducted in 3 replicates. In a split-plot design:

The main factor (cultivation system: ecological vs. integrated) was randomly assigned to the large plots (main plots) in each replication. The subfactor (potato variety) was randomly assigned to the smaller plots (subplots) within each main plot. The main factor (cultivation system: ecological vs. integrated) was randomly assigned to the large plots (main plots) in each replication. The subfactor (potato variety) was randomly assigned to the smaller plots (subplots) within each main plot (Table 2).

**Table 2** Experimental Layout

Block	Main Plot	Cultivation System	Subplots (Potato Varieties)
I	MP1	Ecological	Mila, Salto, Irga, Ania, Arkadia, Jagna
	MP2	Integrated	Jagna, Mila, Salto, Irga, Ania, Arkadia
II	MP1	Integrated	Arkadia, Jagna, Mila, Salto, Irga, Ania
	MP2	Ecological	Ania, Arkadia, Jagna, Mila, Salto, Irga
III	MP1	Ecological	Salto, Irga, Ania, Arkadia, Jagna, Mila
	MP2	Integrated	Mila, Salto, Irga, Ania, Arkadia, Jagna

\*MP1, MP2: Main plots in each replication; \*\*Potato variety: Randomly distributed within each main plot

Table 2 depicts the experimental layout of the main plots and the different split-plot design. The main plots test the cultivation system (Ecological vs Integrated). Subplots test the potato varieties within each cultivation system. Replication (3 blocks) ensures that results are statistically reliable. Rotation of varieties' order across blocks avoids bias due to location effects. The subplot varieties encompass the various varieties of potato. Some major descriptions are described below:

- Field Experiment Design: Split-Plot Layout
- Main Plot Factor: Cultivation System (Integrated vs. Ecological)
- Subplot Factor: Potato Variety (Irga, Jagna, Mila, Arkadia, Salto, Ania)
- Replications: 3 (Blocks I, II, III)
- Design: Split-Plot
- Randomization: Cultivation systems are randomly assigned to main plots within each block; potato varieties are randomly assigned to subplots within each main plot [40].

This design ensures proper randomization at both the main plot and subplot levels, which is crucial for correct statistical analysis in the split-plot design. Summary of the scheme:

Experimental design: Split-plot

Factors: Main: Cultivation system (2 levels); Subordinate: Potato variety (6 levels)

Replications: 3 per cultivation system, which gives a minimum of 18 plots each year.

Years: 2016, 2017, 2018

Location: Parczew

Measurements: Regular assessments of disease and pest development, yield, and their components.

Analysis: Statistical analysis of variance for the split-plot design, post-hoc tests.

This experimental design enables a reliable assessment of the effects of the cultivation system and potato varieties on the parameters studied under field conditions. Including repetitions and experimenting for three years increases the reliability and generalization of the results. The experiment was planned and conducted in accordance with the principles of good agricultural practice (GAP), ensuring the credibility and usefulness of the obtained results [41].

Each cultivation system used a different crop rotation and production technology.

Integrated system:

Crop rotation: potato → spring barley → field bean → winter wheat → catch crops (white mustard).

Fertilization: mineral fertilization was used, compensating for the uptake of components in doses of 110 kg N, 60 kg P, and 60 kg K per hectare, as well as compost at a dose of 35 t ha<sup>-1</sup>.

Tillage treatments: The care included mechanical treatments for emergence (harrowing with a weeder, one-time ridging, and covering), and just before emergence, the herbicide Afalon 450 SC (2 dm<sup>3</sup> ha<sup>-1</sup>) was applied. After emergence (when the plants were 15-20 cm tall), Fusilade Super 125 EC (2 dm<sup>3</sup> ha<sup>-1</sup>) was used.

**Plant protection** included chemical protection agents, applied in accordance with the risk thresholds:

- Potato beetle: Bulldock 0.25 EC (0.25 dm<sup>3</sup> ha<sup>-1</sup>), Bancol 50 WP (0.4 kg ha<sup>-1</sup>).
- Potato blight: Dithane M-45 80 WP, Acrobat MZ 69 WP, Curzate M 72.5 WP, Tat-too C 750 SC, Brestanid 502 S.C. Decisions on the use of agrochemicals were made based on observations of the plantations and State Plant Protection Inspection - State Research Institute reports.

**Ecological system:**

**Crop rotation:** potato → spring barley → red clover + grass (2 years) → winter wheat → catch crop (white mustard + spring vetch).

**Fertilization:** No mineral fertilizers were used. Only compost was used (straw + red clover + manure, 35 t ha<sup>-1</sup>).

**Tillage treatments** included:

- Harrowing with a weeder before emergence.
- Three-time top dressing.
- One-time hand weeding before the last ridging (40-50 h ha<sup>-1</sup>).

**Pesticide use was limited in plant protection:**

- Potato beetle: Novodor 02 SC (2.5 dm<sup>3</sup> ha<sup>-1</sup>, 2 treatments), Permasect 250 EC (0.5 dm<sup>3</sup>ha<sup>-1</sup>, 1 treatment).
- Potato blight: no chemical protection.

## 2.2. Characteristics of potato varieties

Machine Learning Perspective on Potato Cultivar Resistance to Late Blight (*P. infestans*) Resistance to potato late blight (*P. infestans*) is a critical trait influencing the selection of cultivars for specific cultivation systems, particularly under the constraints of

ecological or integrated farming practices. From a machine learning standpoint, the varying levels of resistance across potato cultivars can be treated as categorical or ordinal target variables in classification models, where resistance levels (e.g., high, intermediate, low) are predicted based on environmental, genetic, and agronomic input features. High Resistance Cultivars such as Ania, known for their high natural resistance to late blight, serve as key positive class instances in supervised learning models. These cultivars often possess resistance genes (e.g., Rpi genes), which can be encoded as genomic features or proxy variables in feature engineering. Their reduced dependency on chemical treatments makes them especially relevant in ecological farming systems. In machine learning models, these cultivars are associated with lower disease incidence labels under a range of climatic conditions, contributing to the classifier's ability to generalize well under ecological constraints.

In terms of Intermediate-Resistance Cultivars [42], such as Arkadia and Salto, partial resistance is exhibited, but increased susceptibility is observed under prolonged wet or humid conditions. These varieties offer valuable insight into predictive models, as they represent cases where disease development is highly influenced by temporal environmental variables (e.g., rainfall, humidity). In machine learning, time-series weather data can be integrated with cultivar-specific features to train models that dynamically assess risk and trigger protection recommendations in integrated systems. These cases highlight the need for hybrid decision-support systems combining statistical thresholds with ML-driven forecasting. Finally, Low-Resistance cultivars such as Irga and Mila tend to require intensive fungicidal treatment, especially under high-humidity conditions. In a classification framework, these cultivars often align with high-risk labels, and their disease progression patterns can inform both supervised learning algorithms (e.g., CatBoost, Random Forest) and explainability tools, such as SHAP, for uncovering the relative importance of factors like cultivar genotype, weather trends, and soil type. These cases emphasize the necessity of early detection systems and precise intervention scheduling, which can be optimized using predictive maintenance-style algorithms in crop protection planning.

### **Modeling Implications**

In machine learning models for late blight prediction, cultivar resistance level acts as a critical feature or classification target depending on the modeling goal—either to predict disease incidence given cultivar and environmental context, or to recommend cultivars based on projected disease pressure [9,15]. Furthermore, model training should account for interactions between cultivation system type (ecological vs. integrated), environmental stressors (humidity, temperature), and genetic resistance markers. This can be achieved through ensemble learning methods or interaction-aware models like CatBoost, which inherently handle categorical variables and feature interactions [8, 9, 11, 42].

So, incorporating cultivar resistance levels into machine learning pipelines enhances the precision and interpretability of late blight forecasting models. It also supports data-driven decision-making in sustainable agriculture, enabling dynamic cultivar recommendation systems used for specific climatic and cultivation systems.

### 2.3. Meteorological conditions

Meteorological conditions in the study years (2016–2018) may have significantly influenced the development and spread of potato blight (*P. infestans*), as this pathogen's growth is closely related to air temperature and humidity (Table 3).

**Table 3** Rainfall, Air Temperature, and the Hydrothermal Coefficient of Sielianinov. During the Growing Season of Potatoes, according to the Meteorological Station in Uhnin (2016–2018)

Year	Specification	April	May	June	July	August	September	Total
2016	Rainfall (mm)	17.1	93.0	63.8	63.1	141.0	77.3	455
	Temperature (°C)	9.2	14.9	18.2	21.9	20.0	14.3	-
	Hydrothermal C coefficient (k*)	0.6	2.0	1.2	0.9	2.3	1.2	-
2017	Rainfall (mm)	39.9	46.2	117.0	170.0	42.9	8.9	425
	T Temperature (°C)	14.0	18.4	17.0	18.7	18.1	14.3	-
	Hydrothermal C coefficient (k*)	2.1	1.4	1.1	2.9	0.8	0.2	-
2018	R Rainfall (mm)	30.0	38.0	101.0	53.1	70.1	34.0	326
	Temperature (°C)	9.4	15.0	17.5	21.8	18.7	14.3	-
	Hydrothermal coefficient (k*)	0.8	1.9	0.8	1.2	0.8	0.8	-

\*Hydrothermal coefficient classification according to the formula:  $k = P/\sum T \times 10$ , where: P – total precipitation in a given period (e.g., month) [mm],  $\sum T$  – total average daily temperatures in the same period [°C]. Extremely dry:  $k \leq 0.4$ ; Very dry:  $0.4 < k \leq 0.7$ ; Dry:  $0.7 < k \leq 1.0$ , Rather dry:  $1.0 < k \leq 1.3$ ; Optimal:  $1.3 < k \leq 1.6$ ; Rather humid:  $1.6 < k \leq 2.0$ ; Humid:  $2.0 < k \leq 2.5$ ; Very humid:  $2.5 < k \leq 3.0$ ; Extremely humid:  $k > 3.0$

Table 3 depicts how the weather influences potato blight infection.

Influence of weather conditions on the development of potato blight:

2016 – favorable conditions for potato blight occurred because of high rainfall in May (93.0 mm) and August (141.0 mm), and a high hydrothermal coefficient ( $k > 2.0$  in May and August) created favorable conditions for the development of potato blight. Strong soil and plant moisture in August could have been particularly dangerous, favoring the pathogen's rapid spread. However, dry periods in July ( $k = 0.9$ ) could have temporarily limited the development of the disease.

2017 – there was an intense infection pressure of the pathogen in the first half of the growing season. Exceptionally high rainfall in June (117.0 mm) and July (170.0 mm), and humid conditions ( $k = 2.9$  in July) could have led to rapid infection and a rapid epidemic of potato blight—the presence of high air humidity for an extended period favored secondary infections. However, September was exceptionally dry ( $k = 0.2$ ), which could have limited further development of the disease later.

2018 – conditions limiting the development of potato blight. Lower rainfall totals (326 mm throughout the growing season) and relatively low values of the hydrothermal coefficient (June, August –  $k = 0.8$ ) could have hindered the development of the pathogen. In particular, drier conditions in August could have limited the epidemic because *P. infestans* requires high humidity for spore germination and plant infection. In such conditions, the

disease could have appeared at a lower intensity and developed more slowly than in wetter years.

Summary: The highest risk of an epidemic occurred in 2017 when high rainfall in June and July provided ideal conditions for infection and the rapid spread of potato blight. 2016 local epidemics could have happened, especially in August, but drier periods could have limited their scope. In 2018, the blight risk was lowest because conditions were drier, which could have significantly inhibited disease development. These differences in weather conditions could also affect the effectiveness of plant protection – in wetter years, the efficacy of biological methods could be limited, and in an integrated system, more intensive use of plant protection products would be necessary.

The overall interpretation is that,

- 2016 → Wettest year (455 mm). Good rainfall distribution, especially in August (very wet).
- 2017 → Moderate rainfall (425 mm) but very uneven: heavy rain in July (170 mm), very dry in September (8.9 mm,  $k^* = 0.2$ ).
- 2018 → Driest year (326 mm). Hydrothermal coefficient mostly  $\leq 1$  → dry/stressful conditions for crops.

#### 2.4. Soil conditions

Analysis of the content of available forms of phosphorus ( $P_2O_5$ ), potassium ( $K_2O$ ), and magnesium (Mg) and soil pH in 2016–2018 indicates some variations in soil richness, which may affect potato growth and yield (2016–2018) (Table 4).

**Table 4** Abundance of Soil Available Phosphorus, Potassium, and Magnesium, and pH of the Soil (2016–2018)

Years	$P_2O_5$ ( $mg \cdot 100 g^{-1}$ of soil)	$K_2O$ ( $mg \cdot 100 g^{-1}$ of soil)	Mg ( $mg \cdot 100 g^{-1}$ of soil)	pH (1M KCl)
2010	20.3	11.7	4.3	5.7
2011	21.3	12.7	8.1	6.3
2012	15.9	13.3	7.4	6.1
Mean	19.2	12.6	6.6	-

Phosphorus content ( $P_2O_5$ ): The average content of available phosphorus in the soil was  $19.2 mg \cdot 100 g^{-1}$  and varied from year to year. The highest value was recorded in 2017 ( $21.3 mg \cdot 100 g^{-1}$ ), while in 2018, the content of  $P_2O_5$  was the lowest ( $15.9 mg \cdot 100 g^{-1}$ ). The decrease in phosphorus observed in the last year of the study may indicate intensive plant uptake or lower soil availability [39, 43].

Potassium content ( $K_2O$ ). The soil was characterized by a relatively stable content of available potassium, with an increase in its level in subsequent years. In 2016, it was  $11.7 mg/100 g$ ; in 2018, it increased to  $13.3 mg/100 g$ . This increase may be due to the applied fertilization practices or reduced potassium uptake by plants in each season [39]. The increase in 2017 may have resulted from natural changes in nutrient availability or applied fertilization [39].

Soil pH: The soil pH ranged from 5.7 to 6.3, indicating a slightly acidic nature of the soil. In 2016, the soil had the lowest pH (5.7), which could have affected the limited availability of

some nutrients. In subsequent years, the pH value increased to 6.3 (2017) and 6.1 (2018), which could have promoted better assimilation of nutrients by plants [39, 43].

Summary: In the analyzed period, some fluctuations in the content of nutrients and soil pH were observed. Particularly significant changes were concerned with phosphorus levels (a decrease in 2018) and magnesium levels (a sharp increase in 2017). The stable potassium level and the rise in pH in 2017–2018 could have improved plant growth conditions. These changes may have impacted potato yields and the effectiveness of fertilization methods employed in the ecological and integrated cultivation system.

The overall observations are that:

- Phosphorus ( $P_2O_5$ ): Adequate overall but variable; depletion in 2012 might indicate higher crop uptake or leaching.
- Potassium ( $K_2O$ ): Fairly stable, showing improvement — soils are maintaining K supply.
- Magnesium (Mg): Noticeable improvement from 2010 to 2012 — better nutrient availability for crops.
- pH: Slightly acidic soils throughout (5.7–6.3). Most crops grow well in this range, but strongly acid-sensitive crops may require liming at the lower end (5.7).

## 2.5. Observations and measurements

During the potato growing season, systematic observations were conducted in field experiments to assess the rate of spread of potato blight (*P. infestans*). These observations were performed every 10 days using the methodology developed by Pietkiewicz et al. [44], which allows for precise monitoring of the development of the disease over time.

Methodology for assessing potato blight according to Pietkiewicz et al. [44]. Frequency of observations: Every 10 days, starting from the moment the first symptoms of the disease appear. Scope of assessment: Observations focused on the above-ground parts of plants, mainly leaves, where symptoms of late blight most often occur.

Assessment scale: A 9-point scale was used, where 9 indicated no disease symptoms, while 1 indicated complete plant destruction.

Calculation of the disease's spread rate: Based on the collected data, the blight's spread rate was calculated and expressed as an increase in infection per unit of time. This method allows for assessing the dynamics of disease development depending on various factors, such as weather conditions or plant protection methods used.

Data collection methods:

- Visual observations: Regular inspections of plantations by trained personnel to observe plant conditions.
- Direct measurements: Use measuring tools like tape, scales, and moisture meters.
- Sampling: Collecting soil, leaf, and tuber samples for laboratory analysis.
- Data recording: Accurately recording all observations and measurements in field diaries or electronic databases, Roztropowicz et al. [40].

## 2.6. Statistical analysis

Three-way analysis of variance (ANOVA) was performed using SAS version 9.2 [45]. The Fisher-Snedecor F test was used in the study to assess the significance of sources of variability at the significance level of  $p = 0.05$ . In the case of attributes expressed as percentages, particularly those close to 0 or 100, a logarithmic transformation was used to normalize the data

distribution, following the recommendations of Koronacki et al. [46]. After performing the calculations, the data were retransformed to enable interpretation of the results in the original measurement scale. The analysis aimed to assess the effect of the cultivation systems and potato varieties on the studied variables and determine the significance of their mutual interactions. The experiment was conducted in three repetitions. For detailed comparisons of means, the Tukey multiple comparison test (t-Tukey) was used, which allowed for the separation of statistically homogeneous groups of means (homogeneous groups) and the determination of the least significant differences (LSD), designated as HSD (Tukey's Honest Significant Difference). The significance of the sources of variability was assessed using the Fisher-Snedecor F test, which enabled the verification of hypotheses regarding the influence of the studied factors on the analyzed parameters. The rate of potato blight spreading, depending on the observation date, was calculated using regression calculus. For calculations, observation terms were encoded, with the first date assigned as "0", the second as "10", the third as "20", and so on. Leaf infection was expressed in logarithmic values corresponding to a 9° grade, as determined by the formula. The formula for calculating logarithmically expresses leaf infection using the van der Plank approach [47].

$$Y = \ln x / (100 - x) \quad (1)$$

where:

$y$  – logarithmically transformed value of leaf infection;  $x$  – values expressed in hundredths. They make it possible to express the leaf surface damage percentage in a straight line. The rate of potato blight spreading was regarded as a unitary increase in infection over time.

This formula allows the transformation of percentage values so that the obtained relationship takes the form of a straight line. Assuming a unitary increase in the infection rate over time, it is possible to use regression analysis, where the independent variable is time (coded as 0, 10, 20, ...) and the dependent variable is  $y$ . Such a notation allows for a linear interpretation of the disease progression and facilitates further statistical analyses.

## 2.7. Proposed model

We propose a novel machine learning framework, `Eco_IntegratedModel`, designed to predict the incidence of potato late blight using a hybrid dataset consisting of ecological and integrated cultivation system data. The model architecture incorporates a three-phase machine learning pipeline: data preprocessing using SMOTE, predictive modeling using CatBoost, and explainable AI analysis using SHAP. The pipeline is tailored to handle class imbalance, support accurate classification, and enable interpretable predictions. Our proposed model consists of the following stages, as shown in Figure 1. Figure 1 illustrates the workflow adopted in the present study. The framework is composed of four major modules:

- **Input Data and Preprocessing** – This module involves data collection, cleaning, transformation, and preparation for modeling.
- **Predictive Modeling** – The prepared dataset is used to train and evaluate a CatBoost classifier for accurate prediction.
- **Explainable AI (XAI) with SHAP Analysis** – SHAP (SHapley Additive Explanations) values are employed to interpret the model, identifying the contribution of each feature to the predictions.
- **Global Prediction and Interpretation** – A SHAP summary plot is generated to provide a global view of feature importance and overall prediction behavior.

### 1. Model Input and Data Processing

The present model takes as input a combined dataset representing ecological and integrated potato cultivation systems. Due to natural class imbalance in the data—arising from unequal representation of cultivation system types—we applied SMOTE (Synthetic Minority Oversampling Technique) during preprocessing. SMOTE synthetically generates new samples in the minority class, ensuring a balanced dataset and reducing model bias. This step was essential for enhancing classifier performance and improving generalization across cultivation scenarios.

### 2. Predictive Modeling with CatBoost

After data balancing, we employed the CatBoost classifier, a gradient boosting algorithm optimized for handling categorical features and known for its superior performance on tabular datasets. CatBoost employs ordered boosting and Bayesian bootstrapping to minimize overfitting and reduce randomness in split decisions, thereby providing consistent results across repeated runs. In our experiments, the model was trained, optimizing for classification accuracy in identifying whether the data point belonged to an ecological or integrated system.

### 3. Explainable AI with SHAP Analysis

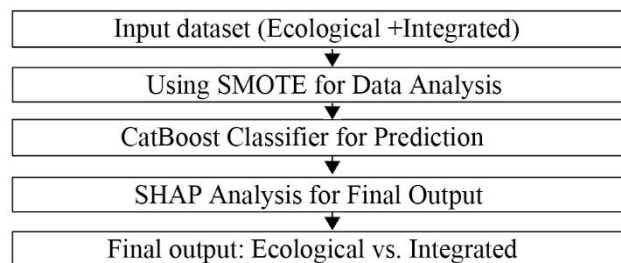
After the training process was completed, we applied SHAP (SHapley Additive Explanations) to interpret model predictions and evaluate feature importance. SHAP assigns each feature an importance value for individual predictions, enabling granular insight into how each variable (e.g., humidity, cultivar, system type) contributes to the final classification. In the case of the present model, the application of SHAP analysis helped us to find:

- The most influential features across both ecological and integrated classes.
- Enabled interpretation of the CatBoost model's decision-making process.

### 4. Global Interpretation of SHAP Summary Plot

To find the global importance of all features, we generated a SHAP summary plot, ranking variables by their average absolute SHAP values. This visualization helped us to determine whether the ecological or the integrated process could be used for efficient prediction of potato blight.

Figure 1 shows Eco\_IntegratedModel represents a novel application of advanced machine learning techniques in sustainable agriculture. Unlike traditional statistical models, our approach effectively helps to predict and understand disease risks under varying cultivation strategies. To the best of our knowledge, this is the first study to incorporate a balanced, multi-year ecological and integrated dataset into a fully interpretable, machine learning–based blight prediction system. This innovation demonstrates the value of combining diverse agronomic data with state-of-the-art ML tools for precision agriculture and decision support.

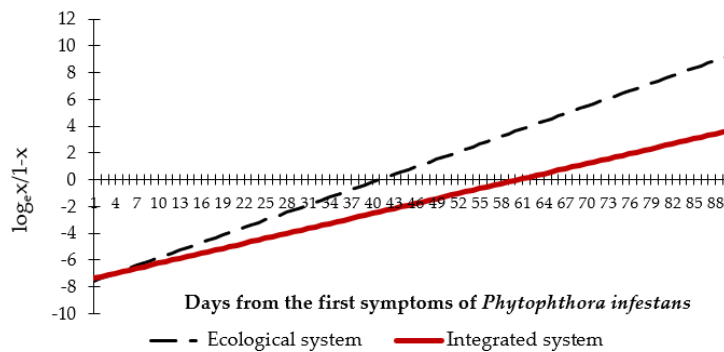


**Fig. 1** Block diagram of the Proposed Model; Source: own

### 3. RESULTS

This section analyzes the results of the importance of features in the CatBoost model. The importance of features was calculated using the permutation method for the CatBoost classifier. The factors in the model using the “integrated” features had a more significant influence than the “ecological” model. This means that the features associated with the “integrated” model system determined the rate of spread of potato blight more significantly than the “ecological” system. We shall divide our experimental results into three sections namely:

**(a) Statistical Results:** In this section, we shall discuss the performance of bio-stimulants in ecological and integrated crop systems using potato blight data. The rate of spread of potato blight over time is illustrated in Figure 2. The 50% leaf blade surface infestation by *P. infestans* in the ecological cultivation system occurred 40 days after the first blight spots were noticed. The use of the integrated cultivation system was delayed by 21 days.



**Fig. 2** Potato late blight in the ecological and integrated crop system (Mean for the years 2018–2020)

Figure 2 shows the rate of spread of potato blight (*P. infestans*) in two cultivation systems: ecological and integrated. The x-axis indicates the number of days from the appearance of the first symptoms, and the y-axis shows the logarithm of the infection quotient  $\log_e(x/(1-x))$ , where  $x$  is the proportion of infected leaf area. In the integrated system, the same 50% infection of leaf blades occurred with a delay of 21 days, i.e., after  $(40 + 21) = 61$  days.

**Reduction of assimilation surface:** Leaves are organs of photosynthesis, the process by which the plant converts solar energy into sugars (mainly starch). These sugars are then transported to the tubers and stored as reserve material, constituting their yield. When 50% of the leaf area is infected by potato blight, the active photosynthetic surface is reduced by half. This drastically reduces the amount of assimilates produced. **Disruption of assimilate transport:** *P. infestans* infection destroyed leaf tissue and disrupted the plant's transport system (phloem). Even if some leaves remain healthy, the damaged tissues hinder the flow of produced sugars to the tubers.

**Diversification of plant resources:** Plants attacked by the pathogen activate defense mechanisms that require energy and nutrients. These resources are redirected from growth and storage in the tubers to fight the infection. The more leaf infestations there are, the more resources are involved in defense, at the expense of tuber development. **Premature leaf dieback:** Severe leaf blight infection leads to premature leaf dieback. If a significant part of the leaf (i.e., leaf surface) dies

before the natural end of the growing season, photosynthesis is abruptly interrupted, which prevents further starch accumulation in the tubers. Therefore, reaching 50% infection of the leaf blades by *Ph. infestans* means that the potato plant has a significantly reduced ability to photosynthesize, transport assimilates, and efficiently store crops in tubers. The earlier such high infection levels occur, the more significant the losses can be expected to be. Delaying the onset of 50% infection in the integrated system by 21 days gave the plants more time to produce and store crops before infection reached critical levels. The effect of plant protection against the blight depended on the plant's resistance towards the pathogen and its reaction to fungicide application (Table 5).

**Table 5** Infection coefficients of *P. infestans* over time

Varieties	Resistance as a 9-degree scale according to COBORU*	Crop production systems	
		ecological	integrated
Ania	8	0.147	0.079
Arkadia	5	0.228	0.127
Irga	2	0.205	0.195
Jagna	5	0.188	0.150
Mila	5	0.229	0.131
Salto	6	0.082	0.07

\*Central Research Centre for Crop Research in Poland

**Influence of cultivar resistance:** Generally speaking, the higher the cultivar resistance score (on the 9-point COBORU scale, where 9 indicates the highest resistance), the lower the *P. infestans* infection rate. Comparing cultivars such as "Ania" (resistance 8) with less resistant cultivars, e.g., "Irga" (resistance 2), "Ania" showed significantly lower infection rates in both cultivation systems. On the other hand, cultivars with lower resistance ("Arkadia", "Irga", "Jagna", "Mila") showed generally higher infection rates compared to more resistant cultivars (e.g., "Ania" and "Salto"). **Influence of cultivation system:** For most potato cultivars studied, the *P. infestans* infection rate was lower in the integrated system compared to the ecological system. This suggests that the methods used in the integrated system (including controlled use of synthetic plant protection products and integrated pest and disease management strategies) are more effective in reducing the development of potato blight. The exception was the cultivar "Irga", where infection rates were similar in both cultivation systems. This may indicate that this cultivar is so susceptible to *P. infestans* that differences in cultivation systems have less impact (Table 3).

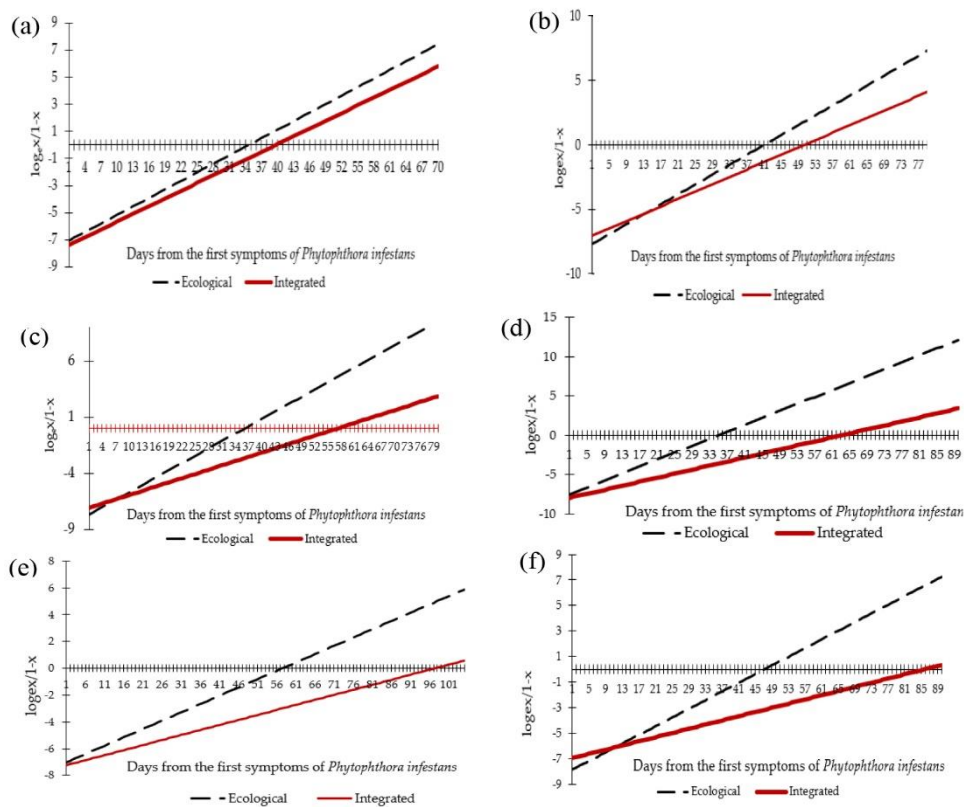
**Interaction between cultivar resistance and cultivation system:** For cultivars with high resistance ("Ania", "Salto"), the difference in infection rates between ecological and integrated systems was relatively small, but still more favorable for the integrated system. This suggests that these cultivars are naturally more resistant, and the cultivation system has less impact on their susceptibility (Table 4).

For cultivars with lower resistance ("Arkadia", "Jagna", "Mila"), the difference in infection rates between systems is more significant. This indicates that the integrated system offers more protection against *P. infestans* infection for susceptible cultivars.

In summary, Potato cultivar resistance is a key factor influencing susceptibility to potato blight. Selecting more resistant cultivars is a fundamental strategy in reducing the risk of infection. The cropping system also plays a significant role in the rate of *P. infestans* infection. The integrated system, probably due to more intensive control methods, is more effective in inhibiting *P. infestans* development than the ecological system. The effectiveness of the

cropping system in reducing infection is more pronounced in less resistant varieties. In the case of highly resistant varieties, natural resistance plays a dominant role. These data underscore the importance of variety selection and appropriate agronomic practices in managing late blights and effectively minimizing yield losses.

Significance of the results: Analysis of infection rates allows for a better understanding of how individual varieties cope with *P. infestans* infection in different cultivation systems. These results can serve as a basis for selecting varieties resistant to the disease and optimizing production systems. It is worth considering additional protection measures in ecological systems, where natural plant defense mechanisms may not be sufficient to limit the spread of the disease. Such an interpretation emphasizes both the role of variety resistance and the influence of production systems on the development of infection, which can be helpful when planning plant protection strategies in agricultural practice.



**Fig. 3** (a) Late blight rate of infection in variety Irga, (b) Late blight rate of infection in variety Jagna, (c) Late blight rate of infection in variety Mila (d) Late blight rate of infection in variety Arkadia (e) Late blight rate of infection in variety Salto (f) Late blight rate of infection in variety Ania

The potato varieties tested reacted differently to the cultivation system. The medium-early, edible variety Irga, popular in Poland and characterized by white flesh, was more susceptible to potato blight than other varieties (Figure 3). Infestation of 50% of the above-ground parts of the

plants occurred 34 days after the first blight spots appeared in the ecological system. In the integrated system, this moment occurred 6 days later.

**(b) Machine Learning Outcomes:** In this section, we will discuss feature ranking and analyze how Ecological and Integrated data affect the prediction of potato blight infection rates using the CatBoost classifier.

The potato varieties tested reacted differently to the cultivation system. The medium-early, edible variety Irga, popular in Poland and characterized by white flesh, was more susceptible to potato blight than other varieties (Figure 3(a)). Infestation of 50% of the above-ground parts of the plants occurred 34 days after the first blight spots appeared in the ecological system. In the integrated system, this moment occurred 6 days later.

In the case of the medium-early variety of Jagna, an infection of 50% of leaf blades in the ecological system occurred 41 days after the first symptoms of the disease appeared (Figure 3(b)). Using chemical protection and mineral fertilization, the integrated cultivation system delayed this moment by 10 days.

The medium-early, edible variety Mila, valued in food processing, showed better resistance to potato blight in the integrated system than the previous varieties. Fifty % of leaf blade infections occurred 36 days after the first symptoms were observed, and the integrated cultivation system extended this period by 22 days (Figure 3(c)). This variety is characterized by higher resistance to *P. infestans*, rated at 6.5° on a nine-point scale.

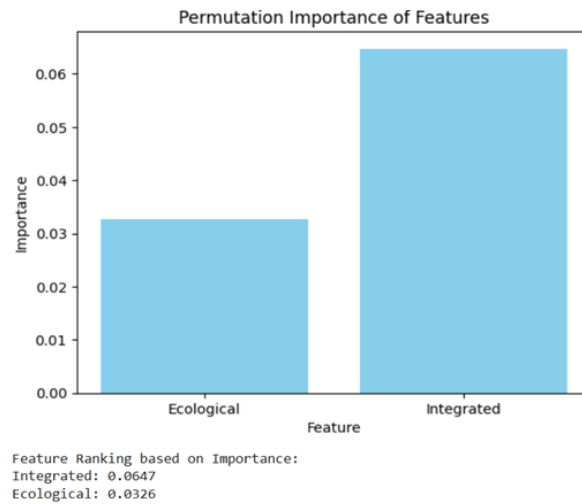
The medium-late variety Arkadia, grown in an ecological system, was infected by *P. infestans* at a rate of 50%, 34 days after the first blight spots appeared. The use of the integrated system extended the vegetation period of this variety by 20 days (Figure 3(d)). The variety Salto, also medium-late and edible, reached a level of infection of 50% in the ecological system after 58 days from the appearance of the first blight symptoms. Cultivation in the integrated system extended the vegetation period of this variety by 40 days (Figure 3(e)).

The late, edible variety Ania, grown in an ecological system, was infected by 50% 46 days after the first blight spots were noticed. The integrated cultivation system extended the vegetation period of this variety by 41 days (Figure 3(f)).

The importance of factors corresponding to the “integrated” model refers to varieties grown in an integrated agricultural system that combines conventional and ecological plant protection methods against potato blight, diseases, and weeds in general. The “ecological” model refers to potatoes grown under ecological farming conditions without synthetic fertilizers and chemical plant protection products. Therefore, integrated agricultural methods have a significantly greater influence on the infection rate than ecological methods, particularly without mineral fertilization and protection against potato blight. From Figure 3, it can be deduced that, integrated technology extended the period of infection of 50% of the leaf blade surface (e.g. by 8-20 days depending on the variety) by 6 days in case of variety Irga, by 9 days in case of variety Jagna, by 21 days in case of variety Mila, by 27 days in case of variety Arkadia, by 40 days in case of variety Salto and by 40 days in case of variety Ania.

Permutation of the importance of Features

The first variety discussed was the late Ania variety. On average, regardless of the variety, the “Integrated” system (importance value: 0.0647) and the “Ecological” system (importance value: 0.0326) had significantly different values (Figure 4).

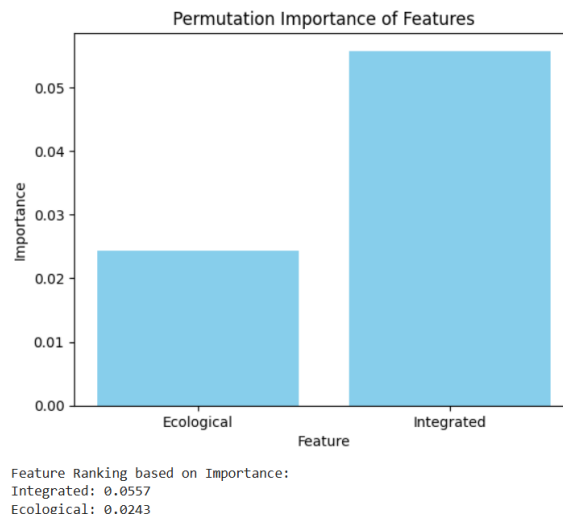


**Fig. 4** The importance of integrated and ecological system features in predicting the rate of potato blight spread for the Ania variety

The significance of the trait importance values for the Ania cultivar indicates how much the cultivation system affects the potato blight's spread rate of the potato blight. The value 0.0647 achieved by the Integrated system means that, in the case of the Ania cultivar, the integrated system's traits significantly impact the prediction of the risk of infection. Integrated methods, combining mineral fertilization and chemical protection with ecological practices, control blight development more effectively, possibly due to better plant nutrition, their excellent resistance to *P. infestans* infection, and more effective protection against the pathogen. Ecological system (0.0326): The lower importance value suggests that factors characteristic of ecological farming have a minor impact on the infection rate in the Ania cultivar. The lack of chemical protection against weeds and potato blight, as well as the absence of synthetic mineral fertilizers, made the plants more susceptible to stress and diseases. Their response to blight depended mainly on the natural defense mechanisms of the cultivar. The difference between these values highlights that in the case of the late Ania variety, the integrated system provides more effective protection against potato blight, translating into a more significant impact of these factors on the model results. It can also be concluded that this variety responds better to more intensive management than to ecological practices.

The two factors of experience analyzed are the Ecological and Integrated Management Systems. The factor 'Integrated' shows a higher significance (0.0647) than the Ecological (0.0326), which suggests that it has a more significant influence on model development. In most cases, the integrated system leads to better results, consistent with the observations of improved model performance through feature engineering. CatBoost, which handles tabular and categorical data well, combined with SHAP analysis and the SMOTE method, allows for more interpretable and fair classification results.

Figure 5 shows the significance calculated using the permutation method for the CatBoost model for the medium-early variety Irga. The results show that the Integrated system had a higher significance value (0.0557) than the ecological system (0.0243), which suggests that it has a more significant impact on the result.



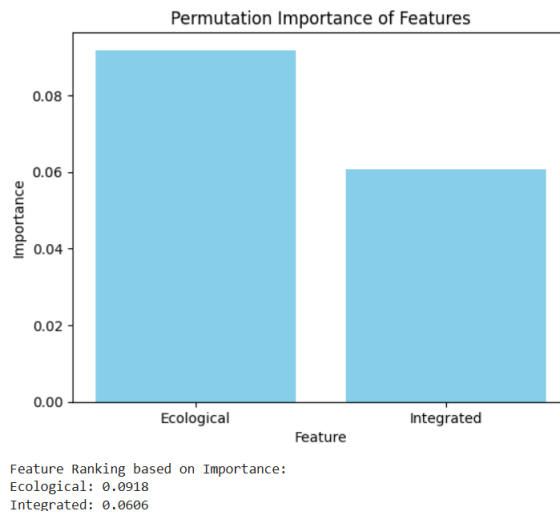
**Fig. 5** The importance of integrated and ecological system features in predicting the rate of spread of late blight for the medium-early potato variety Irga

The higher value for the integrated system (0.0557) means that the factors related to the integrated system had a much more significant impact on predicting the infection rate than those associated with the ecological system. Combining mineral fertilization and chemical plant protection products with ecological practices resulted in more effective integrated methods for reducing the spread of *P. infestans* on Irga potato plants. The lower value for the environmental system (0.0243) suggests that under ecological farming conditions, without synthetic plant protection products, the features related to this system had a negligible impact on the model result. Plants were more susceptible to stress and late blight development, indicating the limited effectiveness of natural protection methods for this variety.

The difference between the evaluated cropping systems highlights that the Irga variety responded better to the more intensive management within the integrated system, resulting in better yield stability and better control of blight spread.

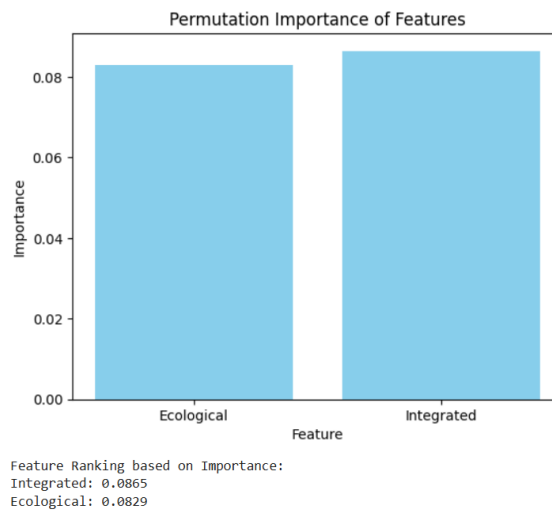
Figure 6 shows the importance of integrated and ecological system features in predicting the late blight spread rate for the medium-early potato variety Jagna.

The analysis of the potato blight spread rate results on the medium early Jagna variety (Figure 6) indicates the factors influencing the disease spread, assessed using the permutation method for the CatBoost model. The significance value for the ecological system (0.0918) was higher than for the integrated system (0.0606), which suggests that ecological methods in cultivating this variety play a more significant role in predicting the spread of potato blight than in the integrated system. This indicated that the environmental factors, such as soil health and overall ecosystem quality, have a more significant impact on the dynamics of disease development compared to the integrated approach, which includes agronomic practices, varietal traits, and economic factors. Therefore, the ecological conditions in which the Jagna variety is grown seem to have a more substantial effect on the spread of the disease than the agricultural practices associated with the integrated system.



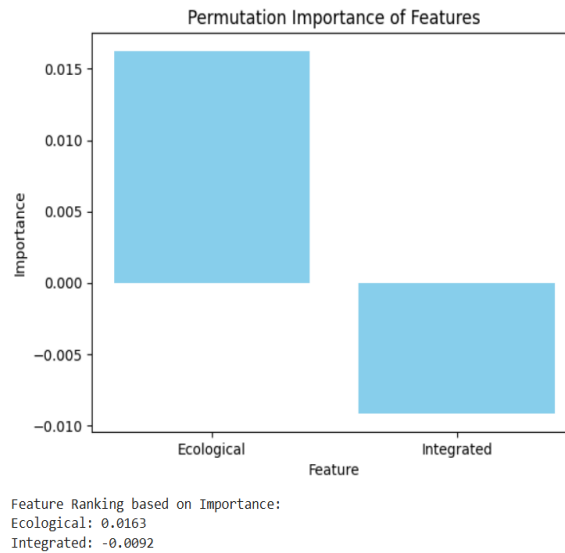
**Fig. 6** The importance of integrated and ecological system features in predicting the rate of spread of late blight for the medium-early potato variety Jagna

The analysis of the data of the medium-early variety Mila (Figure 7) shows the significance of the features calculated using the permutation method for the CatBoost model. Both the analyzed variables—ecological and integrated systems—had a similar impact on the model results. The significance value for the integrated system was 0.0865, while for the ecological system, it was 0.0829, which proves that both systems contributed almost equally to the prediction of the spread of late blight for this variety.



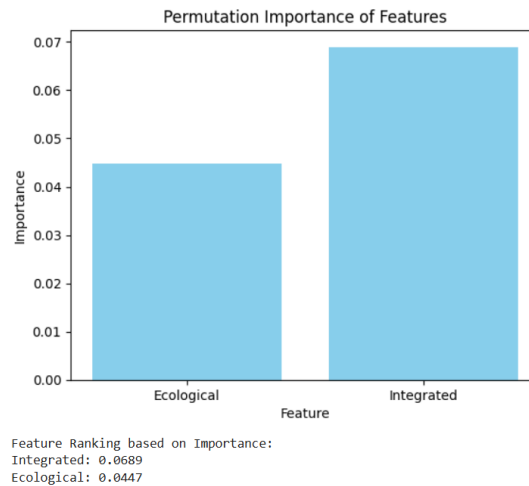
**Fig. 7** The importance of integrated and ecological system features in predicting the rate of spread of late blight for the medium-early potato variety Mila

This indicates a harmonious relationship between the integrated and the ecological aspects, which may mean that both factors similarly impact assessing the area. In the case of the medium-late variety Salto, the significance values are different (Figure 8). The integrated system showed a negative value (0.0162), while the ecological system had a relatively low positive value (0.0163). This suggests neither does the system play a substantial role in predicting the spread of late blight for this variety, with the integrated approach potentially having an inverse effect on the model outcome.



**Fig. 8** The importance of integrated and ecological system features in predicting the rate of spread of late blight for the medium-late potato variety Salto

The analysis of the results of the potato blight infection in the case of the medium-late cultivar Arkadia reveals that there are significant differences in the traits associated with the two cultivation systems (Figure 9). The integrated system showed a higher significance value (0.0689) than the ecological system (0.0447), indicating that agricultural practices, including fertilization and the use of plant protection products, played a more significant role in predicting the spread of potato blight for this cultivar. This also suggests that the Arkadia cultivar responds more strongly to the conditions provided by the integrated approach, in which the combination of conventional and ecological methods increases plant resistance to *P. infestans* infection. On the other hand, the lower significance of the ecological system emphasized its limited impact on the dynamics of this disease development in this cultivar, probably due to the lack of mineral fertilization and chemical protection.



**Fig. 9** The importance of integrated and ecological system features in predicting the rate of spread of late blight for the medium-late potato variety Arkadia

In the case of the Arkadia variety, various factors that are related to the integrated and ecological management systems had a more significant influence on the model than in the previous case. The integrated system still dominated over the ecological one, but the difference between them was smaller than the average for the whole experiment. The Arkadia variety may be more susceptible to factors related to the cultivation system than the late Ania variety. Ecological farming conditions played a more significant role than in the previous case, which may mean that Arkadia is more sensitive to ecological protection methods against potato blight. The increase in the importance of features may suggest that this variety is more dynamic in response to environmental variables. This means that combining different sources of information improves the quality of prediction. Integrating different sets of features leads to better model performance, which is confirmed by the higher value of the significance index. Therefore, it is worth using an approach that combines different data sources to improve classification results.

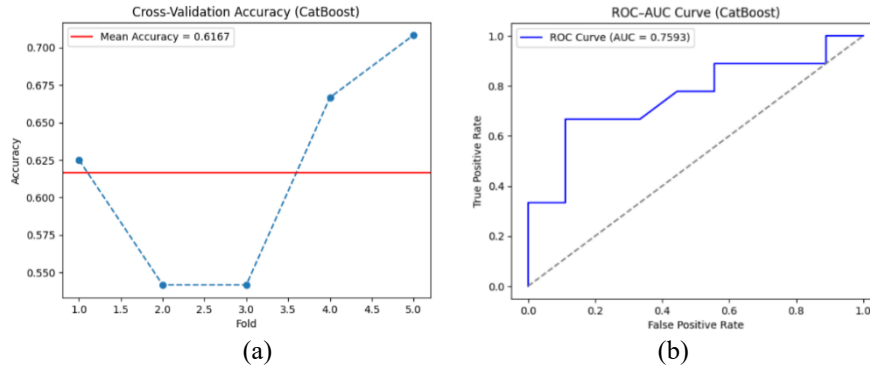
**(c) Data preprocessing and Experimental Setup:** All experiments were conducted in Python using the scikit-learn, imbalanced-learn, CatBoost, and SHAP libraries. To ensure reproducibility, a fixed random seed (SEED = 42) was applied across the Python environment, NumPy, and random number generators.

The dataset (Salto1.csv) was imported in tabular format, and two variables, Ecological and Integrated, were selected as model features. Since the dataset did not include a binary outcome variable, a synthetic target vector (0/1) was generated to simulate classification.

To address potential class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied, which generates synthetic minority class samples based on nearest-neighbor interpolation. This ensured a balanced dataset before model training.

The resampled dataset was divided into training (70%), validation (15%), and test (15%) sets using stratified splitting to preserve class distribution. Also, to perform model evaluation, the model performance was evaluated on training, validation, and independent test subsets using accuracy as the primary metric. In addition, a five-fold stratified cross-validation was performed

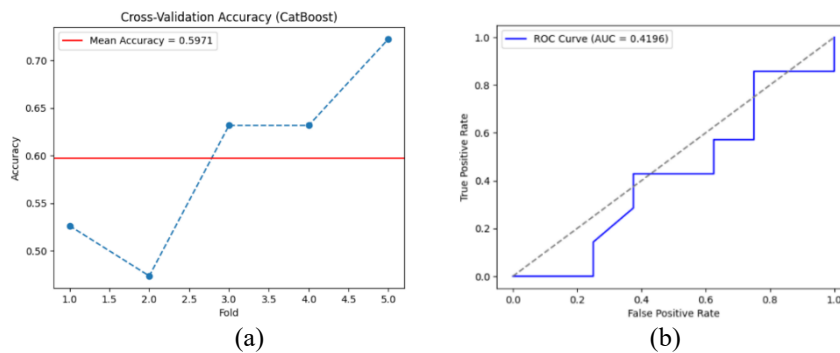
to assess model robustness across different data partitions, and the mean accuracy across folds was reported. Receiver Operating Characteristic (ROC) curves were plotted using predicted class probabilities for the test set, and the Area Under the Curve (AUC) was calculated to quantify discrimination ability.



**Fig. 10** The cross-validation accuracy in the case of the potato tuber Salto

From Figures 10(a) and (b), it is evident that the CatBoost model achieved a training accuracy of 83.3%, indicating that it was able to capture patterns in the training data. However, the validation accuracy was substantially lower at 50.0%, suggesting possible overfitting and limited generalization on unseen data during model development. On the independent test set, the model reached an accuracy of 77.8%, demonstrating moderate predictive capability beyond the training sample. The Five-fold stratified cross-validation provided further insight into model stability, yielding fold accuracy between 54.2% and 70.8% with a mean cross-validated accuracy of 61.7%. The variability across folds indicates that the model’s performance is sensitive to data partitioning, which may be a consequence of the limited feature set (Ecological and Integrated) and relatively small dataset size.

Overall, the results show that the model is capable of learning useful patterns but exhibits inconsistent generalization. Improving performance will likely require expanding the feature set (e.g., climatic, soil, and genetic parameters) and increasing the dataset size to enhance robustness and reduce overfitting. Figure 11(a) and (b) show the model performance on Ania potato tuber.

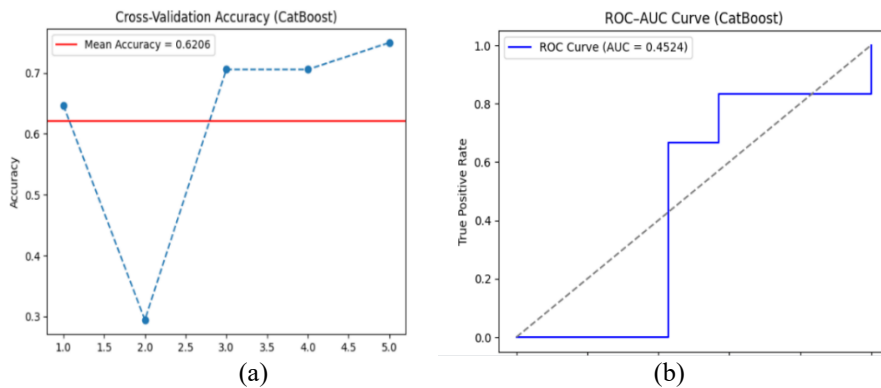


**Fig. 11** The cross-validation accuracy in the case of the potato version Ania

In the case of ‘Ania’, the CatBoost model achieved a training accuracy of 87.7%, but validation (57.1%) and test (46.7%) accuracies were considerably lower, indicating overfitting and limited generalization. Cross-validation analysis showed fold accuracies ranging from 47.4% to 72.2%, with a mean accuracy of 59.7%, further highlighting variability and instability in performance across different data partitions. These results suggest that, while the model can learn patterns in the training data, it struggles to generalize to unseen samples consistently. The observed instability is likely attributable to the limited feature set (Ecological and Integrated) and the relatively small dataset size. Future improvements may be achieved by expanding the dataset, incorporating additional agronomic, climatic, and genetic variables, and exploring regularization or feature-selection strategies to improve model robustness.

In the case of the variety ‘Mila’ shown in Fig 12(a) and (b), the performance analysis depicts a notable discrepancy between training/validation accuracy and test accuracy. While the training (84.48%) and validation (84.62%) accuracies suggest that the model was able to learn and generalize reasonably well during training, the test accuracy drops significantly to 53.85%. This sharp decline indicates that the model may not be generalizing effectively to unseen data for this variety, possibly due to overfitting or high variability in the test set.

Cross-validation results further highlight this inconsistency, with scores ranging from as low as 29.41% to as high as 75%, and a mean CV accuracy of 62.06%. The wide variation suggests that the model’s performance on Mila is highly sensitive to the choice of data split. This instability could be linked to a limited sample size, class representation imbalance, or greater intra-class variation within this variety.

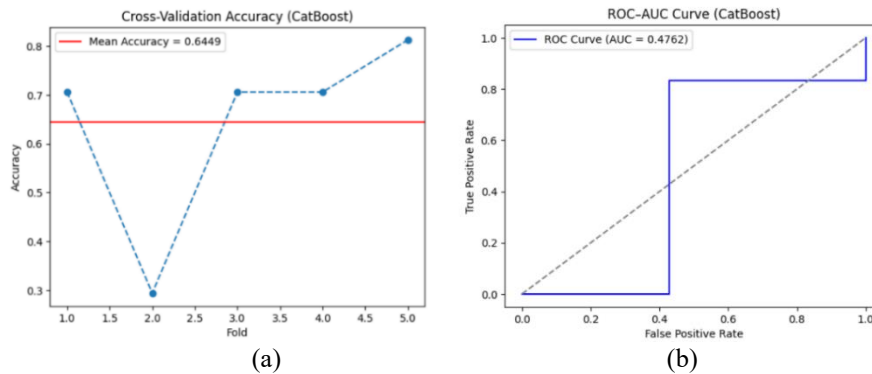


**Fig. 12** The cross-validation accuracy in the case of potato tuber Mila

For the potato variety *Jagna* depicted by Figures 13(a) and (b), the training (84.48%) and validation (84.62%) accuracies are consistent and relatively high, suggesting that the model has learned the classification patterns well during training. However, like the case of *Mila*, the test accuracy drops sharply to 53.85%, indicating a clear gap between learning within the training-validation phase and performance on unseen data. These drops highlight the potential for overfitting or the presence of greater heterogeneity in the test samples of *Jagna*. The cross-validation results provide additional insight. Accuracy scores vary widely, ranging from 29.41% to 81.25%, with a mean CV accuracy of 64.49%. Compared to *Mila*, *Jagna* shows a slightly higher mean CV accuracy, but the variability across folds again reflects instability in the

model's predictive ability for this variety. This inconsistency suggests that the classification of *Jagna* may be influenced by sample distribution or inherent variability in its characteristics.

Overall, while *Jagna* achieves stable learning during training and validation, its fluctuating CV outcomes and poor test accuracy point to the need for model refinement. Techniques such as advanced feature engineering, dataset balancing, or variety-specific modeling approaches could help achieve more consistent and reliable classification performance for this variety.

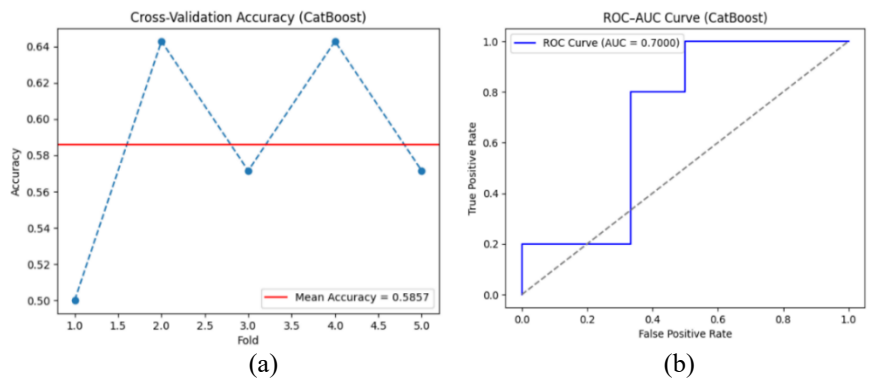


**Fig. 13** The cross-validation accuracy in the case of the potato version *Jagna*

We next come to the potato variety *Irga* shown in Figures 14(a) and (b). The performance metrics from this model show a noticeable gap between training and validation accuracy. Training accuracy reaches 83.67%, but validation accuracy is lower at 70.00%, suggesting that while the model learns patterns from the training data, it struggles to maintain the same level of generalization on unseen validation samples. The test accuracy (63.64%) lies between the two, reflecting moderate predictive performance but still below the training benchmark. Cross-validation outcomes reinforce this observation.

The fold accuracies range between 50.00% and 64.29%, with a mean CV accuracy of 58.57%. This relatively modest mean value, along with the narrow range of scores, indicates that the model's classification performance is consistent but not particularly strong across folds. Unlike the cases of *Mila* and *Jagna*, the variability here is less extreme, though the overall accuracy remains limited. In summary, while the model achieves good training performance, the drop in validation and test accuracy suggests overfitting to the training data and insufficient generalization. The CV results point to stable but moderate predictive capacity. To improve outcomes, strategies such as tuning hyperparameters, incorporating regularization, or expanding the dataset with augmentation could help the model capture more robust and discriminative features.

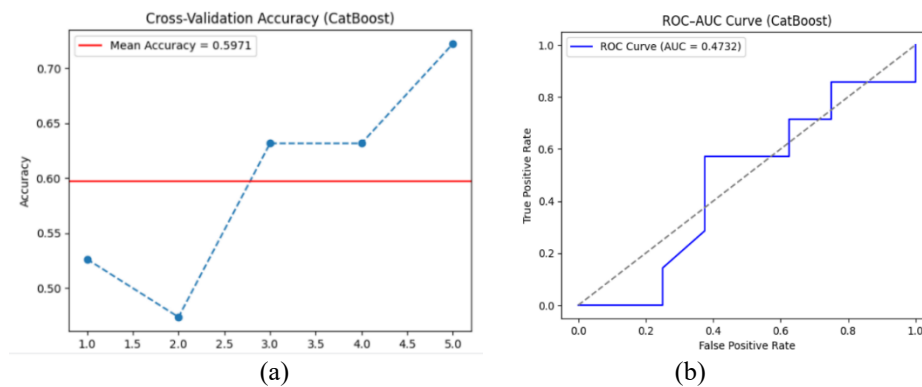
Finally, let us come to the variety *Arkadia*. The performance analysis is shown in Figures 15(a) and (b). The model shows a high training accuracy of 87.69%, but its validation (57.14%) and test accuracy (53.33%) are considerably lower. This gap indicates overfitting, where the model learns the training patterns well but fails to generalize to unseen data.



**Fig. 14** The cross-validation accuracy in the case of the potato version Irga

The cross-validation scores provide additional insight, with accuracies ranging from 47.37% to 72.22% and a mean CV accuracy of 59.71%. While the mean CV result is slightly better than the test accuracy, the variability across folds highlights that the model’s predictive performance is unstable and sensitive to data partitioning.

For all the models, the performance criteria in terms of ROC and AUC are low, but our dataset is limited. The use of Deep learning techniques is more appropriate in the case of pictorial data. In our case, we have tabular data. But in the future, we will try more classifiers to improve the classification rates.



**Fig. 15** The cross-validation accuracy in case of potato version Arkadia

**c) Results on Model Accuracies:** Now, we shall discuss the model accuracies for all the data with respect to the potato versions, namely Ania, Arkadia, Mila Salto, Irga, and Jagna.

Let us talk about the first variety, i.e., Salto. In this variety, the CatBoost classifier achieved a training accuracy of 83.3%, indicating a reasonable fit to the training data. However, the validation accuracy dropped to 50.0%, pointing towards overfitting and limited generalization capability. The independent test set accuracy was 77.8%, suggesting that the model retains some predictive ability when applied to unseen data, although performance remains inconsistent. Cross-validation results further support this

observation, with fold accuracies ranging from 54.2% to 70.8% and a mean accuracy of 61.7%. The variability across folds highlights potential model instability, likely stemming from the limited number of features available (Ecological', Integrated') and the relatively small dataset size. These findings indicate that while the model can capture certain patterns, its generalization remains constrained. Expanding the feature set (e.g., climatic, soil, genotype information) and increasing dataset size are recommended to improve robustness and reliability in future work.

#### 4. PRACTICAL RECOMMENDATIONS

In Ireland, due to the cool and wet climate and the susceptibility of potato cultivars to potato blight (*P. infestans*), producers apply 12 to 15 fungicide applications per year, often weekly from plant emergence. In seasons favorable to the development of the disease, the number of applications may increase. The effectiveness of *P. infestans* control depends on the available fungicides and the stage of plant growth. The emergence of fungicide resistance in the pathogen is a key challenge. In Denmark, since 2019, cases of reduced efficacy of mandipropamide (a fungicide from the carboxylic acid amides - CAA) have been reported, and analysis confirmed resistance of strain EU\_43\_A1 to this substance [21, 48, 49].

This is the first detection of CAA resistance in *P. infestans*, which may have important implications for European potato protection strategies [48]. The emergence of resistance to CAA in *P. infestans* may have significant consequences for potato blight control strategies throughout Europe. Therefore, it is necessary to monitor the effectiveness of the fungicides used and to search for alternative protection methods, such as cultivating varieties more resistant to blight or integrated disease management methods [20]. The results of the analysis of the importance of features in the CatBoost model for different potato varieties indicate a varied effect of the cultivation system (integrated and ecological) on the rate of spread of potato blight, which is confirmed by the results of studies by other authors [20,46]. The differences between the varieties: Ania, Irga, and Arkadia showed a higher value of the importance of features for the integrated system, which suggests that agrotechnical practices, such as mineral fertilization and chemical plant protection, play a key role in limiting the spread of the blight. In the case of the Jagna variety, the ecological system was more critical, indicating its better adaptation to ecological conditions or a more significant role of environmental factors, such as soil health and biodiversity. The medium-early variety Mila was characterized by a similar effect of both systems, which suggests that both ecological and integrated practices may provide a comparable level of protection against light. In the case of the Salto cultivar, both the environmental and integrated systems had low importance values, which may indicate a specific resistance to this cultivar or a limited response to potato blight in both systems [7, 8, 10, 12, 26, 49].

##### 4.1. The rate of spread of potato blight

The rate of spread of potato blight (*P. infestans*) was analyzed depending on the cultivation system. In the ecological system, infection of 50% of the leaf blade surface occurred faster than in the integrated system, where the use of chemical protection and fertilization delayed infection [1].

Potato varieties differed in their susceptibility to blight. Irga was the most susceptible, reaching 50% infection after 34 days (in the ecological system) and after 40 days (in the integrated system). Jagna was infected after 41 days in the ecological system, and the integrated system delayed this moment by 10 days.

Mila showed greater resistance, with infection after 36 days (in the ecological system) and a delay of 22 days in the integrated system. The Arkadia variety reached 50% infection after 34 days (in the ecological system), and the integrated system extended this moment by 20 days. The medium-late Salto variety showed the highest resistance, with 50% infection after 58 days (in the ecological system), while the integrated system delayed this by 40 days. Ania, a late variety, was infected by 50% after 46 days, while the integrated system extended the vegetation period by 41 days.

In summary, the integrated cultivation system significantly slowed the development of the disease, and the resistance of the varieties was a key factor in limiting infection. The latest research on potato blight (*P. infestans*) highlights the importance of integrated plant protection and breeding resistant varieties as key elements in managing this disease. It was indicated that cultivating resistant varieties can significantly reduce the need for fungicides, which are essential in sustainable agriculture [10,50,51,52].

In addition, the research conducted by scientists from Wageningen University & Research in the Netherlands shed new light on the mechanisms of *P. infestans* infection. Specific interactions between the pathogen and the host plant were discovered, which may lead to developing new strategies for protecting potatoes against blight. Analysis of 47 potato blight epidemics in the Netherlands (1950–1996) revealed three periods with mean values, with disease severity strongly associated with the number of days with precipitation and hours with temperature 10°C to 27°C and humidity >90%, and disease reduction with hours with temperature >27°C and global radiation. Linear discriminant analysis, which utilized the previous year's blight status and meteorological variables, correctly classified 87% of cases, highlighting the key roles of days with precipitation and previous blight status in predicting epidemic intensity [53].

In the context of yield losses, the data from 2024 indicates that, on unprotected potato plantations, yields can be as low as 10 to 15 tons per hectare, depending on weather conditions [10]. For this reason, integrated protection methods, which combine the cultivation of resistant varieties with appropriate agrotechnical treatments, are crucial for minimizing losses caused by *P. infestans*.

Resistance to potato blight is often correlated with the length of the growing season of a given variety. Studies indicate that varieties with a longer growing season exhibit higher levels of resistance to *P. infestans*, which may be related to these plants' genetic and physiological characteristics [10,12, 17, 26, 53].

In summary, the latest studies emphasize the need to employ integrated potato protection strategies against blight, including breeding resistant varieties and implementing optimal agrotechnical practices, to manage this disease and minimize yield losses effectively.

The rate of spread of potato blight (*P. infestans*) is closely related to the resistance of individual potato varieties to this pathogen. As the resistance of varieties to leaf blight increased, the coefficient of the rate of spread of *P. infestans* decreased. This means that varieties with higher resistance showed a slower rate of disease development, consistent with previous studies indicating the vital role of variety resistance in limiting the rate of infection [8, 10, 11, 53]. Regression analysis showed that the trend of *P. infestans* spread in the studied varieties is best described by a second-degree polynomial curve, while the resistance of varieties to this pathogen follows a logarithmic curve. This suggests that even

a small increase in variety resistance can lead to a significant decrease in the spread of disease, which emphasizes the importance of breeding varieties with increased resistance in potato blight management strategies.

#### 4.2. Comparison with other studies based on similar ecological-integrated model(s)

The results are consistent with previous studies, which indicate that cultivars grown in an integrated system often achieve higher resistance to potato blight due to the combination of plant protection treatments and appropriate fertilization [11, 39, 40, 54]. The studies by Smith et al. [52] showed that integrated practices can reduce pathogen pressure by up to 40%, compared to ecological systems [3, 8, 11].

At the same time, the results for the Jagna cultivar are consistent with the work of Green [55], Sawicka et al. [10, 12], and Noaema et al. [11], who showed that some cultivars perform better in an ecological system, especially when the role of soil health and biodiversity in limiting pathogen development is emphasized. The maximum detection accuracy obtained by Larson et al. [23] using the PLB-SI-XGBoost model was 70%. Another latest work by Zarrouk et al. [56] used YOLO (You Only Look Once) and the two-pass RCNN (Region-based Convolutional Neural Network) with special focus on the potential use of drone-based agricultural surveillance for the detection of potato blight infections. Now, we will discuss a brief comparative analysis of treating potato blight infection disease using the latest machine learning models, as shown in Table 6. From Table 6, we can see that, even when the best test accuracy of 99.54% was obtained by [57], the datasets on which the authors worked were essentially potato-based images. In our case, our dataset is novel and is a uniform mix of integrated and ecological datasets. None of the existing works, those of which have attained high recognition rates, have worked with images of potato blight infection. In this case, our work is truly novel because we have worked with a new data set spanning ecological and integrated data spanning 2018-2020, and we have improved a machine-learning model, which could further help in predicting potato blight infection.

It is evident from Table 6 that most of the recent studies on potato blight and leaf disease detection have predominantly relied on image-based datasets, often focusing on single cultivation systems or controlled experimental conditions. For example, Anusuya et al. [57] achieved an accuracy of 99.54% using several deep learning models, including VGG16, ResNet50, and InceptionV3, while Dey et al. [61] and Zhu et al. [62] reported similarly high accuracies (98.6% and 98.43%, respectively) on potato leaf image datasets. Likewise, AL Zakari et al. [60] demonstrated that hybrid architectures such as CNN-LSTM can achieve accuracy levels above 97% on standardized datasets. On the other hand, Chi et al. [59] used the COPERNICUS satellite dataset, which is quite different from leaf-based imagery, and their best model (MSTS-RF) achieved a comparatively lower performance ( $R^2 = 0.71$ ). Dolatabadian et al. [58] contributed more from a review perspective, consolidating different detection strategies rather than proposing a single model.

**Table 6** Comparative analysis

Ref.	Dataset details	Accuracy
Anusuya et al. [57]	Leaf disease dataset	After applying several deep learning models, including VGG16, ResNet50, InceptionV3, MobileNetV2, and a custom-developed CNN, the highest test accuracy obtained was 99.54%.
Dolatabadian et al. [58]	Comprehensive review work	Discussion of various techniques aimed at the detection of image-based crop disease
Chi et al. [59]	The COPERNICUS dataset included C-band images.	Various classifiers were used, including CART decision trees (CART), Gradient Tree Boosting (GTB), and Random Forest (RF). Among all of these, the MSTs–RF model performed best, with an RMSE of 20.50 and an R <sup>2</sup> of 0.71.
AL Zakari et al [60]	Z-score standardized dataset	The best performance was achieved by the CNN-LSTM model, which yielded the highest accuracy of 97.1%.
Dey et al [61]	Dataset of potato leaf disease.	The model achieved 98.6% test accuracy.
Zhu et al [62]	Dataset of potato images	The present model, based on MSC-ResViT, MSC-Text CNN, and CT-CNN, rendered an accuracy of 98.43 % on the test dataset.
Present Work	Tabular data of Ecological and Integrated-Based Regression	A maximum AUC of 76% was achieved

In contrast, the present work introduces a novel dataset that integrates both ecological and integrated cultivation systems, which none of the existing studies have addressed. Unlike prior works that rely primarily on direct potato leaf images, our dataset incorporates a balanced mix of ecological and integrated field data, offering more realistic insights into disease prediction under diverse cultivation conditions. While existing models often report very high recognition rates, their applicability remains constrained to image-specific datasets. Our approach, however, emphasizes broader generalization and practical relevance for predicting potato blight across various cultivation systems. Although our current model may not achieve recognition rates as high as some image-based approaches—largely due to the limited size of our dataset—it nevertheless contributes a unique regression-based perspective. Looking ahead, we plan to employ more advanced classifiers to tackle regression-based data better and further strengthen prediction accuracy.

#### 4.3. Summary of results

The research results indicate that the choice of the cultivation system should depend on the farm's priorities. The integrated system offers higher efficiency but requires chemicals, while the ecological system is less invasive but can lead to more significant yield losses in unfavorable conditions. The appropriate cultivation model choice should consider economic and environmental aspects [2,3,8,9,10,17,18,63,64]. Both management systems had a comparable effect on the potato blight model, which suggests that both the integrated and ecological approaches to sowing provide essential information. The lack of clear dominance of one of the

factors indicates the possibility of their complementarity, i.e., both systems may provide different but equally important aspects of information for the model. In contrast to the previous results, where the Integrated system had a much higher significance, the difference was minimal, possibly due to changes in data processing, class balance (e.g., after SMOTE), and other modeling factors. Hence, it is worth analyzing the data more thoroughly to determine whether combining both factors improves the model results or if one brings redundant information.

#### 4.4. Practical significance

The differences between varieties in the rate of spread of *P. infestans* suggest that the choice of cultivation system should be adapted to the specific characteristics of a given variety. Varieties such as Ania, Irga, or Arkadia may be more effectively protected in an integrated system, while the Jagna variety with intermediate susceptibility to *P. infestans* may be preferred in ecological farming [3, 10].

The results of the conducted analysis confirm that the effectiveness of potato blight (PLB) management depends on both the cultivation system and the specific features of potato varieties [63]. The higher importance of the integrated system features for most varieties indicates the vital role of agrotechnical practices in limiting the pathogen's spread, which aligns with current integrated pest management strategies. At the same time, the observed differences between varieties suggest the need for further research on genetic improvement of plant resistance and adaptation of protection strategies to specific cultivation conditions [64].

#### 4.5. Limitations and future research directions

Although the results obtained provide valuable information, it is worth noting that the analysis was based on specific growing conditions and only on six potato varieties. Further studies should include a more significant number of varieties and consider various environmental conditions, allowing for a better understanding of the interaction between the cultivation system and resistance to potato blight.

It would also be advisable to conduct long-term studies considering the variability of weather conditions [56], as climate significantly impacts potato blight development and the effectiveness of the individual cultivation system.

Although the results obtained provide valuable insights, certain limitations should be acknowledged. First, the analysis was conducted under specific growing conditions and included only six potato varieties, which may restrict the generalizability of the findings. Future studies should examine a larger number of varieties across diverse environments to capture better the interaction between cultivation systems and resistance to potato blight.

Second, the study did not account for several potential confounders that could have influenced the results. These include unmeasured environmental variables such as microclimatic differences, soil heterogeneity, and disease pressure, as well as management practices like fertilization regimes, pesticide use, and irrigation strategies. Addressing these factors in future research would allow for a more precise estimation of the true effects of cultivation systems on blight resistance.

Finally, the study was limited to a short time frame, while potato blight development and the effectiveness of cultivation systems are strongly influenced by climate variability across years. Long-term experiments incorporating weather fluctuations would provide

more robust evidence and improve our understanding of how cultivation systems perform under changing climatic conditions.

#### 4.6. Summary of results based on programming context

In conclusion, our analysis demonstrates that the CatBoost classifier accurately predicts the impacts of ‘Ecological’ and ‘Integrated’ varieties across various classes of potatoes, showcasing its robustness and reliability in programming logic.

Additionally, the SHAP analysis has emerged as a valuable tool for effectively interpreting the significance of ecological and integrated varieties across different classes of potatoes. We conclude that, in most of the varieties of potatoes, the integrated varieties were substantially important. This, in turn, will help the farmers to educate themselves and act accordingly so that future crop plantations can be enriched and thereby predict potato blight.

### 5. CONCLUSIONS

The major findings of this study demonstrate that the integrated cropping system provided more effective plant protection against *P. infestans*, mainly due to the intensive use of chemical inputs. This system resulted in better control of weeds, pests, and diseases, and consequently higher production efficiency. However, its reliance on synthetic plant protection measures underscores concerns regarding sustainability and environmental impact.

In contrast, the ecological cropping system fostered more balanced plant growth and improved soil fertility, particularly through crop rotation with red clover and grass. Nevertheless, the absence of adequate blight protection increased the risk of yield losses, and the longer regeneration cycle limited production efficiency. Thus, ecological management offers environmental advantages but requires additional strategies to ensure disease resilience and yield stability.

At the varietal level, differences in performance highlight the importance of matching varieties to cultivation systems:

- Jagna performed best under ecological conditions, reflecting strong adaptability to reduced-input management.
- Mila demonstrated stable performance across both systems, indicating its suitability for diverse production strategies.
- Ania and Arkadia achieved higher efficiency in the integrated system, indicating their dependence on agrotechnical support for optimal yield and disease resistance.
- Salto exhibited inconsistent results, including negative outcomes under the integrated system, pointing to potential structural or management-related limitations.

The results confirm that the varietal characteristics interact strongly with cultivation systems, and the choice of strategy should integrate biological, environmental, and socio-economic considerations.

The predictive model developed in this study supports integrated potato disease management by enabling early identification of blight risk and guiding targeted protection strategies. The future recommendations are as follows:

- Long-term studies are needed to evaluate the cumulative effects of ecological and integrated systems on soil health, biodiversity, and potato quality.
- Variety-specific optimization should be pursued to align potato genotypes with the most suitable management systems.

- Refining ecological protection strategies, including the use of resistant cultivars, biocontrol agents, and optimized crop rotations, is essential to reduce yield losses without compromising sustainability.
- The integration of predictive models with real-time weather and field data can enhance the precision of blight forecasting and reduce unnecessary chemical inputs.
- Socio-economic analyses should be conducted to balance productivity with farmer adoption, cost-effectiveness, and consumer demand for sustainable produce.

Overall, while integrated cropping systems currently provide higher protection efficiency, the ecological systems hold potential for sustainable production if supported by improved varietal selection, optimized rotations, and predictive decision-support tools.

**Acknowledgement:** *The work presented in this paper was supported by the German Federal Ministry for Education and Research in the form of the Brandenburg/Bayern initiative for integrating artificial intelligence hardware subjects in the university curriculum (BB-KI Chips), project no. 16DHBKIO20.*

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