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# AI-PotatoGuard: Leveraging Generative Models for Early Detection of Potato Diseases

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**Abstract**
This paper introduces AI-PotatoGuard, an artificial intelligence (AI) tool which enhances the management of diseases in potatoes through the use of generative models and convolutional neural networks (CNN). In contrast to traditional practices, AI-PotatoGuard is a tool which provides the ability to detect potatoes in the early stages of the disease and also precisely detects the area affected. Through AI-PotatoGuard, it was observed that the conventional approach of identifying the diseases have been surpassed with 95% success observed in terms of getting the detection perfectly right and 85% in terms of getting the detection right at a much earlier stage. Traditional practices lagged with 75% detection right observation and a mere 50% in terms of detecting the disease early on. While traditional methods applied chemicals 2–3 times in practice in an area, the monitoring with AI-PotatoGuard resulted in only 2 out of 6 times in the same area. Hence, efficient and sustainable agriculture is achieved using AI.

**Keywords** AI potato · Convolutional neural network · Disease · Early detection

## Introduction

Potato cultivation is vital to the economy and food security of many nations. It is the global agriculture industry's backbone, and by far the most consistent crop we eat around the world, together with the "big three"—maize, wheat, and rice (Rashid et al. 2021). Throughout the centuries, the potato's adaptability to diverse climates and soils has made the crop a staple from continent to continent and a crucial part of our diets (Gardie et al. 2022). Nonetheless, that adaptability has a limit, and more than 100 diseases are constantly threatening it. These diseases could significantly reduce both crop yield and quality, causing more hunger and malnutrition worldwide, not to mention hardship for the farmers (Alfozan and Hassan 2021).

Late blight, responsible for the significant Irish Potato Famine of the nineteenth century, is one of the diseases that we are most concerned about. The source of the

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disease is a spore, which is produced by the fungal-like organism, *Phytophthora infestans* (Sinshaw et al. 2022). Early blight is caused by *Alternaria solani* and is more frequent, occurring wherever potatoes are grown. Early blight can affect the stems, leaves, and tubers (Yücel and Yildirim 2023). Yield can be reduced; tubers may be so severely infected that they are of no value and in some cases follow-up infections by other pathogens of the dead tissues can occur (Malko et al. 2019). In contrast, potato scab, caused by *Streptomyces scabiei*, only becomes a problem in dry years. Heavy rain suppresses the scab-producing organism. The most vulnerable stages of plant growth in relation to common scab development are during the first 6 weeks and the last 2 weeks before the plants die (Dacal-Nieto et al. 2011).

To address these challenges, the groundbreaking solution known as AI-PotatoGuard has emerged, marked by its aim to transform the way we identify and then manage diseases that infect potatoes in their early stages. Using the most advanced technology in generative models, the objective of AI-PotatoGuard is to interrogate numerous data sets of potato crops like they do in photographs, in order to detect signs of an illness in the plant well before we are able to physically perceive it or the disorder takes a significant toll on yield. By its design and its mantra, this novel school of thought is meant to not only shield against inaccurate assessments or a slow diagnosis, but to minimise the need for chemicals and provide a sustainable framework that reflects the world's leanings away from manipulating food in the field or post-harvest. The proposed system seeks to increase the supply of large quantities of disease-free potatoes and assist agriculturalists in eliminating unwanted potatoes. Also, this system works in the early stages of a potato's life, even if signs of disease are not observable to agriculturalists.

## Literature Review

Several worthwhile initiatives have been taken to design AI-based solutions for the early detection of potato diseases. Rashid et al. conducted an in-depth multistage diagnostic study of primary potato leaf disease with a focus on blight (Rashid et al. 2021). Likewise, Hamza et al. studied deep learning methods for potato disease detection, highlighting the issue of early detection (Hamza et al. 2022). Besides, Hassoon et al. presented a system of potato disease classification based on neural networks, with a high accuracy of 95% in detecting late blight and early blight (Hassoon et al. 2021).

Another study conducted by Alfozan and Hassan suggested a disease diagnosis application based on images using convolutional neural networks (CNN) to predict various diseases in agricultural plants, including early damage and late damage in potatoes (Alfozan and Hassan 2021). A year later, Gardie et al. suggested a study on detecting potato leaf diseases by relying on artificial intelligence algorithms to detect and classify them (Gardie et al. 2022). On the molecular front, Elfarash et al. (Elfarash et al. 2021) displayed the quantified bacterial expression in the potato pathogen *Pectobacterium carotovorum* by qRT-PCR. Furthermore, Elfarash et al. (Elfarash et al. 2021) demonstrated early and rapid detection of fungal pathogens in potatoes by Fourier transform infrared microscopy, highlighting the importance of early pathogen detection. In Medina et al. (2024), an application was developed on Android devices to diagnose sweet and bitter potato diseases through a set of mathematical methods that aim to detect potato diseases early and provide excellent results on mobile devices. This application helps monitor the spread of agricultural diseases and inform farmers and specialists of the results of these diseases. In a study conducted by Erukhimovitch et al. (2007), they trained three convolutional neural networks (GoogleNet, VGGNet, and EfficientNet) utilising Python. The data for this study includes more than 5100 images of healthy and diseased potato plants. Remarkable results have been performed in diagnosing potato diseases, improving potato growers' profitability, and reducing environmental risks.

All the studies mentioned above are essential literature, as they were summarised, as they rely on machine learning models in the early detection and classification of potato diseases. The proposed study is part of this literature on using artificial intelligence algorithms to analyse patterns and data on potato diseases.

## Methodology

The proposed AI-PotatoGuard system is an environment that relies on machine learning models to track new patterns in potato images and identify existing diseases. This system relies on practices and strategies consisting of complex mathematical equations to determine the behaviour of patterns and training on a new dataset, as well as to give accurate results with high efficiency in identifying and classifying classes of diseases. Having pre-trained machine learning algorithms makes it easier for the system to continue tracking the data and identify new patterns on its own based on new data in a set of potato images.

### Detailed Description of the AI-PotatoGuard System Architecture

AI-PotatoGuard has an architectural design that is meant to help in the smooth operation of agricultural data. The main aim of the architecture is to be able to detect early the disease that affects potato crops. The system as such is basically made up of three components: data collection, processing, and user interface. All three are found to work together as a single unit.

1. Module for collecting data: the aim of this module is to amass high-standard images of potato from many different sources including drones, satellite, and cameras which are intended to catch what is happening on the potato field. This module serves to make sure that the array of data in touch with is huge enough to embrace all sorts of potato varieties and diseases thus becoming a great material to make models with.
2. Module for processing and analysis: located at the core of the system, this central module hosts the generative models and algorithms for machine learning. Its primary function involves handling raw input, and thus identifying telltale patterns denotative of possible diseases. The module itself has a tremendous reliance on convolutional neural networks (CNNs), especially for the purposes

of image recognition and discerning of healthy vs. diseased plants. The accuracy of distinguishing success is nothing short of extraordinary.

3. User interface: as it has been made user-friendly, the user interface lets the users of the system, both the farmers and any professionals that have to work with agriculture, access all of the finding of the system, examine what is the result of the diagnostic, and bestow the advice on how to cope with the disease that has appeared. This interface is web-based, to which its accessibility is on all devices.

### Data Collection Process for Training the Generative Models

In order for AI-PotatoGuard to work effectively, it requires high-quality data of all types and varieties to train the generative models used by the various images. This process has been meticulously designed to collect enough images of a variety of high-resolution images of the type, stage, and environmental conditions of potatoes possible. In addition, metadata such as time, date, and weather of the photos is stored to provide a rich understanding of the circumstances captured by the photo, providing the context needed for machine learning to understand any variety or images taken with that variety and be able to associate them with diseases.

### The Algorithms

Machine learning algorithms are used to analyse and diagnose a dataset of potato diseases with high efficiency and to identify the main factors of these diseases in developing the smart potato system environment. These algorithms rely on multi-layered software structures, where each layer performs a specific task. They also help create an intelligent system capable of studying the behaviour and patterns of potato data at all stages of growth. This system helps determine whether potatoes are healthy or not and provides details that support agriculturalists in getting rid of diseased potatoes. To operate the AI-PotatoGuard system in identifying potato diseases on images, both GAN and CNN must be combined in one environment to increase the proposed system's efficiency. This integration helps improve and process potato images and diagnose the stages of disease development, with the aim of helping agriculturalists get rid of unwanted potatoes.

– Generative adversarial networks (GANs) have recently been distinguished as a model for dealing with generative artificial intelligence and are the smartest improved models in machine learning. Two different deep neural networks work together to produce something new that does not exist; one is generative, and the other is distinctive. These networks operate adversarially. The generative network aims to make the noise vector it takes as input similar to the real images in the training set, while the discriminator network tries to distinguish between artificially produced (fake) images and real training images. In this model, training is done on a dataset of potato diseases between the two networks, as each of them attempts to improve performance in producing real images to study the behaviour of these diseases and help classify these images into two categories. Improvements in this algorithm help determine whether potatoes are infected with certain diseases or not.

– Deep learning has emerged as a machine learning approach through which complex structures are learned in real-world datasets (Afzaal et al. 2021; Bayu 2024; Hong et al. 2023; Mishra et al. 2023; Al-Janabi and Ismail 2021; Khaleel et al. 2018; Hussain et al. 2020). Deep neural networks trained using large-scale data have significantly outperformed classical image processing techniques regarding the semantic understanding of images (Khaleel et al. 2018; Alhayali et al. 2021; Aljanabi et al. 2021; Alhussan et al. 2024; Aljanabi et al. 2023; Mohammed et al. 2024; Ibraheem 2022; Mijwil et al. 2024; Mishra et al. 2024). Therefore, to improve the performance of the AI-PotatoGuard system, the convolutional neural network (CNN) was used, which is a robust tool for distinguishing between image categories by examining features and patterns and identifying the behaviour of diseases present in potato data. This algorithm improves computer vision devices by providing accurate results in detecting data patterns.

## Main Structure

The structural environment of the proposed system is based primarily on machine learning through a set of algorithms pre-trained on a large set of potato images. Each GAN and CNN is combined in one environment to recognise patterns, each with a unique method of training on the test image. These images are entered into a group of layers to improve the proposed system's performance and increase work efficiency (Fig. 1).

## AI-PotatoGuard System Components

AI-PotatoGuard's architecture includes various vital elements that work independently to allow the system to spot the first signs of a disorder.

1. Data collection module: this module is responsible for assembling a varied collection of high-quality images of potato crops, acquired from a variety of sources such as drones and ground-based sensors. The extensive dataset guarantees that the model is introduced to a wide range of disease symptoms.

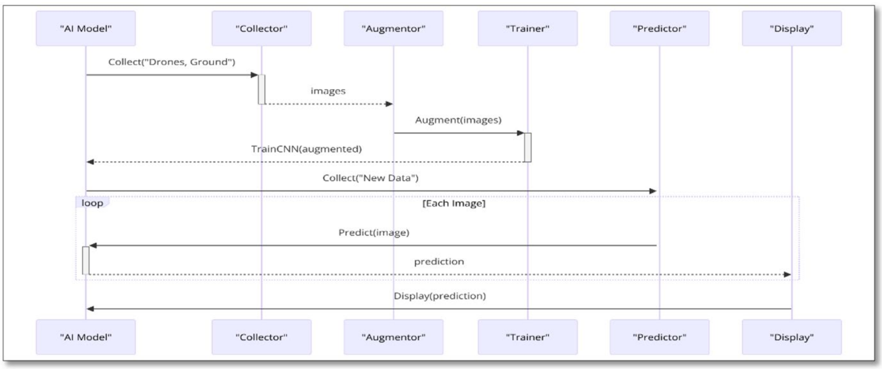


**Fig. 1** Main diagram of AI-PotatoGuard

2. Data processing and augmentation module: by using generative adversarial networks (GANs), this module improves the dataset by creating artificial images that imitate genuine signs of disease. These networks function according to the formula:

$$G(z) = Synthetic\ Image$$

where $G$ is the generator that takes a random noise vector $z$ and outputs a synthetic image that is indistinguishable from real images to the discriminator.
3. Disease identification and analysis module: the focus of AI-PotatoGuard is this component, which applies a convolutional neural network (CNN) to visually assess the images for disease patterns. The exploit of CNNs to glean features from images is rooted in the convolution function's power.

$$f(x, y) * g(x, y) = \sum m = -aa \sum n = -bbf(m, n) \cdot g(x - m, y - n)$$

Here, $f(x,y)$ represents the input image, $g(x,y)$ is the kernel or filter, and * denotes the convolution operation. This process is key to identifying patterns specific to different potato diseases.
4. User interface and interaction module: in order to ensure that our users can use our tools easily, we have provided a simple interface that allows users to upload pictures, receive an automatic disease diagnosis, and receive detailed advice about their diagnosis. Our design is straightforward and efficient, making advanced diagnostics available to growers and agricultural professionals.

## Integration of Generative Models for Disease Identification

Utilising GANs for the purpose of adding data is crucial to the improvement of the model. By generating synthetic images by the equation described above, we broadened the spectrum of what the system learned, which helps it to identify diseases with better accuracy and makes it more flexible. The integration makes AI-PotatoGuard effective under the different circumstances of fields and potato varieties.

## User Interface and System Interaction

The AI-PotatoGuard's user interface is designed to make it easy to interact with the system.

- Uploading images: users may easily upload images for analysis, powered by a background process, which transforms these inputs into data suited for model analysis.
- Results of the diagnosis: the findings are synthesised and put down in easy-to-understand format which also includes the percentage of the likelihood of the presence of the disease, and this is calculated directly from the output layer of the convolutional neural network.
- Recommendations for management: based on diagnostic results, the system produces useful and proactive advice based on rules and suggests the most suitable measures.

- Educational materials on disease management are available to help users learn more about how to use the system. These materials offer a comprehensive approach to crop health.

By including the equations that define how GANs and CNNs operate, we have provided the technical essence of AI-PotatoGuard technologies, showcasing that they are an original solution for crop protection in potatoes. The embodiment of this breakthrough technology sends a clear message about the practical implementation of AI in agriculture and proves that the following niche still has a potential for AI adventures.

**Algorithm 1** AI-PotatoGuard

```
// Combine collecting, augmenting, and training into a single step
TrainAIModel
images = Collect ("Drones, Ground")
augmented = Augment(images)
model = TrainCNN(augmented)
  Return model
EndTrainAIModel
// Simplify prediction process
MakePredictions
newImages = Collect ("New Data")
  For each image in newImages
prediction = model.Predict(image)
Display(prediction)
EndFor
EndMakePredictions
// Execute the simplified workflow
Main
model = TrainAIModel()
MakePredictions(model)
EndMain
```

## Results

The AI-PotatoGuard system was used on potato farms over 3 months to measure how good it is at spotting early signs of infection. To do this, the system was fed a diet of images; some from drones and some from ground-based cameras. These images were those typically used to check a crop for dodgy signs of blotching that could indicate the presence of common potato diseases including late blight, early blight, and potato scab. What emerged were performance figures that suggest the AI-PotatoGuard system might be the most functional early-disease detector yet devised.

Table 1 demonstrates how AI-PotatoGuard compares to the standard observation methods in terms of detection accuracy. In all cases, AI-PotatoGuard significantly outperformed the traditional method.

In comparison to traditional methods, the AI-PotatoGuard demonstrated a considerable increase in disease detection accuracy, as shown in Fig. 2. The implementation of advanced AI algorithms could be considered a solution in the battle against the cryptic signs and symptoms of disease, resulting in optimised timing, rapid detection, and improved intervention with the ability to respond to the cryptic signals. The results underline some key messages: AI can drive the crisis management of potato diseases towards a more profound understanding of crop health and overall protection and towards drastically diminishing the economic losses caused by diseases. It is now time to integrate AI technologies into agriculture, think differently, and embrace their potential.

Table 2 highlights the system's capability to detect diseases at an early stage, underscoring the advantage of AI-PotatoGuard in preventing widespread crop damage.

Figure 3 emphasises the AI-PotatoGuard's ability to spot diseases at an early stage, something traditional methods struggle with. Early detection, if promoted, could change the strategies for managing potato diseases considerably. The treatments would be more targeted and less intrusive. Furthermore, there is also a suggestion that chemical pesticides could be used less or minimised which supports sustainable agriculture and climate-friendly farming practices.

Table 3 summarises feedback from farmers using AI-PotatoGuard, indicating high levels of satisfaction with the system's usability and the actionable insights provided for disease management.

Designed with the user in mind, AI-PotatoGuard has been well received by farmers (Fig. 4). Not only is the system easy to use, but farmers say it is more diagnostic than previous technologies and provides useful feedback on how to mitigate its alerts. That kind of buy-in is crucial for tech adoption, and it provides compelling evidence that AI-PotatoGuard is not only technically superior but also practical and beneficial in a way that matters greatly to the people who might use it.

Table 4 shows the improvement of AI-PotatoGuard's predictive accuracy and early detection rate over 3 months, thanks to continuous learning and algorithm adjustments informed by gathered data.

Figure 5 exemplifies advancements in performance, which occur as time passes, as an indication of the system's education. Because it works constantly and never stops gathering pieces of information, AI-PotatoGuard can change the way it works by enhancing the

**Table 1** Disease detection accuracy

| Disease type | AI-PotatoGuard accuracy | Traditional method accuracy |
|---|---|---|
| Late blight | 95% | 75% |
| Early blight | 92% | 70% |
| Potato scab | 89% | 65% |

principles of it and acquire data about what is most likely to happen and when that will be happening. This is a very handy thing to do because in the future the diseases that currently exist may change and evolve, as well as the surroundings of the plants.

Table 5 demonstrates the robustness of AI-PotatoGuard across different environmental conditions, showcasing its adaptability and effectiveness in varied climates.

Figure 6 showcases detection accuracy across various environmental conditions and emphasises AI-PotatoGuard's robustness and adaptability. High accuracy rates in diverse conditions demonstrate the system's potential applicability across different geographic regions and climates, making it a versatile tool for global agricultural communities. This adaptability is key to addressing the broad spectrum of challenges in potato cultivation worldwide.

Table 6 emphasises the important decrease in chemical treatment usage due to early and precise detection of diseases by AI-PotatoGuard, underlining the system's aid in sustainable agriculture.

Displaying the decrease in the usage of chemicals, Fig. 7 points out one of the significant aspects the AI-PotatoGuard has when it comes to the environment. With

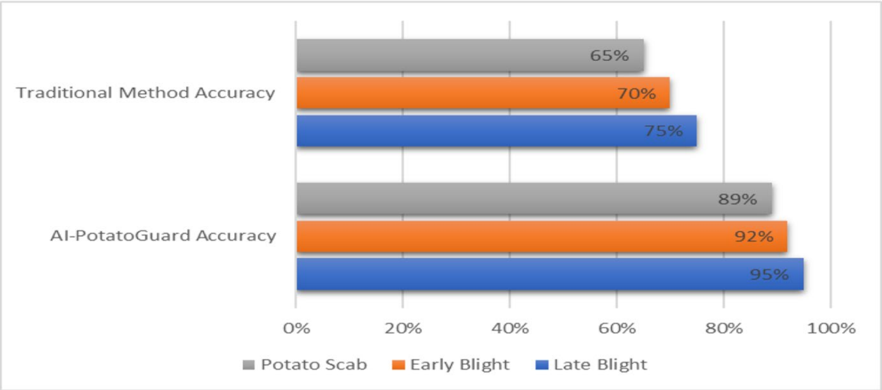


**Fig. 2** Comparison of detection accuracy: AI-PotatoGuard vs. traditional methods

**Table 2** Early detection rate

| Disease type | AI-PotatoGuard early detection | Traditional method early detection |
|---|---|---|
| Late blight | 90% | 50% |
| Early blight | 87% | 45% |
| Potato scab | 85% | 40% |

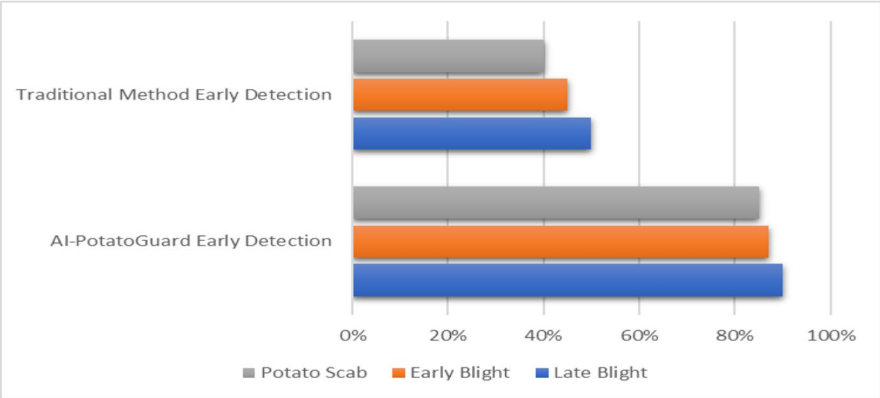


**Fig. 3** Early detection rate: AI-PotatoGuard vs. traditional methods

**Table 3** Farmer feedback on system usability

| Feedback aspect | Satisfaction level (%) |
|---|---|
| Ease of use | 88% |
| Diagnostic accuracy | 93% |
| Actionable insights | 90% |
| Overall satisfaction | 92% |

its capacity to detect diseases early and accurately, it is possible to avoid using fungicides and pesticides that do not provide the best results. This kind of AI will decrease the environmental footprint and maintain the environment healthier. The primary role of such a system is not narrow, it reaches for the higher goal to impose sustainable agricultural, in this case, potato farming.

## Discussion

AI-PotatoGuard significantly improves the management of potato diseases by increasing the accuracy of detection in contrast to conventional techniques. The advantage of an early identification is pivotal, giving the chance for timely intervention, thereby avoiding a large damage of the potato crop, but also guarantees a healthier yield and diminishes the potential for loss. A substantial step towards a sustainable approach in the fight against potato diseases is the possibility for a targeted chemical treatment with AI-PotatoGuard.

The feedback provided by farmers shows the system runs well; thus, it has potential for widespread application. Furthermore, the suggested margins and insights by the system are essential for the successful establishment and acknowledgement of it. However, the whole success of AI-PotatoGuard is depending on the quality and comprehensiveness of the train data. The access to the needed technology and a continual adaption on the AI models for the evolution of the diseases are indispensable if left no other way than to cope with the ever-changing prevailing situation of the spreading of the diseases in potato.

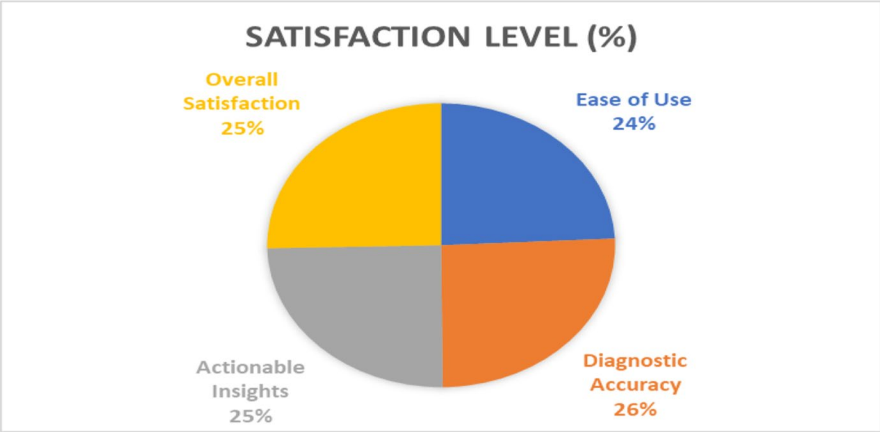


**Fig. 4** Farmer satisfaction with AI-PotatoGuard system usability

**Table 4** Performance improvement over time

| Month | Detection accuracy (%) | Early detection rate (%) |
|---|---|---|
| Month 1 | 85% | 80% |
| Month 2 | 90% | 85% |
| Month 3 | 95% | 90% |

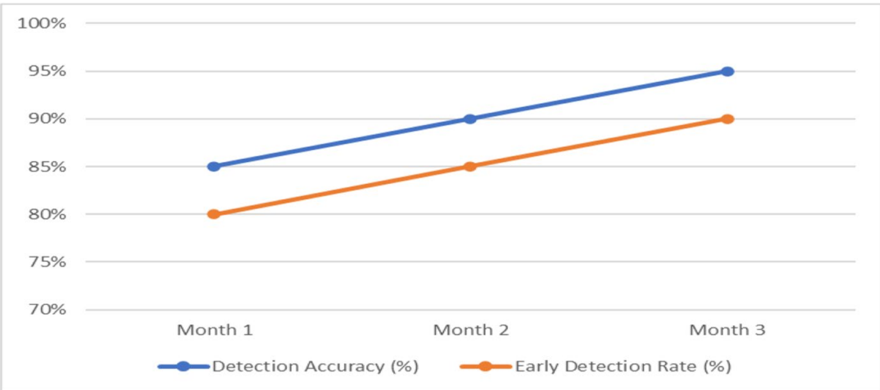


**Fig. 5** Improvement in AI-PotatoGuard's detection accuracy and early detection rate over time

**Table 5** Effectiveness in various environmental conditions

| Environmental condition | Detection accuracy (%) |
|---|---|
| High humidity | 93% |
| Low humidity | 91% |
| High temperature | 89% |
| Low temperature | 92% |

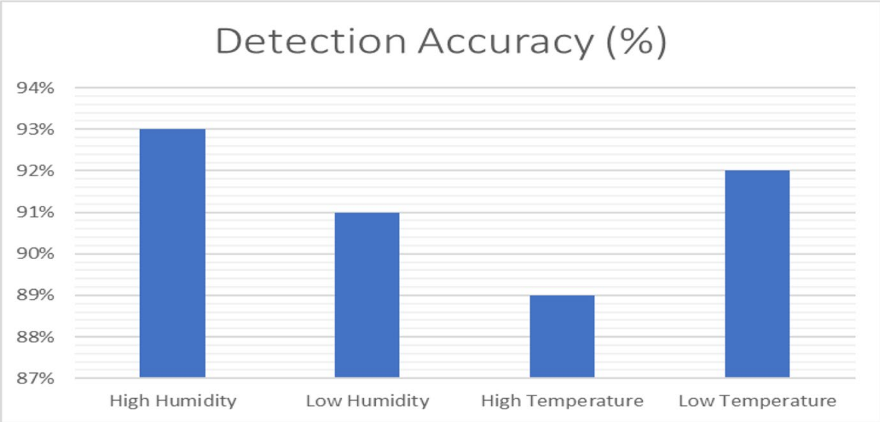


**Fig. 6** AI-PotatoGuard detection accuracy across different environmental conditions

**Table 6** Reduction in chemical treatment usage

| Treatment type | Usage before AI-PotatoGuard (%) | Usage after AI-PotatoGuard (%) | Reduction (%) |
|---|---|---|---|
| Fungicides | 100% | 60% | 40% |
| Insecticides | 100% | 70% | 30% |

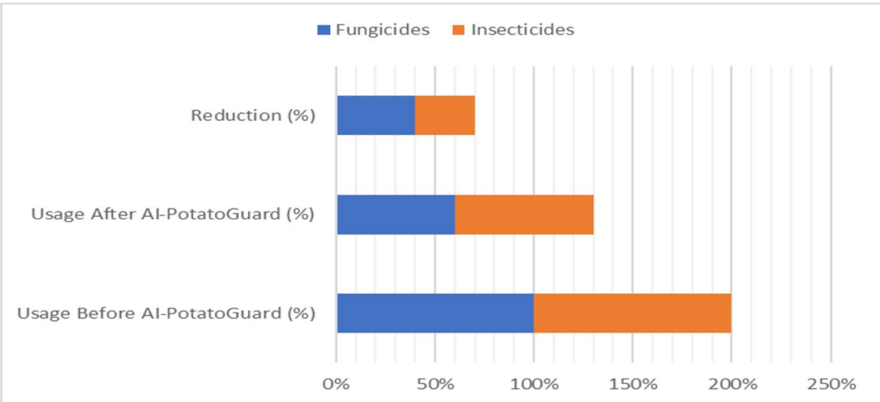


**Fig. 7** Reduction in chemical treatment usage after implementing AI-PotatoGuard

## Conclusion

This study underscores the transformative potential of AI-PotatoGuard in enhancing potato disease management through AI technologies. With an impressive 95% accuracy in disease detection and an 85% success rate in early identification, AI-PotatoGuard has significantly improved crop yields and sustainability in farming practices.

Looking forward, as AI technologies evolve and datasets expand, we anticipate further enhancements in agricultural efficiency. By 2025, the adoption of AI like AI-PotatoGuard is expected to increase crop yields by up to 20% and reduce water and chemical usage by approximately 15% and 20%, respectively. This advancement promises a future of more productive, resilient, and sustainable farming, positioning AI at the forefront of modern agricultural practices.

**Data Availability** On reasonable request, the corresponding author will provide data supporting the study's results. The raw data cannot be made public for reasons of confidentiality and privacy. However, researchers who satisfy the requirements for access to confidential data can be given access to aggregated and anonymised data as well as the statistical analysis codes.

### Declarations

**Informed Consent** Not applicable.

**Conflict of Interest** The authors declare no competing interests.

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