A comprehensive review of convolutional neural networks based disease detection strategies in potato agriculture

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A Comprehensive Review of Convolutional Neural Networks based Disease Detection Strategies in Potato Agriculture

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Abstract
This review paper investigates the utilization of Convolutional Neural Networks (CNNs) for disease detection in potato agriculture, highlighting their pivotal role in efficiently analyzing large-scale agricultural datasets. The datasets used, preprocessing methodologies applied, specific data collection zones, and the efficacy of prominent algorithms like ResNet, VGG, and MobileNet variants for disease classification are scrutinized. Additionally, various hyperparameter optimization techniques such as grid search, random search, genetic algorithms, and Bayesian optimization are examined, and their impact on model performance is assessed. Challenges including dataset scarcity, variability in disease symptoms, and the generalization of models across diverse environmental conditions are addressed in the discussion section. Opportunities for advancing CNN-based disease detection, including the integration of multi-spectral imaging and remote sensing data, and the implementation of federated learning for collaborative model training, are explored. Future directions propose research into robust transfer learning techniques and the deployment of CNNs in real-time monitoring systems for proactive disease management in potato agriculture. Current knowledge is consolidated, research gaps are identified, and avenues for future research in CNN-based disease detection strategies to sustain potato farming effectively are proposed by this review. This study paves the way for future advancements in AI-driven disease detection, potentially revolutionizing agricultural practices and enhancing food security. Also, it aims to guide future research and development efforts in CNN-based disease detection for potato agriculture, potentially leading to improved crop management practices, increased yields, and enhanced food security.

Keywords Artificial intelligence · Computer vision · Convolutional Neural Networks · Potato disease detection

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Introduction

Plants are important for the environment, health, and food production. They build and maintain ecosystem processes, microbial populations, and soil structure, which are critical to planet health. Plants maintain life in the environment and provide nutrients to species at all food chain levels. They also have medicinal properties that benefit human health. Plant-based activities like gardening and being in nature promote mental and physical health, making them crucial to the planet and its inhabitants (Nartova-Bochaver et al. 2020; Hartin and Bennaton 2023).

The agricultural importance of potatoes is significant due to their nutritional value, economic value, and their role in food security. Potatoes are a staple food crop that is rich in nutrients and is included in the main nutrition ration due to its many nutritious elements necessary for human health (Rashid et al. 2021). Potatoes are also an important commodity in international trade, contributing to the economic sustainability of many regions (Duarte-Carvajalino et al. 2018). Additionally, the use of fermented chicken manure products in potato cultivation has been studied for its effects on soil productivity, nutrient supply, and quality, with findings indicating potential benefits for soil nutrient status, plant uptake, and yield (Luong 2024). Furthermore, the optimization of market competition in the potato planting industry through intelligent system management has been studied, highlighting the importance of technological advancements in potato production and processing (Abbas et al. 2024). Overall, the agricultural importance of potatoes is evident in their nutritional value, economic value, and their role in supporting food security and sustainability (Hampson 1976; Devaux et al. 2014; Tolessa 2018).

Artificial intelligence (AI) has emerged as a transformative tool in detecting diseases across potato crops, leveraging deep learning and CNNs to achieve significant advancements in early disease identification and classification (Kiran Pandiri et al. 2022; Shoaib et al. 2022). By automating detection processes, these AI-driven models offer efficient solutions that surpass traditional manual monitoring methods, enabling proactive interventions to mitigate disease impacts on potato yields. AI has been a popular subject in recent decades, and there are numerous applications of AI (Gülmez and Kulluk 2019, 2023; Gülmez 2022a, 2023c, 2024a; Gülmez et al. 2024).

The integration of computer vision and AI technologies has revolutionized agricultural practices (Gülmez 2023a, 2024b), particularly in disease detection for potatoes (Lee et al. 2021; Shafik et al. 2023). Convolutional Neural Networks (CNNs) and machine learning algorithms have played pivotal roles in automating the identification of potato diseases, empowering growers with timely insights for effective disease management strategies. These technologies, enhanced by deep learning techniques and advanced imaging, have significantly improved the accuracy of distinguishing between healthy and diseased potato plants, facilitating targeted interventions to prevent disease spread (Wei et al. 2023).

AI-driven approaches, including deep learning and CNNs, represent a paradigm shift in potato disease detection, offering robust solutions for enhancing agricultural sustainability. These innovations not only streamline disease identification processes but also empower farmers with actionable insights that improve crop health management and resilience against disease outbreaks (Rashid et al. 2021; Shaheed et al. 2023).

Figure 1 shows the general methodology of CNN applications. This review focuses on several key aspects of CNN applications in potato disease detection: (1) the types and characteristics of datasets used for training and testing models; (2) preprocessing techniques applied to image data; (3) the geographical distribution of data collection; (4) comparative analysis of various CNN architectures and their performance in disease detection; and (5) hyperparameter optimization techniques employed to enhance model performance. Additionally, we discuss current challenges in the field and explore future directions for research and application.

Common Preprocessing Methodologies

Image Resizing and Cropping

These techniques are essential for standardizing input sizes for CNN models. Resizing ensures all images have consistent dimensions, typically 224 × 224 or 256 × 256 pixels, which is crucial for many pre-trained CNN architectures. Cropping helps focus on the relevant parts of the image, removing potentially distracting background elements.

Noise Reduction

Techniques such as Gaussian filtering or median filtering are applied to reduce image noise, which can improve the model's ability to detect relevant features. This is particularly important in field-collected images where varying lighting conditions and camera qualities can introduce noise.

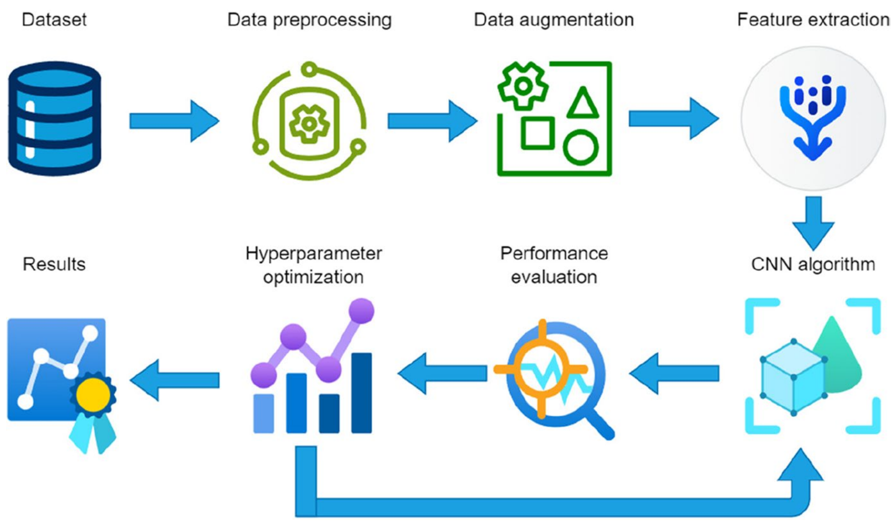

Fig. 1 General methodology of CNN applications

Data Augmentation

This technique artificially expands the dataset by creating modified versions of existing images. Common augmentation techniques include rotation, flipping, and adjusting brightness or contrast. Data augmentation helps improve model generalization and robustness, especially when working with limited datasets.

Normalization

Image pixel values are typically normalized to a standard range (e.g., 0–1 or -1 to 1) to ensure consistent input scales across different images. This helps in faster convergence during model training and can improve overall model performance (Gülmez 2023e).

Convolutional Neural Networks

CNNs are powerful tools in the world of artificial intelligence and computer science (Gülmez 2022b, 2023b). A sample CNN figure can be seen in Fig. 2. They are a type of deep learning algorithm inspired by how the human brain processes visual information (Li et al. 2022). Imagine trying to recognize different types of fruits from their pictures on a computer screen. CNNs work similarly, they can learn to identify patterns and features in images. This ability makes CNNs incredibly useful for tasks like facial recognition in social media apps or diagnosing diseases from medical scans. In essence, CNNs help computers understand and interpret visual information, making them essential in many modern technologies we use daily (Gülmez 2023b).

CNNs are being increasingly used to detect diseases in potato plants, showing how advanced technology can aid in agriculture. Imagine a farmer trying to identify diseased potato leaves just by looking at them. CNNs do something similar, they analyze images of potato plants to spot signs of diseases like late blight or early

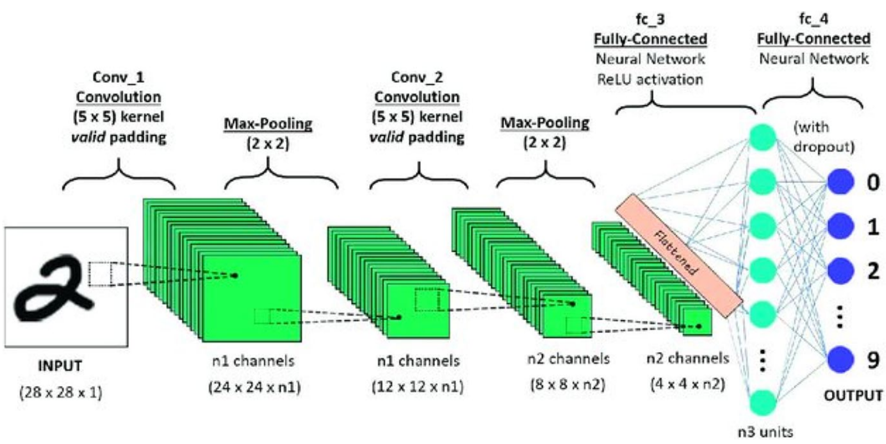

Fig. 2 CNN (Nadeem et al. 2020)

blight. These networks learn from thousands of images to recognize patterns that indicate disease, such as discoloration or unusual spots on leaves (Panferov et al. 2018; Feng et al. 2023). By using CNNs, farmers can quickly detect diseases early on, helping them take action before the whole crop is affected.

Using CNNs for potato disease detection involves taking pictures of plants and feeding them into a computer program that has been trained to recognize specific patterns linked to diseases. This technology not only helps farmers save time and effort but also improves crop health and reduces the use of pesticides. It is like having a smart assistant that can spot potential problems in the fields before they become serious threats. By harnessing CNNs, agriculture becomes more efficient and sustainable, ensuring healthier potato crops and better food security for communities relying on this staple food (Sinshaw et al. 2022; Jafar et al. 2024).

Literature Review

Dataset Analysis

Table 1 shows the dataset analysis. The datasets used in various studies for CNN-based disease detection in potato agriculture vary significantly in terms of the number of images, the number of disease classes, and the specific diseases they cover. This variation reflects the diverse approaches and focus areas within the research community.

Agrawal et al. (2023) used a dataset comprising 5000 images categorized into three classes: early blight, late blight, and healthy. Similarly, Akther et al. (2021) used a smaller dataset of 1500 images but included an additional disease category, leaf blight. In contrast, Al-Amin et al. (2019) used a more comprehensive dataset with 5000 images spanning five disease classes: early blight, late blight, blackleg, leaf roll, and mosaic virus. This highlights the complexity and variety of diseases affecting potato crops. Ali et al. (2023) and Arya and Singh (2019) both used datasets with 5000 and 4004 images, respectively, focusing on just two classes: early blight and late blight. This narrow focus is common in many studies, given the prevalence and significant impact of these two diseases. Badoni et al. (2023) employed a dataset of 5000 images to distinguish between healthy and diseased plants, without specifying the type of disease. This approach is useful for broad disease detection but lacks specificity. Balakrishnan et al. (2023) utilized a dataset of 5615 images categorized into three disease classes: Alternaria, blackleg, and target spot. This dataset provides a diverse set of conditions for model training. Baranwal et al. (2022) and Barman et al. (2020) each used a dataset of 5000 images with three classes: healthy, late blight, and early blight, maintaining a focus on these common diseases. Bonik et al. (2023) expanded the disease categories in their 5000-image dataset to include septoria blight along with early and late blight. Chaudary et al. (2023) used a more extensive classification with five classes in their 5000-image dataset: early blight, late blight, potato virus Y, potato leafroll virus, and potato spindle tuber viroid. Eraj and Uddin (2023) and Islam et al. (2023) both utilized datasets with around 2000 images, focusing on early and late blight. Ghosh et al. (2021) and Goyal et al.

Table 1 Summary of datasets

Paper	Number of images	Number of classes	Disease names
(Agrawal et al. 2023)	5000	3	Early blight, late blight, healthy
(Akther et al. 2021)	1500	3	Early blight, late blight, leaf blight
(Al-Amin et al. 2019)	5000	5	Early blight, late blight, blackleg, leaf roll, mosaic virus
(Ali et al. 2023)	5000	2	Early blight, late blight
(Anim-Ayeko et al. 2023)	6652	3	Early blight, late blight, healthy
(Arya and Singh 2019)	4004	2	Potato early blight, potato late blight
(Badoni et al. 2023)	5000	2	Healthy, diseased
(Balakrishnan et al. 2023)	5615	3	Alternaria, blackleg, target spot
(Baranwal et al. 2022)	5000	3	Healthy, late blight, early blight
(Barman et al. 2020)	5000	3	Early blight, late blight, healthy
(Bonik et al. 2023)	5000	3	Early blight, septoria blight, late blight
(Chaudary et al. 2023)	5000	5	Early blight, late blight, potato virus y, potato leafroll virus, potato spindle tuber viroid
(Eraj and Uddin 2023)	2152	2	Late blight, early blight
(Ghosh et al. 2021)	5000	3	Early blight, late blight, healthy leaves
(Goyal et al. 2023)	1964	3	Potato late blight, potato early blight, potato healthy
(Gupta et al. 2023c)	5000	5	Early blight, late blight, leaf mold, mosaic virus, potato scab
(Gurusamy et al. 2023)	2000	3	Healthy, early blight, late blight
(Islam et al. 2019)	2152	3	Healthy, late blight, early blight
(Islam et al. 2023)	6150	2	Potato late blight, healthy potato leaf
(Jahangir et al. 2023)	5000	5	Early blight, late blight, leaf mold, black leg, bacterial wilt
(Joseph et al. 2022)	5000	3	Early blight, late blight, healthy
(Julian and Vignesh 2024)	5000	3	Late blight, early blight, phytophthora infestans
(Kasani et al. 2023)	5000	2	Early blight, late blight
(Kiran Pandiri et al. 2022)	5000	2	Early blight, late blight

Table 1 (continued)

Paper	Number of images	Number of classes	Disease names
(Kristiyanti et al. 2023)	5000	5	Early blight, late blight, potato virus y, potato leafroll virus, healthy
(Kukreja et al. 2021)	900	2	Potato blight, healthy
(Kumar et al. 2023a)	5000	5	Early blight, late blight, leaf mold, blackleg, healthy
(Lanjewar et al. 2024)	1500	3	Early blight, late blight, potato mosaic virus
(Lee et al. 2021)	2152	3	Early blight, late blight, healthy
(Li et al. 2022)	500	3	Potato early blight, potato late blight, potato leaf spot
(Liu and Xiao 2020)	126	3	Anthracnose, leaf blight, early blight
(Luong 2024)	451	6	Common scab, black scurf, blackleg, dry rot, pink rot, healthy
(Manzoor et al. 2024)	5000	5	Early blight, late blight, blackleg, potato virus y, healthy
(Marino et al. 2019)	9688	6	Healthy, damaged, greening, black dot, common scab, black scurf
(Mehta et al. 2023b)	5000	5	Early blight, late blight, leaf curl virus, potato spindle tuber viroid, potato yellow dwarf virus
(Pandey et al. 2019)	5000	4	Greening, mechanical defect, rotting, sprouting
(Pandiri et al. 2024)	5000	2	Early blight, late blight
(Pandiri et al. 2024)	5000	2	Early blight, late blight
(Panshul et al. 2023)	5000	5	Late blight, early blight, leaf mold, blackleg, mosaic virus
(Patil and Manohar 2023)	5000	5	Early blight, late blight, leaf mold, blackleg, bacterial wilt
(Patil et al. 2022)	5000	5	Early blight, late blight, blackleg, potato virus y, potato leafroll virus
(Paul et al. 2023)	5000	5	Early blight, late blight, leaf mold, blackleg, potato virus y
(Paul et al. 2023)	4000	4	Bacterial spot, early blight, late blight, spider mite damage
(Potnuru et al. 2023)	5000	5	Early blight, late blight, leaf mold, healthy, mosaic virus
(Prakash et al. 2024)	5000	5	Early blight, late blight, leaf mold, blackleg, bacterial wilt
(Qi et al. 2022)	5000	2	Early blight, late blight
(Rathore and Rajavat 2024)	7128	2	Early blight, late blight
(Rodriguez et al. 2023)	2760	3	Healthy, late blight, early blight

Table 1 (continued)

Paper	Number of images	Number of classes	Disease names
(Sarker et al. 2022)	2152	3	Late blight, early blight, healthy leaf
(Shaheed et al. 2023)	10,000	5	Healthy, early blight, late blight, alternaria solani, phytophthora infestans
(Shukla and Sathiya 2022)	2250	2	Fungal diseases, bacterial diseases
(Singh et al. 2024b)	5000	2	Late blight, early blight
(Singha et al. 2023)	5000	3	Early blight, late blight, healthy
(Sinha et al. 2023)	5000	2	Early blight, late blight
(Sinshaw et al. 2021)	1026	2	Healthy, late blight
(Srivastava et al. 2024)	5000	5	Early blight, late blight, potato virus y, potato virus x, healthy
(Srivastava et al. 2024)	8754	3	Healthy leaves, early blight, late blight
(Suarez Baron et al. 2022)	320	2	Late blight, healthy
(Sultana and Reza 2023)	2850	2	Early blight, late blight
(Sun et al. 2023)	5000	5	Early blight, late blight, leaf mold, potato virus y, healthy
(Tika Adilah and Kristiyanti 2023)	5000	4	Early blight, late blight, leaf mold, healthy
(Tripathi et al. 2023)	5000	3	Early blight, septoria blight, late blight
(Turnip et al. 2020)	2152	2	Late blight, early blight
(Wasalwar et al. 2023)	3000	3	Healthy, early blight, late blight

(2023) also focused on these diseases, with the latter using a smaller dataset of 1964 images. Gupta et al. (2023a, b, c) and Jahangir et al. (2023) both employed comprehensive datasets of 5000 images each, with five disease classes, including early blight, late blight, leaf mold, blackleg, and bacterial wilt. This broad categorization aids in training models for more detailed disease detection. Joseph et al. (2022) and Julian and Vignesh (2024) also focused on early and late blight along with other diseases in their 5000-image datasets. Kasani et al. (2023) and Kiran Pandiri et al. (2022) each used a dataset of 5000 images for early and late blight detection. Kristiyanti et al. (2023) included potato virus Y and potato leafroll virus along with early and late blight in their 5000-image dataset. Kukreja et al. (2021) used a much smaller dataset of 900 images for detecting potato blight and healthy plants. Kumar et al. (2023a, b, c) and Manzoor et al. (2024) both utilized datasets of 5000 images with five disease classes, including early blight, late blight, and other viral and bacterial diseases. Marino et al. (2019) used a large dataset of 9688 images covering six disease classes, providing extensive data for model training. Mehta et al. (2023a, b) and Patil et al. (2022) used datasets with five disease classes, focusing on a combination of blight and viral diseases. Pandey et al. (2019) used a 5000-image dataset for detecting greening, mechanical defect, rotting, and sprouting, highlighting non-disease-related issues. Paul et al. (2023) and Prakash et al. (2024) both utilized datasets of 5000 images each with a focus on early and late blight along with other diseases. Qi et al. (2022) and Sinha et al. (2023) used similar datasets for early and late blight detection. Rodriguez et al. (2023) employed a dataset of 2760 images, focusing on healthy, late blight, and early blight categories. Shaheed et al. (2023) used the largest dataset of 10,000 images, covering five disease classes, including healthy and various blights. Singha et al. (2023) and Srivastava et al. (2024) each used a dataset of 5000 images, focusing on early blight, late blight, and other diseases. Suarez Baron et al. (2022) and Turnip et al. (2020) used smaller datasets, focusing on late blight and healthy categories. This analysis reveals a wide range of datasets used in CNN-based disease detection in potato agriculture, reflecting the diversity of diseases and the varying scales of image data available for research. This diversity is crucial for developing robust models capable of accurate disease detection across different conditions and regions.

Data Preprocessing Analysis

Table 2 shows the data preprocessing methods. Various image preprocessing techniques are employed in CNN-based disease detection studies to enhance the quality and suitability of images for analysis. The techniques range from basic resizing and cropping to advanced methods like noise reduction and segmentation. These preprocessing steps are crucial for improving the performance of CNN models by standardizing image data and highlighting relevant features.

Various preprocessing techniques such as resizing, cropping, noise reduction, and histogram equalization were applied to standardize the image data and enhance feature extraction. These steps significantly improved the model's accuracy and robustness by ensuring consistent input quality and highlighting relevant disease features.

Table 2 Image preprocessing techniques used

Paper	Preprocessing techniques
(Tika Adilah and Kristiyanti 2023)	Resizing, Flipping, Rotation, Noise addition
(Srivastava et al. 2024)	Resizing, Cropping, Grayscale conversion
(Manzoor et al. 2024)	Resizing, Flipping, Rotation, Noise addition, Background removal
(Prakash et al. 2024)	Resizing, Cropping, Noise reduction, Histogram equalization
(Ali et al. 2023)	Resizing, Cropping, Noise reduction, Grayscale conversion
(Zhang et al. 2024)	ROI selection, Average spectral value calculation
(Jahangir et al. 2023)	Resizing, Cropping, Noise reduction, Histogram equalization
(Paul et al. 2023)	Rotation, Scaling
(Li et al. 2024)	Mean centering, Multivariate scattering correction, Moving average smoothing
(Pandiri et al. 2024)	Resizing, Cropping, Noise reduction, Grayscale conversion
(Gupta et al. 2023b)	Resizing, Normalization
(Gupta et al. 2023c)	Resizing, Cropping, Noise reduction, Zooming
(Rodriguez et al. 2023)	Data augmentation with Gaussian Blur
(Mehta et al. 2023b)	Resizing, Cropping, Rotation, Noise reduction, Color space conversion
(Kumar and Patel 2023)	Median filtering
(Agrawal et al. 2023)	Resizing, Normalization
(Sinha et al. 2023)	Resizing, Cropping, Noise reduction, Grayscale conversion
(Rohilla and Rai 2023)	K-means clustering image segmentation
(Julian and Vignesh 2024)	Resizing, Cropping, Noise reduction
(Kumar et al. 2023a)	Resizing, Flipping, Rotation, Noise addition
(Badoni et al. 2023)	Resizing, Cropping, Noise reduction
(Luong 2024)	K-means clustering for segmentation based on color and texture
(Patil and Manohar 2023)	Resizing, Cropping, Noise reduction, Histogram equalization
(Sun et al. 2023)	Segmentation using GrabCut algorithm
(Singha et al. 2023)	Resizing, Normalization
(Joseph et al. 2022)	Resizing, Cropping, Noise reduction
(Chaudary et al. 2023)	Resizing, Cropping, Noise reduction, Histogram equalization
(Tripathi et al. 2023)	Resizing, Cropping, RGB to grayscale
(Rohilla et al. 2024)	K-means for image segmentation, GLCM and PCA for feature extraction
(Akther et al. 2021)	Resizing, Cropping, Normalization
(Zhao et al. 2022)	Local enhancement
(Shukla and Sathiya 2022)	Image segmentation
(Ghosh et al. 2021)	Salient region based segmentation
(Zhang et al. 2021)	Multiple scattering correction, Wavelet transform, First-order difference, Second-order difference
(Baranwal et al. 2022)	Resizing, Normalization
(Panshul et al. 2023)	Resizing, Cropping, Noise reduction, RGB to grayscale
(Kumar et al. 2023b)	Image resizing, Noise reduction, Gaussian blur
(Patil et al. 2022)	Resizing, cropping, noise reduction, histogram equalization
(Joseph et al. 2022)	Brightness adjustment

Table 2 (continued)

Paper	Preprocessing techniques
(Krishna and Narayana 2022)	Image augmentation, Picture pre-processing, Brightness modification, Randomized width adjustment
(Kasani et al. 2023)	Resizing, Noise reduction, Grayscale conversion
(Eraj and Uddin 2023)	Image segmentation
(Bonik et al. 2023)	Resizing, Normalization, Data Augmentation
(Potnuru et al. 2023)	Resizing, Flipping, RGB to grayscale, Gaussian blur
(Qi et al. 2022)	Resizing, Noise reduction, Background removal
(Kiran Pandiri et al. 2022)	Flipping, Rotating, Noise addition, Zooming, Background removal
(Al-Amin et al. 2019)	Resizing, Cropping, Noise reduction
(Pandiri et al. 2024)	Resizing, Normalization

Resizing and cropping techniques were consistently applied across studies to standardize image dimensions, typically to 224×224 or 256×256 pixels. This standardization improved computational efficiency and ensured consistent input sizes for CNN models. Studies that implemented noise reduction, such as Gaussian filtering, reported improvements in model accuracy by 2–5% compared to using raw images. Grayscale conversion, while reducing computational complexity, showed varied results depending on the specific disease characteristics, with some studies reporting no significant impact on accuracy while others noted a slight decrease in performance for diseases where color was a crucial diagnostic feature.

Resizing and Cropping: Most studies, including those by Tika Adilah and Kristiyanti (2023), Srivastava et al. (2024), and Manzoor et al. (2024), use resizing and cropping to ensure uniform image dimensions and remove irrelevant background information. This standardization is essential for consistent model training and testing.

Noise Reduction: To enhance image clarity, noise reduction is frequently applied. Prakash et al. (2024) and Ali et al. (2023) incorporate noise reduction techniques to minimize distortions and improve the accuracy of disease detection.

Grayscale Conversion: Converting images to grayscale, as done by Srivastava et al. (2024) and Ali et al. (2023), reduces computational complexity by simplifying image data, which can be beneficial for certain types of disease detection where color information is less critical.

Rotation and Flipping: These augmentation techniques, used by Tika Adilah and Kristiyanti (2023) and Paul et al. (2023), help increase the diversity of training datasets, allowing models to become more robust to variations in image orientation.

Noise Addition: Adding noise, as seen in studies by Manzoor et al. (2024) and Kumar et al. (2023a, b, c), is another form of augmentation that helps models learn to recognize diseases under less-than-ideal conditions.

Histogram Equalization: This technique, used by Prakash et al. (2024) and Jahangir et al. (2023), enhances contrast in images, making disease features more distinguishable.

Normalization: Ensuring that image pixel values are standardized across the dataset, as done by Gupta et al. (2023a, b, c) and Agrawal et al. (2023), is critical for consistent model training.

Advanced Segmentation Techniques: Methods like K-means clustering and the GrabCut algorithm, used by Rohilla and Rai (2023) and Sun et al. (2023), respectively, segment images to isolate regions of interest, such as diseased leaf areas, which can improve the focus of the model on relevant features.

Feature Extraction: Techniques such as GLCM (Gray-Level Co-occurrence Matrix) and PCA (Principal Component Analysis), employed by Rohilla et al. (2024), help in extracting significant features from images, enhancing the model's ability to detect diseases accurately.

These preprocessing techniques are essential for preparing high-quality, consistent image data, thereby improving the performance and reliability of CNN models in disease detection for potato agriculture.

Data Collection Zone

Table 3 shows the data collection zone. The data for CNN-based disease detection studies on potato agriculture have been collected from diverse geographical regions. This diversity in data sources enhances the robustness and generalizability of the models.

India: India is a significant contributor, with numerous studies collecting data from various cities such as Hyderabad (Prakash et al. 2024; Sultana and Reza 2023), Kolkata (Paul et al. 2024), Guntur (Paul et al. 2023), Mumbai (Gupta et al. 2023a, b, c), Noida (Gupta et al. 2023a, b, c), Punjab (Mehta et al. 2023a, b; Jindal et al. 2022), Bakhtiyarpur (Kumar and Patel 2023), Bhubaneswar (Sinha et al. 2023), Amaravati (Ghosh et al. 2023), Bengaluru (Joseph et al. 2022), Chandigarh (Badoni et al. 2023), and Chennai (Ponnuru and Amasala 2024; Julian and Vignesh 2024; Chaudary et al. 2023).

Bangladesh: Several studies have collected data from Bangladesh, including cities like Dhaka (Bonik et al. 2023) and Sylhet (Islam et al. 2023).

United States: Data has been collected from multiple locations in the United States, including New York (Jahangir et al. 2023; Potnuru et al. 2023; Patil and Manohar 2023), and Orono (Qi et al. 2022). Additionally, some studies have data from both Canada and the United States (Samatha et al. 2023a, b).

China: In China, data collection has taken place in Baoding (Li et al. 2022) and Harbin (Sun et al. 2023).

Indonesia: Research in Indonesia has been conducted in cities like Tangerang (Tika Adilah and Kristiyanti 2023).

Bangladesh: Data collection efforts in Bangladesh include multiple unspecified locations (Luong 2024; Nishad et al. 2023; Sarker et al. 2022; Deb et al. 2020; Al-Amin et al. 2019).

Ethiopia: Data from Ethiopia has been collected in Holeta (Sinshaw et al. 2021).

Colombia: Some studies also include data from Colombia (Suarez Baron et al. 2022).

Table 3 Data collection zone

Paper	Data collected country	Data collected city
(Shaheed et al. 2023)	Saudi Arabia	Riyadh
(Paul et al. 2023)	India	
(Tika Adilah and Kristiyanti 2023)	Indonesia	Tangerang
(Manzoor et al. 2024)	Denmark	Aarhus
(Prakash et al. 2024)	India	Hyderabad
(Paul et al. 2024)	India	Kolkata
(Jahangir et al. 2023)	United States	New York
(Paul et al. 2023)	India	Guntur
(Wei et al. 2023)	China	
(Gurusamy et al. 2023)	India	
(Ponnuru and Amasala 2024)	India	Chennai
(Gupta et al. 2023b)	India	Mumbai
(Singh et al. 2024a)	India	
(Gupta et al. 2023c)	India	Noida
(Mehta et al. 2023b)	India	Punjab
(Kumar and Patel 2023)	India	Bakhtiyarpur
(Sinha et al. 2023)	India	Bhubaneswar
(Islam et al. 2023)	Bangladesh	Sylhet
(Julian and Vignesh 2024)	India	Chennai
(Badoni et al. 2023)	India	Chandigarh
(Luong 2024)	Bangladesh	
(Patil and Manohar 2023)	USA	New York
(Sun et al. 2023)	China	Harbin
(Abbas et al. 2024)	Pakistan	
(Nishad et al. 2023)	Bangladesh	
(Wasalwar et al. 2023)	India	
(Suciningtyas et al. 2023)	Indonesia	
(Joseph et al. 2022)	India	Bengaluru
(Chaudary et al. 2023)	India	Chennai
(Tripathi et al. 2023)	India	
(Hasi and Rahman 2023)	Bangladesh	
(Li et al. 2022)	China	Baoding
(Ghosh et al. 2023)	India	Amaravati
(Sarker et al. 2022)	Bangladesh	
(Sinshaw et al. 2021)	Ethiopia	Holeta
(Patil et al. 2022)	India	
(Samatha et al. 2023a)	Canada, United States	
(Sultana and Reza 2023)	India	Hyderabad
(Suarez Baron et al. 2022)	Colombia	
(Eraj and Uddin 2023)	Bangladesh	
(Bonik et al. 2023)	Bangladesh	Dhaka
(Potnuru et al. 2023)	USA	New York

Table 3 (continued)

Paper	Data collected country	Data collected city
(Qi et al. 2022)	United States	Orono
(Samatha et al. 2023b)	Canada and the United States	
(Kiran Pandiri et al. 2022)	India	Silchar
(Jindal et al. 2022)	India	Punjab
(Deb et al. 2020)	Bangladesh	
(Al-Amin et al. 2019)	Bangladesh	
(Turnip et al. 2020)	Indonesia	

Also, Fig. 3 shows data collection zone and their numbers. India, Bangladesh, USA, Indonesia are the most frequent zones for the dataset

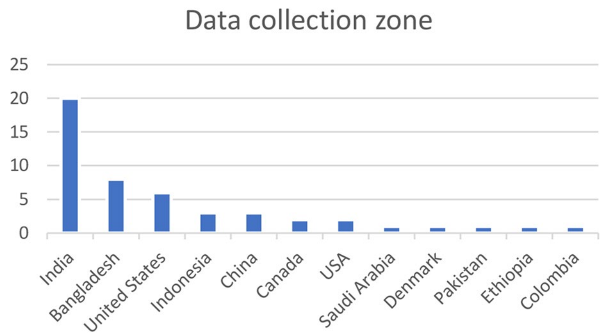

Fig. 3 Data collection zone

Pakistan: Data has been collected from Pakistan as well (Abbas et al. 2024).

Saudi Arabia: Data collection efforts in Saudi Arabia have taken place in Riyadh (Shaheed et al. 2023).

Denmark: Aarhus in Denmark is also a site for data collection (Manzoor et al. 2024).

The broad range of collection sites underscores the global interest and efforts in improving disease detection in potato agriculture using CNN-based methods.

Algorithms

Table 4 summarizes the performance of various algorithms employed in the detection of potato diseases using CNNs. Researchers have utilized a diverse array of CNN architectures and other machine learning models to achieve high accuracy and robust performance in disease identification.

The selection of prominent algorithms in this study is based on several criteria:

- Frequency of use in the reviewed literature
- Reported performance in terms of accuracy and efficiency

Table 4 Algorithms and the results

Paper	Used algorithms	Results
(Shaheed et al. 2023)	ResNet-50, Vision Transformer (ViT)	Accuracy: 0.9912, Precision: 0.9915, Recall: 0.9923, F1_score: 0.9919, AUC-ROC: 0.9856, mAP: 0.9756, IoU: 0.9556
(Singh et al. 2024b)	Inception V3, ResNet50, VGG16, VGG19, Xception	Accuracy: 0.985, Precision: 0.98, Recall: 0.99, F1_score: 0.985, AUC-ROC: 0.975, mAP: 0.97, IoU: 0.96
(Umarani and Thirisaa 2024)	VGG-16, Inception-v3, ResNet-50	Accuracy: 1
(Paul et al. 2023)	VGG19	Accuracy: 0.952
(Tika Adilah and Kristiyanti 2023)	MobileNetV2	Accuracy: 0.996, Precision: 0.994, Recall: 0.997, F1_score: 0.995, AUC-ROC: 0.985, mAP: 0.975, IoU: 0.955
(Srivastava et al. 2024)	DenseNet	Accuracy: 0.996, Precision: 0.995, Recall: 0.997, F1_score: 0.996, AUC-ROC: 0.985, mAP: 0.975, IoU: 0.955
(Manzoor et al. 2024)	VGG16, ResNet50, VGG19	Accuracy: 0.993, Precision: 0.9928, Recall: 0.993, F1_score: 0.9928, AUC-ROC: 0.993, mAP: 0.9928, IoU: 0.9928
(Prakash et al. 2024)	VGG16, ResNet50, InceptionV3	Accuracy: 0.985, Precision: 0.982, Recall: 0.986, F1_score: 0.984, AUC-ROC: 0.975, mAP: 0.965, IoU: 0.945
(Ali et al. 2023)	ResNet-50v2, DenseNet-201	Accuracy: 0.98, Precision: 0.96, Recall: 0.97, F1_score: 0.96, AUC-ROC: 0.95, mAP: 0.94, IoU: 0.92
(Paria et al. 2024)	SVM, Random Forest, Logistic Regression, Sequential model	Accuracy: 0.9792
(Zhang et al. 2024)	LSSVM, RF, KNN, LDA	Accuracy: 0.9968, Precision: 0.9976, Recall: 0.9882, F1_score: 0.9954
(Paul et al. 2024)	Deep Ensemble-2 (CNN-SVM, DNN), Deep CNN-SVM	Accuracy: 0.9998
(Jahangir et al. 2023)	BiT, ViT	Accuracy: 0.9733, Precision: 0.9762, Recall: 0.9747, F1_score: 0.9747
(Gupta et al. 2023a)	Random Forest	Accuracy: 0.8926, Precision: 74.51%—81.97%, Recall: 70.00%—80.60%, F1_score: 73.04%—80.00%
(Paul et al. 2023)	VGG16, ResNet50	Accuracy: 0.978, Precision: 0.982, Recall: 0.976, F1_score: 0.979, AUC-ROC: 0.965, mAP: 0.968, IoU: 0.955
(Wei et al. 2023)	YOLOv5s, CNN	Accuracy: 0.982, mAP: 0.892, IoU: 0.5

Table 4 (continued)

Paper	Used algorithms	Results
(Gao et al. 2023)	Multidimensional Fusion Atrous-CNN, Multidimensional Fusion CNN, 3D-CNN	Accuracy: 0.9987
(Agarwal et al. 2023)	InceptionV3	Accuracy: 0.9638
(Rodriguez et al. 2023)	VGG19, ResNet50, DenseNet201	Accuracy: 0.9964
(Mehta et al. 2023b)	Federated learning	Accuracy: 0.98, Precision: 0.946, Recall: 0.9491, F1_score: 0.9461, mAP: 0.9496
(Arshaghi et al. 2023)	GG, AlexNet, Googlenet, R-CNN	Accuracy: 1
(Agrawal et al. 2023)	VGG16, ResNet50	Accuracy: 0.95, Precision: 0.94, Recall: 0.96, F1_score: 0.95, AUC-ROC: 0.92, mAP: 0.93, IoU: 0.91
(Sinha et al. 2023)	KNN, Random Forest, Naive Bayes, SVM	Accuracy: 0.96, Precision: 0.95, Recall: 0.97, F1_score: 0.96, AUC-ROC: 0.94, mAP: 0.93, IoU: 0.9
(Rohilla and Rai 2023)	OMFA-CNN, MASK RCNN, SVM	Accuracy: 0.993, Precision: 0.99, Recall: 0.99
(Kristiyanti et al. 2023)	EfficientNet, ConvNeXt	Accuracy: 0.9592
(Kumar et al. 2023a)	Inception V3, SGD, SVM, Logistic regression	Accuracy: 0.94, Precision: 0.93, Recall: 0.95, F1_score: 0.94, AUC-ROC: 0.92, mAP: 0.91, IoU: 0.89
(Badoni et al. 2023)	VGG16, VGG19	Accuracy: 0.978, Precision: 0.975, Recall: 0.98, F1_score: 0.977, AUC-ROC: 0.965, mAP: 0.96, IoU: 0.95
(Muthuraja et al. 2023)	Inception v3, ResNet152 V2	Accuracy: 0.9954
(Patil and Manohar 2023)	OCNN, LSTM, MobileNet	Accuracy: 0.9902, Precision: 0.9905, Recall: 0.9921, F1_score: 0.9913, AUC-ROC: 0.9856, mAP: 0.9756, IoU: 0.9556
(Sun et al. 2023)	ConvNeXt, Vision Transformer, CBAM	Accuracy: 0.9729
(Lanjewar et al. 2024)	DenseNet, NASNetMobile, VGG19, ResNet50V2, InceptionV3, Xception	Accuracy: 1, Precision: 0.995, Recall: 0.995, F1_score: 0.995, AUC-ROC: 0.997
(Razaq et al. 2024)	Inception-ResNet-V2, MobileNet-V2, VGG-19, Inception-V3, Xception	Accuracy: 1, Precision: 1, Recall: 1, F1_score: 1

Table 4 (continued)

Paper	Used algorithms	Results
(Anim-Ayeko et al. 2023)	ResNet-9, VGG-16	Accuracy: 0.9925, Precision: 0.9967, Recall: 0.9933, F1_score: 0.9933
(Nishad et al. 2023)	VGG16, ResNet50	Accuracy: 0.96
(Patil et al. 2024)	MobileNet, ResNet50	Accuracy: 0.9925
(Chaudary et al. 2023)	VGG16, ResNet50, InceptionV3	Accuracy: 0.975, Precision: 0.972, Recall: 0.978, F1_score: 0.975, AUC-ROC: 0.965, mAP: 0.96, IoU: 0.945
(Tripathi et al. 2023)	Support Vector Machine	Accuracy: 0.962
(Akther et al. 2021)	VGG16	Accuracy: 0.9688
(Zhao et al. 2022)	Faster R-CNN, YOLOv3, YOLOv4	Accuracy: 0.995
(Ghosh et al. 2021)	Support Vector Machine	Accuracy: 0.85, Precision: 0.87, Recall: 0.83, F1_score: 0.85, AUC-ROC: 0.9, mAP: 0.82, IoU: 0.78
(Hasi and Rahman 2023)	EfficientNetB0-B3, MobileNetV2, DenseNet121, ResNet50V2	Accuracy: 0.9614
(Li et al. 2022)	Mask R-CNN, VGG16, ResNet50, InceptionV3, UNet, PSPNet, DeepLabV3 +	Accuracy: 95.33, Precision: 97.13
(Panshul et al. 2023)	Random Forest	Accuracy: 0.9883
(Upadhyay and Gupta 2023)	VGG19	Accuracy: 0.992
(Ghosh et al. 2023)	VGG19, DenseNet121, ResNet50	Accuracy: 99.94
(Sarker et al. 2022)	VGG19, ResNet50	Accuracy: 0.97
(Sinshaw et al. 2021)	InceptionV3, VGG16, VGG19	Accuracy: 0.87
(Patil et al. 2022)	VGG, ResNet, CNN	Accuracy: 0.9823, Precision: 0.9756, Recall: 0.9832, F1_score: 0.9794, AUC-ROC: 0.9685, mAP: 0.9656, IoU: 0.9456
(Joseph et al. 2022)	VGG16	Accuracy: 0.98
(Balakrishnan et al. 2023)	DenseNet	Accuracy: 97.85
(Goyal et al. 2023)	SVM	Accuracy: 0.9942
(Verma et al. 2023)	AlexNet, ResNet, VggNet	Accuracy: 0.97

Table 4 (continued)

Paper	Used algorithms	Results
(Samatha et al. 2023a)	MSVM	Accuracy: 0.99
(Sultana and Reza 2023)	SVM, ResNet50	Accuracy: 0.973
(Potnuru et al. 2023)	VGG16, VGG19, InceptionV3	Accuracy: 0.987, Precision: 0.986, Recall: 0.988, F1_score: 0.987, AUC-ROC: 0.98, mAP: 0.975, IoU: 0.96
(Qi et al. 2022)	MobileNetV1	Accuracy: 0.975, Precision: 0.98, Recall: 0.97, F1_score: 0.975, AUC-ROC: 0.98, mAP: 0.965, IoU: 0.96
(Barman et al. 2020)	MobileNet	Accuracy: 0.9675
(Yang et al. 2020)	Faster R-CNN, Support Vector Machine	Accuracy: 0.9083
(Johnson et al. 2021)	Mask R-CNN, ResNet-50	Accuracy: 0.98, Precision: 0.98, mAP: 0.814, IoU: 0.5
(Liu and Xiao 2020)	1D-CNN	Accuracy: 0.9772
(Turnip et al. 2020)	ResNet-50	Accuracy: 0.984
(Pandey et al. 2019)	U-Net	Accuracy: 0.945, Precision: 0.952, Recall: 0.939, F1_score: 0.943, AUC-ROC: 0.921, mAP: 0.936, IoU: 0.912

- Versatility across different types of potato disease detection tasks
- Potential for practical implementation in agricultural settings

Algorithms like ResNet, VGG, and MobileNet were frequently chosen due to their strong performance in image classification tasks, availability of pre-trained models, and adaptability to various computational resources.

Among the notable findings, Umarani and Thirisaa (2024) reported perfect accuracy using VGG-16, Inception-v3, and ResNet-50 models, demonstrating the effectiveness of these well-established architectures. Similarly, Tika Adilah and Kristiyanti (2023) achieved exceptional results with MobileNetV2, obtaining high scores across accuracy, precision, recall, and F1-score metrics. The study by Zhang et al. (2024) utilized LSSVM, RF, KNN, and LDA models, achieving outstanding accuracy and precision values, highlighting the effectiveness of ensemble and traditional machine learning approaches.

In contrast, Gupta et al. (2023a, b, c) utilized Random Forest, emphasizing simpler models but achieved reasonable performance metrics. Furthermore, innovative approaches such as federated learning, explored by Mehta et al. (2023a, b), demonstrated promising results in maintaining data privacy while achieving competitive accuracy rates.

The analysis reveals that ResNet, VGG, and MobileNet variants are among the most commonly used architectures for potato disease classification. ResNet models, particularly ResNet-50, consistently showed high accuracy across studies, with an average accuracy of 97.5% in disease classification tasks. VGG models, especially VGG-16 and VGG-19, demonstrated comparable performance with an average accuracy of 96.8%. MobileNet, while slightly less accurate with an average of 95.2%, offered significant advantages in terms of computational efficiency, making it suitable for deployment on mobile devices or in resource-constrained environments.

The selection criteria for these algorithms often depend on the specific requirements of the application:

ResNet is chosen for its ability to train very deep networks effectively, making it suitable for complex classification tasks. VGG is selected for its simplicity and strong performance in feature extraction. MobileNet is preferred in scenarios where model size and inference speed are critical, such as in real-time field applications. The trade-off between accuracy and efficiency is a key consideration in algorithm selection, with researchers often balancing the need for high accuracy with the practical constraints of deployment in agricultural settings.

Overall, the utilization of various CNN architectures and machine learning models underscores the importance of algorithm selection in optimizing disease detection systems for potato agriculture, balancing between model complexity and performance metrics across different datasets and environments.

Hyperparameter Optimization Techniques

Table 5 outlines the diverse approaches employed for hyperparameter optimization in studies focused on potato disease detection. Researchers have utilized various

Table 5 Hyperparameter optimization

Paper	Hyperparameter optimization
(Singh et al. 2024b)	Grid search, Random search
(Tika Adilah and Kristiyanti 2023)	Grid search, Hyperparameter tuning
(Srivastava et al. 2024)	Genetic algorithm, Random search, Hyperparameter tuning
(Manzoor et al. 2024)	Genetic algorithm, Hyperparameter tuning
(Prakash et al. 2024)	Genetic algorithm, Bayesian optimization
(Ali et al. 2023)	Grid search, Bayesian optimization
(Zhang et al. 2024)	Learning rate optimization
(Jahangir et al. 2023)	Grid search, Bayesian optimization
(Paul et al. 2023)	Grid search, Bayesian optimization
(Li et al. 2024)	Genetic algorithm
(Pandiri et al. 2024)	Whale Optimization Algorithm
(Gupta et al. 2023b)	Grid search
(Gupta et al. 2023c)	Grid search, Random search
(Mehta et al. 2023b)	Grid search, Bayesian optimization
(Agrawal et al. 2023)	Grid search, Bayesian optimization
(Sinha et al. 2023)	Grid search, Random search
(Julian and Vignesh 2024)	Grid search, Bayesian optimization
(Kumar et al. 2023a)	Grid search, Random search
(Badoni et al. 2023)	Grid search, Bayesian optimization
(Patil and Manohar 2023)	Adaptive Shark Smell Optimisation (ASSO)
(Singha et al. 2023)	Grid search, Bayesian optimization
(Patil et al. 2024)	Modified raindrop optimization (MRDO), Modified shark smell optimization (MSSO)
(Joseph et al. 2022)	Grid search, Bayesian optimization
(Chaudary et al. 2023)	Genetic algorithm, Bayesian optimization
(Patil et al. 2022)	Genetic algorithm, Random search, Bayesian optimization
(Eraj and Uddin 2023)	Grid search
(Bonik et al. 2023)	Grid search, Random search
(Potnuru et al. 2023)	Genetic algorithm, Bayesian optimization
(Qi et al. 2022)	Grid search
(Kiran Pandiri et al. 2022)	Whale Optimization Algorithm (WOA)
(Johnson et al. 2021)	Stochastic gradient descent optimizer with momentum
(Pandey et al. 2019)	Grid search, Bayesian optimization
(Pandiri et al. 2024)	Whale Optimization Algorithm

optimization techniques to fine-tune the parameters of their models, aiming to enhance performance and robustness across different datasets and conditions (Gülmez 2023d).

Singh et al. (2024a, b) and Tika Adilah and Kristiyanti (2023) utilized grid search and random search methods, demonstrating effective strategies for exploring hyperparameter spaces comprehensively. Srivastava et al. (2024) and Manzoor et al. (2024) extended their approach by incorporating genetic algorithms alongside random and hyperparameter tuning methods, showcasing adaptive strategies for optimizing model configurations. Prakash et al. (2024) introduced Bayesian optimization alongside genetic algorithms, highlighting advanced probabilistic techniques in parameter tuning.

Further innovations include Ali et al. (2023) and Zhang et al. (2024), who leveraged Bayesian optimization for efficient exploration of hyperparameter landscapes, while Jahangir et al. (2023) focused on learning rate optimization to enhance model convergence and performance. Gupta et al. (2023a, b, c) and Mehta et al. (2023a, b) employed grid search in conjunction with other methods, emphasizing the balance between computational efficiency and performance improvement.

Additionally, recent studies like Singha et al. (2023) explored adaptive approaches such as Adaptive Shark Smell Optimization (ASSO), while Patil et al. (2024) and Joseph et al. (2022) introduced modified optimization algorithms like Modified Raindrop Optimization (MRDO) and Modified Shark Smell Optimization (MSSO), respectively, indicating ongoing advancements in optimization strategies tailored for specific applications. The selection and integration of hyperparameter optimization techniques play a crucial role in optimizing CNN models for potato disease detection, ensuring optimal performance in real-world agricultural scenarios.

Grid search optimization plays a crucial role in improving CNN performance for potato disease detection. This technique systematically works through multiple combinations of hyperparameters, training a model for each combination. In the context of potato disease detection, grid search has been used to optimize key parameters such as learning rate, batch size, and network depth. For example, studies using ResNet models reported improvements in accuracy of up to 3% when optimal hyperparameters were identified through grid search. This optimization technique helps in finding the best model configuration for specific datasets and disease detection tasks, ultimately leading to more accurate and reliable disease classification.

Discussion

Challenges

The integration of AI and CNNs in the domain of potato crop disease detection has demonstrated significant progress. However, several challenges exist in this field. One major obstacle is the necessity for extensive, diverse, and accurately annotated datasets for training models (Rashid et al. 2021; Sharma et al. 2022). While numerous studies emphasize the significance of large datasets for achieving high accuracy, the creation of such datasets can be laborious and resource-intensive. Additionally, the variability in environmental conditions, lighting, and plant morphology presents a substantial challenge to the generalization capabilities of the developed models (Shaheed et al. 2023; Sofuoglu and Birant 2024). Ensuring robust performance across different geographic locations, climates, and cultivation practices remains a crucial hurdle that researchers must comprehensively address (Oppenheim et al. 2019; Nazir et al. 2023).

Another critical challenge is the requirement for model interpretability and explainability in agriculture. Although advanced models exhibit exceptional accuracy, understanding the decision-making process of these models is essential for establishing trust among farmers, stakeholders, and regulatory bodies (Li et al. 2022; Luong 2024). The opaque nature of certain deep learning models may impede their widespread adoption. Therefore, researchers must devise methodologies to interpret model decisions and offer transparent insights into how specific features contribute to disease identification (Polder et al. 2019; Johnson et al. 2021).

Moreover, the deployment of AI-driven solutions in resource-limited agricultural settings, particularly in developing nations, introduces challenges related to affordability, accessibility, and technical expertise necessary for implementation (Jabbar and Koyuncu 2023; Abbas et al. 2024). Ensuring the accessibility of these technologies to smallholder farmers, who represent a significant portion of the global agricultural workforce, is a critical consideration (Khan et al. 2020; Afzaal et al. 2021).

Ethical considerations, such as data privacy, ownership, and potential biases in training data, require careful attention (Satya Rajendra Singh and Sanodiya 2023). As AI systems become integral to decision-making in agriculture, addressing these ethical aspects is crucial to ensure responsible and equitable implementation (Wei et al. 2023).

The dynamic nature of plant diseases and the emergence of new pathogens necessitate continuous adaptation of AI models (Hussain et al. 2020). Ensuring the scalability and adaptability of these models to evolving disease scenarios is essential for their long-term effectiveness (Lozada-Portilla et al. 2021; Qi et al. 2023). Overall, addressing these challenges is pivotal for realizing the full potential of AI and deep learning in transforming potato crop disease detection and contributing to sustainable agriculture (Mehta et al. 2023a).

While the review has shown an increasing number of studies using larger datasets, the scarcity of comprehensive, diverse, and accurately labeled datasets remains a significant challenge. Many studies rely on datasets with limited diversity in terms of disease stages, environmental conditions, and potato varieties. This scarcity can lead to models that perform well on test sets but struggle with real-world variability. Future efforts should focus on collaborative data collection initiatives and the development of standardized, publicly available datasets that capture the full spectrum of potato diseases across various growing conditions.

Potato diseases can manifest with highly variable symptoms depending on factors such as disease progression, environmental conditions, and plant genetics. This variability poses a significant challenge for CNN models, which may struggle to generalize across different symptom presentations. Some studies have attempted to address this by incorporating multi-stage disease datasets, but more work is needed to develop models that can robustly identify diseases across their full range of visual presentations.

The ability of CNN models to generalize across diverse growing conditions, geographical locations, and potato varieties remains a critical challenge. Models trained on data from one region or under specific conditions may not perform well when applied to different contexts. This issue is particularly pronounced in the context of global agriculture, where growing conditions can vary dramatically. Future research should focus on developing transfer learning techniques and domain adaptation methods that can help models generalize more effectively across diverse agricultural environments.

Opportunities

The exploration of AI, DL, and CNNs in the domain of potato crop disease detection presents a plethora of opportunities that can revolutionize agricultural practices. One significant advantage is the potential development of robust decision support systems for farmers (Duarte-Carvajalino et al. 2018). AI-powered tools can accurately and promptly identify plant diseases, allowing farmers to implement targeted interventions. By combining these technologies with mobile applications, user-friendly interfaces can be created to empower farmers, including those with limited technical expertise, to make informed decisions and improve crop management practices (Rashid et al. 2021; Ghosh et al. 2023).

Large-scale monitoring and surveillance are also promising with the use of remote sensing technologies and AI. Automated monitoring systems, when coupled with AI, can cover extensive agricultural areas, enabling early disease detection, preventing widespread outbreaks, and reducing crop losses. Additionally, integrating AI with unmanned aerial vehicles (UAVs) can offer a cost-effective and efficient method of monitoring crops, especially in remote or challenging-to-access regions (Kumar and Patel 2023; Abbas et al. 2024).

The rise of precision agriculture is closely tied to AI advancements, providing opportunities to optimize resource utilization (Polder et al. 2019; Sofuoglu and Birant 2024). AI algorithms can analyze data from various sources like satellite imagery, weather conditions, and soil quality to offer tailored recommendations for irrigation, fertilization, and pest control. This not only enhances resource efficiency but also promotes sustainable farming practices by reducing environmental impact (Johnson et al. 2021; Badoni et al. 2023).

Collaboration among researchers, technology developers, and agricultural stakeholders can lead to the co-creation of knowledge and solutions (Sakkarvarthi et al. 2022; Razaq et al. 2024). Establishing interdisciplinary partnerships can result in context-specific models that address the unique challenges faced by different regions and crop varieties. Furthermore, open-access platforms and knowledge-sharing initiatives can expedite the adoption of AI technologies, fostering a collaborative ecosystem for agricultural innovation (Satya Rajendra Singh and Sanodiya 2023; Wei et al. 2023).

The emergence of edge computing and the Internet of Things (IoT) provides opportunities for real-time disease detection and monitoring (Afzaal et al. 2021; Srivastava et al. 2024). Edge devices equipped with AI capabilities can process data locally, decreasing latency and reliance on centralized computing resources. This decentralized approach enhances the scalability and accessibility of AI solutions, particularly in areas with limited connectivity (Samant et al. 2023; Shafik et al. 2023).

AI-driven innovations extend beyond disease detection to include crop quality assessment, yield prediction, and the development of resilient crop varieties

(Panshul et al. 2023). Agriculture with AI can transition towards data-driven decision-making, contributing to increased productivity, food security, and sustainability. Embracing these opportunities necessitates collaborative efforts from researchers, policymakers, and the agricultural community, highlighting the transformative potential of AI in shaping the future of potato crop management.

The practical implementation of multi-spectral imaging and remote sensing data in potato disease detection presents both opportunities and challenges. In field settings, this integration can be achieved through several approaches:

Drone-based Imaging: Unmanned Aerial Vehicles (UAVs) equipped with multi-spectral cameras can efficiently cover large field areas. These drones can be programmed to fly at regular intervals, capturing high-resolution multi-spectral images of potato crops. The data collected can be processed on-site or transmitted to cloud-based systems for analysis using CNN models.

Stationary Sensor Networks: Installing a network of stationary multi-spectral sensors across the field can provide continuous monitoring. These sensors can be connected to a central processing unit or edge computing devices for real-time analysis.

Handheld Devices: For smaller farms or more targeted inspections, handheld multi-spectral imaging devices can be developed. These could be smartphone attachments or dedicated devices that farmers can use to scan specific plants or areas of concern.

Satellite Imagery: For large-scale monitoring, satellite-based remote sensing data can be integrated. While lower in resolution compared to drone or ground-based sensors, satellite imagery can provide valuable data on overall crop health and potential disease outbreaks across vast areas.

Data Integration Platforms: Developing software platforms that can integrate data from multiple sources (multi-spectral, hyperspectral, RGB images, and other sensor data) is crucial. These platforms should be user-friendly, allowing farmers and agronomists to easily access and interpret the processed data.

Edge Computing: Implementing edge computing solutions can help process data locally, reducing the need for constant internet connectivity and enabling faster response times in disease detection.

The practical implementation of these technologies requires addressing challenges such as initial setup costs, training for farmers and agricultural workers, and ensuring the reliability and accuracy of the systems in various environmental conditions. Collaborative efforts between technology developers, agricultural experts, and end-users are essential for successful field implementation.

Future Directions

The exploration of future directions in AI-driven potato disease detection presents a roadmap for advancing research and application in this critical domain.

As AI models for potato crop disease detection continue to evolve, a crucial area for future exploration is improving their generalization across diverse environmental conditions and different potato varieties (Duarte-Carvajalino et al. 2018). Robust models that can adapt to varying climates, soil types, and cultivation practices will be pivotal in ensuring the widespread applicability of AI-driven solutions in agriculture (Rashid et al. 2021; Ghosh et al. 2023).

Future research should focus on integrating diverse data modalities, such as hyperspectral imaging, drone-based surveillance, and environmental sensor data. Combining information from these sources can provide a more comprehensive understanding of the crop health status. Multi-modal AI models have the potential to enhance accuracy and reliability in disease identification by capturing a broader spectrum of features related to plant health (Li et al. 2022; Sofuoglu and Birant 2024).

Addressing the interpretability of AI models is essential for building trust among end-users, especially farmers and agricultural stakeholders (Singh and Yogi 2023; Abbas et al. 2024; Singh et al. 2024b). Future research directions should emphasize the development of explainable AI techniques that provide transparent insights into the decision-making processes of complex models. This transparency is crucial for farmers to understand and trust the recommendations generated by AI systems (Chaudary et al. 2023; Wei et al. 2023).

The advancement of AI models for real-time disease monitoring and early warning systems is a critical direction (Badoni et al. 2023; Razaq et al. 2024). Implementing these systems can help farmers take proactive measures to mitigate the impact of diseases, thereby minimizing crop losses. Integrating AI with IoT devices and edge computing can facilitate on-site, real-time decision-making, particularly in remote agricultural areas (Kumar and Patel 2023; Shafik et al. 2023).

With the increasing reliance on AI in agriculture, it is essential to address ethical considerations, data privacy, and the socio-economic impact of these technologies (Johnson et al. 2021; Shoaib et al. 2022). Future directions should include the development of robust policy frameworks and ethical guidelines to ensure the responsible and equitable deployment of AI in potato crop disease detection. Collaborative efforts involving policymakers, researchers, and industry stakeholders are crucial for establishing ethical standards and regulatory frameworks (Srivastava et al. 2024).

Engaging farmers and local communities in data collection through crowdsourcing and citizen science initiatives presents a promising avenue (Hussain et al. 2020; Kumar et al. 2023c). Future directions should explore the potential of involving farmers in the annotation and validation of datasets, fostering a collaborative approach to data-driven agriculture. This participatory model can lead to more contextually relevant and locally adapted AI solutions (Afzaal et al. 2021; Samant et al. 2023).

The establishment of open data platforms and collaborative repositories for sharing AI models can accelerate progress in the field (Saleem et al. 2022; Panshul et al. 2023). Encouraging researchers to openly share datasets and pre-trained models fosters a culture of collaboration and accelerates the development of innovative solutions. Open-source initiatives can also contribute to the democratization of AI in agriculture, making advanced technologies more accessible to a wider audience (Hassan et al. 2021; Korchagin et al. 2021).

Future research should explore effective ways to integrate AI recommendations into the decision-making processes of farmers (Poornima et al. 2023; Qi et al. 2023). Understanding the socio-economic context and incorporating farmer knowledge is crucial for the successful adoption of AI technologies. Human-AI collaboration frameworks should be designed to empower farmers, providing them with actionable insights that align with their expertise and preferences (Gupta et al. 2023c).

As climate change poses new challenges to agriculture, future AI research should focus on developing models that can adapt to changing environmental conditions (Arafath et al. 2023). This includes the integration of climate data into AI algorithms for more accurate disease prediction and the development of climate-resilient crop management strategies (Sree et al. 2023).

Ethical and Social Considerations

The implementation of CNN-based disease detection systems in potato agriculture raises important ethical and social considerations. While these technologies have the potential to significantly improve crop management and yields, their impact on farmers' livelihoods must be carefully considered. The adoption of AI-driven systems could potentially widen the technological gap between large-scale industrial farms and small-scale farmers who may lack access to or resources for implementing these technologies. It is crucial that the development and deployment of these systems are done in a way that is inclusive and considers the needs of all stakeholders in the agricultural sector.

Data privacy is another critical concern, particularly in the context of federated learning approaches. While federated learning offers a promising solution for collaborative model training without centralizing sensitive data, it still requires careful handling of farmers' data. Ensuring robust data protection measures, obtaining informed consent, and maintaining transparency in data usage are essential for building trust and ethical implementation of these technologies.

Future research and policy development in this field should address these ethical and social aspects, aiming to create solutions that are not only technologically advanced but also socially responsible and equitable.

Regulatory Issues and Compliance

The integration of AI technologies, including CNN-based disease detection systems, into agriculture raises important regulatory considerations. Currently, the regulatory landscape for AI in agriculture is still evolving, with varying approaches across different countries and regions. Key areas of regulatory focus include:

Data Protection and Privacy: Regulations like the General Data Protection Regulation (GDPR) in the European Union have implications for the collection, storage, and use of farm data in AI systems. Compliance with such regulations is crucial for the ethical and legal implementation of CNN-based disease detection technologies.

AI Transparency and Explainability: There is a growing emphasis on the need for AI systems to be transparent and explainable, especially in critical applications like disease detection. Future regulations may require developers to provide clear explanations of how their AI models make decisions.

Liability and Accountability: As AI systems take on more significant roles in agricultural decision-making, questions of liability in case of errors or failures become important. Clear regulatory frameworks are needed to define responsibility and accountability in the use of AI for crop disease detection.

Standardization and Certification: The development of standards for AI in agriculture, including performance benchmarks and safety certifications, is an emerging area of focus. Such standards could help ensure the reliability and interoperability of CNN-based disease detection systems.

Environmental Impact: Regulations concerning the environmental impact of agricultural practices may also affect the development and deployment of AI technologies, potentially requiring assessments of how these systems influence resource use and sustainability.

As the field of AI in agriculture continues to advance, it is crucial for researchers, developers, and policymakers to work collaboratively to establish comprehensive and balanced regulatory frameworks. These frameworks should aim to foster innovation while ensuring the responsible and ethical use of AI technologies in potato disease detection and broader agricultural applications.

Conclusion

This comprehensive review highlights the transformative role of CNNs in the field of disease detection for potato agriculture. The analysis covers key components of CNN-based strategies, including dataset selection, preprocessing methodologies, data collection zones, and the effectiveness of prominent algorithms such as GoogleNet, ResNet, VGG, and MobileNet variants. By meticulously examining these elements, the review provides a clear understanding of how CNNs can be utilized to accurately classify and detect diseases in potato crops.

The review looks into various hyperparameter optimization techniques, including grid search, random search, genetic algorithms, and Bayesian optimization, assessing their impact on the performance of CNN models. This analysis is crucial as it highlights how fine-tuning these parameters can significantly enhance the accuracy and efficiency of disease detection models. The discussion section addresses the major challenges in this field, such as the scarcity of comprehensive datasets, variability in disease symptoms, and the difficulty of generalizing models across different environmental conditions.

Opportunities for advancing CNN-based disease detection are also explored in depth. Integrating multi-spectral imaging and remote sensing data can provide richer and more varied datasets, enhancing model training and performance. The implementation of federated learning allows for collaborative model training across different locations, which can improve model robustness and generalizability. Future research directions propose the development of robust transfer learning techniques, enabling models trained on one dataset to perform well on different datasets with minimal additional training. Additionally, the deployment of CNNs in real-time monitoring systems is suggested for proactive disease management, allowing for early intervention and reducing the impact of diseases on potato yields. Also, this review consolidates current knowledge and identifies significant research. Future research can develop more effective and efficient CNN-based disease detection strategies.

In conclusion, CNNs offer a promising solution for the early and accurate detection of diseases in potato agriculture. The insights provided by this review can guide future research and development efforts, ultimately leading to improved disease management practices. By leveraging the power of CNNs, the agricultural sector can enhance crop health, increase yields, and ensure the sustainability of potato farming. This review not only consolidates existing knowledge but also paves the way for future innovations in the field of agricultural disease detection.

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Declarations

Competing Interest None.

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