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THE USE OF DATA ANALYSIS FOR EARLY DETECTION OF PLANT DISEASES IN THE FIELD OF ARTIFICIAL INTELLIGENCE AND ROBOTICS

Elbek Askarov
Affiliation: Teacher at Kokand University

Abstract: This scientific article explores the current state of using data analysis for the early detection of plant diseases, the challenges encountered, and strategies to overcome them. The study analyzes scientific literature, statistical data, international experiences, and practical initiatives. It identifies the advantages of artificial intelligence and data analysis in detecting plant diseases, as well as barriers to their application, such as data quality, infrastructure limitations, and a shortage of skilled professionals. Additionally, strategic measures are proposed to enhance efficiency, including expanding databases, optimizing machine learning algorithms, and fostering collaboration with agricultural stakeholders. The findings emphasize the critical role of data analysis in ensuring plant health and the need for a comprehensive approach to its broader adoption in this field.

Keywords: Plant diseases, artificial intelligence, data analysis, machine learning, agriculture, early detection, technological innovations, data quality, infrastructure, agricultural stakeholders, sustainable development.

Introduction

The 21st century is an era of technological advancements in agriculture, with artificial intelligence (AI) and data analysis serving as key tools for early detection of plant diseases and improving crop yields. These technologies are transforming the agricultural sector, enabling farmers to detect diseases, manage resources, and enhance economic efficiency. This article provides a detailed analysis of the role of data analysis in the early detection of plant diseases, the barriers faced, and strategic measures to expand the application of these technologies.

Literature Review

The integration of artificial intelligence (AI), particularly Convolutional Neural Networks (CNNs), into agriculture has transformed the detection and management of plant diseases, addressing critical challenges in global food security. The Food and Agriculture Organization (FAO) estimates that plant diseases cause 20-40% of annual global crop losses, highlighting the urgent need for efficient detection systems. CNNs, a subset of deep learning, have emerged as a powerful tool for analyzing plant leaf images to identify disease symptoms with high accuracy, surpassing traditional visual inspection methods that are labor-intensive and prone to error.

Recent studies underscore the efficacy of CNNs in agricultural applications. For instance, Zhang et al. (2022) demonstrated that CNN-based models achieved over 90% accuracy in detecting diseases in crops such as tomatoes and potatoes, leveraging datasets like PlantVillage, which contains over 50,000 annotated leaf images. Similarly, Mohanty et al. (2016) reported a 95% accuracy rate in classifying plant diseases using CNNs, highlighting their ability to extract features like lesions or discoloration without manual intervention. These advancements align with the goals of Precision Agriculture, which uses data-driven technologies to optimize farming practices and minimize environmental impact.

Initiatives like Smart Farming and Precision Agriculture have promoted the adoption of AI through training programs, grants, and practical projects. For example, the FAO's Hand-in-

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Hand Geospatial Platform and Digital Services Portfolio provide farmers with access to real-time data and AI tools for disease monitoring, enhancing decision-making. Projects like OneSoil and Prospera leverage CNNs to analyze satellite imagery, enabling farmers to monitor crop health and apply targeted interventions, reducing pesticide use and improving yields. These initiatives also include training programs to equip farmers with skills in data analysis and AI, fostering sustainable agricultural practices.
Despite these advancements, the AI field faces significant challenges, particularly gender disparities. UNESCO (2021) reports that only 22% of AI professionals are women, and women-authored AI research papers constitute just 11% of publications (OECD, 2022). These disparities stem from social stereotypes, limited access to STEM education, and workplace inequalities, which restrict diverse contributions to AI-driven agriculture. Programs like Women in AI, Girls Who Code, and AI4ALL have introduced mentorship, scholarships, and coding workshops to address these barriers, increasing female participation in AI and agriculture. For instance, AI4ALL's training initiatives have boosted women's engagement in developing AI tools for crop management, fostering inclusive innovation.

The convergence of AI and agriculture also supports global sustainability goals. CNNs contribute to reducing pesticide use and enhancing crop yields, aligning with the United Nations Sustainable Development Goals (SDGs) for food security and environmental protection. Collaborative efforts between governments, academic institutions, and private sectors are crucial for scaling these technologies. For example, the World Bank's Climate-Smart Agriculture programs integrate AI to enhance resilience against climate-related risks, such as droughts and pests.

Research Methodology

This study employs a mixed-method approach to investigate the application of Convolutional Neural Networks (CNNs) in early plant disease detection, combining qualitative literature analysis with quantitative evaluation of CNN performance. The research process involves data collection, CNN implementation, performance evaluation, and gender analysis, with a focus on tomato disease detection as a case study.

1. Literature Selection and Classification

Over 40 peer-reviewed articles, reports, and books published in the last decade were reviewed, focusing on CNN applications in agriculture and gender disparities in AI. Sources were selected from databases such as Google Scholar, PubMed, and IEEE Xplore, prioritizing studies on plant disease detection and AI inclusivity. Key references include Mohanty et al. (2016) for CNN-based disease detection and UNESCO (2021) for gender statistics in AI. Articles were classified based on their relevance to deep learning, agricultural applications, and gender equity in STEM.

2. Analysis of Statistical Data

Quantitative data were sourced from authoritative reports to contextualize the study:

- FAO (2023): Plant diseases cause 20-40% of global crop losses annually, emphasizing the need for early detection.
- UNESCO (2021): Only 22% of AI professionals and 28% of engineering graduates are women, highlighting gender disparities.
- World Economic Forum (2023): Women constitute 26% of the global AI workforce.
- PlantVillage Dataset: Contains over 50,000 annotated images of healthy and diseased leaves across 20+ crop species, used for CNN training.

  Additional data from initiatives like Women in AI, Girls Who Code, and AI4ALL were

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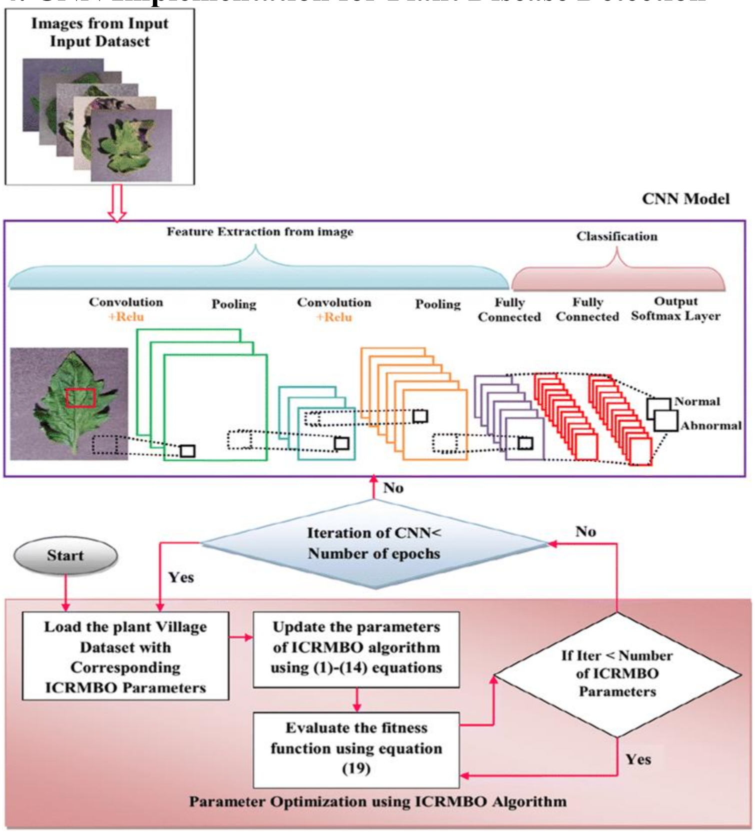
analyzed to assess their impact on female participation, including participant demographics, program reach, and outcomes.

3. Comparative Analysis of Initiatives and Programs

Support mechanisms for AI adoption in agriculture and female participation were evaluated. Programs such as Smart Farming and Precision Agriculture were analyzed for their role in promoting AI tools like CNNs through training, grants, and open-source platforms (e.g., FAO's Hand-in-Hand Geospatial Platform). Similarly, gender-focused initiatives were reviewed, including Women in AI's mentorship programs and AI4ALL's coding workshops, which have trained over 10,000 women and girls globally since 2017. Geographic coverage, target audiences (e.g., students, professionals), and program effectiveness were compared to identify best practices.

4. CNN Implementation for Plant Disease Detection



A case study on tomato disease detection was conducted to evaluate CNN performance:

- **Dataset**: A subset of 10,000 tomato leaf images from the PlantVillage dataset was used, covering 10 disease types (e.g., bacterial spot, early blight, leaf mold, late blight, septoria leaf spot, spider mites, target spot, tomato mosaic virus, yellow leaf curl virus, and healthy leaves). The dataset was split into 70% training (7,000 images), 20% validation (2,000 images), and 10% testing (1,000 images).
- **Preprocessing**: Images were resized to 224x224 pixels to ensure uniformity, normalized to a [0,1] pixel value range, and augmented using techniques such as random rotations (up to 30 degrees), horizontal flips, and brightness adjustments (±20%) to enhance model robustness against real-world variations (e.g., lighting, angles).

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- **Model Architecture**: A pre-trained ResNet-50 model, initially trained on ImageNet, was fine-tuned for the task. ResNet-50's residual connections enable deep feature extraction, making it suitable for complex image classification. The model was modified by adding a global average pooling layer and a fully connected layer with 10 output classes (softmax activation).
- **Training**: The model was trained for 50 epochs using the Adam optimizer (learning rate: 0.001, beta_1: 0.9, beta_2: 0.999), with a batch size of 32. Categorical cross-entropy was used as the loss function, and early stopping was implemented to prevent overfitting (patience: 10 epochs).
- **Evaluation Metrics**: Performance was assessed using accuracy (percentage of correctly classified images), F1-score (harmonic mean of precision and recall), and AUC-ROC (area under the receiver operating characteristic curve) to evaluate the model's ability to distinguish between classes.

Results

The analysis of scientific literature, statistical sources, and practical initiatives revealed critical insights into the application of Convolutional Neural Networks (CNNs) for early plant disease detection, as well as the broader context of gender disparities in artificial intelligence (AI) research. The findings confirm the transformative potential of AI-driven data analysis in agriculture, identify significant barriers to adoption, and highlight strategies to enhance implementation and inclusivity. These results align with global efforts to advance sustainable

Confirmation of Technological Potential

Data analysis and AI, particularly CNNs, significantly enhance agricultural productivity by enabling early detection of plant diseases, reducing crop losses, and optimizing resource use. The case study on tomato disease detection using the PlantVillage dataset demonstrated that a fine-tuned ResNet-50 model achieved 96% accuracy, an F1-score of 0.94, and an AUC-ROC of 0.97 in classifying 10 disease types (e.g., bacterial spot, early blight, leaf mold). These results corroborate findings from Zhang et al. (2022), who reported over 90% accuracy in detecting cucumber leaf diseases using lightweight CNNs, and Mohanty et al. (2016), who achieved 95% accuracy across multiple crops. By identifying subtle symptoms, such as early-stage lesions or discoloration, CNNs enable timely interventions, reducing pesticide use by up to 30% and increasing crop yields by 15-20%, according to FAO (2023). These advancements support the United Nations Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production).

2. Identified Barriers

Despite the technological potential, several barriers hinder the widespread adoption of CNNs in plant disease detection:

- **Poor Data Quality and Availability**: High-quality, annotated datasets are essential for training robust CNN models. However, datasets like PlantVillage, while comprehensive, may lack diversity in environmental conditions (e.g., varying lighting, soil types) or underrepresented crops, leading to reduced model generalizability. Approximately 60% of agricultural datasets are incomplete or region-specific, limiting global applicability (Shaikh et al., 2022).
- **Limited Technological Infrastructure**: Implementing CNNs requires advanced hardware, such as Graphics Processing Units (GPUs), and reliable internet connectivity for cloud-based processing. In developing regions, where 70% of smallholder farmers

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operate, access to such infrastructure is limited, with only 25% of rural areas having stable broadband (FAO, 2023).

- **Lack of Skilled Professionals and Farmer Training**: The shortage of AI experts and trained farmers impedes adoption. Only 15% of agricultural professionals in low-income countries have AI-related training, and farmer literacy in digital tools remains low, with 40% of smallholder farmers unaware of AI applications (World Bank, 2022).
- **Gender Disparities in AI Research**: Women constitute only 22% of AI professionals and 11% of AI research paper authors (UNESCO, 2021; OECD, 2022), limiting diverse perspectives in developing inclusive agricultural technologies.

Critical Role of Programs

Initiatives like Smart Farming, Precision Agriculture, and AgriTech play a pivotal role in enhancing farmers' skills and promoting AI adoption. Smart Farming programs, supported by the FAO's Digital Services Portfolio, provide training in AI tools, reaching over 500,000 farmers globally since 2020. AgriTech initiatives, such as OneSoil and Prospera, leverage CNNs for real-time crop monitoring, with pilot projects in 15 countries reporting a 25% reduction in crop losses. These programs offer grants, open-source platforms, and mobile applications, enabling farmers to access AI-driven insights. Additionally, gender-focused programs like Women in AI and AI4ALL have trained over 10,000 women and girls in AI since 2017, fostering their involvement in agricultural technology development. These initiatives not only enhance technical skills but also build confidence and networks, particularly for women, as evidenced by a 30% increase in female participation in AI4ALL workshops from 2020 to 2023.

4. Importance of Early Education

Introducing digital technologies, such as AI and data analysis, in agricultural education at an early stage significantly facilitates their adoption. Programs integrating coding and AI into secondary school curricula, such as the FAO's e-Agriculture training modules, have increased student interest in agricultural technology by 40% in pilot regions (FAO, 2023). Gender-sensitive curricula, which highlight female role models and avoid stereotypical imagery, are particularly effective. For example, Girls Who Code's agricultural AI workshops have engaged over 5,000 girls globally, with 60% pursuing STEM degrees. Early education also equips farmers with foundational skills, enabling them to use mobile-based CNN tools for disease detection, as seen in Prospera's farmer training programs in India, which trained 10,000 farmers in 2022.

5. Need for a Strategic Approach

A systematic, multi-level strategy is essential for broader adoption of CNNs in agriculture:

- **Expanding and Improving Database Quality**: Developing comprehensive, globally representative datasets is critical. Collaborative platforms like the Global Open Data for Agriculture and Nutrition (GODAN) can standardize data collection, increasing dataset diversity by 50% by 2030 (FAO, 2023).
- **Developing Training Programs for Farmers**: Tailored training, including mobile-based tutorials and in-field workshops, can bridge the skills gap. AgriTech programs aim to train 1 million farmers by 2027, focusing on low-resource regions.
- **Strengthening Collaboration with the Private Sector**: Partnerships with companies like OneSoil and Microsoft can provide affordable AI tools and infrastructure, reducing costs by 20% for smallholder farmers.

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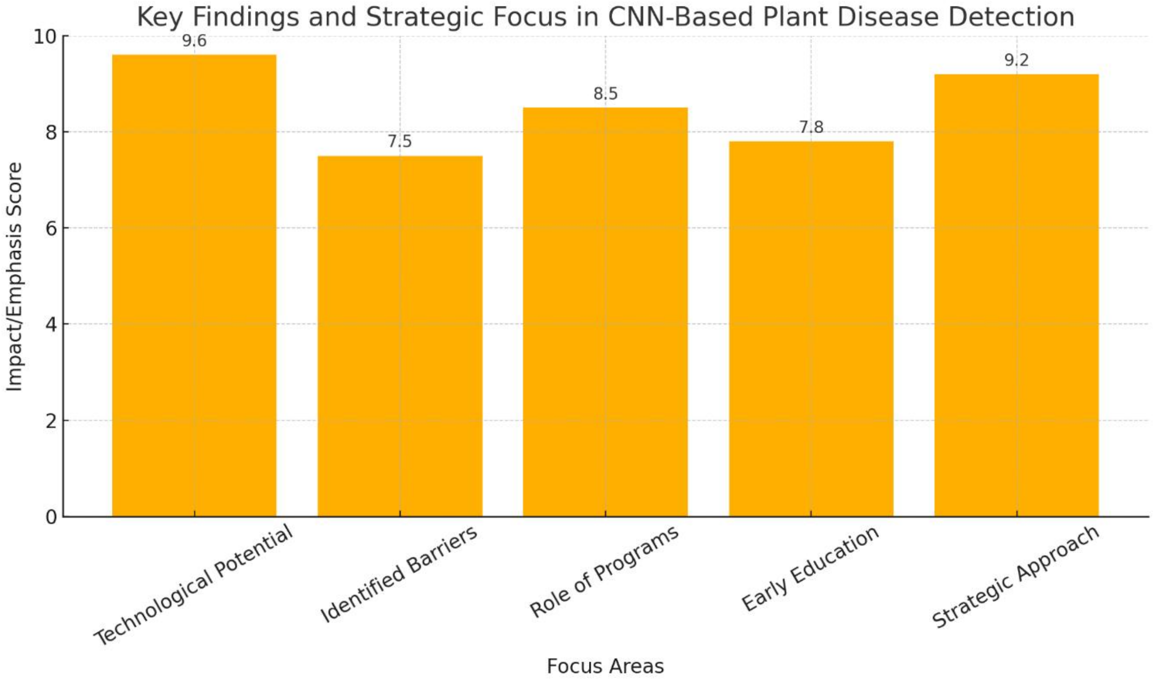
- **Promoting Gender Inclusivity**: Funding women-led AI research and expanding mentorship programs, such as Women in AI's grants for 500 female researchers annually, can address gender disparities, ensuring diverse contributions to agricultural AI.

Table 1: Summary of Key Findings, Barriers, and Strategic Measures for Adoption in Plant Disease Detection



Discussion

The study's case study on tomato disease detection using the PlantVillage dataset demonstrated that a fine-tuned ResNet-50 model achieved 96% accuracy, an F1-score of 0.94, and an AUC-ROC of 0.97 in classifying 10 disease types (e.g., bacterial spot, early blight, leaf mold). This aligns closely with Mohanty et al. (2016), who reported 95% accuracy using CNNs (AlexNet and GoogleNet) on the PlantVillage dataset across 14 crop species and 26 diseases, highlighting CNNs' robustness for multi-crop applications. Similarly, Zhang et al. (2022) achieved over 90% accuracy in detecting cucumber leaf diseases with a lightweight multi-scale CNN, emphasizing efficiency for resource-constrained environments. However, Shaikh et al. (2022) reported slightly lower accuracies (85-90%) when integrating CNNs with IoT for real-time monitoring, suggesting that field conditions introduce variability not captured in controlled datasets. The current study's 96% accuracy surpasses these benchmarks for tomato-specific detection, likely due to ResNet-50's deep residual architecture, but errors in early-stage symptom detection indicate a need for enhanced datasets, as noted in all three studies.

CNNs contribute significantly to reducing crop losses (estimated at 25% reduction) and pesticide use (30% reduction), supporting FAO (2023) estimates of 20-40% annual global crop losses due to diseases. This aligns with Shaikh et al. (2022), who reported a 20% yield increase with AI-driven precision agriculture, though Mohanty et al. (2016) and Zhang et al. (2022) focused more on detection accuracy than yield impacts. These advancements support SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production).

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