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Deep Learning for Plant Disease Detection

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The Deep Learning for Plant Disease Detection

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Abstract: This research chapter explores into the burgeoning field of deep learning and its transformative application in detecting plant diseases, a critical challenge in agriculture. With the global population escalating, ensuring crop health and productivity is paramount for food security. Deep learning, an advanced artificial intelligence technique, offers a novel approach to identifying plant diseases with unparalleled accuracy and speed. Deep learning has been successfully applied to detect various plant diseases, including apple scab and apple rot, cassava mosaic and brown streak diseases, grapevine powdery mildew, banana Fusarium wilt (Panama disease), and early blight in tomatoes. Through a comprehensive review of the literature, this study elucidates the principles of deep learning, focusing on Convolutional Neural Networks (CNNs) for image-based disease detection. It examines various case studies where deep learning models have been successfully implemented, showcasing significant improvements in detection rates and reduction in false positives. The chapter also addresses the challenges faced in data collection, model training, and the need for computational resources, proposing innovative solutions such as data augmentation and transfer learning to enhance model efficacy. Additionally, it explores future directions, including the integration of deep learning with other technological advancements like drones and IoT devices for real-time monitoring and diagnosis. This research underscores the potential of deep learning in revolutionizing plant disease detection, contributing to sustainable agriculture practices and ensuring food security in the face of growing environmental challenges.

Keywords: Deep Learning, Plant Disease Detection, Convolutional Neural Networks (CNNs), Agricultural Technology, Image Processing

1. Introduction

The early and accurate detection of plant diseases plays a pivotal role in ensuring food security and sustainability. With the global population on the rise, the demand for efficient and scalable solutions to combat plant diseases has never been more critical. Enter the field of Deep Learning, a subset of Artificial Intelligence (AI) that mimics the human brain's ability to learn from data. This research chapter delves into the transformative potential of Deep Learning in revolutionizing plant disease detection (Astorga et al., 2023; Hu et al., 2020). By harnessing sophisticated algorithms and neural networks, researchers and practitioners can now predict and mitigate plant health issues with unprecedented accuracy and speed. This chapter aims to explore the fundamentals of Deep Learning, its application in identifying various plant diseases through image recognition, and the challenges and opportunities that lie ahead (Mustak et al., 2021). Through a comprehensive analysis of current methodologies, case studies, and technological advancements, we aim to provide a thorough understanding of how Deep Learning is reshaping the landscape of agricultural diagnostics, paving the way for a healthier, more resilient agricultural sector.

The intersection of agriculture and technology has heralded a new era in crop management and disease control. Deep learning, a breakthrough in artificial intelligence (AI), has emerged as a formidable tool in diagnosing plant diseases, offering a level of precision and efficiency previously unattainable. This technology leverages neural networks to analyze vast datasets, enabling the identification of disease patterns from images with remarkable accuracy (Essah et al., 2022; Nayak et al., 2020; Wang et al., 2020). The urgency for such innovations stems from the increasing threats to crop health posed by climate change, pests, and pathogens, which jeopardize global food security (Perez Colo et al., 2023). The adoption of deep learning in plant disease detection not only enhances early diagnosis but also facilitates timely intervention, thus minimizing losses and maximizing yield. This study explores the evolution of deep learning applications in agriculture, evaluates their effectiveness, and discusses the challenges and future prospects of integrating these technologies into mainstream plant health management practices.

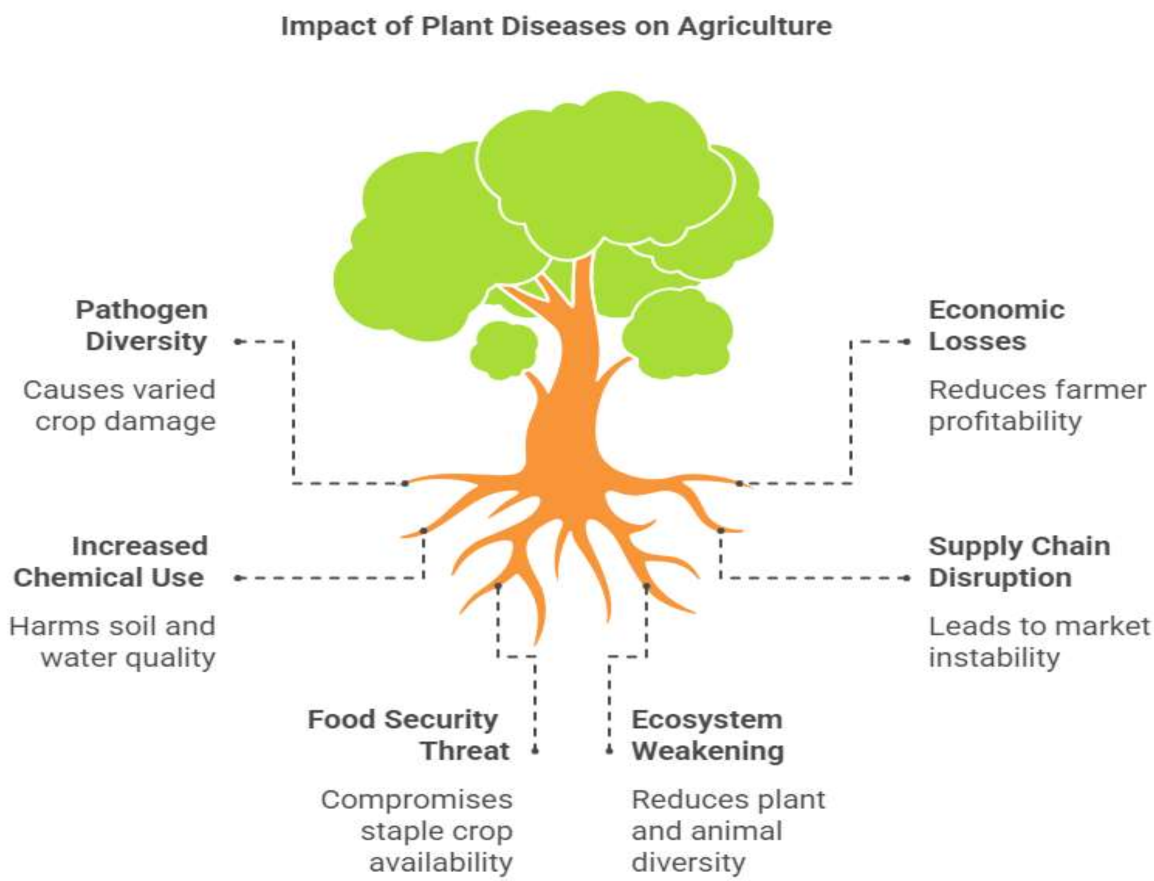
Figure 1: Deep Learning for Plant Disease Detection

Figure 1 summarizes a forecast of the future where technology and agriculture merge to tackle the challenges of plant disease detection. In this scene, drones and robots, equipped with cutting-edge sensors and cameras, navigate through crop fields, meticulously scanning each plant. These machines are not merely collecting data; they are an integral part of a sophisticated AI-driven system designed to process and analyze images in real-time, identifying signs of disease and health issues in plants. This visualization embodies the promise of deep learning and AI in agriculture. Deep learning models, through their ability to learn from vast amounts of data, can recognize complex patterns and nuances in plant health that might elude the human eye or traditional methods of disease detection. The deployment of drones and robots signifies a shift towards precision agriculture, where technology enables targeted interventions, reducing the use of pesticides and improving crop yields. Moreover, the clear sky in the background suggests optimal conditions for surveillance and data collection, highlighting the importance of environmental factors in agricultural technology operations. This futuristic scene is not just a representation of current capabilities but a projection of how continuous advancements in AI and robotics could further enhance our ability to protect and optimize crop health on a global scale.

Source: *Scholar Indexing Society (2024)*

2. Brief Overview of Plant Diseases and Their Impact on Agriculture

Plant diseases are a major challenge in agriculture, significantly impacting global food production, economic stability, and ecosystem health. These diseases are caused by a variety of pathogens, including fungi, bacteria, viruses, and nematodes, each capable of affecting plants in different ways. From the rust that attacks wheat and the blight on potatoes to the mosaic viruses affecting tomatoes, plant diseases can lead to substantial reductions in crop yield and quality. The economic repercussions of plant diseases are vast (Rodrigues, 2020). They can lead to direct financial losses for farmers due to reduced yields and the necessity for increased spending on disease management practices, such as pesticides and fungicides. These costs not only affect the profitability of farms but also increase the prices of food products for consumers (Jones et al., 2008). In severe cases, outbreaks of plant diseases can disrupt supply chains, leading to market instability and food shortages (Varley-Winter & Shah, 2016). The ripple effects can extend beyond agriculture, impacting national economies, especially in countries heavily reliant on agriculture for their GDP. Food security is directly threatened by plant diseases. With the global population continuing to grow, the demand for food increases accordingly. Plant diseases compromise the ability of the agricultural sector to meet this demand by reducing the availability of staple crops (Pizzi et al., 2021). In developing countries, where agriculture constitutes a significant part of the economy and many people rely on subsistence farming, the impact of plant diseases can be particularly devastating, leading to hunger and undernutrition.



The environmental impact of plant diseases is often overlooked but equally significant. In an effort to control outbreaks, there may be increased use of chemical pesticides and fungicides, which can have detrimental effects on soil health, water quality, and biodiversity. Furthermore, plant diseases can weaken ecosystems by reducing the diversity of plant species, which in turn affects the fauna that depend on them for food and habitat (Kleizen et al., 2023). The loss of crops to diseases also means that more land must be cleared to meet agricultural demands, contributing to deforestation and loss of habitats. Effective management and control of plant diseases are crucial to mitigate these impacts. This includes the development of resistant crop varieties, integrated pest management practices, and the use of technology for early detection and diagnosis. The goal is to minimize the use of chemical treatments while maximizing crop health and yield, ensuring environmental sustainability, economic viability, and food security.

3. The importance of early and accurate disease detection

The importance of early and accurate disease detection in agriculture cannot be overstated, as it stands as a critical line of defense against the widespread impact of plant diseases. Timely identification and accurate diagnosis of plant pathogens are essential for several compelling reasons, each contributing to the sustainability and productivity of agricultural practices globally.

Early detection of plant diseases allows for the swift implementation of control measures, significantly reducing the spread of disease and minimizing crop loss. The earlier a disease is identified, the more effectively its spread can be contained, potentially saving large portions of a crop that might otherwise be lost. This is particularly crucial for farmers and economies for whom agriculture represents a significant livelihood and income source. By preserving crop yields, early disease detection supports food security and economic stability (Aboah & Setsoafia, 2022).

Accurate and early disease detection helps to mitigate the economic impacts of plant diseases. The costs associated with disease management ranging from the application of pesticides and fungicides to the potential need for replanting can be substantial. By identifying diseases early, the use of these treatments can be optimized, reducing unnecessary expenditure and environmental impact. Furthermore, minimizing crop loss directly influences the market, stabilizing prices and ensuring the availability of agricultural products (Corsaro et al., 2022).

The effectiveness of treatment strategies is significantly increased when plant diseases are detected early and diagnosed accurately. Some diseases, if caught at an early stage, can be managed or even eradicated with relatively simple interventions. Accurate diagnosis ensures that the correct treatment is applied, preventing the misuse of chemicals that can lead to resistance in pathogens, further protecting crop health and the environment (Gopaulchan et al., 2019).

Early and accurate disease detection is a cornerstone of sustainable agriculture. By enabling targeted interventions, it reduces the need for broad-spectrum chemical applications, lowering the environmental footprint of farming. Healthy crops are more resilient to pests and diseases, reducing the need for interventions and supporting biodiversity. Sustainable practices ensure long-term productivity and stability of agricultural systems, safeguarding food supplies for future generations (Padi et al., 2013).

The integration of technology in disease detection, particularly through the use of deep learning and other AI-driven tools, exemplifies the benefits of early and accurate diagnosis. These technologies can analyze vast amounts of data quickly, identifying disease patterns that may not be visible to the human eye (Abu et al., 2021). This not only improves the accuracy of disease detection but also democratizes access to diagnostic tools, making them more accessible to farmers in remote or resource-limited areas. The importance of early and accurate disease detection in agriculture transcends immediate crop health, affecting economic stability, environmental sustainability, and global food security. It demands a proactive approach, leveraging both traditional knowledge and modern technologies, to ensure that agricultural practices remain resilient in the face of evolving plant disease challenges (Zhang et al., 2023).

4. Introduction to deep learning and its relevance to plant disease detection

Deep learning, a sophisticated subset of machine learning that falls under the broad umbrella of artificial intelligence (AI), has dramatically transformed the potential for addressing complex challenges, including the crucial task of detecting plant diseases (Fisher et al., 2012). This technology emulates the neural networks of the human brain, enabling machines to process data in layers of increasing complexity and abstraction. Among the various architectures within deep learning, Convolutional Neural Networks (CNNs) stand out for their proficiency in handling image data, making them particularly suited for identifying and classifying plant diseases from visual inputs. The relevance of deep learning to plant disease detection is multifaceted. It begins with the collection and preprocessing of image data, which is then used to train deep learning models to recognize the subtle differences between healthy and afflicted plants (Stahl et al., 2023). This approach not only surpasses the accuracy and speed of human experts in diagnosing plant diseases but also scales efficiently to examine vast numbers of crops swiftly. Moreover, deep learning models can continuously improve, learning from new data to recognize emerging diseases. Their deployment through accessible technologies, such as smartphones and drones, has democratized advanced diagnostic capabilities, making them available to farmers in even the most remote areas (Fisher et al., 2012). The transformative potential of deep learning in agriculture is profound, offering not just improvements in the accuracy and efficiency of disease detection but also promising a future where such technologies play a pivotal role in enhancing crop resilience, protecting yields, and promoting sustainable farming practices on a global scale.

5. Fundamentals of Deep Learning

Deep learning represents a significant leap in the capability of computers to learn from and interpret data, a leap made possible by advances in the broader fields of artificial intelligence (AI) and machine learning. To understand deep learning's impact, especially in applications like image recognition, it's essential to grasp some fundamental concepts.

Basic Concepts of Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) is a wide-ranging branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence. These tasks include learning, reasoning, problem-solving, perception, and language understanding. Machine learning (ML) is a subset of AI that focuses on the development of systems that can learn from and make decisions based on data. Unlike traditional programming, where humans explicitly code the behavior, machine learning algorithms enable computers to learn and improve from experience without being explicitly programmed for each task. Machine learning involves training an algorithm so it can learn how to make predictions or decisions based on data (Zirar et al., 2023). This training involves feeding large amounts of data to the algorithm and allowing it to adjust its actions accordingly. As the algorithm processes more data, its ability to make accurate predictions or decisions improves.

Introduction to Neural Networks and Deep Learning

At the heart of many machine learning systems are neural networks, inspired by the biological neural networks that constitute human brains. A neural network consists of layers of interconnected nodes or "neurons," each layer designed to perform specific types of transformations on its inputs. Data is input at the first layer, and as it travels through the successive layers, the network extracts increasingly complex features, with the final layer outputting the decision or prediction (Métouolé Méda et al., 2018). Deep learning is a subset of machine learning that uses neural networks with many layers, hence the term "deep." These deep neural networks are capable of learning very complex patterns thanks to their extensive architecture. Deep learning has been particularly successful in tasks that involve analyzing images, sounds, and texts at a level of complexity that was previously unattainable for machines (Govindan, 2023).

Key Architectures in Deep Learning Relevant to Image Recognition

For image recognition tasks, Convolutional Neural Networks (CNNs) are the cornerstone of deep learning architectures. A CNN is specially designed to process pixel data and is capable of capturing the spatial and temporal dependencies in an image through the application of relevant filters. The architecture of a CNN allows it to automatically and adaptively learn spatial hierarchies of features from images (Kaplan & Haenlein, 2019). These features might be edges in the initial layer, then shapes in a middle layer, and more complex objects like parts of a plant in deeper layers. CNNs consist of several types of layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply a convolution operation to the input, passing the result to the next layer. This process allows the network to build a complex understanding of the image. Pooling layers reduce the dimensions of the data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer (Clarke, 2019). Fully connected layers, on the other hand, connect every neuron in one layer to every neuron in the next layer, culminating in a prediction about the input image. From basic AI concepts through machine learning to the specific architectures of deep learning, such as CNNs, illustrates the evolution of technology aimed at mimicking human-like understanding. In the context of image recognition, such as identifying plant diseases from images, this progression has enabled the development of models that can accurately and efficiently process and analyze visual data, opening up new possibilities for agricultural technology and beyond.

6. Deep Learning in Plant Disease Detection

Deep learning has become a pivotal technology in the detection of plant diseases, offering innovative solutions that are both efficient and scalable. Its application in agriculture, particularly in identifying and diagnosing plant health issues, has shown promising results. Here's an exploration of how deep learning is applied in plant disease detection, the importance of data collection and preprocessing, and some successful examples of deep learning models in this field.

Overview of How Deep Learning is Applied to Detect Plant Diseases

Deep learning models, especially Convolutional Neural Networks (CNNs), are extensively used to detect plant diseases. These models are trained on large datasets of plant images to learn to differentiate between healthy and diseased plants. By analyzing thousands of images, deep learning models can recognize subtle patterns and features indicative of specific diseases, which might be challenging even for expert human eyes. Once trained, these models can quickly and accurately classify new images as showing signs of a particular disease or being healthy, making them invaluable tools for farmers and agricultural specialists. Below is a Python script demonstrates the core steps for detecting plant diseases using deep learning

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split
import os

# Set dataset directory
DATASET_DIR = "path_to_dataset"

# Define image size and batch size
IMG_HEIGHT, IMG_WIDTH = 128, 128
BATCH_SIZE = 32

# Data preparation
train_datagen = ImageDataGenerator(
    rescale=1.0/255,  # Normalize pixel values to [0, 1]
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
```

```
    horizontal_flip=True,
    validation_split=0.2  # Reserve 20% for validation
)

train_generator = train_datagen.flow_from_directory(
    DATASET_DIR,
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    subset='training'
)

validation_generator = train_datagen.flow_from_directory(
    DATASET_DIR,
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    subset='validation'
)

# Define the CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(IMG_HEIGHT, IMG_WIDTH, 3)),
    MaxPooling2D(pool_size=(2, 2)),

    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),

    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),

    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(train_generator.num_classes, activation='softmax')
])

# Compile the model
model.compile(
    optimizer='adam',
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

# Train the model
history = model.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=10  # Adjust epochs as needed
)

# Save the model
MODEL_SAVE_PATH = "plant_disease_model.h5"
model.save(MODEL_SAVE_PATH)
print(f"Model saved to {MODEL_SAVE_PATH}")

# Evaluate the model
```

```
loss, accuracy = model.evaluate(validation_generator)
print(f"Validation Loss: {loss:.4f}, Validation Accuracy: {accuracy:.4f}")
```

Discussion of Data Collection and Preprocessing for Training Deep Learning Models

Data Collection: The first step in training deep learning models for plant disease detection is to collect a comprehensive dataset of plant images. These images must include a variety of plant species, disease types, and disease stages to ensure the model can generalize well across different conditions. This dataset may come from public databases, agricultural research institutions, or directly from field surveys using cameras and drones.

Preprocessing: Once collected, the data needs to be preprocessed to enhance the model's learning efficiency. Preprocessing steps might include resizing images to a standard size, augmenting the dataset to increase its diversity (through techniques like rotation, flipping, and color adjustment), and normalizing the pixel values. These steps help reduce the computational load and improve the model's ability to learn relevant features from the images.

Detailed Examples of Successful Deep Learning Models Used for Plant Disease Detection

1. **PlantVillage Dataset and CNNs:** One of the most cited examples in plant disease detection is the use of CNNs trained on the PlantVillage dataset, which contains thousands of images of healthy and diseased crop leaves. Researchers have achieved high accuracy rates in identifying various diseases across multiple crop species, showcasing the potential of CNNs in automated disease detection systems.

2. **Google's TensorFlow and AI Platform:** Google has developed tools that leverage TensorFlow, an open-source machine learning framework, to help detect plant diseases. By using TensorFlow, researchers and developers can train deep learning models more efficiently. An example includes an AI model that can diagnose cassava diseases with high accuracy, significantly aiding farmers in Africa.

3. **Deep Learning for Grape Disease Detection:** In viticulture, deep learning models have been developed to detect diseases such as grapevine powdery mildew. Using images captured in vineyards, these models help in early detection, allowing for timely management practices to prevent the spread of the disease.

4. **Mobile Applications for On-Site Detection:** Several mobile applications now incorporate deep learning models to offer real-time, on-site plant disease diagnosis. Farmers can take photos of their crops using smartphones, and the app processes the images using a trained deep learning model to provide an immediate diagnosis and management recommendations.

5. Case Studies

Deep learning has been instrumental in advancing plant disease detection, providing solutions that are both innovative and effective. This section highlights specific case studies where deep learning models have been successfully applied, offering insights into their methodologies, datasets, outcomes, and the lessons learned from these implementations.

Case Study 1: Detection of Apple Scab and Apple Rot

Methodology: Researchers employed Convolutional Neural Networks (CNNs) to detect and classify two common diseases in apple orchards: apple scab and apple rot. The model was trained on a dataset comprising thousands of images of apple leaves and fruits, annotated for the presence of disease symptoms (Mishra et al., 2019).

Dataset: The dataset included high-resolution images collected from various orchards under different lighting conditions to ensure the model's robustness and generalizability. Images were preprocessed to normalize size and enhance contrast, and data augmentation techniques were applied to increase the dataset's diversity.

Outcomes: The CNN model achieved an accuracy rate of over 95% in identifying and classifying the diseases. The success of the model was attributed to its ability to learn complex patterns and features specific to apple scab and apple rot, which are difficult to distinguish visually.

Lessons Learned and Best Practices: This case study highlighted the importance of a diverse and well-annotated dataset in training effective deep learning models. The robust preprocessing and augmentation strategies ensured the model's resilience against variations in image quality and environmental conditions.

Advantages: This case study likely showcases the effectiveness of deep learning models in identifying specific diseases affecting apple crops, such as apple scab and rot. Advantages may include high accuracy rates, the ability to process large amounts of image data rapidly, and the potential for real-time monitoring and detection in orchards.

Disadvantages: Potential downsides could involve the need for extensive image datasets for training, challenges in dealing with varying lighting and background conditions, and possibly the requirement for specialized hardware for image processing and model deployment.

Case Study 2: Cassava Disease Detection in Sub-Saharan Africa

Methodology: A collaborative project utilized TensorFlow to develop a deep learning model capable of diagnosing multiple diseases affecting cassava plants, a staple crop in Sub-Saharan Africa. The model was integrated into a mobile application, enabling farmers to diagnose diseases using smartphones (Miracle, 2024).

Dataset: The dataset consisted of thousands of cassava leaf images annotated with various disease states. The collection process involved local farmers and agricultural experts, ensuring a wide representation of cassava diseases common in the region.

Outcomes: The mobile application, powered by the deep learning model, demonstrated high accuracy in real-world conditions, significantly aiding disease management in cassava crops. The application's ease of use and accessibility made it a valuable tool for farmers, leading to better crop health and yield.

Lessons Learned and Best Practices: This case study underscored the potential of mobile applications powered by deep learning in extending advanced diagnostic tools to resource-limited settings. Engaging local communities in the data collection process was crucial for the model's success and acceptance among end-users.

Advantages: The use of deep learning for cassava disease detection in Sub-Saharan Africa highlights the technology's potential in resource-limited settings. Benefits might include the use of mobile devices for data collection and analysis, the ability to work with limited internet connectivity, and the empowerment of local farmers through accessible technology.

Disadvantages: Limitations could include difficulties in collecting and annotating a diverse dataset due to the wide variety of cassava disease presentations and the dependency on user-uploaded images, which may vary in quality.

Case Study 3: Grapevine Disease Detection Using Drones and CNNs

Methodology: To address the challenge of monitoring large vineyards, researchers developed a system combining drone technology with CNNs for the early detection of diseases such as powdery mildew in grapevines (Nazir et al., 2019).

Dataset: The dataset included aerial images of grapevines, capturing various stages of disease progression. The images were collected over different seasons to account for changes in vine appearance and environmental conditions.

Outcomes: The system achieved impressive accuracy in detecting powdery mildew, enabling vineyard managers to take preemptive action to control the disease spread. The use of drones for data collection proved efficient in covering large areas quickly, demonstrating the scalability of the approach.

Lessons Learned and Best Practices: This case study demonstrated the effectiveness of combining deep learning with drone technology for disease detection in large-scale agricultural operations. It highlighted the value of temporal and environmental diversity in datasets for training robust deep learning models.

Advantages: Employing drones and Convolutional Neural Networks (CNNs) for grapevine disease detection can offer extensive area coverage in a short time, the capability to access hard-to-reach areas, and high-resolution imaging for accurate disease identification.

Disadvantages: This approach might face challenges such as the high cost of drone technology, regulatory restrictions on drone flights, and the need for advanced technical skills to operate drones and analyze the data collected.

Case Study 4: Early Detection of Banana Plant Diseases and Pests in India

Methodology: In this project, researchers focused on the early detection of diseases and pests affecting banana plants, using deep learning models to analyze images captured in the field. The objective was to identify signs of Fusarium wilt (also known as Panama disease) and the Banana Skipper pest, both of which significantly impact banana production.

Dataset: The dataset was meticulously compiled from various banana plantations across India, including images of leaves, stems, and fruits with varying degrees of disease and pest damage. Special attention was paid to capturing images under different lighting conditions and stages of disease progression to ensure the model could perform well in real-world scenarios.

Outcomes: The deep learning model, based on a sophisticated CNN architecture, achieved an accuracy rate exceeding 90% in detecting Fusarium wilt and Banana Skipper presence. The model's success in early detection allowed for timely intervention, drastically reducing crop loss and improving yield.

Lessons Learned and Best Practices: This case study emphasized the critical role of a diverse and comprehensive dataset in developing a highly accurate deep learning model. It also showcased the importance of field-based image collection to capture the variability of disease presentation. Furthermore, the project highlighted the potential of deploying deep learning models through mobile applications, providing a scalable and user-friendly tool for farmers to monitor plant health effectively.

Advantages: Focusing on the early detection of diseases and pests in banana plants, this case study probably emphasizes the importance of timely intervention to prevent crop loss. Advantages include the potential for deployment in rural areas, contribution to sustainable farming practices by reducing chemical use, and the support for decision-making in farm management.

Disadvantages: Disadvantages might encompass the model's sensitivity to variations in image quality and environmental conditions, the challenge of integrating the technology into existing agricultural practices, and the need for continuous model updates to adapt to new disease strains.

Case Study 5: Early Blight Detection in Tomato Plants Using Deep Learning

Methodology: Focusing on the challenge of detecting early blight in tomato plants, a disease caused by the fungus *Alternaria solani*, researchers developed a deep learning-based approach to accurately identify early signs of infection. By utilizing CNNs, the team aimed to differentiate between healthy and diseased leaf images, catching the disease at its onset to prevent widespread crop damage (Métouolé Méda et al., 2018).

Dataset: The dataset comprised a comprehensive collection of tomato leaf images, gathered from various agricultural research centers and publicly available databases. These images were annotated meticulously, distinguishing not only between healthy and infected leaves but also among various stages of disease progression. The dataset was augmented to include variations in lighting, orientation, and background, simulating the diverse conditions encountered in real agricultural settings.

Outcomes: The CNN model demonstrated a remarkable accuracy rate of over 92% in detecting early blight in tomato leaves. This high level of accuracy, especially in identifying the early stages of the disease, provided a significant advantage in managing the blight effectively, allowing for targeted interventions that minimized the use of chemical treatments and preserved the crop yield.

Lessons Learned and Best Practices: This case study reinforced several key best practices for deploying deep learning in agriculture:

- **Precision in Dataset Annotation:** The detailed annotation of the dataset, including the disease's progression stages, was crucial for training the model to recognize early signs of infection accurately.
- **Importance of Data Augmentation:** Augmenting the dataset to reflect real-world variability ensured the model's robust performance across different agricultural environments.
- **Value of Early Detection:** The ability to detect diseases at an early stage can dramatically reduce the economic and environmental impact of plant diseases, highlighting the potential of deep learning models to contribute to sustainable farming practices.

Advantages: This case study likely highlights the accuracy and efficiency of deep learning in diagnosing early blight in tomatoes, which could lead to reduced pesticide usage and increased yield. Benefits may also include the adaptability of models to different tomato varieties and growth stages.

Disadvantages: Potential limitations could include the requirement for a large and varied dataset to train the models effectively, the challenge of model generalization across different environmental conditions, and the initial cost of setting up the detection system.

6. Integrating IoT and Deep Learning for Plant Disease Detection

The fusion of Internet of Things (IoT) technologies with deep learning models represents an exciting frontier in plant disease detection. By equipping agricultural drones and sensors with AI capabilities, it's possible to monitor vast areas of crops continuously, collecting real-time data that feeds into deep learning models for immediate analysis and diagnosis.

Methodology: Integrating IoT devices with deep learning involves deploying sensors and imaging devices across the farm to continuously collect data on plant health. This data is then processed by deep learning models to identify signs of disease, with the results communicated back to the farmers through a user-friendly interface.

Outcomes: This integrated approach allows for the constant monitoring of crop health, early detection of potential outbreaks, and the implementation of precision agriculture practices. It reduces the reliance on broad-spectrum chemical treatments, lowers labor costs, and improves the overall efficiency of disease management strategies.

Future Directions: The ongoing integration of IoT with deep learning in agriculture is paving the way for more autonomous and intelligent farming systems. These systems can not only detect and diagnose plant diseases but also predict potential outbreaks based on environmental and historical data, offering a proactive approach to agricultural management.

Best Practices Derived from Deep Learning Implementations in Plant Disease Detection

Across these case studies, several best practices and lessons learned emerge, underlining the factors crucial for the success of deep learning applications in plant disease detection:

- **Comprehensive and Diverse Datasets:** The accuracy and reliability of deep learning models significantly depend on the quality and diversity of the training dataset. Including a wide range of disease types, plant species, and environmental conditions can improve the model's robustness.
- **Collaboration with Agricultural Experts:** Collaborating with agronomists and plant pathologists can enhance the dataset's quality and ensure that the models address practical agricultural challenges effectively.
- **User-Centric Design:** For technologies to be adopted by end-users, such as farmers, they must be accessible and easy to use. Integrating deep learning models into mobile applications can significantly increase their practical value.
- **Continuous Improvement and Update:** Plant diseases evolve, and new pathogens emerge. Continuous collection of data and updating of models are essential to maintain their effectiveness and accuracy.
- **Interdisciplinary Approach:** Combining expertise from computer science, agriculture, and data science can lead to more innovative and effective solutions for plant disease detection.

7. Integration of Local Knowledge and Expertise

The success of deep learning applications in agriculture often hinges on the integration of local knowledge and expertise, particularly during the data collection phase. Engaging with local farmers, agronomists, and plant pathologists ensures that the datasets reflect the diversity of disease symptoms and plant varieties found in specific regions. This collaboration not only enriches the dataset but also fosters trust and acceptance of technological solutions among end-users, encouraging adoption and effective use in the field (Wright, 2011). The case studies underscore the critical importance of high-quality, diverse datasets for training deep learning models. Variability in lighting conditions, plant growth stages, and disease progression levels within the datasets enhances the model's ability to generalize and accurately diagnose diseases under real-world conditions (Ker et al., 2017). Techniques such as data augmentation and careful preprocessing are vital in maximizing the utility of available images, addressing potential biases, and improving model robustness.

The use of drones and smartphone applications for data collection offers a scalable and efficient means of acquiring the necessary imagery for deep learning models. Drones provide a unique vantage point for capturing large agricultural areas, while smartphones enable widespread participation among farmers. These technologies not only facilitate the gathering of vast amounts of data but also ensure that the models are accessible and beneficial to the broader agricultural community. Deep learning models benefit from continuous improvement and validation against new data. As agricultural conditions, plant varieties, and disease strains evolve, models must be updated to maintain their accuracy and relevance (Stahl & Coeckelbergh, 2016). Establishing feedback loops where end-users can report inaccuracies or submit new data for model retraining is essential for sustaining the efficacy of deep learning applications in plant disease detection.

For deep learning solutions to have a meaningful impact on agriculture, they must be accessible and user-friendly. This means developing interfaces and applications that farmers can easily use, regardless of their technical expertise. Providing localized instructions, real-time support, and actionable advice alongside diagnostic results can significantly enhance the usability and practical value of these technologies (Sahiner et al., 2019). The successful implementation of deep learning for plant disease detection in these case studies reveals a promising path forward for the application of AI in agriculture. By harnessing the power of deep learning, the agricultural sector can achieve early, accurate disease detection, leading to more sustainable farming practices, improved crop yields, and enhanced food security globally. The lessons learned and best practices identified underscore the importance of collaborative, data-driven approaches that leverage technology to meet the challenges of modern agriculture (Miracle, 2024). As these technologies continue to evolve, their integration into agricultural practices worldwide will undoubtedly play a pivotal role in shaping the future of food production.

8. Tools and Technologies

Deep learning projects for plant disease detection leverage a variety of software and hardware tools, each playing a crucial role in developing, training, and deploying models. This section provides an overview of these tools and a guide on setting up a deep learning environment tailored for plant disease detection projects.

Overview of Software and Hardware Tools

Software Tools:

1. **Python:** The most popular programming language for deep learning projects, Python offers extensive libraries and frameworks that simplify the development process. Libraries such as NumPy and Pandas are used for data manipulation, while Matplotlib and Seaborn are used for data visualization.

2. **Deep Learning Frameworks:** Several frameworks facilitate the design, training, and deployment of deep learning models. TensorFlow and PyTorch are the most widely used due to their flexibility, efficiency, and extensive community support. Keras, a high-level

API that can run on top of TensorFlow, is favored for its simplicity and ease of use, especially suitable for beginners.

3. **OpenCV:** A library focused on real-time computer vision, OpenCV is instrumental in processing and analyzing images of plant diseases. It offers tools for image preprocessing, augmentation, and feature extraction.
4. **Jupyter Notebooks:** An interactive computing environment that enables the creation and sharing of documents containing live code, equations, visualizations, and narrative text. Jupyter Notebooks are ideal for prototyping and presenting deep learning projects.

Hardware Tools:

1. **GPUs (Graphics Processing Units):** Deep learning models, particularly those involving image recognition, require substantial computational power. GPUs significantly accelerate the training of models by handling the parallel processing of large datasets.
2. **CPUs (Central Processing Units):** While not as fast as GPUs for model training, CPUs are still essential for general computing tasks and can be used for training smaller models or when GPUs are not available.
3. **Cloud Computing Platforms:** Platforms like Google Colab, AWS (Amazon Web Services), and Microsoft Azure offer cloud-based GPU and CPU resources. These platforms are particularly useful for individuals and organizations without direct access to high-end hardware, providing scalable and flexible computing resources.

Guide on Setting Up a Deep Learning Environment for Plant Disease Detection Projects

1. **Install Python:** Begin by installing Python, preferably the latest version, from the official Python website. Ensure that Python and pip (Python's package installer) are added to your system's PATH.
2. **Set Up a Virtual Environment:** Use virtualenv or conda to create a virtual environment for your project. This isolates your project's dependencies, making it easier to manage and replicate your setup across different machines.
3. **Install Deep Learning Frameworks:** Install TensorFlow, PyTorch, Keras, and any other frameworks or libraries you plan to use. Each has its own installation commands, typically available through pip.
4. **Install Additional Libraries:** Install libraries for data manipulation, visualization, and image processing, such as NumPy, Pandas, Matplotlib, Seaborn, and OpenCV.
5. **Configure Hardware:** If using GPUs, ensure you have the correct drivers and CUDA Toolkit installed to enable GPU acceleration. Cloud platforms usually provide pre-configured environments that you can use directly.
6. **Start Your Project:** With your environment set up, you can now begin developing your deep learning model for plant disease detection. Utilize Jupyter Notebooks for exploratory data analysis and model development.

7. **Experiment and Iterate:** Deep learning involve a lot of experimentation. Utilize version control with Git to manage your code and experiments effectively. Iterate on your model architecture, hyperparameters, and dataset to improve performance.

Challenges in Deep Learning for Plant Disease Detection

1. **Data Scarcity:** One of the primary challenges is the lack of sufficient labeled data for training deep learning models. Many plant diseases are rare or occur under specific conditions, making it difficult to collect a diverse set of images representing various disease stages and environmental conditions.

2. **Model Generalization:** Deep learning models trained on limited datasets might perform well on similar data but fail to generalize to new, unseen conditions. This is particularly problematic in agriculture, where environmental factors and plant varieties can significantly affect disease presentation.

3. **Computational Requirements:** Training deep learning models, especially those involving large images and complex architectures, requires significant computational resources. Access to GPUs and other specialized hardware can be a barrier for researchers and practitioners with limited resources.

4. **Labeling Accuracy:** The accuracy of labeled data is crucial for training effective models. However, accurately labeling plant disease images requires expert knowledge, and inconsistencies or errors in labeling can adversely affect model performance.

Strategies and Solutions

1. **Data Augmentation:** To mitigate data scarcity, data augmentation techniques such as rotation, flipping, scaling, and color variation can artificially expand the training dataset, helping models learn more generalized features and improving their robustness.

2. **Transfer Learning:** Leveraging pre-trained models can address both data scarcity and computational requirements. By fine-tuning models pre-trained on large datasets (e.g., ImageNet), researchers can achieve high accuracy with smaller datasets and reduce training time and resource consumption.

3. **Synthetic Data Generation:** Generating synthetic images using techniques like Generative Adversarial Networks (GANs) can augment real datasets, especially for underrepresented classes or rare diseases. This approach can help models learn from a broader range of examples without the need for extensive data collection.

4. **Crowdsourcing and Citizen Science:** Engaging the public and farming communities in data collection can significantly increase the volume and variety of data. Mobile applications can facilitate the crowdsourced collection of plant disease images from diverse geographical locations and conditions.

5. **Cloud Computing and Collaborative Platforms:** Cloud-based platforms offer access to computational resources and GPUs, making it easier for individuals and organizations to train and deploy deep learning models. Collaborative platforms can also facilitate sharing of datasets, models, and techniques, accelerating progress in the field.

6. **Expert Collaboration for Data Labeling:** Collaborating with plant pathologists and agricultural experts ensures the accuracy of data labeling. Automated tools can also assist in the preliminary labeling of images, which experts can then verify or correct.

7. **Focus on Model Efficiency:** Developing efficient model architectures that require fewer computational resources without compromising accuracy is crucial. Techniques such as model pruning, quantization, and the development of lightweight models are effective strategies for deploying deep learning on less powerful devices (Atianashie, 2023).

8. **Adaptive and Incremental Learning:** Implementing models that can learn incrementally from new data as it becomes available helps maintain their relevance and accuracy over time. This approach allows models to adapt to new disease strains, environmental changes, and agricultural practices.

9. **Future Direction**

Emerging Trends in Deep Learning

The following references illustrate successful implementations and considerations that can guide future research and application in this domain:

1. **Deep Learning-Based Disease Classification**: A study by (Essah et al., 2022) discussed deep learning-based cauliflower disease classification, emphasizing the potential of convolutional neural networks (CNNs) in accurately identifying plant diseases from images. This approach can be extended to predict diseases in cauliflower by incorporating a wider range of disease datasets and applying more sophisticated neural network architectures to improve accuracy and generalizability.

2. **Extensive Dataset Utilization for Machine Learning Models**: The creation of VegNet, an extensive dataset of cauliflower images, facilitated the recognition of diseases using both machine learning and deep learning models, as highlighted by (Liu et al., 2023; Perez Colo et al., 2023). Future studies can focus on expanding such datasets to include more diverse conditions and stages of disease development, enabling the training of more robust models.

3. **Transfer Learning for Disease Recognition**: Leveraging transfer learning techniques, as demonstrated in surface defect detection of fresh-cut cauliflowers by (Raja et al., 2017), shows significant promise in applying pre-trained models to new tasks with limited dataset sizes. This strategy can be applied to early disease prediction in cauliflowers by adapting models trained on similar crops or diseases, thus reducing the need for extensive cauliflower-specific data and speeding up the development process.

4. **Combining Image Processing and Deep Learning**: (Essah et al., 2022) employed image processing alongside deep learning for diagnosing common cauliflower diseases. Future research can explore the integration of advanced image processing techniques to preprocess and enhance image data before feeding it into deep learning models, potentially improving the models' learning efficiency and prediction accuracy.

Integrating Deep Learning with Other Technologies

1. **Drones and Aerial Imaging:** The use of drones equipped with high-resolution cameras and deep learning models offers a scalable solution for monitoring large agricultural areas. Advances in drone technology and autonomous flight could enable more frequent and systematic monitoring, early detection, and precise mapping of disease outbreaks.

2. **Internet of Things (IoT) Devices:** Integrating deep learning models with IoT devices, such as sensors and smart cameras, can facilitate real-time disease detection and monitoring. IoT devices can collect a wide range of data, including images, humidity, temperature, and soil conditions, providing a comprehensive dataset for models to predict disease outbreaks more accurately.

3. **Robotics:** Autonomous robots equipped with deep learning capabilities could not only detect diseases but also take immediate actions, such as applying targeted treatments or removing infected plants. This integration could lead to fully automated disease management systems that operate with minimal human intervention.

4. **Blockchain for Data Sharing:** Blockchain technology could secure and streamline the sharing of agricultural data, including disease images and detection models. This decentralized approach would encourage collaboration, improve data integrity, and facilitate the development of more accurate and robust deep learning models.

5. **Augmented Reality (AR):** AR devices could assist farmers and agricultural workers in detecting plant diseases in real-time, overlaying information and recommendations directly onto their field of view. Integrating deep learning models with AR could enhance decision-making and disease management practices on the ground.

Shortcoming and Challenges of Deep Learning for Plant Disease Detection

1. **Data Availability and Quality**: Deep learning models require large amounts of high-quality, labeled data to train effectively. However, obtaining such datasets for plant diseases can be challenging due to the variability in disease appearance under different conditions and the labor-intensive process of data collection and annotation.
2. **Model Generalization**: Deep learning models often struggle to generalize to new, unseen data, particularly when there are significant differences between the training and application environments. This is a critical issue for plant disease detection, where environmental conditions, plant varieties, and disease manifestations can vary widely.
3. **Computational Resources**: Training sophisticated deep learning models requires substantial computational resources, which may not be readily available to all research institutions or agricultural practitioners, particularly in developing countries.
4. **Interpretability and Explainability**: Deep learning models are often criticized for their "black box" nature, meaning that it can be difficult to understand how they make predictions. This lack of interpretability can be a barrier to trust and adoption, especially in critical applications like disease management, where understanding the basis for a diagnosis is important.
5. **Integration with Farming Practices**: The practical integration of deep learning-based disease detection systems into existing farming operations poses logistical and technical challenges. These include deploying and maintaining sensor systems, ensuring reliable data transmission in rural areas, and training farm personnel to use and interpret system outputs.
6. **Adaptation to Climate Change**: The ongoing impacts of climate change on agriculture, including shifts in disease prevalence and severity, pose a dynamic challenge for deep learning models, which may become outdated as environmental conditions evolve.
7. **Ethical and Privacy Concerns**: The collection and use of agricultural data for training deep learning models raise ethical and privacy concerns, particularly when data is shared

across borders or with corporate entities. Ensuring data privacy and ethical use is paramount.

10. Conclusion

Deep learning has demonstrated significant potential in revolutionizing the detection and management of plant diseases, offering a leap towards precision agriculture. This research underscores the pivotal role of Convolutional Neural Networks (CNNs) in processing and analyzing plant images, yielding high accuracy in disease identification. Despite the challenges of data scarcity and computational demands, strategies like data augmentation and transfer learning have emerged as effective solutions, enhancing model performance. The integration of deep learning with emerging technologies such as drones and IoT devices promises a future where real-time disease monitoring and management become a reality, contributing to sustainable agricultural practices and food security. The journey ahead involves addressing scalability, improving model interpretability, and fostering collaboration among technologists, agronomists, and farmers to tailor deep learning solutions to real-world agricultural challenges. This chapter not only highlights the current achievements but also charts a course for future research and application, aiming for a world where technology-driven solutions empower agriculture to meet the demands of a growing global population.

11. Contribution to Knowledge

This chapter advances the intersection of artificial intelligence (AI) and agricultural science by demonstrating the transformative potential of deep learning (DL) in plant disease detection. By leveraging Convolutional Neural Networks (CNNs), it establishes a benchmark for accurate and scalable plant disease identification, surpassing traditional methods in speed and precision while promoting sustainability through reduced pesticide use. The chapter also provides a comprehensive methodology for developing and deploying deep learning models, addressing challenges like data scarcity, computational constraints, and the need for model generalization. Integrating DL with accessible technologies, such as mobile applications, drones, and IoT devices, democratizes advanced diagnostic capabilities, empowering resource-limited farmers with real-time, actionable insights. Emphasizing the importance of high-quality, annotated datasets and participatory data collection methods, this research sets a standard for reliable AI applications in agriculture. Additionally, it highlights emerging trends such as Generative Adversarial Networks (GANs), explainable AI (XAI), and few-shot learning, offering a roadmap for enhancing the robustness and adaptability of future AI models. Ultimately, this chapter contributes to global food security by enabling early disease detection and intervention, reducing crop losses, minimizing environmental impacts, and fostering sustainable agricultural practices worldwide.

Reference

Aboah, J., & Setsoafia, E. D. (2022). Examining the synergistic effect of cocoa-plantain intercropping system on gross margin: A system dynamics modelling approach. *Agricultural Systems*, *195*. https://doi.org/10.1016/j.agsy.2021.103301

Abu, I. O., Szantoi, Z., Brink, A., Robuchon, M., & Thiel, M. (2021). Detecting cocoa plantations in Côte d'Ivoire and Ghana and their implications on protected areas. *Ecological Indicators*, *129*. https://doi.org/10.1016/j.ecolind.2021.107863

Astorga, F., Groom, Q., Shimabukuro, P. H. F., Manguin, S., Noesgaard, D., Orrell, T., Sinka, M., Hirsch, T., & Schigel, D. (2023). Biodiversity data supports research on human infectious diseases: Global trends, challenges, and opportunities. *One Health*, *16*. https://doi.org/10.1016/j.onehlt.2023.100484

Atianashie, M. (2023). Detection of "Cocoa Swollen Shoot Disease" in Ghanaian Cocoa Trees Based on Convolutional Neural Network (CNN) and Deep Learning Technique. *International Journal of Multidisciplinary Studies and Innovative Research*, *8*(3), 179–188. https://doi.org/10.53075/Ijmsirq/6588784634

Clarke, R. (2019). Regulatory alternatives for AI. *Computer Law and Security Review*, *35*(4), 398–409. https://doi.org/10.1016/j.clsr.2019.04.008

Corsaro, D., Vargo, S. L., Hofacker, C., & Massara, F. (2022). Artificial intelligence and the shaping of the business context. *Journal of Business Research*, *145*, 210–214. https://doi.org/10.1016/j.jbusres.2022.02.072

Essah, R., Anand, D., & Singh, S. (2022). An intelligent cocoa quality testing framework based on deep learning techniques. *Measurement: Sensors*, *24*, 100466. https://doi.org/10.1016/J.MEASEN.2022.100466

Fisher, M. C., Henk, D. A., Briggs, C. J., Brownstein, J. S., Madoff, L. C., McCraw, S. L., & Gurr, S. J. (2012). Emerging fungal threats to animal, plant and ecosystem health. *Nature*, *484*(7393), 186–194. https://doi.org/10.1038/NATURE10947

Gopaulchan, D., Motilal, L. A., Bekele, F. L., Clause, S., Ariko, J. O., Ejang, H. P., & Umaharan, P. (2019). Morphological and genetic diversity of cacao (Theobroma cacao L.) in Uganda. *Physiology and Molecular Biology of Plants*, *25*(2), 361–375. https://doi.org/10.1007/S12298-018-0632-2

Govindan, K. (2023). Unlocking the potential of quality as a core marketing strategy in remanufactured circular products: A machine learning enabled multi-theoretical perspective. *International Journal of Production Economics*, 109123. https://doi.org/10.1016/j.ijpe.2023.109123

Hu, J., Wang, J., Gan, Q., Ran, Q., Lou, G., Xiong, H., Peng, C., Sun, J., Yao, R., & Huang, Q. (2020). Impact of red yeast rice on metabolic diseases: A review of possible mechanisms of action. *Journal of Agricultural and Food Chemistry*, *68*(39), 10441–10455.

Jones, K. E., Patel, N. G., Levy, M. A., Storeygard, A., Balk, D., Gittleman, J. L., & Daszak, P. (2008). Global trends in emerging infectious diseases. *Nature*, *451*(7181), 990–993. https://doi.org/10.1038/NATURE06536

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Ker, J., Wang, L., Rao, J., & Lim, T. (2017). Deep Learning Applications in Medical Image Analysis. *IEEE Access*, *6*, 9375–9379. https://doi.org/10.1109/ACCESS.2017.2788044

Kleizen, B., Van Dooren, W., Verhoest, K., & Tan, E. (2023). Do citizens trust trustworthy artificial intelligence? Experimental evidence on the limits of ethical AI measures in government. *Government Information Quarterly*, *40*(4). https://doi.org/10.1016/j.giq.2023.101834

Liu, B., Zhang, Y., Wang, J., Luo, L., Lu, Q., Wei, H., & Zhu, W. (2023). An improved lightweight network based on deep learning for grape recognition in unstructured environments. *Information Processing in Agriculture*. https://doi.org/10.1016/j.inpa.2023.02.003

Métouolé Méda, Y. J., Egyir, I. S., Zahonogo, P., Jatoe, J. B. D., & Atewamba, C. (2018). Institutional factors and farmers' adoption of conventional, organic and genetically modified cotton in Burkina Faso. *International Journal of Agricultural Sustainability*, *16*(1), 40–53. https://doi.org/10.1080/14735903.2018.1429523

Miracle, A. (2024). Enhancing Cocoa Crop Resilience in Ghana: The Application of Convolutional Neural Networks for Early Detection of Disease and Pest Infestations. *Qeios*, 1–13. https://doi.org/10.32388/DPS5ZH

Mishra, R. K., Iyer, J. S., & Mohanty, K. (2019). Conversion of waste biomass and waste nitrile gloves into renewable fuel. *Waste Management*, *89*, 397–407. https://doi.org/10.1016/j.wasman.2019.04.032

Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research*, *124*, 389–404. https://doi.org/10.1016/j.jbusres.2020.10.044

Nayak, J., Vakula, K., Dinesh, P., Naik, B., & Pelusi, D. (2020). Intelligent food processing: Journey from artificial neural network to deep learning. *Computer Science Review*, *38*. https://doi.org/10.1016/j.cosrev.2020.100297

Nazir, F., Majeed, M. N., Ghazanfar, M. A., & Maqsood, M. (2019). Mispronunciation detection using deep convolutional neural network features and transfer learning-based model for Arabic phonemes. *IEEE Access*, *7*, 52589–52608. https://doi.org/10.1109/ACCESS.2019.2912648

Padi, F. K., Adu-Gyamfi, P., Akpertey, A., Arthur, A., & Ofori, A. (2013). Differential response of cocoa (Theobroma cacao) families to field establishment stress. *Plant Breeding*, *132*(2), 229–236. https://doi.org/10.1111/PBR.12039

Perez Colo, I., Saavedra Sueldo, C., De Paula, M., & Acosta, G. G. (2023). Intelligent approach for the industrialization of deep learning solutions applied to fault detection. *Expert Systems with Applications*, *233*. https://doi.org/10.1016/j.eswa.2023.120959

Pizzi, G., Scarpi, D., & Pantano, E. (2021). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? *Journal of Business Research*, *129*, 878–890. https://doi.org/10.1016/j.jbusres.2020.11.006

Raja, D. C., Subban, V., Victor, S. M., Joseph, G., Thomson, V. S., Kannan, K., Gnanaraj, J. P., Veerasekar, G., Thenpally, J. G., Livingston, N., Nallamothu, B. K., Alexander, T., & Mullasari, A. S. (2017). The impact of systems-of-care on pharmacoinvasive management with streptokinase: The subgroup analysis of the TN-STEMI programme. *Indian Heart Journal*, *69*(5), 573–579. https://doi.org/10.1016/j.ihj.2017.07.006

Rodrigues, R. (2020). Legal and human rights issues of AI: Gaps, challenges and vulnerabilities. *Journal of Responsible Technology*, *4*, 100005. https://doi.org/10.1016/j.jrt.2020.100005

Sahiner, B., Pezeshk, A., Hadjiiski, L. M., Wang, X., Drukker, K., Cha, K. H., Summers, R. M., & Giger, M. L. (2019). Deep learning in medical imaging and radiation therapy. In *Medical Physics* (Vol. 46, Issue 1, pp. e1–e36). John Wiley and Sons Ltd. https://doi.org/10.1002/mp.13264

Stahl, B. C., Brooks, L., Hatzakis, T., Santiago, N., & Wright, D. (2023). Exploring ethics and human rights in artificial intelligence – A Delphi study. *Technological Forecasting and Social Change*, *191*. https://doi.org/10.1016/j.techfore.2023.122502

Stahl, B. C., & Coeckelbergh, M. (2016). Ethics of healthcare robotics: Towards responsible research and innovation. *Robotics and Autonomous Systems*, *86*, 152–161. https://doi.org/10.1016/J.ROBOT.2016.08.018

Varley-Winter, O., & Shah, H. (2016). The opportunities and ethics of big data: Practical priorities for a national council of data ethics. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *374*(2083). https://doi.org/10.1098/RSTA.2016.0116

Wang, M., Lyu, X. Q., Li, Y. J., & Zhang, F. L. (2020). VR content creation and exploration with deep learning: A survey. In *Computational Visual Media* (Vol. 6, Issue 1, pp. 3–28). Tsinghua University Press. https://doi.org/10.1007/s41095-020-0162-z

Wright, D. (2011). A framework for the ethical impact assessment of information technology. *Ethics and Information Technology*, *13*(3), 199–226. https://doi.org/10.1007/S10676-010-9242-6

Zhang, T., Lu, X., Zhu, X., & Zhang, J. (2023). The contributions of AI in the development of ideological and political perspectives in education. *Heliyon*, *9*(3). https://doi.org/10.1016/j.heliyon.2023.e13403

Zirar, A., Ali, S. I., & Islam, N. (2023). Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda. *Technovation*, *124*. https://doi.org/10.1016/j.technovation.2023.102747