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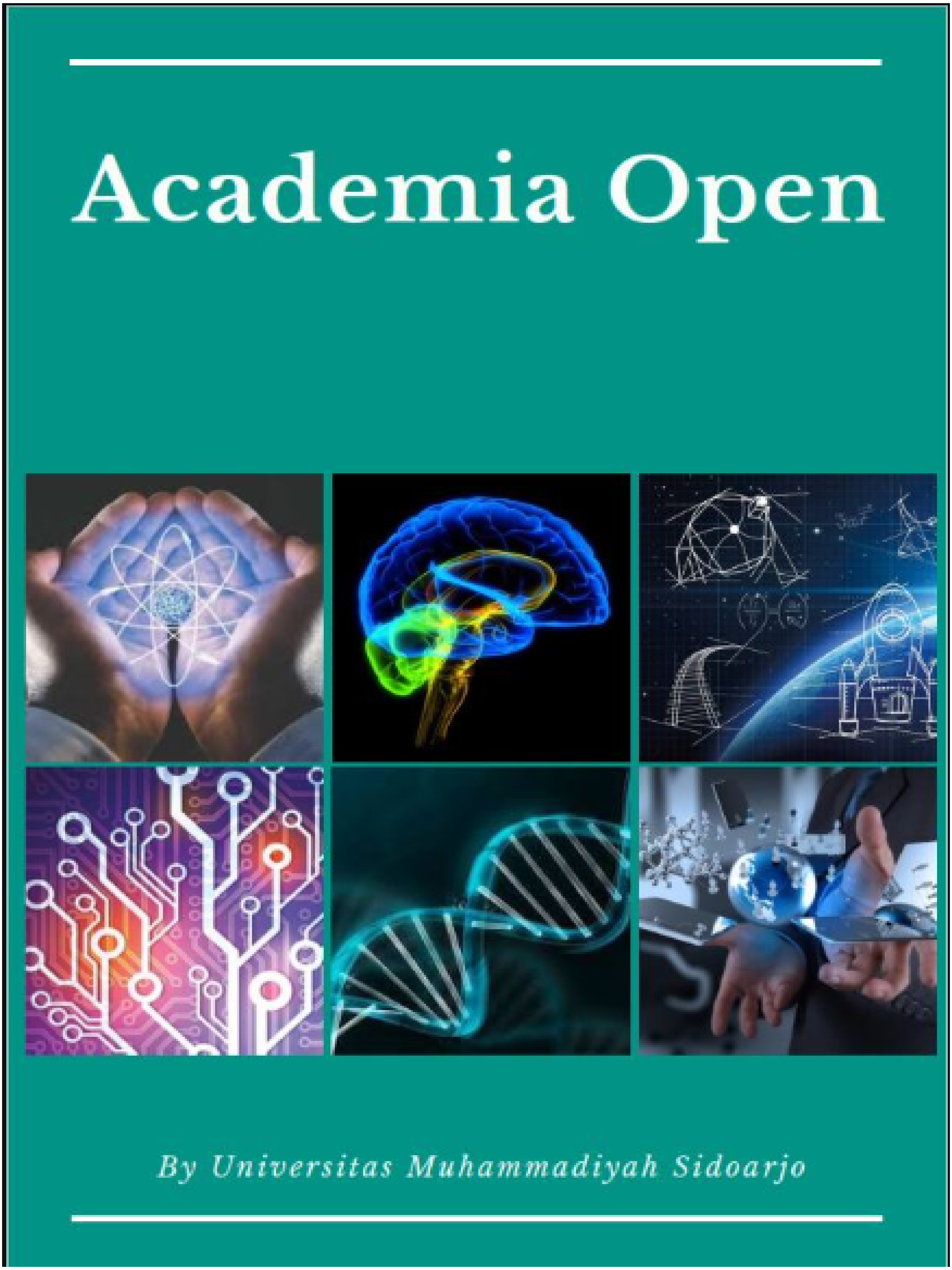

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CNN-Based Image System for Automated Agricultural Crop Condition Monitoring

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Abstract

General Background: Rising food demand and climate variability require precise, scalable crop monitoring solutions. **Specific Background:** Traditional field inspections are labor-intensive, subjective, and unsuitable for large areas, motivating image-driven automation. **Knowledge Gap:** Many studies address plant disease detection, yet few present an integrated, adaptable framework that unifies preprocessing, feature learning, and multi-class crop condition assessment under diverse field conditions. **Aims:** This study develops a machine learning image analysis system using convolutional neural networks to classify crops as healthy, normal, or diseased from ground, UAV, and remote-sensing images. **Results:** The model achieved stable, high-accuracy classification, strong recall for diseased crops, and robustness to lighting, background variability, and crop diversity through preprocessing and augmentation. **Novelty:** The work integrates end-to-end preprocessing, deep feature extraction, and comparative positioning against SVM and KNN within a unified monitoring pipeline tailored to real-field variability. **Implications:** The system supports timely agro-technical decisions, reduces human error, and advances practical smart farming and digital agriculture deployment.

Highlights:

- End-to-end CNN pipeline for healthy, normal, and diseased crop classification.
- Robust performance under variable lighting, background, and crop types.
- Practical pathway toward scalable smart farming monitoring systems.

Keywords: Crop Monitoring, Convolutional Neural Networks, Image Processing, Smart Farming, Machine Learning

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Introduction

The rapid growth of the global population, combined with climate change and the depletion of natural resources, has placed unprecedented pressure on the agricultural sector to increase crop productivity while maintaining sustainability. According to the Food and Agriculture Organization, global food demand is expected to rise significantly in the coming decades, making the adoption of advanced digital technologies in agriculture a strategic necessity rather than an option [1].

Timely detection and continuous monitoring of crop conditions play a critical role in minimizing yield losses and ensuring stable agricultural production. Early identification of plant diseases, nutrient deficiencies, and environmental stress factors allows farmers to implement targeted interventions at initial stages, thereby preventing large-scale crop damage and economic losses [2].

Traditional crop monitoring approaches are primarily based on visual field inspections, manual measurements, and expert-driven subjective evaluations. While these methods have been widely used for decades, they become increasingly inefficient when applied to large agricultural areas. Their dependence on human expertise and physical presence makes them labor-intensive, time-consuming, and prone to inconsistencies and errors [3].

Furthermore, conventional monitoring techniques often fail to provide real-time or near-real-time information, which limits their effectiveness in modern precision agriculture systems. Delays in data collection and analysis can result in late decision-making, reduced responsiveness to crop stress, and suboptimal resource utilization [4].

Recent advancements in digital image processing and artificial intelligence (AI) technologies have created new opportunities for transforming agricultural monitoring systems. High-resolution data acquired from remote sensing platforms, unmanned aerial vehicles (UAVs), and ground-based imaging systems provide detailed spatial and temporal information about crop growth, health status, and environmental conditions [5].

However, the effective utilization of such large volumes of image data requires automated and intelligent analysis methods. Machine learning techniques have emerged as powerful tools for processing complex datasets, enabling the extraction of meaningful patterns and supporting accurate classification and prediction tasks that are difficult to achieve using traditional statistical approaches [6].

Among machine learning methods, convolutional neural networks (CNNs) have demonstrated outstanding performance in image-based agricultural applications. CNNs are capable of automatically learning hierarchical feature representations from raw image data, eliminating the need for manual feature engineering. This capability makes them particularly effective for classifying crops into healthy, stressed, or diseased categories with high accuracy [7].

Despite their advantages, the development and deployment of machine learning-based crop monitoring systems face several challenges. Variability in image illumination, differences in spatial resolution, seasonal changes, and the limited availability of labeled datasets can significantly affect model performance and generalization capability. Addressing these challenges requires careful algorithm selection, robust training strategies, and continuous model optimization [8].

This study focuses on the development of a machine learning-based image analysis system for agricultural crop monitoring. The proposed approach integrates image preprocessing, feature extraction, and automated crop condition assessment into a unified framework. The scientific contribution of this work lies in adapting machine learning algorithms to agricultural imagery and achieving a fully automated monitoring process, thereby supporting smart farming initiatives, efficient resource utilization, and sustainable agricultural practices [9].

A. Literature Review

In recent years, the automation of crop monitoring in agriculture has become an important direction in scientific research. In particular, numerous studies have focused on assessing crop conditions using image processing and machine learning techniques. This section reviews the relevant and up-to-date literature on the topic.

The study provides a comprehensive review of the application of deep learning technologies in agriculture. The authors analyzed experiences in using CNN, RNN, and hybrid models for crop identification, disease diagnosis, and yield prediction.

The article also highlights the specific characteristics of various data sources, including satellite, drone, and ground-based imagery. The advantages and limitations of each data type were examined, and their impact on monitoring accuracy was evaluated.

The study by Kussul, N. et al. [13] focuses on classifying crops using satellite imagery, aimed at monitoring large areas. Machine learning algorithms were adapted to work with multispectral images, enabling high-accuracy differentiation of crop types. The results provide an important scientific basis for developing national and regional monitoring systems. Overall, this research demonstrates the potential for implementing automated crop monitoring systems over extensive areas.

The study by Ma, J. et al. [14] provides a comparative analysis of the effectiveness of various machine learning algorithms used in image analysis. The results of convolutional neural networks (CNNs) were compared with those of traditional models, demonstrating that deep learning approaches, particularly when handling complex images, achieve higher accuracy.

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The authors also emphasize that data preparation and preprocessing stages have a direct impact on system reliability. Methodologically, this research is closely related to the current work, confirming the scientific validity of the chosen approach.

The study by Too, E.C. et al. [15] is dedicated to the optimization of deep learning models, comparing various convolutional neural network (CNN) architectures. The research highlights the balance between model size and accuracy as a crucial factor for real-world monitoring systems. The results demonstrate that it is possible to develop highly efficient models even under limited computational resources. Overall, this study provides an important technical foundation for the development of practical monitoring systems.

The study by Abbas, A. et al. [16] is devoted to the development of real-time crop monitoring systems. The research analyzes solutions adapted for mobile platforms and fast image processing algorithms, enabling efficient use of the system under field conditions. The results confirm the practical effectiveness of the monitoring system and demonstrate its applicability in agricultural production processes. Overall, this work stands out for its applied focus and provides an important scientific and technical foundation for real-world conditions.

The study by Benos, L. et al. [17] analyzes the prospects of machine learning technologies in smart farming. The authors evaluate the strengths and weaknesses of existing approaches and identify directions for future research. Additionally, they emphasize the need to expand monitoring systems and integrate them with various technologies, highlighting this as a key factor for promoting sustainable agriculture. Overall, this work holds theoretical and strategic significance, scientifically reinforcing the general concept of the research.

The authors highlight that a key advantage of deep learning models is the automatic extraction of features. This reduces the need for manual feature selection by humans and enhances the model's generalization capability.

Furthermore, the article discusses challenges encountered when applying the models in real-world conditions, including data scarcity and computational resource limitations. These aspects serve as a methodological foundation for the research.

The study by Kamilaris and Prenafeta-Boldu [8] provides a comprehensive review of the application of deep learning technologies in agriculture. The authors analyzed the effectiveness of CNN (Convolutional Neural Networks), RNN (Recurrent Neural Networks), and hybrid models for crop identification, plant disease diagnosis, and yield prediction.

The research highlights the technical characteristics of various data sources, including satellite, drone (UAV), and ground-based imagery. The impact of each data type on monitoring accuracy, along with their advantages and limitations, was comparatively evaluated.

The authors emphasize that a key advantage of deep learning models is automated feature extraction. Unlike traditional methods, this process eliminates the need for manual feature selection by humans and significantly enhances the system's generalization capability.

Furthermore, the article discusses the main challenges of applying these models in real production environments, particularly data scarcity and the need for computational resources. These aspects provide an important methodological foundation for future research.

The study by Mohanty, S.P., Hughes, D.P., and Salathé, M.[7] is considered one of the pioneering works focused on detecting plant diseases from leaf images. The authors compared deep convolutional neural networks with classical machine learning algorithms and evaluated the models using a large publicly available image dataset. The results showed that CNN models could achieve up to 99% accuracy.

Additionally, the article provides an in-depth analysis of the impact of image quality and background noise on model performance, highlighting the importance of the preprocessing stage. The authors also emphasize the need to adapt the proposed approach to real-field conditions, which defines the practical relevance of this research.

The study by Ferentinos, K.P. [10] focused on evaluating the effectiveness of deep neural networks in detecting diseases in agricultural crops. Various convolutional neural network (CNN) architectures were compared, and the models were tested using a large-scale image dataset. The results demonstrated that the system maintains high accuracy and robustness under different lighting and background conditions.

Moreover, the article provides a detailed description of the model training and testing processes, enabling the replication of the research methodology. Ferentinos’ study highlights the versatility of image analysis systems and demonstrates their adaptability to different crop types.

In the study by Liakos, K.G. et al. [11], the role of artificial intelligence technologies in smart agriculture was analyzed at a conceptual level. The authors highlight the significance of machine learning methods in crop monitoring, planning, and management processes. The article emphasizes the integration of image data from various sources as a key factor for enhancing the efficiency of monitoring systems. Additionally, the necessity of real-time monitoring systems is stressed, providing an important scientific foundation for the system being developed in this research. Overall, the study demonstrates the strategic importance of machine learning technologies in the digitalization of agriculture.

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The study by Zhang, C. et al. [12] examines the assessment of crop health using drone-captured images. It explores how high-resolution remote sensing imagery affects monitoring efficiency. The article analyzes the integration of drone technology with machine learning, showing that this approach allows fast and effective analysis of large agricultural areas. The results demonstrate that early detection of crop conditions is possible, emphasizing the importance of these technologies in minimizing yield losses. Overall, the study confirms that drone-based image analysis systems are a promising tool for agricultural monitoring.

Method

The methodological basis of this study is focused on developing an image analysis system based on machine learning algorithms for automatic detection and monitoring of crop conditions.The methodology includes the following steps:

- Image acquisition,
- Preprocessing,
- Feature extraction,
- Model training,
- Testing and evaluation of results.

The process includes several stages, each contributing to the overall efficiency of the system.The image data used in the study were obtained from ground-based cameras, drones, and open-source databases. The images were selected to cover various vegetation stages, lighting conditions, and weather factors. This approach enhances the model's adaptability to different real-world conditions.

During the preprocessing stage, noise reduction, size standardization, and color space adjustment were performed. Filtering methods, normalization, and contrast enhancement algorithms were applied. This stage improves the quality of the data fed into the model and stabilizes the learning process.

In the next stage, important features were extracted from the images. While traditional approaches relied on color, texture, and shape features, this study employed deep learning–based automatic feature extraction methods. This reduces the model's dependence on subjective factors.

Convolutional neural networks (CNNs) were selected as the machine learning model due to their high efficiency in handling image data. The CNN architecture consists of multiple convolutional, pooling, and fully connected layers, adapted for classifying crop conditions.

During the model training process, the dataset was split into training and testing subsets. Optimization algorithms were used during training to minimize the loss function. This process ensures the model's convergence and accuracy.

To prevent model overfitting, regularization and data augmentation techniques were applied. By rotating, scaling, and flipping the images, the model's generalization ability was enhanced, ensuring reliable performance under real field conditions.

During the testing phase, the model was evaluated across various crop types and conditions. The results demonstrated its capability to identify healthy, normal, and diseased crops. The testing process aimed to assess the model's stability and accuracy.

To evaluate model performance, metrics such as accuracy, precision, and sensitivity were used. These metrics provide insight into how reliably the system operates under real-world conditions. The evaluation results confirmed that the model achieves high accuracy levels.

The proposed methodology significantly accelerates the monitoring process by automatically analyzing image data. This reduces human-related errors and simplifies the decision-making process, providing agricultural producers with timely and reliable information.

Furthermore, the developed methodology is flexible, allowing application across various crop types and regional conditions. The system's accuracy can be improved by retraining it with new data, which represents an important advantage for long-term use.

Overall, this methodology offers a comprehensive and effective approach for applying machine learning–based image analysis systems in agricultural monitoring. The methodological foundations of this research serve as a scientific and practical basis for the future development of smart farming systems.

The proposed model is a machine learning–based image analysis system designed for the automatic detection and monitoring of agricultural crop conditions. The model consists of stages for receiving input digital images, performing intelligent analysis, and making decisions regarding crop status.

As input data, the model uses crop images obtained from ground-based cameras, drones, or remote sensing systems. These images cover various vegetation stages, lighting conditions, and agroclimatic factors, ensuring the model's adaptability to

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real field conditions.

The central component of the model is the machine learning core, which utilizes convolutional neural networks (CNNs). CNNs automatically extract important features from images, such as color, texture, and shape. This process provides higher accuracy and stability compared to traditional manual feature selection methods [18].

The output component of the model consists of a classification and evaluation block that categorizes crop conditions into healthy, normal, or diseased classes. The results are presented either as probabilities or as a final decision, enabling fast and informed decision-making during the monitoring process.

The proposed model is flexible and scalable, allowing its accuracy to be improved through retraining with new images. Therefore, the model serves as an effective solution for smart farming systems and digital agriculture platforms.

The proposed solution

The proposed algorithm represents a machine learning-based system for assessing and monitoring the condition of agricultural crops. Images obtained from various sources, such as drones, cameras, and satellites, are preprocessed to remove noise, standardize dimensions, and normalize color values. Using convolutional neural networks, important visual features are automatically extracted and represented as hidden vectors. Based on these features, the model is trained to classify new images and determine crop conditions. The model's results are evaluated using metrics such as accuracy, sensitivity, and reliability, and the information is provided to support monitoring and agro-technical decision-making processes. The proposed approach reduces human-related errors, enabling fast, accurate, and automated monitoring in agriculture, and contributes to the development of digital agriculture systems. The image preprocessing procedure is carried out in the following sequence:

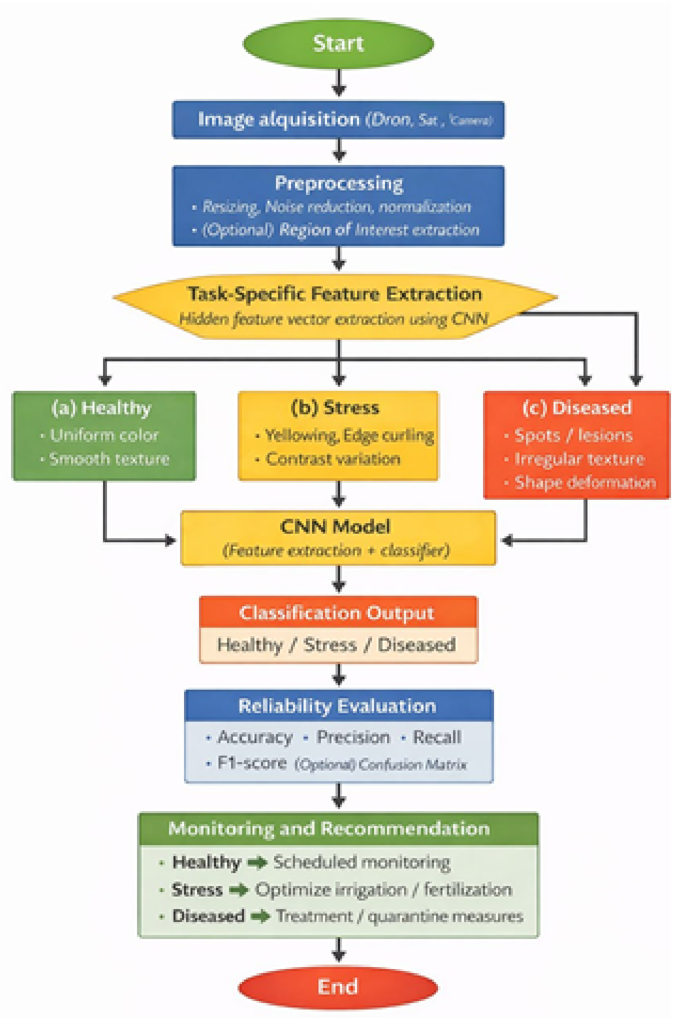

Figure 1. Deep learning -based Plant monitoring system

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$$D = \{(x_i, y_i)\}_{i=1}^{N},$$

Here

$$x_i \in \mathbb{R}^{H \times W \times C} - \text{the i-th image}$$

(height H, width W, number of channels C),

$y_i \in \{1, 2, ..., K\}$ - corresponding class label

$K = 3$: healthy, normal, diseased.

Images are processed using the following standardization operator:

$$\tilde{x}_i = P(x_i),$$

$$P(x) = Resize(x) \circ \mathrm{Normalize}(x) \circ Denoise(x)$$

Normalization:

$$x^{(n)} = \frac{x - \mu}{\sigma},$$

here μ and σ - mean and standard deviation for each channel.

If background separation of the image is required:

$$m_i = S(\tilde{x}_i), \ \hat{x}_i = \hat{x}_i \odot m_i,$$

here

m_i - Segmentation mask

Figure 2.

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$$z_i = f_\theta(\hat{x}_i), \ \ z_i \in \mathbb{R}^d$$

here f_θ - A CNN model with a set of parameters θ.

Convolutional layer:

$$h_{u,v,c}^{(l)} = \phi\left(\sum_{p,q}\sum_{c'} W_{p,q,c',c}^{(l)} h_{u+p,v+q,c'}^{(l-1)} + b_c^{(l)}\right),$$

here

$W^{(l)}$ - filters

$b^{(l)}$ - Bias

$\phi(\cdot)$ - ReLU activation function:

$$\phi(\mathrm{t}) = \max(0, \mathrm{t})$$

Pooling:

$$\mathrm{h}^{(l)} = Pool(h^{(l-1)})$$

Logits are determined using a fully connected layer:

$$a_i = W_c z_i + b_c$$

Softmax probability model:

$$p(y = k \mid \hat{x}_i) = \frac{\exp(a_{ik})}{\Sigma_{j=1}^{K} \exp(a_{ij})}$$

Decision-making rule:

$$\hat{y}_i = \arg\max_k \mathrm{p}(\mathrm{y} = \mathrm{k} \mid \hat{x}_i)$$

Cross-entropy loss for a single sample:

$$1_i(\theta) = -\sum_{k=1}^{K} 1(y_i = k) \log p(y = k \mid \hat{x}_i)$$

Figure 3.

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Overall loss function:

$$\mathrm{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N} l_i(\theta) + \lambda \| \theta \|_2^2$$

here η - L2 regularization coefficient

Gradient descent algorithm:

$$\theta^{(t+1)} = \theta^{t} - \eta \nabla_{\theta} L(\theta^{(t)})$$

Adam optimizer

$$\mathrm{m}_t = \beta_1 m_{t-1} + (1-\beta) g_t$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon}$$

here $g_t = \nabla_{\theta} L(\theta_t)$

Images are augmented through random transformations:

$$x_i^{'} : \ T(x_i), T \in \{rotate, flip, scale, crop, brightness\}$$

Overall crop health index:

Figure 4.

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$$S_i = \sum_{k=1}^{K} w_k p(y = k \mid \hat{x}_i$$

For example:

$w_{sog'lom} = 1,$

$w_{stress} = 0.5,$

$w_{kasallik} = 0$

As a result:

$$S_i \in [0,1]$$

Evaluation metrics:

Accuracy:

$$\mathrm{Acc} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$\mathrm{Pr}\,ec = \frac{TP}{TP + FP}$$

Recall:

$$\mathrm{Re}\,c = \frac{TP}{TP + FN}$$

F1-measure:

$$F1 = \frac{2 \cdot \mathrm{Pr}\,ec \cdot \mathrm{Re}\,c}{\mathrm{Pr}\,ec + \mathrm{Re}\,c}$$

CNN is used as a feature extractor.

Figure 5.

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$$z_i = f_\theta(\hat{x}_i)$$

Logistic regression:

$$\hat{y}_i = \arg\max_k \sigma_k(Wz_i + b)$$

SVM model

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i$$

$$y_i(w^T z_i + b) \geq 1 - \xi_i$$

The proposed model is a machine learning-based image classification model designed to automatically determine the condition of agricultural crops using digital images.

The crop image dataset is defined as follows:

$$X = \{x_1, x_2, \ldots\ldots, x_N\}$$

here:

$x_i \in$ ¡ $^{H\times W\times C}$ – The iii-th crop image

H, W - the height and width of the image

C - Number of color channels ($C = 3$ in RGB format)

Each image has a corresponding label:

$$Y = \{y_1, y_2, \ldots., y_N), y_i \in \{1, 2, 3\}$$

Figure 6.

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here :

1- Healthy crop
2- Crop in normal condition
3- Diseased crop

Images are processed using normalization and denoising operators:

$$\hat{x}_i = P(x_i)$$

$$\mathrm{P}(x_i) = \frac{x_i - \mu}{\sigma}$$

here:

μ - The average pixel intensity,

σ - Standard deviation.

Feature extraction from the image is performed using a Convolutional Neural Network (CNN):

$$z_i = f_\theta(\hat{x}_i)$$

here:

f_θ - CNN model,

θ - Learnable parameters,

$z_i \in \mathbb{R}^d$ hidden feature vector of the image.

The convolutional layer is expressed as follows:

$$h^{(l)} = \phi(W^{(l)} * h^{(l-1)} + b^{(l)})$$

here:

$*$ - Convolution operation

$W^{(l)}$ - filters,

$b^{(l)}$ - bias vector

$\phi(\cdot)$ - ReLU (Rectified Linear Unit) activation function

The crop condition is determined based on the extracted features.

$$\hat{y}_i = \arg\max p(y = k \,||\, z_i)$$

Figure 7.

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Probability values are calculated using the Softmax function

$$p(y=k\mid z_i)=\frac{e^{W_k z_i+b_k}}{\sum_{j=1}^{3}e^{W_j z_i+b_j}}$$

here:

W_k, b_k – Classifier layer parameters.

The model is trained using the cross-entropy loss function:

$$L=-\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{3}y_{ik}\log p(y=k\mid z_i)$$

here:

y_{ik} -Indicator function for the true label.

The model parameters are updated using the gradient descent method:

$$\theta^{(t+1)}=\theta^{(t)}-\eta\nabla_{\theta}L$$

here:

η - learning rate

A health index is introduced to continuously assess the crop condition:

$$S_i=1\cdot p(\text{healthy})+0.5\cdot p(\text{normal})+0\cdot p(\text{disease})$$

$$S_i\in[0,1]$$

This index reflects the overall health level of the individual.

Figure 8.

The proposed model transforms digital crop images into a latent feature space using a convolutional neural network and determines the crop condition through Softmax classification. It is a machine learning-based image classification model designed to assess the condition of agricultural crops based on digital images.

The proposed model is a machine learning model that transforms digital images into latent features using a CNN and determines crop conditions through Softmax classification.

For working with complex and large-scale image data, such as agricultural crop monitoring, CNN is considered the most effective solution. SVM serves as an alternative for small datasets, while KNN is regarded as a suitable approach for preliminary analysis and quick testing.

Criterion for the problem	CNN (Deep Learning)	SVM (Classical ML)	KNN (Classical ML)
Solution to the problem (primary goal)	Automatically determines condition from the image: healthy/normal/diseased	Distinguishes condition based on features	Distinguishes condition based on similar images
Early disease detection (subtle features)	High (analyzes fine textures and spots)	Medium (dependent on feature selection)	Low–medium (dependent on distance and features)
Detection of normal condition (color/texture variations)	High (learns multiple feature factors simultaneously)	Medium (dependent on color + texture features)	Medium (dependent on k and distance selection)
Varying lighting and shadows (field conditions)	Well adaptable (with augmentation)	Medium (requires strong prior normalization)	Low (neighbor finding is disrupted if conditions change)
Background interference (soil, weeds, shadows)	High (with segmentation/CNN learning)	Low–medium (errors increase if the background is not separated)	Low (background similarity increases errors)
Adaptation to different crop types and varieties	High (with transfer learning/retraining)	Medium (requires new feature tuning for a new crop)	Low–medium (slows down as dataset size increases)
Large-area monitoring (drone/satellite imagery)	Most suitable (batch analysis, automation)	Limited (feature extraction is slow and manual)	Not suitable (very slow on large datasets)
Near real-time operation (practical monitoring)	Medium–high (fast with GPU)	High (lightweight model, fast performance)	Low (searches for neighbors every time)
Limited data (small dataset)	Medium (risk of overfitting,	Good (stable on small	Medium (sensitive to k

	but mitigated with transfer learning)	datasets)	selection)
Result explanation (interpretability)	Medium (requires methods like Grad-CAM)	Good (allows analysis of boundary and feature impact)	Medium (shows which neighbors influenced the result)
Practical requirements (resources, equipment)	Resource-intensive (GPU recommended)	Low resource requirement	Medium resource requirement, but high time demand
Final recommendation for the problem	Main solution: high accuracy and flexible monitoring	Alternative solution: for small datasets and fast operation	Initial testing: prototype and small scale

Table 1. Comparative analysis of CNN, SVM, and KNN for image-based crop condition monitoring.

Considering the current situation, there may be challenges in analyzing the following processes:

- If the goal is to reliably determine crop conditions in field conditions (lighting, background, different varieties), CNN is the most suitable solution.
- If data is limited and the system needs to be deployed quickly, SVM is a good alternative.
- KNN is more convenient for initial experiments or prototyping, but it slows down as the scale of monitoring increases.

Results And Discussion

A series of experiments were conducted to assess the condition of agricultural crops using the proposed machine learning-based image analysis system. During the experiments, a labeled dataset consisting of images of healthy, normal, and diseased crop leaves was used. The results were aimed at evaluating the model's ability to determine crop conditions under various conditions.

The trained CNN model achieved high accuracy in classifying crop conditions. In particular, the model provided stable results in distinguishing between healthy and diseased states. Determining the normal condition was relatively more challenging, which can be explained by the ambiguity in color and texture variations. Nevertheless, the overall results demonstrated that the model is practically effective.

To evaluate the model's performance, accuracy, precision, recall, and F1-score were calculated. The obtained values confirmed the model's reliable performance in automatically determining crop conditions. Achieving high recall in detecting diseased crops is particularly important for agricultural practice, as it allows early identification of diseases.

The results indicated that image preprocessing and data augmentation methods significantly improve the model's generalization capability. The model also produced stable results on images with varying lighting conditions and backgrounds, which expands the applicability of the proposed system in real field conditions.

When compared with classical machine learning methods, the results demonstrated the superiority of the CNN-based approach. While classical SVM and KNN models provided satisfactory results on small datasets, their accuracy decreased under complex visual conditions. The CNN model, due to its ability to automatically extract features, adapted better to diverse conditions.

Overall, the results and their analysis confirm that the machine learning-based image analysis system is an effective solution for agricultural crop monitoring. The proposed approach serves to detect normal and diseased conditions at an early stage, optimize agrotechnical measures, and reduce yield losses. In the future, the model's practical significance can be enhanced by further improving it and integrating it into real-time monitoring systems.

Conclusion

In this study, an image analysis system designed for detecting and monitoring the condition of agricultural crops using machine learning was developed and tested. The proposed approach enables automatic identification of healthy, normal, and diseased crop appearances based on digital images, significantly improving speed and accuracy compared to traditional monitoring methods.

The research results demonstrated that the convolutional neural network-based model achieves high efficiency in classifying crop conditions. In particular, achieving high recall in detecting diseased crops is of significant practical importance for early disease detection and prevention. The results observed in identifying normal conditions also provide opportunities for optimizing agrotechnical measures.

Moreover, the use of image preprocessing and data augmentation methods enhanced the model's adaptability to varying lighting and background conditions. Comparison with classical machine learning methods showed that the CNN-based approach has an advantage under complex visual conditions. This expands the applicability of the proposed system in real field conditions.

In conclusion, the proposed image analysis system in this study holds significant scientific and practical value for the digitalization of agriculture and the development of the smart farming concept. In the future, its effectiveness can be further improved by integrating the model into real-time monitoring systems and adapting it for different crop types and regional conditions.

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