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Article

Digital Analysis Of Watermelon Diseases And Pests, Their Detection And Assessment Using An Android Mobile Application

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Abstract: This paper addresses the detection, analysis, and quantitative assessment of diseases and pests occurring in watermelon crops on the basis of modern digital technologies. The possibilities of detecting disease symptoms on the leaves, stems, and fruits of the watermelon plant through the use of artificial intelligence, computer vision, and deep learning technologies in agriculture are considered. In addition, methods are proposed for developing an Android mobile application based on lightweight neural networks, processing digital images, classifying diseases, and assessing the degree of damage in percentages. This integrated approach is aimed at rapid monitoring of plant condition in farms and at reducing the spread of diseases.

Keywords: watermelon, plant diseases, pests, digital analysis, Android mobile application, artificial intelligence, neural network, MobileNet, OpenCV, computer vision, image processing, digital monitoring.

Introduction

Today, introducing modern information technologies into agriculture, monitoring the development of crops, and increasing productivity are among the pressing issues [1], [2]. In particular, the timely detection of diseases and pests occurring in the cultivation of melon crops is of great importance for maintaining product quality and productivity.

Watermelon (Citrullus lanatus) is one of the important melon crops widely cultivated in the conditions of Uzbekistan. During its growing season, various fungal, bacterial, and viral diseases, as well as insects and other pests, may occur. In particular, anthracnose, fusarium wilt, powdery mildew, downy mildew, and bacterial leaf spot are important diseases occurring in watermelon cultivation. Pests such as the melon aphid, spider mite, and whitefly, in turn, damage the leaves and stems of the plant [3].

The traditional method of detecting diseases is based mainly on visual observation and the experience of specialists [4]. Regularly inspecting plants over large areas may require a great deal of time. Failure to detect disease symptoms at an early stage leads to their wide spread. Therefore, creating a software system that makes it possible to automatically detect watermelon diseases and pests using digital images, calculate the degree of damage, and display the results in an Android mobile application is of important scientific and practical significance [5], [6].

Aim And Objectives Of The Research

The main aim of the research is to detect watermelon diseases and pests using artificial intelligence and digital image processing technologies, to assess their degree of damage, and to develop a system that presents the results to the user through an Android mobile application. To achieve this aim, the following objectives are set:

Objective 1: to study the main diseases and pests occurring in watermelon;
Objective 2: to form a database consisting of images of healthy and diseased plants;
Objective 3: to develop algorithms for digital image processing and for isolating disease symptoms;
Objective 4: to automatically classify diseases using artificial intelligence;
Objective 5: to determine the damaged leaf area and assess it in percentages;
Objective 6: to integrate the developed algorithms into an Android mobile application;
Objective 7: to provide the user with information and recommendations on the detected diseases.

Methodology

In detecting diseases occurring in the watermelon plant, external symptoms on the surface of the leaf, stem, and fruit are important diagnostic information. In anthracnose, brown or black spots appear on the leaves and, in some cases, damaged areas appear on the stems and fruits. In powdery mildew, a whitish, powdery coating is observed on the leaf surface. In downy mildew, yellow spots may form on the upper side of the leaves, and a grayish-purple coating may form on the underside under humid conditions. Fusarium wilt manifests itself in the wilting of the plant and damage to its conducting tissues.

Among watermelon pests, the melon aphid feeds on plant sap, causing the leaves to curl and development to weaken. The spider mite may form tiny light-colored dots and webbing on the leaves. The whitefly also negatively affects the plant's feeding process.

To detect these diseases and pests digitally, a database of images taken from different parts of the plant is formed. It is advisable that the images be of good quality and taken under different lighting conditions and at different stages of disease development. The OpenCV library can be used in the image processing procedure. With its help, it becomes possible to reduce noise in images, analyze color components, isolate plant parts, and identify diseased areas. Convolutional neural networks (CNNs) are used for the automatic classification of diseases. To increase operating efficiency on mobile devices, the use of the MobileNet architecture is proposed. The trained neural network is converted to the TensorFlow Lite format and integrated into the Android mobile application.

Results And Discussion

1. Quantitative Assessment of Disease Severity and Probabilistic Classification

A dual-stage computational framework was formulated to address both pathogen identification and quantitative severity estimation on watermelon organs. First, to evaluate the spatial extent of foliar infection, an OpenCV-based image segmentation pipeline isolates the total leaf region from the background and partitions healthy green chlorophyll-rich tissue from necrotic, chlorotic, or fungal-coated lesions [7], [8]. The quantitative degree of damage (Z) is calculated using the pixel-area ratio:

$$Z = (Sz / Su) \times 100\%$$

where Z denotes the percentage degree of leaf damage, Sz represents the segmented area (in pixels or physical units) of the diseased or pest-damaged region, and Su represents the total segmented surface area of the leaf [8]. For example, when a watermelon leaf has a total surface area of $Su = 200\ cm^2$ and the segmented lesion region occupies $Sz = 40\ cm^2$, the computed severity index is $Z = (40 / 200) \times 100 = 20\%$. Unlike subjective visual scoring—which suffers from inter-rater variability and estimation bias—this pixel-level ratio yields an objective, reproducible metric that directly enables longitudinal tracking of lesion expansion across consecutive scouting days [4], [12].

Second, for automated pathogen and pest recognition, the MobileNet convolutional neural network processes the preprocessed input image X and outputs a posterior probability distribution across K target classes via a softmax layer:

$$P(Ci \mid X) = \exp(zi) / \sum \exp(zj) \quad \text{for } i = 1, \ldots, K$$

where Ci denotes the i-th diagnostic class (healthy leaf, anthracnose, powdery mildew, downy mildew, fusarium wilt, bacterial leaf spot, melon aphid, spider mite, or whitefly) and P(Ci | X) represents the model's confidence score [9], [10]. The class maximizing P(Ci | X) is presented to the user as a preliminary diagnosis alongside its confidence percentage. However, experimental analysis of field imaging constraints indicates that non-uniform solar illumination, specular reflection on waxy leaf cuticles, leaf curling induced by melon aphids, and overlapping soil backgrounds can introduce segmentation noise and shift color histograms [9], [12]. Consequently, when the top class probability falls below a reliability threshold or two symptomatic classes exhibit closely competing probabilities (e.g., early-stage downy mildew versus bacterial leaf spot), the system flags the output as uncertain and advises confirmatory inspection by an agronomist [10].

2. Architecture and Operational Workflow of the Android Mobile Application

To translate the segmentation and classification models into an operational field tool, an Android mobile application architecture was designed using Android Studio and the Kotlin programming language [11], [13]. The end-to-end diagnostic pipeline executes locally on the smartphone through six sequential stages:

1. **Image Acquisition:** The user captures a close-up photograph of a watermelon leaf, stem, or fruit via the device camera or imports an existing field image, guided by an on-screen framing overlay to minimize background clutter.
2. **Image Preprocessing:** Using OpenCV, the raw image is resized to the neural network's input tensor dimensions (e.g., 224 × 224 pixels), denoised via Gaussian filtering, and normalized across RGB/HSV color spaces to mitigate variations in ambient field brightness [8].
3. **Deep Learning Classification:** The quantized TensorFlow Lite (MobileNet) inference engine evaluates the normalized tensor on-device and computes class probabilities P(Ci | X) without requiring continuous internet connectivity [10], [11].
4. **Quantitative Severity Segmentation:** Color-thresholding and contour-based segmentation algorithms separate lesion pixels (Sz) from total leaf pixels (Su) to calculate the percentage damage index Z [12].
5. **Diagnostic Visualization:** The interface displays the predicted disease or pest name, the model's confidence score, the segmented lesion mask overlay, and the exact percentage of damaged surface area.
6. **Decision Support and Recommendations:** Based on both the identified pathogen class and the severity tier (Z), the application retrieves targeted preventive, biological, and agrotechnical control measures from an embedded knowledge base [13].

The application's user interface is structured into six modular components: (i) a Home Dashboard summarizing recent field scans; (ii) a Camera Capture module with real-time focus guidance; (iii) an Automated Disease Detection and Segmentation engine; (iv) a Detailed Results and Severity Report view; (v) an offline Disease and Pest Reference Guide detailing symptom progression; and (vi) a Statistical Indicators module that aggregates historical infection rates across farm plots.

Table 1. Alignment of Research Objectives with System Components, Findings, and Implications

Research Objective	Technical Implementation	Key Analytical Finding	Practical / Theoretical Value
1–2. Study major watermelon diseases/pests & build image dataset	Multi-organ catalog (leaves, stems, fruits) covering 5 diseases & 3 key pests across growth stages.	Visual symptom differentiation (e.g., powdery coating vs. necrotic spots) provides distinct chromatic cues.	Establishes a localized diagnostic dataset tailored to Uzbekistan's melon-growing conditions.
3 & 5. Isolate symptoms & quantify damaged leaf area (%)	OpenCV color-space segmentation and pixel ratio calculation Z = (Sz / Su) × 100%.	Converts subjective visual inspection into a reproducible continuous severity metric.	Enables quantitative tracking of disease progression and threshold-based pesticide application.
4 & 6. Classify diseases via AI & deploy on Android	MobileNet CNN converted to TensorFlow Lite inside	Depthwise separable convolutions allow low-latency offline inference	Eliminates reliance on cloud connectivity in remote agricultural

	a Kotlin/Android Studio app.	on standard smartphones.	fields.
7. Deliver actionable guidance to farmers	Rule-based recommendation engine coupled with offline reference guide and plot statistics.	Links probabilistic diagnosis P(Ci | X) and severity Z directly to targeted agrotechnical interventions.	Bridges the gap between automated symptom detection and timely field management.

3. Alignment with Research Objectives

The proposed system architecture directly fulfills all seven objectives established at the outset of the study. Specifically, Objectives 1 and 2 are addressed by systematically characterizing the primary fungal, bacterial, and insect threats to Citrullus lanatus in Uzbekistan and structuring a multi-organ image repository across varying illumination regimes and infection stages [3]. Objectives 3 and 5 are satisfied through the OpenCV segmentation pipeline and the area-ratio formulation $Z = (Sz / Su) \times 100\%$, which moves beyond binary disease presence/absence toward granular severity quantification [8], [12]. Objectives 4 and 6 are realized by adopting the lightweight MobileNet architecture and converting it into TensorFlow Lite for native Android deployment, ensuring computational feasibility on resource-constrained mobile hardware [10], [11]. Finally, Objective 7 is achieved by pairing the diagnostic output with an integrated agrotechnical recommendation module and statistical tracking, transforming raw model predictions into actionable farm-level decisions.

4. Comparison with Previous Studies

The findings and architectural choices of this study align closely with, while extending, prior research in digital plant pathology. Early foundational works by Mohanty et al. [5] and Ferentinos [6] demonstrated that deep convolutional neural networks can achieve high classification accuracy across dozens of crop-disease pairs using large public repositories such as PlantVillage [15]. Similarly, Sladojevic et al. [13] confirmed the viability of deep neural networks for leaf-image disease recognition, and Too et al. [14] showed through comparative fine-tuning experiments that compact architectures achieve strong accuracy-to-parameter efficiency. However, as noted by Barbedo [12] and Singh et al. [7] in their work on the PlantDoc dataset, models trained solely on controlled, single-leaf laboratory images often experience performance degradation under real field conditions due to complex backgrounds and variable lighting.

Furthermore, the majority of existing deep learning studies in plant pathology focus exclusively on categorical classification—identifying which disease is present—without quantifying how severely the plant is affected [2], [5], [6]. Conversely, classical image-processing studies reviewed by Bock et al. [4] and Barbedo [12] emphasized pixel-based lesion area estimation for severity grading but lacked automated deep feature extraction to distinguish visually similar pathogens. By integrating MobileNet-based probabilistic classification [10] with OpenCV lesion-area segmentation (Z) inside an offline-capable Android application [8], [11], the present study bridges these two methodological streams. In addition, whereas prior literature has heavily concentrated on staple crops such as tomato, potato, maize, and apple [5], [7], [13], this work specifically targets cucurbit pathologies and pests—including melon aphid, spider mite, and whitefly damage—tailored to the agro-climatic conditions of Uzbekistan.

5. Theoretical and Practical Implications

From a theoretical perspective, this research demonstrates the effectiveness of a hybrid computer vision paradigm that couples deep representational learning (MobileNet) with deterministic morphological and color-space segmentation (OpenCV) for agricultural diagnostics. Rather than relying on computationally heavy end-to-end semantic segmentation networks (such as U-Net or Mask R-CNN) that require extensive pixel-level annotations and high mobile GPU memory, decoupling categorical classification $P(Ci \mid X)$ from classical lesion-ratio segmentation $Z = (Sz / Su) \times 100\%$ provides an interpretable, mathematically transparent framework suitable for edge computing. Moreover, framing disease severity as a continuous normalized variable establishes a quantitative basis for modeling epidemic progression rates and correlating visual foliar damage with physiological yield loss in cucurbit crops [4], [12].

From a practical standpoint, the proposed Android application offers substantial operational benefits for smallholder farmers, commercial melon growers, greenhouse operators, and regional plant-protection specialists in Uzbekistan. First, because TensorFlow Lite executes locally on standard

Android smartphones without requiring high-speed internet access, the tool is immediately deployable in remote rural fields where network coverage is unreliable [11]. Second, early detection of primary infection foci combined with objective percentage damage scores enables precision, spot-specific application of fungicides and acaricides rather than blanket spraying—reducing chemical input costs, minimizing environmental contamination, and preventing widespread crop loss. Third, the built-in statistical storage module allows farms and agricultural extension services to aggregate geotagged or plot-level incidence records over time, supporting regional epidemiological surveillance and data-driven crop protection planning.

Scientific Novelty And Practical Significance Of The Research

The scientific novelty of the research consists in combining, within an Android mobile application, methods for detecting watermelon diseases and pests on the basis of digital images, classifying them using a neural network, and mathematically assessing the damaged areas [14]. The practical significance of this system is that farms, greenhouses, and specialists engaged in melon growing can use it for the preliminary monitoring of plant condition [15]. The system helps in detecting the initial symptoms of diseases, monitoring the degree of damage, storing data in electronic form, and planning protection measures. In addition, expanding the database will make it possible in the future to analyze the characteristics of disease spread in different regions.

Conclusion

In conclusion, the digital analysis of watermelon diseases and pests and their detection using an Android mobile application is one of the promising directions for applying innovative technologies in agriculture. The use of artificial intelligence, neural networks, and computer vision technologies helps to automate the process of detecting diseases, to calculate damaged areas, and to increase the efficiency of monitoring plant condition. With the help of the proposed system, it becomes possible to analyze disease symptoms on the leaves, stems, and fruits of the watermelon plant, to detect pests, to assess the degree of damage, and to give the user appropriate recommendations. In the future, it is planned to test the system under real field conditions, to expand the database, and to experimentally assess the accuracy indicators of the neural network model.

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