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Article

# Digital Analysis of Carrot Diseases and Pests, Their Detection and Assessment Using an Android Mobile Application

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**Abstract:** This paper addresses the detection of diseases and pests occurring in carrot (Daucus carota L.) plants using digital technologies, as well as the quantitative assessment of their spread and degree of damage. The possibilities of processing digital images of carrot leaves and roots, classifying diseases and pests using artificial intelligence algorithms, and performing offline diagnostics through the CARROT DIAGNOSE AI Android mobile application are examined. In addition, the paper formulates mathematical models for calculating both individual leaf damage severity and field-level disease incidence in percentages, building an electronic database on diseases, and creating a decision-support system that provides practical agrotechnical recommendations to the user.

**Keywords:** carrot, disease, pest, digital analysis, artificial intelligence, Android, mobile application, computer vision, diagnostics, degree of damage.

## Introduction

Today, introducing digital technologies into agriculture, increasing crop productivity, and protecting plants from diseases and pests are among the important scientific and practical tasks [1]. Carrot (Daucus carota L.) is a vegetable crop that occupies an important place among food products, and its productivity and product quality may decline under the influence of various diseases and pests that occur during the growing season [2].

In carrot cultivation, diseases such as alternaria blight, cercospora leaf spot, and root rot, as well as pests such as the carrot fly and aphids, cause economic damage. These diseases lead to damage to plant leaves, weakening of photosynthesis, deformation of roots, and deterioration of the storage properties of the product.

In traditional diagnostic methods, the detection of diseases often depends on the experience and visual observation of a specialist [3]. In some cases, such a method may not be sufficiently effective in identifying the initial symptoms of a disease. Therefore, the automatic detection of diseases based on

artificial intelligence, computer vision, and mobile software technologies is considered relevant [4], [5]. Through digital image processing, it is possible to detect color changes, spots, necrosis, and other external signs observed on plant organs [6]. Integrating this process with an Android mobile application makes it possible to carry out rapid diagnostics of diseases under field conditions [7].

**Materials and Methods**

The main aim of the research is to detect carrot diseases and pests on the basis of digital images, to assess the degree of damage by a mathematical method, and to develop an automated diagnostic system using an Android mobile application. The carrot plant, its leaves, stems, and roots, as well as the diseases and pests occurring on them, are selected as the object of the research. The subject of the research consists of algorithms for digital image processing, disease classification using artificial intelligence, and assessment of the degree of damage.

The following methods are proposed for use in the research:

**1. Phytopathological Observation:** Visual observation and phytopathological diagnostics across developmental stages;

**2. Digital Image Acquisition:** Digital photography and image processing under field and laboratory lighting;

**3. Deep Learning & Computer Vision:** Computer vision, object detection, and convolutional neural networks;

**4. Quantitative Modeling:** Mathematical modeling of foliar severity and field-level epidemiological statistics;

**5. System Validation:** Software testing and comparative evaluation against specialist diagnoses.

First, digital images of healthy and diseased leaves of the carrot plant, as well as of organs damaged by pests, are collected. These images are grouped by disease type, and a database is formed for training the artificial intelligence model. For image processing, the Python programming language, the OpenCV library, and the TensorFlow or PyTorch platforms can be used. For operation on a mobile device, the use of lightweight neural networks such as MobileNetV3 or EfficientNet-Lite is proposed.

**3. DIGITAL DETECTION OF CARROT DISEASES AND PESTS**

One of the main diseases occurring in the carrot plant is alternaria blight, which develops under the influence of the fungus Alternaria dauci. The symptoms of the disease appear as brownish-black spots on the leaves, necrosis, and drying of the leaf margins. By analyzing digital images, it is possible to determine the color, shape, and affected area of these spots [8]. Cercospora leaf spot (Cercospora carotae) is characterized by the appearance of small spots on the leaves. As the disease develops, the photosynthetic activity of the leaves weakens. In digital diagnostics, the size, density, and color characteristics of the spots are important features [9].

In addition, rot diseases occurring on carrot roots negatively affect product quality. In detecting them, color changes, softening, and signs of rot on the root surface are analyzed using digital images. Among pests, the carrot fly (Psila rosae) and aphids are of particular importance. The larvae of the carrot fly feed in the tissues of the root and reduce the quality of the product. Aphids, in turn, suck plant sap from leaves and young shoots, slowing the growth process. Object detection algorithms such as YOLO can be used to detect pests [10]. These algorithms help determine the location and number of insects in an image. In this case, separate images and additional diagnostic methods are required to detect larvae that develop hidden inside the root.

**4. MATHEMATICAL ASSESSMENT OF THE DEGREE OF DAMAGE**

The following formula is proposed for the quantitative assessment of the degree of disease damage to carrot leaves:

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

where Z is the degree of damage (%), Sz is the damaged leaf area, and Su is the total leaf area. For example, if the total area of a leaf is 100 $cm^2$ and the damaged part is 25 $cm^2$, the degree of damage is 25 percent. On the basis of digital images, this indicator is directly computed through pixel segmentation:

$$Z = (Nz / Nu) \times 100$$

where Nz is the number of damaged pixels, and Nu is the total number of pixels belonging to the leaf. In addition, the following formula is used to determine the degree of disease spread in the crop field:

$$T = (n / N) \times 100$$

where n is the number of plants in which the disease was detected, and N is the total number of plants examined. Using these two complementary indicators, it becomes possible to assess separately the severity of damage on an individual leaf (Z) and the epidemiological spread of the disease across the entire crop field (T).

**5. OPERATING TECHNOLOGY OF THE ANDROID MOBILE APPLICATION**

As the practical result of the research, the development of an Android mobile application called CARROT DIAGNOSE AI is proposed. The application is intended to capture an image of the carrot plant through a smartphone camera, analyze it using artificial intelligence, and present the diagnostic results to the user. The Kotlin programming language, Android Studio, CameraX, and Jetpack Compose technologies are utilized to construct the application, while LiteRT technology is integrated to execute the neural network model locally on a mobile device independently of internet connectivity [11], [12].

The application architecture comprises six interconnected functional modules:

**1. Camera Module:** Captures high-resolution images of carrot leaves or roots via CameraX with real-time framing guidance;

**2. Image Processing Module:** Normalizes image resolution, brightness, and color channels via OpenCV to prepare tensors for inference;

**3. Diagnostic Module:** Classifies foliar diseases (MobileNetV3 / EfficientNet-Lite) and localizes surface pests (YOLO) on-device via LiteRT [10], [11];

**4. Assessment Module:** Segments necrotic/chlorotic pixels (Nz) relative to total leaf pixels (Nu) to compute the damage percentage Z;

**5. Recommendations Module:** Delivers targeted agrotechnical, biological, and chemical protection measures matched to the diagnosed condition and severity tier;

**6. Database Module:** Stores geotagged diagnostic records locally and aggregates field-level incidence statistics (T).

**Results**

***6.1. In-Depth Interpretation of Diagnostic and Quantitative Assessment Results***

The proposed CARROT DIAGNOSE AI framework establishes a multi-tier diagnostic pipeline that resolves a critical limitation in conventional visual scouting: the inability to simultaneously identify a causal agent and quantify both individual plant severity and field-wide incidence. By coupling lightweight convolutional neural networks (MobileNetV3 and EfficientNet-Lite) for foliar and root disease classification with YOLO-based object detection for mobile insect pests such as aphids and adult carrot flies, the system addresses fundamentally distinct visual tasks within a unified mobile workflow [10], [15]. Specifically, classification models capture diffuse textural and chromatic patterns characteristic of Alternaria dauci (dark necrotic margins) and Cercospora carotae (dense circular lesions), whereas bounding-box object detection isolates discrete, small-scale insect morphologies that would otherwise be lost in global image pooling [8], [9], [10].

Equally important is the dual-scale mathematical formulation linking pixel-level segmentation $Z = (Nz / Nu) \times 100$ with plot-level epidemiological tracking $T = (n / N) \times 100$. In practical field diagnostics, a high leaf-damage index (Z) confined to a small incidence rate ($T < 5\%$) indicates an early-stage localized infection focus suitable for spot treatment, whereas a moderate leaf-damage index ($Z = 15–25\%$) paired with high field incidence ($T > 30\%$) signals an active epiphytotic requiring immediate field-wide intervention. Furthermore, explicitly distinguishing surface-visible symptoms from endophytic damage caused by Psila rosae larvae inside carrot roots highlights an essential diagnostic boundary: while RGB computer vision reliably grades external root rot and foliar lesions, internal larval tunneling requires supplementary physical sampling or post-harvest cross-sectional imaging to prevent false-negative field assessments [2], [3].

### *6.2. Alignment with Research Objectives and Validation Framework*

The architectural design and mathematical formulations directly fulfill every objective defined at the outset of this investigation. First, structuring an annotated multi-organ image repository covering Alternaria blight, Cercospora leaf spot, root rot, carrot fly, and aphids directly satisfies the requirement to systematize local phytosanitary threats into a machine-readable dataset. Second, integrating OpenCV preprocessing with MobileNetV3/EfficientNet-Lite and YOLO models fulfills the objective of automated AI-driven classification and pest localization under mobile hardware constraints [11], [15]. Third, deriving percentage damage scores from segmented pixel ratios (Nz / Nu) and aggregating incidence across sampled plants (n / N) operationalizes the mathematical assessment objective, replacing subjective visual estimation with reproducible numeric indicators [3], [6].

Fourth, embedding these algorithms into the Kotlin/Jetpack Compose Android application via LiteRT satisfies the core engineering objective of delivering an offline-capable field tool coupled with actionable agrotechnical recommendations [11]. Finally, establishing a standardized validation protocol centered on Accuracy, Precision, Recall, and F1-score—benchmarked against expert phytopathological diagnoses under both controlled laboratory and variable field conditions—ensures that model deployment is governed by rigorous statistical reliability rather than raw classification accuracy alone [14]. In agricultural diagnostics, high Recall is particularly critical so that early-stage infections are not missed, while balanced Precision prevents unnecessary chemical spraying.

**Table 1.** Synthesis of Research Objectives, Technical Findings, and Agronomic Value in CARROT DIAGNOSE AI

| Research Objective | System Mechanism | Analytical Interpretation | Theoretical / Practical Impact |
|---|---|---|---|
| **1. Automated detection of carrot diseases & pests** | Hybrid MobileNetV3 / EfficientNet-Lite classifier + YOLO pest detector via LiteRT. | Separates diffuse foliar/root texture classification from small-object insect localization. | Enables comprehensive multi-threat screening on standard Android smartphones. |
| **2. Mathematical assessment of damage & spread** | Pixel-ratio severity $Z = (Nz / Nu) \times 100$ and field incidence $T = (n / N) \times 100$. | Distinguishes isolated high-severity hotspots from widespread early-stage outbreaks. | Provides objective thresholds for precision pesticide application and yield-loss modeling. |
| **3. Offline Android field deployment & decision support** | Kotlin + CameraX + Jetpack Compose app with local database and advisory rules. | Eliminates cloud latency and connectivity bottlenecks during remote field scouting. | Empowers farmers and agronomists with immediate, standardized protection plans. |
| **4. Experimental benchmarking & reliability control** | Evaluation via Accuracy, Precision, Recall, and F1-score vs. specialist diagnoses. | Balances false negatives (missed early blight) against false positives (over-spraying). | Establishes a replicable validation standard for regional agricultural AI systems. |

*Comparison with Relevant Previous Studies*

The methodological design and expected outcomes of this study build upon, while addressing key gaps in, existing agricultural computer vision literature. Seminal studies by Mohanty et al. [4] and Ferentinos [13] demonstrated that deep convolutional neural networks achieve high classification performance on curated plant pathology datasets such as PlantVillage [5]. Similarly, Sladojevic et al. [8] validated deep neural networks for leaf-based disease recognition, and Too et al. [15] confirmed through comparative fine-tuning that lightweight architectures offer superior computational efficiency for mobile deployment. However, as highlighted by Barbedo [6] and Singh et al. [7] in introducing the field-collected PlantDoc dataset, models trained exclusively on uniform laboratory backgrounds suffer substantial accuracy drops when exposed to complex natural foliage, overlapping carrot leaves, and variable solar illumination.

Moreover, prior deep learning studies in plant protection have predominantly treated diagnosis as a single-label image classification problem, overlooking quantitative severity grading and multi-organ root/pest inspection [1], [4], [13]. Conversely, classical image-analysis studies synthesized by Bock et al. [3] and Barbedo [6] established pixel-counting methods for measuring necrotic leaf area (Z) but lacked deep feature extractors capable of distinguishing visually overlapping fungal symptoms such as Alternaria blight and Cercospora leaf spot. By uniting LiteRT-accelerated MobileNetV3/EfficientNet-Lite classification [11], [15], YOLO pest localization [10], and dual-level mathematical quantification (Z and T) within a single offline Android ecosystem, CARROT DIAGNOSE AI bridges the divide between qualitative deep learning and quantitative phytopathometry. Additionally, whereas existing benchmarks focus heavily on solanaceous and cereal crops [4], [7], [8], this research contributes domain-specific digital diagnostics tailored to root vegetable production (Daucus carota L.) under Uzbekistan's agro-ecological conditions.

*Theoretical and Practical Implications*

From a theoretical standpoint, this research advances a modular edge-AI architecture for plant pathology by demonstrating how heterogeneous vision tasks—global texture classification, small-object pest detection, and deterministic pixel-ratio segmentation—can be decoupled into lightweight sequential stages rather than relying on memory-intensive end-to-end semantic segmentation networks. This decoupling preserves mathematical transparency: because $Z = (Nz / Nu) \times 100$ and $T = (n / N) \times 100$ are explicitly formulated as continuous biophysical variables, the resulting outputs can be directly integrated into epidemiological progression models and crop-loss prediction equations [2], [3]. Furthermore, defining multi-metric evaluation criteria (Precision, Recall, F1-score) alongside field-vs.-laboratory cross-validation establishes a rigorous methodological template for addressing domain shift in agricultural computer vision [7], [14].

From a practical perspective, the CARROT DIAGNOSE AI mobile application delivers immediate operational value to smallholder vegetable farms, commercial agro-clusters, seed-production enterprises, and plant-quarantine inspectors in Uzbekistan. First, on-device execution via LiteRT eliminates dependence on continuous cellular internet coverage, enabling real-time diagnostics directly in remote irrigated carrot fields [11]. Second, early differentiation between Alternaria blight, Cercospora leaf spot, and aphid infestations—combined with objective severity thresholds (Z and T)—supports precision, targeted application of fungicides and insecticides, thereby lowering production costs, reducing pesticide residues in edible roots, and preserving post-harvest storage quality. Third, the electronic database module transforms routine smartphone inspections into structured longitudinal phytosanitary records, empowering regional agricultural extension services to map disease outbreaks and coordinate preventive interventions.

## Conclusion

Digital analysis of carrot diseases and pests and their detection using an Android mobile application is considered a promising scientific and practical direction in modern agriculture. Through

digital image processing, dual-scale mathematical severity assessment (Z and T), and lightweight artificial intelligence algorithms, it becomes possible to detect disease symptoms in the carrot plant, calculate the damaged area, and monitor the epidemiological spread of diseases.

The proposed CARROT DIAGNOSE AI mobile application can help farmers and agronomists assess the phytosanitary condition of carrot crops rapidly and objectively. Training this system on expanded datasets obtained under local agro-climatic conditions and verifying its Precision, Recall, and F1-score indicators through multi-season field experiments remain essential steps for maximizing its practical effectiveness.

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