

AgroScan: A Mobile Application for the Diagnosis and Management of Corn Crops

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ABSTRACT

Agriculture represents the foundation of human society, and in Romania, corn cultivation holds a strategic position due to its vast distribution area. However, production is extremely vulnerable to foliar diseases, which can compromise a harvest in a very short time. Traditional diagnostic methods, based on visual inspection, can be subjective, difficult to scale for large farms, and often time-inefficient. To address these limitations, this paper proposes AgroScan, an offline-first mobile application designed to operate as a dual ecosystem: providing AI-based phytosanitary diagnosis through Convolutional Neural Networks (CNN) and offering parcel-level economic management. By combining artificial intelligence [1] with the portability of mobile devices [6], the system provides an accessible diagnostic tool capable of functioning completely independent of an internet connection, aiming to mitigate production losses and solve the practical problem of deficient telecommunications infrastructure in rural areas.

AUTHOR KEYWORDS

Artificial intelligence; edge computing; convolutional neural networks; smart farming; precision agriculture; offline-first.

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INTRODUCTION

The current agricultural context is undergoing an accelerated transition towards "Smart Farming", aiming to optimize resources and maximize yields. In this ecosystem, the automatic detection of plant diseases through artificial intelligence has become a vital research domain [2, 5].

Corn (*Zea mays*) holds a strategic position globally, being widely utilized for human consumption, animal feed, and biofuel production. However, despite its high productive potential, this crop is extremely vulnerable to foliar diseases such as *Puccinia sorghi* (Common Rust) and *Exserohilum turcicum* (Northern Leaf Blight), which can cause massive economic losses if left undetected in their early stages [10]. Traditionally, phytosanitary monitoring relies primarily on manual visual inspection. This method can be hindered by a lack of scalability across large agricultural farms and delayed intervention times that allow infection hotspots to spread [10]. To address these practical issues, this paper introduces AgroScan. Rather than acting solely as a diagnostic scanner, AgroScan was developed as a comprehensive dual ecosystem that integrates automated phytosanitary monitoring with parcel-level economic management (ROI calculation). The AI component focuses specifically on identifying three of the most frequent corn diseases: Common Rust, Gray Leaf Spot, and Northern Leaf Blight. The proposed approach uses modern Convolutional Neural Networks (CNNs) to effectively assist farmers in distinguishing the features of foliar

lesions, seamlessly connecting these agronomic insights with the financial management of the farm.

The main motivation for developing this solution stems from the operational limitations encountered in the field. Most existing diagnostic applications require a stable cloud connection to process data, which poses a significant constraint in isolated agricultural areas with poor signal coverage. By integrating optimized models directly on the mobile device (Edge Computing), the proposed application addresses this specific barrier, bringing advanced technology directly to the field. To achieve this, the main objectives of this work encompass:

- Adapting and augmenting an existing public dataset of corn foliar diseases to ensure robust model training.
- Developing and optimizing a CNN architecture capable of high-accuracy classification while maintaining a small computational footprint.
- Implementing an offline-first Android application that integrates the trained model for instant, on-device diagnosis and farm management.

RELATED WORK

The integration of Deep Learning in agriculture is an active research domain. Recent academic literature emphasizes a global trend of migrating from cloud-based diagnostic systems toward Edge Computing. Studies have demonstrated the feasibility of deploying Convolutional Neural Network (CNN) models directly on mobile devices for leaf disease classification [8]. Parallel to academic research, the expansion of the Smart Farming concept has led to the development of numerous commercial mobile platforms.

Plantix and PlantVillage are widely used applications relying on deep learning algorithms for disease detection. Plantix, for instance, is a highly comprehensive tool capable of recognizing over 100 crop pests and diseases [9]. However, the primary limitation of these platforms in the context of isolated agricultural areas is their strict dependency on an active internet connection to process images on external servers. This requirement poses a critical obstacle in rural areas where GSM coverage is often fluctuating or absent. Other applications, such as LeafSnap [7], are primarily oriented towards general botanical identification rather than intensive agricultural management.

To address these technological gaps, AgroScan was developed to provide total independence from network connectivity. By executing the AI inference locally via TensorFlow Lite, AgroScan directly targets the practical needs of farmers working in disconnected environments, trading the massive multi-crop databases of cloud applications for a specialized, offline-first tool tailored for corn crops.

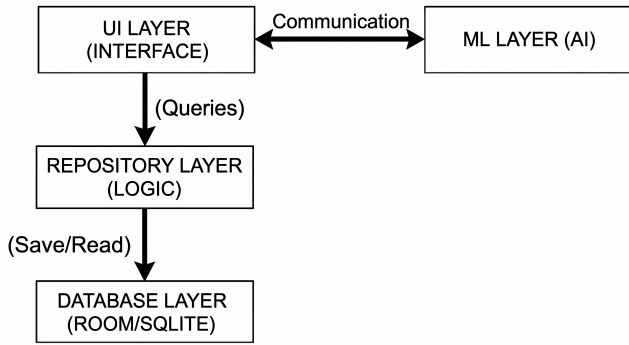


Figure 1: The offline-first layered architecture of AgroScan.

PROPOSED SOLUTION

System Architecture and User Interface

To guarantee full functionality in isolated rural environments, AgroScan adopted a strict offline-first paradigm. Data storage, profitability calculations, and deep neural network processing are executed 100% locally on the device. The software utilizes a Layered Architecture structured into four decoupled levels (see Figure 1):

- **UI Layer:** Built with Android native components following Material Design guidelines. The interface relies on a BottomNavigationView to orchestrate four main modules: a Dashboard for quick statistics, a GIS Map for parcel management, a Phytosanitary Health center for AI diagnosis, and a Financial Profile for reporting.
- **Repository and Database Layers:** The Repository coordinates background threads for asynchronous calculations. The Database Layer ensures local persistence using the Room Persistence Library over an SQLite engine.
- **ML Layer:** An independent module acting as the on-device inference engine.

Geospatial Delimitation and ROI Calculation

To manage agricultural operations, the system integrates a geospatial module (using the OSMDroid library) that allows users to delimit parcels by interactively drawing polygons on a satellite map. To calculate the area of these irregular polygons directly on the device, the application implements the Shoelace algorithm adapted for spherical projections, utilizing the Earth's equatorial radius ($R = 6378137$ m).

Financially, the *Repository Layer* automatically deducts operational costs (e.g., fertilizer dose $\times$ price $\times$ area) from the harvest revenue. To calculate the Return on Investment (ROI) per parcel, the system uses a proportional allocation algorithm. Since harvests are often stored and sold in bulk, the estimated revenue for a specific parcel is calculated by distributing the farm's total revenue based on the parcel's physical production share: $V_{parcel} = (V_{total}/P_{total}) \times P_{parcel}$.

Dataset and CNN Hyperparameters

To develop the AI module, a public dataset of corn leaf diseases was curated and balanced using offline augmentation techniques (e.g., arbitrary rotations, perspective distortions, and simulated occlusions), resulting in 5,224 images. The dataset covers three primary pathologies: Common Rust, Gray Leaf Spot, and Northern Leaf Blight, alongside a "Healthy"

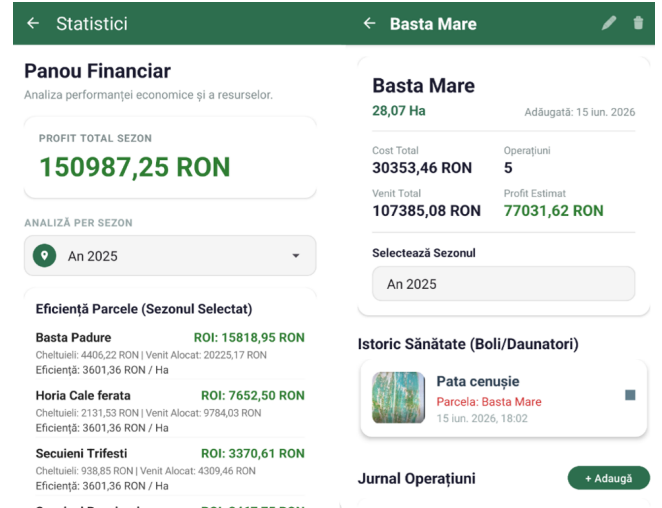


Figure 2: AgroScan financial dashboard illustrating parcel-level ROI calculation.

class [3]. Crucially, a fifth "Background/Unknown" class was introduced to explicitly train the network to reject non-agricultural imagery.

The VGG16 architecture, pre-trained on ImageNet [4], was optimized using a two-stage Transfer Learning strategy with the Adam optimizer and Categorical Cross-Entropy loss. Over the base convolutional layers, a custom classification block was attached (GlobalAveragePooling2D, Dense 512, Dense 256, Dropout 0.3, and Softmax). The first stage involved a 10-epoch warm-up with frozen base layers and a learning rate of 10^{-4} . The second stage consisted of a 60-epoch full-network fine-tuning phase with a reduced learning rate (5×10^{-5}) to preserve edge detectors.

On-Device AI Pipeline

Running convolutional neural networks on resource-constrained devices represents a technical challenge. AgroScan addresses this by guiding the raw captured image through a highly optimized four-stage processing pipeline:

1. Heuristic HSV Filtering: The image is reduced to 32x32 pixels and converted to the HSV color space. If the cumulative weight of vegetal pixels is less than 15%, the system rejects the analysis, preventing the processing of non-agricultural backgrounds.

2. Preprocessing and Normalization: Valid images are resized to the network's fixed input resolution (224x224 pixels, RGB) and mathematically normalized to a [0.0, 1.0] floating-point interval.

3. Asynchronous Inference: The inference engine utilizes the optimized TensorFlow Lite (.tflite) model on background threads, preventing UI blocking.

4. Post-processing and Decision Logic: To eliminate ambiguous diagnoses, the system converts raw output vectors into probabilities using a Softmax activation function. A *Confidence Threshold* dictates that the top predicted class must exceed a 50% probability, and a *Margin Threshold* requires a minimum 0.5% difference between the top-1 and top-2 classes.

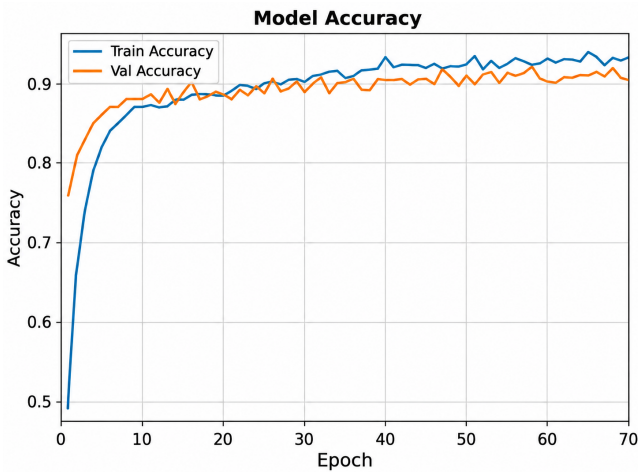


Figure 3: Training and validation curves of the optimized VGG16 model.

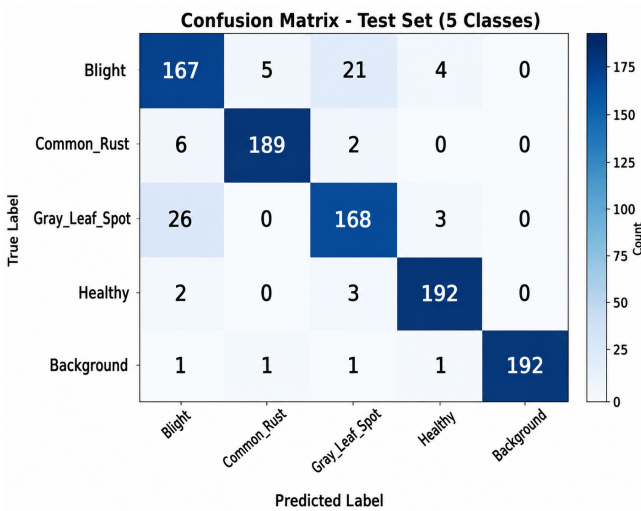


Figure 4: Confusion matrix of the optimized VGG16 model.

EXPERIMENTAL EVALUATION

AI Model Performance

The optimized VGG16 model was evaluated on an isolated test set of 788 images. By implementing Test-Time Augmentation (TTA), the system achieved a final global accuracy of 92.51%. Analysis of the F1-Scores highlighted high precision for morphologically distinct classes such as Common Rust (96.68%) and Healthy leaves (97.71%). The network successfully distinguished between the visually similar necrotic lesions of Northern Leaf Blight and Gray Leaf Spot, achieving F1-scores of 84.79% and 85.93%, respectively. The introduction of the "Background" control class yielded a 100% precision rate, successfully preventing the system from issuing phytosanitary alerts on non-agricultural imagery.

While these laboratory results demonstrate high classification accuracy on the curated public dataset, we acknowledge this as a limitation; future evaluations must validate the model against photographs collected specifically under Romanian field conditions to fully confirm its in-field diagnostic utility.

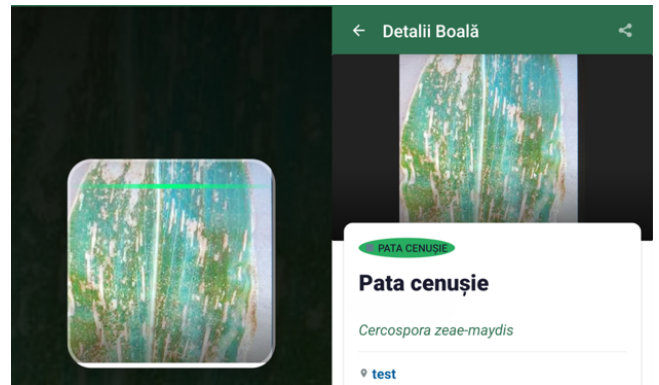


Figure 5: Real-time leaf scanning and disease diagnosis.

Field Testing and User Validation

To evaluate the system's utility and ergonomics in real-world conditions, an empirical study was conducted with a sample of 17 participants. The demographic encompassed active farmers (managing operations ranging from under 5 hectares to over 50 hectares), agricultural engineers, and students, aged between 18 and 60, with digital literacy levels ranging from beginner to advanced. The evaluation methodology comprised two stages. First, a pre-use questionnaire assessed current monitoring practices and infrastructure constraints. Second, following a supervised field-testing session, participants completed a post-use evaluation questionnaire based on a 5-point Likert scale (ranging from 1 - Strongly Disagree to 5 - Strongly Agree) to measure usability, technical performance, and user trust.

The pre-use phase confirmed severe infrastructure limitations in traditional agriculture: a significant percentage of participants declared that mobile data signal quality in the field is either "poor" or "non-existent," entirely justifying the offline-first architectural decision. During field testing, the TensorFlow Lite engine demonstrated excellent speed. The only hardware limitation observed was thermal throttling on mobile processors caused by prolonged camera and screen usage under direct sunlight, which temporarily slowed inference for one user. The post-use quantitative results indicated high user satisfaction. The application's response time was rated as "very fast, above expectations" by 90% of the users. The leaf scanning process and the overall UI design received maximum scores (4/5 and 5/5), with users praising the high-contrast color scheme that remained readable in direct sunlight (Figure 5). When assessing trust in the AI's diagnostic capabilities, responses varied slightly; while most reported a "High" level of trust, some cautious farmers rated it "Medium," indicating they view the application as a complementary tool and would still prefer occasional verification by an agronomist.

The primary usability issue identified through the questionnaire pertained to the initial application onboarding. Certain users found the initial profile setup and the geospatial delimitation of their first parcel to be "confusing" and "non-intuitive." To address this limitation in future work, an interactive onboarding tutorial will be implemented to guide new users through the initial setup steps. Overall, participants highlighted the 100% offline functionality, rapid in-field disease detection, and integrated cost management as the most valuable features of the AgroScan system.

DISCUSSION AND CONCLUSIONS

This paper presented AgroScan, a specialized mobile application designed to assist in the diagnosis and management of corn crops. Compared to state-of-the-art generalist applications that require persistent cloud connectivity, our proposed system trades broad multi-crop recognition for a highly specialized, 100% offline diagnostic and financial tool.

The technical implementation validated the hypothesis that running Deep Learning models directly on mobile devices (Edge Computing) is an optimal solution for the rapid in-field classification of foliar diseases. By integrating the VGG16 convolutional neural network via TensorFlow Lite, correlated with a robust local data management system (Room SQLite) and topographic mapping tools (OSMDroid), the project proved that a modern smartphone possesses the necessary computing resources to provide agronomic assistance without relying on external servers.

The empirical study conducted on a diverse sample of users confirmed the practical utility of the application, particularly in infrastructure-deficient environments. While improvements are required regarding the onboarding process and the validation of the AI model on locally sourced field data, AgroScan constitutes a robust and accessible ecosystem. It serves as a proof of concept that the digitalization of the agricultural sector, including complex ROI tracking and AI diagnosis, is

no longer strictly conditioned by permanent network connectivity.

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