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AI-powered Solution for Plant Disease Detection in Viticulture

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Abstract

In an era dominated by the intersection of advanced technology and traditional industries, the domain of agriculture is on the verge of a revolutionary transformation. This article introduces a solution for vineyard producers, harnessing satellite imagery, weather data, and deep learning (DL) to identify vineyard diseases robustly. This solution, designed for proactive plant health management, stands as a transformative tool towards digital viticulture. Such tools transition from luxuries to essentials as vineyards confront evolving challenges like climate change and new pathogens. Our research builds on the hypothesis that customising deep learning architectures for specific tasks is crucial in enhancing their effectiveness. We contribute by introducing a tailored convolutional neural network (CNN) architecture, developed specifically for the classification of plant diseases using vineyard imagery. The experimental results demonstrate that our custom CNN architecture exhibits performance on par with established state-of-the-art models like ResNet50 and MobileNetV2, underscoring the value of specialized solutions in addressing the unique challenges of viticulture. This paper introduces an overview of the solution's architecture, presents the implementation of DL modules with their corresponding results, and describes use case scenarios.

Keywords: Plant Disease Detection; Viticulture; Digital Agriculture; Data Visualization; Deep Learning; Convolutional Neural Networks

1. Introduction

Viticulture, the ancient practice of growing grapes, faces new challenges due to global market demands and environmental changes. Therefore, the need for efficient and precise vineyard management has never been greater [10]. In the Fourth Industrial Revolution era, digital transformation offers solutions to these challenges [23]. Traditionally, vineyard producers relied on manual methods and past experience to manage vineyards. Still, these methods are in-

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adequate for early disease detection and accurate plant health monitoring, leading to reduced yields and economic losses.

Precision agriculture aims to enhance the precision, efficiency, and sustainability of farming through advanced technologies [5]. Moreover, Digital Agriculture seeks to combine the power of Artificial Intelligence/Machine Learning (AI/ML) and data from precision agriculture to deliver decision-support systems to address the unique challenges faced by farmers [4]. ML and Deep Learning (DL) have been at the core of AI-based contributions in digital agriculture by enabling and optimizing data-driven decision-making in farm processes. While ML, at the intersection of statistics and computation, empowers machines to learn from data and offers adaptive solutions in various fields [3], DL is a specialized branch of ML capable of autonomously extracting crucial features from data [18], enabling ”end-to-end learning” [24, 16].

Leveraging the potential of ML and DL, our research provides a digital application in viticulture, aiming to promote efficient farm decision-making processes further. This paper introduces an approach to digital viticulture, particularly focused on plant disease assessment towards better plant health monitoring. It utilizes satellite imagery, real-time weather data, and DL algorithms to create a solution that can improve how farmers detect and manage vineyard plant issues [8]. Such an approach aims to be an important step towards turning vineyards into digital twins [25], facilitating dynamic interaction between virtual simulations and real-world situations. These capabilities not only expedite decision-making but also enhance crop quality and yield.

The following sections will briefly introduce related work, describe the solution and its core modules, provide preliminary results, discuss its practical use in real-world scenarios, showing its potential to transform viticulture digitally, and present future work.

2. Related Work

In the context of viticulture, ML offers significant opportunities for optimizing vineyard management. One of the primary challenges in this field is the variability of environmental conditions affecting grapevine growth, such as soil composition, climate, and disease pressure. ML models, particularly those using DL techniques, can analyze vast amounts of data collected from sensors in vineyards to provide insights into these variables. These insights can be used for precision agriculture practices, enabling vineyard managers to make data-driven decisions about irrigation, fertilization, and disease management [22, 7].

For instance, ML algorithms can predict the optimal time for grape harvesting by analyzing weather patterns, soil moisture levels, and grape maturity indices [1, 2]. This prediction helps in achieving the desired grape quality for wine production. Deep learning models have also been successfully implemented for disease detection in vineyards. These models can identify early signs of diseases like downy mildew or botrytis by analysing images of grape leaves and clusters, allowing for timely and targeted interventions [21].

Among prevalent prediction models used in digital agriculture, convolutional neural networks (*CNNs*) have notably featured in numerous studies, especially in vision tasks like plant disease classification [6]. Within this context, recent work such as the study of Mohanty et al. examined the performance of traditional *CNN* architectures, *AlexNet* and *GoogLeNet*, in classifying crop species and diseases using a dataset comprising 54,306 images across 38 classes (14 crop species and 26 diseases) [20]. Notably, *GoogLeNet* achieved a top accuracy of 99.35%. While traditional ML models continue to offer significant contributions in agriculture [11, 14], the versatility, power, and scalability of DL models, capable of automatically learning features from data, present promising research in digital agriculture [12].

Moreover, while traditional deep learning architectures excel across various application domains, the research of Koraiala et al. underscores the importance of customizing DL architectures for specific applications [15]. To assess the detection of mango fruits in orchard images, the authors propose a benchmarking study comparing the performance of state-of-art DL architectures (such as *YOLOv2* and *Faster-CNN*) with a novel architecture named *MangoYOLO*, particularly tailored to this task. Although the baseline architectures demonstrated similar accuracy in fruit detection, their performance was surpassed by the custom-tailored *MangoYOLO* architecture. With a F1-score of 0.97 in fruit detection, *MangoYOLO* maintained exceptional processing speed and low memory usage, thus emphasizing the potential of developing custom deep learning architectures for particular application tasks.

The utility of ML and DL in this field is further enhanced by efficient data visualization, which transforms complex datasets into intuitive, interpretable formats [9]. Data visualization is crucial in presenting large amounts of data in ways that reveal patterns, trends, and insights. Innovative techniques such as stream graphs, heat maps, and geographic maps are incredibly useful for farmers, who require data to be displayed clearly and concisely for quick and informed decision-making [17, 9].

Key principles that address the diverse needs of stakeholders are required for effective visualization. Simplicity and readability are of paramount importance to farmers, who may be viewing data on mobile devices in a variety of field conditions. Advisers and technicians, on the other hand, may benefit from more detailed, interactive visualizations that allow for more in-depth analysis. Regardless of the end user, the goal of data visualization in agriculture is to present readily actionable information that improves the day-to-day management and the long-term strategy of vineyard operations.

The intersection of ML, DL, and efficient data visualization represents a paradigm shift towards more efficient, sustainable, and productive agricultural practices. As research and development in these areas continue to progress, they promise to revolutionize viticulture further, making them indispensable tools for modern agriculture.

3. The AI-powered Solution

The solution's architecture, depicted in Figure 1, is a dual-structured design that ensures seamless integration of front-end and back-end components. The back-end serves as the system's data processing powerhouse, utilizing a Python-based framework to manage a complex array of satellite data libraries. The back-end is where advanced data processing occurs, utilizing *TensorFlow* for deep learning and Google Earth Engine (*GEE*) for acquiring and managing satellite data.

The architecture was designed to operate with two distinct environments given the challenge of reconciling the dependencies of *TensorFlow* and *GEE*. While the primary environment is dedicated to general back-end processes, a specialized microserver environment is reserved for the intensive task of training CNNs. Hence, this environment dichotomy allows for an efficient utilization of computational power, enabling resource-intensive operations to execute independently from general backend processes.

The technological decisions favoured Python because of its extensive ecosystem, ideal for data-centric operations and compatibility with numerous satellite data libraries. This decision also reflects the ubiquity of Python in ML solutions, given its adaptability and integration capabilities, which are critical for the smooth development of both deep learning processes and web-based back-end services.

In parallel, the front-end is designed to act as the user's gateway to the insights produced by the back-end. Developed with HTML and JavaScript, it employs Mapbox for intuitive satellite data visualization. This decision to utilize basic HTML and JavaScript, rather than contemporary frameworks like React, was strategic. The objective was to provide a clear and efficient user interface that simplifies the visualization process and avoids the complexities that might arise with more advanced frameworks.

The advanced architecture is not only a display of technical skill but also showcases the significant influence of machine learning since its promise to empower machines with the ability to learn from data is being realized as we harness its capabilities to automate and refine decision-making processes in viticulture. It should provide more informed and precise agricultural practices. DL is leveraged to automatically identify key features within vineyard imagery, enabling "end-to-end learning". The adoption of a *CNN* solution underscores our commitment to precision and accuracy in disease image classification.

In pursuit of this goal, the application's architecture is geared to leverage the capabilities of CNNs for disease classification in vineyards, as part of the back-end deep learning capabilities [13]. Our research extends beyond the application of existing *CNN* architectures, focusing on the refinement of established models and the development of a custom CNN tailored for the unique challenges presented by vineyard imagery.

Our approach involved the fine-tuning of three distinct models– Custom CNN, *ResNet50*, and *MobileNetV2* – against a dataset of 12,000 images categorized into four classes: Healthy, Leaf Blight, Black Rot, and ESCA. A rigorous evaluation process, using metrics such as accuracy, precision, recall, and F1 score, revealed the superior performance of MobileNetV2, which achieved an accuracy of 99.375% (see table 1).

The superior performance of *MobileNetV2* highlights its efficiency in handling complex image classification tasks within the domain of viticulture. Its architecture, optimized for mobile and embedded vision applications, balances

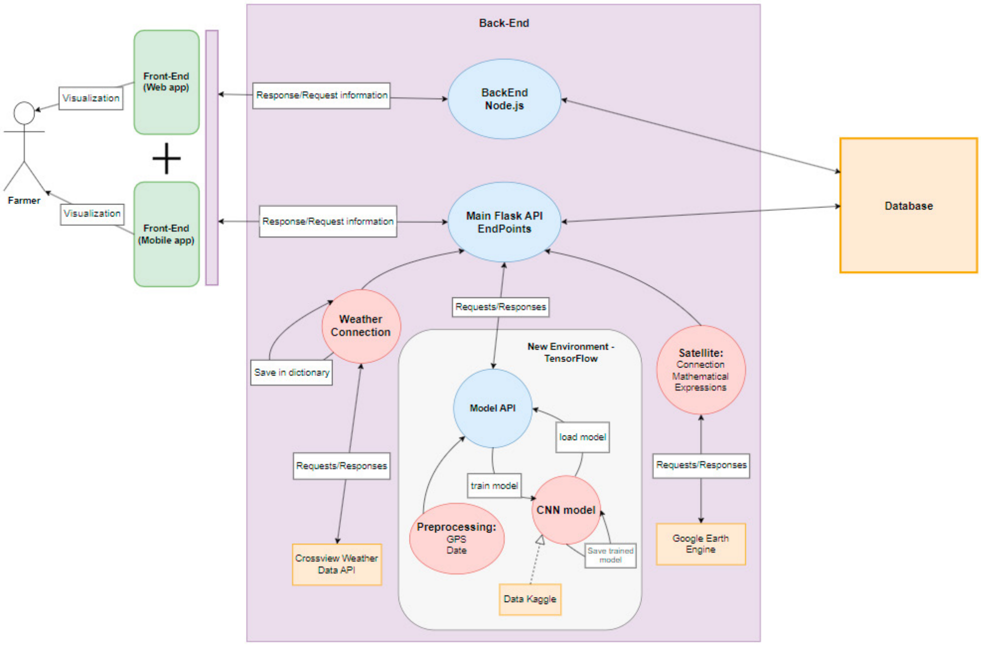


Fig. 1: Architecture of the solution.

Table 1: Evaluation metrics for each model.

	Custom CNN	ResNet50	MobileNetV2
Accuracy	97.500%	79.581%	99.375%
Precision	97.504%	81.665%	99.375%
Recall	97.500%	79.583%	99.375%
F1 score	97.501%	79.796%	99.374%

speed and accuracy, making it highly suitable for real-time disease detection and management in vineyard environments.

However, the potential of developing a custom *CNN* model remains significant. While *MobileNetV2* provides remarkable performance, a custom CNN can be tailored more specifically to vineyard imagery's unique challenges and nuances. Custom models allow for greater flexibility in adapting to specific characteristics of vine diseases, such as subtle variations in leaf discolouration or textural differences. This level of customization is crucial for capturing the intricate details that might be unique to a specific region or grape variety.

Moreover, a custom *CNN* can be optimized to balance computational efficiency with accuracy, which is particularly important for on-site applications where computing resources might be limited. By refining and adjusting the model architecture, we aim to develop a solution that fits the specific needs of vineyard disease classification and is also viable for deployment in various agricultural settings.

4. Usage Scenarios and User Interaction

The solution's design provides a clear framework for the interactions between users and a provided API. This facilitates a comprehensive understanding of the system's capabilities for winegrowers, technicians, and third-party system integrators.

Through the API, users gain access to three integral functionalities: 1) Disease Classification and Treatment that enables precise identification of vineyard diseases and the corresponding treatments; 2) Weather Data Visualization delivering essential climatic insights for informed agricultural planning; and 3) Satellite Data Visualization that offers an expansive view of the vineyard's environmental conditions, supporting targeted interventions.

Winegrowers can benefit directly from disease diagnosis and weather consultation tools, while technicians can utilize system features to ensure data accuracy. Moreover, the clear representation aids third-party integrators in seamlessly connecting with the API, which enhances the system's functionality and collaborative potential.

4.1. Disease Classification and Treatment

A key application of the system is the identification and treatment of vineyard diseases. The process is initiated when users upload an image of a vine leaf. The system then processes this image and presents a classification label along with a confidence score. This information is displayed in a dual-pane interface for easy comparison, as shown in Figure 2. On the left side is the original image, and on the right side is the classification result with a corresponding confidence score.

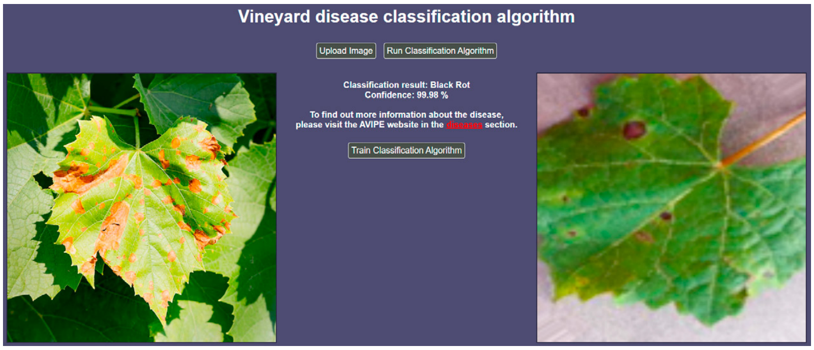


Fig. 2: Vineyard disease classification interface.

The system's user interface was carefully designed for user-friendliness and quick verification, allowing for a side-by-side comparison with a database of annotated images. This feature is particularly beneficial for technicians who need to assess the model's accuracy and ensure that the machine learning algorithms remain precise and do not overfit the dataset.

Once a disease is classified, the system employs geo-tagging features to link each disease instance with a specific location and timestamp derived from the image's EXIF data. The outcome is a map-based interface that uses colour-coded markers to intuitively display the vineyard's health status across different plots, as depicted in Figure 3. This visualization tool is crucial for winegrowers, enabling them to identify disease hotspots accurately and apply treatments in a targeted manner, thereby reducing the unnecessary use of pesticides and optimizing vineyard management.

Fig. 3: Geospatial visualization of vineyard health.

4.2. Weather and Satellite Data Visualization

The system's weather data visualization module is an advanced tool that combines both real-time and historical meteorological data. By employing reverse geocoding, it acquires precise weather information relevant to the vineyard's location, thus enabling winegrowers to make informed decisions based on accurate weather forecasts and climate patterns.

The satellite data visualization feature further complements this by providing high-resolution, dynamic maps incorporating multiple vegetative and soil condition indices such as NDVI (Normalized Difference Vegetation Index) and MSAVI (Modified Soil Adjusted Vegetation Index) (see Figure 4). These tools and the ability to adjust layer opacity allow for an in-depth analysis of the satellite imagery, offering valuable insights into the vineyard's conditions.

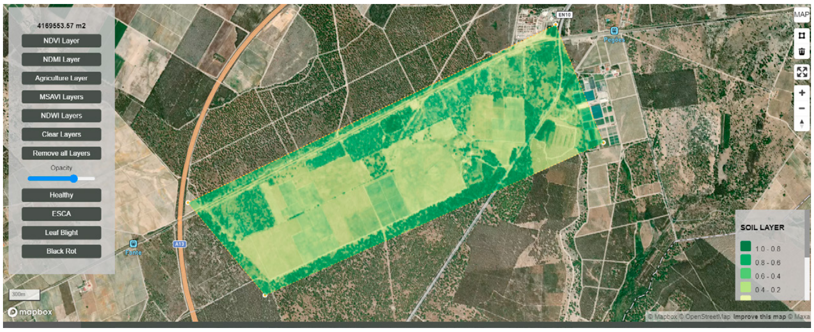


Fig. 4: Visualization of MSAVI layer over the Satellite layer.

Integrating disease classification with weather and satellite data visualization offers a holistic approach to precision viticulture. The system equips stakeholders, winegrowers and technicians, with immediate and strategic insights, aiding in identifying and treating plant health issues while promoting long-term sustainability and productivity within the vineyard.

4.3. Treatment Efficacy and Monitoring

The API further extends its utility after post-disease classification by facilitating treatment efficacy monitoring. Leveraging the geo-tagging data, stakeholders can track the progress of disease treatment over time. With the aid of a 'Treated' button (Figure 3), users can update the vineyard's health status, providing a dynamic and live representation of the vineyard's condition. This capability ensures efficient monitoring and targeted treatment of vineyard ailments and serves as a historical record, contributing to a data repository that can inform future disease prevention strategies.

Therefore, this comprehensive system embodies the confluence of advanced ML techniques with practical viticulture needs, empowering stakeholders to manage vineyard health proactively and effectively.

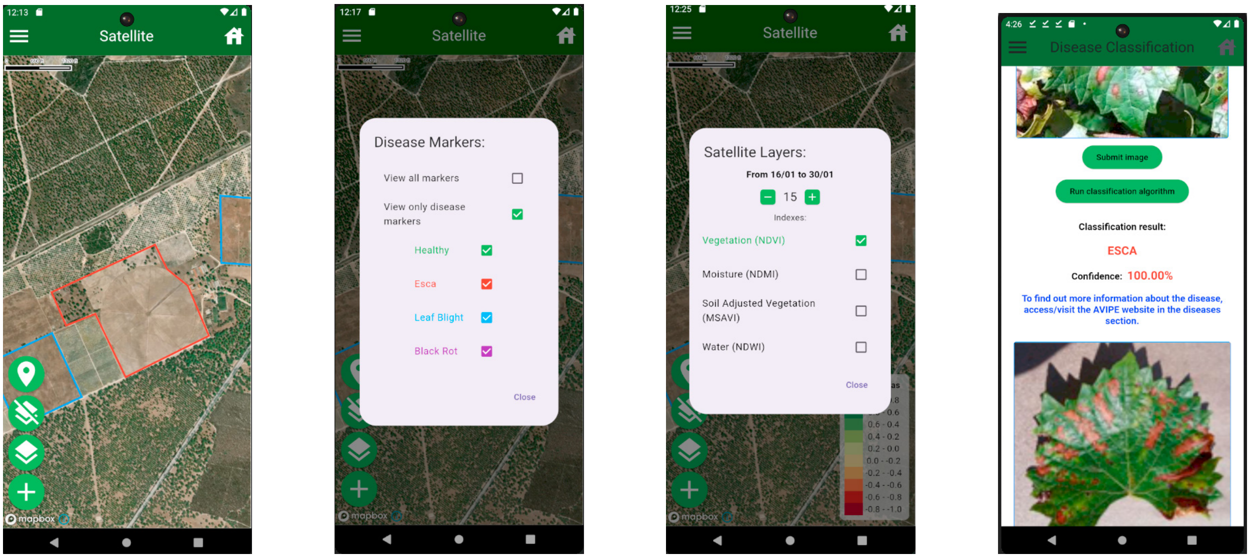
4.4. The Mobile Interface Prototype

Agri-Dash is a mobile application prototype being developed as part of the TWINSOR project [19]. The aim of TWINSOR is to provide farmers with a "digital twin", i.e., a monitoring ecosystem that allows them to visualize multi-sensor data collected from their fields but also to "plug in" predictive models, e.g., for frost or plant disease prediction. The system should allow the use of a wide range of "sensors" ranging from free satellite images to low-cost off-the-shelf sensors. Agri-Dash is being designed with the participation of Association of Winegrowers of the Municipality of Palmela (AVIPE)[1], in Portugal, aiming to assist small to medium farmers in their daily activities by providing them with useful information and recommendations, which may be manually provided by associations and/or technicians that support the farmers. Moreover, they can also be (semi-)automatically generated by the TWINSOR system based on the current status of the digital twin and any associated predictive models.

The initial application prototype was expanded to include the same features introduced in our solution for plant disease detection, similarly to the already presented web-based interfaces. Figures 5a to 5c show the features related to the visualization and analysis of satellite imagery, namely markers for several common diseases in viticulture and

[1] Associação de Viticultores do Concelho de Palmela (AVIPE): https://www.avipe.pt

layers with information about vegetative and soil condition indices. Besides that, the disease classification interface is also available in the mobile application (see Figure 5d).



(a) Satellite view. (b) Markers. (c) Layers. (d) Classification.

Fig. 5: Mobile user interfaces.

5. Conclusions and Future Work

This research highlights the transformative capabilities of ML and DL within the specialized domain of precision viticulture. By harnessing these technologies, we crafted a robust solution that provides an API to identify and classify vineyard diseases through sophisticated image analysis. The practical implementation of our research will equip vineyard managers and technicians with a powerful tool, facilitating early detection and timely intervention to prevent the spread of disease and maintain crop health.

Regarding future work, incorporating sensor data and intricate weather patterns holds the promise of refining the predictive capabilities of our models. By accounting for these dynamic environmental factors, we anticipate more accurate diagnoses of plant health conditions, tailored to the nuanced interactions between climate and disease.

While MobileNetV2 demonstrated outstanding performance in our current dataset, exploring and developing a custom CNN model holds promise for more specialized applications in vineyard disease detection. Future work will involve further refining our custom model, ensuring it matches the accuracy of established models and provides additional benefits in terms of adaptability and computational efficiency.

The goal is to evolve towards a continuous monitoring system, one that not only recognizes the current health of vineyard crops but also predicts future disease risks. This predictive model would enable preemptive measures, transforming how vineyard health is managed by anticipating issues before they manifest visibly.

By continuously integrating more sophisticated machine learning techniques and expanding our datasets, we aim to enhance vineyard management, making it more proactive and data-driven.

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