MLP-Powered Smart Application to Enhance Efficiency and Productivity in Algerian Agriculture

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***Abstract*—Artificial Intelligence (AI) has emerged as a pivotal driver of global economic growth, expanding its applications across various sectors. This paper introduces a smart application for crop selection tailored to the Algerian environment, aimed at enhancing smart agriculture in Algeria. By harnessing AI's capabilities to enhance efficiency and productivity, our system promises to stimulate economic growth and contribute to the well-being of the agricultural sector. It assists in making informed crop choices, maximizing yields, and resulting in significant time and cost savings for farmers. Our study presents a comprehensive analysis of the Multi-Layer Perceptron Classifier (MLP) model, standing out with an accuracy rate of 91.81%. This underscores its potential as a reliable tool for crop selection in Algerian agriculture.**

***Index Terms*—Smart application, Machine learning, Crop selection, MLP classifier, Smart agriculture, Algerian environment.**

I. Introduction

Evolved beyond its technological origins, AI stands as a driving force propelling global economic growth. Its widespread applications across sectors like healthcare and finance are reshaping societies and economies on a global scale. One arena where AI, Blockchain technology, and smart agriculture are set to make an indelible mark is agriculture in Algeria—an environment characterized by unique challenges and opportunities. This integration offers unprecedented potential to reshape the farming landscape. Several related works have underscored the efficacy of AI-driven and Blockchain-based solutions in agriculture, inspiring our endeavour [1] [9].

In related works, significant strides have been made in AI-driven agricultural solutions. For instance, in [2], a crop recommendation system based on various machine learning models, including Support Vector Machine (SVM), Random Forest (RF), Light Gradient Boosting Machine (LGBM), Decision Tree (DT), and K-Nearest Neighbors (KNN), was developed. These models trained using a dataset containing 22 crop types, demonstrated high accuracy, with RF performing best at 99.24%. This system is critical for informed decision-making, reducing land resource wastage for farmers and the government.

In [3], authors introduced a crop recommendation system leveraging machine learning algorithms and IoT sensors to collect soil moisture, temperature, macro-nutrient content, and other environmental factors. Various algorithms, such as Artificial Neural Networks (ANN), Random Forest, Logistic Regression, and K-Nearest Neighbor (KNN), were assessed to optimize the crop recommendation system, aiding precise crop yield predictions for sustainable practices.

The aim of [4] is to develop a smart crop recommendation system using machine learning to enhance agricultural productivity. Gathering input from farmers, the system utilizes Random Forest, XGBoost, and Decision Tree algorithms, with XGBoost achieving the highest accuracy at 99.31%. The system's recommendations are expected to improve crop yields and reduce farmer losses.

Researchers in [5] introduced a crop recommendation system leveraging soil and climate information, using machine learning models. The XG-Boost classification model excelled in accuracy, recall, precision, and F1 score, resulting in a website aiding informed crop selection for farmers.

This study [6] focuses on a crop recommendation system using machine learning algorithms like Support Vector Machines, Random Forest, and Naive Bayes. The Naive Bayes classifier outperformed Random Forest and SVM with a 99.09% accuracy rate.

The primary focus of [7] is to use machine learning methods to create a crop recommendation system that meets farmers' needs. Achieving a remarkable 99.5% accuracy rate, this system considers variables like climate suitability, soil conditions, and market demands.

This study proposes a smart application tailored for the Algerian agricultural setting, utilizing MLP models that consider intricate soil characteristics and climate conditions. This advancement significantly enhances agricultural productivity and sustainability within the Algerian environment.

II. Methodology

This section outlines the system components and our methodology, as demonstrated in Fig. 1. Further details will be elaborated upon in the following subsections.

A. Dataset

The dataset utilized in this proposed system, sourced from Kaggle, comprises 22 different crop types and a total of

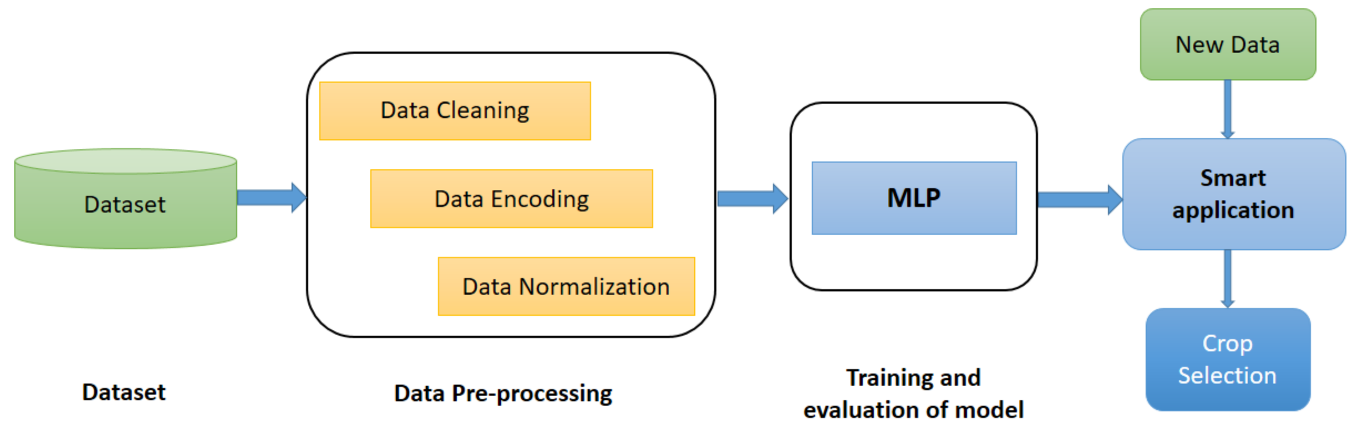

Fig. 1. System Architecture.

2200 data entries. This dataset is rich in agricultural parameters, including Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, pH, and rainfall. Each of these parameters plays a vital role in understanding and predicting crop behaviour.

N (Nitrogen): Nitrogen is an essential nutrient for plant growth and is often required in large quantities. It is a primary component of chlorophyll, which is crucial for photosynthesis. Nitrogen deficiency can lead to stunted growth and reduced crop yields [8].

P (Phosphorus): Phosphorus is vital for energy transfer within plants and is involved in the formation of DNA, RNA, and ATP. It plays a key role in root development and flowering. Insufficient phosphorus can result in poor root growth and delayed maturity [8].

K (Potassium): Potassium is critical for various plant processes, including photosynthesis, water uptake, and enzyme activation. It helps plants resist diseases and improves overall stress tolerance. A lack of potassium can lead to reduced fruit quality and increased susceptibility to pests [8].

Temperature: Temperature affects the growth and development of crops. Each crop has an optimal temperature range for growth. Variations outside this range can affect germination, flowering, and fruiting, potentially leading to reduced yields [10].

Humidity: Humidity levels influence the rate of transpiration, which affects a plant's water and nutrient uptake. High humidity can encourage fungal diseases, while low humidity may lead to water stress in plants [10].

pH: Soil pH is a measure of its acidity or alkalinity. Different crops have specific pH preferences for optimal growth. Deviations from the ideal pH range can affect nutrient availability in the soil and, consequently, plant health [11].

Rainfall: Adequate rainfall is essential for crop irrigation, as it provides the necessary moisture for plant growth. Droughts or excessive rainfall can have adverse effects on crop production, potentially leading to crop failure [12].

However, the development of our intelligent application is tailored to the specific agricultural conditions in Algeria. To ensure relevance and accuracy, we carefully curated the dataset by selecting only those crops that are well-suited to the environmental conditions prevalent in Algeria. This selection process resulted in a refined dataset featuring eleven crops: maize, chickpea, mungbean, lentil, pomegranate, banana, grapes, watermelon, muskmelon, apple, and orange.

B. Data preprocessing

In this section, we meticulously cleaned the dataset by eliminating duplicate entries, addressing missing data using appropriate imputation techniques, and identifying and treating outliers to enhance data reliability. Categorical data underwent transformation through one-hot encoding to render it compatible with machine learning algorithms, minimizing potential bias. To facilitate model development, we judiciously split the dataset into distinct training and testing sets, allocating 70% for training and 30% for testing. This proportion was carefully chosen to ensure effective model training, robust performance assessment, and thorough evaluation, resulting in a well-structured dataset perfectly primed for analysis and the development of our intelligent application.

C. Model and Performance Evaluation

1) MLP Classifier (Multi-Layer Perceptron Classifier): The MLP Classifier represents a type of artificial neural network employed for classification tasks in machine learning and falls within the broader category of feedforward neural networks. Comprising multiple layers of interconnected nodes, including an input layer, one or more hidden layers, and an output layer [13], the primary function of the MLP Classifier involves learning intricate patterns and relationships within input data to make predictions or classifications based on acquired knowledge. Each node within the neural network operates as a perceptron, conducting weighted summations of its inputs, applying an activation function, and conveying the outcome to the subsequent layer. The hidden layers act as intermediate stages to extract and transform features from the input data [14]. Renowned for their capability to manage non-linear relationships and intricate data structures, MLP Classifiers prove suitable for a diverse spectrum of classification tasks [15].

2) Performance Evaluation: Performance evaluation in machine learning is a critical phase that examines the effectiveness and accuracy of predictive models. Metrics such as accuracy, precision, recall, and F1 Score offer a comprehensive understanding of their predictive capabilities.

Accuracy: Accuracy represents the ratio of correctly predicted outcomes to the total number of predictions generated by the model. It evaluates the consistency of the model's predictions with actual outcomes. Although accuracy is a straightforward metric, it might not be the most suitable choice for datasets with imbalanced distributions [16].

Precision: Precision, also known as positive predictive value, measures the model's ability to accurately identify positive instances among all instances it labels as positive. Precision is particularly valuable in scenarios prioritizing the reduction of false positives, such as in medical diagnosis [16], [17].

Recall: Recall, commonly referred to as sensitivity, quantifies the model's effectiveness in recognizing all relevant instances within the dataset. It represents the ratio of true positives to the total actual positives. Recall is especially relevant when minimizing false negatives is a critical objective, such as in tasks involving the identification of spam emails [17].

F1 Score: The F1 Score is the harmonic mean of precision and recall. This metric provides a balanced evaluation, particularly useful in situations where the dataset exhibits class imbalance. The F1 Score is essential when mitigating both false positives and false negatives concurrently [17].

III. Experimental Results

In this study, we employed a dataset encompassing 22 diverse crop varieties and meticulously narrowed down our focus to 11 crops suitable for cultivation in Algeria's multifaceted agricultural terrain. The dataset comprises seven crucial features, incorporating nutrient composition, temperature, humidity, precipitation, and soil pH levels. To optimize our crop selection model utilizing Multilayer Perceptron (MLP), we identified the most influential features for crop prediction, which specifically include temperature, humidity, rainfall, and pH. Deliberately excluding nutrient-related features from the predictive set is a strategic decision, as it allows farmers greater control over nutrient management. Accordingly, we prioritize environmental factors such as temperature, humidity, rainfall, and pH in our MLP model, recognizing their more direct impact on crop selection and yield optimization.

The MLP model has demonstrated remarkable effectiveness in crop classification within the Algerian agricultural context, as depicted in Fig. 2. Boasting an outstanding accuracy rate of 91.81%, this model furnishes reliable recommendations for crop selection.

Moreover, achieving a precision of 92.25% assures that when the model predicts a crop, it is highly likely to be accurate. The model's recall rate of 91.81% indicates its ability

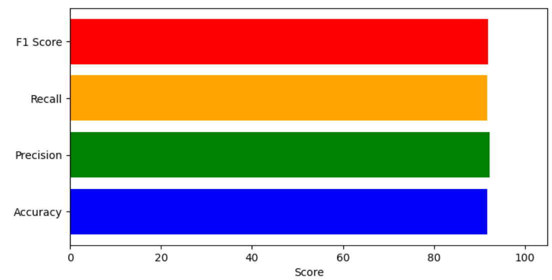

Fig. 2. Crop Classification Metrics Overview.

to identify a significant portion of actual crop varieties, thereby minimizing the risk of missed planting opportunities.

The well-balanced F1 Score, standing at 91.87%, signifies a practical equilibrium between minimizing false predictions and accurately capturing the majority of actual crop classifications.

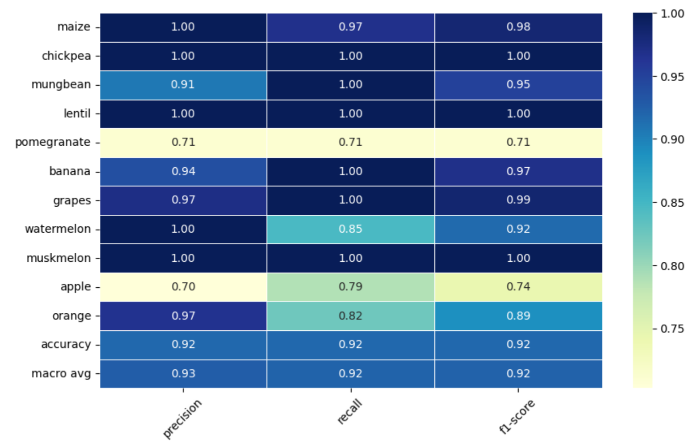

Fig. 3. Model Performance Report.

The performance metrics of the MLP model in classifying different crop types indicate its proficiency in agricultural applications, as depicted in Fig. 3. Particularly noteworthy are the remarkable precision and recall values, achieving an F1-score of 1.00 for crops like Chickpea and Lentil, indicating perfect accuracy. This demonstrates the model's exceptional performance in correctly identifying these specific crops. However, for crops like Grapes, Watermelon, and Oranges, lower precision and recall result in reduced F1-scores. These discrepancies suggest that while the model excels in certain crop classifications, there is room for improvement in accurately distinguishing others.

IV. Conclusion and Future Works

In conclusion, the MLP model demonstrates significant potential for crop classification in Algerian agriculture, delivering exceptional accuracy, precision, and recall for various crop types, ensuring reliable crop selection recommendations. This indicates its promising role in optimizing agricultural practices and enhancing crop yield. Looking ahead, there are avenues for improvement. Firstly, focusing on enhancing the model's capability to distinguish crops with lower precision and recall, like Grapes, Watermelon, and Orange, can be beneficial. Additionally, incorporating more advanced deep learning architectures and expanding the dataset's size and diversity could further augment the model's capabilities, offering substantial benefits to the Algerian farming community.

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