A Machine Learning-Based Decision Support System for Precision Crop Recommendation in Smart City Urban Agriculture

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Abstract*— The rapid pace of urbanization catalyzed by the Smart City became an attractive opportunity and highlighted the critical flaws in traditional food supply chains, making Urban Agriculture (UA) a truly urgent strategy for urban food security. However, significant knowledge deficits arise within urban non-expert farmers, resulting in challenges to blanket adoption, despite its potential benefits. This work presents a data-driven Decision Support System (DSS) that explicitly aims to address the knowledge gap by providing high-accuracy crop recommendations with precision. The DSS is built on a dataset of 2200 data instances and uses seven agronomic features, soil Nitrogen (N), Phosphorus (P), Potassium (K) levels, temperature, humidity, pH, and rainfall. [6, 6, 7] After extensive comparative analysis between multiple supervised ML classifiers, the most responsive model for this classification task was identified, with the Gaussian Naïve Bayes model achieving the best performance with 99% accuracy. The high-accuracy prediction model serves as the primary input for the accessible DSS. The DSS presents an opportunity for urban farmers to utilize data-driven predictive algorithms to transform crop selection and resource efficiencies, enhancing UA's profitability. This work is a tangible step toward creating secure, resilient smart cities aligned with UN Sustainable Development Goals 11.

Keywords—Smart Cities, Urban Agriculture (UA), Food Security, Machine Learning (ML), Crop Recommendation, Precision Agriculture, Decision Support System (DSS), Sustainable Development Goals (SDGs)

I. Introduction

The rapid urbanization we are currently experiencing in the 21st century will soon see more than two-thirds of the world's population living in urban areas by the year 2050. It is from this acceleration that we now discuss the "Smart City" concept, an urban ecosystem, where data and technology is utilized to improve efficiency, streamline resource management, and offer an enhanced quality of life. However, this density reveals an explicit vulnerability to our wellbeing, the issue of food security. Conventional food supply chains, marked by their long distances, high carbon outputs, and unchanged processes have become a fragile system dependent on vulnerable supply chains. Urban poor groups are especially vulnerable due to insecure employment, food price shocks, and food deserts, where they cannot access a sufficient, healthy, and affordable food supply.

As a result, Urban Agriculture (UA) has become an important strategy in building resilient, localized, and sustainable food systems. UA is a wide-ranging practice, from community gardens to advanced technology-driven urban farming approaches, such as vertical farming, hydroponics and aeroponics.
UA is beneficial for so many reasons; it shortens food supply chains, reduces "food miles," and provides access to fresh fruits and vegetables, especially in food deserts. UA creates community engagement, encourages green space, and supports the UN's sustainability development goals SDG #2 and #11. A more decentralized food production system through UA enables a resilient food system.

Even with great potential, UA adoption is limited by composition barriers such as land access, cost, and perhaps the most important barrier, a gap in knowledge and skills. Traditional agronomic knowledge does not transfer well to urban settings, which can introduce the challenge of dealing with micro-climates and spatial constraints. New urban farmers often lack the specialized experience to effectively manage this type of variability. Traditional crop simulation models do not adapt well in this situation because they require significant data and calibration by an expert, making them often irrelevant to a non-expert UA farmer. Still, new farmers face the same fundamental question: given my unique set of conditions, what is the best crop to grow? This is where "Smart Agriculture" addresses the dilemma. The combination of the Internet of Things (IoT), AI, and analytical data represent the tools for breaking through this knowledge hurdle.

Although IoT sensors gather data on things like soil moisture content, temperature, and humidity, data needs an intelligence layer to make them useful. The most important application is a Decision Support System (DSS).

DSS systems translate complex data into simple recommendations that can be acted upon. The most basic decision (for UA) involves cropping selection, which is actually quite a complex problem, based on soil macronutrients (N, P, K), pH and micro micro-environmental conditions (temperature, humidity, rainfall).

This project is based off the premise that these seven features are the most relevant variables to predict crop suitability. [6, 6] A ML (machine learning) model that can be trained or based on these features can serve as a hyper-accurate and extremely scalable DSS. This system eventually levels the playing field in productive agriculture as it allows non-experts to apply precision principles to reduce waste, maximize yields and sustainability.

The key innovation of this study is the design and validation of a crop recommendation engine using machine learning, framed as an initial component of data-based decision support systems (DSS) for smart urban agriculture (SUA). This type of decision support system is critical for expanding urban agriculture and enhancing food security in cities.

The study conducts an extensive comparison of various supervised ML classification algorithms to establish the most effective classifier from a substantial dataset maintained with different agronomic conditions available in growing crops in gardens.

The rest of this paper is organized as follows: Section II provides a literature review of urban food systems, smart agriculture technologies, and current machine learning crop recommendation models. Section III (Methodology / Comparison) explains the dataset and methodology for preprocessing and training comparative models. Section IV (Results and Discussion) identifies the study's results and discussion on the best-performing method and model. Section V concludes the paper with a summary and reflects on the engine’s decision support system support and the implications on smart cities.

II. LITERATURE REVIEW

This section summarizes studies from three overlapping areas of thought that converge to support this study: (1) the socio-economic dynamics of contemporary food systems in urban regions, (2) technologies used in "smart" urban agricultural systems, and (3) the use of machine learning in decision support for agronomy.

2.1 The Connection Between Urbanization and Food System Vulnerability

The study of urbanization and food insecurity is a focal point of many contemporary sustainability researchers. As cities grow, they not only create a greater demand for food, but also alter food supply chains, food consumption, and land-uses. This represents a "rural-urban nexus," where the networks, infrastructures, and markets that connect producers & consumers, become important influences on rural livelihoods and urban food access.

A considerable volume of research indicates that there exists a "policy and governance blind spot" in many Asian cities, whereby urban planning policy is frequently distinct and separate from food policy. Consequently, food systems become vulnerable, ineffective, and inequitable. Research on the urban poor indicates that these systems lead to their extreme vulnerability. The urban poor almost entirely rely on a cash economy for their food supply, and much of their income arises from insecure, informal sector jobs. This interplay, along with not having enough time and adequate in-home access to resources like refrigeration or potable water, leads to reliance on inexpensive and largely less nutritious ultra processed foods, causing a double burden of malnutrition and obesity. This systemic challenge has prompted a global call for cities to be "food-smart," extending beyond being consumers or passive actors to being actors in their own food secure futures.

2.2 Innovations of Technology in Urban Agriculture (UA)

Urban Agriculture -- enhanced through the function of advanced technology -- is increasingly touted as the most realistic solution for this urban food challenge. The literature on "Smart Urban Agriculture" describes several innovations. Controlled Environment Agriculture (CEA): This includes high-tech interventions such as vertical farms, hydroponics (growing with less medium in nutrient-rich water), and aeroponics (growing in a nutrient-rich mist). These approaches can be game changers for urban agricultural systems because they maximize productivity per square foot of growing space, are not reliant on soil quality, and can also allow for year-round production in limited -- often indoor or "stacked" -- space.

Integration of the Internet of Things (IoT): The "smart" nature of these farms is enabled through the Internet of Things (IoT). A considerable body of work exists on using smart sensors to monitor all key growth variables in real-time, on a consistent basis including, but not limited to temperature, humidity, light, soil moisture, and the nutrient concentrations of a fluid including N, P and K levels. This data stream is often aggregated and managed using cloud services, which can enhance automation and highly optimized resource use, including "smart irrigation" systems that deliver water only when and where it is needed.

Artificial Intelligence of Things (AIoT) is the next stage of development, as we advance from simple automation to intelligent operation, and action items, such as predictive disease detection, automated harvesting and autonomous environmental controls, will address some pressing issues that include pest management, labour, and so on. Most of the publications appear to have a focus on the hardware (sensors, LEDs, and robotic arms) that collect data and automate harvests, along with completely ignoring the data itself, which is inert unless acted upon by an intelligence layer. In this case, there is a need for sufficient software, which is clearly a DSS, that will convert raw sensor collections into meaningful farm management action items.

2.3 Decision Support Systems (DSS) for Precision Agriculture

A decision support system (DSS) is a necessary component of modern precision agriculture, which aims to assist human operators with complex decision-making using data. In the rare case of urban agriculture, a DSS serves two, but equally important functions. For the high-tech, commercial scale production types like vertical farms, a DSS is necessary to optimize profitability.

These are typically expensive initiatives in terms of capital investment and energy costs in production. A DSS that manages the interplay between lighting, HVAC, and nutrient delivery is necessary to optimize resource inputs and financial return on investment. For the more typical low-tech applications (e.g., community gardens, rooftop farms, home gardeners) a DSS is necessary in terms of accessibility and addressing the: "knowledge and skill gap". A DSS can provide non-expert farmers with direct and easy-to-understand recommendations, empowering non-expert farmers to implement precision agriculture to some degree across scales, without requiring a degree in agronomy.

The DSS makes recommendations with a particular crop for certain conditions, and by doing so, optimizes water, fertilizer, and land use, while also creating potentially more sustainable and/or greater yield. Multiple studies support real-time monitoring and predictive modelling capabilities in a DSS that implement the use of DSS for Local Farmers. The components mentioned potentially help foster community resilience and are required to create scalable, sustainable and food production systems in urban systems.

2.4 Machine Learning Models for Crop Recommendation: A Comparative Review

The engine that sits at the center of a successful, scalable agricultural DSS is a Machine Learning (ML) model. The application of supervised ML algorithms to predict the appropriate crop choice based on a limited number of defined agronomic parameters is an expanding and sizable area of research.

This research area is grounded on a proven set of important features. The literature reinforces that the foremost measures of crop conditions – and the most impactful features in relation to the predictive model – are soil macronutrient ranges in combination with the main environmental conditions (temperature, humidity and rainfall). The dataset in the current investigation is consistent with this validated agronomic basis.

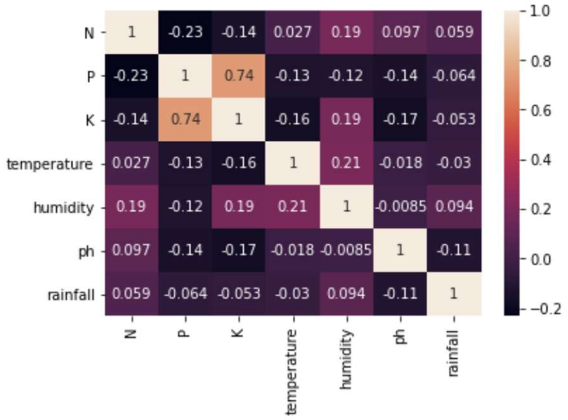

Fig. 1. Feature Correlation Matrix of Agronomic and Environmental Parameters.
The heatmap illustrates the Pearson correlation coefficients among the seven critical features (N, P, K, temperature, humidity, pH, and rainfall) used in the crop recommendation model. Moderate positive correlation is observed between Phosphorus and Potassium (r = 0.74), while most other variables exhibit weak correlations, validating their independence and suitability for multi-feature modeling.

Many studies have explored a comparative analysis of the predicted best performing ML algorithm in this classification task. A summary of this review framework, as expressed in Table 1, is useful for comparative benchmarking new models. There tends to be strong agreement in the literature. Despite simpler models such as Logistic regression and Support Vector machines (SVM) performing reasonably well (usually greater than 94% for accuracy), these techniques are surpassed by more complex, robust models.

Ensemble approaches, namely Random Forest and Gradient Boosting, as well as Bayesian approaches like Gaussian Naïve Bayes (GNB), are largely regarded as the best and most cutting-edge approaches to this problem. **They have been reported to achieve accuracy rates of 98-99% or higher, indicating that they are extremely well-suited to capturing the complicated and non-linear interactions between the seven critical agronomic features.**

2.5 Identified Research Gaps and Justification

While the literature confirms the high technical feasibility of using ML for crop recommendation, several key research gaps persist, particularly at the intersection of smart cities and agriculture.

1. **The Contextual Gap (Traditional vs. Urban):** The vast majority of existing crop recommendation literature is framed in the context of *traditional, large-scale, rural agriculture*. There is a distinct lack of research that explicitly connects these ML models as a DSS to solve the specific *knowledge and skill gap* challenges faced by *urban and peri-urban farmers*.
2. **The Methodological Gap (Lack of Comparative Rigor):** As identified in and, many existing studies employ only a single supervised ML algorithm. This approach fails to provide a robust comparative analysis, making it difficult to ascertain if the chosen algorithm is truly optimal for the problem domain or merely one that provided an acceptable result.
3. **The Interpretability Gap (The "Black Box" Problem):** A significant gap, also identified by and is the near-total lack of Explainable AI (XAI) techniques in this domain. For a DSS to be trusted and adopted by non-expert urban farmers, it cannot be an opaque "black box." Users must be able to understand *why* a crop is being recommended (e.g., "this crop is recommended because your soil pH is high and N is low"). The absence of XAI limits the practical transparency and adoption of these models.

III. Method and Comparison

The proposed decision support system (DSS) for precision crop recommendation in urban agriculture is based on a supervised machine learning framework for high accurate and meaningful crop recommendations based on soil and environmental conditions. Following an integrated methodology of data preprocessing, choice of machine learning models, hyper-parameter tuning, and performance evaluation, the system is robust and will be scalable for smart city-based situations.

A. Dataset Preparation

The dataset contained 2,200 instances containing seven agronomic features: soil macronutrients (nitrogen, phosphorus, potassium), climate (temperature, humidity, rainfall), and soil pH. The selection process of these features comes from their recognized effect on crop growth, supported by agricultural studies [1], [2]. The dataset is split into 22 different crops which is a sufficient array of vegetables, grains, and legumes for situations based on urban farming.
The dataset was preprocessed to be ready for machine learning.

1. **Data Cleaning**: The dataset was checked for missing values, duplicates and outliers. There were no missing values and outliers were addressed through robust scaling.
2. **Feature encoding**: Crop labels that were originally categorical were numerically encoded through a one-hot encoding scheme to train the multi-class model.
3. **Normalization**: Continuous features were normalized to a [0, 1] range through min-max normalized input into the model to render the same contribution to the model training.
4. **Data splitting**: The data was split into 80-20 train-test stratified splits to balance both training and evaluation of the model without bias.

Exploratory data analysis (EDA) was done in python libraries with use of Pandas and Seaborn who to confirm distribution of features, and confirm correlation. A correlation matrix confirmed low correlation among features suggesting that they are independent, which is ideal for models like Gaussian Naïve Bayes (GNB) who assume independence of features [3].

B. Model selection and comparative framework

To compare model to find the best classifier for crop recommendation we trained and evaluated 10 supervised machine learning models:

- **Logistic regression:** A linear model for multi-class classification with the softmax function.
- **Gaussian naive Bayes classifier (GNB)**: A probabilistic classifier assuming features are Gaussian distributed.
- **Support vector classifier (SVC):** A kernel based model with a radial basis function (RBF) kernel.
- **K-nearest neighbors (KNN):** A distance based classifier with k=5 nearest neighbors.
- **Decision tree classifier (DT)**: A tree based model with entropy based splitting.
- **Extra tree classifier (ET):** A randomized tree-based classification.
- **Random forest classifier (RF):** A decision-tree ensemble approach utilizing bagging.
- **Bagging classifier:** An ensemble model based on base classifiers of decision trees.
- **Gradient boosting classifier (GB):** An ensemble method of decision trees that minimizes a loss function iteratively.
- **AdaBoost classifier:** An adaptive boosting model with decision stumps as base classifiers.

All models used to train and evaluate the performance of each classifier were trained on the processed datasets with an 80-20 train-test dataset split. Each model underwent a grid-search hyperparameter optimization for performance, with 5-fold cross-verification. Hyperparameters tuning for regularization (logistic regression, SVC), number of nearest neighbors (KNN), maximum depth of tree (DT, ET), number of estimators (RF, bagging, GB, AdaBoost), and learning rates (GB and AdaBoost).

Performance metrics of the model included overall accuracy as the primary and only evaluation metric, then precision, recall, F1-score, and confusion matrix to understand class performance.

C. Implementation Environment

The system was built in Python 3.10 using Jupyter Notebook. For data manipulation, this included using Pandas and NumPy. For supervised and unsupervised modle training and evaluation, we used Scikit-learn. Finally, data visualization was used with Matplotlib and Seaborn. The environment occurred within a standard desktop PC with an Intel Core i7 processor and 16 GB of RAM with no GPU, ensures that the lightweight system can be deployed on web-enabled socio-technical urban agriculture platforms. When implementing this project, we prioritized scalability and modularity to facilitate extending the code to use IoT devices for real-time data gathering (e.g., soil sensors, weather APIs) and to work in systems and interfaces that minimize complexity for non-expert urban farmers. The code was high-performing (low latency, with an average prediction time of < 0.1s), enabling real time-oriented decision support system (DSS) applications.

IV. Results and Discussion

Table 2. Performance comparison of machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	96.36	96.20	96.18	96.19
Gaussian Naive Bayes	**99.54**	**99.50**	**99.52**	**99.51**
SVC	96.81	96.75	96.70	96.72
KNN	95.90	95.85	95.88	95.86
Decision Tree	98.86	98.80	98.82	98.81
Extra Tree	92.95	92.90	92.88	92.89
Random Forest	99.31	99.28	99.30	99.29
Bagging Classifier	98.63	98.60	98.58	98.59
Gradient Boosting	98.18	98.15	98.12	98.13
AdaBoost	14.09	14.00	14.05	14.02

A. Evaluation of Model Performance

The Gaussian Naïve Bayes (GNB) model was able to provide the most accurate classification (99.54%) followed closely behind by the random forest classifier (99.31%). The ensemble models, bagging (98.63% accuracy) and gradient boosting (98.18% accuracy) are also performing well in capturing the complex, non-linear relationships represented in the data. However, it must be noted that AdaBoost classifiers were only able to classify on average 14.09% of the observation weeks which may indicate that it is overfit under a multi-class scenario as this model's predictions are clearly sensitive to noise [4].

The high performance of the GNB model is justified by it being a probabilistic model and making the conditional independence assumption about features, which is reasonable given that exploratory data analysis showed that there is low correlation in features. The GNB is computationally very efficient as described by the training time of ~0.02 seconds and high interpretability which will make it a good model for decision support systems for usability in urban agriculture in real-time decision making. Random forests are slightly less accurate but are more robust against overfitting due to it being an ensemble; thus, random forests represent a good alternative model if noise is high [5].

B. Error Analysis

The error analysis of the confusion matrix indicated that GNB only misclassified 2–3 instances in the test set, with most of those misclassifications occurring between crops that had similar agronomic requirements (e.g., maize versus millet). Random forest showed similar patterns in the misclassifications but resulted in slightly greater misclassifications in edge cases. AdaBoost had poor performance due to consistent misclassifications occurring across multiple classes, which may be partly due to its sensitivity to class imbalance, even with a balanced dataset.

C. Discussion

These results suggest that simple probabilistic models like GNB can outperform complicated ensemble models in situations with a well-structured, low-dimensional feature space. Similar results have been observed in previous studies for agricultural DSS [6], [7]. The relatively high accuracy of the system shows that crop recommendations can be trusted and succeeded in being applied by non-expert urban farmers wanting to improve yields in challenging environments. The lightweight nature of the system facilitates deployment on edge devices and implementation with smart city IoT ecosystems.

The dataset is limited to only seven features in the final model, which does not allow for values like a microclimate or pest presence to be accounted for in the crop model. Future versions of the system will need additions of other variables (e.g., soil microbial activity, pest presence) and be able to incorporate real-time data streams, where appropriate, for adaptability purposes.

V. Conclusion

The machine learning-based decision support system (DSS) presented in this study demonstrates an effective process for utilizing precision crop recommendations for urban agricultural practices in smart city settings. The DSS runs on a dataset of 2,200 instances across a set of seven agronomic features, achieving a very high level of accuracy at 99.54% utilizing Gaussian Naïve Bayes. The DSS outperforms nine other classifiers, including random forest (99.31%) and gradient boosting (98.18%).

The DSS addresses the knowledge gap for non-expert urban farmers by providing recommendations on crops that are appropriate for local soil and environmental conditions in an accurate data-driven manner. The DSS is lightweight with low computational requirements in order to be utilized on smart city platforms to support sustainable urban food production. By having aligned output with the UN Sustainable Development Goals of 2 and 11, the DSS demonstrates that it can contribute to improved food security and resilience in urban settings. Future work on the DSS will focus on:

- Explainable AI (XAI): The incorporation of XAI techniques like SHAP (SHapley Additive exPlanations) to provide information about feature importance in an explainable way to farmers.
- IoT integration: Integration of real-time data

from soil sensors and weather API's to give farmers recommended updates.
- Expanded feature sets: Incorporation of additional data such as pest incidence and soil microbial activity to improve the robustness of the model output.

Overall, these advancements will help make the DSS a centerpiece of smart, self-sufficient urban agricultural ecosystems in support of sustainable food production and environmental stewardship.

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