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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 Naive 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.

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.

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.

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 nutrien

FAQs

What is GPTZero?

GPTZero is the leading AI detector for checking whether a document was written by a large language model such as ChatGPT. GPTZero detects AI on sentence, paragraph, and document level. Our model was trained on a large, diverse corpus of human-written and AI-generated text with support for English, Spanish, French, German, and other languages. To date, GPTZero has served over 10 million users around the world, and works with over 100 organizations in education, hiring, publishing, legal, and more.

When should I use GPTZero?

Our users have seen the use of AI-generated text proliferate into education, certification, hiring and recruitment, social writing platforms, disinformation, and beyond. We've created GPTZero as a tool to highlight the possible use of AI in writing text. In particular, we focus on classifying AI use in prose. Overall, our classifier is intended to be used to flag situations in which a conversation can be started (for example, between educators and students) to drive further inquiry and spread awareness of the risks of using AI in written work.

Does GPTZero only detect ChatGPT outputs?

No, GPTZero works robustly across a range of AI language models, including but not limited to ChatGPT, GPT-5, GPT-4, GPT-3, Gemini, Claude, and AI services based on those models.

What are the limitations of the classifier?

The nature of AI-generated content is changing constantly. As such, these results should not be used to punish students. We recommend educators to use our behind-the-scene Writing Reports as part of a holistic assessment of student work. There always exist edge cases with both instances where AI is classified as human, and human is classified as AI. Instead, we recommend educators take approaches that give students the opportunity to demonstrate their understanding in a controlled environment and craft assignments that cannot be solved with AI. Our classifier is not trained to identify AI-generated text after it has been heavily modified after generation (although we estimate this is a minority of the uses for AI-generation at the moment). Currently, our classifier can sometimes flag other machine-generated or highly procedural text as AI-generated, and as such, should be used on more descriptive portions of text.

I'm an educator who has found AI-generated text by my students. What do I do?

Firstly, at GPTZero, we don't believe that any AI detector is perfect. There always exist edge cases with both instances where AI is classified as human, and human is classified as AI. Nonetheless, we recommend that educators can do the following when they get a positive detection: Ask students to demonstrate their understanding in a controlled environment, whether that is through an in-person assessment, or through an editor that can track their edit history (for instance, using our Writing Reports through Google Docs). Check out our list of several recommendations on types of assignments that are difficult to solve with AI.

Ask the student if they can produce artifacts of their writing process, whether it is drafts, revision histories, or brainstorming notes. For example, if the editor they used to write the text has an edit history (such as Google Docs), and it was typed out with several edits over a reasonable period of time, it is likely the student work is authentic. You can use GPTZero's Writing Reports to replay the student's writing process, and view signals that indicate the authenticity of the work.

See if there is a history of AI-generated text in the student's work. We recommend looking for a long-term pattern of AI use, as opposed to a single instance, in order to determine whether the student is using AI.