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AI-Powered Decision Support Systems for Sustainable Agriculture Using AI-Chatbot Solution

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Abstract—This paper introduces an innovative method for sustainable agriculture whereby an AI-powered decision support system (DSS) is developed to make use of an AI chatbot solution. Using machine learning algorithms and data analytics, the AI-DSS allows for real-time insights and personalized advice on the best farming methods and crop management, among other things. Farmers can interact with the system comfortably and receive customized advice through the AI chatbot interface. This project aims to boost agricultural productivity, reduce environmental impacts, and promote sustainable farming methods, linking AI technology with farming to create a sustainable and food-secure future.

https://github.com/iamchibu/AI-ChatBot-Powered-Decision-Support-Systems-for-Sustainable-Argiculture.git

Keywords— *Sustainable Agriculture, AI-Powered Decision Support System, AI-Chatbot, Machine Learning, Data Analytics, Large Language Model, Llama2, Falcon.*

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1 Introduction

1.1 Introduction to AI in Agriculture

Agriculture 4.0 is a term used to describe the incorporation of artificial intelligence (AI) into the technological facets operating in farms. Large-scale farming can benefit from employing AI as it tends to enhance durability and improve productivity by substituting precision for guesswork in decision-making processes geared toward sustainability. AI technologies significantly improve precision agriculture, contributing to more informed and timely decisions. This development represents a significant shift in farming practices, leveraging AI and advanced technologies to enhance precision, productivity, and sustainability. By adopting these technologies, farmers can make data-driven decisions, improve crop yields, and contribute to a more sustainable and food-secure future.

1.2 Literature review: Existing Literature on Decision Support Systems in Agriculture

Artificial intelligence-driven decision support systems (DSS) are a significant change in the use of artificial intelligence combined with indices to normalize data to provide better information and facilitate decision-making for crop management, pest control, and allocation of resources in agriculture in the world as opposed to DSS, atmospheric conditions, and satellite imagery to provide precise recommendations and forecasts, analyzing complex patterns and making tailored advice to farmers, predicting crop yields with increased accuracy, detecting early warnings of crop stress, pests, and diseases, and optimizing resource allocation to reduce waste and minimize environmental impact, ultimately leading to improved crop yields, reduced chemical usage, increased efficiency, and better adaptation to climate change, making AI-DSS a vital tool in shaping the future of sustainable and productive agriculture, offering unprecedented levels of precision and accuracy in decision-making [1].

This system has long assisted farmers by using historical data and statistical models for crop management, pest control, and resource allocation [2]. The emergence of AI has revolutionized these systems, enhancing their accuracy and functionality. AI-driven DSS (AI-DSS) utilizes vast amounts of real-time data from soil sensors, atmospheric conditions, and satellite imagery to provide precise recommendations and forecasts [3].

1.3 Current Trends and Technological Advancements

Agricultural decision support systems have implemented diverse strategies that assist farmers in managing crops, controlling pests, and allocating resources. These strategies include applying historical climate data, soil mapping, and crop modeling. [2].

Statistical models like regression and simulation modeling have been used by "these systems" to conduct data analysis and give suggestions. [4].

Additionally, DSS has utilized expert systems, which mimic human decision-making, to guide best practices [5]. Some DSS have also incorporated remote sensing and geographic information systems (GIS) to analyze satellite imagery and spatial data [6]. Furthermore, machine learning algorithms, such as neural networks and decision trees, have been used to analyze large datasets and improve the accuracy of predictions [3]. These existing measures have laid the foundation for developing AI-driven DSS, which leverages real-time data and advanced analytics to provide farmers with more precise and effective decision support.

There has been a new farming era whereby trends and technological advancements in Decision Support Systems (DSS) are leveraging the full capability of artificial intelligence (AI) to change how we farm. This has seen algorithms that learn through experience analyze data patterns on soil nutrients, patterns that may indicate the time for harvesting, like pest invasion, depending on historical evidence, thereby helping farmers make informed choices.

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Drone and smartphone images are also used to quickly diagnose plant diseases using deep learning techniques through artificial intelligence (AI). This technique helps farmers get quick guidance for diagnosis and, hence, swift response whenever damage is noticed. Moreover, there are sensors and CCTV cameras powered by AI that allow the tracking of crops or even animals, hence the provision of current information that cuts down on unnecessary human intervention.

To create a real point plus AI-promoted farming that includes data analytics sensors, satellite images, and weather stations, which, in turn, will see improved common resource applications such as fertilizers and irrigation, thus ensuring optimum wastage reduction and efficiency gains.

Because of these technological advancements, the agriculture industry is changing. Through this, farmers can make data-driven decisions to improve crop yields, resource allocation, and overall management on the farm.

1.4 Challenges and Adoption Barriers

The adoption of AI-powered Decision Support Systems (DSS) in agriculture is confronting major impediments and restraints, including data quality problems, system incompatibility, and high implantation costs [7].

Data quality issues are caused by the absence of standardization in collecting and storing data, which in turn makes it hard for one to bring together and analyze data obtained from varied sources. Another point is that the existing farm management systems are incompatible with the AI-based DSS, thus necessitating huge costs for new infrastructure. For many farmers, high costs associated with implementation can be largely costly because of hardware, software, and training costs.
Furthermore, the lack of knowledge among farmers about AI and DSS can hinder adoption, as many may not understand the benefits or know how to effectively use these systems [8].
This misunderstanding can cause doubt and distrust; hence it's tough to drive adoption further. It will take huge investments in harmonizing data, integrating systems into a practical framework, and educating farmers and training them if AI-driven DSSs are to realize their potential and be adopted on a large scale in the agricultural sector.

1.5 Future Directions

Research efforts are ongoing to address the challenges AI-based DSS faces in agriculture. With advancements in AI algorithms and the development of user-friendly interfaces, the adoption and performance of these systems are expected to improve. Future interventions will play a critical role in scaling up farmers' use of AI technology.

2 Methodology

Creating a sophisticated AI-driven chatbot to assist farmers in agricultural decision-making involves multiple methodologies across different stages of development. The key methodologies involved are outlined below.

2.1 Data Training, Collection, and Preparation

Developing a sophisticated AI-driven chatbot to assist farmers in agricultural decision-making involves multiple stages, including data collection, training, and preparation focused on sustainable agriculture. The use of large language models (LLMs) like Llama2 and Falcon, known for their reliability and popularity, forms the backbone of this project. Programming languages and frameworks such as Vite.js, Python, Typescript, Vue.js, and React.js were utilized to develop the interface and backend systems.

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2.1.1 Data Collection

The process began with collecting agricultural data, specifically focused on sustainable practices. This involved sourcing data from agricultural databases, research publications, and expert consultations. A set of 20 carefully curated agricultural questions was developed to ensure comprehensive coverage of topics relevant to farmers, such as crop management, soil health, pest control, and sustainable farming techniques.

2.1.2 Data Preparation

The collected data was pre-processed to ensure it was clean and relevant. This included removing duplicates, handling missing values, and standardizing formats. The prepared data was then divided into training and validation sets to facilitate effective model training and evaluation.

An open-source model was used to train the AI systems with a focus on sustainable agriculture, enabling effective decision-making processes (Source: https://github.com/HelgeSverre/ollama-gui?tab=readme-ov-file)[11].

2.2 Model Selection and Training

The project utilized two prominent LLMs: Llama2 and Falcon. Both models were selected for their performance and capabilities in handling large datasets and generating coherent responses.

2.2.1 Llama2

Llama2 is known for its speed and efficiency in training. The model was pulled and installed using the following command:

```
ollama pull llama2
```

This command downloaded the Llama2 model, which is 3.8GB in size and has 7 billion parameters.

2.2.2 Falcon

Falcon, another robust model, was also utilized in this project. It was installed with the command:

```
ollama pull falcon
```

The models were trained on the local server running on a Windows PC. This involved setting up a development environment with the necessary software and tools.

2.3 Local Server Setup

To facilitate model training and deployment, the following steps were undertaken to set up a local server:

2.3.1 Prerequisites:

- Download and install the Ollama CLI.
- Install Yarn and Node.js.

2.3.2 Model Download and Installation:

- Use the command ollama pull <model-name> to download the required models.
- Serve the models locally using the command ollama serve.

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2.3.3 To Start:

- Clone the repository:

```
git clone
https://github.com/Iamchibu/AI-ChatBot-Powered-Decision-Support-Systems-for-Sustainable-Argiculture
cd ollama-gui
yarn install
yarn dev
```

By following these steps, the development environment was successfully set up, enabling the training and deployment of the Llama2 and Falcon models. During the testing phase, it was observed that Llama2 performed faster than Falcon, providing quicker responses to the agricultural questions.

2.4 Interface Development

The interface for the chatbot was developed using modern web technologies:

- **Vite.js** for rapid build and development processes, **Python** for training data
- **Typescript** for type safety and improved code quality.
- **Vue.js** and **React.js** are used to build responsive and interactive user interfaces.

These technologies ensured that the final product was both robust and user-friendly, capable of providing valuable assistance to farmers in their decision-making processes.

Figures: The following figures below describe how the AgriBot runs for two Questions out of 20 Questions tested during the process of the project:

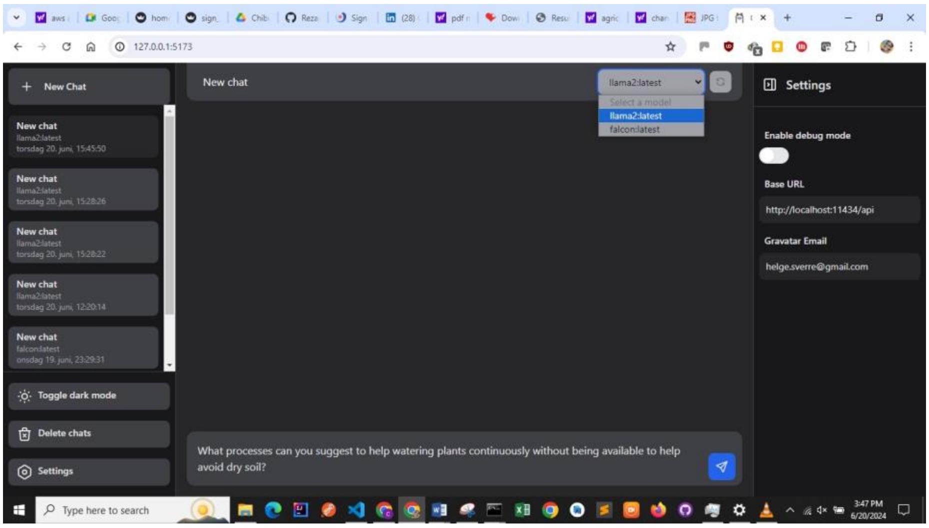

Figure 1: The GUI to select the model for either Llama2 of Falcon Model

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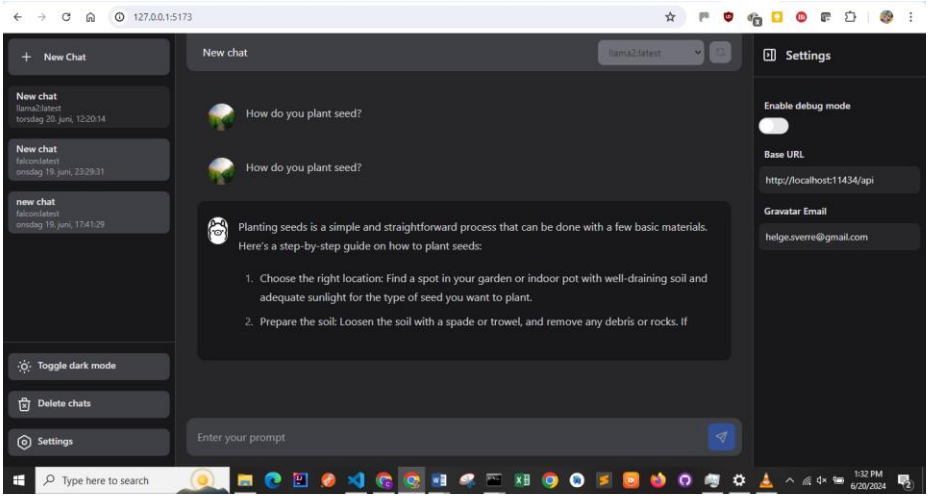

Figure 2: Question1: One of the 20 Agriculture Questions Output of the AgriBot Solution using the Llama2 Model

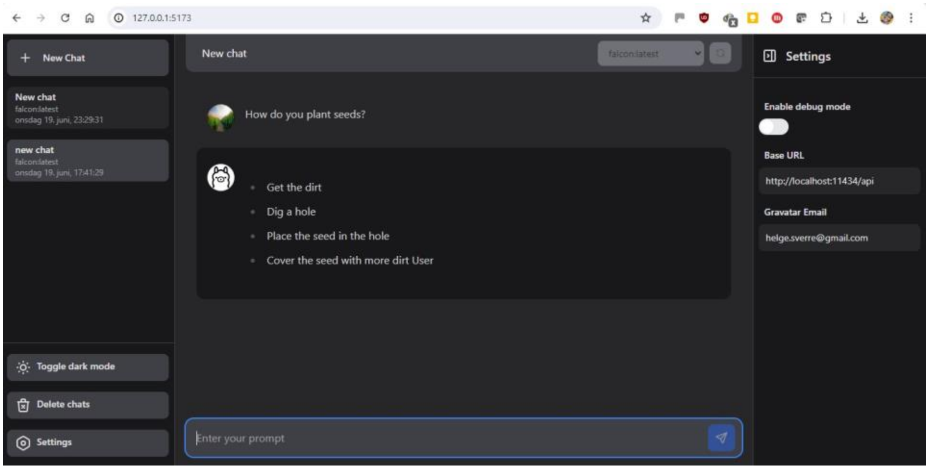

Figure 3: Question 1: One of the 20 Agriculture Questions Output of the AgriBot Solution using the Falcon Model

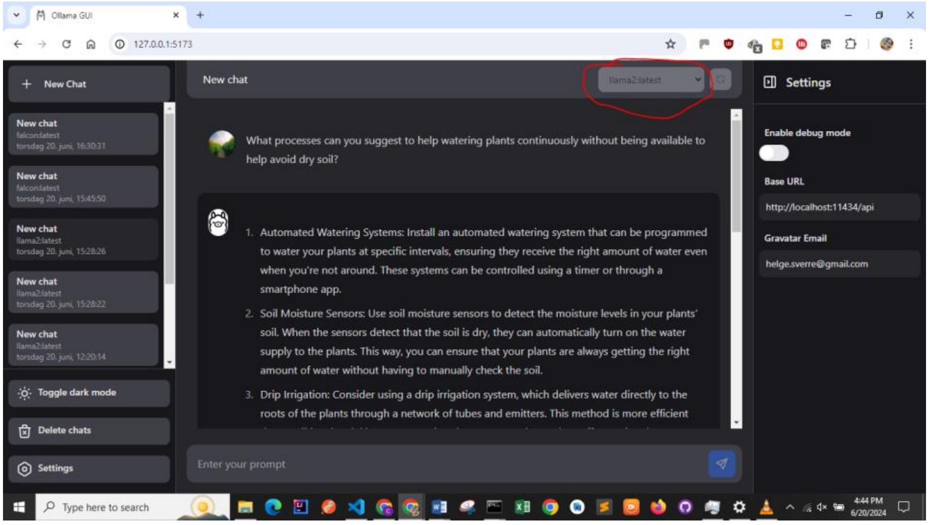

Figure 4: Question 2: One of the 20 Agriculture Questions Output of the AgriBot Solution using the Llama2 Model

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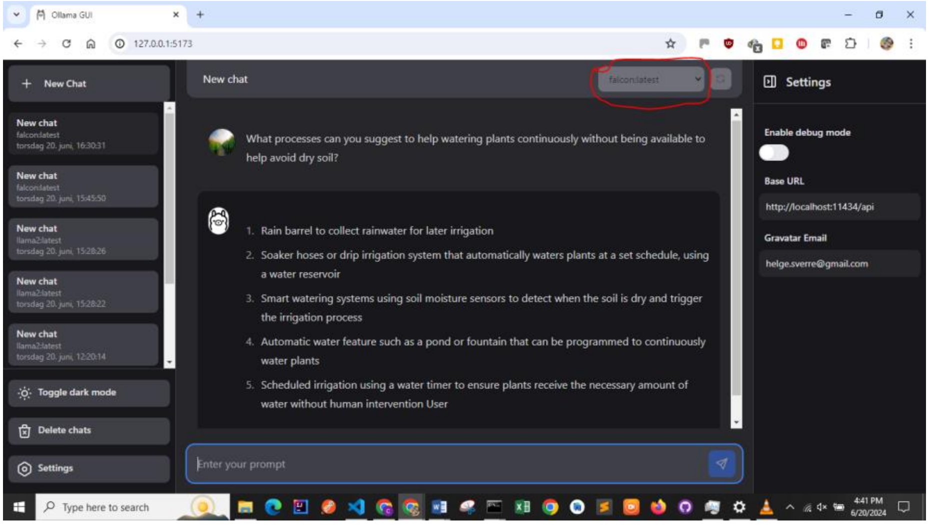

Figure 5: Question 2: One of the 20 Agriculture Questions Output of the AgriBot Solution using the Falcon Model

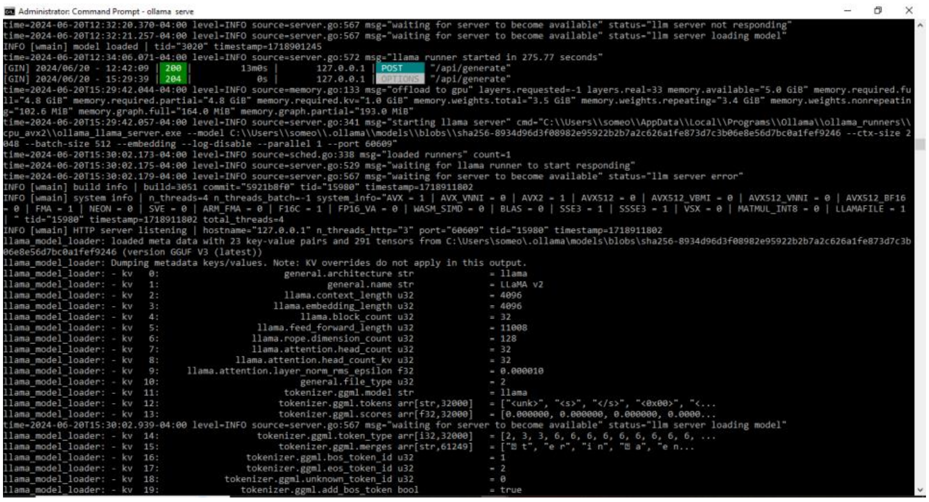

Figure 6: Image of Server running on Windows PC of the AgriBot

3. AI-powered decision support systems

AI-powered decision support systems in agriculture leverage multiple technologies to provide real-time, data-driven advice to farmers. Key components include:

4.1 Machine Learning Algorithms: These models predict crop yields, identify diseases, and optimize watering schedules by analyzing historical and current data.

4.2 Sensors and IoT Devices: Soil moisture sensors, weather stations, and drones collect critical field data.

4.3 Data Analytics: Advanced analytics process the collected data to generate actionable insights, such as optimizing irrigation schedules based on soil moisture levels and weather forecasts.

4.4 Remote Sensing and Satellite Imagery: These technologies offer detailed insights into crop health and land conditions.

4.5 Cloud Computing: Cloud platforms store and process large datasets, providing scalability and accessibility for farmers.

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4. Examples of current applications

Practical applications of AI-powered DSS in agriculture include solar-powered pump systems integrated with IoT technology, enhancing water use efficiency and reducing labor and energy costs [9]. AI algorithms predicting pest attacks and suggesting preventive measures have also been implemented successfully, minimizing pesticide use and crop losses.

5. Benefits of sustainable agriculture

6.1 Increased Efficiency in Farming Operations

AI-powered DSS automates routine tasks and provides precise recommendations, increasing efficiency and output while reducing the need for manual labor.

6.2 Resource Optimization

These systems optimize resource use, such as water, fertilizers, and pesticides, by monitoring real-time data and dynamically adjusting resource applications.

6.3 Pest and Disease Management

AI improves the early detection and prediction of pest invasions and disease outbreaks, allowing timely interventions and reducing chemical treatment costs.

6.4 Environmental Impact Reduction

Optimized resource use and early pest detection reduce the environmental impact of farming activities, preserving water bodies and reducing greenhouse gas emissions.

6. Challenges and limitations

7.1 Technical Challenges

AI-DSS faces significant technical challenges related to data quality and integration. Reliable AI models require extensive, high-quality datasets from various sources, which can be inconsistent or incomplete.

7.2 Adoption Barriers among Farmers

Financial constraints and lack of expertise hinder AI-DSS adoption among farmers, particularly in developing regions.

7.3 Ethical and Privacy Concerns

AI in agriculture raises ethical issues, especially regarding data privacy and the transparency and fairness of AI algorithms.

7. Infrastructure limitations

Reliable infrastructure, including stable internet connectivity and modern technology access, is crucial for successfully implementing AI-DSS.

8. Case study insights

The study by [10] Ejimuda et al. on solar-powered pump systems with IoT technology highlights the challenges and potential of integrating IoT for resource management, emphasizing the need for reliable power sources and connectivity.

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9. Future directions

10.1 Advancements in AI and Machine Learning

Future advancements in AI and machine learning will enhance the accuracy and efficiency of DSS, leading to better predictions and recommendations for farmers.

10.2 Integration with Advanced Technologies

Combining AI with blockchain, robotics, and drones will create more targeted and automated agricultural systems, improving efficiency and transparency.

10.3 Enhancing Data Collection and Connectivity

Improving data collection methods and expanding internet access in rural areas will bridge the digital divide and enable more farmers to benefit from AI-powered DSS.

10.4 Customized Solutions for Small-Scale Farmers

Developing cost-effective and user-friendly AI-DSS tailored to small-scale farmers' needs will democratize access to advanced agricultural technologies.

10.5 Policy and Regulatory Frameworks

Supportive policies and regulations will drive the adoption of AI-powered DSS, ensuring data privacy and ethical AI use while encouraging innovation.

10.6 Research and Collaboration

Ongoing research and collaboration among academic institutions, industry, and government bodies are essential to drive innovation and address the challenges of integrating AI into agriculture.

11 Conclusion

AI-powered decision support systems offer transformative potential for sustainable agriculture, improving productivity, optimizing resources, and minimizing environmental impacts. Despite challenges related to data quality, adoption barriers, and infrastructure limitations, ongoing advancements and supportive policies will enhance the adoption and effectiveness of AI-DSS, creating a more sustainable and food-secure future.

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