SenAgriPreci: Improving Precision Agricultural Yields Through a Crop Recommender System

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Abstract. Agriculture represents an important pillar in the global economy. It plays a preponderant role in social life. Africa alone represents 30% of the earth's arable land, or 30 million km^2 of usable agricultural land. This sector employs more than 65% of the active Senegalese population. However, inappropriate weather or climate change have a deep effect on agricultural production or crop yields. Consequently, the conformance of precision agriculture requires effective decisions by stakeholders in the agricultural field. This can be achieved through an innovative recommender system. A recommender system filters data using different algorithms and suggests the most relevant items to users in a particular domain using relevant entities. To address the above issue, we propose a recommender system for farmers in Senegal called *SENAgriPreci* which enables users to make good and precise agricultural decisions using various parameters (Example: pH, crop type, soil type, temperature etc.). Using relevant datasets, namely: SAED and CRNA, we conducted benchmarking experiments to validate our proposed *SENAgriPreci* recommendation methodology. Experimental results in terms of Root Mean Square Error (RSME) validates that of our proposed recommendation method is more favorable and outperforms other related and contemporary recommendation methods in relation to accuracy and precise crop recommendations.

Keywords: IoT, Machine learning, Agriculture, Crop recommender system

1 Introduction

Agriculture is one of the most powerful levers in the fight against poverty in Africa and in Senegal in particular. It contributes to strengthening prosperity, sharing and feeding more than eight billion people around the world [1]. Agriculture mobilizes nearly 70% of the active population in Senegal, i.e. 4.51 million agricultural workers out of an active population of 6.55 million people, and plays an essential social and economic role.

Unlike other sectors of an economy, agricultural growth not only fights against famine, but also considerably reduces the unemployment rate. According to a study published in 2023, 65% of poor adult workers depend on the agricultural sector [2]. This sector has undergone a drastic change with the arrival of new technologies. This change gave rise to what has been called precision agriculture. Indeed, in this type of agriculture, Artificial Intelligence (AI) and Internet of Thing (IoT) techniques are used to improve the performance of agricultural operations. These are part of the Agricultural Technology (Agri-Tech) mechanism which makes it possible to optimize agricultural yields but also to rationalize production costs and have a better ecological footprint [3]. In other words, precision agriculture ensures improved working comfort for farmers and better crop management [4], [5]. Unfortunately, the means of agricultural production generally used in Africa, particularly in Senegal, no longer meet the economic and environmental challenges of globalization. Irregularity or internally climatic and rainfall variation also constitutes one of the causes of the attenuation of the African agricultural system [6], [7].

The other main problem is the applicability of precision agriculture recommender systems proposed by Europeans in the context of Africa, more precisely Senegal which encounters rainfalls only three months in a year. Considering all of these situations cited above, African agriculture must evolve and move to precision agriculture to meet the challenges of tomorrow. But how can we help our farmers improve and increase their agricultural yields? In order to respond to this problem, we seek to propose an effective, practical and simple recommender system to be used by our farmers in the context of Senegal who are generally not educated. Our proposed recommender system uses AI and IoT technologies to provide farmers with better and precise decision-making. The paper is organized and structured as follows: Section 2 presents related work, Section 3 provides a background of our proposed solution, Section 4 elaborates on our experimentation procedure and presents experimental result and Section 5 finally concludes the study.

2 Related Studies

Precision agriculture uses new technologies, such as robotics, AI and connected objects, to improve the performance of agricultural operations. This area has been the subject of several research studies. Kulkarni et al. [8] established a crop recommender system using technical assembly to increase agricultural productivity. This system is capable of selecting the right crop based on different soil types, rainfall and surface temperature parameters. Similarly, Kuanr et al. [9] proposed a collaborative recommender system capable of predicting agricultural crop according to weather conditions. Their system uses a fuzzy logic similarity measure to identify similar user based on the farmer's location and crop yield.

Vincent et al. [10] proposed an expert system by integrating sensor networks with AI systems such as neural networks and Multi-Layer Perception (MLP) for agricultural land suitability assessment. Their proposed system will help farmers evaluate agricultural land for cultivation based on four decision classes, namely more suitable, moderately suitable, and unsuitable.

Boursianis et al. [11] applied IoT and unmanned aerial vehicle (UAV) in agriculture. They described the main principles of IoT technology, including smart sensors, types of IoT sensors, networks and protocols used in agriculture, and IoT applications and solutions in smart agriculture. Additionally, they presented the role of drone technology in smart agriculture, analyzing drone applications in various scenarios, including irrigation, fertilization, pesticide use, weed management, monitoring plant growth, crop disease management and field level phenotyping. Additionally, the use of drone systems in complex agricultural environments was also analyzed.

Our conclusion is that IoT and drones are two of the most important technologies that transform traditional agricultural practices into a new perspective of intelligence in precision agriculture. The authors in [12]-[15] presented different opportunities offered by ICT in agricultural management. These authors conducted prospective analyzes in terms of AI and IoT. Additionally, in relation to crop recommendation, quite a number of authors have proposed innovative recommender algorithms/systems.

Notable among these include: Desai et al. [16] proposed an intelligent system that can help Indian farmers make informed decisions about which crop to grow by considering variables like soil features, geographic location, and sowing season. The technology will also help the farmer by predicting the yield in the event that he plants the recommended crop. Similarly, Pande et al. [17] proposed a workable and intuitive yield prediction system. Farmers can connect to the proposed system through a mobile application. GPS facilitates user location identification. The user enters the area and type of soil. Selecting the most profitable crop list or forecasting the crop yields for a crop that the user has chosen are made possible by machine learning algorithms.

In order to suggest the best crop, Madhuri and Indiramma [18] proposed a novel recommender system that makes use of Artificial Neural Networks (ANN). Based on (a) soil characteristics, (b) crop characteristics, and (c) climate parameters, the recommended crops are identified. Furthermore, Banerjee et al. [19] proposed a fuzzy logic-based crop recommendation system. Eight major crops grown in the state of West Bengal are covered by the proposed model. For each crop, distinct fuzzy rule bases were developed in order to facilitate faster parallel processing. A wide range of datasets have been used to validate the model’s performance, which has produced an accuracy of roughly 92%.

Similarly, Sharma et al. [20] proposed crop recommendations for farmers by predicting which crop will thrive in their particular environment and circumstances. It does this by analyzing a variety of machine learning models, including decision trees, Gaussian Naive Bayes, logistic regression, random forests, and XGBoost, to determine the composition of nitrogen, phosphorus, and potassium in the soil, as well as its pH value, humidity, and rainfall.

3 Proposed Solution: SENAgriPreci

Our main goal in this paper is to propose a decision support tool called *SenAgriPreci* based on various recommendation approaches. This tool is based on a set of data from the SAED (Societ´e´ nationale D’Amenagement´ et d’Exploitation des Terres du Delta de Fleuve Sen´egal´ et des Vallees´ du Fleuve Sen´egal´ et de la Falem´e)´ and CNRA (Centre National de Recherches Agronomiques), with the aim of recommending the best crops suitable for each type of soil with as much precision as possible. This will really help to overcome the problems encountered by farmers in choosing the appropriate crop in order to obtain better yields. The most important aspect in this approach is to offer a personalized recommender system that will adapt to the Senegalese reality by using our own data with AI and IoT.

3.1 System Model

Data collection is a very important phase in setting up a recommender system. As stated above, the data used in this work was gathered from local structures such as the SAED and the CNRA. For each type of crop, there is the preferred soil type of the crop, the average temperature for the good development of the plant, the PH, the estimated rainfall in months, and the variety and maturation cycle of culture.

The designed system needs parameters such as: soil temperature, soil type, pH and crop type coming from the field to make a crop recommendation. These parameters are obtained via IoT with temperature, pH, and humidity sensors. Once this information is provided, all data is inserted into the database for processing and analysis. After processing the data, it is divided into training data and test data to evaluate the performance of the models used.

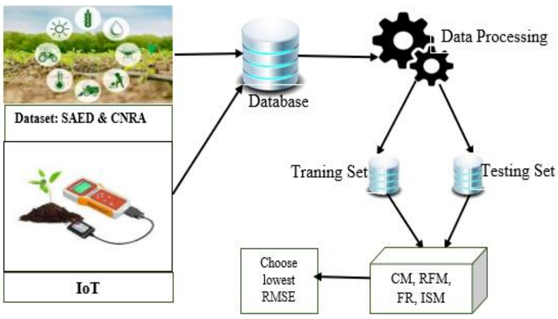

Fig. 1. Architecture of SenAgriPreci

SenAgriPreci recommends crops from these models to the user by choosing the model with the minimum Root Mean Square Error (RMSE) as an evaluation/performance metric. Fig. 1 shows the architecture of *SenAgriPreci*. The RMSE is a standard evaluation metric for recommender systems. It evaluates the prediction error for each user-item pair in the available dataset [21], [22].

$$RMSE = \sqrt{\frac{1}{n}\sum_{(u,i)\in\tau}(\bar{r}_{u,}i - r_{u,}i)^2} \quad (1)$$

with $r_{u,}i$ the culture type assigned by user *u* to culture *i*, $\bar{r}_{u,}i$ the predicted culture, *n* is the number of crops, and τ, the basis of the test. Precision (P) is defined as the number of true positives (*TP*) over the number of *TP* plus the number of false positives (*FP*) [21], [22].

$$P = \frac{TP}{TP+FP} \quad (2)$$

$$R = \frac{TP}{TP+FN} \quad (3)$$

Recall is defined as the number of *TP* over the number of *TP* plus the number of False Negatives (*FN*). The choice between these two metrics depends on the data used to set up the models. Since our data includes target values, our models will be evaluated based on RMSE [21], [22].

Implementation of Proposed Solution. Crop recommendation is a major area of precision agriculture. In this paper, we use AI, more specifically machine learning algorithms, to recommend the best crop for the farmer based on their field parameters. The use of IoT facilitates the recovery of real field data so that we can verify this data with that obtained via GPS and weather before using different algorithms methods. Algorithm 1 explains in detail how our system works.

Algorithm 1: *SenAgriPreci* pseudocode for crop recommendation.

Start

// Declaration

W_l, ph_l : Integer
S_l, C_l, H_l : String
l_a, l_a^c: List
1 : Input: DataSet (CNRA & SAED)
2: Output: l_a^c best order of Crop recommender
3: S_g, $W_g \leftarrow$ GPS localise
4: **for** each algorithm
5: l_a= Apply (A_a in training set)
6 : l_a^c =Apply RMSE (for each method) to use the best results in order
7: **end for**

End

// C_l is the Crop
S_l is the ground type of land
S_g is the ground type of the area
W_g is the weather of the area
Ph_l is the ph of land
W_l is the weather of land
H_l is the humidity of land
l_a, l_a^c are respectively the list of algorithm results and the list of crop recommenders

First, the user logs in via the app and then follows the recommendation process. After login, the GPS locates the farmer to retrieve the region, and the Senegalese weather data is used to retrieve the ambient temperature and soil type of the corresponding region. There are two constraints with our system: poor internet connection in Senegalese rural areas and the fact that our farmers are not very highly educated. This is the reason why our algorithm provides two possibilities for the farmer. First, the farmer is invited to enter the pH (pH_l) of land, humidity (H_l), culture type (C_t), soil of land (S_l), temperature of the land (T_l), and Crop (C). The pH and H_l can be entered automatically via the IoT equipment made available to him. This data is verified with meteorological data.

When a connection is established, the data is retrieved directly from the system. Then this data as well as the data obtained from the SAED and the CNRA are already processed and used by the algorithms in order to offer a crop recommendation to the farmer. The RMSE applies to all the algorithms to finally choose the best crops with the best yields. Thus, this list is ordered and offers the best harvest.

4 Experimental Results and Analysis

In this paper, we used TuriCreate which provides toolboxes for image classification, object detection, text classification, etc. Python 3 is used for the implementation with the PyCharm IDE, which is an integrated development environment dedicated to the Python and Django languages. We also used the libraries, and Pandas to analyze, structure and organize the data as well as scikit-learn. Django was used to generate the database which is subsequently stored in the MySQL database management system. Each model predicts a score for each possible combination of users and items. The internal coefficients of the model are learned from known user and item scores. Recommendations are then based on these scores. This section presents the results of each of these models. Instead of recommending crops to all users in our database, we chose only users 4 and 7 so as not to have a long list and we also limited ourselves to the three best crops.

4.1 Item Similarity, Factorization and Rank Factorization

Table 1 shows the result of Item Similarity. The elements similarity algorithm recommends the crops Sorghum, Maize, and Tomato to user 4 with different scores, as we can see Sorghum is at the top with the highest score, so it is the most adequate. In the case of user 7, the same crops are recommended with Sorghum always in first place. In Table 2, the factorization algorithm recommends the Maize, Peanut and Tomato crops to user 4 with different scores. Maize is in first place with the highest score, so it is the most suitable crop. In the case of user 7, the recommendation of Rice, Maize and Peanut crops are illustrated with different respective scores, but in this case, Maize is in first place with the highest score. Table 3 shows the result of ranking factorization algorithm. Recommendation in this category involves Tomato, Peanut, and Sorghum crops to user 4 with different scores. Tomato is in first place with the highest score, so it is the most suitable crop.

In the case of user 7, Rice, Maize and Peanut crops are recommended with different scores. Rice is in first place with the highest score. Each user gave their own inputs, the crops recommended by the system do not have the same varieties. Indeed, the system considers the fact that each crop has several varieties before making the recommendation. As illustrated in Table 4, the user can choose any crop from the three recommended, but would be advised to choose the crop that ranks first.

Table 1. Item similarity

User ID	Crop Name	Score	Rank
4	Maize	0.1666666666666666	1
4	Peanut	0.1666666666666666	2
4	Tomato	0.13333332538604736	3
7	Rice	0.30952381236212595	1
7	Maize	0.30952381236212595	2
7	Peanut	0.24761904988970077	3

Table 2. Factorization

User ID	Crop Name	Score	Rank
4	Maize	0.3619248985845887	1
4	Peanut	0.3309040856615000	2
4	Tomato	0.3626736999978954	3
7	Rice	0.3626736999978954	1
7	Maize	0.3573406727586233	2
7	Peanut	0.3287493533056521	3

Table 3. Rank factorization

User ID	Crop Name	Score	Rank
4	Tomato	0.263555587191939	1
4	Peanut	0.2594019781166979	2
4	Sorghum	0.2229278232024658	3
7	Rice	0.39459635515905106	1
7	Millet	0.31413989060766184	2
7	Peanut	0.3098689393440553	3

Table 4. Comparison of models

Test	5	10	15	20	25	30	35	40	45	50
Factorization	0.124	0.015	0.035	0.014	0.047	0.018	0.021	0.041	0.039	0.048
Item Similarity	0.412	0.514	0.452	0.439	0.445	0.507	0.481	0.441	0.449	0.419
Rank Factorization	0.059	0.068	0.119	0.053	0.052	0.145	0.038	0.064	0.111	0.110

In terms of comparison of methods, we utilized RMSE as stated earlier. To do this, we evaluated the models with 5 to 50% of the test data in order to make a good choice based on the results obtained. Fig. 2 shows the RMSE of each model with all 10 iterations. Fig. 2 illustrates the performance of three different algorithms using the dataset in our proposed recommendation method. Fig. 2 illustrates that the maximum RMSE for all iterations is approximately 0.12 obtained in the first iteration, for the rest of the iterations the RMSE values vary between 0.01 and 0.04. The lowest RMSE is the highest performer in terms of recommendations.

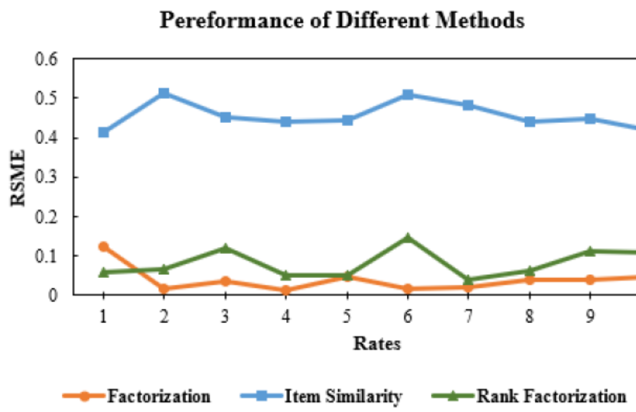

Fig. 2. Performance comparison of different methods

A careful view of Fig. 2 shows that the Factorization algorithm performed the best in terms of our proposed recommendation method. This is followed by rank factorization and finally item similarity. Specifically, the minimum RMSE is around 0.4, the maximum RMSE for all iterations is around 0.55 in the second iteration, after which we see convergence until the 5th iteration and also from the 7th iteration until the end. Furthermore, in the ranking factorization model, the maximum RMSE for all iterations is approximately 0.15 located in the 6th iteration, for the rest of the iterations the RMSE values vary between 0.01 and 0.13. We can therefore substantially conclude that the factorization model is the best model because it has the lowest RMSE compared to the other models since the idea is to minimize the RMSE.

SenAgriPreci Application. Fig. 3 shows the home page of our application which provides the user with an interface to verify details of culture. Fig. 4 shows the detail of each crop and its corresponding varieties. We can see the details of the rice in the Table 5. If the user can have a result of recommendation, he has to connect in the SenAgriPreci Application. After connection, the GPS localises the user's (farmer's) region. Consequently, our proposed recommendation solution recommends crops to all users in our database, but we chose only users 4 and 7 so that we don't have a long list and limit ourselves to the three best crops.

Table 5. Rice information

Variety	Type of crop	Yield	Ground	Humidity	Maturation Cycle
I King Pao	Irrigated	9t/ha	Clay	300mm/month	100days
IR442	Irrigated	8t/ha	Clay	300mm/month	125days
IR8(288-3)	Irrigated	8t/ha	Clay	300mm/month	125days
JAYA	Irrigated	8t/ha	Clay	300mm/month	120days
DJ11-509	Rained	45t/ha	Clay	160 to 300 mm/month	100days
Sahel 108	Irrigated	10t/ha	Clay	300mm/month	100days
Sahel 134	Irrigated	10t/ha	Clay	300mm/month	110days
Sahel 177	Irrigated	10t/ha	Clay	300mm/month	122days
Neurika 1	Rained	45t/ha	Clay	160 to 300 mm/month	95days
Neurika 5	Rained	4t/ha	Clay	160 to 300 mm/month	90days
Neurika 8	Rained	4t/ha	Clay	200 to 300 mm/month	90days

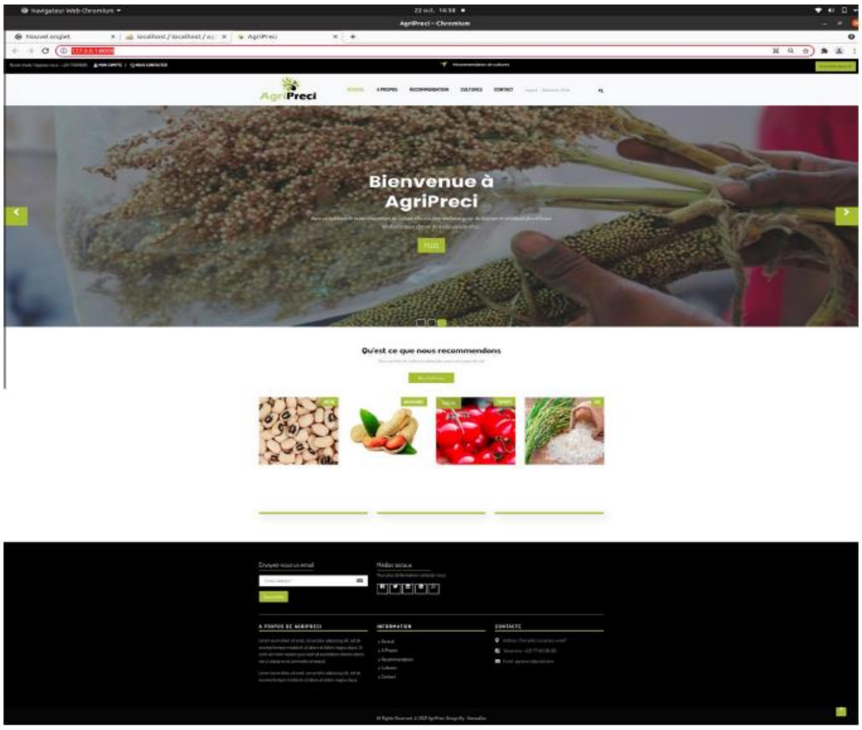

Fig. 3. Homepage of SenAgriPreci

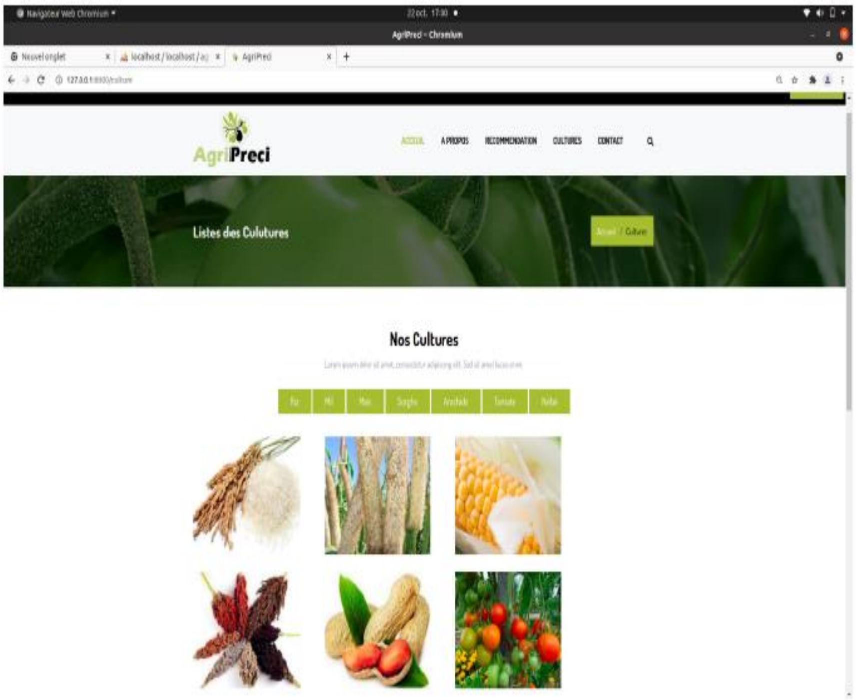

Fig. 4. Variety of crops

5 Concluding Remarks

As a result of the challenges faced by farmers in Senegal such as inappropriate weather conditions, and lack of highly educated farmers in the majority, this paper proposed a crop recommender system focused on precision agriculture using AI and IoT. We also simulated data in order to initially run the implemented algorithms. Our proposed recommender system called *SENAgriPrec* provides good and precise agricultural decisions using various parameters (Example: pH, crop type, soil type, temperature etc.). We conducted benchmarking experiments using datasets, namely: SAED and CRNA. Results of our experiments authenticate that in terms of the RMSE evaluation metric, *SENAgriPrec* performs best in terms of the factorization algorithm in comparison with item similarity and rank factorization. Furthermore, we focused on recommendation models with TuriCreate to add recommendations to an application. As shown in our paper, the TuriCreate toolkit provides a unified interface for training a variety of recommendation models and using them to make recommendations. In future, we will further evaluate *SENAgriPrec* in terms of other evaluation metrics such as precision and recall with other relevant datasets to verify its authenticity.

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