Recommendation of Crop Based on Parameters of Field and Surrounding Environment

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RECOMMENDATION OF CROP BASED ON PARAMETERS OF FIELD AND SURROUNDING ENVIRONMENT

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Abstract: A sizable portion of India's populace views agriculture as their primary employment. The production of crops is crucial to our economy. Inadequate understanding of the growth potential of various crops or choosing the incorrect crops on the incorrect soil are common causes of low-quality crop production. The proposed system uses previously recorded measurements of soil parameters to inform crop recommendations based on machine learning. By using this technique, the chance of soil degradation is decreased and crop health is preserved. Many factors, including precipitation. Temperature, pH, N, P, K, and humidity are investigated using the machine learning algorithm KNN. Recommendations for growing a suitable crop are given based on this analysis.

Keywords- Soil quality, agricultural practices, experimental analysis, K-Nearest Neighbor (KNN) algorithm, and crop recommendation

1. INTRODUCTION

In recent years, agriculture has witnessed a transformative shift towards data-driven decision- making processes aimed at optimizing crop selection and improving agricultural productivity.

Combining cutting-edge technologies with algorithms for machine learning has empowered farmers with valuable insights into factors influencing crop performance, enabling them to make informed choices tailored to specific environmental conditions. Of these algorithms, the K-Nearest Neighbors (KNN) approach is particularly useful and efficient for crop recommendation, leveraging similarities between instances to provide accurate predictions. Traditional crop selection methods often rely on anecdotal knowledge, historical practices, and generalized guidelines, which may not fully capture the complexities of local soil, climate, and environmental dynamics. Because of this, farmers encounter difficulties in determining which crops are best suited for their soil, which can result in yields that are below average, resource waste, and heightened susceptibility to changes in the market and climate. This study's goal is to use the KNN algorithm to develop and implement an advanced crop recommendation system, integrating multidimensional data sources to enhance the accuracy and reliability of recommendations. By leveraging information on soil characteristics, climate patterns, geographical features, and historical crop yields, the system aims to provide farmers with personalized and context aware recommendations tailored to their specific agricultural context.

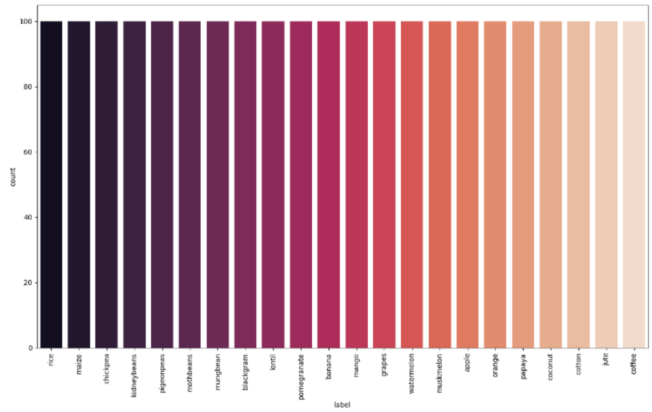


Fig1: Above 21 recommended crops shows the performance of knn model using Count plot.

Additionally, the system will incorporate optimization techniques to fine-tune the KNN parameters and adapt dynamically to changing environmental conditions, ensuring robust performance across diverse agricultural landscapes.

2. LITERATURE SURVEY

Finding the best crops to grow while accounting for a range of factors is the aim of the crop recommendation problem, including soil characteristics, climate, and past crop performance.

Traditional methods rely on empirical knowledge and generalized guidelines, whereas machine learning approaches leverage data-driven techniques to provide more accurate and personalized recommendations.

Regression and classification issues are addressed by KNN, an instance-based, non-parametric learning algorithm. By examining the majority class among its closest neighbors, it ascertains the class of a given data point. In addition to being easy to use and computationally efficient, Regarding the distribution of the underlying data, KNN makes no assumptions. Through this research, we aim to contribute to the advancement of precision agriculture and sustainable food production by empowering farmers with actionable insights derived from data-driven approaches. By utilizing KNN-based algorithms and machine learning.

KNN can handle complex and nonlinear relationships between input variables, making it suitable for diverse agricultural datasets. KNN-based systems can adapt to changing environmental conditions and evolving agricultural practices by retraining the model with updated data. Selection of relevant features and appropriate distance metrics is crucial for the effectiveness of KNN-based crop recommendation systems.

Scalability of KNN can be a concern with large datasets, requiring efficient algorithms or data preprocessing techniques to computational resources.

The theoretical background of the crop recommendation problem highlights the advantages of utilizing the KNN algorithm, including its flexibility, adaptability, Scalability and accuracy, while also acknowledging challenges that need to be addressed for successful implementation.

2.1 Existing System

According to our research, all people use agricultural factors like soil type and nutrients (such as potassium and nitrogen) as well as meteorological factors like sunlight and rainfall. However, the issue lies in the fact that we must collect the data, have a third party make the prediction, and then explain it to the farmer. This requires a lot of work on the part of the farmer, who is also unaware of the science underlying these factors.

2.2 Disadvantages of Existing System

Limited data availability can restrict the system's ability to generate accurate recommendations. Early-stage crop recommendation systems may face challenges related to data quality, including missing values, inaccuracies, and inconsistencies in the collected data. Addressing these concerns requires careful consideration and collaboration with stakeholders to ensure that the system benefits all users and respects their rights and values.

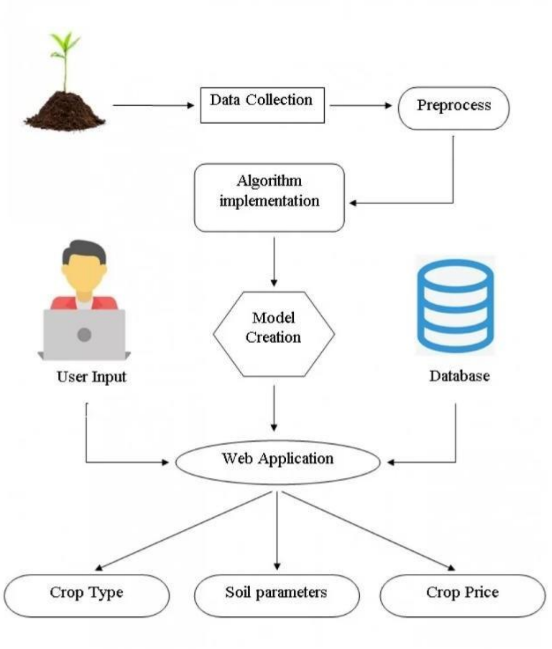


Fig2: Existing system for crop recommendation.

3. PROPOSED WORK

3.1 Proposed System

Our suggested system is an application that calculates the yield of a crop and predicts its name. A crop's name is determined by a number of factors, including temperature, humidity, wind speed, rainfall, and so forth; yield is influenced by production and area. KNN and Random Forest are used for prediction in this project. It will achieve the most accurate crop prediction.

3.2 Advantages of Proposed System

The advantages of using KNN a compelling choice for crop recommendation systems, offering simplicity, flexibility, adaptability, and transparency in generating accurate recommendations for farmers. This flexibility allows it to capture complex patterns in agricultural data without imposing constraints.

With sufficient and relevant training data, KNN can achieve high accuracy, especially in scenarios where the decision boundaries are well-defined and the class distributions are balanced. However, it's important to note that KNN also has limitations, such as computational inefficiency with large datasets and sensitivity to irrelevant features.

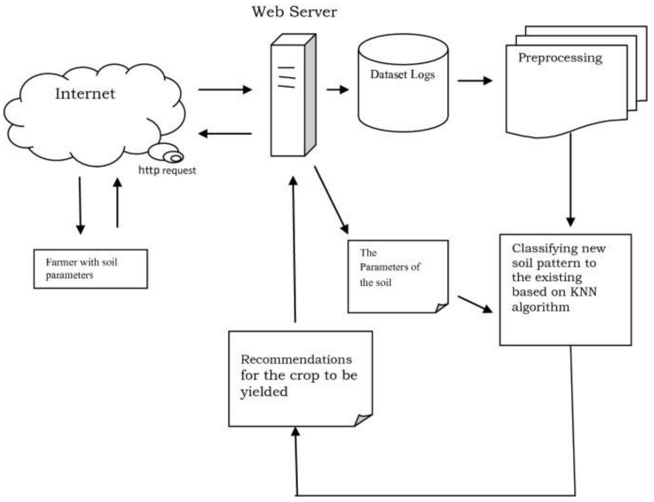


Fig 3: proposed system for Crop recommendation system using knn algorithm

3.3 FEASIBILTY STUDY

Examining the project's feasibility and putting up a business plan with a basic project plan and some cost estimates are the tasks of this phase. System analysis necessitates examining the viability of the proposed system. This is to ensure that the proposed system won't put undue strain on the business. For feasibility analysis to be performed, a fundamental understanding of the system's requirements is required.

The feasibility analysis takes into account four important factors, which are:

1. Possibility from an economic standpoint
2. Practicality in Technology
3. Practicality in Society
4. Practicality of Operation

3.4 POSSIBILITY FROM AN ECONOMIC STANDPOINT

Assessing the system's possible financial impact on the business is the aim of this investigation. Systems research and development can only be funded to a limited extent by the company. Expenses must be rationalized. The majority of the technologies were freely available, and only the customized products needed to be purchased, so the system was developed within the budget allotted.

3.5 PRODUCTION FEASIBILITY

The technical feasibility, or requirements, of the system are to be assessed in this study. It is imperative that any system developed does not overtax the available technical resources. The resulting availability of technical resources will lead to high demand for them. The customer will thus have to adhere to stringent specifications.

It must have reasonable requirements because putting the developed system into use will only require minor or no changes.

3.6 SOCIAL FEASIBILITY

One of the study's goals is to assess the level of system acceptance among users. Here, the user must be instructed on how to properly use the system. Instead of viewing the system as a threat, users must come to see it as necessary. To what degree the users accept the system will depend on how well-informed and comfortable the user is made with it. It will take more confidence for him to provide some constructive criticism, which is appreciated, given that he is the system's final user.

3.7 OPERATIONAL FEASIBILITY

Given that the user has some basic computer and Internet knowledge, the project is operationally feasible. The foundation of Mask Predictor is client-server architecture, in which users are the client and the server is the computer hosting the datasets.

3.8 METHODOLOGY

3.8.1 DATACOLLECTION

Determine the soil's pH, amount of organic matter, nutrients (nitrogen, phosphorus, and potassium), texture, and drainage capabilities. Climate data may be sourced from meteorological stations, weather databases, or remote sensing satellites. Get past information on crop performance, such as yields, growth trends, occurrence of pests and diseases, and harvest dates. Geospatial data can be acquired from satellite imagery, Geographic information systems (GIS) databases, or digital elevation models (DEM). Gather information on farm management practices such as crop rotation, irrigation methods, tillage practices, and pest/weed management strategies. Consider farmers' preferences, constraints, and objectives in crop selection, such as market demand, crop profitability, labor availability, and land tenure arrangements. Evaluate the trained KNN model using the testing dataset to assess its performance in recommending crops. Apply the trained KNN model to new or unseen data instances to generate crop recommendations for specific locations and conditions. Gather feedback from farmers and stakeholders on the usability, relevance, and accuracy of the recommendations to iteratively improve the system.

By following this data collection and methodology framework, researchers can develop a robust and effective KNN algorithm-based crop recommendation system, providing valuable decision support for farmers and enhancing agricultural productivity and sustainability.

3.8.2ALGORITHM & ARCHITECTURE

Regression and classification issues are resolved by the K-Nearest Neighbors (KNN) algorithm through the use of supervised machine learning. Evelyn Fix and Joseph Hodges developed this algorithm in 1951, and Thomas Cover improved it subsequently. The foundations, operation, and applications of the KNN algorithm are examined in this article. KNN is among the most basic yet significant machine learning classification algorithms. It belongs to the supervised learning domain and finds extensive application in pattern recognition, data mining, and intrusion detection. It is widely applicable in real-life scenarios because it is non-parametric, meaning it does not make any underlying assumptions about the distribution of data (unlike other algorithms like GMM, which assume a Gaussian distribution of the given data). We are given some historical data, also known as training data, which classifies and groups coordinates according to a feature.

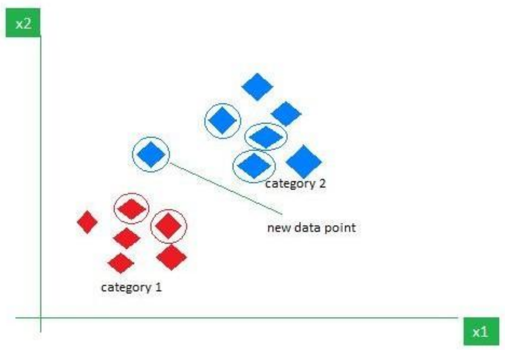


Fig4: Data points divided using KNN

The (K-NN) algorithm is a well-liked and flexible machine learning method due to its simplicity and ease of use. There is no need to make any assumptions about how the underlying data will be distributed. Its ability to handle both numerical and categorical data makes it a flexible choice for a variety of dataset types in classification and regression tasks. This non-parametric method makes predictions based on the degree of similarity between data points in a given dataset. When it comes to outliers, the K-NN algorithm is less vulnerable than other algorithms.

With a given data point, the K-NN algorithm finds the K closest neighbors using a distance metric such as Euclidean distance.

The data point is then found by averaging the K neighbors or by using the majority vote. By doing so, the algorithm is able to adapt to different patterns and predict results by using the local structure of the data.

3.8.3 KNN Algorithm's Use of Distance Metrics

As is well known, the KNN algorithm aids in locating the groups or closest points to a query point. But, to find the nearest points or groups for a given query point, we need a metric. The distance metrics listed below are used by us for this:

The Euclidean Distance

This represents only the cartesian difference between the two points in the plane or hyperplane. Consider Euclidean distance as the length of the straight line that connects the two points in question as an additional visualization.

Manhattan Separation

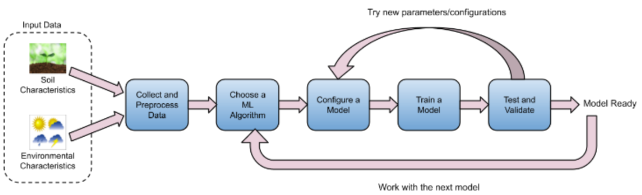
The Manhattan Distance Metric is usually used when we are more concerned with the object's total distance traveled than its displacement. The total of the absolute differences between the point coordinates in n dimensions is required to calculate this metric.

Minkowski Length

In particular, we can say that the Manhattan and Euclidean distances are instances of the Minkowski distance.

3.8.2 The KNN algorithm's operation

Using the K nearest neighbors in the training dataset as a basis, the K-Nearest Neighbors (KNN) algorithm predicts the label or value of a new data point based on the similarity principle.



5. RESULT

Accuracy and Loss

Based on our model by generating the captions of the images, the accuracy of the proposed system achieves 97% which enhances the efficiency of the model in generating captions according to the previous existing models.

Fig 7: AxesSubplot

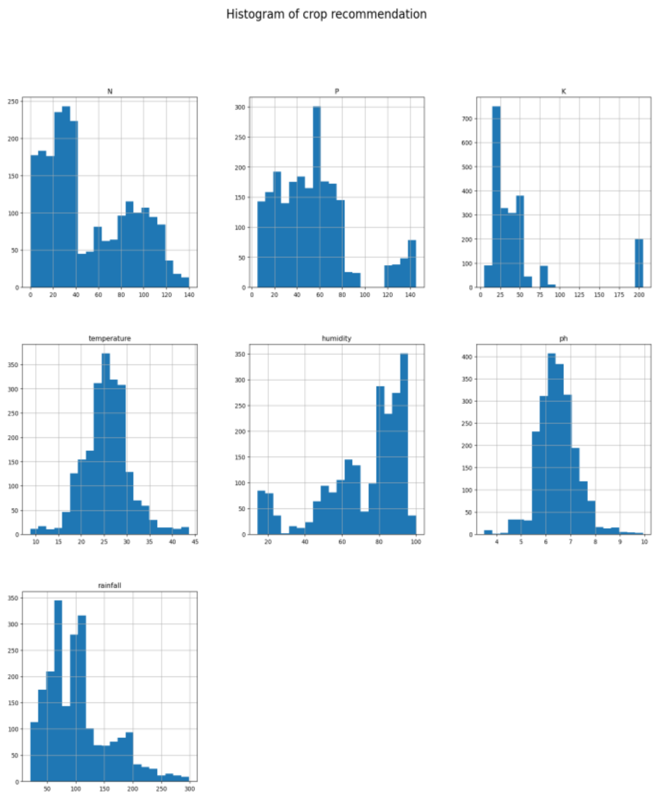


Fig 8: Visualize our data with the help of matplotlib library.

5.1 ACCURACY

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	18
banana	1.00	1.00	1.00	18
blackgram	0.88	0.95	0.91	22
chickpea	1.00	1.00	1.00	23
coconut	0.94	1.00	0.97	15
coffee	1.00	1.00	1.00	17
cotton	1.00	1.00	1.00	16
grapes	1.00	1.00	1.00	18
jute	0.78	1.00	0.88	21
kidneybeans	0.95	1.00	0.98	20
lentil	0.89	0.94	0.91	17
maize	1.00	1.00	1.00	18
mango	0.91	1.00	0.95	21
mothbeans	1.00	0.92	0.96	25
mungbean	1.00	1.00	1.00	17
muskmelon	1.00	1.00	1.00	23
orange	1.00	0.87	0.93	23
papaya	1.00	1.00	1.00	21
pigeonpeas	1.00	0.82	0.90	22
pomegranate	0.92	1.00	0.96	23
rice	1.00	0.76	0.86	25
watermelon	1.00	1.00	1.00	17
accuracy			0.96	440
macro avg	0.97	0.97	0.96	440
weighted avg	0.97	0.96	0.96	440

5.2 Output Screen

```
if predict[0] in crop_dict:
    crop = crop_dict[predict[0]]
    from IPython.core.display import Image, display
    url = crop + ".jpg"
    img = display(Image(url, height=300, width=300, unconfined=True))
    print("{} is a best crop to be cultivated ".format(crop))
else:
    print("Sorry are not able to recommend a proper crop for this environment")
```

[41]

```
Banana is a best crop to be cultivated
```

Fig 9: Final Outcome

6. CONCLUSION AND FUTURE WORK

KNN algorithm-based crop recommendation system coupled with random classifier is an effective tool for providing accurate recommendations to farmers. The KNN algorithm is able to classify crops based on similar characteristics and patterns while the random classifier uses a random selection method to provide diverse recommendations. The combination of these two algorithms helps to reduce bias and increase the accuracy of crop recommendations.

This system can help farmers reduce crop losses and increase their profits. Generally speaking, the crop recommendation system and random classifier powered by the KNN algorithm are useful tools for enhancing farming methods and encouraging sustainable farming. It is essential to continue exploring and refining these algorithms to improve the precision and effectiveness of this system.

In the proposed work, data collected from multiple sources is processed using the KNN algorithm. We intend to use Internet of Things (IOT) devices with temperature and moisture-detecting sensors to collect soil characteristics for our next study. In this manner, crop characteristics can be instantly predicted based on changing crop characteristics, saving us the trouble of transporting sample material to a lab. The crop prediction accuracy of the methodology is improved by substituting eager learning algorithms for KNN, which is a lazy learning algorithm, by adding extra features like electrical conductivity and soil texture.

7. REFERENCES

[1] X. Li et al., “Oscar: Object-Semantics Aligned Pre-training for vision language tasks,” arXiv [cs.CV], 2020.

[2] Kuznetsova, Alina; “Unified image classification, object detection, and visual relationship detection at scale”, 2018.

[3] Caesar, Holger ; “nuScenes: A multimodal dataset for autonomous driving”, 2019.

[4] Cai, Han ;Zhu, Ligeng ;Han, Song; Proxyless NAS: Direct Neural Architecture Search on Target Task and Hardware,2018.

[5] Smith, Leslie N.; A disciplined approach to neural network hyper-parameters: Part 1 -- learning rate, batch size, momentum, and weight decay,2018.

[6]A.Karpathy, Li Fei-Fei; Deep visual-semantic alignments for generating image descriptions,2014.

[7] Polina Kuznetsova, Vicente Ordonez, Collective Generation of Natural Image descriptions,2012.

[8]A.Rohrbach, A. Torabi, M. Rohrbach, N. Tandon, C. Pal,H. Larochelle, A. Courville, and B. Schiele, „„„Movie description,““ Int. J. Comput. Vis., vol. 123, no. 1, pp. 94–120, 2017.

[9] Marcus Rohrbach, Wei Qiu,Translating video content into natural language descriptions,2013.

[10] Michaela Regneri, Marcus Rohrbach , GroundingAction descriptions in videos,2013

[11] Borneel Bikash Phukan, Amiya Ranjan Panda;An Efficient Technique for Image Captioning using Deep Neural Network,2020

[12] A. Karpathy, Li Fei-Fei; Deep visual-semantic alignments for generating image descriptions,2014.

[13]S. G. Shiva prasad Yadav, S. Itagi , B. V. N. V. Krishna Suresh, H. K.L and R. A C, "Human Illegal Activity Recognition Based on Deep Learning Techniques," International Journal on Integrated Circuits and Communication Systems, pp. 01-07, 2023.

[14]Viswanath. V, Ramachandra. A. C, S. B. M, A. Kumari P, V. S. Reddy R and S. Murthy R, "Custom Hardware and Software Integration , Bluetooth Based Wireless Thermal Printer for Restaurant and Hospitals Management," International Conference, pp. 1-5, 2022.

[15] Mohana Priya, Punithavalli and Rajesh Kanna, “Machine Learning Algorithm for Development of Enhanced Support Vector Machine Technique to, Predict Stress,” Journal of Computer Science and Technology, Volume 20, Issue 2, pp12-20, Nov 2020.

[16] Ashwini Kumari. P, Pradeep. Kumar. S, M. K. A, S. B. S, P. B. D and D. K.R, "Recurrent Neural Network based Data-Driven SOC Estimation in Lithium-Ion Battery," International Conference on Distributed Computing and Electrical Circuits and Electronics, pp. 1- 6, 2023.

[17] Akshitha. M, Siddesh. G. M, S. R. M. Sekhar and Parameshachari. B. D,"Paddy Crop Disease Detection using Deep Learning Techniques," International Conference, Mysuru, India, pp. 1-6, 2022

[18] Dwivedi, A. K., & Sharma, A. K. (2021). EE-LEACH: energy enhancement in LEACH using fuzzy logic for homogeneous WSN. Wireless Personal Communications, 120(4), 3035-3055..

[19] Karkee, M., Adhikari, P., Lewis, K. and Zhang, Q., "A Review of Precision Agriculture Technologies for Crop Management", Computers and Electronics in Agriculture, vol. 162, pp. 99-111, 2019.

[20] Srinivasan, A. and Gohari, M., "Precision Agriculture: A Review of Recent Trends and Applications", Proceedings of the 2018 IEEE Global Humanitarian Technology Conference, pp. 1-8, 2018.