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Optimizing Crop Yields By Capitalizing On Computer Vision And Machine Learning

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Abstract: This research focuses on to develop a machine learning application for aiding farmers with crop choice, disease detection, advice translation to local languages, and chatbot assistance using of computer vision and machine learning to optimize crop yields. Traditional farming practices often rely on manual labor and subjective decisions. However, recent advancements in computer vision and machine learning have allowed for the development of intelligent agricultural systems that can aid in crop monitoring, disease detection, and yield prediction. By leveraging data from sensors, drones, and satellites, these systems can analyze plant growth patterns, soil conditions, weather data, and other relevant factors to provide real-time recommendations for optimal crop management. This approach has the potential to revolutionize agriculture by increasing crop yields, reducing waste, and improving the overall sustainability of the industry.

Index Terms-Computer Vision, Machine Learning, Agricultural, Optimization

I. Introduction

Computer vision techniques have the potential to enable computers to interpret visual information. Yield prediction is one of the applications of computer vision technology which enables predictions of crop yield using images. Machine learning algorithms help to recognize patterns in data and learn from it. Research aims to create a machine learning-powered application to help farmers boost productivity and achieve higher crop yields. This application will predict crop yields, detect diseases, and suggest measures to mitigate potential crop damage, along with offering support via a chatbot to address farmers' questions and concerns. However, it will operate under certain limitations, relying solely on publicly available datasets, which may affect prediction accuracy, and excluding mobile application development, potentially limiting user accessibility. Accurate predictions will depend on the availability and reliability of regional data. Despite these constraints, the application has significant potential to revolutionize the agricultural industry by enhancing yields and reducing waste, ultimately benefiting farmers and contributing to more efficient and sustainable farming practices.

II. Literature survey

S. P. Raja et.al [1] used polish crop data and observer that Crop prediction in agriculture is affected by environmental factors. Machine learning techniques can predict crop yield but require efficient feature selection. Ensemble techniques offer better accuracy than current classification methods. Y. Ma and Z. Zhang,[2] perform analysis on Corn crop dataset available in the US. BDANN utilizes Bayesian domain adversarial neural network for unsupervised domain adaptation in predicting county-level corn yield, exhibiting superior efficacy over current state of-the-art techniques. Observation says, Machine learning and satellite remote sensing can predict corn yield, but representative ground truth labels are limited. BDANN offers superior effectiveness .S. M. M. et al. [3] US soybean database used. Two proposed models outperformed recent techniques using MODIS data on county-level soybean yield in the USA.It has been observed that using machine learning methods led to improved predictions of crop yields. Two suggested models demonstrated superior performance compared to recent techniques, when using MODIS data to predict county level soybean yields in the United States.N. Hussain et.al [4], The study examines machine learning for crop yield prediction. It analyzes 37 research articles and identifies the most common algorithms used are (RF, SVM, CNN) Y. Zhao et al.[5] Images of healthy and unhealthy plant leaves as seed are used in this study. DoubleGAN was used, comprising WGAN and SRGAN, to generate high- resolution images of unhealthy plant leaves and balance the unbalanced dataset. Using DoubleGAN resulted in clearer images than DCGAN, improving the accuracy of plant disease recognition to 99.80 and 99.53 percent, respectively.S. C. K. et al.[6] Real life images from a Cardamom plantation in Chinnahalli, India, from April to June 2021 are used for this study. Input images were cleared of unwanted background information. For this purpose, U2-Net was utilized. Model performance was compared with EfficientNet and CNN. 98.26% accuracy was achieved by the presented model on detection.V. K. Vishnoi et.al [7] study public dataset called PlantVillage. A CNN model with a smaller number of layers is used to reduce the computational burden. Augmentation techniques such as shift, shear, scaling, zoom, and flipping were used to generate more samples. The proposed model achieves 98% classification accuracy and needs less resources compared to existing models. It is highly suitable for deployment in handheld devices.H. Amin et.al[8] A subset of a public dataset called PlantVillage are used. The research proposes a deep learning model using two pretrained CNNs to extract features from corn plant images. An attempt was made to increase the size of the dataset and the variety of the images by applying data augmentation techniques. The proposed model achieved a classification accuracy of 98.56%, which outperformed ResNet152 and InceptionV3 models in terms of classification accuracy.M. H. Saleem et.al[9] NZDL Plant Disease-v1 dataset (New Zealand crops). A comprehensive deep learning-based optimization approach has been proposed. DL architectures were compared, and modification was done on the best performing model. The presented methodology has successfully solved three identified agricultural problems. An improved mAP of 93.80% is achieved, which was 19.33% better than the default setting. Y.S.Lim et.al[10] Nine widely used machine translation benchmark sets. A novel machine translation model with a new non- autoregressive decoder named Iterative and Length-Adjustive NonAutoregressive Decoder (ILAND). The experimental results on nine benchmark translation data sets showed that the proposed NAT model generates better translations at a faster speed.K.Mrinalini et.al[11] used WMT2020 dataset. In this work, SBSim - a new and individual sentence-BERT based similarity metric - has been proposed. Here, output evaluation is carried out by leveraging a paraphrase BERT model and sentence level embedding. SBSim scores show a high correlation of 0.9123 and 0.9052 in evaluation of English-Tamil and English Hindi MT systems.

L.Li,S. et.al[12] introduces foundational knowledge related to deep learning and builds on it by presenting an exhaustive review of the recent developments in plant leaf disease detection, done using deep learning. Using training data, deep learning techniques achieve a high accuracy for detection of plant diseases, averaging in the range of 90% - 95%.

III. PROPOSED SYSTEM DESIGN

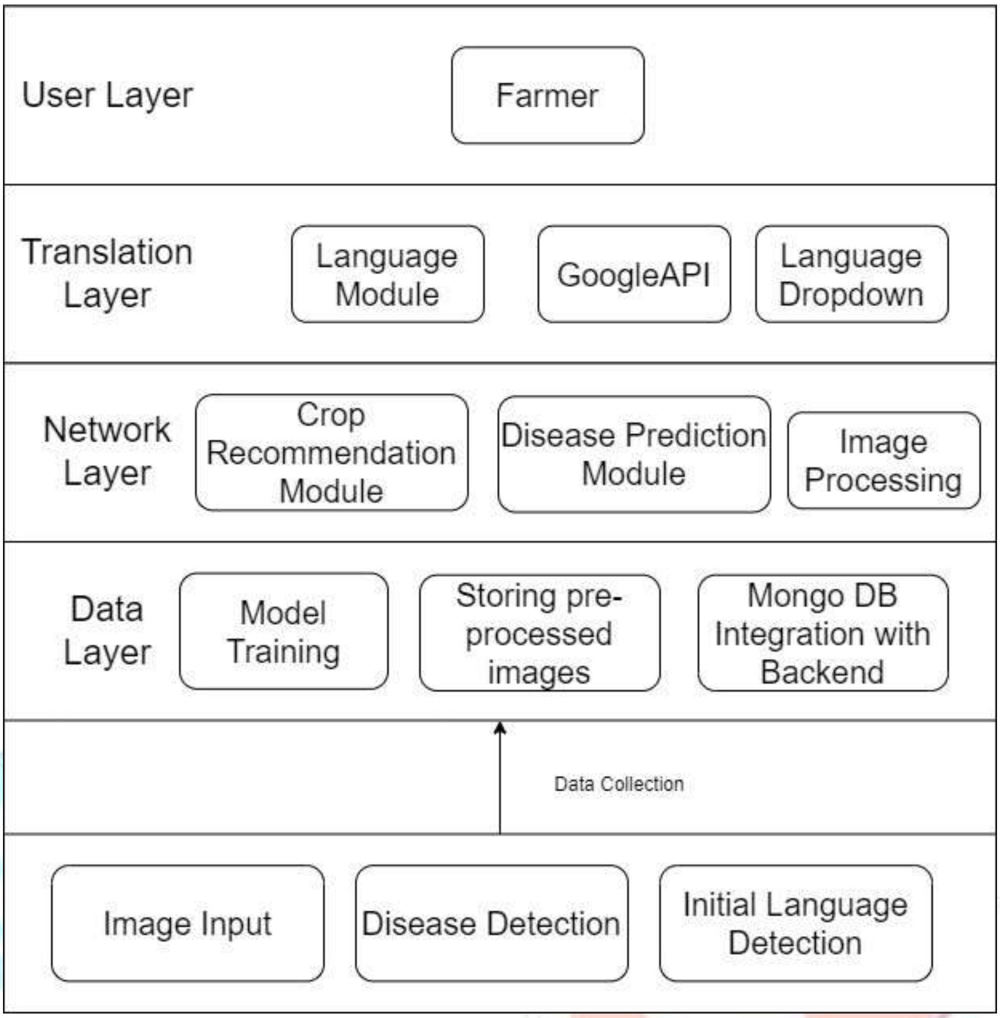

Fig 1: Architecture Diagram

As shown in fig1.collected data is given to data Layer where Model training, storing preprocessed images and Mango DB integration with Backend is done, Network Layer focus on the Crop Recommendation Module, disease Prediction and Image processing. Users can interact with the system by User Interface.

III a. The Crop Recommendation Model

In this module, we use machine learning to recommend the ideal crop to the farmer which should be sown in the coming few months. We consider the environmental context in which the crops would be grown, such as temperature, rainfall, pH level, humidity, and the N:P:K ratio of the soil.

III b. Disease Detection Algorithm

In this module, we use deep learning to predict whether a given plant grown by the farmer is infected by a disease or not. The farmer can simply upload a picture of the plant’s leaf to the system which will then display the results to the farmer. To facilitate this, we will train a deep learning model on approximately 70,000 images, containing different plants and diseases.

- Model Architecture

The deep learning model we used to predict plant diseases was a CNN (convolutional neural networks) model that had a number

of layers, with the overall architecture as shown below. Overall, there are over 65,00,000 parameters in the model.

Table 1: Model Architecture

Sr. No.	Layer Type	Output Shape	Param Count
1	Conv2d	[−1, 64, 256, 256]	1,792
2	BatchNorm2d	[−1, 64, 256, 256]	128
3	ReLU	[−1, 64, 256, 256]	0
4	Conv2d	[−1, 128, 256, 256]	73,856
5	BatchNorm2d	[−1, 128, 256, 256]	256
6	ReLU	[−1, 128, 256, 256]	0
7	MaxPool2d	[−1, 128, 64, 64]	0
8	Conv2d	[−1, 128, 64, 64]	147,584
9	BatchNorm2d	[−1, 128, 64, 64]	256
10	ReLU	[−1, 128, 64, 64]	0
11	Conv2d	[−1, 128, 64, 64]	147,584
12	BatchNorm2d	[−1, 128, 64, 64]	256
13	ReLU	[−1, 128, 64, 64]	0
14	Conv2d	[−1, 256, 64, 64]	295,168
15	BatchNorm2d	[−1, 256, 64, 64]	512
16	ReLU	[−1, 256, 64, 64]	0
17	MaxPool2d	[−1, 256, 16, 16]	0
18	Conv2d	[−1, 512, 16, 16]	1,180,160
19	BatchNorm2d	[−1, 512, 16, 16]	1,024
20	ReLU	[−1, 512, 16, 16]	0
21	MaxPool2d	[−1, 512, 4, 4]	0
22	Conv2d	[−1, 512, 4, 4]	2,359,808
23	BatchNorm2d	[−1, 512, 4, 4]	1,024
24	ReLU	[−1, 512, 4, 4]	0
25	Conv2d	[−1, 512, 4, 4]	2,359,808
26	BatchNorm2d	[−1, 512, 4, 4]	1,024
27	ReLU	[−1, 512, 4, 4]	0
28	MaxPool2d	[−1, 512, 1, 1]	0
29	Flatten	[−1, 512]	0
30	Linear	[−1, 38]	19,494

Total params	6,589,734
Trainable params	6,589,734
Non-trainable params	0

IV. IMPLEMENTATION

We have implemented a website with the frontend in ReactJS. React is a popular, robust framework which suits perfectly for this project. There are two backend servers, one is running on NodeJS and the other on Flask. Our machine learning model is being run on Flask. We're using MongoDB as our primary database. We've imported all 47000 images for training our disease prediction model and around 5000 records for crop recommendation.

Here are some screenshots of our website and its features:

Fig.3. Home Page

Fig.4. Crop Recommendation inputs

Fig.5. Crop Recommendation

Fig.6. Image input for Disease Prediction

Fig.7. Predicted Disease Consultation

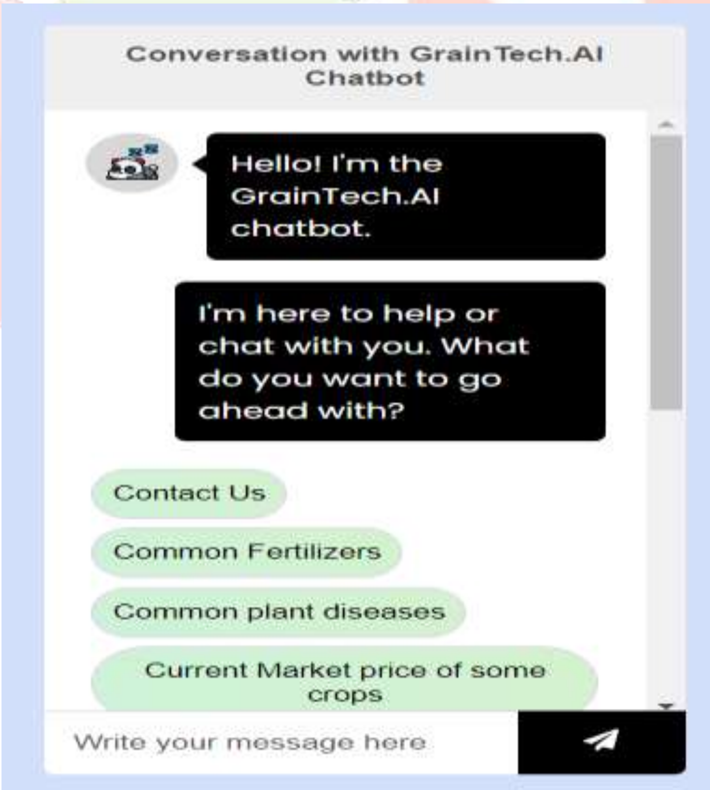

Fig.8. Chatbot

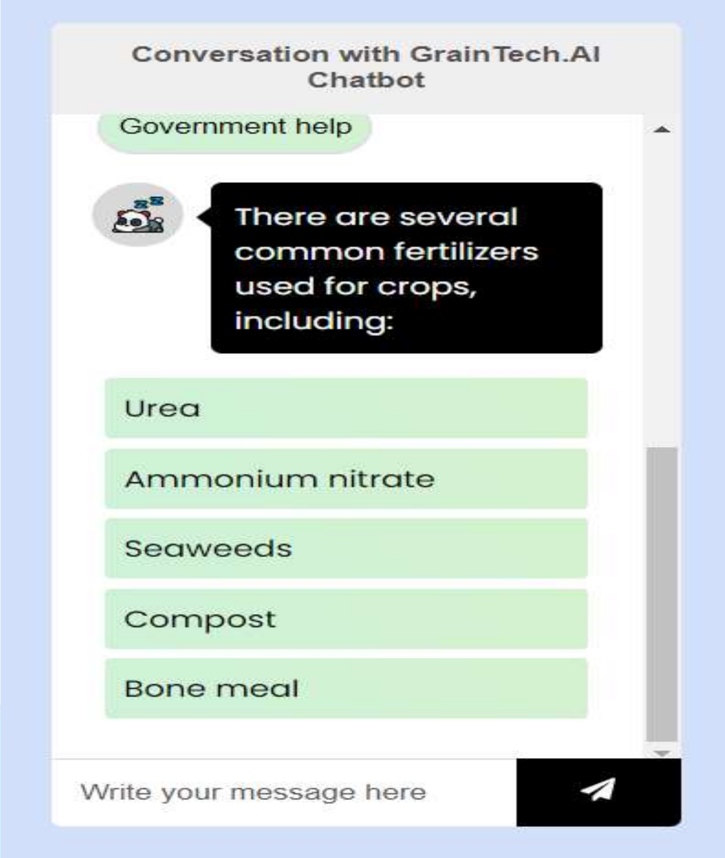

Fig.9. List of Common Fertilizers by ChatBot

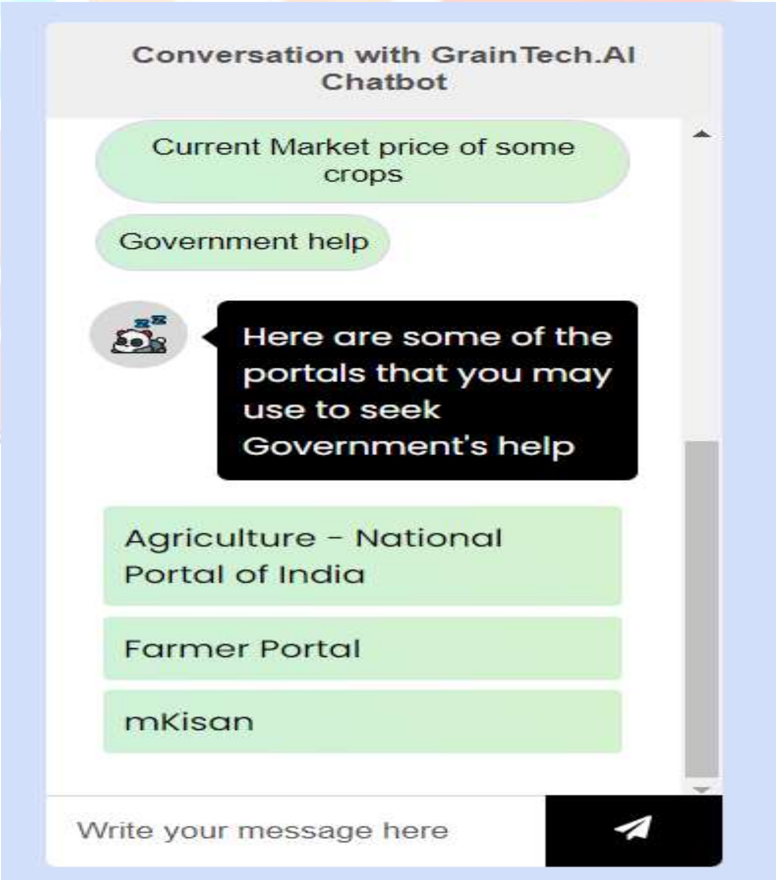

Fig.10. List of Government help by ChatBot

These screenshots have hopefully provided you with a good understanding of the flow of our website.

V. RESULT AND ANALYSIS

Following is a screenshot of the machine learning algorithms that we used for our crop recommendation model along with their accuracy scores. Here, the training time is in milliseconds (ms).

	Accuracy	Training Time	Model Factor
Decision Tree Classifier	90.0%	0.032143	2799.956683
Gaussian Naive Bayes	99.09%	0.006486	15277.24302
Support Vector Machine	97.95%	0.019933	4914.193431
Logistic Regression	95.23%	0.190395	500.156693
Random Forest Classifier	99.09%	0.104253	950.488823
XGBoost Classifier	99.32%	0.752232	132.031346

Fig.11. Comparative study of ML algorithms

The above fig.11 describes six separate machine learning models that can be used to predict the recommendation of the crop to be grown at a given location with its environmental characteristics like rainfall, temperature, humidity, and soil characteristics, like the pH level and the N:P:K ratio (i.e the ratio of the Nitrogen, Phosphorous and Potassium content in the soil). We have introduced a separate attribute called ”model factor”, which evaluates how ”good” a model is by considering both accuracy and training time:

Model Factor = Accuracy/ Training Time

here, the unit for the model factor is: ms-1

- Translated Consultation
  Following fig.12 shows the translated consultation text in Marathi language.

Fig.12. Translation Consultation in Marathi

VI. CONCLUSION

This research aims to optimize crop yields by utilizing advanced technologies to support farmers in a comprehensive manner. By analyzing key inputs such as soil parameters, precipitation, pH and humidity, our system intelligently recommends the best crops to grow or sow in a given area. This enables farmers to make informed decisions to maximize their chances of harvest success and improve overall agricultural productivity. Additionally, our project goes beyond crop selection by incorporating advanced image recognition algorithms. By analyzing leaf pictures, our system can pinpoint potential diseases affecting plants. By detecting diseases early, farmers can take proactive measures to minimize their impact or eradicate them completely. Our system provides detailed advice and guidance on the preventive measures farmers should take to reduce the impact of disease and protect their crops. This not only improves plant health, but also reduces the economic losses associated with plant diseases. To improve accessibility and usability, our research also offers language translation options. We currently support local languages such as Marathi, so farmers who prefer to communicate in their native language can take full advantage of the system’s advice and recommendations. In the future, we plan to add more languages to our language options so that farmers in different regions can access the system in their preferred language.

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