RECOMMENDER SYSTEMS

KISHAN MITRA

INTEGRATED AI PLATFORM FOR PESTICIDE, FERTILIZER AND CROP RECOMMENDATION

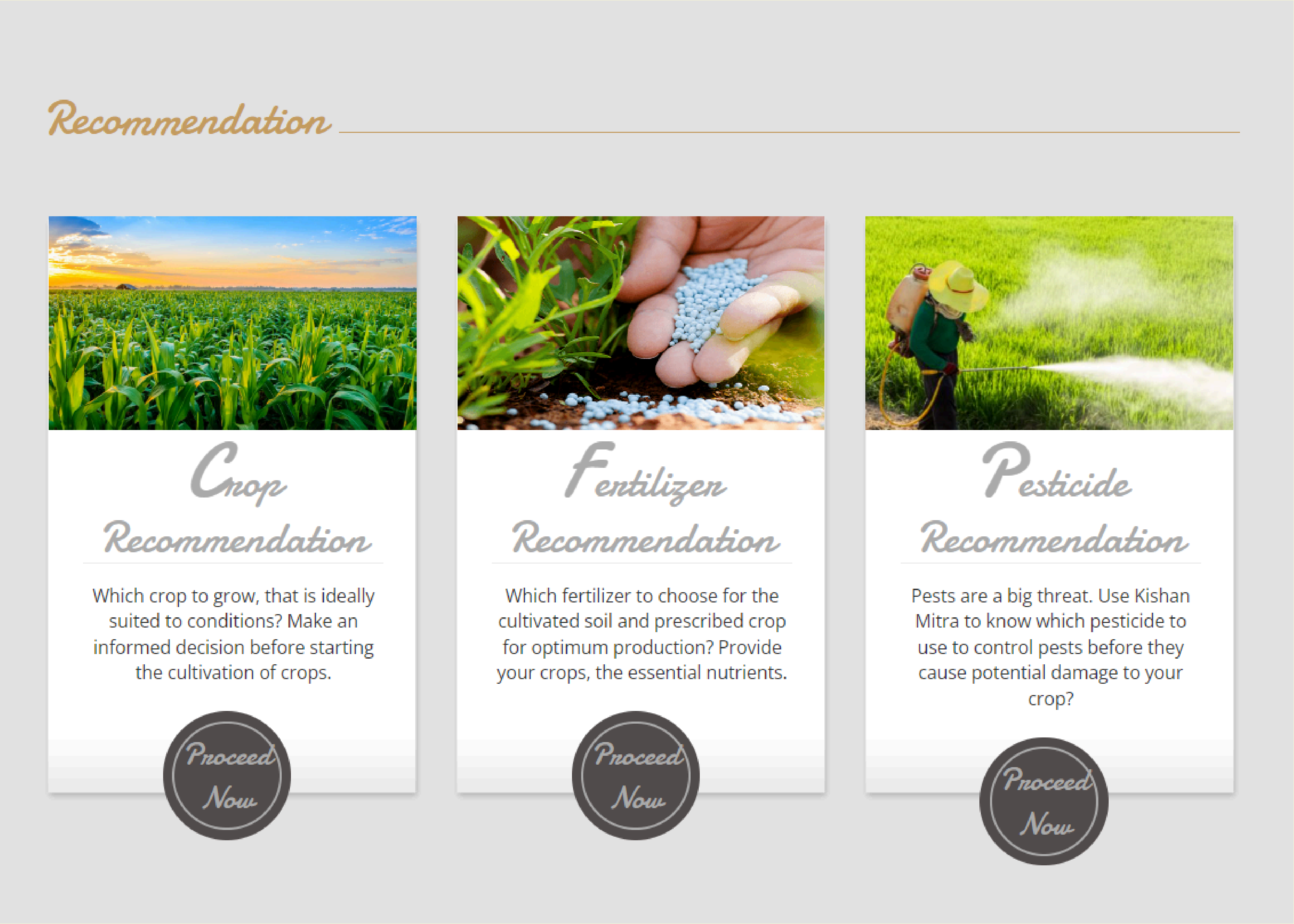
Group Members

Atul R Patel
Shashank Pandey
Gaurav Sharan
Pratyansh Soni

Table of content

Our Website


Kishan Mitra
HOME
CROP
PESTICIDE
FERTILIZER
Welcome To
KISHAN MITRA
Farm = AI + Crop + Fertilizer + Pesticide. We take of your soil's health. We at Kishan Mitra, honor the Indian Farmer's love, hard work and character. They help to feed a nation whose population is nearly 1.4 billion. However their productivity is threatened by some natural factors that can ruin their crops and their livelihoods. Kishan Mitra is a small initiative enhancing agriculture, make smart decisions to consider the demographics of your field, the factors affecting your crop, as well as how to keep them healthy for a super awesome yield.


Recommendation
Crop Recommendation
Which crop to grow, that is ideally suited to conditions? Make an informed decision before starting the cultivation of crops.
Proceed Now
Fertilizer Recommendation
Which fertilizer to choose for the cultivated soil and prescribed crop for optimum production? Provide your crops, the essential nutrients.
Proceed Now
Pesticide Recommendation
Pests are a big threat. Use Kishan Mitra to know which pesticide to use to control pests before they cause potential damage to your crop?
Proceed Now

Abstract

This project report, titled "Recommendation System for Crop, Fertilizer, and Pesticide," introduces "Kishan Mitra," a web-based platform designed to support Indian farmers by providing accurate recommendations for crops, fertilizers, and pesticides based on site-specific parameters. The platform consists of three main modules: Crop Recommendation, Fertilizer Recommendation, and Pesticide Recommendation. The Crop Recommendation module uses an ensemble machine learning model with a majority voting technique to suggest the best crops based on parameters like nitrogen, phosphorus, potassium, temperature, rainfall, relative humidity, and pH levels. The Fertilizer Recommendation module recommends appropriate fertilizers, including organic options, based on N, P, K values and crop type to prevent soil degradation and promote sustainable farming. The Pesticide Recommendation module employs MobileNet to identify pests from images and suggest corresponding pesticides, ensuring effective pest control. By integrating these functionalities into a single platform, Kishan Mitra aims to enhance agricultural productivity, support informed decision-making, and ultimately improve the livelihood of farmers.

Introduction

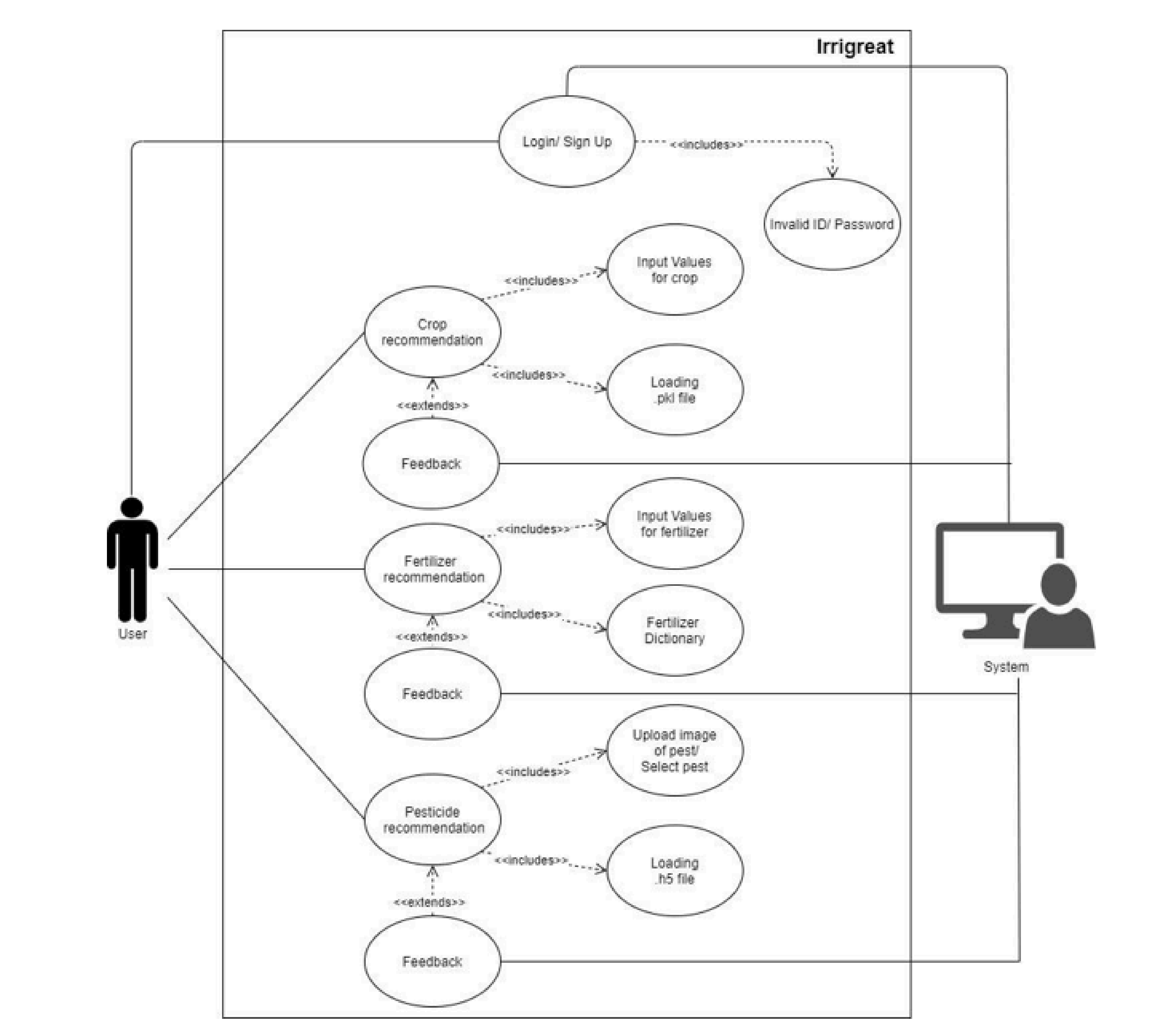
Definition & history

“Kishan Mitra” defines in its slogan, Farm = AI + Crop + Fertilizer + Pesticide, taking care of soil’s health.Kishan Mitra honors the Indianfarmer’s love, hard work and character. Farmershelp to feed a nation whose population is nearly 1.4 billion, however the productivity of farms is threatened by various naturalfactors that ruin the crops and farmer’slivelihood. Kishan Mitra is a small initiative enhancing agriculture, makingsmart decisions to consider the demographics of the field, the factors affecting the crop, as well as how to keep the farm healthy for a super awesome yield. This will be implemented in the form of a website providingfeatures of Crop Recommendation, Fertilizer Recommendation and PesticideRecommendation based on site specific parameters.

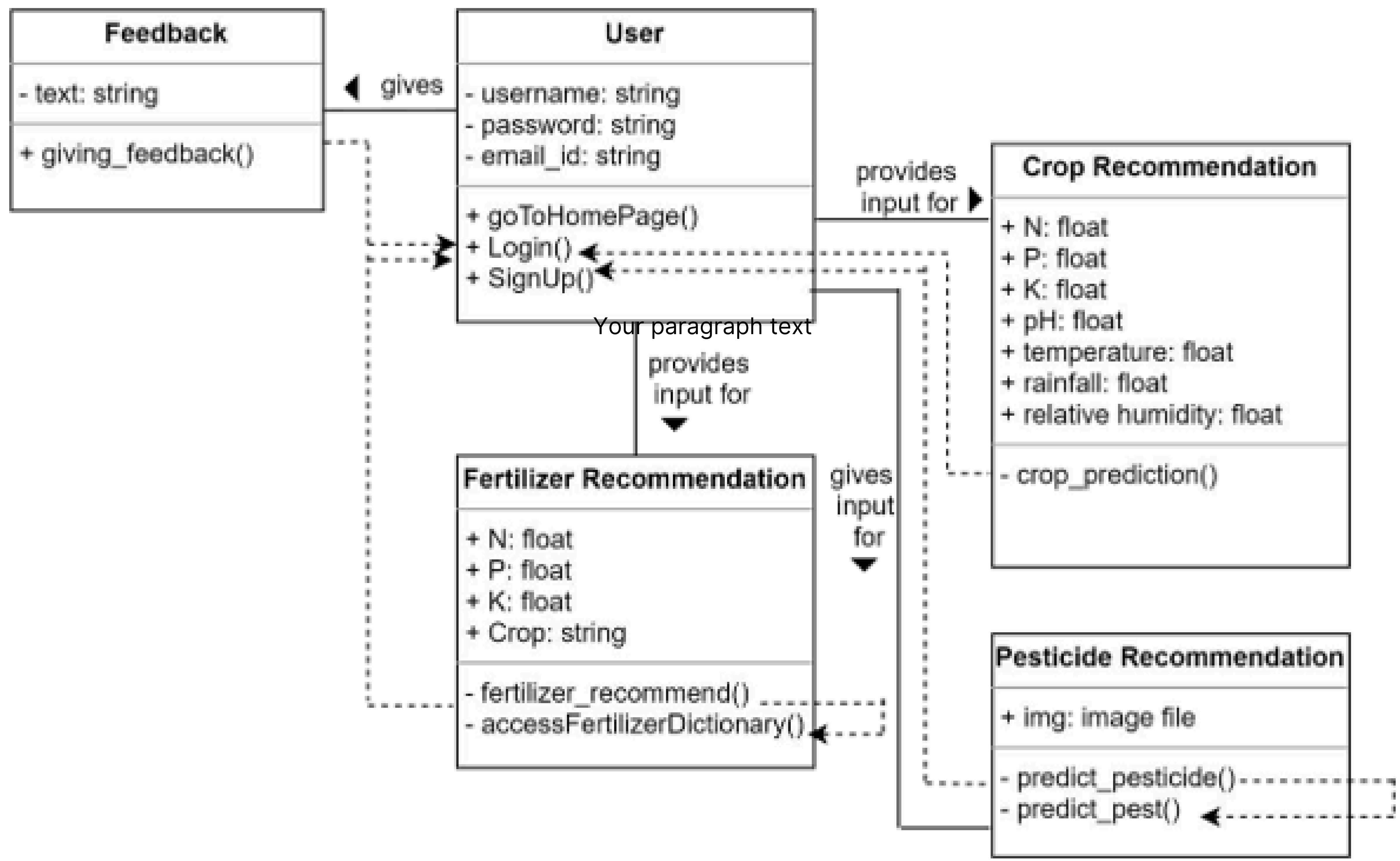
“Kishan Mitra” defines in its slogan, Farm = AI + Crop + Fertilizer + Pesticide, taking care of soil’s health.Kishan Mitra honors the Indianfarmer’s love, hard work and character. Farmershelp to feed a nation whose population is nearly 1.4 billion, however the productivity of farms is threatened by various naturalfactors that ruin the crops and farmer’slivelihood. Kishan Mitra is a small initiative enhancing agriculture, makingsmart decisions to consider the demographics of the field, the factors affecting the crop, as well as how to keep the farm healthy for a super awesome yield. This will be implemented in the form of a website providingfeatures of Crop Recommendation, Fertilizer Recommendation and PesticideRecommendation based on site specific parameters.

USE CASE DIAGRAM

System Architecture



CLASS DIAGRAM



Literature Survey

Title	Description	Method	Results	Limitations
Automatic classification for field crop insects via multiple-task sparse representation and multiple-kernel learning **Chengjun Xie b,1, Jie Zhang b,⇑, Rui Li b, Jinyan Li c, Peilin Hong b, Junfeng Xia a,⇑, Peng Chen a,⇑**	Paper introduces novel insect image classification method using sparse representation. Utilizes multiple-task sparse representation and multiple-kernel learning for classification accuracy.	Feature-level fusion based on joint sparse coding. [1] Multiple-kernel classifier using sparse-coding histograms for insect classification. [1]	Proposed method outperformed state-of-the-art insect classification techniques. [1] Achieved higher categorization rates by combining color, shape, and texture. [1] Performance not sensitive to kernel type in insect classification. [1]	Variability within species affects classification due to color, texture differences. [1] Color histogram lacks spatial information, sensitive to noise in classification. [1]
Pose estimation-dependent identification method for field moth images using deep learning architecture **Chenglu Wen a, Daoxi Wu a, Huosheng Hu b, Wei Pan a,***	Paper focuses on moth identification using deep learning architecture. Addresses challenges in identifying field moth species accurately.	Pose estimation, moth segmentation, feature extraction, deep learning architecture. [1] Evaluation criteria, precision, recall, F-measure, IpSDAE model, SVM, RF. [2] SSIM index, performance comparisons, supervised learning methods, IpSDAE architecture. [3]	Pose estimation-dependent method achieved 96.9% moth identification accuracy. [1] Segmentation method handled background cluttering, grid lines, and complete object extraction. [2] Pose estimation applied to achieve two estimated classes for each species. [3]	Traditional methods lack feature extraction and misidentify due to pose variety.[1] Emphasis not on pose estimation accuracy but on moth identification.[2]
Transformative Role of Artificial Intelligence in Advancing Sustainable Tomato (Solanum lycopersicum) Disease Management for Global Food Security: **A Comprehensive Review** **Bharathwaaj Sundararaman 1,†, Siddhant Jagdev 2,† and Narendra Khatri 3**	AI enhances tomato disease detection for improved crop yields and security. ML and DL models classify tomato leaf diseases accurately and efficiently.	Review of ML and DL techniques for tomato leaf disease classification. [1] Evaluation of CNN models for disease classification. [1]	Evaluation of ML and DL models for tomato leaf disease classification. [1] Highlighted features and techniques in data acquisition and model evaluation. [1] Proposed new research directions in AI-assisted tomato leaf disease classification. [1]	Challenges include symptom similarity, growth phase changes, and external noise. [1] ML and DL models enhance disease classification accuracy. [1] Difficulty in distinguishing diseases with similar symptoms. [1]

Literature Survey

A smart-vision algorithm for counting whiteflies and thrips on sticky traps using two-dimensional Fourier transform spectrum **Yurui Sun a,1, Hong Cheng a,b,1, Qiang Cheng a,*, Haiyang Zhou a, Menghua Li a, Youheng Fan a, Guilin Shan a, Lutz Damerow c, Peter Schulze Lammers c, Scott B. Jones d**	Novel 2DFT algorithm for pest counting on sticky traps accurately. Compares human counting with 2DFT, proving efficiency and accuracy.	2DFT spectrum for pest counting on sticky traps. [1] Image processing with Matlab for spectral data processing. [2]	2DFT-based index provides accurate pest estimates on traps. [1] High correlations in counting whiteflies and thrips on sticky traps. [2] Excellent R2 value between 2DFT-algorithm and human-vision counts. [3] Proposed algorithm is reliable and accurate for pest counting. [4]	Limitations include species segmentation challenges with close colors.[1] Human counting errors may increase with time due to limitations.[1]
A sensing approach for automated and real-time pesticide detection in the scope of smart-farming **T Evangelos Skotadisa,*, Aris Kanarisa, Evangelos Aslanidisa, Panagiotis Michalisb, Nikos Kalatzisb, Fotis Chatzipapadopoulosb, Nikos Marianosb, Dimitris Tsoukalasa**	Evaluation of gas-sensing array for smart farming with pesticide detection. [1] Sensors coated with 4 polymers differentiate between Chloract and humidity. [2]	Hybrid chemical sensors with metallic nanoparticles and polymer films. [1] Employed Platinum NPs and polymeric films for gas sensing. [1] Used PCA for statistical analysis of sensor response patterns. [2]	Sensors detected Chloract and Relative Humidity with distinct responses.[1] Principal Component Analysis separated and quantified Chloract and Relative Humidity.[1] Low limit of detection for chlorpyrifos was 73.95 ppb.[1]	No limitations were explicitly mentioned in the provided contexts.
An Innovative Smart and Sustainable Low-Cost Irrigation System for Anomaly Detection Using Deep Learning **Rabaie Benameur 1 , Amine Dahane 1,2,* , Bouabdellah Kechar 1 and Abou El Hassan Benyamina 3**	Low-cost fog-IoT/AI system for smallholder farmers enhances irrigation efficiency. Uses AI to detect anomalies in soil moisture, air temperature, and humidity.	Autoencoder and GAN for anomaly detection. [1] Deep learning prediction models for anomaly correction. [1] Generator, Discriminator, and Autoencoder neural networks implemented. [2]	Autoencoders outperformed GANs with 97.60% accuracy and F1 score. [1] GANs detected anomalies in sensor behavior with high accuracy. [1] Autoencoders showed high precision in anomaly detection compared to GANs. [1] Models were optimized using TensorFlow Lite for IoT deployment. [1]	Lack of agricultural expertise, financial resources, climate change, and market access[1] High cost, implementation complexity, and malfunctioning sensors deter adoption[2]
Effectiveness of artificial intelligence integration in design-based learning on design thinking mindset, creative and reflective thinking skills: An experimental study **Mustafa Saritepeci1 · Hatice Yildiz Durak1**	AI collaboration enhances reflective thinking in educational design-based learning processes. DST processes support reflective thinking skills in various learning areas.	Quasi-experimental method study with pretest-posttest control group.[1] Participants randomly assigned to AI integration intervention at departmental level.[1]	Creative self-efficacy and reflection development improved in both groups [1] Design thinking mindset levels did not significantly differ between groups [1] AI contributes to students' creativity in learning and teaching processes [2]	Lack of significant difference in design thinking mindset levels post-intervention. [1] No experimental interventions in literature examining AI integration effects. [1]

Literature Survey

Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making **Mahmoud Y. Shams1 • Samah A. Gamel2 • Fatma M. Talaat1,3,4**	XAI-CROP system benefits farmers, managers, and researchers in agriculture. [1] No conflicts of interest reported in the study. [2]	XAI-CROP algorithm compared with Gradient Boosting, Decision Tree, Random Forest.[1] Evaluation metrics: MSE, MAE, R-squared used for performance assessment.[1]	XAI-CROP outperformed other models in predicting crop yield accurately.[1] XAI-CROP provided interpretable explanations for its predictions.[1]	Limited transparency in current crop recommendation systems.[1]
Use of Data Mining in Crop Yield Prediction **Shruti Mishra Priyanka Paygude Snehal Chaudhary Sonali Idate**	Paper focuses on crop yield prediction using Data Mining techniques. Various classifiers like J48, LWL, LAD Tree, IBK are compared.	J48, LAD Tree, LWL, IBK classifiers used for crop yield prediction.[1] Data mining techniques like ensemble model, K-means clustering, SVM utilized.[2]	Comparison of classifiers based on RMSE, MAE, RAE, and accuracy.[1] [2] Performance evaluation of J48, LWL, LAD Tree, and IBK classifiers.[1] [2]	Trivial methods affect crop yield due to various factors. [1] Data mining techniques may not eliminate all unsatisfactory yields. [2]
Sustainable Crop Protection via Robotics and Artificial Intelligence Solutions **Vasiliki Balaska 1,* , Zoe Adamidou 2, Zisis Vryzas 2 and Antonios Gasteratos 1**	Agriculture 5.0 integrates robotics, AI, and digital technologies for sustainability. [1] Robotic systems address agricultural threats through AI and smart solutions. [1] Data collection, monitoring, and user interface modules enhance agricultural practices. [2] Decision support system for low-risk pesticide selection in agriculture. [3]	Integration of robotics and AI for crop protection strategies. [1] AI monitoring for real-time crop protection adjustments. [2]	Robotics and AI enhance crop protection with precision, efficiency, and cost-effectiveness.[1] Future research areas include advanced sensors, improved algorithms, and automated treatments.[1] Collaboration needed for sustainable agriculture practices integrating technology with legislation.[1] Addressing data privacy concerns essential for transforming agriculture with technology.[1]	Challenges include climate change, invasive pests, diseases, and costs.[1] Limited number of active ingredients escalates resistance potential.[1] Biopesticides' efficacy depends on uncontrollable factors.[1]
Crop and Fertilizer Recommendation System using Machine Learning **Palaniraj A1, Balamurugan A S2, Durga Prasad R3,Pradeep P4**	Data mining for crop yield analysis in India using machine learning. Predicts crop yield accurately based on soil and atmospheric parameters.	Line regression, ANN, and KNN for classification [1] Hybrid approach with K-means clustering and modified KNN [1]	SVM accuracy over 90.01 with mean AUC 0.934 and F1 score 0.903.[1]	Missing data affects prediction accuracy. [1] Limited to specific crop types and regions. [2]
Automatic moth detection from trap images for pest management **Weiguang Ding, Graham Taylor**	Paper focuses on pest detection using convolutional neural networks. Utilizes image processing for moth detection in agricultural settings.	Deep learning for pest detection without pest-specific engineering. [1] Evaluation metric based on pedestrian detection literature. [2]	Automatic moth detection method shows promising performance qualitatively and quantitatively. [1] Approach adapts to various species and environments with minimal human effort. [1] Capable of real-time deployment due to implementation on parallel hardware. [1]	Limited discussion on environmental factors affecting pest detection accuracy. [1] No detailed comparison with other existing pest detection methodologies. [2]

Literature Survey

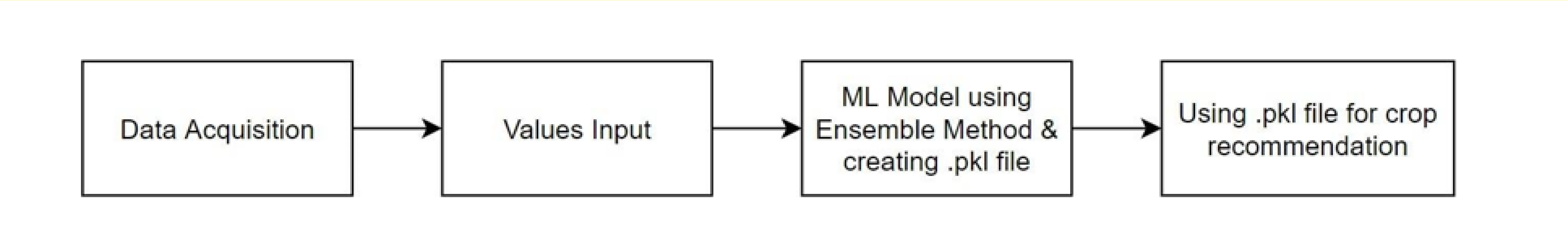
Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques **Muhammad E. H. Chowdhury 1,* , Tawsifur Rahman 1 , Amith Khandakar 1 , Mohamed Arselene Ayari 2,*, Aftab Ullah Khan 3 , Muhammad Salman Khan 3,4, Nasser Al-Emadi 1, Mamun Bin Ibne Reaz 5, Mohammad Tariqul Islam 5 and Sawal Hamid Md Ali 5**	Deep learning classifies tomato diseases using EfficientNet on segmented leaf images. U-net and Modified U-net models for leaf segmentation. Achieved high accuracy in binary, six-class, and ten-class classification.	Utilized EfficientNet for classification with segmented tomato leaf images. [1] Employed U-net and Modified U-net for leaf segmentation. [1]	EfficientNet-B7 excelled in binary and six-class classification.[1] Modified U-net achieved high accuracy for leaf image segmentation.[1] EfficientNet-B4 performed best in ten-class classification.[1]	Manual plant disease monitoring is laborious and error-prone.[1] No specific limitations mentioned in the provided contexts.
A Software Model for Precision Agriculture for Small and Marginal Farmers **Satish Babu**	Precision Agriculture model for small farmers in Developing Countries. Empowers farmers with crop-level advisories for profitability and sustainability.	Software model for precision agriculture for small and marginal farmers.[1] Empower farmers with crop-level information for profitability and sustainability.[2] Adapt PA principles for small farms with centralized expertise benefits.[3]	Empowers small farmers with crop-level actionable information for profitability. [1] Reduces crop vulnerability and negative environmental effects of fertilizer and pesticides. [1] Model adaptable to small farmers in various regions with modifications. [2]	Precision level lower than original definition due to farm variability. [1] Model designed for short-term crops like vegetables. [2]
Responsible AI in Farming: A Multi-Criteria Framework for Sustainable Technology Design **Kevin Mallinger 1,2,* and Ricardo Baeza-Yates 3**	AI impact on farmers' autonomy analyzed for responsible model development. Transparent AI crucial for trust, collaboration, and decision-making competence.	Qualitative analysis of AI impact on farmers' autonomy and risks. [1] Data management, transparent AI, and user experience design. [1] Responsible AI framework based on social, technological, and ecological challenges. [1]	Qualitative analysis of AI impact on farmers' autonomy and technological risks. [1] Framework for responsible AI technology creation based on social challenges. [1]	AI risks on farmers' lives analyzed from social, tech, environmental views.[1] Challenges in AI tech design for responsible, sustainable implementation discussed.[1]
M2F-Net: A Deep Learning-Based Multimodal Classification with High-Throughput Phenotyping for Identification of Overabundance of Fertilizers **J. Dhakshayani and B. Surendiran**	Amaranth crop nutrient analysis using AI for fertilizer overuse identification. M2F-Net fusion model enhances classification performance by 91%.	Multimodal fusion network M2F-Net with agrometeorological and image data. [1] Trained MLP on agrometeorological data and DenseNet-121 on image data. [1] Evaluated model performance in accuracy and Area Under Curve (AUC). [1]	Fusion models outperformed individual models with 91% accuracy. [1] Multimodal fusion network boosted classification performance for fertilizer overabundance. [2]	No specific limitations were mentioned in the research paper.

Literature Survey

AI breeder: Genomic predictions for crop breeding **Wanjie Fenga,1** **, Pengfei Gaoa,1** **, Xutong Wanga,b**	Deep learning enhances genome prediction models by integrating environmental factors. Poisson deep neural network model predicts count data in genome-based prediction.	Genomic prediction models like SoyDNGP for crop breeding. [1] Leveraging deep learning for gene-environment interaction in crop breeding. [2] Predicting phenotypes by exploring genetic combinations in offspring. [3] Overcoming challenges in high-dimensional marker spaces with AI algorithms. [4]	AI models accelerate crop breeding with accurate genetic predictions. [1] SoyDNGP identifies loci for soybean traits like flower and pod colors. [2]	Challenges include parent selection, trait prediction, explainable deep learning. [1] Difficulty with high-dimensional marker data and genotype-phenotype relationships. [2]
Artificial intelligence-based techniques for adulteration and defect **detections in food and agricultural industry: A review** **Suhaili Othman a,b** **, Nidhi Rajesh Mavani a** **, M.A. Hussain c** **, Norliza Abd Rahman a** **,** **Jarinah Mohd Ali a**	AI techniques authenticate food quality using convolutional neural networks. [1] Fuzzy logic aids in food quality classification and control systems. [2]	Random Forest (RF) for classification and regression with ensemble learning. [1] Artificial Intelligence (AI) techniques integrated with various sensing devices. [2] Machine learning with manual feature extraction for data processing. [3]	AI techniques achieved 81.2-100% accuracy in food adulteration and defect detection.[1] SVM accuracy was 97.74, outperforming KNN and LDA for classification.[2]	Standardization challenges in AI techniques for food and agriculture industries. [1] Need for framework architecture to recommend algorithms for practical use. [1] Challenges in integrating multiple sensor types for data fusion. [1] Limitations of computer vision in agriculture industry for defect detection. [1]
Integrating explainable artificial intelligence and blockchain to smart **agriculture: Research prospects for decision making and improved security** **Hsin-Yuan Chen a,** ***** **, Komal Sharma b** **, Chetan Sharma c** **, Shamneesh Sharma c**	Paper analyzes smart agriculture, blockchain, and explainable AI literature. Identifies top authors, countries, journals, and keywords in the research.	Scientometric review, Webometrics, Altmetrics, bibliographic analysis for analysis. [1] VOSviewer for network analysis, visualization, and bibliometric data representation. [1]	Analysis of integrating XAI and blockchain into smart agriculture. [1] Implications of combining XAI, blockchain, and smart agriculture technologies. [2]	Search terms may limit paper retrieval in Scopus database.[1] Authors plan to compare databases like Scopus and Web of Science.[1] Use of Vosviewer alone may limit future research investigations.[1]

Methodology

CROP RECOMMENDATION



Step 1: Data Acquisition

Dataset can be acquired from kaggle.

Step 2: Values Input

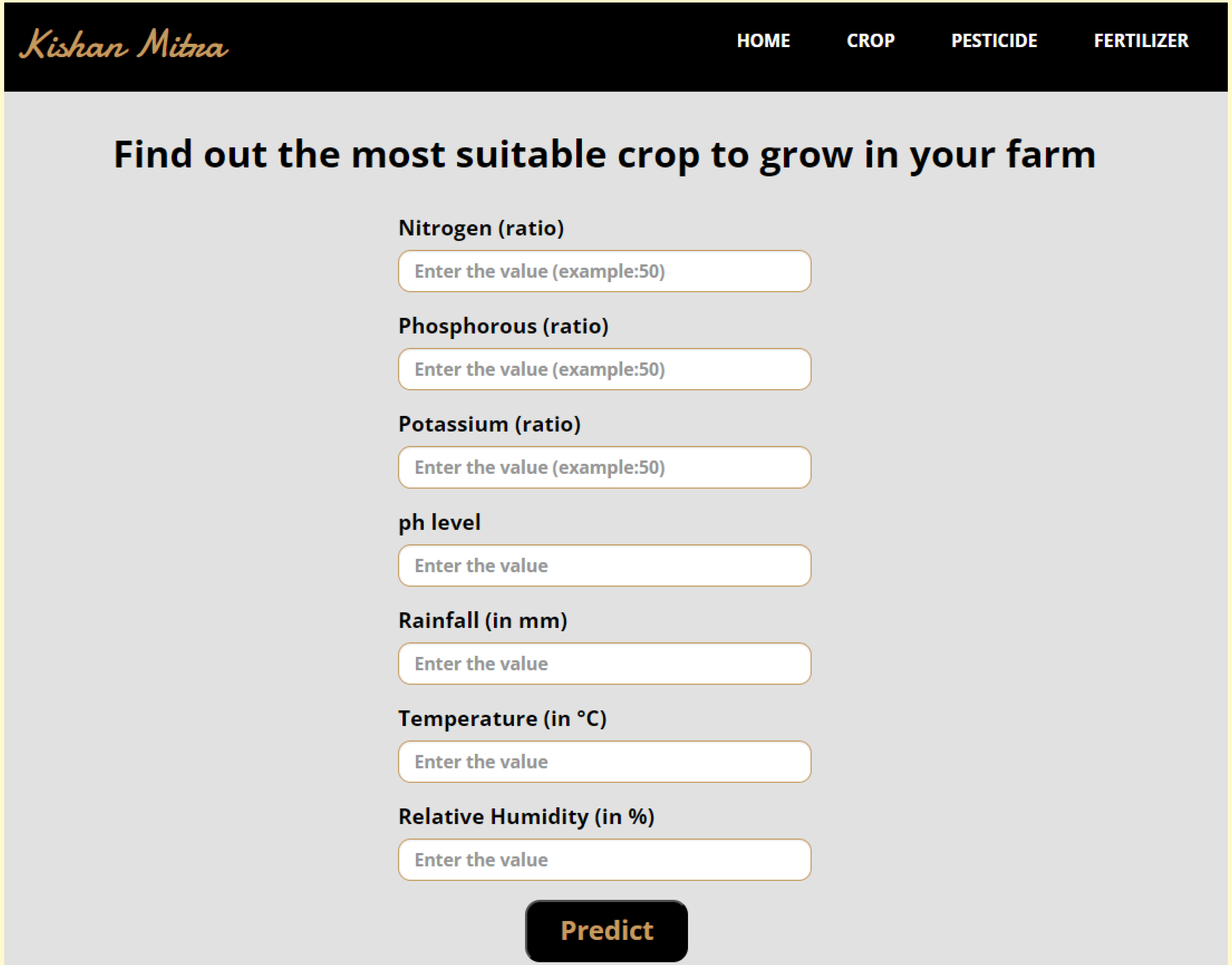
Users are expected to input the site specific parameters like: N, P, K (all of them in %), temperature (in °C), relative humidity (in %), rainfall (in mm) and pH.

Step 3: ML Model Training and creating .pkl file
Recommendation system is based on the ensemble model with majority voting technique.

Step 4: Crop Recommendation

.pkl file is loaded to recommend the crop based on input.ion

CROP RECOMMENDATION



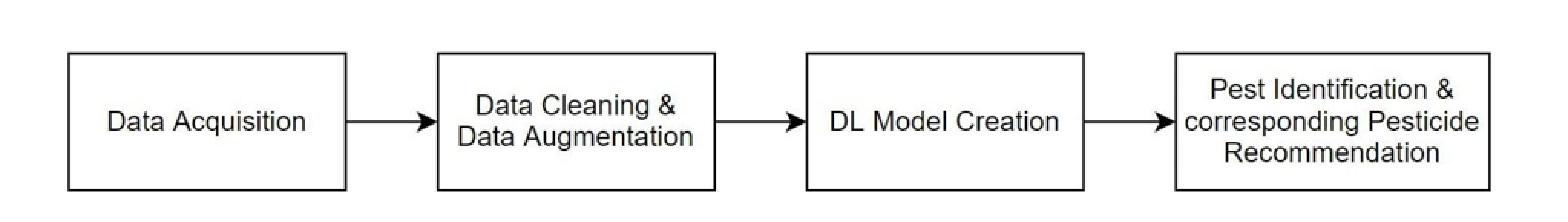
CROP RECOMMENDATION

Kishan Mitra

HOME CROP FERTILIZER PESTICIDE

You should grow *papaya* in your farm

PESTICIDE RECOMMENDATION



Step 1: Data Acquisition

Dataset will be created by scraping images from Google via automatic script using Selenium and Chrome Driver.Along with that, pest labels will be provided as well.

Step 2: Data Cleaningand Data Augmentation

The data collectedfrom Google needsto be cleaned manually to get rid of non-useful content e.g: In case of scraping imagesof pest named“beetle” there are also few images of “car calledbeetle”. Later on, the dataset needs to be augmented so as to increase variability.

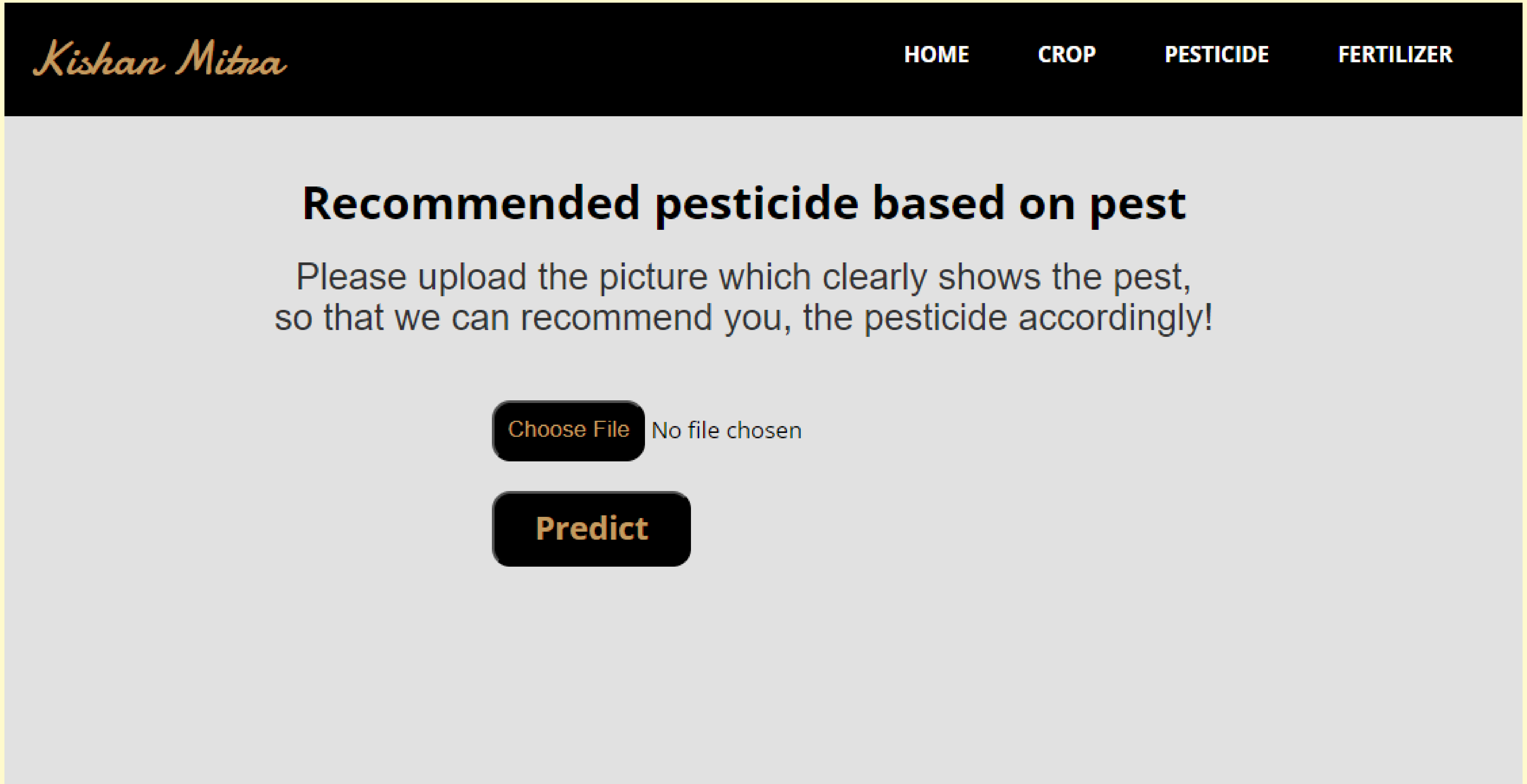
Step 3: DL Model Creation

This involves model configuration, trainingconfiguration and model evaluation. Later on, .h5 file will be created to store the model.

Step 4: Pest Identification and corresponding Pesticide Recommendation

.h5 model will be loaded to identify the pest, later on based on the result, corresponding pesticidewill be recommended based on dictionary based solution.

PESTICIDE RECOMMENDATION



PESTICIDE RECOMMENDATION

Kishan Mitra

HOME CROP FERTILIZER PESTICIDE

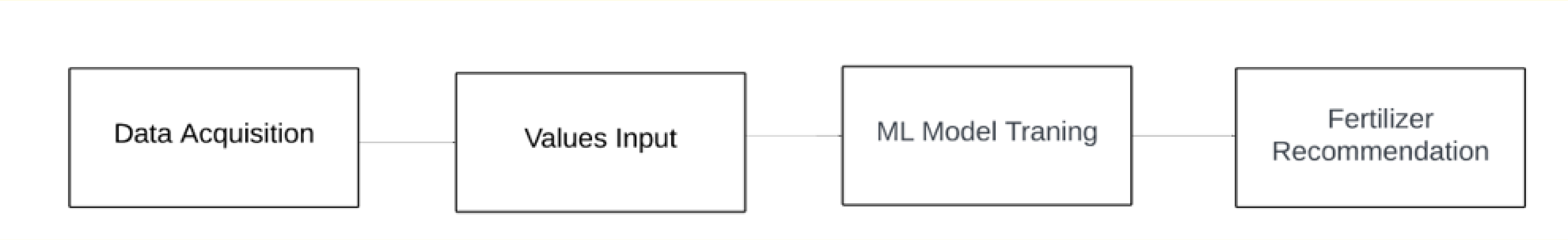
Identified Pest: *armyworm*

Recommended Products

Dose: 2.5-3.5 Tbsp/ 16 L

Dose: 500 gm/L

FERTILIZER RECOMMENDATION



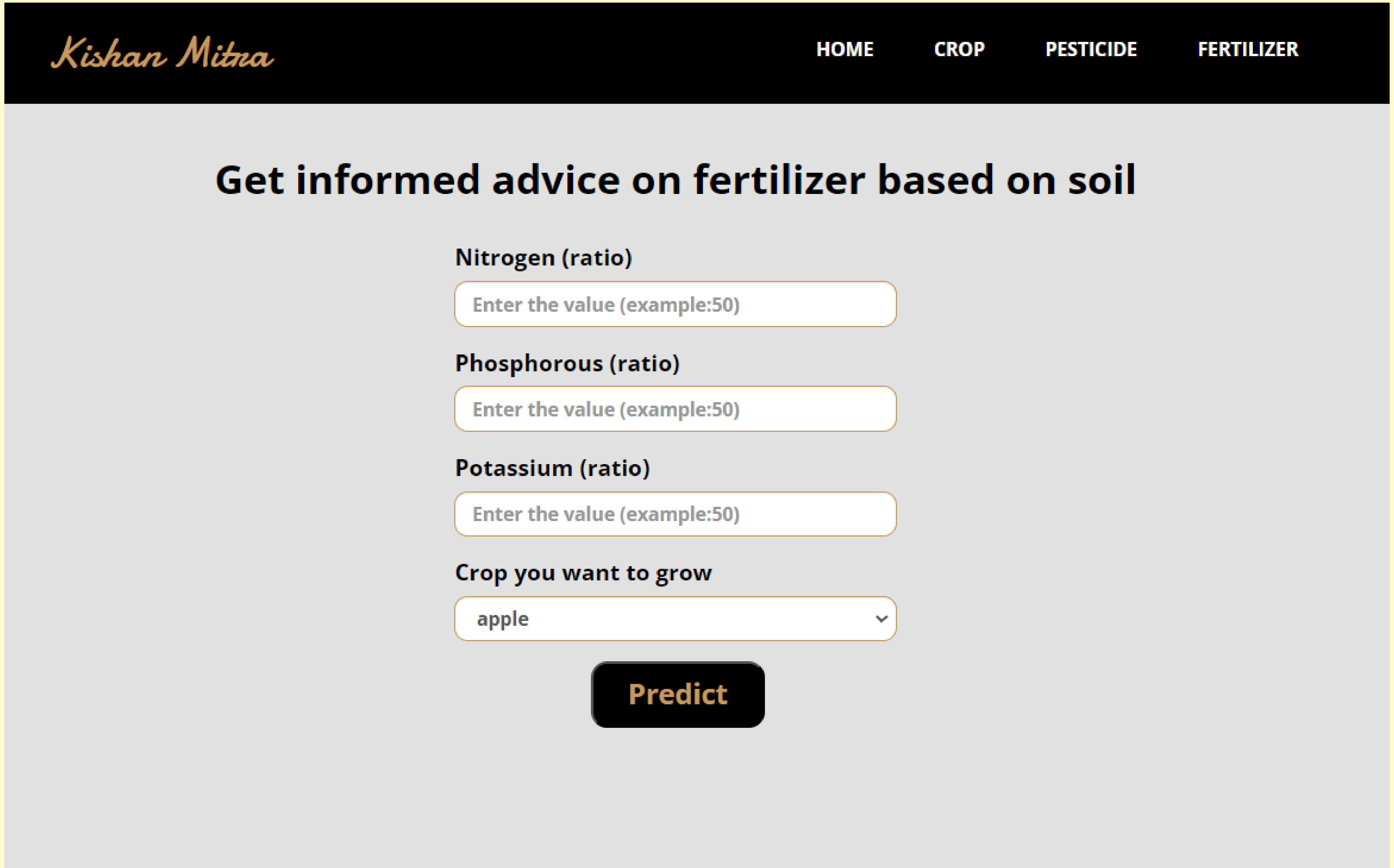
Step 1: Data Acquisition
Dataset will be createdmanually after collecting data from verifiedsources listed below:
1.The Fertilizer Association of India
2.Indian Institute of Water Management
3.Kaggle
The columnsof the dataset are: N, P, K (all of them in %) and crop.

Step 2: ValuesInput
Users are expectedto input the site specific parameters like: N, P, K (all of them in %), and crop (select from list - only 22 crops supported).

Step 3: ML Model Trainingand creating .pkl file
Recommendation system is based on the ensemblemodel with majorityvoting technique
8.AdaBoost
After the model is trained, a .pkl file is created.

Step 4: Fertilizer Recommendation
pkl file is loaded to recommend the crop based on input.

FERTILIZER RECOMMENDATION



FERTILIZER RECOMMENDATION

Difference between desired value of N and your farm's N value is 3.0

The N value of soil is high and might give rise to weeds.

Please consider the following suggestions:

1. *Manure* – adding manure is one of the simplest ways to amend your soil with nitrogen. Be careful as there are various types of manures with varying degrees of nitrogen.

2. *Coffee grinds* – use your morning addiction to feed your gardening habit! Coffee grinds are considered a green compost material which is rich in nitrogen. Once the grounds break down, your soil will be fed with delicious, delicious nitrogen. An added benefit to including coffee grounds to your soil is while it will compost, it will also help provide increased drainage to your soil.

3. *Plant nitrogen fixing plants* – planting vegetables that are in Fabaceae family like peas, beans and soybeans have the ability to increase nitrogen in your soil

4. Plant 'green manure' crops like cabbage, corn and brocolli

5. *Use mulch (wet grass) while growing crops* - Mulch can also include sawdust and scrap soft woods

---

Difference between desired value of P and your farm's P value is 93.0

The P value of your soil is low.

Please consider the following suggestions:

1. *Bone meal* – a fast acting source that is made from ground animal bones which is rich in phosphorous.

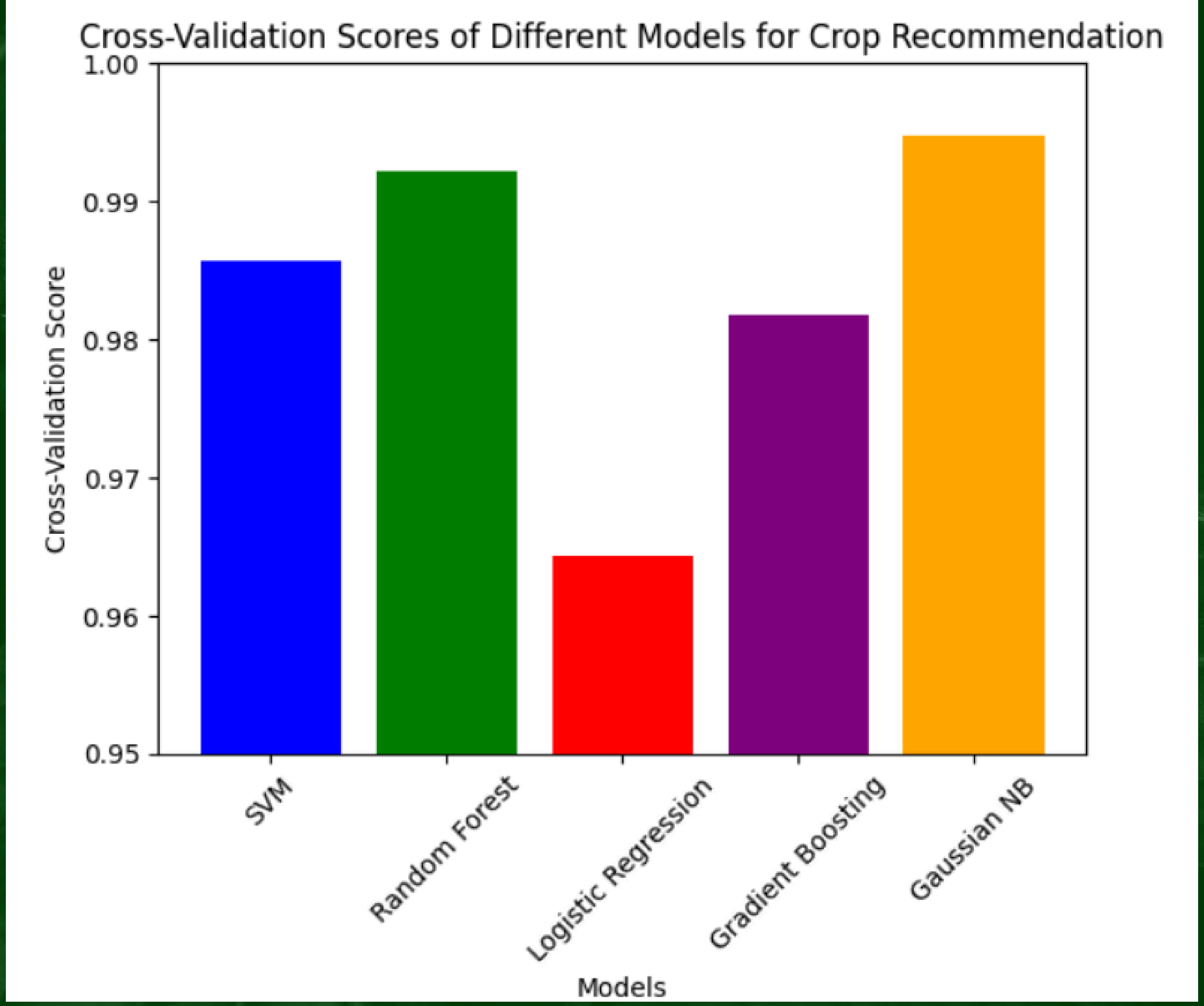
2. *Rock phosphate* – a slower acting source where the soil needs to convert the rock phosphate into phosphorous that the plants can use.

3. *Phosphorus Fertilizers* – applying a fertilizer with a high phosphorous content in the NPK ratio (example: 10-20-10, 20 being phosphorous percentage).

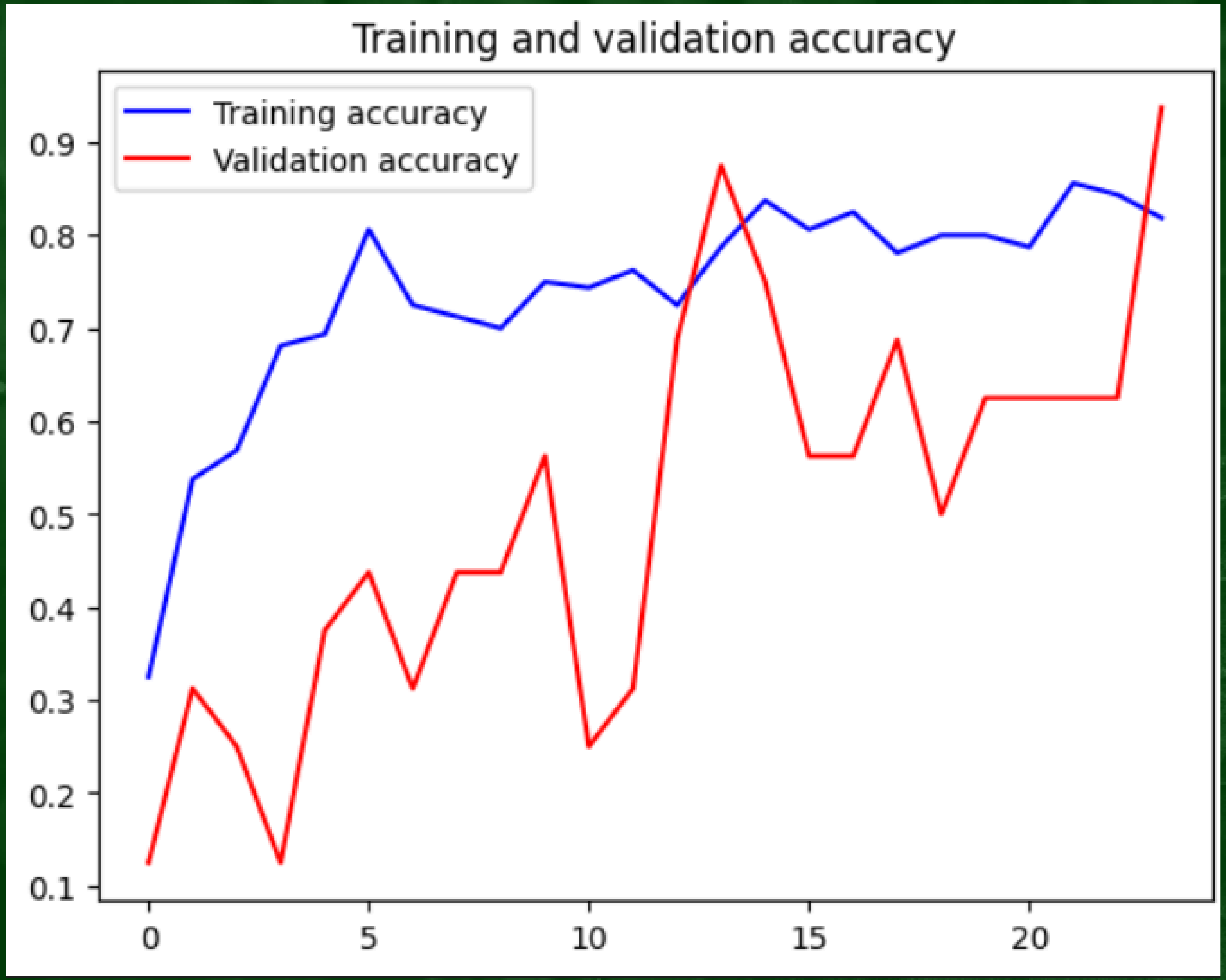
4. *Organic compost* – adding quality organic compost to your soil will help increase phosphorous content.

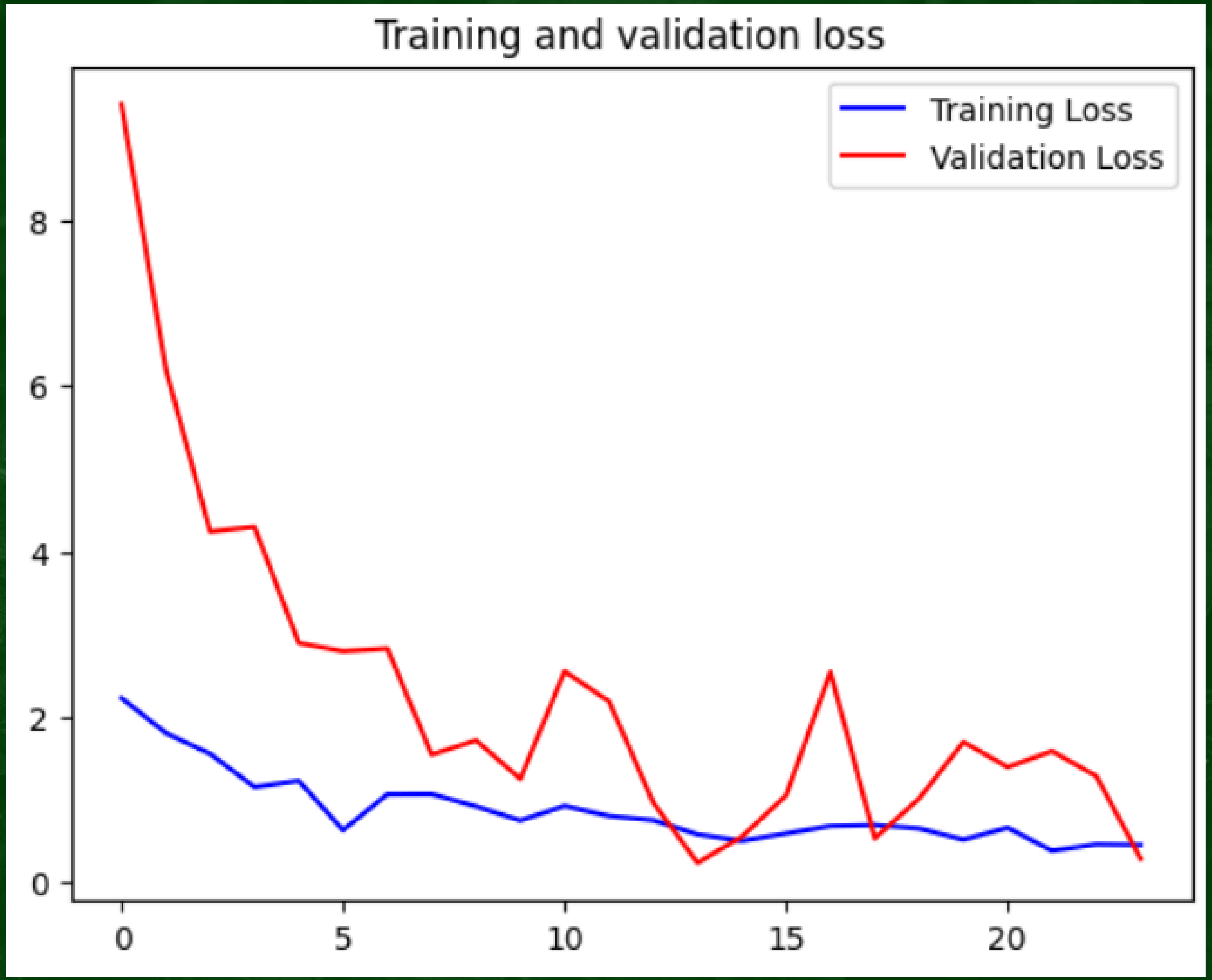
RESULTS: CROP RECOMMENDATION

- Best Models: Random Forest, Naive Bayes
  - Achieved near-perfect cross-validation scores and perfect accuracy.
- Other High Performers: Logistic Regression, Decision Tree
  - Also achieved perfect accuracy.
- Less Effective Models: SVM, AdaBoost
  - Lower accuracy scores, suggesting they may not be ideal for crop recommendation.



RESULTS: PESTICIDE RECOMMENDATION

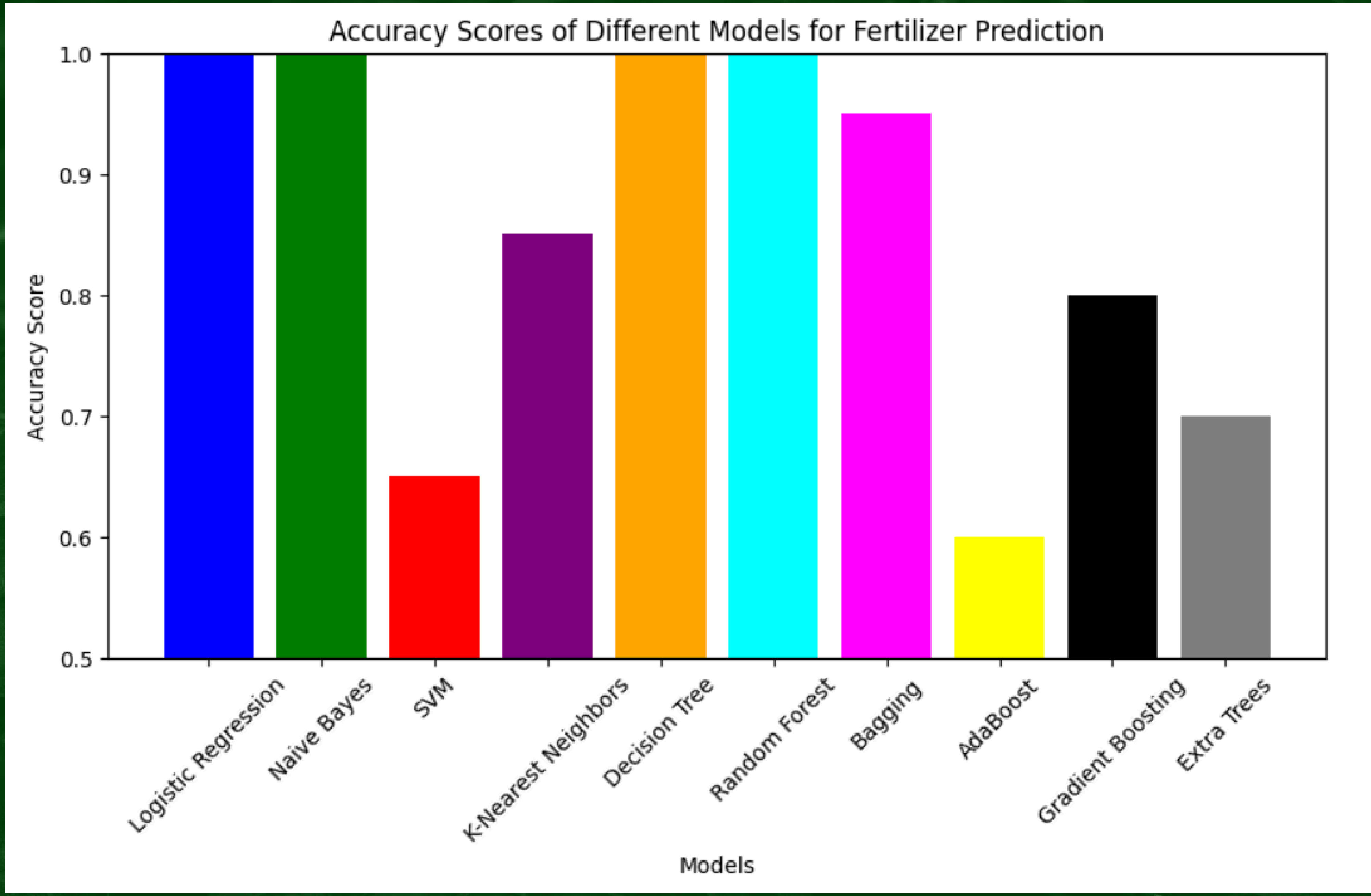




Model Used: MobileNet
Achieved a training accuracy of 0.8707.

RESULTS

FERTILIZER RECOMMENDATION



- **Best Models: Logistic Regression, Naive Bayes, Decision Tree, Random Forest**
  - Achieved perfect accuracy, making them highly reliable.
- **Other High Performer: Bagging**
  - Achieved an accuracy of 0.95.
- **Less Effective Models: SVM, AdaBoost**
  - Lower accuracy scores, indicating they may not be suitable for fertilizer prediction.

CONCLUSION

For crop recommendation, Random Forest and Naive Bayes were the most effective models, achieving near-perfect cross-validation scores and perfect accuracy, with Logistic Regression, Decision Tree, and Random Forest also performing exceptionally well. For fertilizer prediction, Logistic Regression, Naive Bayes, Decision Tree, and Random Forest achieved perfect accuracy, while Bagging performed well with 0.95 accuracy; SVM and AdaBoost were less effective for both tasks. For pest detection, the MobileNet model showed moderate promise with a training accuracy of 0.7707, indicating potential for improvement through further tuning and dataset expansion. Overall, Random Forest and Naive Bayes are highly reliable for crop and fertilizer predictions, while MobileNet is suitable for pest detection with some enhancements.


THANK
YOU