E-Krushi: Agricultural Assistance using Deep Learning and Natural Language Processing

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ABSTRACT

Agriculture is one of the main contributing sectors in the Indian economy. There are various issues hampering the growth of agricultural production in India. Plant disease is one major problem among others. The system proposes to aid the farmers in combating and taking quick actions to prevent losses due to disease proliferation. Deep learning tools are employed to generate analysis for the same. The farmers can acquire a quick analysis of the plant's health by providing an image of the plant's leaf. The application provides facilities to interact in various regional languages in order to cater the needs of its vernacular audience. Natural language processing techniques are used to translate the queries of the farmers. A website and an android application are a part of the proposed solution in order to provide a user-friendly interface. Chatbot embedded in the application and the website will assist the farmers with their queries by providing multilingual support.

General Terms

Farmers, Plant Disease detection, Deep Learning, Language translation, NLP.

Keywords

Porter Stemmer algorithm, ANN, CNN, Bag of Words

1. INTRODUCTION

Agriculture, constituting the backbone of India's economy, sustains the livelihoods of 70 percent of the rural households, with 82 percent being small and marginal farmers. The country, recognized as the largest producer of milk, jute, and pulses, is second only to China in various key crops. India's agricultural landscape, encompassing rice, wheat, sugarcane, cotton, and more, plays a pivotal role in socio-economic development. The sector's significance necessitates technological advancements to empower farmers, thereby catalyzing India's overall growth.

Despite its pivotal role, the agricultural sector faces a pressing challenge in the form of plant diseases. These diseases exhibit dynamic patterns influenced by factors such as pathogens, environmental conditions, and crop varieties. According to the survey conducted by The Economic Times "Crops worth Rs 50,000 crore are lost owing to pest and disease attacks every year".

Existing agricultural applications offer valuable insights but fall short in meeting the diverse linguistic needs of farmers. With a multitude of non-Hindi speaking states, such as West Bengal, Telangana, Tamil Nadu, Karnataka, and Kerala, and a preference for regional languages like Marathi in Maharashtra, addressing farmers' queries in vernacular languages is imperative.

The objective of this project transcends conventional approaches by providing enhanced agricultural assistance in regional languages. The initial focus is on Marathi and Hindi, with plans to expand to other state languages. What sets this system apart is its comprehensive approach—offering disease detection for nine different plants, each categorized into specific diseases. This results in a multiclass classification system tailored to the unique challenges posed by each plant type.

Crucially, the system introduces a novel aspect by integrating a multilingual chatbot. This chatbot not only provides information on plant diseases but also facilitates interaction in different regional languages. Farmers can now receive tailored assistance, enhancing their understanding of diseases, causes, and solutions in their preferred language.

The innovation lies in the amalgamation of disease detection for multiple plants and a chatbot interface, making it a holistic solution. This system doesn't merely diagnose diseases; it educates and engages farmers through an accessible, multilingual platform, contributing to a more informed and empowered agricultural community.

2. OVERVIEW

2.1 Motivation

The motivation for this project stems from the critical role that agriculture plays in the Indian economy and the numerous challenges faced by farmers, including plant diseases that can lead to significant crop losses. The project aims to empower farmers with advanced technology solutions to combat these challenges effectively. By leveraging deep learning tools, the system can provide quick and accurate analysis of plant health based on images of leaves.

Furthermore, the project is motivated by the need to cater to the diverse linguistic and regional preferences of Indian farmers. By offering multilingual support through natural language processing techniques, the system ensures that farmers from various regions can easily interact with and benefit from the solution. This inclusivity is essential for reaching a wider audience and making the technology accessible to all.

The development of a user-friendly website and Android application, along with the integration of a chatbot, is another crucial aspect of the project's motivation. These interfaces provide a convenient and accessible means for farmers to access plant health analysis and seek assistance with their queries. Overall, the project's motivation lies in leveraging cutting-edge technology to enhance agricultural productivity, empower farmers, and address the unique challenges faced in the Indian agricultural sector.

2.2 Problem Statement

Plant disease is one of the biggest challenges faced by the farmers of India. The loss incurred each year due to the disease outbreak is huge and is increasing every year. The information regarding the causes, symptoms and treatment of diseases will help the farmers to reduce the losses incurred. But this alone is not enough. The identification of the disease type can be tricky and difficult for the farmers. To accelerate the treatment of the infested crops, an accurate and quick analysis of their state is required. There are various applications in the market producing insights regarding the crop disease, but they are mostly taking inputs and giving outputs in English language. The farmers from within the interiors of Indian villages need multilingual assistance in order to profit from the analysis.

2.3 Project Contribution

The proposed system aims to give a comprehensive solution to plant disease proliferation faced by farmers in India. The system will take in user input in the form of an image, and provide a consolidated analysis on the crop health. This analysis will help the farmers take quick action to save the crop and thus reduce the losses. Deep learning tools will be employed to produce the analysis. The project aims to deliver the information to the farmers in varied languages other than English. In order to reach out to the farmers from remote places in India who are not comfortable with English, the system will be providing multilingual support. An NLP based chatbot will be embedded in the website and android application to provide assistance in vernacular languages.

2.4 Related Work

In the paper "Smallholder farmer-centric integration of IoT and Chatbot for early Maize diseases detection and management in pre-visual symptoms phase" by T. Maginga et al., the authors address the global challenge of crop diseases causing substantial yield loss. Traditional methods relying on visual symptoms are limited, as they often miss early asymptomatic phases. To overcome this, the paper proposes leveraging Internet of Things (IoT) sensors to monitor pre-visual signs, such as Volatile Organic Compound emissions and changes in soil nutrition patterns. The authors advocate for an integrated framework that combines IoT sensing with Natural Language Processing (NLP) chatbots, aiming to empower low-literacy smallholder farmers in East Africa to autonomously identify and understand potential maize crop diseases before visible symptoms emerge, thereby enhancing early detection and management.

In the paper titled "SMART KISAN: A Mobile App for Farmers' Assistance in Agricultural Activities" by T. Yadav, P. Sable, and D. Kalbande, the authors highlight the challenges faced by Indian farmers, including a lack of knowledge about the latest agricultural technologies, practices, and disease identification and management. Additionally, issues such as finding suitable storage facilities and determining fair market prices for produce add to their struggles. To address these challenges, the authors propose a digital solution in the form of a mobile application called SMART KISAN. The app encompasses six key features, including a technology library, plant disease identification and diagnosis, an automated chatbot for answering queries, weather alerts, information on nearby warehouses, and market prices for produce. The development of the application is informed by a survey conducted with 50 farmers from Maharashtra and Madhya Pradesh, utilizing a Google form. SMART KISAN aims to empower farmers with essential tools for independent problem-solving, providing multilingual support to cater to diverse user needs.

2.5 Dataset Description

Total 9 plants are considered in the plant disease detection model. Including the different disease categories for each plant we have total 33 categories of images.

The dataset is customized using information from KCC, internet articles, FAQs, etc. This dataset provides structured information in a JSON format covering various topics related to agriculture. It includes different "intents(tags)" representing categories, each with associated "patterns" that users might input to inquire about a particular topic. For each tag, there are corresponding "responses," which are concise answers related to the user's input. The dataset covers topics including plant diseases, farming practices, equipment, policies, and more. The tags associated with each intent serve as identifiers, for easy reference and organization of the dataset.

Table. 1: Plant Disease Images Dataset Description

Disease Type	Training Images	Testing Images
Strawberry: healthy	1528	752
Strawberry: Leaf scorch	1486	731
Peach: Bacterial spot	1545	761
Peach: healthy	1447	712
Potato: Early blight	1624	799
Potato: healthy	1527	752
Potato: Late blight	1624	799
Corn (maize): Cercospora leaf spot Gray leaf spot	1374	677
Corn (maize): Common rust	1597	786
Corn (maize): healthy	1557	766
Corn (maize): Northern Leaf Blight	1597	787
Pepper, bell: Bacterial spot	1601	789
Pepper, bell: healthy	1664	820
Grape: Black rot	1581	778
Grape: Esca (Black Measles)	1614	795
Grape: healthy	1417	697
Grape: Leaf blight (Isariopsis Leaf Spot)	1441	710
Apple: Apple scab	1688	831
Apple: Black rot	1670	822
Apple: Cedar apple rust	1474	726
Apple: healthy	1681	828
Cherry (including sour): healthy	1528	753
Cherry (including sour): Powdery mildew	1409	694
Tomato: Tomato Yellow Leaf Curl Virus	1642	808
Tomato: Tomato mosaic virus	1499	738
Tomato: Target Spot	1530	753
Tomato: Spider mites Two-spotted spider mite	1457	718
Tomato: Septoria leaf spot	1474	726
Tomato: Leaf Mold	1575	776
Tomato: Late blight	1550	763
Tomato: healthy	1612	794
Tomato: Early blight	1608	792
Tomato: Bacterial spot	1425	701

```
683 patterns
227 tags: ['apple_additional_tips', 'apple_advantages', 'apple_black_rot_causes', 'apple_black_rot_cure', 'apple_black_rot_prevention', 'apple_black_rot_symptoms', 'apple
_common_challenges', 'apple_fertilization', 'apple_harvesting', 'apple_scab_causes', 'apple_scab_cure', 'apple_scab_prevention', 'apple_scab_symptoms', 'apple_seeds_condi
tions', 'apple_soil_conditions', 'apple_storage', 'apple_uses', 'apple_water_supply', 'askinghelp', 'bacterial_spot_causes', 'bacterial_spot_control', 'bacterial_spot_pre
vention', 'bacterial_spot_symptoms', 'bell_pepper_advantages', 'bell_pepper_bacterial_spot_causes', 'bell_pepper_bacterial_spot_cure', 'bell_pepper_bacterial_spot_prevent
ion', 'bell_pepper_bacterial_spot_symptoms', 'bell_pepper_challenges', 'bell_pepper_fertilization', 'bell_pepper_harvesting', 'bell_pepper_post_harvest_handling', 'bell_p
epper_seeds_conditions', 'bell_pepper_soil_conditions', 'bell_pepper_storage', 'bell_pepper_uses', 'bell_pepper_water_supply', 'bell_pepper_yield_tips', 'buy', 'buy_agric
ultural_equipment', 'cedar_apple_rust_causes', 'cedar_apple_rust_cure', 'cedar_apple_rust_prevention', 'cedar_apple_rust_symptoms', 'cercospora_leaf_spot_causes', 'cercos
pora_leaf_spot_cure', 'cercospora_leaf_spot_prevention', 'cercospora_leaf_spot_symptoms', 'cherry_plant_advantages', 'cherry_plant_common_challenges', 'cherry_plant_ferti
lization', 'cherry_plant_pollination', 'cherry_plant_pruning', 'cherry_plant_soil_conditions', 'cherry_plant_storage', 'cherry_plant_uses', 'cherry_plant_water_supply', '
cherry_plant_yield_max', 'cherry_powdery_mildew_causes', 'cherry_powdery_mildew_cure', 'cherry_powdery_mildew_prevention', 'cherry_powdery_mildew_symptoms', 'corn_additio
nal_tips', 'corn_advantages', 'corn_common_challenges', 'corn_common_rust_causes', 'corn_common_rust_cure', 'corn_common_rust_prevention', 'corn_common_rust_symptoms', 'c
orn_fertilization', 'corn_harvesting', 'corn_northern_leaf_blight_causes', 'corn_northern_leaf_blight_cure', 'corn_northern_leaf_blight_prevention', 'corn_northern_leaf_b
light_symptoms', 'corn_seeds_conditions', 'corn_soil_conditions', 'corn_storage', 'corn_uses', 'corn_water_supply', 'corn_yield_maximization', 'early_blight_causes', 'ear
ly_blight_control', 'early_blight_prevention', 'early_blight_symptoms', 'goodbye', 'grape_black_rot_causes', 'grape_black_rot_cure', 'grape_black_rot_prevention', 'grape_
black_rot_symptoms', 'grape_esca_causes', 'grape_esca_cure', 'grape_esca_prevention', 'grape_esca_symptoms', 'grape_leaf_blight_causes', 'grape_leaf_blight_cure', 'grape_
leaf_blight_prevention', 'grape_leaf_blight_symptoms', 'grapefruit_additional_tips', 'grapefruit_advantages', 'grapefruit_common_challenges', 'grapefruit_fertilization',
'grapefruit_harvesting', 'grapefruit_seeds_conditions', 'grapefruit_soil_conditions', 'grapefruit_storage', 'grapefruit_uses', 'grapefruit_water_supply', 'grapefruit_yiel
d_maximization', 'greeting', 'indian_farmer_policies', 'indian_farmer_rules', 'late_blight_causes', 'late_blight_control', 'late_blight_prevention', 'late_blight_symptoms
', 'leaf_mold_causes', 'leaf_mold_control', 'leaf_mold_prevention', 'leaf_mold_symptoms', 'peach_additional_tips', 'peach_advantages', 'peach_bacterial_spot_causes', 'pea
ch_bacterial_spot_cure', 'peach_bacterial_spot_prevention', 'peach_bacterial_spot_symptoms', 'peach_common_challenges', 'peach_fertilization', 'peach_harvesting', 'peach_
seeds_conditions', 'peach_soil_conditions', 'peach_storage', 'peach_uses', 'peach_water_supply', 'peach_yield_maximization', 'potato_additional_tips', 'potato_advantages'
, 'potato_common_challenges', 'potato_early_blight_causes', 'potato_early_blight_cure', 'potato_early_blight_prevention', 'potato_early_blight_symptoms', 'potato_fertiliz
ation', 'potato_harvesting', 'potato_late_blight_causes', 'potato_late_blight_cure', 'potato_late_blight_prevention', 'potato_late_blight_symptoms', 'potato_seeds_conditi
ons', 'potato_soil_conditions', 'potato_storage', 'potato_uses', 'potato_water_supply', 'potato_yield_maximization', 'sell', 'sell_agricultural_equipment', 'septoria_caus
es', 'septoria_control', 'septoria_prevention', 'septoria_symptoms', 'spider_mite_causes', 'spider_mite_control', 'spider_mite_prevention', 'spider_mite_symptoms', 'straw
berry_additional_tips', 'strawberry_advantages', 'strawberry_common_challenges', 'strawberry_fertilization', 'strawberry_harvesting', 'strawberry_leaf_scorch_causes', 'st
rawberry_leaf_scorch_cure', 'strawberry_leaf_scorch_prevention', 'strawberry_leaf_scorch_symptoms', 'strawberry_seeds_conditions', 'strawberry_soil_conditions', 'strawber
ry_storage', 'strawberry_uses', 'strawberry_water_supply', 'strawberry_yield_maximization', 'target_spot_causes', 'target_spot_control', 'target_spot_prevention', 'target
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'tomatofertilizationdeficiencies', 'tomatofertilizer', 'tomatoflowering', 'tomatofruitsetting', 'tomatogrowingseason', 'tomatoharvesting', 'tomatohumidity', 'tomatoleafcu
rl', 'tomatolightrequirements', 'tomatonutrientdeficiency', 'tomatopaste', 'tomatopests', 'tomatopestscontrol', 'tomatoplanting', 'tomatopowderymildew', 'tomatopreservati
on', 'tomatopruning', 'tomatosauce', 'tomatoseeds', 'tomatosoil', 'tomatostorage', 'tomatosupport', 'tomatotemperature', 'tomatotransplanting', 'tomatotrellis', 'tomatotr
ellising', 'tomatovarieties', 'tomatowatering', 'tomv_causes', 'tomv_cure', 'tomv_prevention', 'tomv_symptoms', 'tylcv_causes', 'tylcv_cure', 'tylcv_prevention', 'tylcv_s
ymptoms']
```

Figure 1: Dataset showing 683 Patterns and 227 Tags

2.6 Limitations and Boundary Conditions of Proposed System

2.6.1 Limited Language Support:

The system may not cover all regional languages, and the effectiveness of the chatbot may vary across different dialects within supported languages.

2.6.2 Plant-Specific Limitations:

The system currently supports disease detection for only nine different plants, potentially limiting its applicability to a broader range of crops.

2.6.3 Data Quality and Variability:
Accuracy in disease prediction relies on the quality and variability of the training dataset, and the chatbot's performance is influenced by the availability of diverse language data.

2.6.4 Limited Technological Literacy:
Farmers with limited exposure to technology may face challenges in effectively using the application and chatbot.

2.6.5 Environmental Factors:
Adverse environmental conditions, such as poor lighting or extreme weather, may impact the quality of images captured for disease detection.

2.6.6 Chatbot Understanding Complexity:
The chatbot's understanding of regional languages may not be perfect, leading to potential misinterpretation of user queries.

2.6.7 Legal and Ethical Considerations:
Adherence to data privacy laws and ethical considerations is crucial, and any breaches could impact user trust and compliance with regulations.

2.6.8 Dialect Variations:
The system may struggle with dialect variations within supported regional languages, affecting the accuracy of chatbot interactions.

2.6.9 Limited Plant and Disease Coverage:
The system may not cover all plant varieties and diseases, potentially leaving some farmers without relevant information.

2.6.10 User Engagement Challenges:
Encouraging consistent user engagement may be challenging, as farmers might not use the system regularly or may face difficulties in adopting new technologies.

2.6.11 Resource Constraints:
Limited resources, both in terms of technological infrastructure and personnel, may impact the scalability and efficiency of the system.

2.6.12 Cultural Sensitivity:
The system may need to adapt to cultural nuances and sensitivities within different regions, considering diverse farming practices and traditions.

2.6.13 Scalability Issues:
As the user base grows, scalability issues may arise, requiring careful consideration of system architecture and capacity planning.

2.6.14 Integration Challenges:
Integrating the system with existing agricultural practices and infrastructure may pose challenges, requiring collaboration with local agricultural ecosystems.

3. PROPOSED DESIGN

3.1 Architecture

3.1.1 Plant Disease Prediction Model

3.1.1.1 Data Collection:
Gathering a comprehensive dataset of plant images, including healthy and diseased samples, is essential. PlantVillage dataset is used which contains 9 types of plants along with several diseases pertaining to each plant. Collect data related to different plant varieties and diseases.

3.1.1.2 Data Preprocessing and Cleaning:
This block involves tasks like image resizing, noise reduction, and data augmentation to prepare the dataset for training. Data cleaning ensures high-quality input for the model.

3.1.1.3 Model Training:
Train deep learning models (e.g., Convolutional Neural Networks - CNNs) using the pre-processed dataset. The training process involves feature extraction and model optimization.

3.1.1.4 Model Evaluation:
Assess the model's performance using validation datasets and metrics such as accuracy, precision, recall, and F1-score. Fine-tune the model based on the results of the evaluation.

3.1.1.5 Quantization & Deployment:
Quantization is a technique to optimise the model for deployment on resource-constrained devices. Deploying the model to production environments using tflite.

3.1.1.6 Integration with mobile and web application:
Ensuring seamless integration of the Prediction Model with the Mobile and Web Application. Developing APIs or endpoints for communication between the application and the model.

3.1.1.7 Input image from user:
Implementing functionality in the application to allow users to upload plant images for analysis. Processing user input to convert images in the format that can be used to make predictions.

3.1.1.8 Analysis of the image:
The inference engine runs predictions on user-submitted images using the trained model. It interprets the model's output, determining the likelihood and type of disease.

3.1.1.9 Final output to the user:
Present the analysis results to users in an understandable format. Include information about the detected disease, severity, and recommended actions. Present the analysis results to users in an understandable format. Include information about the detected disease, severity, and recommended actions.

3.1.2 Chatbot with Multilingual Support

3.1.2.1 Knowledge Base:
This contains the information and data that the chatbot uses to respond to user queries. It can include structured databases, FAQs, documents, or other data sources.

3.1.2.2 Natural Language Understanding:
NLU is responsible for processing user queries and

understanding their intent, entities, and context.
Building blocks within NLU may include:
Intent Recognition: Identifying the user's intent or purpose behind the query.
Entity Extraction: Extracting specific pieces of information from the user's query.
Context Management: Maintaining context throughout the conversation for more coherent responses.

3.1.2.3 Data preprocessing and Cleaning:
This block involves tasks like stemming, stop-words removal, etc. to prepare the dataset for training. Data cleaning ensures high-quality input for the model.

3.1.2.4 Model Training and Evaluation:
Training the model using Artificial Neural Networks (ANN) and Natural Language Processing (NLP). Evaluating the model using parameters like accuracy, loss function, etc.

3.1.2.5 Integration with Large Language Models:
Creating a large language model. This block involves integrating with external services or APIs to leverage the model's capabilities.

3.1.2.6 Query from user:
This is the user-facing component where users interact with the chatbot. It includes elements like chat windows, input fields, buttons, and menus for user interaction.

3.1.2.7 Dialogue Management:
Dialogue management controls the flow of the conversation and decides what responses to generate. It may involve a rules-based system, a decision tree, or more advanced techniques like reinforcement learning for dialogue optimization.

3.1.2.8 Response Generation:
This block creates the chatbot's responses based on the user's query and the knowledge base. Techniques may include template-based responses, dynamic content insertion, or even natural language generation using large language models.

3.1.2.9 Final Response to the user:
This block involves tracking the performance of the chatbot, including user interactions, errors, and user satisfaction. Analytics help improve the chatbot's capabilities over time.

3.1.3 Output in the desired format:
Output for the image analysis and the chatbot in the proper format is presented to the users via the mobile and web applications.

3.1.4 Helpline numbers and further assistance if required:
This block focuses on the fact that some of the queries cannot be solved by our chatbot hence further assistance is required. In case of disease detection, for further purchase of pesticides, fertilisers, etc requires contact information.

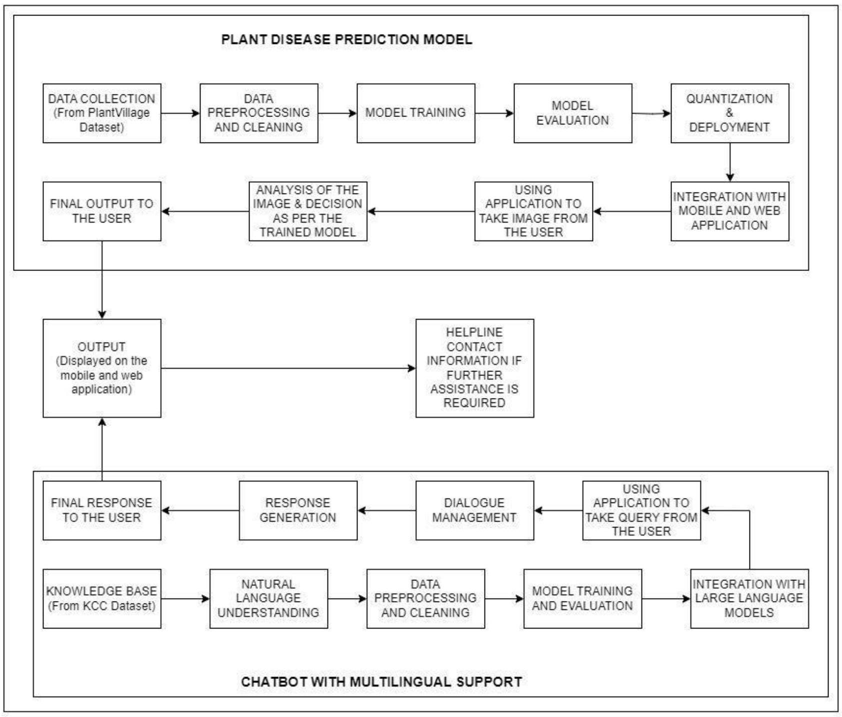

Figure 2 : Modular Diagram

3.2 Proposed Algorithm

3.2.1 NLP Pipeline
The different phases of the NLP pipeline include -

3.2.1.1 Tokenization:
The entire query is converted into different tokens.

3.2.1.2 Lower case + Stemming:
The tokens are converted to lowercase and then stemming is performed using the Porter Stemmer Algorithm.

3.2.1.3 Excluding punctuation characters:
Punctuation characters such as "?,:,;,,,*,<,>" are excluded.

3.2.1.4 Bag of Words:
Bag of Words Approach is used to and after using Softmax the final probability is calculated. If the probability is greater than 0.9 then the query is classified into that tag and the appropriate response from the response array is returned.

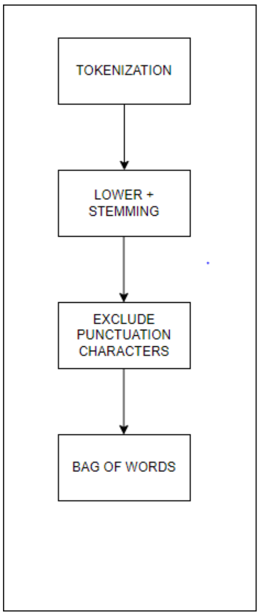

Figure 3: NLP Pipeline

3.2.2 Chatbot Pipeline
The different phases of the chatbot pipeline are-

3.2.2.1 Training data:
The training data is in the JSON format. The JSON file has several tags along with the query and the responses. This is used for training the ANN model.

3.2.2.2 Train-Test Split:
The queries and responses are used as the input data and the tags are the predicted output.

3.2.2.3 Bag Of Words:
Bag of Words Approach is used to and after using Softmax the final probability is calculated. If the probability is greater than 0.9 then the query is classified into that tag and the appropriate response from the response array is returned.

3.2.2.4 Feed Forward Neural Network:
The neural network used has 3 layers. Then Softmax is used for calculating the probabilities and the final output.

3.2.2.5 Output:
The output is the tag if the probability calculated is greater than 0.9.

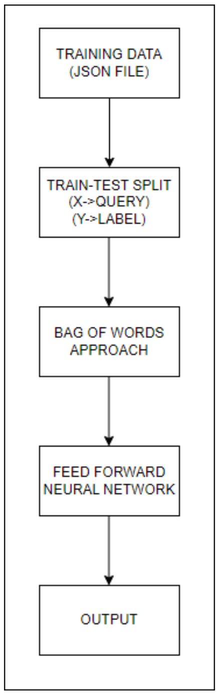

Figure 4: Chatbot Pipeline

3.2.3 Feed Forward Neural Network

3.2.3.1 Model Architecture:
The model has three linear layers, the input_size (The size of the input features), the hidden_size (The size of the hidden layer), and the num_classes (The number of output classes).

3.2.3.2 Activation Function:
The Rectified Linear Unit (ReLU) activation function is applied after each linear layer. ReLU introduces non-linearity to the model, allowing it to learn complex patterns in the data.

3.2.3.3 Forward Pass:
In the forward method, the input tensor x is passed through the linear layers and ReLU activation functions. The output of the final linear layer is returned without applying any activation function.

3.2.3.4 Softmax:
Softmax activation is used to obtain class probabilities.

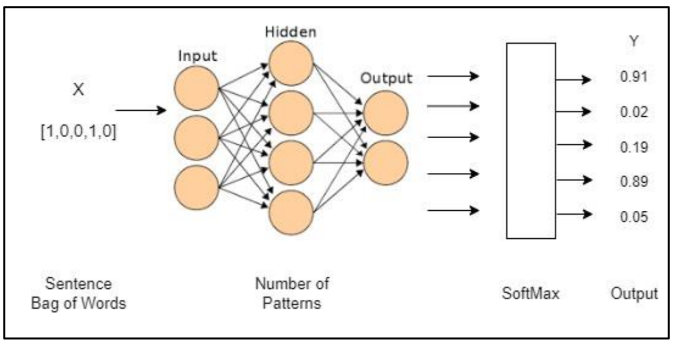

Figure 5: Feed Forward Neural Network

4. RESULTS AND EVALUATION

4.1 Confusion Matrix

Confusion Matrix is a machine learning method used to measure a classifier's performance. It helps to visualize and summarize the performance of a classification algorithm. It plots actual vs. predicted i.e., actual classes vs. the classes predicted by the model.

Darker diagonals in the confusion matrix represents a more accurate classification.

Given below are the Confusion Matrices for all the 9 plant varieties considered in the proposed solution.

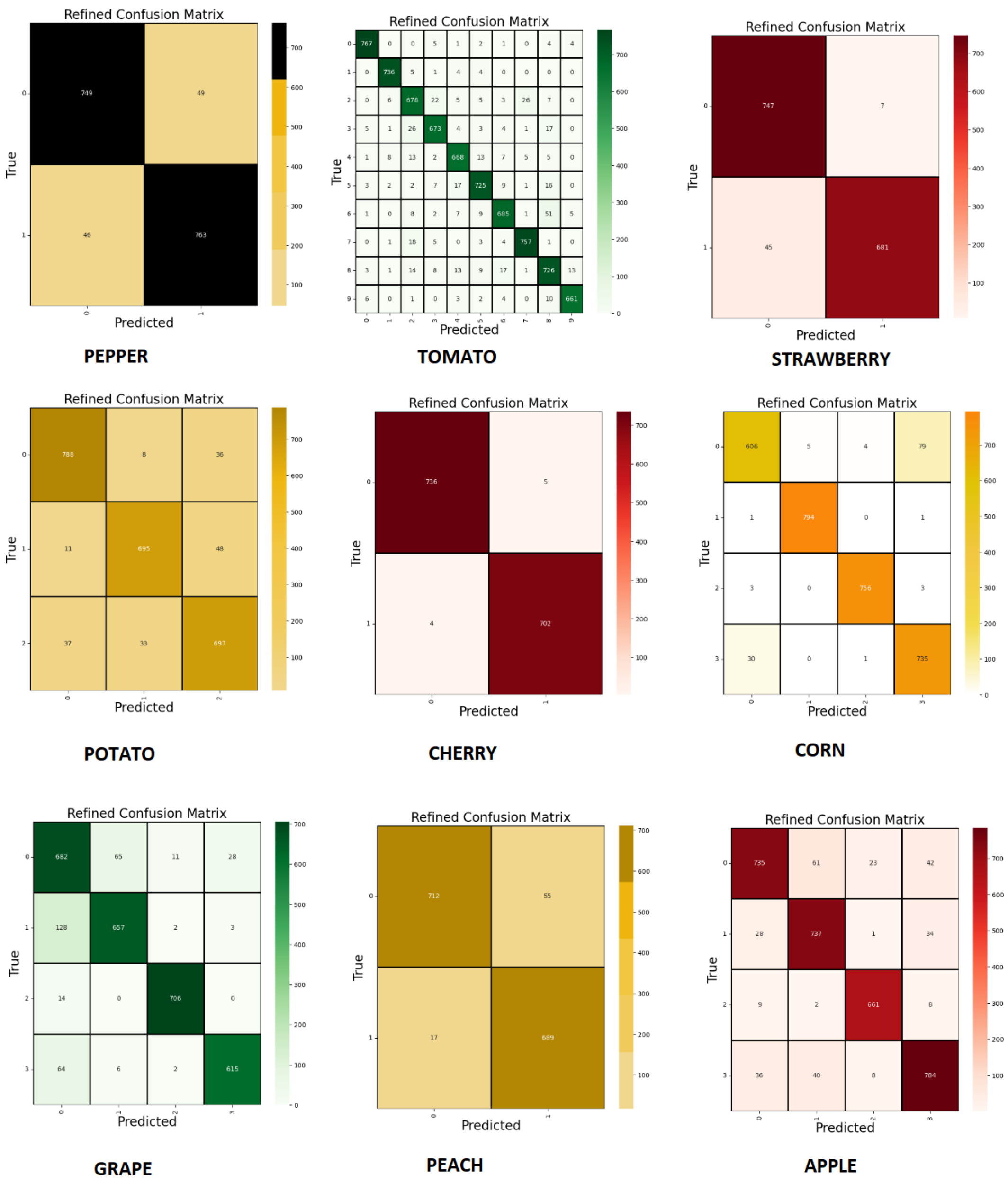

Figure 6: Confusion Matrix

4.2 Chatbot Loss Function

4.2.1 Number of Epochs:

1000 epochs are used for training the chatbot. Epochs refer to the number of times the entire training dataset is passed through the neural network. Typically, multiple epochs are used to allow the model to learn patterns in the data.

4.2.2 Loss Function:

The loss function is a measure of how well the model is performing. A loss of 0.0000 is ideal and suggests that the model has perfectly learned the training data. However, in real-world scenarios, achieving exactly 0.0000 loss is rare and could potentially indicate overfitting to the training data

```
272 227
Epoch [100/1000], Loss: 0.1749
Epoch [200/1000], Loss: 0.0011
Epoch [300/1000], Loss: 0.0001
Epoch [400/1000], Loss: 0.0000
Epoch [500/1000], Loss: 0.0000
Epoch [600/1000], Loss: 0.0000
Epoch [700/1000], Loss: 0.0000
Epoch [800/1000], Loss: 0.0000
Epoch [900/1000], Loss: 0.0000
Epoch [1000/1000], Loss: 0.0000
final loss: 0.0000
training complete. file saved to data.pth
```

Figure 7: Chatbot Performance

5. CONCLUSION

The proposed project aims to address the pressing issue of plant diseases and their detrimental impact on farmers in India. By leveraging deep learning tools and natural language processing techniques, the system endeavors to provide quick and accurate analysis of plant health based on leaf images, assisting farmers in combating diseases and preventing losses. The incorporation of regional languages, starting with Marathi and Hindi, demonstrates a commitment to catering to the vernacular audience and ensuring accessibility for farmers across diverse linguistic backgrounds. The implementation of a user-friendly website and android application with a multilingual chatbot further enhances the platform's usability and effectiveness. Overall, this project's objective is to provide better agricultural assistance to farmers in their regional languages, significantly contributing to reducing losses caused by disease proliferation and empowering farmers with vital information for improved crop management.

6. FUTURE WORK

To begin with the Chatbot implementation, focus will primarily be on Marathi and Hindi and later the scope will be broadened to different state languages. Extra Features such as information regarding the price and demand of certain crops in the available markets will be provided. Quick access to various government schemes and facilities available for the farmers will be provided. The disease predicting model will be expanded to more species of plants and other types of vegetations.

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