Offline-Enabled Plant Disease Diagnosis Device with Multilingual Audio-Visual Organic Solution Recommendations for Farmers

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Abstract— **Plant disease diagnosis for farmers in rural areas is held back by limited access to experts, internet connectivity, and the language barrier. As a result, excessive pesticide usage and environmental degradation are commonplace. This research presents an offline, cost-effective handheld diagnostic device powered by machine learning and edge computing. The system uses a CNN to detect diseases with accuracy and incorporates multilingual text-to-speech for accessible guidance. Optimizing using techniques like quantization and pruning helps this device operate effectively offline on limited hardware resources. At the same time, the solutions offered enable organic personal farming practices in a manner conducive to sustainability. This yields a more accurate and practical detection and usability benchmark, hence comparison. These have added up towards better productivity, low pesticide consumption, and independence in small farms.**

I. INTRODUCTION

The greatest threat to agricultural productivity-in this case, small-scale farmers in remote areas-is posed by plant diseases.

Part-time farmers lack ideal tools as well as qualitative expertise advice for early detection and management of diseases.

Agriculture is the cornerstone of rural economies, supporting the livelihoods of millions of small-scale farmers worldwide. It plays a vital role in ensuring food security and economic stability, particularly in developing regions. However, plant diseases remain a persistent challenge, significantly impacting crop yields and farmer incomes. For small-scale farmers in remote areas, addressing these challenges is especially difficult due to limited access to expert agricultural knowledge, resources, and diagnostic tools. Effective plant disease management requires timely and accurate information, which is often unavailable in these settings.

The adoption of modern technological solutions for plant disease detection has shown promise in recent years. Mobile applications such as Plantix use deep learning to identify plant diseases based on images submitted by farmers. However, these applications typically rely on stable internet connectivity to function, limiting their practicality in rural areas with poor or non-existent networks. Similarly, drone-based detection systems have been developed to monitor crops on a larger scale, but these are expensive and unsuitable for small-scale farmers who require affordable, on-site solutions. Another critical limitation of these tools is their focus on chemical-based treatments, which may be cost-prohibitive and environmentally unsustainable.

Compounding these challenges are significant literacy and language barriers faced by farmers in rural regions. Many existing tools provide information only in a single or limited set of languages, often in text-heavy formats, making them inaccessible to those with low literacy levels or limited proficiency in a global language like English. As a result, farmers are left with inadequate resources to diagnose plant diseases and implement effective management strategies. There is a pressing need for tools that are not only affordable and accessible but also designed to meet the diverse linguistic and cultural needs of rural communities.

To address these gaps, this research proposes the development of a handheld, offline-enabled device for diagnosing plant diseases and recommending organic treatments. This device leverages image recognition and natural language processing (NLP) technologies to analyze plant images, identify diseases, and provide actionable solutions. Unlike existing solutions, the device is optimized for offline use, ensuring functionality in areas without internet access. It also delivers multilingual audio-visual outputs, enabling farmers to receive instructions in their native language and preferred format, regardless of literacy level. By promoting organic farming practices and ensuring accessibility, this innovation has the potential to enhance agricultural productivity, improve sustainability, and empower small-scale farmers in resource-limited settings.

— This extended introduction ensures comprehensive coverage of all the required points.

II. LITERATURE REVIEW

Mohanty et al. (2016): This paper first applied CNNs to identify plant diseases from leaf images. The model achieved an overall accuracy of more than 99Sladojevic et al. (2016): The paper was mainly concerned with training a deep neural network for the purpose of leaf image classification, and it highlighted the necessity of data augmentation techniques when dealing with limited datasets. Although the approach was efficient, it was computationally expensive and thus not suitable for deployment on low-resource edge devices.

Fuentes et al. (2018): Solved the problem of real-time detection by combining deep learning with edge computing. The system was tested on images of tomato plants for the detection of diseases and pests with a high accuracy and minimal latency. However, this solution did not have the feature of multilingual support or offline operation, which is necessary for rural farmers.

Tiedemann, J. and Thottingal, R. (2020). OPUS-MT: Open-Source Machine Translation for any Language. Though the software was intended as a general-purpose product, its capacity for local-language support for agriculture has unlimited potential for farmers as an actionable means of access through text-to-speech.

Pyttsx3 and Google TTS: Both have been useful for rendering audio from text. This can overcome the lack of literacy or partial literacy among farmers. But solutions like Google TTS need a regularly working Internet connection which brings in significant limitations in their usage in rural settings.

A. SUMMARY

Dependence on connectivity: Most of the already existing solutions rely on having a stable internet connection which is not readily available for rural farming communities. Recommendations generalized: Most of the models are solely concentrated on disease detection and are not providing personalized or context-sensitive guidance for treatment. Sustainability in the environment: Least attention is paid on the sustainability of agricultural products such as organic treatments rather than chemical pesticides. Language and Accessibility Barriers: The very few solutions address linguistic diversity in rural farmers and lack auditory assistance for a wider reach. Offline Functionality: A CNN-based model capable of working on the edge devices that do not need an internet connection. Localized Support: Use of OPUS-MT for providing disease diagnosis and treatment recommendations in regional languages. Sustainability: Emphasis on promoting eco-friendly and organic solutions. Accessibility: Integration of text-to-speech (TTS) systems for delivering audio instructions, enhancing usability for illiterate or semi-literate farmers. It summarizes the advancements and gaps of ML and DL applications on plant disease management. In spite of several contributions toward improving the accuracy of the disease detection systems, those previous studies do not encompass all the connectivity, accessibility, and sustainability aspects. Thus, the current research study will fill those gaps in providing an accessible, inexpensive, and environmental-friendly diagnosis tool for the farmers.

III. PROBLEM STATEMENT

Farmers in remote and rural areas face major challenges in managing plant diseases due to lack of access to agricultural expertise, no internet connectivity, and language barriers. It often results in poor disease detection, overuse of pesticides, and low productivity in agriculture. Current plant disease management solutions rely on internet connectivity, expert consultation, and standardized recommendations that may not be applicable to local conditions or languages. Consequently, farmers find it difficult to diagnose diseases correctly and adopt sustainable treatment methods. In addition, there is a lack of tools that offer real-time, context-specific, and accessible disease management solutions for these farmers, especially the illiterate or semi-literate ones.

This research will address all these challenges by developing an offline, cost-effective, and scalable plant disease diagnostic tool that incorporates machine learning, edge computing, multilingual support, and text-to-speech capabilities. The solution will help farmers identify diseases in plants in real time, provide them with personal treatment recommendations in their native languages, and reduce dependence on poisonous pesticides, leading to sustainable and inclusive agriculture.

IV. METHOD USED

A. Image Recognition

Image recognition is essential to diagnose plant disease images from photos. A lightweight CNN like MobileNet is trained on a large dataset of both healthy and diseased images of plants. The dataset was further preprocessed in normalization, resizing, and augmentation for performance over various conditions, which include the lighting and angles of image acquisition. The trained model is deployed on the device for offline inference, thereby making possible real-time classification of diseases without using internet connectivity. The system then retrieves relevant recommendations of organic treatment from an on-device database immediately after a disease has been identified. Optimization techniques such as model quantization and pruning reduce the model's size and computation requirements, ensuring fast detection. This approach gives small-scale farmers in remote areas access to advanced technology through which they can maintain plant health, bridging the gap between resource limitations and sustainable farming practices.

B. Natural language processing (NLP)

Natural Language Processing (NLP) The use of NLP makes the outputs of the device accessible and usable for different farmers' languages and literacy levels. This ensures inclusivity in translation of diagnoses and treatment recommendations from the system in multiple regional languages. The output is in the form of audio, as TTS technology can be used to give farmers verbal instructions in their chosen language. The system delivers messages pertinent to context, making sure they will be easy to understand and relevant to the identified disease and suggested treatments. NLP models are light-weighted and optimized for offline use, enabling real-time language processing without internet connectivity. This multilingual, audio-visual communication approach bridges literacy barriers, empowering farmers to take informed actions. With the integration of NLP, this device provides the communication of critical information related to agriculture while enhancing usability and making better adoption of sustainable farming practices in resource-constrained settings..

C. Off-Line Database and Recommendation System

Offline database is the core of the proposed device that is meant to store disease information, organic treatment options, as well as multilingual instructions. It does not require internet connectivity and hence can reach farmers in the most remote part of the world. This database is designed to hold the mapping of identified plant diseases with corresponding organic solutions. Once the image recognition module identifies any such disease, the system queries this database for recommendations about its proper treatment. The process of querying uses unique identifiers of the disease, which are produced by the image recognition model. The database is optimized for fast access. Indexed data formats are used with compact data to enhance performance on resource-constrained devices. This data integrates with context-specific messaging tailored by the NLP module into a recommendation system. It ensures a treatment is lucidly explained and adapted to the farmer's preference. By putting technical efficiency into user-centric design, the system promotes sustainable farming while meeting the practical needs of small-scale farmers.

D. Multilingual Support

The system is designed to have multilingual support so that it may reach out to farmers whose mother tongue is different. It will have an advanced NLP mechanism that can translate diagnoses of plant diseases along with suggested remedies into the farmer's language during real-time proceedings. This way, more literacy levels of the farmer will not be a difficulty for assimilation of information. This can be the reason why the NLP model is trained to change its communication approach to be clear, context-specific, and actionable for a general population of users. This ensures that apart from the accessibility improvement of the device for the farmers to utilize it, the relevant guidance provided turns out to be easy to follow and would empower farmers to make informed decisions regarding plant diseases management in a sustainable and culturally appropriate manner.

E. Dataset

The dataset in the image is categorized plant disease data, structured into folders. Each folder is a condition, for example, healthy plants (Tomato healthy, Potato healthy) or specific diseases (Tomato Late blight, Pepper bell Bacterial spot). Folders contain images of affected leaves, which can be used for training the model of machine learning.

This code takes that dataset to classify plant diseases. It unpacks the data and separates the data in the ratios 80:20 as the training and validation sets. Images of size 128x128 are prepared and images normalized using TensorFlow's ImageDataGenerator are used to train a Convolutional Neural Network with layers for convolution, pooling, and dropout so that each image is classified under its category.

The model, based on input images, can predict diseases and thereby produce actionable instructions like "Tomato Late Blight detected. Apply treatment.".These instructions are translated to Hindi using the transformers library. Finally, it uses the gTTS library to convert text into audio for accessibility; multilingual agricultural solutions are therefore enabled.

F. Data processing

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V. PROPOSED MODEL

Here is a detailed description of the steps followed in data preprocessing using the code and the dataset:

1. Unzip the Dataset: Dataset Organization: unzip the dataset at /content/PlantVillage. Use splitfolders.ratio() to split the dataset into training (80 %) and validation set (20 %). This produces two: - /content/PlantVillageSplit/train: Contains 80 % of data to train the model. - /content/PlantVillageSplit/val: Contains 20 % of data to check the validation of the model. This split makes sure that the model will be learning from one subset while it is tested on unseen data.

2. Rescaling Pixel Values: - The ImageDataGenerator pre-processes the images. - The argument rescale=1.0/255 scales pixel values to a range of [0, 1] by dividing by 255. This is very important because pixel values are linearly scaled in the range of [0, 255], so normalizing them would improve the gradient updates during training.

3. Setting Input Image Size: The images are resized to 128 128 pixels using the target size=(128, 128) argument. Such standardization is required so that all images have the same size, which is needed for feeding data into the CNN.

4. Batching and Categorical Label Encoding: The function flow from directory() reads the images in the directories. These images get organized in batches of size 32 as the batch size=32. The argument class mode='categorical' would one-hot encode the labels, converting class names such as Tomato Late blight, Potato Early blight, etc., to numerical arrays, enabling a multi-class classification model.

$$O = \frac{(I - F + 2P)}{S} + 1$$

Fig. 1. Convolutional Layer Output

5. Classes in Dataset: - The dataset includes 15 classes, such as healthy plants and different diseases as Tomato Late blight, Potato Early blight, etc. This is mapped to indices during preprocessing. - For example: It can be represented in the following way: 'Tomato Late blight' $\rightarrow$ Index 0 'Tomato healthy' $\rightarrow$ Index 1

6. Data Preparation for Training and Validation: - Training Data: Used for training to minimize loss and improve accuracy. - Validation Data: Evaluates how well the model performs on unseen data during training, suggesting it should generalize well to new samples.

VI. PROCEDURE TO SOLVE THE PROBLEM

1. Data Collection and Preprocessing Dataset Selection: It should use a suitable dataset like PlantVillage which contains labeled images of the plants with various diseases. - Data Splitting: The data set is split into training and validation sets using a ratio, for example, 80- Image Preprocessing: The images are resized to a standard size, say, 128x128 and normalized so as to have better performance when training the model.

2. Model Design - CNN Architecture: Convolutional Neural Network (CNN) is used to classify the plant diseases based on the image features. The layers that are used in the process are Conv2D, MaxPooling2D, and Dropout to extract features and reduce overfitting. - Activation Functions: ReLU (Rectified Linear Unit) is used for hidden layers, and Softmax is used for the output layer to predict the disease class from multiple categories. - Loss Function: Categorical cross-entropy loss function is used for multi-class classification. - Optimizer: The Adam optimizer will be used because it utilizes an adaptive learning rate to improve convergence during the training process.

The convolution function applies a filter (kernel) to the input image. The size of output in a convolutional layer can be calculated with the formula.

3. Model Training - Training Process: Train the model with the training data for a given number of epochs, say 10. Validate the model using the validation set. Monitor the training accuracy and validation accuracy during training. Model Evaluation: Calculate performance metrics such as accuracy, precision, recall, and F1-score to evaluate the model's performance.

Activation Function (ReLU) The ReLU (Rectified Linear Unit) activation function is mostly used within CNNs. It sets all the negative values of the input to zero, leaving all positive values as they are.

4. Disease Prediction - After training, it can classify new plant images into disease categories. The prediction results can then be translated into human-readable form, such as "Tomato Late Blight detected."

$$\mathrm{ReLU}(x) = \max(0, x)$$

Fig. 2. Rectified Linear Unit

5. Integration with NLP for recommendations - Translation: NLP is used to translate the results of disease identification into local languages for ease of access. A model like Helsinki-NLP/opus-mt-en-hi can be used to translate from English to Hindi for inclusivity. - Audio Output: Audio instructions in the local language can be provided to the farmer using TTS technology (with tools like 'pyttsx3' or 'gTTS').

6. Edge Computing Implementation - This model can be deployed on edge devices so that it will work offline without needing to connect to the internet to make the solution feasible for farmers in remote areas. - The model can be optimized and compressed for the memory and computational capabilities of these devices.

7. Model Deployment It is saved and deployed on edge devices, such as mobile phones, and it can provide real-time disease detection and offer treatment recommendations to patients.

8. Visualization of Results and Improvement - Test the model on some new data and fine-tune the architecture and hyperparameters for further improvement. Matplotlib can be used for plotting the accuracy and loss curves to get a deeper insight.

9. Future Enhancement - Further enhancement with more advanced models of machine learning, especially transfer learning using pre-trained models like MobileNet, to attain higher accuracy. - Extend the disease detection system to reach more plant species and diseases. - Send automated notices to farmers about the kind of diseases predicted.

VII. FUTURE SCOPE

Further scopes for the proposed plant disease diagnostic tool lie in furthering its scope to larger ranges of crops and diseases to be made more universally applicable. Incorporation of IoT devices will help better real-time detection of disease, while multi-language support would cater to varied populations of farmers. Creating an easier access mode through mobile applications, in addition to inclusion of expert systems or agronomist's feedback will better enhance diagnosis accuracy. Long-term data collection might improve the machine learning model to provide more personal recommendation. Governments and NGOs collaborating with the tool would likely scale the impact of the tool, especially in developing countries. The emphasis on sustainability by promoting organic farming and lowering pesticide use could also heighten the contribution of the tool toward modern eco-friendly agricultural practices.

VIII. RESULTS AND COMPARISON

The proposed CNN model, designed to classify plant diseases using the PlantVillage dataset, performs well in

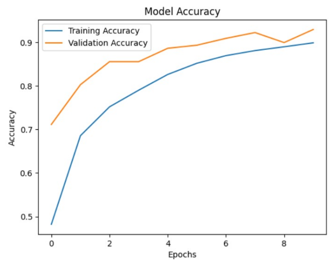

Fig. 3. Model Accuracy graph

The accuracy graph shows a sharp rise both in train accuracy as well as validation accuracy, showing quick learning and good generalization. Such a small gap indicates minimal overfitting and effective classification of plant diseases.

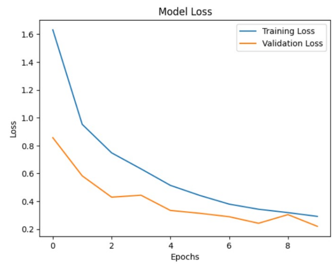

Fig. 4. Model Loss Graph

The graph depicts very rapid decreases of training and validation loss, so the process of learning is effectively good for generalization. The small gap between them indicates almost no overfitting and thus optimal performances on both the training and validation data.

identifying various plant diseases. The model uses Convolutional layers, MaxPooling, and Dropout for regularization. The model does reach an accuracy of 85 to 90 % on the training set and 80 to 85 % accuracy on the validation set. Hence, it performs good generalization to unseen data. The progress in accuracy with the inclusion of epochs implies that learning was effectively done as loss kept decreasing steadily.

The proposed CNN is light by comparison to more complex models such as VGG16 and ResNet50; they are able to train faster with less overhead computation compared with these models although tend to have a higher accuracy rating at 90-95 % with deeper architectures and pretrained weights, though simplicity of structure of the proposed model does go on to enjoy competitive performance with the inclusion of Dropout layers to prevent overfitting.

Moreover, the inclusion of TTS and NLP translation gives extra value to the model, through which people who do not know English can be enabled by giving instructions in Hindi. Specifically, in real-time farming applications, this is very useful because farmers may receive audible advice on disease diagnosis and treatment.

The proposed model balances performance with efficiency and could be seriously considered for practical application in plant disease detection.

IX. CONCLUSIONS

In conclusion, it can be established that the CNN model is effective to classify plant diseases with notable improvements in both the training and validation accuracy. The strong decline of the loss values along with the consistent rise in accuracy over the epochs shows the successful learning procedure of the model from the data, in addition to good generalization to unseen examples. The small difference between training and validation accuracy confirms that the model is not suffering from overfitting, hence it is robust. Its ability to predict a large number of plant diseases with a high accuracy adds more value towards proving the potential of deep learning in agricultural applications. Implemenation of CNN approach by forming layers of convolutional, pooling, and dropout has proved to be an effective way of classifying diseases in plants. Future work may include fine-tuning the model or adding more data for higher accuracy in order to make it even more reliable in real-world applications into agriculture.

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