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An AI Powered Farmer's Associate for the Cooperative Smart Farming Ecosystem

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Abstract: *In the face of global challenges such as population growth, climate change, and dwindling natural resources, the agricultural sector is under immense pressure to boost produc- tivity while minimizing environmental impact. The integration of Artificial Intelligence (AI) technologies presents a promising solution to address these challenges.*

The Argo Farm Project represents a pioneering initiative that harnesses the power of AI to revolutionize traditional farming practices, optimize resource allocation, and enhance agricultural sustainability. This abstract provides an overview of the Argo Farm Project, focusing on its key components, objectives, and anticipated outcomes. The project leverages advanced AI algorithms and data analytics techniques to analyze diverse datasets, including weather patterns, soil composition, crop health indicators, and market demand trends. By processing and interpreting these data streams in real-time, the AI system generates actionable insights and recommendations for farmers, enabling them to make informed decisions at every stage of the process.

This project aims to address these challenges by leveraging the power of artificial intelligence and machine learning to build an intelligent chatbot and crop disease classification system.

Keywords: AI in plant disease detection, Machine learning in agriculture, Crop health monitoring system, Weather prediction, Precision agriculture technologies

I. INTRODUCTION

A. Background

AgroInsight was founded out of a deep-seated concern for the difficulties that farmers encounter all across the world. Plant diseases may be detected using traditional methods, but these approaches are often insufficient, leaving farmers suscep- tible to unplanned outbreaks that might wipe out whole crops and livelihoods. A varied group of agricultural professionals, engineers, and data scientists got together with the common goal of revolutionizing the way farmers approach disease control after seeing the urgent need for a better solution.

Understanding how important agriculture is to the world's food security and sustainability, the team made it a top priority to develop a solution that will support ecological balance, resource efficiency, and resilience.

B. Problem Statement

Agricultural yields across various crops are expected to fall significantly due to adverse weather conditions and the proliferation of pests and diseases, which are causing concern among farmers throughout the world.

- Declining Agricultural Productivity: Adverse weather conditions, pests, and crop diseases are significantly re- ducing global crop yields, posing a critical challenge for farmers.
- Farmer Challenges: Small-scale farmers, particularly in economically disadvantaged regions, face heightened risks due to a lack of crop insurance, government aid, and minimum price guarantees.
- Limitations of Current Detection Methods: Existing plant disease detection methods are inaccurate, worsening yield losses.

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Proposed Solution with Advanced Technology: A deep learning model using localized datasets and photographic inputs to detect plant diseases early, providing farmers with actionable insights to enhance crop health and agricultural productivity.

II. OBJECTIVES

The main objective is to lessen the negative effects of pests and diseases on agricultural products. Specific aims include:

- The development of a deep learning model that leverages native datasets to identify diseases in plants.
- Enable early and precise diagnosis of diseases using image inputs, facilitating timely intervention by farmers.
- Assist farmers in reducing crop losses and financial hardships associated with plant disease outbreaks.
- Reduce the spread of diseases by providing actionable insights that allow farmers to take proactive measures.
- Enhance farmers' decision-making capabilities by provid- ing a reliable, AI-driven tool for continuous monitoring of plant health and disease risks.
- Foster greater collaboration between farmers and agricul- tural experts by providing a platform for sharing disease data and insights.

III. RELATED WORK

Previous studies have explored various machine learning and deep learning models for plant disease detection.

• Agarwal & Reddy (2019):

- Approach: Pre-trained CNN for feature extraction and SVM for classification of plant diseases.
- Dataset: Kaggle dataset with 477 training and 127 testing samples.
- Drawback: The reliance on pre-trained models limits the flexibility of the system for new or unknown diseases.

• Jiang et al. (2020):

- Approach: Used CNN and SVM for detecting rice leaf diseases such as rice blast, bacterial leaf blight, and brown spot.
- Dataset: 8,911 images of rice leaves.
- Drawback: The model's generalizability may be limited when dealing with a larger variety of crops or diseases not represented in the training dataset.

• Ullah et al. (2021):

- Approach: CNN combined with computer vision to clas- sify plant diseases.
- Dataset: Plant Village dataset (54,303 images, 38 cate- gories).
- Drawback: Database size and feature extraction limi- tations impacted the model's ability to detect diseases accurately in real-world conditions with varying image quality and light conditions.

• Nishit Jain & Akshay Chopade (2022):

- Approach: Introduced a lightweight deep CNN architec- ture without transfer learning for leaf disease detection. Dataset: Plant Village dataset (54,303 leaf images, 38 categories).
- Drawback: The method is limited to leaf diseases and does not consider other factors like environmental condi- tions that may affect plant health.

IV. PROPOSED METHODOLOGY

This project utilizes transfer learning for plant disease detection, leveraging pre-trained ResNet50 on the ImageNet dataset. Performance is evaluated and compared with Inception Net and VGG16 to identify the most effective model.

A. System Requirement

The tool adopts a modular architecture.

1) Hardware Requirements:

- Minimum multi-core processor (e.g., Intel Core i5).

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- Recommended: Multi-core processor with higher clock speed.
- Minimum 8GB RAM, Recommended 16GB or more.
- Software Requirements.
- Image processing libraries (e.g., Keras ,OpenCV) for preprocessing uploaded images.
- Dependency management tools like pip for Python pack- ages.
- TensorFlow for implementing the deep learning model.

2) Software Requirements:

- Operating System: Compatible operating system such as Windows, macOS, or Linux.
- Text Editor or Integrated Development Environment (IDE): To write and edit code, a popular choice includes Visual Studio Code and PyCharm.
- Web Browser: A modern web browser to test and interact with the React UI during development and deployment.
- Node.js: A JavaScript runtime environment for executing JavaScript code on the server-side. It is required to run the React framework.
- Python: A programming language used for developing the Flask API, training machine learning models, and executing various scripts.
- Flask: A Python web framework used for building the API endpoints and handling requests from the React UI.
- TensorFlow: An open-source machine learning frame- work used for training and deploying the RNN-based chatbot model and the MobileNetV2 crop disease classi- fication model.
- React: A JavaScript library for building user interfaces. It is used for developing the user interface (UI) of the chatbot application.
- Libraries and Dependencies: Install the necessary li- braries and dependencies required by the project, such as NumPy, Pandas, scikit-learn, TensorFlow, Keras, etc.

B. Workflow

1) Dataset: The ”Plant Village dataset” is a publicly available collection of images featuring diseased and healthy plant leaves from 38 plant species, covering multiple disease categories.Widely used in research, this dataset supports the development and evaluation of machine learning models for plant disease detection.
2) Data Splitting: The Plant Village dataset is divided into training (80%), validation (10%), and testing (10%) sets, with 34,727, 8,702, and 10,876 samples, respectively. The training set includes 38,400 RGB images of 14 crop species (2,400 images per class), labelled as ”healthy” or ”diseased.” Images vary in resolution (256x256 to 2560x1920) and include metadata on crop species, disease type, and severity. The validation set (16,906 images) assesses model generalization during training to prevent overfitting.
3) Data Pre-Processing and Augmentation: Image Pre- Processing enhances image data for classification through techniques like scaling, translation, and rotation. All images were resized to 256x256 pixels to ensure uniform resolution, and pixel values were normalized to the range [0, 1], making it easier for the model to learn and reducing the impact of outliers. Data augmentation further improved training data di- versity by applying random transformations such as rotations, translations, shears, zooms, and flips. These transformations created variations in the dataset, enabling the model to learn more generalizable features, with a fill mode used to manage empty spaces generated during transformations
4) ResNet50 (Modification): ResNet50, pre-trained on Im- ageNet, is adapted for plant disease detection by replacing and training its fully connected layers on a new dataset while fine- tuning select layers to enhance accuracy. This approach efficiently overcomes deep CNN challenges and improves model performance.
5) Tuning and Training: We fine-tune ResNet50 by freez- ing layers before the 154th and training the remaining layers with optimized parameters for plant disease classification. Performance is evaluated using metrics like accuracy, F1 score, and recall, leveraging transfer learning to improve accuracy and reduce overfitting.

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V. EXPERIMENTAL INVESTIGATIONS

Evaluate the accuracy and response time of the AI chat- bot by collecting a diverse dataset of farmer queries and corresponding expected responses. Measure the accuracy of the chatbot's generated responses compared to the expected responses..

- Chatbot Accuracy and Response Time: Evaluate the accuracy and response time of the AI chatbot by collecting a diverse dataset of farmer queries and corresponding expected responses. Measure the accuracy of the chatbot's generated responses compared to the expected responses..
- Chatbot User Satisfaction Survey: Conduct a user satisfaction survey or feedback collection mechanism to gather farmers' opinions and feedback on the chatbot's performance
- Chatbot NLP Performance:Analyse the chatbot's natu- ral language processing (NLP) capabilities by evaluating its understanding and interpretation of various query types, including questions, statements, and requests for specific information.
- Crop Disease Classification Accuracy: Measure the accuracy of the crop disease classification model by using a labeled dataset of crop disease images. Compare the predicted disease classifications with the ground truth labels .
- Weather API Integration: Evaluate the performance and reliability of the weather API integration by comparing the fetched weather data with external sources or official weather reports.
- Scalability and Performance Testing: Perform scalabil- ity and performance tests to assess the system's capability to handle a large number of concurrent users and requests.
- Error Handling and Robustness Testing:Test the sys- tem's robustness by simulating different error scenarios and edge cases. Evaluate the error handling mechanisms to ensure proper error reporting and graceful degradation of the system.
- Usability Testing: Conduct usability testing with a group of farmers or end users to assess the system's overall user experience, interface intuitiveness, and ease of navigation. Gather feedback on the UI/UX design, identify any usability issues, and make necessary improvements based on user suggestions.

VI. WORKFLOW

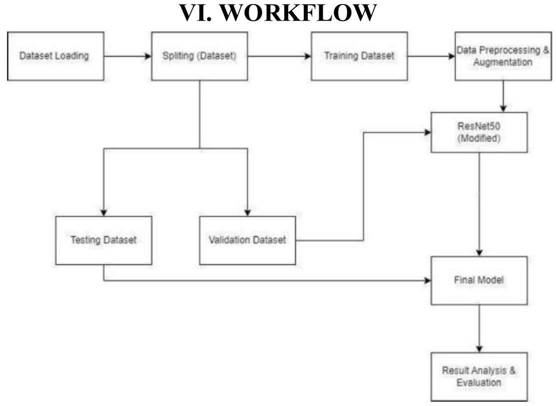

Fig. 1. Workflow diagram

VII. RESULTS AND APPLICATIONS

A. Subjective Result

- ResNet50: Achieved 95.68% accuracy with strong pre- cision and recall. Ideal for plant disease detection due to its complex and deep architecture.
- Modified ResNet50: Achieved 98.72% accuracy with high precision and recall. Excellent for tasks requiring high accuracy, though it demands more computational resources.
- InceptionV3: Achieved 91.68% accuracy with high pre- cision and recall. Efficiently handles varied image

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sizes, making it suitable for applications needing a simpler architecture.

- VGG16: Achieved 90.33% accuracy with higher preci- sion but lower recall. Suitable for tasks with limited com- putational resources and where simplicity is important.

B. Objective Result

From the comprehensive evaluation metrics presented in Table I, we observe that ResNet50 with Transfer Learning achieves superior performance (98.72% accuracy) compared to other architectures. The model demonstrates exceptional capability in learning hierarchical feature representations from plant disease imagery, with precision and recall scores of 98.78% and 98.72% respectively. This performance advantage stems from ResNet50's residual learning framework, which effectively addresses the vanishing gradient problem in deep networks through skip connections. The architecture's 50- layer depth enables robust extraction of both low-level texture features and high-level semantic patterns that are criti- cal for accurate disease classification. Comparative analysis with shallower networks (VGG16, InceptionV3) confirms that ResNet50's deeper architecture provides significant benefits for this computer vision task, particularly in handling the subtle visual differences between healthy and diseased plant specimens across various growth stages.

TABLE I: MODEL PERFORMANCE COMPARISON

S.N	Model	Accuracy	Precision	Recall
1.	Inception V3	91.68%	91.95%	91.68%
2.	Vgg16	90.33%	91.49%	90.33%
3.	Resnet 50	95.68%	95.98%	95.68%
4.	Resnet50 (Fine-tuned)	98.72%	98.78%	98.72%

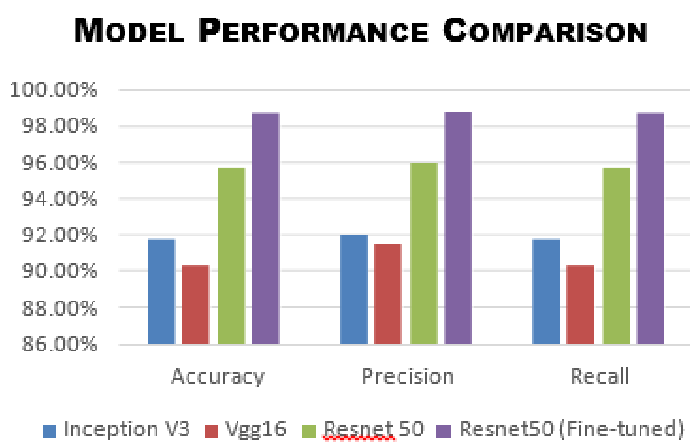

TABLE II: COMPARISON WITH EXISTING METHODS

S.N	Model	Accuracy	Precision	Recall
1.	Resnet50 TL [8]	96%	–	–
2.	Modified Resnet50	98.72%	98.78%	98.72%
3.	Efficient DL [7]	74.10%	88.13%	94.06%
4.	Deep CNN [12]	98.18%	98.31%	98.16%
5.	Efficient DL+BiFPN [7]	74.10%	88.13%	94.06%
6.	CNN+CV [13]	93.8%	99.1%	95.9%

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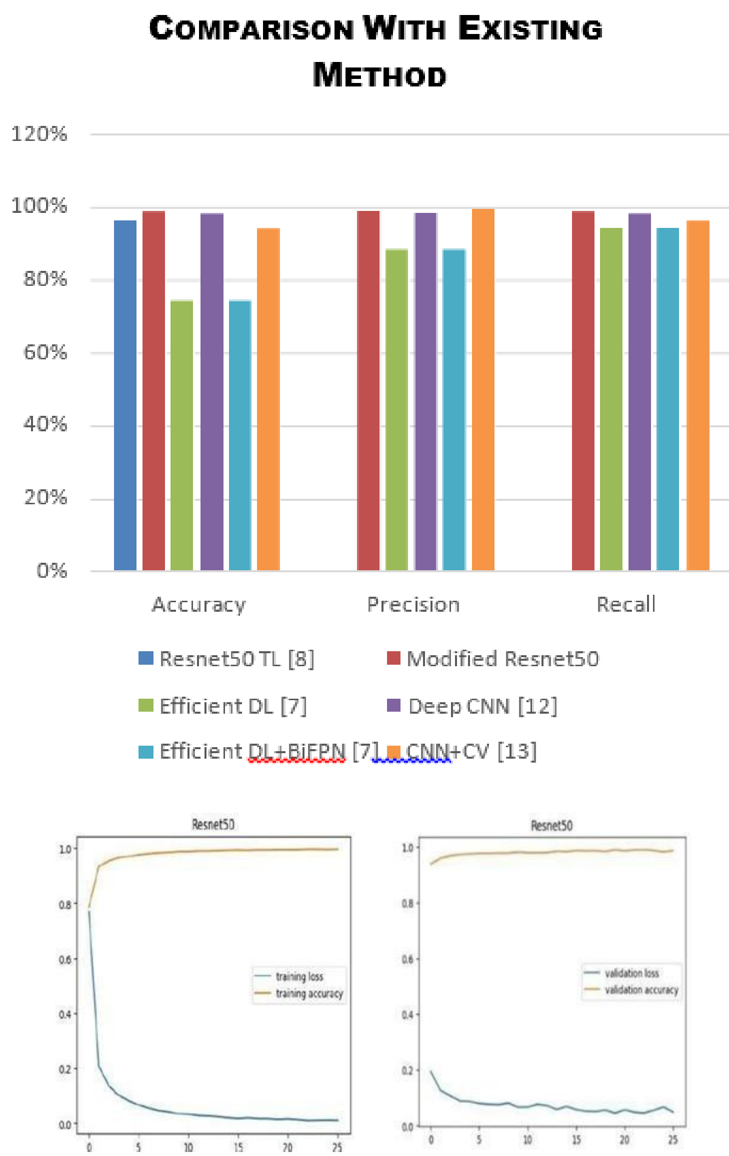

Fig. 2. Performance metrics visualization

VIII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

In conclusion, this paper presents a project that integrates an AI chatbot and crop disease classification system for farmers. The chatbot, trained on an RNN model, enables farmers to obtain prompt and accurate answers to their queries. The crop disease classification system, based on the MobileNetV2 archi- tecture, assists farmers in identifying crop diseases efficiently.

B. Future Scope

• Advanced NLP Techniques: Implement sentiment anal- ysis and entity recognition to improve the chatbot's response accuracy.

• Voice-based Interaction: Integrate speech recognition for farmers to interact using voice commands.
• IoT Integration: Use real-time data from IoT sensors for enhanced decision-making and crop health management.
• Predictive Analytics: Utilize data for forecasting irriga- tion needs and providing proactive alerts to farmers.

REFERENCES

[1] Agarwal, A., & Reddy, S. (2019). Plant disease detection and classifi- cation using deep neural networks. Journal of Artificial Intelligence in Agriculture, 3, 45-51.
[2] Jiang, F., Lu, Y., Chen, Y., Cai, D., & Li, G. (2020). Image recognition of four rice leaf diseases based on deep learning and support vector machine. Computers and Electronics in Agriculture, 179, 105824.
[3] Ullah, F., Khan, R. U., Khan, K., Albattah, W., & Qamar, A. M. (2021). Image-based detection of plant diseases: From classical machine learning to deep learning journey. Wireless Communications and Mobile Computing, 2021, 5541859.
[4] Adeleke, B. S., & Babalola, O. O. (2022). Roles of plant endospheric microbes in agriculture—A review. Journal of Plant Growth Regulation, 41(4), 1411-1428.
[5] Mondal, J., Islam, M., Zabeen, S., Islam, A. B. M. A. A., & Noor, J. (2022). Plant leaf disease network (PLeaD-Net): Identifying plant leaf diseases through leveraging limited-resource deep convolutional neural network. Computers and Electronics in Agriculture, 198, 107011.
[6] Lakshmi, R. K., & Savarimuthu, N. (2022). PLDD—A deep learning- based plant leaf disease detection. IEEE Consumer Electronics Maga- zine, 11(3), 44–49. doi:10.1109/MCE.2021.3083976
[7] Venkataramanan, A., & Agarwal, P. (2019). Plant disease detection and classification using deep neural networks. International Journal of Computer Applications, 178(25), 21-25.
[8] Syed-Ab-Rahman, S. F., Hesamian, M. H., & Prasad, M. (2022). Citrus disease detection and classification using end-to-end anchor-based deep learning model. Applied Intelligence, 52, 927–938.
[9] Wu, Y. (2021). Identification of maize leaf diseases based on convolu- tional neural network. Journal of Physics: Conference Series, 1748(3), 032004. IOP Publishing.
[10] Hughes, D., & Salathe´, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv preprint arXiv:1511.08060.
[11] Mohanty, S. P., Hughes, D. P., & Salathe´, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
[12] Smart Farming—Automated and Connected Agriculture. Accessed: Jul. 22, 2020. [Online]. Available: https://www.engineering.com/ DesignerEdge/DesignerEdgeArticles/ArticleID/16653/SmartFarmingAuto mated-and-Connected-Agriculture.aspx
[13] Global Smart Agriculture Solution Demand. Accessed: Jul. 22, 2020. [Online]. Available: https://www.smartcitiesdive.com/press-release/ 20190712-global-smart-agriculture-solution-market-demand-likely toexpand-by-technol
[14] The Co-op Farming Model Might Help Save America's Small Farms. Accessed: Jul. 22, 2020. [Online]. Available: https://geo.coop/content/coop- farming-model-might-help-save-america's-small-farms.
[15] A. Boghossian, ''Threats to precision agriculture,'' U.S. Department of Homeland Security, Washington, DC, USA, Tech. Rep. 20181003a, 2018.
[16] M. Gupta, M. Abdelsalam, S. Khorsandroo, and S. Mittal, ''Security and privacy in smart farming: Challenges and opportunities,'' IEEE Access, vol. 8, pp. 34564–34584, 2020.
[17] Lottes, R. Khanna, J. Pfeifer, R. Siegwart, and C. Stachniss, ''Uavbased crop and weed classification for smart farming,'' Tech. Rep., May 2017.
[18] S. S. L. Chukkapalli, A. Piplai, S. Mittal, M. Gupta, and A. Joshi, ''A smart- farming ontology for attribute based access control,'' in Proc. IEEE IEEE 6th Intl Conf. Big Data Secur., May 2020, pp. 1–8.
[19] X. Jin, R. Krishnan, and R. Sandhu, ''A unified attribute-based access control model covering DAC, MAC and RBAC,'' in Proc. IFIP Annu. Conf. Data Appl. Secur. Privacy. Cham, Switzerland: Springer, 2012, pp. 41–55.

[20] M. Gupta and R. Sandhu, ''The GURAG administrative model for user and group attribute assignment,'' in Proc. Int. Conf. Netw. Syst. Secur., 2016,
pp. 318–332.
[21] L. Zavala, P. K. Murukannaiah, N. Poosamani, T. Finin, A. Joshi, I. Rhee, and M. P. Singh, ''Platys: From position to place-oriented mobile computing,'' AI Mag., vol. 36, no. 2, p. 50, Jun. 2015.