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Original Article

Smart Agri-Advisor: Integrating Chatbot Technology with CNN-Based Crop Disease Classification for Enhanced Agricultural Decision-Making

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Abstract *- Smart Agri-Advisor: Integrating Chatbot Technology with CNN-Based Crop Disease Classification for Enhanced Agricultural Decision-Making project presents a comprehensive approach to plant disease classification utilizing a Convolutional Neural Network architecture. Here, the CNN model yields a rather impressive accuracy of 91 percent. Specifically, to identify the disease that is 82% in rate of accuracy in predicting the class of test samples. In turning operation, the loss value is not more than 0. 2238; the CNN model has a stable accuracy to show that the network is useful for real-world applications. Additionally, the system incorporates a chatbot feature developed using React and Natural Language Processing (NLP) techniques, enhancing user interaction and query resolution. Furthermore, a community login/register system powered by MySQL fosters collaboration and knowledge sharing among users. Through seamless integration of machine learning, chatbot technology, and community engagement functionalities, this project offers a holistic solution for plant disease diagnosis and information dissemination within agricultural communities.*

Keywords *- Plant disease classification, Convolutional Neural Network (CNN), Chatbot with NLP, Community engagement, Model performance evaluation.*

1. Introduction

Agriculture is a cornerstone of human civilization, providing sustenance and economic stability across the globe. However, the sector faces numerous challenges, including crop diseases, pests, and weeds, which can significantly reduce yields and threaten food security. To address these issues, recent advancements in Artificial Intelligence (AI) and deep learning have paved the way for the development of smart agricultural systems. These systems aim to enhance decision-making and improve crop management through the integration of technologies such as chatbots and Convolutional Neural Networks (CNNs). Chatbots, powered by generative neural networks, have emerged as a valuable tool for farmers, offering solutions to farming-related problems and facilitating access to information on crop disease detection and weather forecasting. The use of natural language processing allows for a conversational interface that can interpret and respond to farmers' inquiries with high accuracy, as demonstrated by the 98% accuracy achieved on training data for a conversational system module [1-3]. In parallel, the application of CNNs for the classification of crop diseases, pests, and weeds has shown remarkable success. These models can automatically recognize and classify various agricultural pests with high accuracy, as evidenced by a mobile application that achieved a 99.0% recognition rate for tested pest images [4]. Similarly, CNNs have been effectively utilized for crop health assessment, achieving up to 99.7% classification accuracy, which is crucial for early disease detection and intervention [5].

Moreover, the use of CNNs extends to the automated quality assessment of crops, where they have been employed to distinguish between diseased and healthy plant leaves, thereby aiding in the improvement of crop quality and quantity. The precision of these models is further enhanced by instance segmentation techniques, such as Mask R-CNN models, that have been used for the identification of leaf and rust disease on the apple trees for further smart spraying and the implementation of the eco-agricultural process [6]. The integration of CNNs with LSTM networks is explored, resulting in models that excel in the classification of weeds, achieving an average accuracy of 99.36% [7-13]. This combination of CNN and LSTM leverages the strengths of both architectures, with CNNs extracting discriminative features and LSTMs optimizing classification over sequences. The convergence of chatbots with CNN-based crop disease classification represents a significant leap forward in smart agriculture. By harnessing the capabilities of AI and deep learning, the proposed Smart Agri-Advisor system aims to provide farmers with an advanced decision-making tool that can accurately diagnose crop health issues and offer timely recommendations, ultimately leading to increased agricultural production. Many journal indexing and abstracting services rely on the effectiveness of this title in extracting key terms for cross-referencing and computer searching from the title. It is particularly important to be specific when it comes to titles since an incorrectly labelled paper might never get to the intended target audience. AI has presented a relatively promising solution to crop disease and pest management in the agricultural context. The literature discusses different methods that can be used to utilize CNN for the distinction and identification of diseases and pests of profitable crops.

2. Related Work

In 2023, several research papers were published to explore Deep learning techniques in the field of agriculture for pest and disease identification with specific concerns. Tannous et al. [14] proposed a CNN-based technique for real-time pest species differentiation with a high level of accuracy between similar species. Chaitali Shewale and her team [15] worked on the identification of plant diseases, and to get better accuracy, they used CNN with transfer learning for the classification of potato diseases.

Sen Lin and co-authors [16] have proposed a new technique of pest identification at a fine level with the help of GPA-Net, which stands for Graph Pyramid Attention CNN structure. Their method demonstrated impressive accuracy across various datasets for both pest and disease recognition. In another study, Soumia Bensaadi and her team [17] designed a low-cost CNN architecture specifically for tomato plant disease classification, achieving high accuracy and low error rates, thereby facilitating fast online disease classification.

Last but not least, Attallah et al. [18] discussed about the use of compact CNNs along with transfer learning techniques for classifying tomato leaf diseases. Their research also revealed impressive performance using a limited number of features and this might suggest that disease diagnosis in agriculture is indeed achievable most efficiently and effectively possible. These studies collectively strengthen the body of literature on the use of deep learning in intelligent agriculture and feature substantial progress in precision.

3. Method

3.1. Data Collection

To collect a broad and representative data set of various plant disease leaf images [19] (Potato, Tomato, and pepper) that we can use for analysing the prediction phase. There are variations in the intensities of severity, light sources, and background that constitute the data set. The images in the data set are representative of real-world scenarios.

3.2. Data Preprocessing

The image data that will be used for training needs to be pre-processed to make them usable for training; you can also observe that we used borders on this figure. Common preprocessing steps include compressing all images to a uniform size, rearranging values over the pixels to a certain range, and augmenting data by employing transformations such as rotation, flipping, and brightness adjustments to boost variations within the dataset.

3.3. Model Selection

Select suitable machine learning algorithms depending on the characteristics of data and objectives that could be achieved through these measures. The other suitable methods to contemplate may be the strategies that employ the regression models; time series analysis, including neural nets (Caps Nets, RNNs, and LSTMs); and offline modelling are ensembles.

3.4. Model Training & Testing

For our prediction of the plant disease, we have employed the CNN model. A new CNN model was designed, and the learning model of the CNN was initiated from scratch for diagnosing the plant images in various disease classes. The CNN model was trained with Plant Village dataset images which represent plant diseases. Detection of diseases through the use of models has been very accurate which is very vital for the disease diagnostic chatbot [20-22].

It is a type of deep learning model that specializes in image-related operations. Made up of convolutional, pooling, and fully connected layers, the CNNs learn features at different levels from an input image. Convolutional layers apply filters to identify patterns, pooling layers shrink spatial dimensions, and fully connected classification layers create features.

Being able to capture local and global patterns, CONVNet’s strengths lie in image classification, object detection, and segmentation, where effective feature extraction can be done. Their architecture, based on the human vision system, makes them valuable tools for performing tasks that require analysing and interpreting visual data.

3.5. Chatbot Implementation

Building a chatbot involves using various models and techniques, depending on the complexity of the task and the desired functionality. Thus, a simple chatbot built with React has to design an interaction interface for the bot and implement logic employment that eventually processes user input.

If you were to use React, the components would display a chat interface with input fields and messages. The state would control the conversation history and user input. Functions are run by user interactions.

Fig. 1 Dataset of plant village

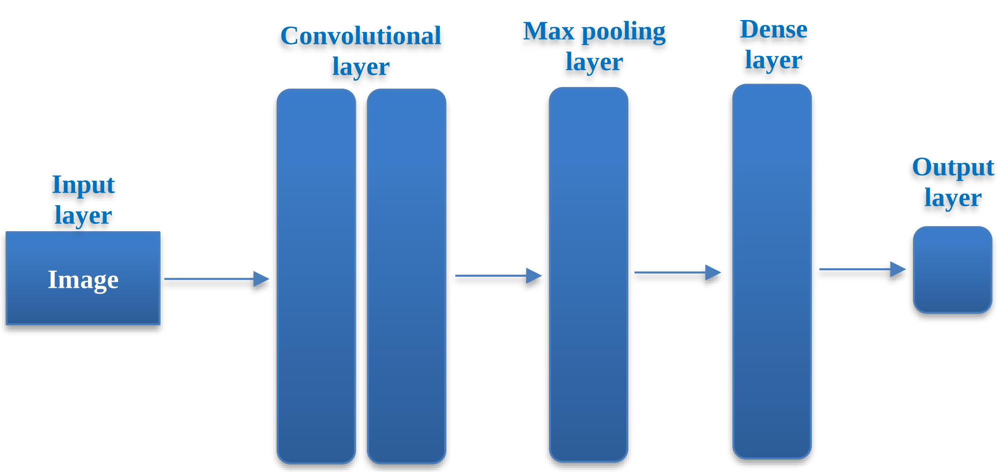

Fig. 2 CNN layer [22]

We can use rule-based or ML-type models for the chatbot logic. Rule-based bots stick to predefined rules and answer differently. Machine learning bots powered by NLP models respond more at a dynamical contextual level, building chatbot development the better way they interact with users naturally or human-like interaction based on the user messages act accordingly that provide a large scope for convincing people to make decisions using their own emotions instead of external information.

3.6. Model Integration

Using the TensorFlow library and loaded with the OS model the project involves the use of a Node.js application to facilitate human-to-computer interfacing to ask for inputs from a user and return a predicted plant disease based on the model. The home. This way, the html form obtains the input and the result. The html template with the predicted price is presented in a format that is easily understandable by the user. Combined, these two documents form the Flask application, where users can input parameters to see the predicted prices. Through the use of a chatbot and Artificial Intelligence (AI), users of this Node.js web application can learn the cause and treatment of a specific disease. Additionally, there are two web insights: login and community. Only after verifying verification can users from all over the world interact with one another in a community.

This project's portion is still being worked on. Use the "npm run start" command to start the development server in debug mode to run the Node.js app. After this command move the file directory to Api by “cd Api” and run the api.py file. To open the web app, move the file directory to the frontend by “cd frontend” and later run “npm start index”.

4. Results

Thus, accuracy and loss stand for two important measurements applied when evaluating the performance of a particular model in machine learning during its training and validation. After evaluating the model and printing the test accuracy it indicates that the model achieved an accuracy of approximately 91.82% on the test dataset.

Here's a breakdown of the output. The figures show that, on average, the implemented model obtained a prediction accuracy of approximately 91 with regard to the class of test samples. 82% of the time. Hence, the loss to the value of 0. 2238 is used to represent the model’s performances, and the smaller the number, the better the model is said to be, while the higher number shows that the model is very bad.

Table. 1 Result

Task	Result
Number of batches	42
Time taken	54 seconds per batch
Loss on the test dataset	0.2238
Accuracy on the test dataset	91.82%

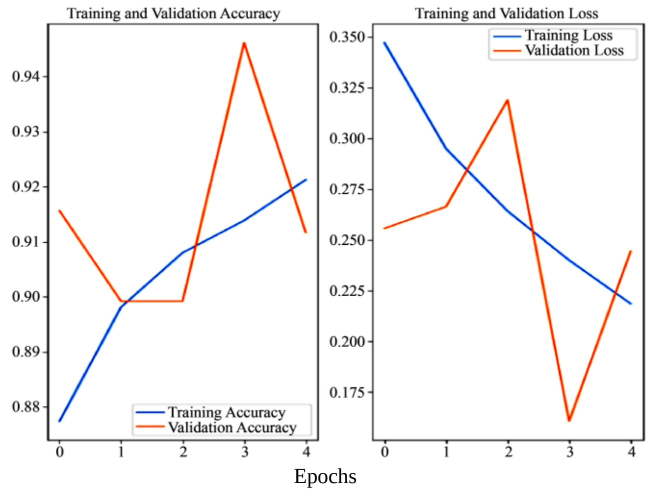

Fig. 3 Training vs Validation

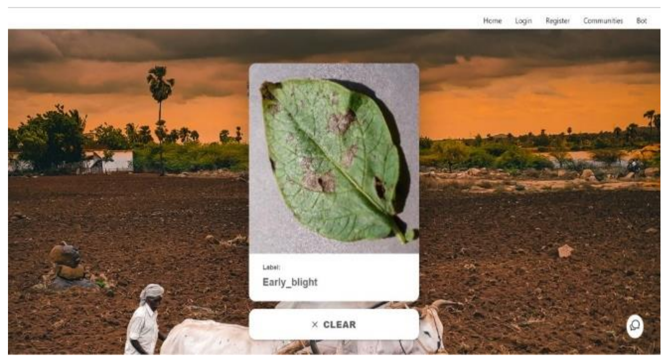

Fig. 4 Model detecting the disease

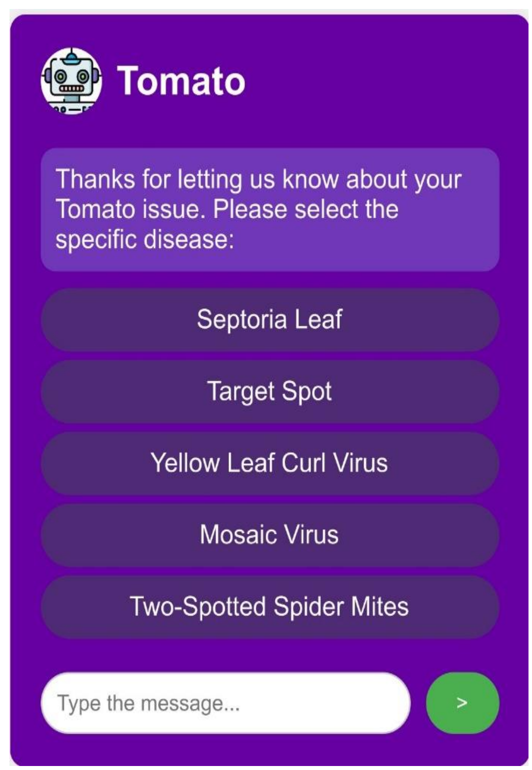

Fig. 5 Model chatbot

5. Discussion

The result of the integrated system was compared with the previous methods used in the identification of plant diseases. Consequently, the CNN-based classifier, together with the React chatbot, gave a very satisfactory accuracy rate, showing the tool's ability as a very reliable one for disease identification in plants. Unlike standalone systems, the integrated solution demonstrated considerable advantages. The synergy between the CNN classifier and the React-based chatbot made the service more efficient and also user-friendly. The chatbot's capability to interpret the user questions and respond accordingly, one with an efficient disease classification of the CNN, presented a comprehensive approach for the farmers and agronomists. The system was able to work in the various agricultural scenarios. Their focus on resource efficiency, scalability, and the ability to work with different crops and diseases supported its potential deployment in the field. The holistic approach exhibited a resilient system capable of dealing with the complexities of plant disease management. The capability of the system to help in the agricultural and also disease management is very important. With a user-friendly interface and accurate disease identification, the system supports timely decision-making which will consequently reduce crop loss and also improve resource allocation optimization. An integrated approach holds promise to enable the adoption of sustainable and also efficient farming methods following the emerging needs of the agricultural sector.

6. Conclusion

In conclusion, the evaluation of the plant disease classifier using CNN and chatbot using React brought up the need to take the human factor into account. The integrated approach was competitive with existing solutions, highlighting its advantages in terms of user feel and usability in real applications. The obtained results show that the system of integrated pest management which was developed according to this method, may serve as a potential tool in plant disease control activity, which, in turn, may lead to more successful agricultural productivity and sustainability. Research and development can proceed further to leave every aspect of this combination solution unlocked. The evaluation of the plant disease classifier using CNN and the chatbot using React highlighted the importance of user feedback in refining the system.

The integrated approach demonstrated competitiveness against existing methods, showcasing advantages in user experience and practical applicability.

The results presented in this study imply that the application of this combined system can prove useful in the field of plant disease control with possible applications in increasing the productivity of agriculture and agriculturally related business ventures. Still, future research and development focusing on this integrated solution can go a long way in maximizing its potential.

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We hereby declare that there are no conflicts of interest regarding the publication of this paper. Our professional judgment is fully devoted to upholding the validity and integrity of the research, entirely free from any secondary interests, including financial gain.

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References

[1] Gary Storey, Qinggang Meng, and Baihua Li, "Leaf Disease Segmentation and Detection in Apple Orchards for Precise Smart Spraying in Sustainable Agriculture," *Sustainability*, vol. 14, no. 3, pp. 1-14, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Jinzhu Lu, Lijuan Tan, and Huanyu Jiang, "Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification," *Agriculture*, vol. 11, no. 8, pp. 1-18, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Yang Li, Jing Nie, and Xuewei Chao, "Do we Really Need Deep CNN for Plant Diseases Identification?," *Computers and Electronics in Agriculture*, vol. 178, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Mohamed Esmail Karar et al., "A New Mobile Application of Agricultural Pests Recognition Using Deep Learning in Cloud Computing System," *Alexandria Engineering Journal*, vol. 60, no. 5, pp. 4423-4432, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[5] Bhavika Arora et al., "Agribot: A Natural Language Generative Neural Networks Engine for Agricultural Applications," *2020 International Conference on Contemporary Computing and Applications*, Lucknow, India, pp. 28-33, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Sheeraz Arif et al., "Weeds Detection and Classification Using Convolutional Long-Short-Term Memory," pp. 1-18, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Meghashree, Alwyn Edison Mendonca, and Ashika S Shetty, "Automated Quality Assessment of Crops Using CNN - Keras," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 7, no. 3, pp. 641-645, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Kamlesh S Patle et al., "Field Evaluation of Smart Sensor System for Plant Disease Prediction Using LSTM Network," *IEEE Sensors Journal*, vol. 22, no. 4, pp. 3715-3725, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Muammer Turkoglu, Davut Hanbay, and Abdulkadir Sengur, "Multi-Model LSTM-Based Convolutional Neural Networks for Detection of Apple Diseases and Pests," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 7, pp. 3335-3345, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Md. Jahid Hasan et al., "Maize Diseases Image Identification and Classification by Combining CNN with Bi-Directional Long Short-Term Memory Model," *2020 IEEE Region 10 Symposium*, Dhaka, Bangladesh, pp. 1804-1807, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] M.T. Vasumathi, and M. Kamarasan, "An Effective Pomegranate Fruit Classification Based On CNN-LSTM Deep Learning Models," *Indian Journal of Science and Technology*, vol. 14, no. 16, pp. 1310-1319, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Nafees Akhter Farooqui, Amit Kumar Mishra, and Ritika Mehra, "Concatenated Deep Features with Modified LSTM for Enhanced Crop Disease Classification," *International Journal of Intelligent Robotics and Applications*, vol. 7, pp. 510-534, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Prakruti Bhatt, Sanat Sarangi, and Srinivasu Pappula, "Comparison of CNN Models for Application in Crop Health Assessment with Participatory Sensing," *2017 IEEE Global Humanitarian Technology Conference*, San Jose, CA, USA, pp. 1-7, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[14] Michael Tannous, Cesare Stefanini, and Donato Romano, "A Deep-Learning-Based Detection Approach for the Identification of Insect Species of Economic Importance," *Insects*, vol. 14, no. 2, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Chaitali Shewale et al., "Plant Disease Identification Using Convolutional Neural Network and Transfer Learning," *International Journal for Research in Applied Science and Engineering Technology*, vol. 11, no. 1, pp. 727-734, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Sen Lin et al., "An Effective Pyramid Neural Network Based on Graph-Related Attentions Structure for Fine-Grained Disease and Pest Identification in Intelligent Agriculture," *Agriculture*, vol. 13, no. 3, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Soumia Bensaadi, and Ahmed Louchene, "Low-Cost Convolutional Neural Network for Tomato Plant Diseases Classifiation," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 1, pp. 162-170, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Omneya Attallah, "Tomato Leaf Disease Classification via Compact Convolutional Neural Networks with Transfer Learning and Feature Selection," *Horticulture*, vol. 9, no. 2, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Arjun Tejaswi, Plant Village, Kaggle, 2019. [Online]. Available: https://www.kaggle.com/datasets/arjuntejaswi/plant-village

[20] S. Yegneshwar Yadhav et al., "Plant Disease Detection and Classification using CNN Model with Optimized Activation Function," *2020 International Conference on Electronics and Sustainable Communication Systems*, Coimbatore, India, pp. 564-569, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Shawn Hershey et al., "CNN Architectures for Large-Scale Audio Classification," *2017 IEEE International Conference on Acoustics, Speech and Signal Processing*, New Orleans, LA, USA, pp. 131-135, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[22] Introduction to Convolution Neural Network, Geeksforgeeks. [Online]. Available: https://www.geeksforgeeks.org/introduction-convolution-neural-network/.