Context-aware AgriBot using dual intent and entity transformer and hybrid deep learning model

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Article Info

Article history:

Received May 31, 2025
Revised May 15, 2026
Accepted Jun 19, 2026

Keywords:

AgriBot
Dual intent and entity transformer classifier
Natural language processing
Rice disease detection
Transfer learning

ABSTRACT

The agriculture sector has gone through vast technological improvement, leading to increased productivity and sustainability. This research introduces AgriBot, a context-aware virtual assistant (VA) that helps farmers in rice cultivation and identifies diseases while providing instant suggestions for subsequent task. Using the RASA framework, AgriBot has been designed to understand the farmer's queries. Dual intent and entity transformer (DIET) classifier has been used for entity classification, achieving training and testing accuracy of up to 98% and 97%, respectively. Additionally, the system incorporates machine learning (ML) models for rice disease detection, utilizing a dataset of 4,624 images covering three major rice diseases: bacterial blight, brown spot, and blast. Among the tested models—neural network (NN), random forest (RF), support vector machine (SVM) and naive Bayes (NB) achieved an accuracy of up to 99.9%, demonstrating excellent classification performance. Using text-based query handling with image-based disease identification and instant suggestion makes it a more robust support system for the farmers.

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1. INTRODUCTION

Over the past few decades, the agricultural industry has undergone significant technological changes, even in urban environments. Not only does the implementation of artificial intelligence (AI) systems and the use of advanced tools reduce the labor requirements of farmers, but it also enables them to achieve the expected yield levels [1]. Unmanned air vehicles can continuously monitor crop health, enabling the use of pesticides in hazardous areas and allowing for targeted application with high precision. Similarly, agrarians are protected from health risks as robotic apparatuses undertake hazardous tasks [2].

The advent of mobile platforms with an agricultural orientation and virtual assistant (VA) technologies has brought significant benefits to farmers in various fields, including meteorological forecasting, phytopathological diagnosis, and crop management. Such inventions also make farmers more aware of supply-chain dynamics and various government programs, most often translated into native languages [3]–[6]. VAs, such as ChatGPT, Alexa, Siri, and Gemini, have become essential parts of daily operations, accelerating routine processes and providing information quickly, which increases productivity in general.

In the agricultural domain, AI, including VAs and convolutional neural networks (CNNs), has been widely applied to support farmers. However, a gap remains in developing user-friendly systems that seamlessly integrate textual and image-based data for plant disease detection through CNNs into a unified platform with reasonable accuracy. Such a system should prioritize accessibility for farmers and intuitive interfaces to bridge the digital divide and simplify complex tasks. The research using AgriBot fills this gap with great accuracy and an easy-to-use unified interface.

2. LITERATURE SURVEY

The latest developments in the field of deep-learning methods have produced significant achievements in agriculture-based research and implementation. Such applications as unmanned aerial vehicles, the internet of things (IoT), not only allow detecting and mitigating crop diseases early, but also support a closer interaction between farmers and emerging technologies [7], [8]. Koopman *et al.* [9] introduced AgAsk, a conversational agricultural information retrieval system designed to answer farmers' natural language queries by extracting relevant information from scientific documents using advanced neural ranking techniques. The authors show that the assistant is capable of answering questions about fertilizers, pesticides, and optimal irrigation regimes to an acceptable degree, reaching 86% when using Sen2Vec and Word2Vec embeddings. Similar to this, Anekar *et al.* [10] designed a regional-language VA that produces speech and provides crop- and fertilizer-related suggestions based on the weather and soil properties. Their application brings an accuracy of a maximum of 71%.

Temniranrat *et al.* [11] focused on optimizing services provided to rice farmers and agronomists. The researchers came up with a dedicated chatbot that can detect rice diseases and it is able to do this by using an object-detection system to differentiate between five significant disease phenotypes namely, blast, blight, brown spot, narrow-brown spot, and stripe. The average true-positive rate increased by 91.1 to 95.6%. Comparison with RetinaNet, Mask region-based convolutional neural network (R-CNN), and Faster R-CNN also confirmed that the YOLOv3 solver has better performance. Nayak *et al.* [12] presented a research paper that developed a VA to assist farmers. This VA provided knowledge on various agricultural practices, soil characteristics, and modern tools used in agriculture. The researchers used the Levenshtien distance formula, the natural language processing (NLP) approach, to calculate sentence similarity. The chatbot automatically redirected any unanswered questions through email to the agricultural experts or administrators. This VA reached an accuracy level of 96%. Moreover, this study tested a deep convolutional neural network (DCNN) based on InceptionResNetV2 with transfer learning for rice disease classification.

Momaya *et al.* [13] created the chatbot Krushi, which uses the WhatsApp messaging network's NLP technology to deliver farmers agricultural information, weather forecasts, and government programs. This software aims to save agricultural operations expenses and boost crop output among individual farmers. It had an outstanding overall accuracy of 96.1% and resolved 70% of the questions asked through the helpline number of Kisan Call Center (KCC), which went beyond what contact center service could do presently. Krushi, created using RASA X, helped underrepresented groups by addressing issues regarding agriculture and horticulture, animal husbandry, fisheries and market prices. Families who wished to know more about these specific areas were provided with this chatbot for knowledge acquisition and further study. Jain *et al.* [14] investigated the classification of farmers based on their literacy levels, categorizing them as low, semi, and high literacy users. For those with low literacy, the user interface is designed to prioritize visuals over text. Additionally, the study incorporates audio and audio-plus-text-based VAs. The results show that systems featuring more visual elements are easier to understand and more user-friendly for this target group. IBM Watson is employed to analyze queries that are submitted through the chatbot.

Usip *et al.* [15] focused on developing a customized mobile chatbot designed for crop farmers in Uyo. Chatbot training data was collected from the Akwa Ibom State Ministry of Agriculture and local farmers using questionnaires, and interviews. To represent the dataset effectively, the chatbot employed an ontology-based approach employing a hybrid machine learning (ML) method consisting of word permutation combined with the Jacquard Similarity algorithm. Consequently, it operates like a knowledge center where farmers can get helpful responses, information, and personalized suggestions regarding their unique farming questions. Chandolikar *et al.* [16] demonstrate that AgroBot successfully provides real-time responses to farmer queries related to crop conditions, weather forecasts, soil requirements, fertilizers, and market prices. It helps farmers plan their activities by predicting future crop prices.

In 2018, a few researchers developed AgronomoBot, a chatbot created to obtain and display information from a wireless sensor network. The bot can interact with sensor data and generate reports in various formats as the user requires. This chatbot used Telegram application programming interface (API) to communicate with users and capture information from eKo field sensors. This chatbot platform embraced IBM Watson cognition services to enhance user experience through natural language interaction and identify user intent [17]. Arora *et al.* [18] work on AgriBot, which uses multilayered long short-term memory (LSTM) to answer farmers' queries and uses CNN for disease detection. After training, 98% accuracy was achieved for conversational system module on training data and 94% for disease detection module on test data.

The FourCropNet framework is a new deep-learning model that can detect multi-crop plant diseases in cotton, grape, soybean, and corn, as proposed by Khandagale *et al.* [19]. The architecture uses residual blocks to improve feature extraction, attention to emphasize the diseased areas, and compact layers to maintain the computational cost. FourCropNet achieves excellent results with multi-crop data with a maximum accuracy of 99.7% with grape and 99.5% with corn. Alhassan *et al.* [20] create a new ML-based Arabic chatbot to resolve technical problems and detect problems by troubleshooting through the creation of a chatbot. The datasets are compiled using web extraction and this is supplemented with an open-source corpus called MADRA PROJECT that specializes in the Saudi dialect, hence making it linguistically relevant and rich.

As a hybrid AI model, Hasan *et al.* [21] use a DCNN with a support vector machine (SVM) to identify and differentiate nine major diseases in rice plants. With this method, the prediction accuracy on the test set is found to be high, at 97.5%, which proves the effectiveness of combining deep learning of representations with classical ML methods. Daniya and Vigneshwari [22] introduce a deep learning-based scheme of detecting rice plant diseases, which utilizes statistical, textural (LOOP), and CNN characteristics. The approach will involve image pre-processing and segmentation using SegNet, and classification using a deep recurrent neural network (DRNN) that has been trained using RideSpider water wave (RSW) algorithm. The end performance measures are 90.5% accuracy, 84.9% sensitivity, and 95.2% specificity, which stresses the efficiency of the suggested pipeline.

3. METHOD

The proposed research integrated the RASA framework as an open-source tool that optimizes flexibility for customizations, adaptiveness, and ease of data processing using natural language. RASA is composed of two core components: natural language understanding (NLU) and RASA core. This framework begins with the step of user tokenization, which clusters user utterances into discrete user tokens. This is followed by the user information text fragmentation, referred to as entity extraction. The framework then converts the tokens and extracted entities into numeric values. This transformation is termed as the featurization of the text. Finally, based on the numerical features of the user text, the framework classifies user intent, decoding the data using the RASA NLU component.

Considering the above steps, as a VA, AgriBot is empowered to understand the users' text and, when necessary, provide user contextual responses. Figure 1 illustrates and captures the overall system workflow and architecture of the proposed study. This figure describes the entire processing framework, from the input of a user query, through the RASA framework of NLP, and the extraction of user intents and entities for the generation of the final system response. Google Translator and the OpenWeather API are utilized to support regional languages and retrieve weather conditions based on the location provided by the farmer to answer the queries.

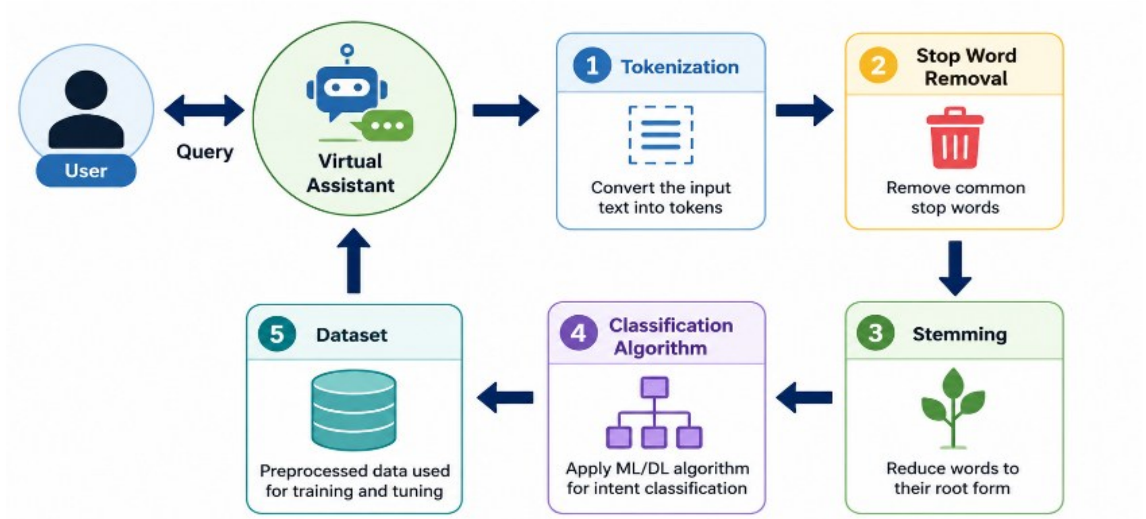
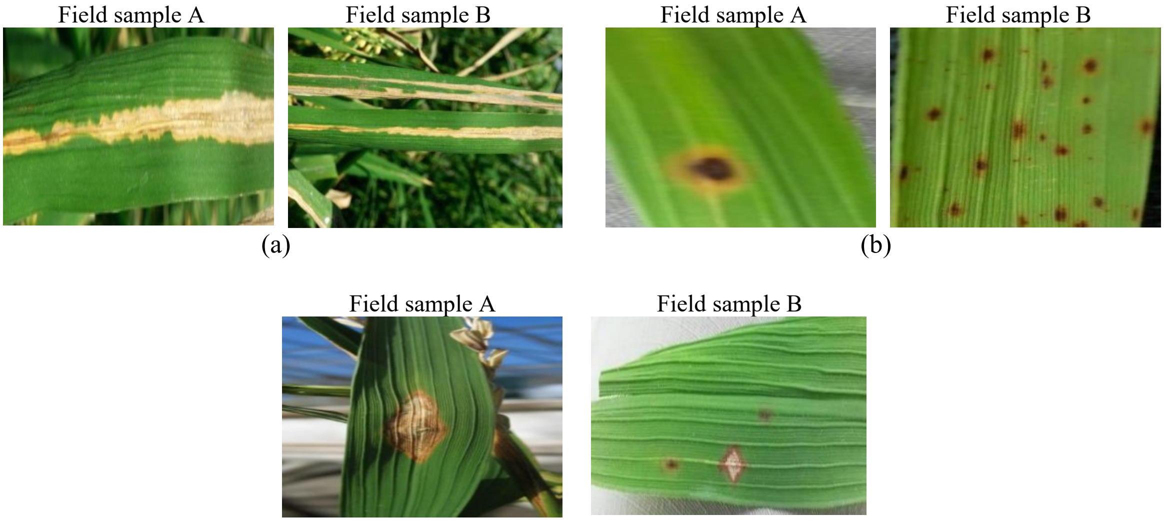


Figure 1. Overall process for developing the AgriBot for rice farming

3.1. Dataset used

The proposed AgriBot was developed using the data collected from the KCC Guwahati call center, which provided valuable context for designing the conversation flow. In addition to textual data collected from various sources, including KCC Guwahati, a data set for rice disease, namely bacterial blight, brown spot, and blast, had also been collected from the field using mobile devices with varying illumination and classified with the help of experts to train the same in an ML model. Figure 2 presents representative sample images from the rice disease image dataset used in this study. The figure includes visual examples of three major rice diseases, namely bacterial blight (1,584 images) as shown in Figure 2(a), brown spot (1,600 images) as shown in Figure 2(b), and blast (1,440 images) as shown in Figure 2(c), which were collected and validated with expert assistance. These images demonstrate the visual variations in color, texture, and lesion patterns that are critical for effective feature extraction and accurate disease classification.



(c)

Figure 2. The rice disease image dataset used for training and evaluation of the proposed AgriBot system: (a) bacterial blight, (b) brown spot, and (c) blast

The research conducted alongside the development of the AgriBot also enabled the identification of rice leaf diseases based on symptoms described in the query. Additionally, the AgriBot provided necessary suggestions for managing the crops. All the interactions were stored in a MYSQL database using a tracker store to monitor and track the conversations between the farmers and the chatbot. Two datasets were used in this research: i) textual data for AgriBot to handle farmers' queries, and ii) images of rice leaves to detect disease. In the first case, the dual intent and entity transformer (DIET) classifier was used to accurately identify intent and entity, i.e., for response selections. With an image dataset, random forest (RF), SVM, naive Bayes (NB), and neural networks (NNs) were used to identify the type of rice diseases. After evaluating the model, it was integrated with the action server RASA framework, i.e., AgriBot, to predict the disease.

3.2. Machine learning algorithms for rice disease detection

Figure 3 depicts the complete process flow for rice disease detection implemented in the proposed system. The figure shows the key stages, including image acquisition, resizing, feature extraction using SqueezeNet, and classification using different ML models. It clearly illustrates how the extracted features are processed and evaluated to identify the most accurate model for rice disease prediction. All the image data sets are resized to 300×300 for further processing. RF, SVM, NB, and NN, ML models were used for disease identification with parameters shown in Table 1 against each model.

In order to differentiate among particular diseases afflicting rice plants, the color, shape, and texture appearance of rice leaves were studied. A deep-learning model was used to extract features based on SqueezeNet and further machine-based methods were used to train the model. The result of this process was a set of 2048 extracted features. The data were partitioned into three separate subsets, including training (80% of the total dataset), testing (10% of the total dataset), and validation (10% of the total dataset) after preparation.

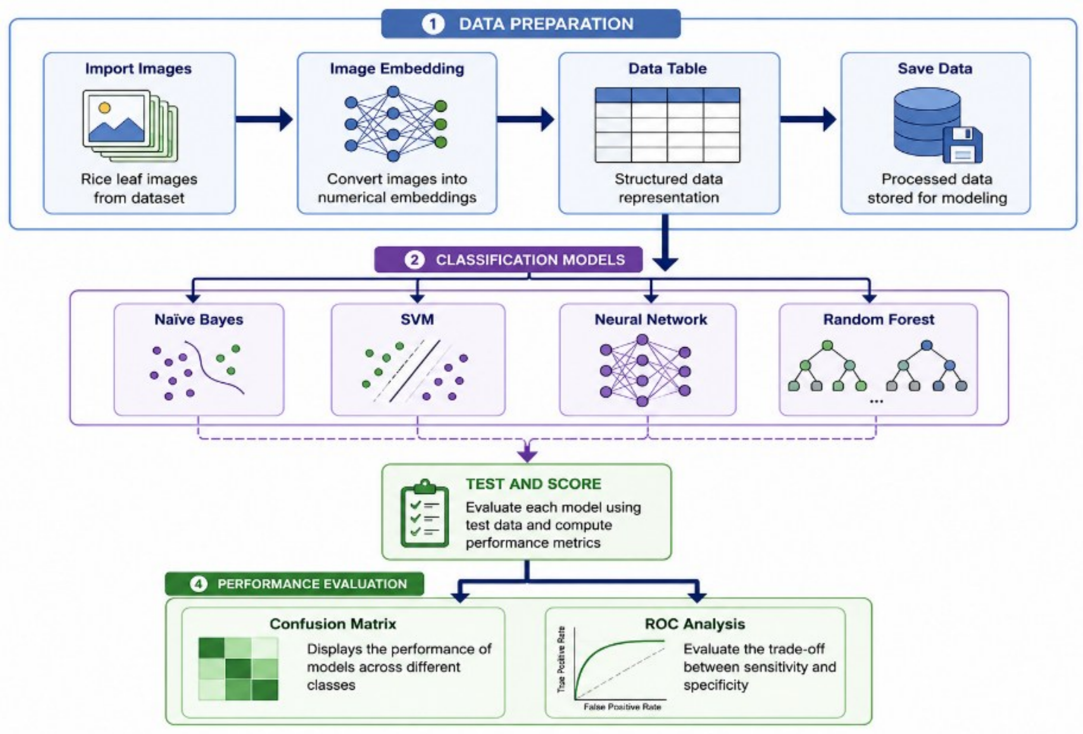


Figure 3. Workflow of the proposed rice disease detection and evaluation pipeline

Table 1 gives a detailed overview of the ML models used to detect the disease in rice with the corresponding hyperparameters. The table presents accurate, model-specific settings - tree depth in the case of RF, choices of kernel parameters in the case of SVM, and architectural hyperparameters in the case of NNs, along with the feature extraction methods used. This careful specification of parameters makes it easier to reproduce the experimental protocol, and also makes it easy to have a sound and fair comparison of the model performance throughout the study.

Table 1. ML models and parameters for rice disease detection

Model used	RF	SVM	NN	NB
Model parameter	No of trees: 10 Replicable training: No Tree depth: unlimited Minimum instances per node to continue splitting: 5	Model type: standard SVM Regularization constant (C): 1.0 Epsilon (ε): 0.1 Kernels used: Sigmoid, Tanh with auto x·y + 1.0 mapping Tolerance for numerical precision: 0.001 Maximum iterations: 100	Hidden layers: 100 Activation function: ReLu Optimizer: Adam Learning rate (α): 0.0001 Max iterations: 200 Replicable training: True	Feature extraction method: histogram of oriented gradients (HOG)

3.3. Experimental setup

To develop the proposed AgriBot system, Python 3.6 and RASA's open-source conversational AI framework was used. The conversational module used the DIET classifier as both an intent classifier and an entity recognizer. Custom actions were built using the RASA SDK for response generation and rice disease identification. Rice leaf images were collected in the field. These images were processed and resized, and the features were extracted and classified. For feature extraction, transfer learning was used, and the extracted features were classified using NN, RF, SVM, and NB classifiers. The assessment was conducted using 4,624 rice leaf images capturing bacterial blight, brown spot, and blast diseases, along with textual datasets collected from interactions with farmers. The dataset was divided in the ratio 80:10:10 to create training, validation, and testing datasets. The system used an Intel Core i5 processor with 16 GB of RAM on Windows 11. The implementation of the system used TensorFlow, OpenCV, NumPy, and Scikit-learn libraries. The system was evaluated based on accuracy, precision, recall, the F1-score, and the area under the curve (AUC). The overall system and the experimental process are shown in Figures 1 to 3.

4. RESULTS AND DISCUSSION

Table 2 reports the evaluation results of the DIET classifier used for intent and entity recognition in the AgriBot system. The table presents training and testing accuracy, F1-score, and precision values, providing a comprehensive view of the model's performance. These results demonstrate the robustness and generalization capability of the conversational component of the proposed system.

RASA chatbot has a training accuracy of 98%, which means that the model has stochastically learned the patterns and characteristics of the training corpus. The slightly reduced test accuracy of 97%, marginally lower test accuracy proves that the model is well-generalized to situations it has never encountered before, which serves as evidence of the fact that the model is well-performing outside of the training set. The slight decreasing in accuracy indicates that the overfitting is minimal and hence improves reliability of the system in its functioning.

The F1-score of training of 82% versus the test F1-score of 64% explains the tradeoff between precision and recall of the model. When the training F1-score is high, it suggests that the model has been able to capture the precision and recall when using the training data as an indicator of good performance. On the other hand, the test F1-score is relatively low to show that this balance might be in jeopardy when using new data. The precision of the training that is 81% with test accuracy of 66% also indicates a decrease in optimistic predictions when tested on unseen cases. To address this shortcoming, future studies will examine regularization schemes, cross-validation, and larger data-augmentation. Within the framework of rice disease identification, the generated dataset was tested with the help of the RF, SVM, NB, and NN classifiers, and feature extraction was implemented with the local SqueezeNet architecture. All of the samples yielded 2,048 features as shown in Table 2.

Table 2. Entity evaluation results (entity extractor: DIETClassifier)

Dataset	Accuracy (%)	F1-score (%)	Precision (%)
Train	98	82	81
Test	97	64	66

The comparative performance of various ML algorithms employed for rice disease detection is presented in Table 3. This table reports key evaluation metrics, including AUC, classification accuracy, F1-score, precision, and recall for each model. The results clearly indicate that the NN and RF approaches achieve consistently better performance than the SVM and NB classifiers. NNs (0.999) and RF (0.984) achieved high classification accuracy, showing the prediction accuracy of those models. As previously discussed, NNs and RF outperform both SVM and NB, achieving high values of AUC, classification accuracy, F1-score, precision, and recall. A balance of precision and recall makes them suitable for use cases that have constraints on false positives and false negatives. The confusion matrix for the four classifiers was generated in order to assess the best performing models.

Table 3. Results of the different ML algorithms for rice disease detection

Model	AUC	Accuracy	F1-score	Precision	Recall
NN	1	0.999	0.999	0.999	0.999
SVM	0.667	0.474	0.457	0.475	0.474
RF	0.999	0.984	0.984	0.984	0.984
NB	0.879	0.764	0.764	0.764	0.764

Table 4 provides a detailed confusion matrix analysis for the rice disease classification task using NN, SVM, RF, and NB models. The table illustrates the distribution of correctly and incorrectly classified instances across the three disease categories, offering insights into class-wise prediction accuracy. This representation enables a clear evaluation of misclassification trends and confirms the reliability of the best-performing classifiers in distinguishing between visually similar rice diseases. All confusion matrices are row-normalized and values are expressed in percentage.

A performance comparison between the proposed model and related studies is provided in Table 5. The table shows that the proposed approach achieves higher accuracy than most existing methods. This demonstrates the effectiveness of the adopted transfer learning strategy. It can be seen that both NNs and RF models have accurately detected rice disease. The proposed model achieved better accuracy using transfer learning (SqueezeNet) for feature extraction.

Table 4. Confusion matrix of the different classifiers for rice disease detection

Model	Actual		Predicted		
		Diseases	Bacterial blight (%)	Blast (%)	Brown spot (%)
NN	Actual data	Bacterial blight	99.9	0.00	0.1
		Blast	0.00	99.8	0.2
		Brown spot	0.00	0.01	99.8
SVM	Actual data	Bacterial blight	53.2	23.7	23.1
		Blast	27.5	43	29.5
		Brown spot	19.3	17.6	63
RF	Actual data	Bacterial blight	98.0	1.40	0.1
		Blast	1.5	97.9	0.7
		Brown spot	0.4	0.7	99.2
NB	Actual data	Bacterial blight	78.7	16.9	4.7
		Blast	13.9	71.3	14.8
		Brown spot	7.5	13.7	78.8

Table 5. Comparison of work done with our research model

Reference	Model	Accuracy (%)
Hassan *et al.* [23]	CNN with transfer learning (Inception V3)	98.42
Al-Gaashani *et al.* [24]	Self-attention network (SANET) based on the ResNet50	98.71
Bijlwan *et al.* [25]	EfficientNetB7	99.72
Proposed work	SqueezeNet-based feature extraction with classical ML classifiers	99.90

5. CONCLUSION

This research presents a context-sensitive AgriBot, which is designed to assist rice farmers with a combination of conversational intelligence and automated disease detection. The system was developed on the RASA framework using a DIET classifier with competent intent and entity recognition with a training and test accuracy of 98% and 97%, respectively. A NN model was better at rice disease detection, with an accuracy of up to 99.9%, than other classifiers, such as the RF, SVM, and NB, due to the effective feature extraction achieved through transfer learning with the help of SqueezeNet. AgriBot is a viable decision support solution that will address the language and literacy barrier by combining text-based query management with image-based disease diagnostics to encourage the adoption of AI-driven solutions in modern rice production.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [BD], upon reasonable request.

REFERENCES

[1] K. Jha, A. Doshi, P. Patel, and M. Shah, "A comprehensive review on automation in agriculture using artificial intelligence," *Artificial Intelligence in Agriculture*, vol. 2, pp. 1–12, Jun. 2019, doi: 10.1016/j.aiia.2019.05.004.

[2] A. Sharma and P. Tripathi, "Artificial intelligence in agriculture: a literature survey," *International Journal of All Research Education and Scientific Methods*, vol. 9, no. 8, pp. 2455–6211, 2021.

[3] J. Mendes *et al.*, "Smartphone applications targeting precision agriculture practices—a systematic review," *Agronomy*, vol. 10, no. 6, Jun. 2020, doi: 10.3390/agronomy10060855.

[4] P. K. Maduri, P. Dhiman, M. R. Shukla, S. Anand, and S. P. Singh, "Farmers agriculture assistance Chatbot," in *2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, Dec. 2021, pp. 1884–1889, doi: 10.1109/ICAC3N53548.2021.9725634.

[5] U. Kiruthika, S. K. S. Raja, V. Balaji, and C. J. Raman, "E-agriculture for direct marketing of food crops using chatbots," in *2020 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*, Dec. 2020, pp. 1–4, doi: 10.1109/ICPECTS49113.2020.9337024.

[6] C. W. Okonkwo and A. A. Ibijola, "Chatbots applications in education: a systematic review," *Computers and Education: Artificial Intelligence*, vol. 2, 2021, doi: 10.1016/j.caeai.2021.100033.

[7] U. I. Ismail, H. N. Chua, R. Nordin, and M. K. Ahmed, "A comprehensive review of deep learning approaches for rice disease detection: datasets, methodologies, and future directions," *Smart Agricultural Technology*, vol. 11, Aug. 2025, doi: 10.1016/j.atech.2025.100976.

[8] G. Dhanush, N. Khatri, S. Kumar, and P. K. Shukla, "A comprehensive review of machine vision systems and artificial intelligence algorithms for the detection and harvesting of agricultural produce," *Scientific African*, vol. 21, Sep. 2023, doi: 10.1016/j.sciaf.2023.e01798.

[9] B. Koopman *et al.*, "AgAsk: an agent to help answer farmers' questions from scientific documents," *International Journal on Digital Libraries*, vol. 25, no. 4, pp. 569–584, Dec. 2024, doi: 10.1007/s00799-023-00369-y.

[10] D. R. Anekar, S. Suryavanshi, D. Auti, P. Lokhande, and A. Deshmukh, "Farmer's assistant using AI voice bot," *International Journal of Advanced Research in Science, Communication and Technology*, vol. 3, no. 2, pp. 224–230, Apr. 2023, doi: 10.48175/IJARSCT-9121.

[11] P. Temniranrat, K. Kiratiratanapruk, A. Kitvimonrat, W. Sinthupinyo, and S. Patarapuwadol, "A system for automatic rice disease detection from rice paddy images serviced via a Chatbot," *Computers and Electronics in Agriculture*, vol. 185, Jun. 2021, doi: 10.1016/j.compag.2021.106156.

[12] V. Nayak, P. R. N. Nayak, Sampoorna, Aishwarya, and N. H. Sowmya, "Agroxpert - farmer assistant," *Global Transitions Proceedings*, vol. 2, no. 2, pp. 506–512, Nov. 2021, doi: 10.1016/j.gltp.2021.08.016.

[13] M. Momaya, A. Khanna, J. Sadavarte, and M. Sankhe, "Krushi – the farmer Chatbot," in *2021 International Conference on Communication, Information, and Computing Technology (ICCICT)*, Jun. 2021, pp. 1–6, doi: 10.1109/ICCICT50803.2021.9510040.

[14] M. Jain, P. Kumar, I. Bhansali, Q. V. Liao, K. Truong, and S. Patel, "FarmChat: a conversational agent to answer farmer queries," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 2, no. 4, pp. 1–22, 2018, doi: 10.1145/3287048.

[15] P. U. Usip, E. N. Udo, D. E. Asuquo, and O. R. James, "A machine learning-based mobile Chatbot for crop farmers," in *Electronic Governance with Emerging Technologies (EGETC 2022)*, 2022, pp. 192–211, doi: 10.1007/978-3-031-22950-3_15.

[16] N. Chandolikar, C. Dale, T. Koli, M. Singh, and T. Narkhede, "Agriculture assistant Chatbot using artificial neural network," in *2022 International Conference on Advanced Computing Technologies and Applications (ICACTA)*, Mar. 2022, pp. 1–5, doi: 10.1109/ICACTA54488.2022.9753433.

[17] G. M. Mostaço, Í. R. C. D. Souza, L. B. Campos, and C. E. Cugnasca, "AgronomoBot: a smart answering Chatbot applied to agricultural sensor networks," in *14th International Conference on Precision Agriculture (ICPA)*, 2018, pp. 1-13.

[18] B. Arora, D. S. Chaudhary, M. Satsangi, M. Yadav, L. Singh, and P. S. Sudhish, "Agribot: a natural language generative neural networks engine for agricultural applications," in *2020 International Conference on Contemporary Computing and Applications (IC3A)*, Feb. 2020, pp. 28–33, doi: 10.1109/IC3A48958.2020.233263.

[19] H. P. Khandagale, "Design and implementation of fourCropNet: a CNN-based system for efficient multi-crop disease detection and management," *Journal of Information Systems Engineering and Management*, vol. 10, no. 7s, pp. 461–471, 2025, doi: 10.52783/jisem.v10i7s.877.

[20] N. A. Alhassan, A. S. Albarrak, S. Bhatia, and P. Agarwal, "A novel framework for Arabic dialect chatbot using machine learning," *Computational Intelligence and Neuroscience*, pp. 1–11, Mar. 2022, doi: 10.1155/2022/1844051.

[21] M. J. Hasan, S. Mahbub, M. S. Alom, and M. A. Nasim, "Rice disease identification and classification by integrating support vector machine with deep convolutional neural network," in *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, May 2019, pp. 1–6, doi: 10.1109/ICASERT.2019.8934568.

[22] T. Daniya and S. Vigneshwari, "Deep neural network for disease detection in rice plant using the texture and deep features," *The Computer Journal*, vol. 65, no. 7, pp. 1812–1825, Jul. 2022, doi: 10.1093/comjnl/bxab022.

[23] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, "Identification of plant-leaf diseases using CNN and transfer-learning approach," *Electronics*, vol. 10, no. 12, Jun. 2021, doi: 10.3390/electronics10121388.

[24] M. S. A. M. Al-Gaashani, N. A. Samee, R. Alnashwan, M. Khayyat, and M. S. A. Muthanna, "Using a Resnet50 with a kernel attention mechanism for rice disease diagnosis," *Life*, vol. 13, no. 6, May 2023, doi: 10.3390/life13061277.

[25] A. Bijlwan *et al.*, "Enhancing rice disease and insect-pest detection through augmented deep learning with transfer learning techniques," *Smart Agricultural Technology*, vol. 11, Aug. 2025, doi: 10.1016/j.atech.2025.100954.

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