



AI-POWERED AGRIBOT FOR RICE VARIETY CLASSIFICATION AND FARMING ASSISTANCE: A DUAL DATA INTEGRATION APPROACH

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Abstract: Rice, a vital element in global food security, showcases remarkable genetic diversity with its various textures, shapes, and colors. This research unveils “Agribot”, an advanced Conversational AI system powered by the RASA framework. Agribot assists farmers by integrating image-based rice variety identification with informative text responses. It helps the end users to make correct decisions about quality of seed, while also providing personalized recommendations for optimal crop management. This research highlights the impact of AI-driven solutions on agriculture by focusing on five rice varieties: Karacadag, Basmati, Jasmine, Arborio, and Ipsala. This dataset was used to train a Convolutional Neural Network (CNN) model achieving an accuracy up to 99%. The Agribot with the RASA framework achieves 98% training accuracy, showing high prediction accuracy, and an 82% F1-score, indicating a good balance between precision and recall. The integration of dual data modalities—image-based analysis and text-based conversation support—highlights the potential of AI to bridge the gap between technology and agriculture.

IndexTerms - Convolutional Neural Network (CNN), RASA framework, Dual data modalities, Agribot, Conversational AI

1. INTRODUCTION

Rice is the third most important grain product in the world after wheat and corn, based on production values. It is rich in carbohydrates and starch, making it an important source of nutrition. Rice is both affordable and nutritious, which adds to its importance in human diets. Additionally, it is widely used in various industries. Rice varieties are evaluated based on many factors, including appearance, cooking characteristics, flavor and fragrance, and efficiency (Tipi et. al 2009). Traditionally, checking these physical features manually can be costly and unreliable, as human judgment is often inconsistent, subjective, and slow. Machine vision systems offer a better alternative. They are non-destructive, cost-effective, fast, and accurate.

Rice variety classification offers several advantages - (a) Quality Control: Ensures that rice meets industry standards and consumer expectations by accurately identifying and categorizing different varieties. (b) Yield Optimization: Helps in selecting the best rice varieties for specific growing conditions, leading to improved crop yields. (c) Trade Facilitation: Streamlines the process of rice trading by providing clear and consistent classification, which is crucial for international trade. (d) Efficiency: classification using deep learning models reduces the time and labour required for manual inspection, minimizing human error and increasing consistency. (e) Resource Management: Enhances resource use by selecting the most appropriate rice types for various applications, including culinary objectives and specialized market requirements. These benefits collectively improve the overall efficiency, reliability, and profitability of rice production and distribution.

The most recent technological enhancements are providing farmers worldwide with the ability to obtain precise information at a minimal expense. These advancements lead to increased crop production by allowing farmers to avoid potential diseases in advance and choose the right rice seeds based on environmental conditions. One key application is Virtual Assistant, an artificial intelligence-based software tool that may mimic a discussion (or a chat) with a user in human language via messaging apps, websites etc.

In our research, we integrated the concept of an Agribot with image processing to develop a unified interface that facilitates the identification of various rice varieties, as well as information regarding rice cultivation. Furthermore, the system has the capability to autonomously provide personalized textual responses in response to user inquiries.

2. RELATED WORK

Yadav & Jindal et. al (2001) used image analysis to assess ground rice for whiteness and broken seed percentage. They extracted and quantified length, perimeter, and shape features of rice grains. Dubey et. al (2006) and his team used 45 different physical characteristics of grains to classify them using a computer model called an artificial neural network. They found that the more features they used, the better the model became at classifying the grains. Their model was able to correctly classify about 88% of all the grains. Demirbas et. al (2007) employed image processing techniques to quantify morphological features of 13 distinct wheat varieties. Utilizing UTHSCSA Image Tool version 3.0, they analysed digital images of the grains. The results demonstrated a high degree of congruence between manual and image-processed measurements, suggesting the feasibility of image processing for determining specific physical characteristics of wheat grains.

An aspect ratio analysis was conducted by Aggarwal et. al (2010) evaluated the quality of market-sold rice using image processing techniques. The study involved sampling three distinct classes of rice—full, semi, and broken—which are typically priced based on grain size. The primary objective was to establish a reference aspect ratio for market-available rice. Silva et. al (2013) employed an artificial neural network (ANN) to classify nine different rice varieties. The algorithm which was developed can extract a total of 34 features from images: 13 morphological, 6 color, and 15 texture features. The researchers conducted separate classifications for each feature type and found that texture features yielded the highest success rate compared to morphological and color features. Abirami et. al (2014) employed neural network techniques and image processing to classify Basmati rice grains. They trained a neural network to accurately identify various varieties of rice by capturing images of rice grains and extracting their physical characteristics. Their model got classification accuracy of 98.7%. Sethy et. al (2018) used a multi-class support vector machine (M-SVM) algorithm to classify six distinct rice varieties based on their geometric and textural features. Through this method, they achieved a classification accuracy of 92%.

N. Prakash et. al (2022) investigates the utilization of a variety of deep learning models, such as Vanilla Neural Network (VNN) and VGG16, to accurately classify various rice varieties, attaining an overall accuracy of 95.30%. Mustafa et. al (2023) presents a method for classifying rice varieties using Quantized Neural Networks (QNN), specifically Lanet-5, achieving an overall accuracy of 99.80% with reduced computational resources. Gunawan et. al (2019) discussed about a chatbot where users can inquire about plant conditions, and the chatbot responds using NLP techniques on sensor data. The system integrates IoT to monitor plant conditions. The chatbot effectively provided real-time information about plant conditions, enabling users to take necessary actions such as watering the plants. B. Arora et. al (2020) proposed a chatbot that assists farmers, detects crop diseases, and predicts weather using a CNN model. Achieved an accuracy of 98% for the chatbot module and 94% for the crop detection module.

This review examines the use of machine learning in agriculture from 2016 to 2023, covering crop management, livestock monitoring, soil analysis, and water management. It highlights key trends, challenges, and the role of ML and deep learning in improving productivity through disease detection, yield prediction, and resource optimization while addressing issues like data quality and scalability. (C. B. Thangammal et al., 2024). As per Acharya et al. (2025), Agentic AI is a sophisticated system that can make decisions on its own and learn from experience. Their research discusses its applications in healthcare, finance, and software systems, as well as the ethical issues that come with it. The same can be applied to agriculture sector also to support farmers.

3. DATASET PREPARATION

In our research, we utilized two types of datasets: a text-based dataset for a Virtual Assistant developed using the RASA Framework, and an image dataset focused on rice varieties. The text-based dataset was created using inputs from KCC Guwahati and various Internet resources related to rice crop management. The image dataset consisted of 75,000 images sourced from Kaggle, covering rice varieties such as Karacadag, Basmati, Jasmine, Arborio, and Ipsala.



Figure 1: Distribution of Rice Image Dataset

To optimize the pre-processing of images and enhance the model performance, several key techniques were implemented. First, image generators were created for both the training and testing datasets to efficiently load and process images in batches. This approach minimizes memory usage and ensures a continuous supply of data to the model, significantly enhancing the efficiency of the training and testing phases. The model's generalization capability and robustness were enhanced by the application of data

augmentation techniques to the training dataset. These transformations encompassed random rotations to replicate the various orientations of rice varieties, random scaling to simulate varying distances from the camera, and horizontal and vertical flipping to generate mirrored images and further diversify the dataset. These variations enabled the model to learn more generalized features. Additionally, pixel values were normalized by scaling them to fall between 0 and 1. By ensuring that all input characteristics were on the same scale, this standardization sped up convergence during training and enhanced model performance. Furthermore, every photograph was downsized to a consistent 50 x 50-pixel size. The dataset was standardized by this scaling, guaranteeing input data integrity and simplifying further processing and analysis. These pre-processing steps collectively enhanced the model's efficiency, scalability, and accuracy, enabling it to perform effectively across diverse scenarios.

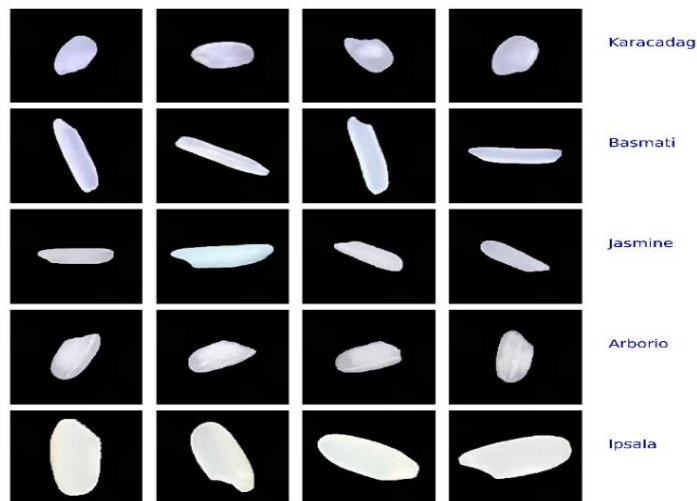


Figure 2: Sample Image of each class

We created 100 unique intents for the Agribot based on the RASA framework for rice farming. For efficient processing of sequential input, an LSTM (Long Short-Term Memory) model was used to train the system. LSTM is a type of neural network that helps computers understand and remember information over time. LSTM works by keeping track of important information for a longer period, while ignoring less relevant details. Furthermore, for reliable intent classification and entity identification, the DIET (Dual Intent and Entity Transformer) classifier was used, guaranteeing the provision of personalized answers suited to user inquiries. The DIET classifier can recognize both the user's intent (what they want) and important details (entities, like rice diseases or weather conditions), ensuring the Agribot provides personalized and accurate answers to user inquiries.

Table 1: Sample Textual Data Utilized in Agribot Training.

Category	Training Samples	Response Sample
About Rice Farming	<ul style="list-style-type: none"> - Can you tell me about rice farming? - What is rice farming? - How is rice grown? - What are the different types of rice? 	Rice farming is the cultivation of rice, a cereal grain and staple food for over half of the world's population. Rice farming involves the planting, growing, and harvesting of rice paddies or fields, which are typically flooded with water for a portion of the growing cycle to control weeds and pests, and to provide nutrients to the rice plants.
About Pesticides	<ul style="list-style-type: none"> - What pesticides can I use to control pests in rice farming? - Why are pesticides used in agriculture? 	Pesticides are chemicals used to control or eliminate pests, such as insects, weeds, and fungi, that can damage crops, human health, or the environment.

4. RESEARCH METHODOLOGY

In our research, we developed a dual dataset comprising textual and image-based data to enhance the accuracy and robustness of the models. Data augmentation techniques were applied to improve the quality of the datasets. For textual model development, the machine learning model for Agribot was trained using the RASA framework with an LSTM-based DIET Classifier. This training

was performed on a local machine equipped with an Intel i5 processor and 8GB RAM. Concurrently, the image dataset underwent preparation with augmentation to enhance its variability and improve model performance, followed by training using a Convolutional Neural Network (CNN) on Kaggle Cloud with a GPU P100 for accelerated processing and scalability. Subsequently, the image-based model was integrated with the Action Server of Agribot via the RASA framework to enable seamless interaction. Finally, both the textual and image-based models were validated for deployment readiness, demonstrating their robustness and accuracy for practical real-world applications.

4.1 Model specifications

The rice variety classification model uses a Convolutional Neural Network (CNN) to identify and classify images of rice into five varieties: Karacadag, Basmati, Jasmine, Arborio, and Ipsala. The model begins by resizing input images to 224 x 224 pixels to ensure uniformity. It processes the images through two convolutional layers, where small filters extract basic patterns (like edges) and higher-level details (like shapes), with ReLU activation ensuring the retention of significant features. After each convolutional layer, max-pooling reduces the image size, simplifying computations and preventing overfitting. After that, the processed input is flattened into a one-dimensional vector and fed into a thick layer of 128 neurons where complicated interactions between characteristics are learnt. At last, the five- neuron output layer generates probabilities for every kind of rice by means of a “softmax” function, therefore forecasting the class with maximum likelihood. The model has 1,011,781 overall parameters, all of which are trainable.

```

- name: Whitespace Tokenizer
- name: RegexFeaturizer
- name: LexicalSyntacticFeaturizer
- name: CountVectorsFeaturizer
- name: CountVectorsFeaturizer
  analyzer: char_wb
  min_ngram: 1
  max_ngram: 4
- name: DIETClassifier
  epochs: 100
  constrain_similarities: true
- name: EntitySynonymMapper
- name: ResponseSelector
  constrain_similarities: true
- name: FallbackClassifier
  threshold: 0.3
  ambiguity_threshold: 0.1
    
```

Figure 3 RASA Model Configuration

Layer	Type	Output Shape	Parameters	Description
Input	Input Layer	(50, 50, 3)	-	Input image with dimensions 50x50 pixels and 3 color channels (RGB).
Conv2D (1st Layer)	Convolutional Layer	(48, 48, 32)	$(3 \times 3 \times 3 + 1) \times 32 = 896$	Extracts features using 32 filters of size 3x3; ReLU activation is applied.
MaxPooling2D (1st)	Pooling Layer	(24, 24, 32)	0	Downsamples feature maps using a 2x2 pooling window, reducing spatial dimensions.
Conv2D (2nd Layer)	Convolutional Layer	(22, 22, 64)	$(3 \times 3 \times 32 + 1) \times 64 = 18,496$	Extracts deeper features using 64 filters of size 3x3; ReLU activation is applied.
MaxPooling2D (2nd)	Pooling Layer	(11, 11, 64)	0	Further downsamples feature maps using a 2x2 pooling window.
Flatten	Flattening Layer	7744	0	Converts 3D feature maps into a 1D vector for input into the dense layers.
Dense (1st Layer)	Fully Connected Layer	(128)	$7744 \times 128 + 128 = 991,744$	Dense layer with 128 neurons; ReLU activation is applied.
Dense (Output Layer)	Fully Connected Layer	(5)	$128 \times 5 + 5 = 645$	Output layer with 5 neurons for classification; softmax activation is applied.

Figure 4: Model Architecture for Image Classifications

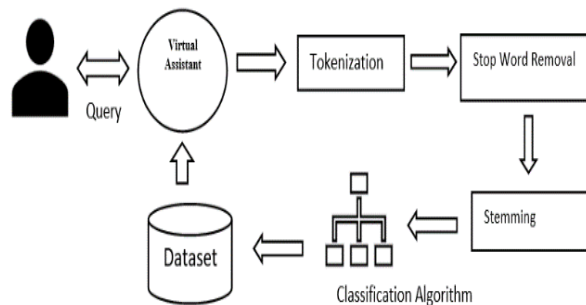


Figure 5: Agribot Development Process using RASA

When users send queries to the Agribot, the system processes them through a pre-processing stage in the second step. During this stage, the text of the query is prepared for analysis by breaking it down into individual words, removing insignificant words (such as "the" or "is"), and reducing words to their root forms. After pre-processing, the Agribot classifies the query to determine the most appropriate answer or response. Agribot with RASA framework efficiently classifies Intent, recognize entity for accurate delivery of customized response to the user. All kinds of communication with users are stored on MYSQL database for further analysis.

5. RESULTS

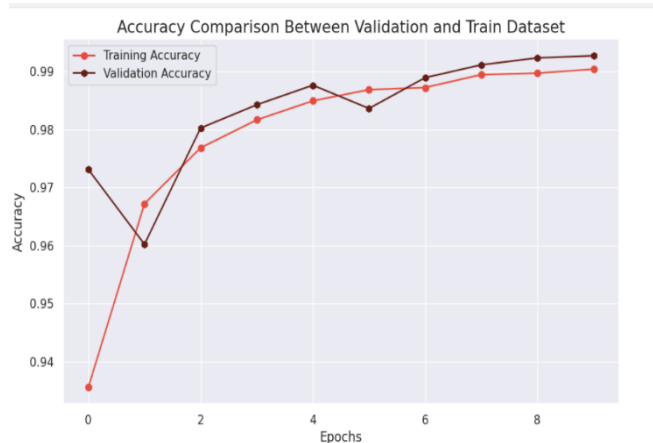


Figure 6: Training and Validation Accuracy Curve of the CNN Model

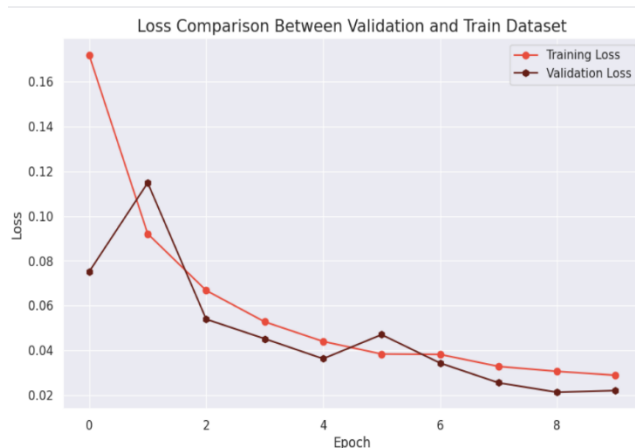


Figure 7: Training and Validation Loss Curve of the CNN Model

As seen in Figure 6, the training accuracy (red line) starts approximately 94% and quickly improves, reaching 99% in the subsequent epochs, signifying proficient learning from the training data. The validation accuracy (brown line) starts somewhat elevated but subsequently declines, indicative of a transient overfitting phenomenon. Nonetheless, the validation accuracy ultimately converges with the training accuracy, indicating that the model generalizes well. Both accuracies settle at roughly 99%, indicating that the model accurately identifies about 99% of the photos from both the training and validation datasets. The narrow disparity between training and validation accuracies signifies little overfitting, affirming the model's robustness and its proficiency in reliably categorizing rice types across many categories (Karacadag, Basmati, Jasmine, Arborio, Ipsala) without bias towards the training data.

The plot as seen in Figure 7, depicts the loss curves for both the training and validation datasets over 9 epochs. The graphs show training loss consistently decreases from 0.17 to 0.02, indicating that the model is learning effectively on the training data. However, the validation loss curve shows an initial decrease up to epochs 2 (reaching 0.05), followed by an increase and subsequent decrease again. This behaviour suggests potential overfitting to the training data. The validation loss curve plateaus around 0.02 after epochs 8, suggesting that the model has reached its capacity to generalize to new data.

Metric	Value
Accuracy	0.9923
Precision	0.9923
Recall	0.9923
F1-Score	0.9923

Table 2: Performance Metrics of the CNN Model for Rice Classification

	Accuracy	F1-score	Precision
Train	0.989	0.824	0.810
Test	0.973	0.645	0.662

Table 3: Entity evaluation results

The CNN model performance is stated by the given metrics: accuracy, precision, recall, and F1-score. With values 99% the model performs very well and earns excellent marks on every criterion as seen in Table 2. As seen in Table 3, the model's performance on entity evaluation for Agribot, as indicated by the F1 scores, is promising on the training data but less so on the test data. While the high training F1 score of 0.824 suggests a good balance between precision and recall, the lower test F1 score of 0.645 indicates a potential overfitting issue and need improvement. The model's ability to accurately identify positive cases, as measured by precision, is also affected by this. On the training data, the model shows encouraging performance based on F1 scores; on the test data, this is less so. Although the low test F1 score of 0.645 points to a possible overfitting problem, the high training F1 score of 0.824 shows a reasonable balance between accuracy and recall. This overfitting also affects the model's capacity to precisely identify affirmative instances, as gauged by precision; the training data's 0.810 value decreases to 0.662 on the test data.

6. CONCLUSION

The research presented in this paper demonstrates the significant potential of AI-driven solutions in agriculture, specifically through the development of Agribot, an advanced Conversational AI system powered by the RASA framework. By integrating image-based rice variety identification with informative text responses, Agribot empowers farmers to make informed decisions about seed quality and crop management. Utilizing a Kaggle dataset of approximately 75,000 images, the machine learning model achieved an impressive accuracy rate of up to 99% in classifying five rice varieties: Karacadag, Basmati, Jasmine, Arborio, and Ipsala. The dual data integration approach, combining image analysis with text-based conversation support, demonstrates AI's ability to enhance agricultural decision-making, improve efficiency, and promote sustainable crop management. The successful deployment readiness of both the textual and image-based models underscores the robustness and practical applicability of this innovative technology in real-world agricultural settings. In the future, the number of rice varieties can be expanded, and the integration of Agentic AI—an

advanced AI system capable of autonomous decision-making and adaptive learning—can further enhance Agribot’s decision-making capabilities, making it a more robust and intelligent support system for farmers.

REFERENCES

- [1] B. O. Juliano, Rice in Human Nutrition. *Cereals International*, 1991, pp. 31-34.
- [2] T. Tipi, N. Yildiz, M. Nargelecekenler, & B. Cetin (2009). Measuring the technical efficiency and determinants of efficiency of rice (*Oryza sativa*) farms in Marmara region, Turkey. *New Zealand Journal of Crop Horticultural Science* 37(2): 121-129. DOI: 10.1080/01140670909510257.
- [3] Niranjana, P. Y., Rajpurohit, V. S., & Malgi, R. (2019). A survey on chat-bot system for agriculture domain. In 2019 *1st International Conference on Advances in Information Technology (ICAIT)* (pp. 99–103). IEEE. <https://doi.org/10.1109/ICAIT47043.2019.8987429>
- [4] Yadav, B., & Jindal, V. (2001). Monitoring milling quality of rice by image analysis. *Computers and Electronics in Agriculture*, 33(1), 19–33. [https://doi.org/10.1016/S0168-1699\(01\)00169-7](https://doi.org/10.1016/S0168-1699(01)00169-7)
- [5] Dubey, B., Bhagwat, S., Shouche, S., & Sainis, J. (2006). Potential of artificial neural networks in varietal identification using morphometry of wheat grains. *Biosystems Engineering*, 95(1), 61–67. <https://doi.org/10.1016/j.biosystemseng.2006.06.001>
- [6] Demirbas, Hande & Dursun, Ilknur. (2007). Determination of Some Physical Properties of Wheat Grains by Using Image Analysis. *Tarim Bilimleri Dergisi*. 13. 176-185.
- [7] Aggarwal, Amit K and Mohan, Ratan. "Aspect Ratio Analysis Using Image Processing for Rice Grain Quality" *International Journal of Food Engineering*, vol. 6, no. 5, 2010. <https://doi.org/10.2202/1556-3758.1788>
- [8] Silva, Chathurika Sewwandi and Upul J. Sonnadara. "Classification of Rice Grains Using Neural Networks." (2013). Proceedings of Technical Sessions, 29 (2013) 9-14 Institute of Physics – Sri Lanka <https://ips.lk/documents/TechSession/2013/ips13-02.pdf>
- [9] Abirami, S. and Neelamegam, P.H.K. (2014) Analysis of Rice Granules Using Image Processing and Neural Network Pattern Recognition Tool. *International Journal of Computer Applications*, 96, 20-24. <https://doi.org/10.5120/16806-6530>
- [10] Sethy P K & Chatterjee A (2018). Rice Variety Identification of Western Odisha Based on Geometrical and Texture Feature. *International Journal of Applied Engineering Research* 13(4) : 35-39
- [11] Murat Koklu, Ilkay Cinar, Yavuz Selim Taspinar, Classification of rice varieties with deep learning methods, *Computers and Electronics in Agriculture*, Volume 187, 2021, 106285, ISSN 0168-1699, <https://doi.org/10.1016/j.compag.2021.106285>
- [12] Hasan, M. J., Mahbub, S., Alom, M. S., & Nasim, M. A. (2019). Rice disease identification and classification by integrating support vector machine with deep convolutional neural network. *1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT) 2019* (pp. 1-6). IEEE. <https://doi.org/10.1109/ICASERT.2019.8934568>
- [13] Daniya, T., & Vigneshwari, S. (2022). Deep neural network for disease detection in rice plant using the texture and deep features. *The Computer Journal*, 65(7), 1812-1825. <https://doi.org/10.1093/comjnl/bxab022>
- [14] Alhassan, N. A., Albarrak, A. S., Bhatia, S., & Agarwal, P. (2022). A Novel Framework for Arabic Dialect Chatbot Using Machine Learning. *Computational Intelligence and Neuroscience*, 2022, Article ID 1844051, 11 pages. <https://doi.org/10.1155/2022/1844051>
- [15] Okonkwo, C. W., & Ade-Ibijola, A. (2021). Chatbots applications in education: A systematic review. *Computers and Education: Artificial Intelligence*, 2, 100033. <https://doi.org/10.1016/j.caeai.2021.100033>
- [16] N Prakash, R Rajakumar, N Leela Madhuri, M Jyothi, Image Classification for Rice varieties using Deep Learning Models, June 2022 *YMER Digital* 21(06):261-275, DOI:10.37896/YMER21.06/25
- [17] Tasci, M., Istanbulu, A., Kosunalp, S., Iliev, T., Stoyanov, I., & Beloev, I. (2023). An Efficient Classification of Rice Variety with Quantized Neural Networks. *Electronics*, 12(10), 2285. <https://doi.org/10.3390/electronics12102285>
- [18] B. Arora, D. S. Chaudhary, M. Satsangi, and M. Yadav, "Agribot: A Natural Language Generative Neural Networks Engine for Agricultural Applications," *2020 International Conference on Contemporary Computing and Applications (IC3A)*, Feb. 2020, doi: 10.1109/IC3A48958.2020.233263.
- [19] Gunawan, R., Taufik, I., Mulyana, E., et al. (2019). Chatbot application on internet of things (IoT) to support smart urban agriculture. In *Proceedings of the 5th International Conference on Wireless and Telematics (ICWT)*. IEEE.
- [20] Chintakunta, A. N., Koganti, S., Nuthakki, Y., & Kolluru, V. K. (2023). Deep Learning and Sustainability in Agriculture: A Systematic Review. *International Journal of Computer Science and Mobile Computing*, 12(8), 10-47760.
- [21] C. B. Thangammal, P. Saai M, M. T. Umar N, N. S S and M. K, "Agribot: An IoT and Deep Learning-Based System Empowering Precision Farming," *2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)*, Vellore, India, 2024, pp. 1-6, doi: 10.1109/ic-ETITE58242.2024.10493822.
- [22] D. B. Acharya, K. Kuppan, and B. Divya, "Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey," *IEEE Access*, vol. 13, pp. 1-25, Jan. 2025, doi: 10.1109/ACCESS.2025.3532853.