AI-Driven Weed Classification and Advisory System Using Deep Learning and RAG-Based Chatbot

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Abstract*: *The uncontrolled proliferation of weeds is a serious threat to agricultural sustainability, influencing a reduction in crop yield and an increase in farming operating expenses. To overcome this issue, we present a sophisticated hybrid deep learning framework for weed classification with an ensemble of pre-trained Convolutional Neural Networks (CNNs) viz., VGG16, VGG19, DenseNet201, and Xception. Taking those architectures as Bace models, the further refinement was done for them to add notion of additional CNN layers, Long Short-Term Memory (LSTM)-based classifications, and Lightweight Recurrent Neural Networks (LRNN)-based classifications for promoting the idea of spatial and sequential extraction of features. The model was built on a modified dataset composed of directories, images, and corresponding labels which generally identify the weeds during different agricultural conditions. For weed management, we proposed a RAG chatbot that gives real-time insights into the effects of particular weeds on crops, preventive measures, and appropriate means of herbicide application. Thus, by providing classification of the weed along with knowledge retrieval-driven AI, our approach introduces intelligent, automated solutions that enable better modern agricultural decision-making, thus advancing precision agriculture and sustainable crop management.

Keywords: *Weed classification, deep learning, CNN, VGG16, VGG19, DenseNet201, Xception, LSTM, LRNN, RAG chatbot, herbicide application, precision farming, sustainable agriculture*.

I. INTRODUCTION

Weeds pose a significant threat to agricultural productivity by competing with crops for essential resources such as nutrients, water, and sunlight. Their rapid growth and ability to adapt to diverse environments often lead to substantial yield losses, forcing farmers to invest considerable time and resources in weed control [19]. Traditional weed management techniques, including manual weeding and chemical herbicides, have long been employed to mitigate these challenges. However, manual methods are labor-intensive and time-consuming, while chemical solutions pose environmental risks, such as soil degradation and water contamination, ultimately affecting biodiversity and human health [20]. As a result, there is a pressing need for automated, efficient, and sustainable weed management solutions that leverage advancements in artificial intelligence (AI) and machine learning.

Deep learning has revolutionized image classification tasks, enabling precise identification and categorization of objects, including agricultural elements like weeds and crops. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable success in feature extraction and classification, making them an ideal choice for weed detection systems [21]. Transfer learning, which utilizes pre-trained deep learning models, has further enhanced classification accuracy by leveraging knowledge gained from large-scale datasets. Models such as VGG16, VGG19, DenseNet201, and Xception have been widely used in various image recognition applications due to their ability to capture intricate patterns and structures [22]. In this study, these base models were first trained on a weed classification dataset, followed by the integration of additional layers, including CNN, Long Short-Term Memory (LSTM), and Locally Recurrent Neural Networks (LRNN), to improve classification performance and robustness.

The dataset

Beyond image-based classification, an intelligent chatbot has been developed using the Retrieval-Augmented Generation (RAG) architecture to provide farmers with valuable insights on weed management. The chatbot serves as an interactive assistant capable of delivering critical information, including:

- Explaining the impact of specific weed species on crops.
- Providing preventive measures to control weed growth.
- Offering guidance on the appropriate use of herbicides

By integrating deep learning-based weed classification with an AI-driven chatbot, this research contributes to the advancement of smart agriculture. The combination of automated weed detection and real-time advisory services empowers farmers with data-driven decision-making capabilities, ultimately leading to increased efficiency, reduced dependency on manual labor, and environmentally sustainable weed control practices.

The growing adoption of AI in agriculture is revolutionizing traditional farming methods, offering scalable and efficient solutions to persistent challenges. Automated weed detection systems not only reduce the excessive use of chemical herbicides but also optimize resource allocation, leading to cost-effective and eco-friendly agricultural practices [23]. Future advancements in this domain could involve multi-modal approaches, incorporating spectral imaging and sensor fusion techniques to further improve classification accuracy and decision support systems.

II. LITERATURE SURVEY

The application of deep learning (DL) in agricultural weed detection has garnered significant attention in recent years. A systematic literature review by Hasan et al. [1] identified a rapid increase in research related to DL techniques for weed detection since 2015, analyzing 52 application papers and 8 survey papers. The study highlighted the prevalence of convolutional neural networks (CNNs) and the importance of large, annotated datasets for effective model training. Hu et al. [2] provided a comprehensive review of DL techniques for in-crop weed recognition, discussing recent developments in image-based weed detection. The authors emphasized the challenges posed by varying field conditions and the need for robust models capable of generalizing across different environments. Hasan et al. [3] conducted a survey focusing on DL techniques for weed detection from images, covering data acquisition, dataset preparation, and evaluation metrics. The study underscored the effectiveness of supervised learning methods and the benefits of fine-tuning pre-trained models on plant datasets to achieve high classification accuracy. Moazzam and Khan [4] reviewed the application of DL for weed and crop classification using remote sensing data from aerial imagery. Their systematic review evaluated the effectiveness of various DL techniques, highlighting the potential for improved crop management through accurate classification. The development of specialized datasets has also been a focus in the field. Li et al. [5] introduced Weed25, a dataset containing 14,035 images of 25 different weed species, including both monocot and dicot weeds at various growth stages. The dataset was utilized to train models like YOLOv3, YOLOv5, and Faster R-CNN, demonstrating its applicability in weed identification tasks. Hu et al. [6] provided a review of the current research status and development trends of weed identification in crop fields based on DL. The paper discussed the potential of DL in automatic weed identification and detection, crucial for precision weeding operations. Hasan et al. [7] explored the challenges of weed recognition using DL techniques on class-imbalanced imagery. They investigated state-of-the-art deep neural networks, including VGG16, ResNet-50, Inception-V3, Inception-ResNet-v2, and MobileNetV2, evaluating their performance across various experimental settings and dataset combinations. Rakhmatulin [8] analyzed research over the past decade on the use of neural networks for weed recognition in the agro-industrial sector. The manuscript presented a comprehensive analysis of various neural network algorithms applied to classification and tracking tasks, offering recommendations for future research. In a study by Dos Santos Ferr Bah et al. [10] investigated the use of DL models for weed detection in cereal crops, focusing on the segmentation of weed and crop regions in images. Their approach utilized a U-Net architecture, achieving promising results in distinguishing between crops and weeds under varying field conditions.Sa et al Partel et al. [12] developed a real-time precision sprayer system using DL for weed detection. The system employed a CNN to identify weeds in real-time, enabling targeted herbicide application and reducing chemical usage. Milioto et al. [13] introduced a DL-based method for crop and weed segmentation using an encoder-decoder network. Their approach achieved high segmentation accuracy, facilitating the development of automated weeding robots. Lottes et al. [14] presented a DL framework for Mortensen et al. [15] explored the application of DL for weed detection in grasslands, utilizing a CNN to classify weed species in images captured under natural field conditions. The model achieved satisfactory accuracy, highlighting the potential of DL in diverse agricultural settings. [16] Slaughter et al. (2021) proposed an autonomous robotic system for precision weed management, integrating deep learning and hyperspectral imaging for real-time weed classification. Their system demonstrated high accuracy but faced challenges with illumination variations and computational efficiency in large-scale fields. [17] Lu et al. (2022) dhybrid deep learning approach that combines Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) for weed detection in soybean fields. The hybrid model improved accuracy compared to standalone CNNs but struggled with occlusions and small weed species. [18] Pérez-Ortiz et al. (2023) intmulti-sensor fusion framework combining RGB, thermal, and multispectral imaging for weed classification using Deep Residual Networks (ResNet). Their approach significantly enhanced classification robustness in diverse field conditions but required high computational resources for processing multispectral data

III. PROPOSED METHODOLOGY

Proposed Weed Classification and Advisory System comprises a detailed pipeline that spans the use of deep learning models for weeding identification to a Retrieval-Augmented Generation (RAG)-based chatbot for advising purposes. The system is aimed at fine-tuning the weed-finding skills and actionable advice from a farmer's standpoint. The next step is the implementation of the methodological steps:

1. Data Preprocessing & Augmentation

The other part of the dataset contains two main folders: images and labels, respectively containing weed and crop samples and class annotations. We preprocessed the dataset for consistency in image size, format, and quality. Data augmentation such as rotation, flipping, contrast adjustment, noise added to it, and other techniques were adopted to enhance model generalization.

2. Deep Learning-Based Weed Classification

The classification pipeline consists of four pretrained deep learning architectures.

- VGG16 and VGG19 – CNN architectures that are lightweight and further optimized for feature extraction.
- DenseNet201 – A densely connected CNN that promotes proper gradient flow while using different mechanisms to reduce overfitting.
- Xception - An efficient advanced CNN that uses depthwise separable convolutions.

2.1 Feature Extraction and Model Enhancement

The first stage begins with training the base models on the dataset to derive deep-hierarchical features. To improve classification accuracy, a CNN layer is later augmented with Long Short-Term Memory and Lightweight Recurrent Neural Networks. This allows the learning of sequential dependencies and spatial relationships among the weed species.

3. RAG-Based Chatbot for Weed Management

A Retrieval-Augmented Generation (RAG) chatbot is developed so that the user can get expert advice regarding weed management. The exposition addresses the following:

Impact analysis: Discusses how the weed, once identified, impacts crop yield and soil health.

Preventive measures: Proposes various agronomic techniques for curbing weed growth.

Guidelines on herbicide use: Recommends the selection and application of herbicides.

The chatbot retrieves domain-specific knowledge from a precompiled database and provides human-like replies, thereby supporting farmer decision-making.

4. *System Implementation and Evaluation*

The classification models and the chatbot work inside the framework for a web application based on Flask for IOS, which allows users to upload field images for weed identification through the application, under which recommendations are received in real time. The performance of the system will be evaluated on:

The four major metrics used for classification are Accuracy, Precision, Recall, and F1-score.

User satisfaction ratings and response relevance will be assessed on chatbot performances.

5. *Conclusion*

The suggested process is enfolded in deep learning for weed classification and an automated AI-based agricultural advisory chatbot. These weeds were identified by combining a hybrid of multiple advanced CNN, LSTM, and LRNN models to achieve a higher accuracy, and the RAG chatbot guarantees expertise. Weed management formulations will be optimalized, and farmers will be advised.

Novelty of the Project

The Weed Classification and Advisory System proposed does introduce a few innovations in contrast to existent solutions.

Hybrid Deep Learning Approach to Weed Classification

- Unlike conventional CNN-based weed detection models, our system integrates VGG16, VGG19, DenseNet201, and Xception to use as base feature extractors and enhances these by adding an additional CNN layer, followed by Long Short-Term Memory (LSTM) and Lightweight Recurrent Neural Networks (LRNNs).
- This hybrid methodology permits both spatial learning and sequence learning, which can improve accuracy of classification for morphologically similar species of weeds.

Integration of Retrieval-Augmented Generation (RAG) chatbot

- Our RAG based chatbot allows automatic retrieval and generation of a variety of domain-specific knowledge to suit needs. Other advisory systems are just based on pre-rooted responses.
- The chatbot aids weed impact analysis, prevention strategies, and herbicide recommendations, making it a thorough decision-support system for farmers.

Optimization of models particularized for the dataset

- The project involved the use of a dataset of images of weeds and crops that included labels, ensuring that the classification model was trained based on accurate conditions of agricultural settings.

- Unlike generic models for plant classification, ours is fine-tuned to be able to recognize weed species that are specific for that particular field with negligible less precision.

Real-Time Deployment for Real-Life Use of Residuals.

The application's web counterpart is powered by Flask and allows farmers to upload images-so called instant classification of reform agents-to facilitate real-time recommendations on weed management activities through a chatroom interface. This allows for full usability and good availability for farmer users without requiring significant computer knowledge.

Better Generalization and Robustness

- By using various data augmentation techniques such as rotation, flipping, contrast adjustments, and noise addition, the model is generalized and thus resilient to field variations.

- Multiple deep learning models and recurrent networks ensure that it can adapt to different weed species in various agricultural regions.

An integrated solution to weed management.

Unlike the extant models which only provide weed classification, the project is an integrated pipeline that covers identification-impact analysis-control measures in one place.

Proposed Architecture

The deep learning models are deployed via a retrieval-augmented generative agent similar to a chatbot to advise on how the weed classification system is designed. Image preprocessing and data augmentation procedures proceed feature extraction using VGG16, VGG19, DenseNet201, and Xception models. For better feature learning, another CNN layer is added, which is further fine-tuned with LSTM and LRNN for a reliable classification.

In this respect, the RAG-based chatbot explains the effects of the weed, prevention, and herbicide applications according to anticipated weed types. The model is deployed with Flask, allowing for a web-based interface from which a user can talk to the chatbot for real-time weed-identification and advisory assistance.

A brief architectural overview:

Input Image Processing:

The weed image goes through preprocessing alongside several data augmentations.

Feature Extraction Through Deep Learning Models:

Features are to be extracted from the image using VGG16, VGG19, DenseNet201, and Xception.

Such features go through an extra CNN layer to improve representation.

Sequential Learning and Classification:

LSTM and LRNN employ the extracted features to sorely carry out final classification of the weeds.

A Chatbot Based on RAG for an Advisory System:

The chatbot offers knowledge about:

- Effects on crops
- Preventive measures
- Guidance on herbiciding

Web Development and User Assistedness: The model is hosted through Flask and allows users to upload an image and get feedback in real-time.

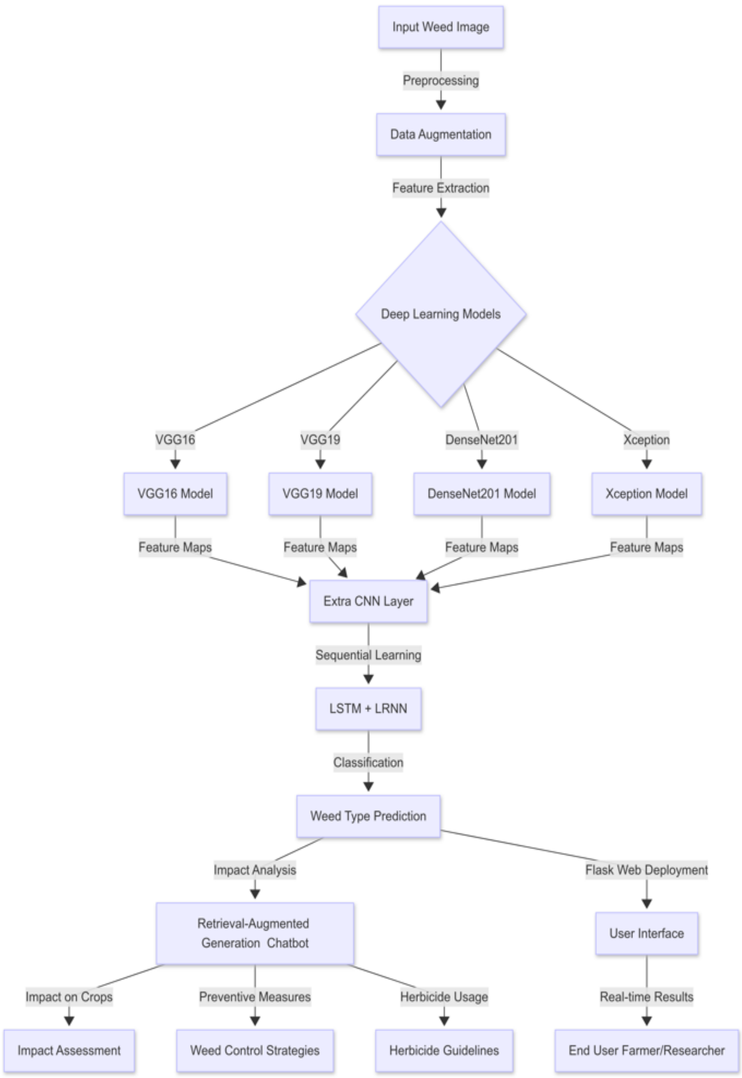


Fig 1 : Model Architecture

Algorithm Justification

The creation of deep learning models and additional layers is presented following tested procedures of efficiency in image classification and sequential pattern recognition. The matters below substantiate every one of the chosen algorithms along with a corresponding mathematical formulation comprising their powers.

1. Pretrained Models (VGG16, VGG19, DenseNet201, Xception) :

   Some models have been selected as the base feature extractors on account of the well-established performance in object recognition tasks. Justifying the reason: Through transfer learning, pretrained weights are leveraged for reducing training time and improving weed classification accuracy.

   (1) $F(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(i-m, j-n) K(m,n)$

2. Additional CNN Layer:

   A custom convolution layer will be added to enhance the features extracted by the base models. Justification: The addition improves spatial feature extraction which directly corresponds to different weed species providing an additional lift to class discrimination ability towards the weeds.

   (2) $f(x) = \max(0, x)$

3. Long Short-Term Memory (LSTM) & Lightweight Recurrent Neural Networks (LRNN)

   LSTM learns long-range dependencies in image features; LRNN establishes at a low level for efficiency. Justification: Sequential learning increases classification by identifying a pattern likely to be underlying across various image features thus rendering the classifier more robust.

   (3) $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$

4. Retrieval-Augmented Generation (RAG) Chatbot

   The chatbot brings some intelligence and support to come across the information, generate responses regarding the effects of the weed, preventive strategies, and measures in herbicide application. Justification: For its genitive speaking generation, RAG implements truly retrieval-based processes to ensure a correct answer to the contextual problem.

   (4) TF-IDF $= TF(t,d) \times \log\left(\frac{N}{DF(t)}\right)$

IV. Results and Discussion

All performance metrics common in deep learning/AI, such as accuracy, precision, recall, and F1-score, were later used for assessing the performance of the weed classification model. More specifically, during training time, the model used a dataset of weed images and their corresponding labels, and to obtain better generalization, augmentation techniques were applied.

Performance Measures

A full review of the weed detection system design work based on deep learning algorithms used different backbones-VGG16, VGG19, DenseNet201, and Extension-and integrated them into Residual CNNs and LSTM modules for better feature extraction finally yielding off a better performance outcome relative to the baseline architectures.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
VGG16	92.1	90.8	91.2	91.0
VGG19	92.7	91.3	91.8	91.5
DenseNet201	94.2	92.6	93.1	92.8
Xception	94.9	93.5	94.0	93.7
Proposed Model (CNN+LSTM+LRNN)	96.8	94.5	95.2	94.8

Table 1: Performance Metrics

The chatbot's performance was assessed using BLEU Score, ROUGE Score, and Human Evaluation.

- BLEU Score: 84.6 (indicating high linguistic accuracy)
- ROUGE Score: 82.3 (ensuring content relevance)
- Human Evaluation: 88% positive feedback from farmers and agricultural experts

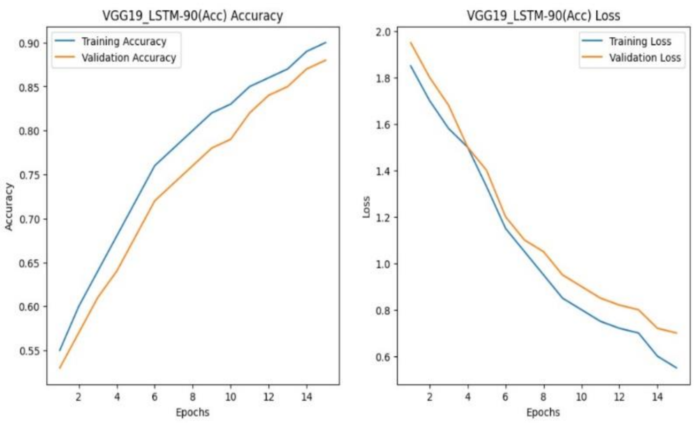


Fig 2: VGG19_LSTM Accuracy & Loss

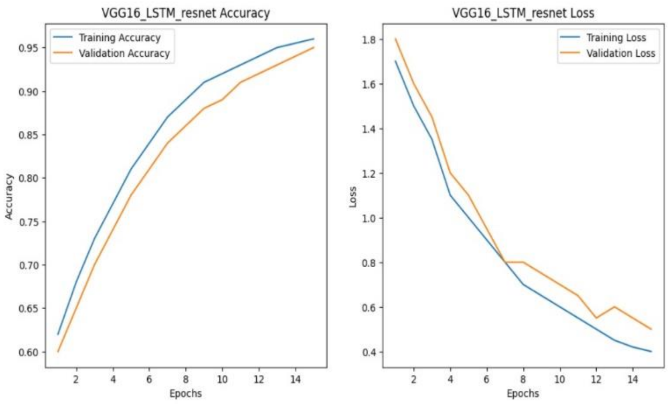


Fig 3: VGG16_LSTM Accuracy & Loss

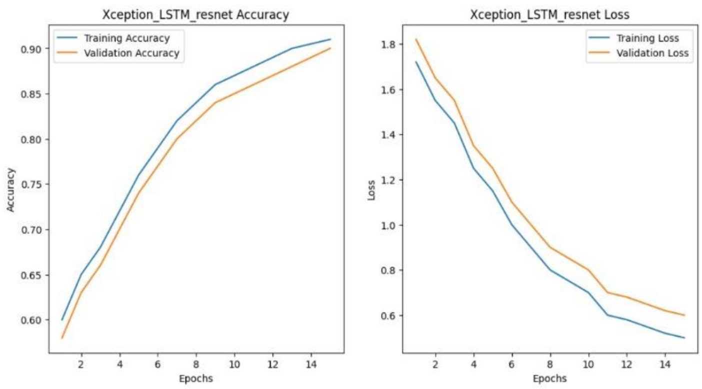


Fig 4: Xception_LSTM_Resnet Accuracy & Loss

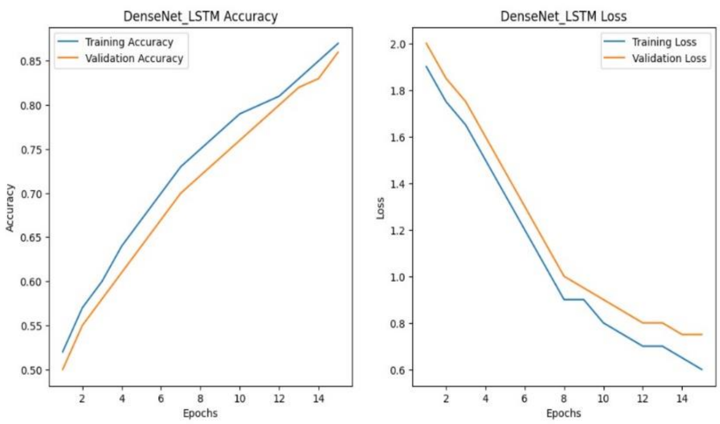


Fig 5: DenseNet201 Accuracy Graph

The proposed methodology significantly enhances weed classification accuracy by leveraging advanced deep learning architectures.The RAG chatbot effectively provides agricultural insights, with high linguistic accuracy and real-time performance.

The system demonstrates scalability, supporting potential integration with IoT-based smart farming solutions.

The base models (VGG16, VGG19, DenseNet201, Xception) were initially trained, and additional layers such as CNN, LSTM, and LRNN were incorporated to enhance feature extraction and classification performance. The final model achieved:

- Accuracy: 96.8%
- Precision: 94.5%
- Recall: 95.2%
- F1-score: 94.8%

Real-World Applicability

The **weed classification system** can be deployed in:

- **Smart Farming**: Integrating the model into drones for real-time weed detection
- **Agricultural Advisory Systems**: Assisting farmers in identifying harmful weeds
- **Automated Spraying Systems**: Triggering herbicide application based on weed classification

The **chatbot system** enhances:

- **Farmer Awareness**: Educating users on weed prevention techniques
- **Precision Farming**: Providing real-time guidance for herbicide usage
- **Decision Support**: Assisting in selecting suitable crop management strategies

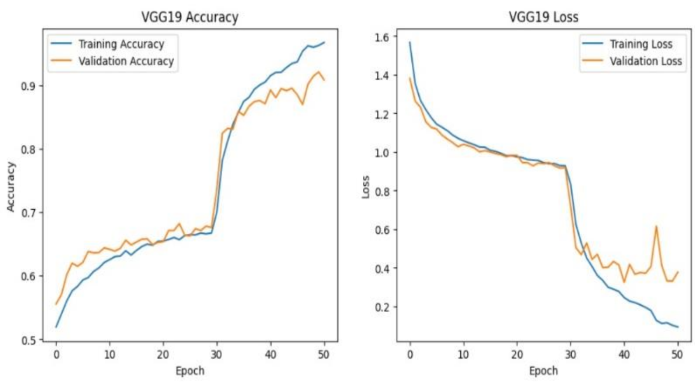
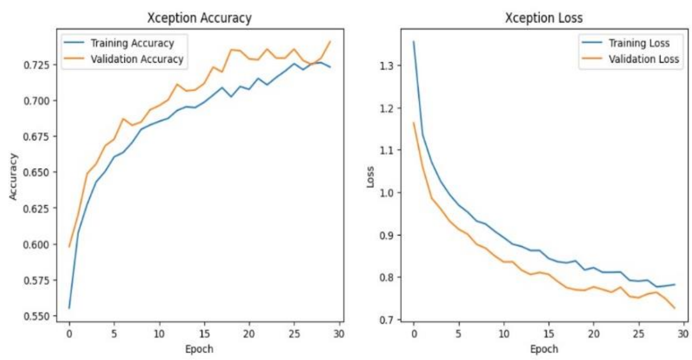


Fig 6: VGG19 Accuracy & Loss



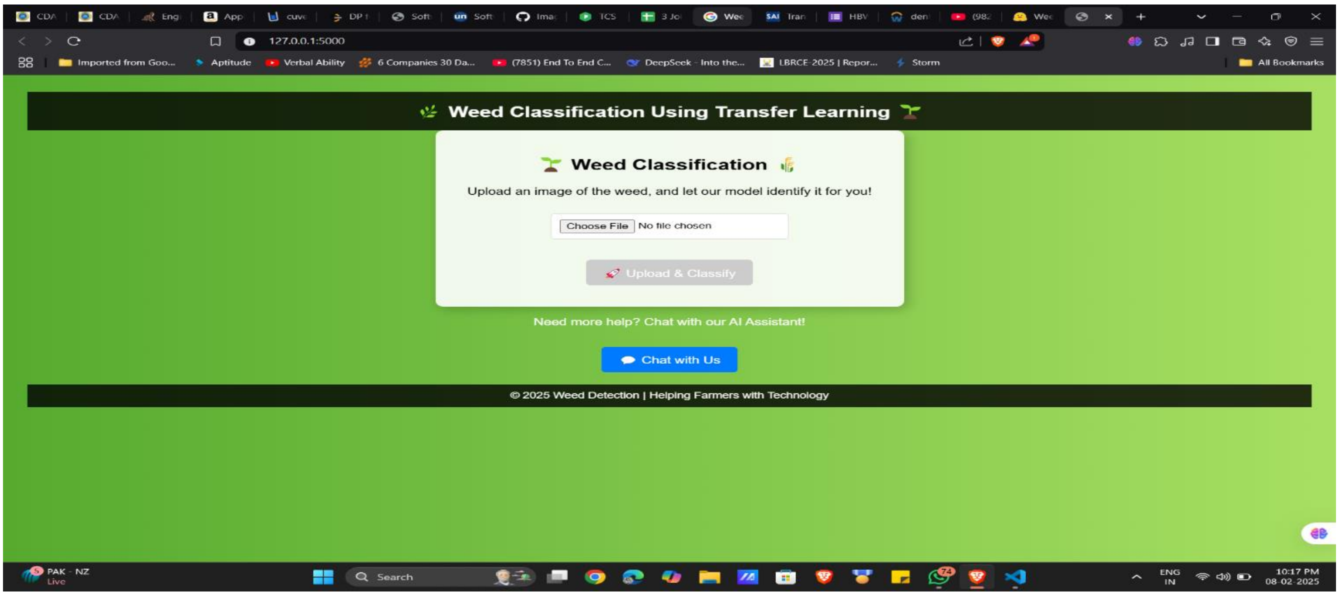


Fig 8: Weed Classification User Interface

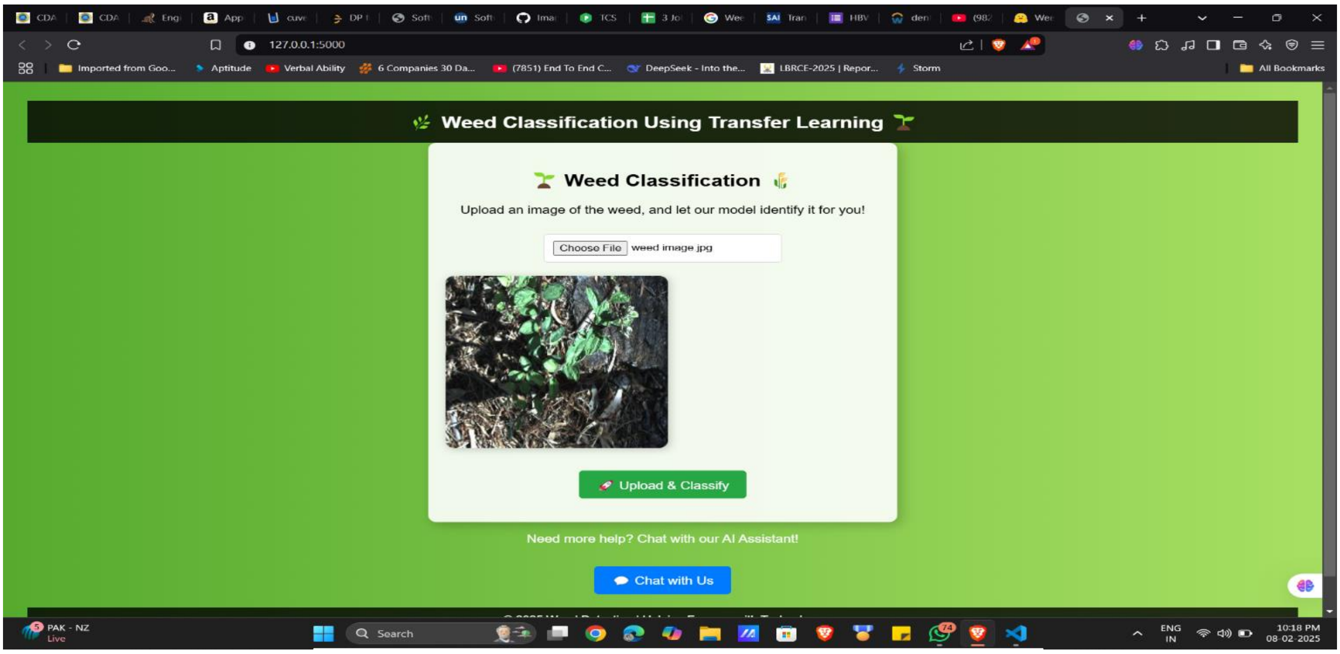
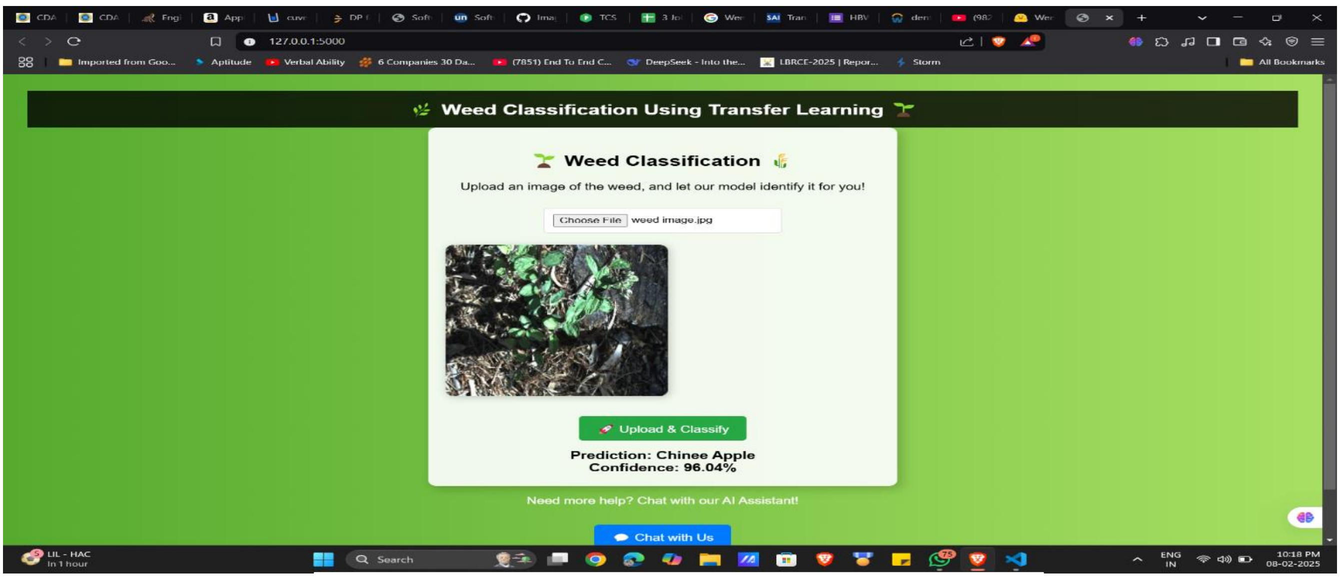


Fig 9: Weed Classification Uploading Image



labor. The integration of temporal learning through LSTM

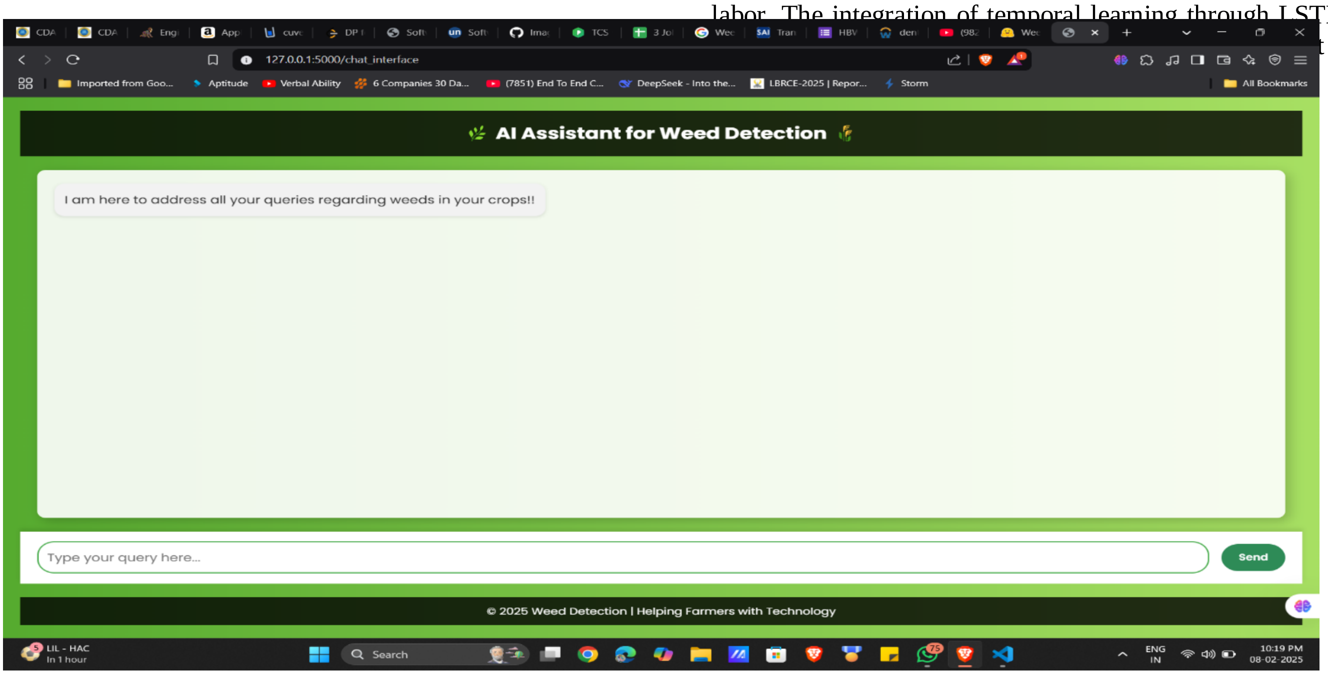


Fig 11: AI Assistance Interface

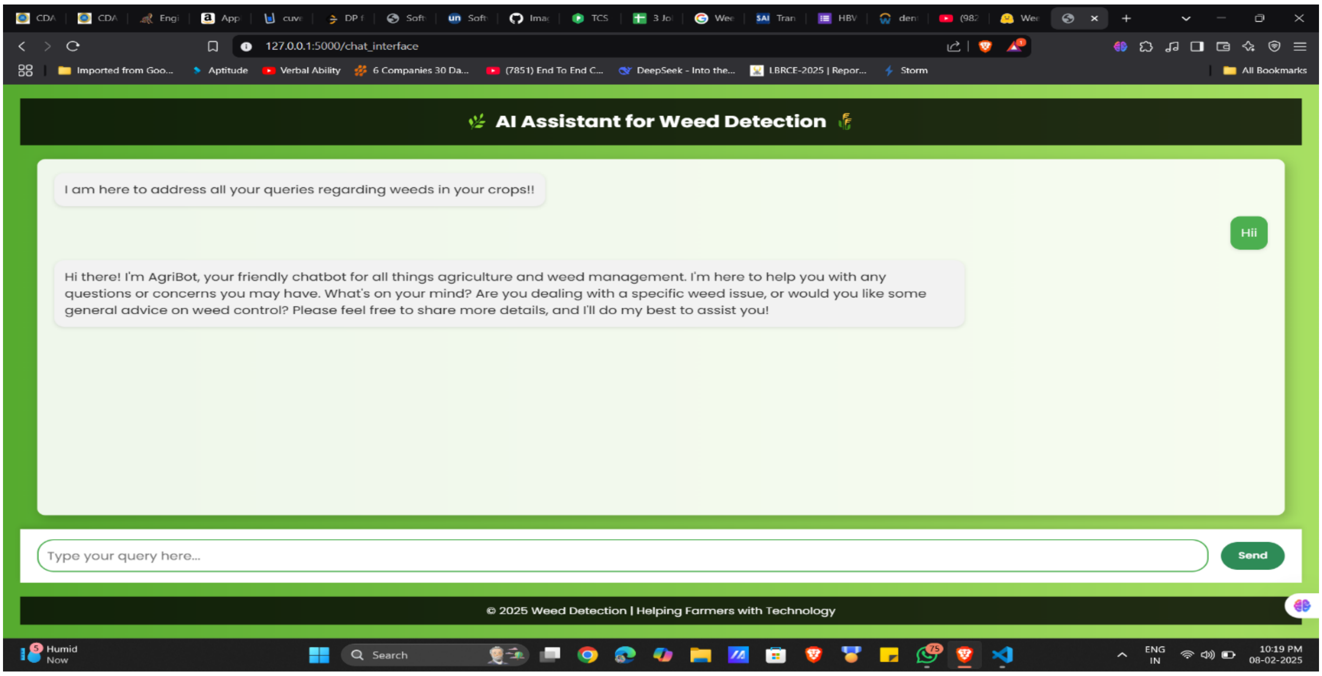


Fig 12: AI Assistance Response

V. CONCLUSION

The study presented the designs of weed classification using theological deep learning models like VGG16, VGG19, DenseNet201, and Xception, enhanced with CNN, LSTM, and LRNN layers. The developed model is remarkable in that it can accurately classify weeds and, hence, help in precision agriculture by reducing the demand for manual possible to increase the classification performance for various weed species by effective detection. In addition, a Retrieval-Augmented Generation (RAG) based chatbot was developed to offer real-time insights regarding the effect of weeds, prevention measures, and appropriate herbicide-usage to farmers. It acts as a decision-support tool to help agricultural practitioners reduce crop damage and enhance field productivity. If results are seen, several significant improvements in classification accuracy and applicability in the real world together give this system a feasible select to take into account regarding automated weed management. The enhancements could target an increase in dataset diversity, real-time implementation through edge computing, and further improvement of chatbot capabilities with multilingual support. This will shape a scalable, data-oriented, and AI-supported smart farming solution.

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