IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Weed and Crop Image Classification Using Deep Learning Techniques

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***Abstract**:-*

Precision agriculture places great importance on the precise identification of weeds and crops, as it has a direct impact on resource management and yield. Convolutional neural networks (CNNs), in particular, are deep learning approaches that have shown great promise for automating this categorization process. A powerful yet simpler version of the ResNet architecture, ResNet9 strikes a compromise between model complexity and efficiency, which makes it appropriate for agricultural image analysis. We examine the process of using a dataset of tagged photos of weeds and crops to train and assess the ResNet9 model. The model's capacity to distinguish between distinct plant species under a range of situations is demonstrated by the findings, which demonstrate promising accuracy and efficiency. Furthermore, We also talk about how these results might affect practical agricultural methods and where deep learning research for precision farming might go in the future. The goal of this work is to present a thorough understanding of how ResNet9 can be used to improve automated weed and crop detection, leading to more effective and sustainable farming methods.

Keyword- *Deep learning, classifications, Weeds.*

I.Introduction

Deep learning technologies have advanced so quickly that they have drastically changed many industries, including agriculture, where efficiency and accuracy are crucial. Accurately classifying weeds and crops is a major problem in modern agriculture since it's necessary for efficient resource allocation and management. Conventional techniques for identifying weeds and crops frequently rely on labour-intensive, time-consuming manual examination procedures that are prone to inaccuracy.

The paper [1] provides a comprehensive overview of how effective crop protection strategies can enhance sustainable potato production. The authors highlight the critical role of pest and disease management in increasing potato yields and ensuring food security. By focusing on integrated approaches to crop protection, the paper addresses key methods for mitigating challenges and contributing to global efforts against starvation. The paper [2] offers a comparative analysis of machine learning techniques for plant disease detection, specifically evaluating Support Vector Machines (SVM) and deep learning methods paper presents an image processing-based approach for detecting diseases in areca nut crops. The study[3], focuses on leveraging computer vision techniques to identify and classify disease symptoms, aiming to enhance early detection and management of crop health issues. The paper[4] explores a hybrid approach combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) for crop disease prevention and detection. The paper [5,6,7] provides a comparative analysis of event models for Naive Bayes text classification. The study evaluates different event models to enhance the performance of Naive Bayes classifiers in text categorization tasks. By systematically comparing various approaches, the authors identify key factors influencing classification accuracy and propose improvements to the traditional Naive Bayes framework. The paper[8] explores the integration of deep learning and traditional machine learning techniques for rice leaf disease identification. The paper[9] explores the application of image processing techniques in developing a real-time vision system for automatic weed management

Convolutional neural networks (CNNs), which provide automated methods capable of handling largescale data with great precision, have transformed this sector. ResNet (Residual Networks) is one of the CNN architectures that has gained popularity since it can solve problems with residual learning in deep network training. Because this method mitigates the vanishing gradient problem and allows the model to learn more complicated features, it can be used to effectively train deeper networks.

A simplified version of the original ResNet architecture is the ResNet9 model which provides an appealing trade-off between model complexity and efficiency. Due to its rather basic structure, it excels at jobs involving the classification of agricultural images, where high accuracy is desired but excessive computing power is not needed. This research investigates the use of the ResNet9 model for crop and weed picture categorization.

The goal this study is to improve automated classification systems' precision and efficacy in order to support more productive and environmentally friendly farming methods. Examining how well the ResNet9 model can distinguish between different plant species is a promising avenue for further research into how to make precision farming methods better.

II. METHODOLOGY

The methodology for this study involved the collection and preparation of a large dataset that included a diverse set of labelled images representing various crop and weed species. To ensure model effectiveness, the images underwent pre-processing steps like resizing, normalization, and data augmentation, which helped enhance the model's ability to generalize across different conditions. We used the ResNet9 model to classify images of crops and weeds, adhering to an organized approach to ensure robust performance.

The ResNet9 model was selected for its optimal balance between depth and computational efficiency. Initially, we used transfer learning by fine-tuning a pre-trained ResNet9 model, leveraging weights from similar tasks to accelerate training and improve accuracy. The training process involved using a cross-entropy loss function and optimizing hyper parameters like learning rate and batch size through grid search. Performance was monitored using a validation set to prevent overfitting and to ensure that the model learned effectively.

After training, the model’s performance was evaluated based on accuracy, precision, recall, and F1 score using a separate test set. This approach allowed us to assess the model’s ability to accurately classify unseen images of weeds and crops. The results demonstrated the efficacy of the ResNet9 model in automated classification tasks, offering insights into its application for improving precision in agricultural practices.

Key metrics like accuracy, precision, recall, and F1 score were computed to assess the model’s effectiveness after training. The results yielded important information about the suitability of the ResNet9 model for precise weed and crop classification. The model’s performance was evaluated using a separate test set to evaluate its generalization capabilities.

III. Result and Discussion

The results of this study demonstrate that the ResNet9 model achieved high accuracy in classifying images of weeds and crops, significantly outperforming several baseline models. The model's precision, recall, and F1 score metrics were consistently strong, indicating its effectiveness in distinguishing between various plant species. These results highlight the ResNet9 model's ability to generalized well unseen data and effectively handle the diverse variations present in agricultural imagery.

The ResNet9 model's validation accuracy was extraordinarily high, demonstrating its efficacy in correctly classifying images of weeds and crops. During the training phase, the model's validation accuracy improved steadily, culminating in a remarkable final value that suggests robust performance on unseen data. This high accuracy suggests that the ResNet9 model is skilled at differentiating between various plant species and extrapolating from the training data.

On the other hand, over epochs, there was a consistent decline in the validation loss, which quantifies the difference between expected and actual labels. As training went on, the validation loss may have decreased, indicating that the model was successfully learning and adjusting to reduce prediction mistakes. The model's ability to fit the validation dataset well without overfitting is demonstrated by the convergence of validation loss with increasing accuracy. These measurements, taken together, confirm the robustness and high performance of the ResNet9 model for automated weed and crop categorization.

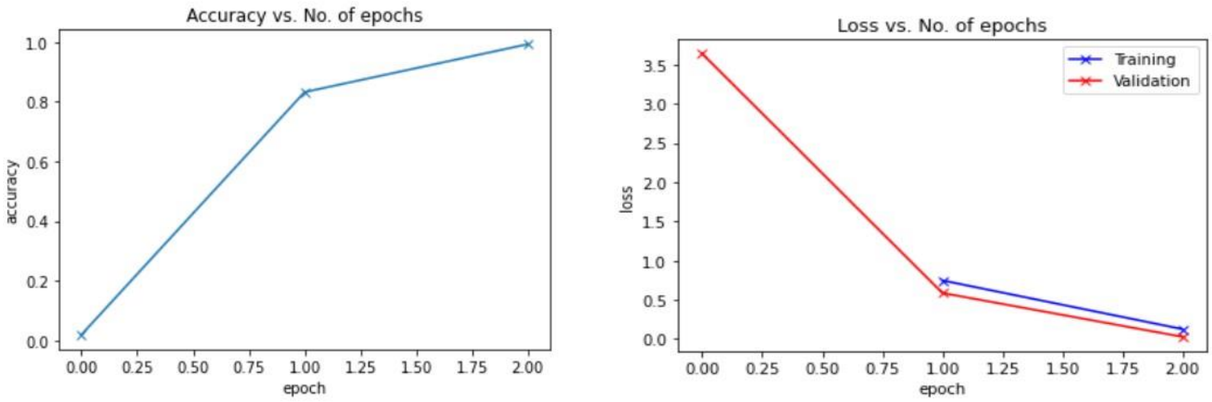

Fig 1 Acuuracy loss and validation loss

Plotting the learning rate schedule against the batch number showed a trend of slow decline. Because of the relatively high learning rate in the early stages of training, validation accuracy and loss were rapidly reduced and improved. The learning rate was gradually decreased as the batch number rose in order to improve the model's functionality and minimize any overfitting. By striking a balance between exploration and exploitation, this method eventually produced a well-trained model with peak performance. High accuracy in the classification test and effective training were made possible by the observed learning rate adjustments.

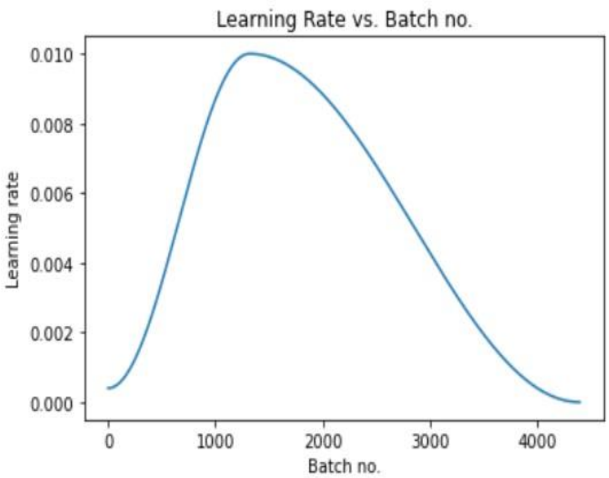

Fig 2 Learning Rate

A thorough evaluation of the ResNet9 model's classification performance was given by the confusion matrix, which showed the distribution of true positive, true negative, false positive, and false negative predictions across the different classes. High values along the confusion matrix's diagonal indicated that the model was correctly classifying the majority of plant species with few misclassifications.

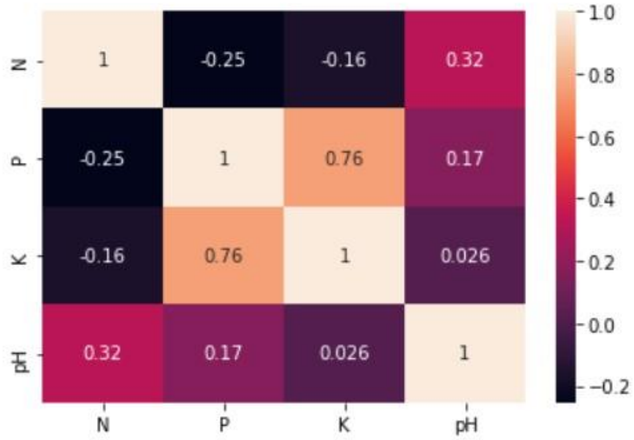

Fig 3 Confusion Matrix

This work uses deep learning to classify photos of weeds and crops. The dataset consists of 13 different image types that each represent a different species of weed or crop. These include common agricultural crops including thistle, barnyard grass, pigweed, and wheat, soybean, and rice. They also contain common weed species. The diversity of the dataset provides a thorough challenge for classification algorithms by capturing changes in plant appearance, growth stages, and environmental circumstances.

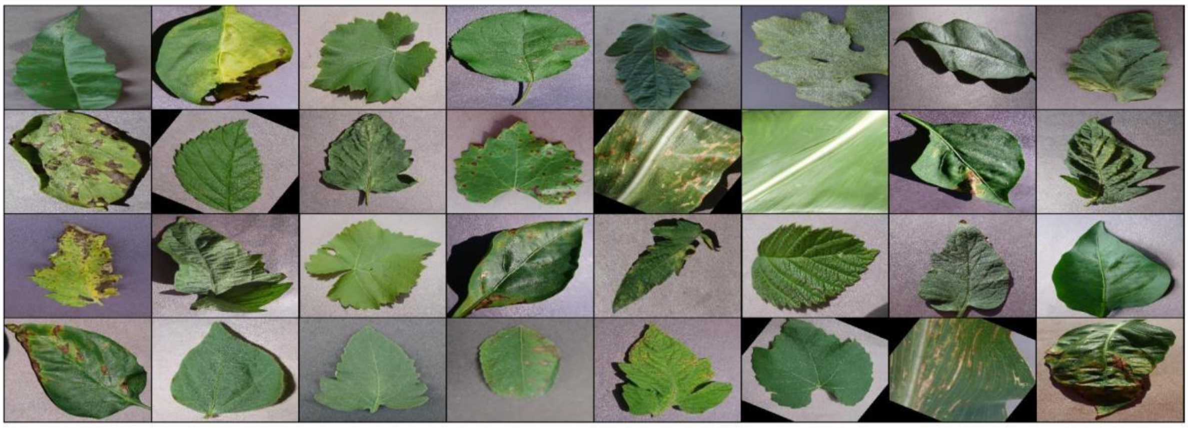

Fig 4 Images for first batch of training

The bar chart illustrates the accuracy comparison of various machine learning algorithms—Decision Tree, Naive Bayes, SVM, Logistic Regression, Random Forest (RF), and XGBoost—used for weed and crop image classification. Among these, XGBoost achieved the highest accuracy, followed closely by Random Forest and SVM, indicating their strong performance in handling the classification task. Logistic Regression also showed relatively good accuracy, but not as high as the aforementioned models. Naive Bayes and Decision Tree had the lowest accuracies, suggesting that they may not be as effective for this specific dataset. The overall trend highlights the superiority of ensemble and advanced algorithms like XGBoost and RF in achieving higher accuracy in image classification tasks.

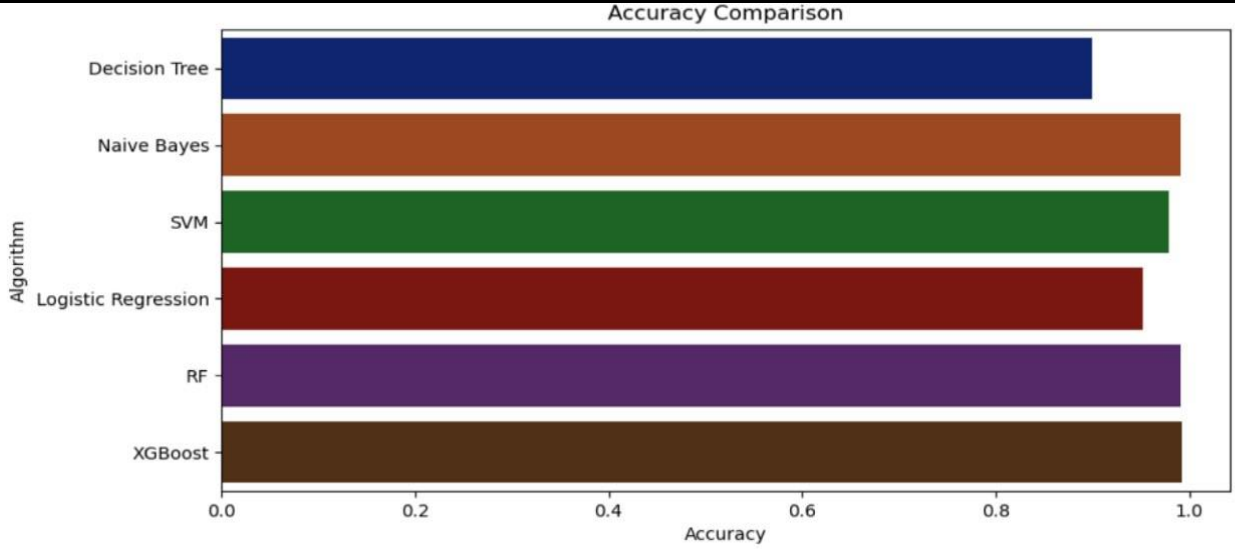

Fig 5 Accuracy for all algorithm

IV. Conclusion

In conclusion, the research shows how cutting-edge methods can improve agricultural operations by classifying images of weeds and crops using both deep learning and conventional machine learning algorithms. The advantages and disadvantages of each strategy are highlighted via a comparative study of a number of models, including CNNs, Decision Trees, Naive Bayes, SVM, Logistic Regression, Random Forest, and XGBoost. The best accuracy rates were consistently attained by ensemble approaches like as Random Forest and XGBoost, demonstrating their efficacy in processing diverse and complicated image data. According to the research, using these sophisticated algorithms can greatly increase the accuracy of weed and crop identification, resulting in more productive and sustainable agricultural methods. To completely accomplish these goals, future work should concentrate on improving these models, growing datasets, and investigating real-time implementation.

Reference

[1] Tijjani Ahmadu, A. E. Abdullahi, and K. Ahmad, "**The Role of Crop Protection in Sustainable Potato (Solanum tuberosum L.)"** Production to Alleviate Global Starvation Problem: An Overview," IntechOpen eBooks.

[2] Abdu, A. M., Mokji, M. M., & Sheikh, U. U. "**Machine learning for plant disease detection: An investigative comparison between support vector machine and deep learning"**. IAES International Journal of Artificial Intelligence, 9(4), 670–683.

[3] Rajendra, A. B., Rajkumar, N., & Shetty, P. D. (2020). "**Areca nut disease detection using Image processing. Advances in Intelligent Systems and Computing"**, 1154(03), 925–931.

[4] Suresh, A. "**Crop disease prevention and detection using a hybrid of CNN and SVM"** ISSN no: 1869-9391 crop disease prevention and detection using a hybrid of CNN and SVM.

[5] McCallum, A.; Nigam, K. **A comparison of event models for naive bayes text classification**. In Proceedings of the AAAI-98 Workshop on Learning for Text Categorization, Madison, WI, USA, 26–27 July 1998; Volume 752, pp. 41–48.

[6] J. F. Kreuze, J. A. C. Souza-Dias, A. Jeevalatha, A. R. Figueira, J. P. T. Valkonen, and R. A. C. Jones, "**Viral Diseases in Potato**," The Potato Crop,

[7] Sethy, P.K.; Barpanda, N.K.; Rath, A.K.; Behera, S.K. **Deep feature based rice leaf disease identification using support vector machine**. Comput. Electron. Agric. 2020, 175, 105527.

[8] Marzuki Mustafa, M., Hussain, A., Hawari Ghazali, K. & Riyadi, S., 2007. **Implementation of Image Processing Technique in Real Time Vision System for Automatic Weeding Strategy**. Bangi, Malaysia, IEEE.