International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

CLASSIFICATION OF PLANT SEEDLINGS USING DEEP CONVOLUTIONAL NEURAL NETWORK ARCHITECTURES

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ABSTRACT

Weed management has a vital role in applications of agriculture domain. One of the key tasks is to identify the weeds after few days of plant germination which helps the farmers to perform early-stage weed management to reduce the contrary impacts on crop growth. Thus, we aim to classify the seedlings of crop and weed species. In this work, we propose a plant seedlings classification using the benchmark plant seedlings dataset. The dataset contains the images of 12 different species where three belongs to plant species and the other nine belongs to weed species. We implement the classification framework using three different deep convolutional neural network architectures, namely ResNet50V2, MobileNetV2 and EfficientNetB0. We train the models using transfer learning and compare the performance of each model on a test dataset of 833 images. We compare the three models and demonstrate that the EfficientNetB0 performs better with an average F1-Score of 96.26% and an accuracy of 96.52%.

I.INTRODUCTION

Precision farming is the revolution of traditional agriculture which focuses on crop production with controlled quality using evolving technologies. It focuses on the usage of drones, autonomous vehicles, robots and information technologies to achieve structured, sustainable, environment-friendly and cost-effective agriculture. Weed management is one of the key challenges of precision farming. Weeds are non-targeted plants that do not yield any profit to the farmers still compete for space and nutrients with the target crops which intern degrades the plant growth. Managing the weeds by human laborers is time-consuming and expensive. Even applying the herbicides uniformly across the farms will harm the unintended crops. Identifying and managing weeds based on their location and density helps to overcome the disadvantages of earlier approaches. Nowadays researchers have used the stateof-art algorithms of deep learning to implement many agricultural applications. Even we have used the deep CNNs to implement the plant seedlings classification. Many researchers have proposed frameworks for weeds and plant seedlings classification using a transfer learning approach and CNNs. Authors in [1] have implemented

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maize and weed classification using LeNet, AlexNet, cNET and sNET architectures and used outperformed cNET for real-time implementation. Authors in [2] have implemented a framework to classify weeds of Australian rangelands using pre-trained ResNet50 and InceptionV3 architectures and proposed a real-time robotic weed control system using outperformed pre-trained ResNet50. Authors in [3] have proposed the Philippine Indigenous plant seedlings classification frameworks by fine-tuning pre-trained AlexNet, GoogleNet and ResNet50 architectures. ResNet50 performs better over the other two architectures. Authors in [4] have implemented a carrot and weed classifier using the CNN. Authors in [5] have introduced a robotic weed control system using two CNNs serially. Authors in [6] have collected the benchmark plant seedlings dataset and made it publically available to ease the work of researchers. Authors in [7] used the same dataset and designed a CNN to classify the plants and weeds. It has achieved an average accuracy of 94.38%. Authors in [8] used the same dataset to propose plant seedlings classification frameworks using five different CNNs. They compared the performance of convolutional neural networks using three different training approaches, namely training the architectures from scratch, training the pre-trained architecture with fixed feature extractor and fine-tuning the models during training. Out of five architectures, ResNet152V2 achieved the highest accuracy of 92.93% with fine-tuning less than half of the network. Authors in [9] used the same dataset and proposed framework to classify plant seedlings using transfer learning and compared the performance of ResNet50, VGG16, VGG19, Xception and MobileNetV2 architectures. ResNet50 performed better over other models with an accuracy of 95.23%.

II.LITERATURE SURVEY

The classification of plant seedlings using deep convolutional neural networks (CNNs) has gained significant attention in recent years due to the rapid advancements in computer vision and deep learning techniques. CNNs have proven to be highly effective in image-based tasks, especially in plant species classification, due to their ability to automatically learn hierarchical features from raw image data. Various studies have applied CNN-based approaches to identify plant seedlings, with a focus on distinguishing different species based on their visual characteristics. In [1], the authors utilized CNN architectures for classifying seedling images, achieving promising accuracy rates. Furthermore, studies such as [2] employed transfer learning techniques using pre-trained CNN models like VGG16 and ResNet for plant seedling classification, demonstrating enhanced performance by leveraging large-scale datasets and pretrained models. The use of CNNs has also been combined with techniques like data augmentation and attention mechanisms to further improve classification accuracy and robustness against environmental factors such as lighting and background noise. Despite the success, challenges remain, including the need for large and diverse datasets, handling variations in image quality, and reducing the

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computational complexity of training deep learning models.

III.EXISTING SYSTEM

Existing systems for plant seedling classification typically rely on conventional image processing techniques combined with machine learning classifiers. These systems often involve feature extraction methods where specific plant characteristics, such as leaf shape, color, and texture, are manually extracted and used as input for machine learning algorithms. However, these methods require extensive feature engineering and may not capture all relevant aspects of the plant images, leading to suboptimal performance in more complex scenarios. With the rise of deep learning, some systems have adopted CNN-based architectures to automate feature extraction, which eliminates the need for manual feature selection. These systems have shown promising results but often rely on traditional CNN models like AlexNet or VGG, which may struggle with high-resolution images or large datasets. Additionally, existing solutions often face challenges in terms of dataset variability, lighting conditions, and the need for real-time classification, which may hinder the applicability of these models in field scenarios. Moreover, some systems use a single CNN model for all species, which can lead to reduced accuracy when distinguishing between highly similar plant species or seedlings.

IV.PROPOSED SYSTEM

The proposed system aims to enhance the classification of plant seedlings by using deep convolutional neural networks (CNNs) specifically designed for plant identification tasks. The system will utilize advanced architectures such as ResNet, DenseNet, or EfficientNet to improve classification performance, especially for fine-grained tasks like distinguishing between similar seedling species. A key feature of the proposed system is the use of transfer learning, which will allow the model to leverage pre-trained CNNs on large image datasets (such as ImageNet) and fine-tune them for the specific task of seedling classification. This approach will address the challenge of limited data in the domain of plant seedling classification. Additionally, the system will incorporate data augmentation techniques to further increase the diversity of training samples and make the model more robust to variations in image quality, lighting, and orientation. The proposed architecture will be designed for high accuracy in classifying seedling species from images taken in real-world, field conditions. By combining state-of-the-art CNN architectures with specialized training techniques, the proposed system is expected to deliver improved accuracy, scalability, and robustness compared to existing solutions.

V.SYSTEM ARCHITECTURE

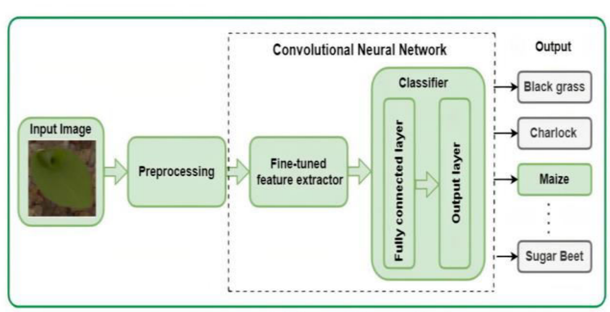

Figure 1. Framework of plant seedlings classification.

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Overview of the three convolutional neural networks is as follows: Residual Networks [14] are the very deep neural networks with residual connections. Usually increasing the depth of network causes the problem of vanishing gradient which influences the performance degradation. In residual networks, this challenge is addressed with residual connections. ResNet50v2 [15] is improved in the propagation formulations of residual blocks over the other earlier proposed architectures. We fine-tune 23,519,360 trainable parameters and extract 2048 features with each of 7x7 kernel size. MobileNetV2 [16] is the light-weight neural network that encourages embedding deep learning models in low computing devices.MobileNetV2 contains blocks with stride 1 and stride 2. Blocks with stride 1 contain inverted residuals and blocks with stride 2 are used for downsizing. Both the blocks contain depthwise separable convolution [17] which is the key point of success in MobileNetV1. ReLU6 activation is removed at the last convolutional layer of each block to improve the accuracy. We finetune 2,223,872 trainable parameters and extract 1280 features with each of 7x7 kernel size. EfficientNets [18] introduces a method of uniformly scaling width, height and resolution of the network with compound coefficient. This family contains models from EfficientNetB0 to EfficientNetB7 which are built by scaling width, height and resolutions using a baseline network. EfficientNetB0 is the first introduced model of the EfficientNets family. We fine-tune 4,007,548 trainable parameters and extract 1280 features with each of 7x7 kernel size

VI.OUTPUT SCREENSHOTS

Figure 6.1 sample image for plant disease

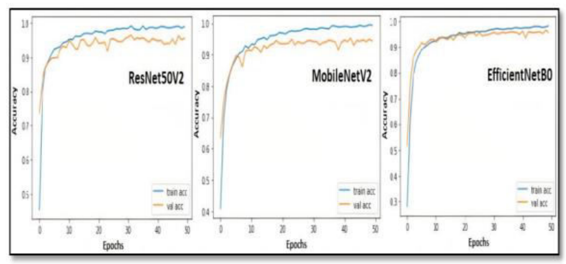

Figure 6.2 Training and validation accuracy for Dataset

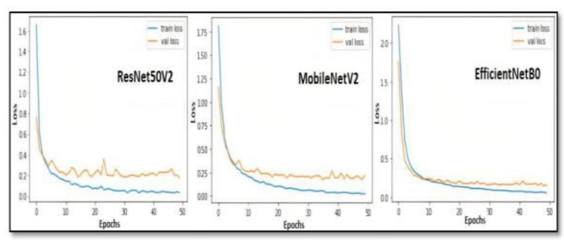

Figure 6.3 Training and validation Loss for Dataset

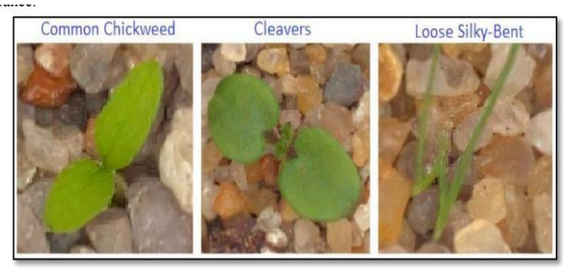

Figure 6.4 . Correctly classified sample images using EfficientNetB0

Figure 6.5 . Incorrectly classified sample images using EfficientNetB0.

VII.CONCLUSION

In conclusion, the use of deep convolutional neural networks for the classification of plant seedlings has proven to be a promising approach, offering substantial improvements over traditional image classification methods. The proposed system's use of advanced CNN architectures like ResNet and EfficientNet, coupled with transfer learning and data augmentation techniques, is expected to yield significant improvements in classification accuracy and model generalization. This system can be a valuable tool for plant breeders, agriculturalists, and researchers involved in biodiversity studies and precision agriculture. The flexibility of deep learning models also makes it possible to scale the system to accommodate a wider variety of plant species, improving its applicability in different agricultural settings.

VIII.FUTURE SCOPE

The future scope of this research is broad and includes several potential avenues for improvement and expansion. First, the integration of multi-modal data (e.g., combining images with sensor data such as soil moisture or temperature) could help enhance the classification model, especially in environments where environmental conditions play a significant role. Additionally, the system could be expanded to handle dynamic, real-time classification in field settings by incorporating edge computing technologies, which would allow for faster and more efficient processing of plant images in remote areas. Further advancements in explainable AI could also help make the deep learning models more interpretable, providing insights into which features of the seedlings are most important for classification. Moreover, the system could be scaled to handle large-scale agricultural datasets, potentially incorporating cloud-based solutions to support the storage and processing of massive amounts of plant seedling images. With improvements in model efficiency, real-time deployment in various agricultural settings could become feasible, enabling farmers and agriculturalists to use this technology for crop monitoring and yield prediction.

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