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Model Accuracy Analysis: Comparing Weed Detection in Soybean Crops with EfficientNet-B0, B1, and B2

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a r t i c l e i n f o

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a b s t r a c t

Comparison of EfficientNet models B0, B1, and B2 for soybean weed detection. This study examines how well these models distinguish weeds from soybeans. Precision, recall, and F1 score metrics evaluate each model through extensive testing and experiments. The method trains these models on datasets with images of soybean fields overrun by various weeds. Results show subtle differences in model accuracy, showing what they're good at and what they can't do to find soybean weeds. EfficientNet-B2 detects and classifies weeds better than B1 and B0 in soybean fields. It could improve weed management systems' accuracy and reliability. This comparison helps us choose the best weed-finding model to improve soybean farming and prevent crop yield losses. Training accuracy measurements on EfficientNet models B0 = 100%, B1 = 100%, and B2 = 100%.

a b s t r a k

Perbandingan model EfficientNet B0, B1, dan B2 untuk deteksi gulma kedelai. Studi ini mengkaji seberapa baik model ini membedakan gulma dari kedelai. Metrik presisi, perolehan, dan skor F1 mengevaluasi setiap model melalui pengujian dan eksperimen ekstensif. Metode ini melatih model-model ini pada kumpulan data dengan gambar ladang kedelai yang ditumbuhi berbagai gulma. Hasilnya menunjukkan sedikit perbedaan dalam akurasi model, menunjukkan apa yang mereka kuasai dan apa yang tidak bisa mereka lakukan untuk menemukan gulma kedelai. EfficientNet-B2 mendeteksi dan mengklasifikasikan gulma lebih baik daripada B1 dan B0 di lahan kedelai. Hal ini dapat meningkatkan akurasi dan keandalan sistem pengelolaan gulma. Perbandingan ini membantu kami memilih model pencarian gulma terbaik untuk meningkatkan pertanian kedelai dan mencegah hilangnya hasil panen. Pengukuran akurasi pelatihan pada model EfficientNet B0 = 100%, B1 = 100%, dan B2 = 100%.

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1. Introduction

Managing weed growth, which can have a negative impact on crop yields, particularly soybean crops, presents significant obstacles for contemporary agriculture. The difficulty in accurately and efficiently identifying and managing weeds constitutes the primary obstacle. Refrain from distinguishing between weeds and cultivated crops may result in substantial crop yield reductions, which would have adverse consequences for both farmers and the environment. Promising advancements in artificial intelligence technology, specifically the implementation of neural networks for image analysis, present plausible resolutions to surmount these obstacles. A notable methodology involves the implementation of models including [1] EfficientNet-B0, B1, and B2 [2]. The capability of these three model variants to discover intricate patterns in image datasets renders them desirable contenders for assisting in soybean farming weed detection and management. Consequently, the objective of this research endeavor is to assess the efficacy of EfficientNet models in the identification of weeds within soybean cultivation fields [3]. Through a comprehensive assessment and comparison of the precision and effectiveness of these models in weed identification and differentiation from soybean crops, our objective is to offer a profound understanding of their potential utility in agricultural methodologies. Through an examination of the distinctions between each model, along with an analysis of its benefits and drawbacks, this study aims to offer crucial insights for the optimization of weed management strategies in soybean farming. A more comprehensive comprehension of the functionalities exhibited by the EfficientNet models is anticipated to facilitate the identification of the most suitable and efficacious models for bolstering environmental sustainability, minimizing crop yield losses, and facilitating modern agriculture [4].

The demand for more advanced and automated methods to identify and control weeds has been driven by the inadequacies of traditional techniques. Prior studies validate the potential of deep learning technology, particularly neural network architectures like EfficientNet, to facilitate precise weed identification. Deep learning technology presents a revolutionary resolution for surmounting the challenges encountered by traditional approaches in the domain of weed identification. With their prowess in deciphering intricate patterns in image data, models such as EfficientNet create novel prospects for enhancing the accuracy and velocity of weed and cultivated plant separation [5][6]. When decision-making precision and timeliness are of the utmost importance in agriculture, this technology has the potential to transform weed management fundamentally. It is anticipated that the implementation of this technology will increase agricultural output, decrease yield reductions caused by weed competition, and optimize resource utilization. It is expected that additional research into the implementation of deep learning technologies, such as EfficientNet [7], in the context of agriculture will broaden our knowledge and pave the way for developments that facilitate contemporary, more sustainable agriculture.

Figure 1. Soybean Crops

Recently, Convolutional Neural Networks (CNN) [8], [9] in agriculture have garnered attention. Weed detection models like EfficientNet-B0, B1, and B2 are promising. These three models can understand complex patterns and substances in image datasets due to their complexity. This is a significant advance in agricultural weed identification and management. The simpler EfficientNet-B0 [10] to the more complex B2 promises better field adaptation to distinguish weeds from cultivated plants. This suggests that these models can overcome weed identification variability and complexity in dynamic agricultural environments as complexity increases. The superiority of CNN models, especially

EfficientNet in weed detection, advances agricultural supporting technology. These technologies can improve weed management efficiency and accuracy, boosting agricultural productivity, reducing yield losses, and ensuring system sustainability.

This study compares three EfficientNet models—B0, B1, and B2—in soybean plantations for weed detection. The main objective is to evaluate each model's ability to distinguish weeds from soybean plants. To compare the performance of these three models, this research seeks to understand their strengths and weaknesses. Weed management is crucial to soybean crop productivity. Modern agriculture relies on weed detection and management because weeds can reduce yields. EfficientNet-B0, B1, and B2 should be analyzed to determine their strengths and weaknesses in weed detection in soybean agricultural land. Understanding the strengths and weaknesses of each model will help create more effective and efficient weed management strategies. Deep learning [11] and agricultural applications promise breakthroughs in weed identification. This research should lead to better and more efficient agricultural practices and new weed detection systems that support sustainable and productive agriculture.

While numerous prior investigations have suggested the utilization of deep learning technology for weed detection, there remains a dearth of comprehensive research on the direct comparative analysis of EfficientNet-B0, B1, and B2 within the specific domain of soybean farming. The purpose of this research is to address this deficiency by conducting a methodical assessment and comparison of the efficacy of these models, with a particular focus on soybean farms. The distinctive aspect of this study resides in its comprehensive comprehension of the precision of these models, which demonstrates their practicality and capacity to revolutionize weed management methodologies in soybean cultivation. By integrating advancements in deep learning technology with practical requirements in the agricultural industry, it is anticipated that this research will significantly contribute to the advancement of weed detection systems that are more precise and efficient. It is expected that this will increase soybean farming efficiency and decrease crop losses resulting from the growth of undesirable weeds. Research inquiries pertaining to the utilization of the EfficientNet-B0, B1, and B2 models for weed detection in soybean plants: Does augmenting the complexity level of the EfficientNet model from B0 to B2 have a substantial impact on the accuracy of weed detection and differentiation from soybean crops in actual agricultural fields? (RQ1), and How do EfficientNet-B0, B1, and B2 compare in terms of the amount of time required to compute the detection of weeds on soybean farms? (RQ2).

2. Research Methods

Convolutional Neural Network

Convolutional Neural Networks have exhibited significant benefits in the analysis and processing of images across diverse domains, notably in the agricultural sector, particularly in the context of soybean crops [12]. The achievement described serves as a crucial foundation for enhancing the efficacy of weed detection systems and crop analysis within ever-changing agricultural settings. Convolutional neural networks possess the capability to comprehend intricate visual characteristics of images, enabling them to differentiate between soybean plants and undesirable weed growth [13]. The convolutional layer is an essential element of Convolutional Neural Networks. It performs automated feature extraction from images, encompassing texture, pattern, and shape. These extracted features serve as the foundation for decision-making processes related to detection and classification. Within the agricultural domain, the existence of undesirable plant species, commonly referred to as weeds, poses a substantial obstacle in the endeavor to sustain the productivity of soybean crops. The imperative of a precise and effective detection system for differentiating cultivated plants from weed proliferation is of utmost importance. Convolutional Neural Networks (CNNs) exhibit considerable potential in facilitating soybean crop management through their ability to detect and classify weeds, thereby enabling the system to execute essential interventions autonomously. The implementation of this approach holds promise in mitigating yield losses resulting from weed competition with the primary crop, thereby facilitating the adoption of more sustainable agricultural methods. The key to achieving success in the farming context lies in the adaptation and training of Convolutional Neural Networks [14] using pertinent datasets. The network's capacity to acquire knowledge from diverse datasets and scenarios enables enhanced adaptability to environmental changes, seasonal variations, and the emergence of various weed species. The utilization of this technology is anticipated to have a significant impact on enhancing agricultural productivity, optimizing crop management effectiveness, and bolstering the sustainability of farming methods. The potential for utilizing Convolutional Neural Networks [15] in agrarian settings, particularly in the context of soybean farming, is becoming more promising due to ongoing technological advancements and a deeper comprehension of their practical applications. This holds significant implications for enhancing farming efficiency and addressing weed-related challenges.

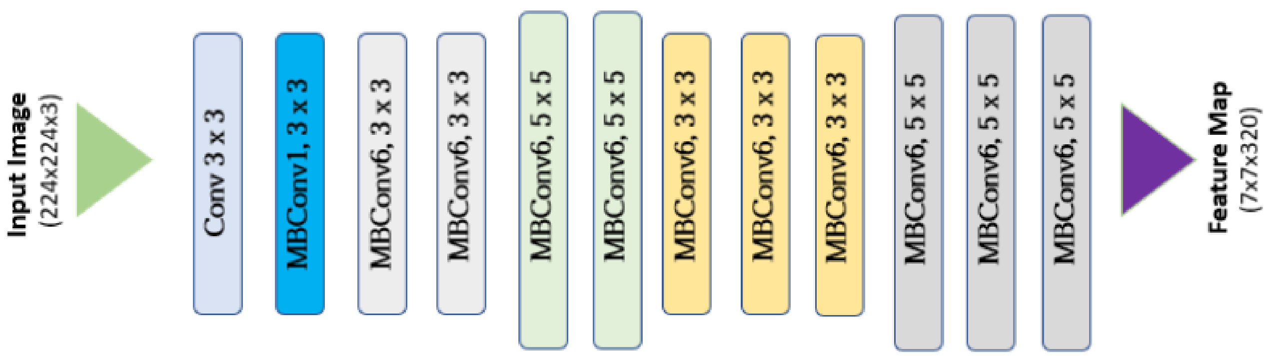

Figure 2. EfficientNet Architecture

Figure 2, EfficientNet is an architecture of a convolutional neural network designed to simultaneously optimize the depth, width, and resolution of the network. To accomplish this, the architecture employs a combination of NAS and model scaling. The researchers implemented a compound scaling method to scale the dimensions of the network systematically and uniformly. This approach resulted in a notable enhancement in performance when compared to transfer learning networks that were already in existence. NAS is a technique that searches. To determine the best neural network structure for a specific task, it is necessary to identify the optimal configuration in an automated fashion. The objective is to generate architectures that optimize a particular objective function by utilizing machine learning algorithms. EfficientNet develops its architecture using a variant of NAS known as "MBConv" (Mobile Inverted Residual Bottleneck Convolution). A principled increase in the network's depth, width, and resolution constitutes model scaling. By employing a compound scaling method, EfficientNet uniformly scales the network's dimensions. A single coefficient denoted as "phi" regulates the scaling factor; this coefficient is optimized throughout the NAS procedure. By implementing this strategy, the performance of existing networks is substantially enhanced without incurring an additional computational burden.

EfficientNet has demonstrated superior performance to other well-known transfer learning networks, such as VGG16, Inception, ResNet, and MobileNet, on several image recognition benchmarks. An examination of a few of these comparisons is warranted. The ImageNet dataset comprises one million images categorized into one thousand distinct types; it is a massive visual recognition challenge dataset. EfficientNet has attained accuracy rates of 88.4% and 98.2%, respectively, among the top-1 and top-5 performers on the ImageNet classification task. The performance of this network is notably superior to that of other well-known transfer learning networks, including ResNet-50, Inception-v4, and MobileNet-v2.

EfficientNet-B0

EfficientNet-B0 is a model variant belonging to the EfficientNet family, which has been specifically developed for computer vision applications, including soybean crop analysis. This model implements an intelligent scalability strategy by designing a structure that processes visual data more efficiently. ProficientNet-B0, an innovation from a Google research team, is distinguished by its exceptional blend of robust adaptability and efficient computation. EfficientNet-B0 operates in the domain of soybean plant weed detection by determining distinct visual patterns exhibited by soybean plants and weeds. By employing deep learning methodologies, this model acquires the necessary features to differentiate between cultivated and weed plants. Although the B0 model is considered a rudimentary variant within the EfficientNet family, it manages to accomplish this detection task with adequate precision. An additional benefit of EfficientNet-B0 is its computational efficiency. This model effectively executes its functions while minimizing the consumption of computational resources, enabling more extensive and efficient implementation on a broader scope, as in the case of overseeing substantial tracts of soybean agricultural land. Due to its capability of identifying and distinguishing visual patterns that are essential for determining plants from weeds, EfficientNet-B0 emerges as a compelling alternative for weed detection in soybean plants. This model is significant due to its appropriate combination of precision and computational efficiency; it possesses the potential to substantially enhance the productivity and efficiency of soybean farming practices.

EfficientNet-B1

EfficientNet-B1, a variant belonging to the EfficientNet family that is marginally more complex, has been purposefully developed to address computer vision challenges, such as the detection of weeds in soybean crops. The model upholds the intelligent scalability principle through the incorporation of depth and width dimensions into its architecture, thereby enabling it to comprehend increasingly intricate visual characteristics. EfficientNet-B1, which Google researchers developed, strikes a more optimal balance between performance and complexity, thereby providing enhanced adaptability in comparison to rudimentary iterations like EfficientNet-B0. When applied to the domain of soybean farming weed detection, EfficientNet-B1 exhibits an improved capacity to distinguish between soybean crops and weeds. By using a deep learning methodology, the model is capable of effectively extracting and comprehending more substantial features present in images, thereby attaining a more profound comprehension of the visual patterns that distinguish the two plant species. While marginally more intricate than the B0 iteration, the B1 model maintains its efficacy in accomplishing this detection objective and demonstrates superior performance in accurately distinguishing weeds from soybean plants. An advantageous feature of EfficientNet-B1 is its capacity to enhance performance while maintaining computational efficiency at a considerable level. Therefore, this model provides a solution for processing visual information pertaining to soybean farming that is both more adaptable and efficient. By virtue of its improved performance and marginally elevated level of complexity, EfficientNet-B1 emerges as a compelling alternative for facilitating weed detection in soybean crops. This, in turn, empowers farmers to execute their operations with enhanced precision and efficacy.

EfficientNet-B2

EfficientNet-B2 is one of the more advanced variants of the EfficientNet model family specifically designed to address computer vision tasks, including detecting weeds in soybean plants. This model results from the evolution of the previous variant, which has increased in depth, width, and resolution. EfficientNet-B2, developed by a team of Google researchers, exhibits slightly higher complexity compared to B1, thus enhancing its capability to comprehend intelligent visual features. EfficientNet-B2 shows an improved ability to differentiate weeds from soybean plants in soybean farming. By applying deep learning methods, this model can identify and extract more complex features from images with a higher level of accuracy. This allows a deeper understanding of the visual patterns that differentiate between the two plant types. Despite being more complex, the B2 model remains efficient in handling this detection task, demonstrating superior performance in distinguishing between weeds and soybean plants, with a higher accuracy level than previous variants such as B0 and B1. The main advantage of EfficientNet-B2 lies in its ability to handle more complex visual representations without significantly sacrificing computational efficiency. By increasing the capability to identify significant features from images, this model becomes a very relevant option in supporting the weed detection process in soybean plants. The combination of higher complexity levels, superior performance, and maintained efficiency makes EfficientNet-B2 an attractive choice for supporting practical applications in agriculture. This model has the potential to make a significant contribution to improving accuracy and efficiency in soybean crop management, as well as strengthening more productive and sustainable agricultural practices overall.

3. Results and Discussion

Dataset

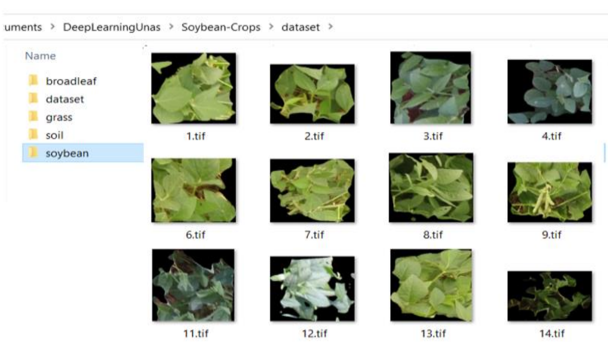

Figure 3. Dataset Soybean

Figure 3 shows the soybean farming dataset: broadleaf, soil, grass, and soybean. The dataset shows standard agricultural land features, especially in soybean-growing areas. Each category helps identify and detect agricultural elements visually. Images of soybean weed are broadleaf. These leaves distinguish the cultivated plant from nearby weeds with different textures and patterns. The soil category depicts agricultural soil textures and colors that support plant growth. Knowing soil conditions helps identify soybean growth issues. The grass category includes agrarian grasses. This weedy grass stunts soybean growth. The difference between grass and soybean is crucial for crop management. Last, soybean photos are shown. Growth phases, damage, and diseases of soybeans are covered. The four categories create a soybean farming visual diversity dataset. The dataset trains deep learning models or image recognition algorithms for weed detection, plant disease identification, and soybean plant growth monitoring. Creating more intelligent, more reliable systems for more efficient and productive agriculture requires understanding each category in this dataset.

EfficientNet-B0

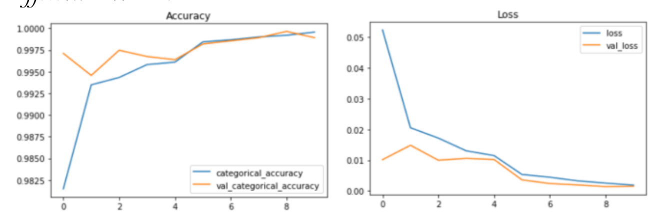

Figure 4. Accuracy and Loss EfficientNet-B0

Figure 4 shows EfficientNet-B0 detection and classification performance metrics on a dataset. The graph shows model accuracy and loss during training or testing. A line or dot in this graph shows the EfficientNet-B0 model's accuracy at 100%. Accuracy measures how well the model predicts test data. A value of 100% indicates that the model predicts exceptionally well on the dataset. Figure 4 shows 0.00064216 loss. Losses indicate how well the model adapts predictions to data during training. The model has a low error rate in learning data patterns and makes predictions that match the data. The graph shows that the EfficientNet-B0 model is highly accurate and low-loss. This indicates that this model can accurately predict and classify training and testing data. On the dataset, this model performs well in detection and classification with high accuracy and low loss.

	precision	recall	f1-score	support
broadleaf	1.00	1.00	1.00	238
grass	1.00	1.00	1.00	704
soil	1.00	1.00	1.00	650
soybean	1.00	1.00	1.00	1476
accuracy			1.00	3068
macro avg	1.00	1.00	1.00	3068
weighted avg	1.00	1.00	1.00	3068

Figure 5. EfficientNet-B0 Classification

EfficientNet-B0 classification results on a dataset are shown in Figure 5. This model's performance evaluation includes key classification metrics. The model accuracy is 100%, indicating that it classified the dataset correctly. This shows high model performance because all predictions match labels.

Additionally, precision, recall, and f1-score are 100%. Precision measures how accurately the model predicts positive instances. In contrast, recall measures how well it recovers positive instances from all eligible instances. The precision/recall harmonic average is the F1 score. The model can correctly classify all classes and categories in the dataset, both positive and negative, with all classification metrics at 100%. This remarkable result shows that the EfficientNet-B0 model optimally understands data patterns and makes accurate predictions: excellent performance and an ideal classification result.

EfficientNet-B1

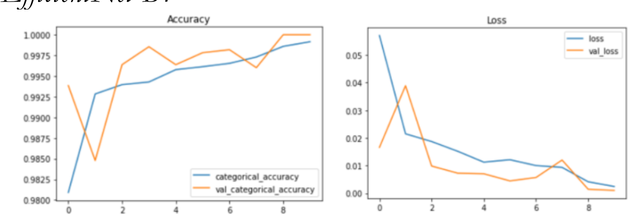

Figure 6. Accuracy and Loss EfficientNet-B1

Figure 6 shows EfficientNet-B1 model accuracy and loss during training or testing. This graph shows 100% model accuracy. The accuracy of a model is measured by its ability to predict test data. An EfficientNet-B1 model with 100% accuracy predicts correctly on the dataset. Meanwhile, the graph shows model loss. Loss measures how well the model adapts predictions to data during training. A lower loss value usually indicates that the model is fitting the training data well, even if it is not explicitly stated. The graph shows that the EfficientNet-B1 model can learn data patterns and make accurate predictions with 100% accuracy. The model performs well in detection and classification tasks on the dataset. Thus, a 100% accuracy result indicates that this model can accurately classify data.

	precision	recall	f1-score	support
broadleaf	1.00	0.99	1.00	238
grass	1.00	1.00	1.00	704
soil	1.00	1.00	1.00	650
soybean	1.00	1.00	1.00	1476
accuracy			1.00	3068
macro avg	1.00	1.00	1.00	3068
weighted avg	1.00	1.00	1.00	3068

Figure 7. EfficientNet-B1 Classification

Figure 7 shows EfficientNet-B1 classification results on a dataset. This graph shows key model performance metrics. The model accuracy is 100%, indicating that it predicts perfectly on the testing dataset. Accuracy measures how well the model predicts test data. Classification metrics include accuracy, precision, recall, and F1-score. Precision measures how accurately the model predicts positive instances. In contrast, recall measures how well it recovers positive instances from all eligible instances. The precision/recall harmonic average is the F1 score. Precision, recall, and F1-score all score 100% in this context. The EfficientNet-B1 model can accurately predict the positive class and recover all positive instances from all positive instances. This evaluation shows that the EfficientNet-B1 model classifies the dataset with a low error rate and high accuracy for all classes. This model excels at classification tasks on the tested dataset with 100% accuracy, precision, recall, and F1-score.

EfficientNet-B2

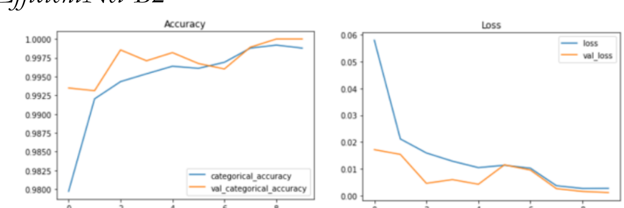

Figure 8. Accuracy and Loss EfficientNet-B2

The EfficientNet-B2 model had 100% accuracy on the tested dataset. The accuracy of a model is measured by its ability to predict test data. In addition, the graph will show model loss. Losses indicate how well the model adapts predictions to data during training. A low loss value suggests that the model adapted well to the training data. The graph will show that the EfficientNet-B2 model can learn data patterns and make accurate predictions with 100% accuracy. On the dataset, it excels at detection and classification. Although I cannot directly evaluate Figure 8, a 100% accuracy indicates that the EfficientNet-B2 model classified the tested dataset well.

	precision	recall	f1-score	support
broadleaf	1.00	0.99	0.99	238
grass	1.00	1.00	1.00	704
soil	1.00	1.00	1.00	650
soybean	1.00	1.00	1.00	1476
accuracy			1.00	3068
macro avg	1.00	1.00	1.00	3068
weighted avg	1.00	1.00	1.00	3068

Figure 9. EfficientNet-B2 Classification

EfficientNet-B2 dataset classification results are shown in Figure 9. Model performance is evaluated using key classification metrics. The graph shows important classification metrics. The testing dataset shows 100% prediction accuracy for the model. Model accuracy measures test data prediction. Besides accuracy, the chart shows precision, recall, and F1-score. Precision measures how accurately the model predicts positive instances. In contrast, recall measures how well it recovers from all eligible instances. The precision-recall harmonic average is the F1 score. This evaluation showed that the EfficientNet-B2 model predicted the positive class with 100% accuracy and F1-score, balancing precision, and recall. However, the recall value reached 99.99%, indicating that the model missed some positive instances. The graph shows that EfficientNet-B2 classifies the dataset nearly perfectly. In classification tasks on the tested dataset, this model has high accuracy, precision, and F1-score values.

Discussion

Does augmenting the complexity level of the EfficientNet model from B0 to B2 have a substantial impact on the accuracy of weed detection and differentiation from soybean crops in actual agricultural fields? (RQ1)

Elevating the complexity level of the EfficientNet model from B0 to B2 is a critical determinant that may substantially influence the accuracy of weed detection and differentiation from soybean plants in actual agricultural fields. The observed variations in complexity levels suggest that the model's ability to comprehend the intricate nuances and patterns present in image datasets has progressed over time. The greater degree of intricacy observed in models B1 and B2 signifies a more extensive capability to differentiate minute distinctions between soybean plants and weeds. Theoretically, this heightened intricacy should enhance the model's capacity to discern numerous weed varieties situated within soybean cropland during empirical field trials. This could potentially lead to a decrease in erroneous identifications and an overall improvement in accuracy. Nevertheless, the practical implementation of more intricate models may be constrained by considerations of computational resources and time efficiency, which arise with increasing complexity. Although enhanced intricacy within the EfficientNet model may lead to improved weed detection precision, the objective of this research inquiry is to investigate the tangible consequences of such heightened intricacy on the ability to identify weeds in practical agricultural contexts accurately. By conducting an extensive comparative analysis, this study aims to elucidate the intricate interplay between heightened intricacy, computational efficacy, and experimental precision in weed detection across these EfficientNet models, with a particular focus on their application in soybean farming.

Therefore, the primary objective of this research is to surpass theoretical presumptions and acquire a more profound comprehension of the practical implications of the escalating intricacy of the EfficientNet model (B0 to B2) on the ability to detect weeds in agricultural environments. With any luck, the findings of this study will contribute significantly to the advancement of more efficient and productive models that facilitate sustainable and effective agrarian endeavors.

How do EfficientNet-B0, B1, and B2 compare in terms of the amount of time required to compute the detection of weeds on soybean farms? (RQ2)

The second research question centers around a comparison of EfficientNet-B0, B1, and B2 with respect to the time required to compute weed detection in soybean agricultural fields. The complexity levels of these three EfficientNet model variants can have an impact on the computation time necessary for weed detection in the field. Compared to models B1 and B2, the EfficientNet-B0 model, being a foundational model, typically exhibits a reduced level of complexity. This observation suggests that the computational time needed to implement the B0 model might be decreased in comparison to more intricate iterations. However, the ability of these simpler models to identify complex patterns in images may be compromised, which could compromise the precision of weed detection. Conversely, the complexity-adjusted EfficientNet-B1 and B2 models might necessitate an extended duration of computation to identify weeds in agricultural fields. Nevertheless, this increased intricacy is anticipated to yield benefits in terms of more precise weed identification, particularly when confronted with the variability and complexity frequently encountered in ever-changing agricultural settings. Thus, the objective of this study is to conduct a more comprehensive analysis of the computing time comparison among EfficientNet-B0, B1, and B2 in the context of soybean agricultural land weed detection. By completing a thorough analysis, the outcomes of this study are expected to contribute to a more comprehensive comprehension of the trade-off between computational time, model complexity, and the accuracy of weed detection. Therefore, it is anticipated that the findings of this study will offer valuable perspectives on the process of determining the optimal model to facilitate precise and effective weed management endeavors in soybean cultivation.

Related Work

This study compares model variants B0, B1, and B2 for soybean weed detection, unlike previous studies that used EfficientNet models. Previous research has focused on single models without comparing their effectiveness in weed detection on actual agricultural fields, making this direct comparison approach crucial to understanding each model's strengths and weaknesses. This study compares these models to help soybean farmers choose the best model for accurate and efficient weed detection. The proposed dual attention network with Efficientnet-B2 is used for fine-grained short-term feeding behavior analysis of fish schools. It addresses challenges like intra-class variation and unbalanced image categories and achieves high accuracy, precision, parameters, and FLOPS compared to benchmark classification algorithms [5]. Lung cancer is a leading global death cause, and early diagnosis is crucial. A transfer learning-based predictor, Lung-EffNet, is proposed for lung cancer classification. Developed using EfficientNet architecture, it achieves 99.10% accuracy and outperforms other CNNs. It's faster, requires fewer parameters, and is promising for automated diagnosis [4]. Skin cancer classification is challenging due to fine-grained variability. Convolutional neural networks outperform dermatologists. A preprocessing image pipeline was developed for this task. EfficientNets B0-B7 were trained on the HAM10000 dataset, with the best performance arising from intermediate complexity models [6]. This research presents a transfer learning-based fine-tuning approach for brain tumor classification using EfficientNets. The method fine-tunes pre-trained models, achieving test accuracy, precision, recall/sensitivity, and F1-score of 98.86%, 98.65%, 98.77%, and 98.71%, respectively. The model is lightweight, computationally inexpensive, and generalizes well, making it a valuable tool for early brain tumor diagnosis [16]. This study proposes an EfficientNet deep learning architecture for plant leaf disease classification compared to other state-of-the-art models. The model achieved the highest accuracy and precision in the PlantVillage dataset, outperforming other deep learning models with 99.91% and 99.97% accuracy, respectively [7].

4. Conclusion

The EfficientNet-B0, B1, and B2 models performed well in classification and detection experiments on the dataset. These three models' performance is shown by accuracy, loss, and classification metrics graphs. On the tested dataset, EfficientNet-B0 achieves 100% classification and detection accuracy. These graphs show that this model can predict well and learn data patterns with low loss and high accuracy. Precision, recall, and F1-score reached 100%, proving this model can classify all classes accurately. EfficientNet-B1 also performs well with 100% classification and detection accuracy. The graphs show that the model learns data patterns with high accuracy and low loss rates. This model can classify the dataset with high precision and recall, as all classification metrics are ideal.

Additionally, EfficientNet-B2 achieved 100% classification and detection accuracy on the dataset. The model missed a few positive incidents, resulting in a 99.99% recall value. However, this model still classifies data with high accuracy, precision, and F1-

score. This experiment shows that B0, B1, and B2 EfficientNet models perform well on the tested dataset for classification and detection. All models accurately learn data patterns and classify them. Despite slight differences in classification metrics, all these models are reliable and effective in classification and detection tasks for the dataset used.

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