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Improving Seedling Quality and Predict Plant Growth Using Convolutional Neural Networks

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***Abstract*—Plant seedling classification is a crucial task in the field of agriculture as it plays a significant role in the evaluation of the seedling quality and the prediction of plant growth and yield. With the advancements in computer vision and machine learning techniques, various methods have been proposed for automating this task, ranging from traditional machine learning algorithms such as decision trees and k-nearest neighbors to deep learning techniques such as Convolutional Neural Networks (CNNs). The choice of method depends on various factors, including the quality and size of the data, the computational resources available, and the desired level of accuracy. In recent years, deep learning methods have shown promising results in plant seedling classification due to their ability to automatically learn stratified representations of the data. Despite these advances, there are still significant challenges in this field, including the variability of seedling shapes, the limited availability of annotated data, and the difficulty of generalizing models to new species. To address these challenges, ongoing research focuses on improving the performance of existing methods and developing new methods that are more robust and generalizable. This proposed work deals with applying CNNs to the plant seedling dataset. The dataset contains 5545 train images and 794 test images, based on images of approximately 960 unique plants belonging to 12 species at several growth stages, when the models' convolution blocks were decreased, the reduced layers gave a validation accuracy of 93 percent, while the model without reduced layers provided a validation accuracy of 95 percent.**

Keywords—Convolutional Neural Networks (CNN), Deep Learning, Plant Seedling, Machine Learning

I. INTRODUCTION

CNNs are well-suited for plant seedling classification due to their ability to learn features from images and their effectiveness in image classification tasks. However, it's important to consider the specific problem and available data when choosing a machine-learning technique. The task of classifying diverse varieties of plant seedlings based on different characteristics is known as "plant seedling classification." Due to their capacity to automatically learn and extract information from pictures, convolutional neural networks (CNNs) are the popular choice for this purpose. However, depending on the issue and the data at hand, different machine learning models like K-Nearest Neighbors (KNN), Support Vector Machines (SVMs), and Decision Trees can also be used to classify plant seedlings.

Using decision trees, it is possible to categorize subtrees according to their size, form, and color. Decision trees may efficiently understand the relationship between the features and the target class by segmenting the data into smaller subsets based on the most crucial feature.

K-Nearest Neighbor (KNN) is a non-parametric classification method that can be used to categorize subtreesaccording to how closely they resemble known examples. The KNN algorithm can categorize a new subtree given a set of previously labeled subtrees by locating the k nearest neighbors in the training data and applying the majority class label.

By utilizing the spatial hierarchical learning of characteristics from photos, CNNs can be utilized to classify seedlings. To forecast the properties of a novel type of seedling, the network can be trained to recognize traits of the seedling, such as the form and texture of the leaves.

Support Vector Machines (SVMs), Random Forests, Naive Bays, and Artificial Neural Networks are additional methods that can be utilized for subtree categorization (ANNs). These methods can help in capturing intricate connections between things and target classes and in producing precise predictions based on learned models.

It is significant to remember that the technique used will rely on the particular situation, the data at hand, and the desired result. Synchronous learning is the process of using many methodologies and combining their predictions to produce more accurate predictions.

As can be seen from the above plot, The bar chart with the maximum number of images belongs to the class Loose Silky-bent. There is class imbalance with 5 classes having a really low number of images while 2 classes have a high number of images with the rest around the median.

Fig. 2 shows the class imbalance and can also be inferred from the pie chart, but this shows that it is not as steep as compared to the bar chart. It is advisable to normalize the count to give a better representation of the data present.

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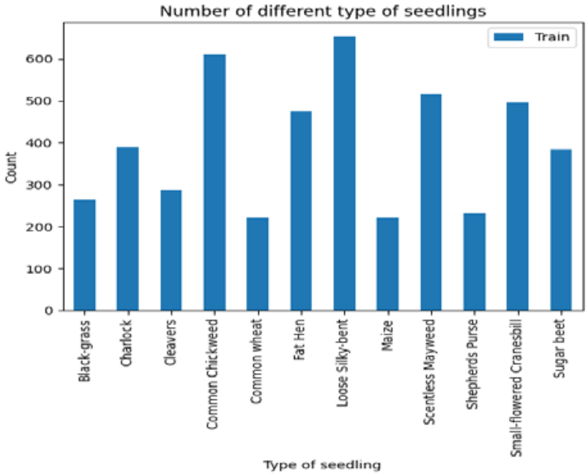

Fig. 1. A bar graph displaying the prevalence of various seedling kinds

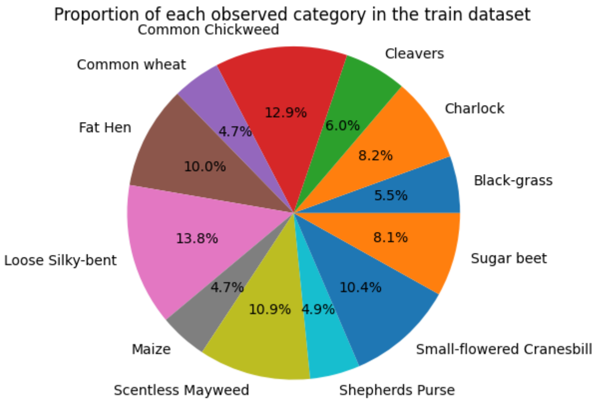

Fig. 2. Pie Chart representing proportions of each observed category in the training dataset.

II. Literature Survey

After surveying the available literature, we understand the architecture of learning methods, deep learning image models, transfer learning approaches using deep convolutional neural networks, and the methodology used to determine the classes of the plant seedlings.

A. *Convolutional Neural Networks have the following advantages:*

- Image Recognition: CNNs are particularly adept at classifying images because they can learn spatial feature hierarchies.
- Automated Feature Extraction: CNNs can recognize and learn about features automatically from input images, doing away with the requirement for manual feature engineering.
- Translation Invariant: CNNs can recognize entities in any location within a picture because they are translation invariant.
- Sparsity of Connections: CNNs are computationally effective due to their sparse connections, which enables them to process high-dimensional data such as images.
- Shared Parameters: By minimizing the number of parameters that must be learned, shared parameters in a CNN's convolutional layers enable the network to learn many features from various regions of the image.
- End-to-End Training: CNNs can be trained from beginning to end, increasing the automation and effectiveness of the learning process.

B. *Limitations are also there while using Convolutional Neural Networks, those are listed below*

- Data Diversity: One of the major limitations of current CNN-based methods is the limited diversity of the training data. Most existing methods use small and homogeneous datasets, which may not accurately represent the diversity of plant species and growth stages. To overcome this limitation, larger and more diverse datasets need to be collected and used for training the models.
- Transfer Learning: Another challenge is the limited availability of annotated data for training the models from scratch. To get around this problem, transfer learning—which involves fine-tuning previously trained models for the task—can be an effective strategy. However, the performance of transfer learning can be affected by the differences between the pre-trained model and the target task, and appropriate methods need to be developed to address these differences.
- Model Robustness: CNN-based methods can be sensitive to variations in the images, such as changes in lighting conditions and image resolution. To make the models more robust and effective in real-world scenarios, methods need to be developed to address these variations and improve the robustness of the models.
- Explanation and Interpretability: While CNNs have shown to be effective in plant seedling classification, they are often considered black box models, making it difficult to understand the reasons behind the predictions. To improve the transparency and interpretability of the models, methods need to be developed to provide explanations and interpret the decisions made by the models.

As a whole, while CNNs have shown to be effective in plant seedling classification, there is still much work to be done to overcome the limitations and gaps in the current methods and improve the performance of the models for real-world applications.

III. About the Dataset

The Aarhus University Signal Processing group, in collaboration with the University of Southern Denmark, has recently released a dataset containing images of approximately 960 unique plants belonging to 12 species at several growth stages.

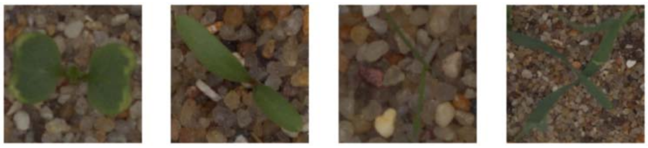

Fig. 3. Arbitrary selection from the data

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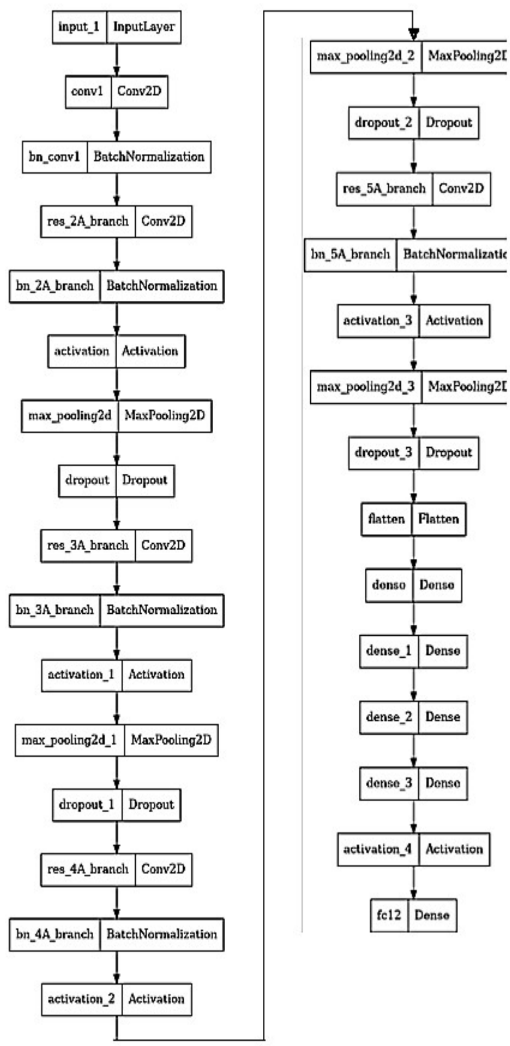
IV. Proposed Work

The proposed work for plant seedling classification using Convolutional Neural Networks (CNNs) involves the development of a deep learning model to classify images of plant seedlings. The process will start with the collection of 5545 images representing different species and stages of growth, which will then be preprocessed and divided into training, validation, and testing sets. The CNN architecture will be designed to extract hierarchical features from the images using multiple convolutional, max pooling, and fully connected layers. The model will then be trained using the training set, validated using the validation set, and finally tested using the test set. The results will be evaluated using various performance metrics, such as accuracy and F1 score, and compared with other methods. The trained model will be capable of automatically classifying images of plant seedlings and providing valuable insights into the quality and growth potential of the seedlings, making it a useful tool for farmers and researchers in agriculture.

V. Model Architecture

C. *General Structure*



Proposed General Model Architecture

```
Model: "CNN"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 150, 150, 3)]     0

 conv1 (Conv2D)              (None, 73, 73, 64)        4864

 bn_conv1 (BatchNormalizatio  (None, 73, 73, 64)       256
 n)

 res_2A_branch (Conv2D)      (None, 73, 73, 64)        102464

 bn_2A_branch (BatchNormaliz  (None, 73, 73, 64)       256
 ation)

 activation (Activation)     (None, 73, 73, 64)        0

 max_pooling2d (MaxPooling2D  (None, 36, 36, 64)       0
 )

 dropout (Dropout)           (None, 36, 36, 64)        0

 res_3A_branch (Conv2D)      (None, 36, 36, 128)       73856

 bn_3A_branch (BatchNormaliz  (None, 36, 36, 128)      512
 ation)

 activation_1 (Activation)   (None, 36, 36, 128)       0

 max_pooling2d_1 (MaxPooling  (None, 12, 12, 128)      0
 2D)

 dropout_1 (Dropout)         (None, 12, 12, 128)       0

 res_4A_branch (Conv2D)      (None, 12, 12, 256)       819456

 bn_4A_branch (BatchNormaliz  (None, 12, 12, 256)      1024
 ation)

 activation_2 (Activation)   (None, 12, 12, 256)       0

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 256)        0
 2D)

 dropout_2 (Dropout)         (None, 4, 4, 256)         0

 res_5A_branch (Conv2D)      (None, 4, 4, 512)         6423040

 bn_5A_branch (BatchNormaliz  (None, 4, 4, 512)        2048
 ation)

 activation_3 (Activation)   (None, 4, 4, 512)         0

 max_pooling2d_3 (MaxPooling  (None, 1, 1, 512)        0
 2D)

 dropout_3 (Dropout)         (None, 1, 1, 512)         0

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 256)               131328

 dense_1 (Dense)             (None, 256)               65792

 dense_2 (Dense)             (None, 256)               65792

 dense_3 (Dense)             (None, 256)               65792

 activation_4 (Activation)   (None, 256)               0

 fc12 (Dense)                (None, 12)                3084

=================================================================
Total params: 7,759,564
Trainable params: 7,757,516
Non-trainable params: 2,048
_________________________________________________________________
```

Proposed Work Architecture

VI. Results

From Figure 4 and Figure 5 below we can observe that the model has arrived at the global minimum. It's excellent

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that the model isn't overfitting. However, the terrain is too uneven; the optimizer's momentum and learning rate may need to be changed.

Figure 6 Confusion Matrix, shows that our model is biased toward the loose silky bent plant seedling class.

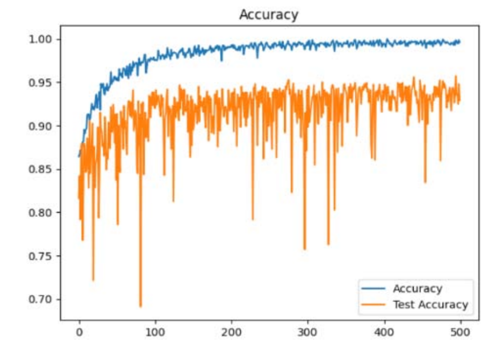


Fig. 4: Train Accuracy compared with Test Accuracy

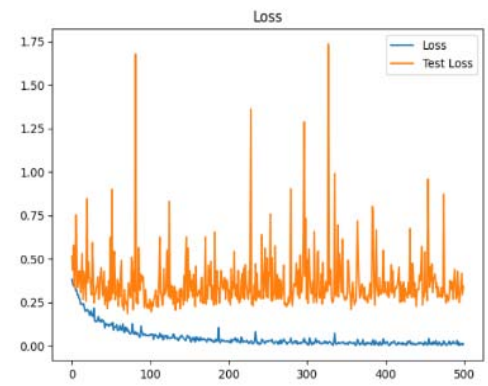
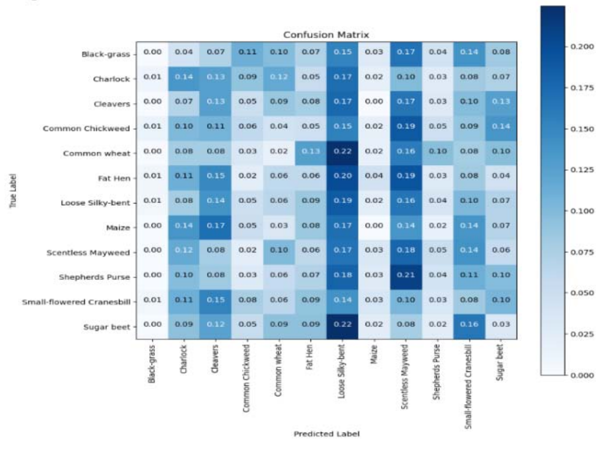


Fig. 5: Train Loss compared with Test Loss

Fig. 6. Confusion Matrix



VII. Conclusion

The results from the plant seedling classification using Convolutional Neural Networks (CNNs) show promising performance, with a validation loss of 0.25 and validation accuracy of 95.80%. This indicates that the model was able to learn the representations of the images and make accurate predictions for the validation set. The loss of 0.01 indicates that the model was able to generalize well to unseen data and avoid overfitting, which is a common challenge in deep learning. The high accuracy of 95.80% indicates that the model was able to correctly classify a large percentage of the images in the validation set. These results suggest that the proposed CNN-based method is a promising approach for plant seedling classification and can provide valuable insights into the quality and growth potential of the seedlings. But more research is required to verify the findings and assess how well it performs in comparison to alternative approaches. The resulting test score was 85%.

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