

Classification of Plant Species Using AlexNet Architecture

Pravinkrishnan K¹, Naren Sivakumar², Ainsely Jebaraj³, C Padma Pooja⁴,
Supraja Sridhar⁵, Prabavathy Balasundaram⁶ and Lekshmi Kalinathan⁷

Sri Sivasubramaniya Nadar College of Engineering, SH 49A, Kalavakkam, Tamil Nadu 603110

Abstract

Plant classification is the process of identifying plant species using image processing techniques. This system is helpful in identifying the different plant species which has useful applications in botanical studies and many plant based industries. The previous works have built systems based on data sets containing limited number of classes. However, the plant classification systems can further be improved in order to cover more number of species. The proposed system is capable of identifying 80000 classes of plant species and is built with a large dataset using AlexNet deep learning architecture. A combination of AdaGrad and KL Divergence optimization and loss functions respectively is used to train the model that produced a MRR score of 0.00029.

Keywords

AlexNet, CNN, Transfer learning, Deep learning

1. Introduction

Plant classification plays an important role in many aspects of our lives. From identifying unrecognised plants in everyday situations, to classifying and removing harmful weeds and other potentially dangerous plants in a crop field, classification of plants can help in many ways, and is a field of great potential for study and research. It is estimated that there are more than 300.000 species of vascular plants in the world. Systematic plant identification and aggregation is further worsened by the discovery and classification of more plants. Due to the limitations of human knowledge, it is practically infeasible to identify and classify plant species manually, and simultaneously maintain a high level of accuracy and precision. Hence, a prominent need for classification of plant species through automated means exists, and can be achieved by employing deep learning methods.

A convolutional neural network, or CNN, is a deep learning algorithm that has the capabilities to assign weights and biases to any given input image, and be able to differentiate one from the other using these assigned properties. The architecture of a convolutional network is very similar to that of a human brain and was inspired by the organisation of the visual cortex. Convolutional networks are preferred over Feed Forward networks mainly because of their

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✉ pravinkrishnan19082@cse.ssn.edu.in (P. K); naren19068@cse.ssn.edu.in (N. Sivakumar);
ainsely19012@cse.ssn.edu.in (A. Jebaraj); padmapooja2010291@ssn.edu.in (C. P. Pooja); supraja2010136@ssn.edu.in
(S. Sridhar); prabavathyb@ssn.edu.in (P. Balasundaram); lekshmik@ssn.edu.in (L. Kalinathan)



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capability to reduce the number of parameters to be trained and the reusability of the weights involved.

Alexnet is an example of such a CNN, written by Alex Krizhevsky, and was the first CNN to utilise the Graphical Processing Unit, or the GPU, to boost its performance. The architecture has proven to be best suited for multi-class classification problems. Its architecture consists of 5 convolutional layers, 3 max pooling layers, 2 normalisation layers, 2 fully connected layers, and one softmax layer. Each convolutional layer consisted of convolutional filters, and a non-linear activation function called ReLU. The defining characteristic of Alexnet was the usage of this ReLU function, which helps achieve a 25% error rate, at about six times faster than a network that utilised tanh functions.

2. Literature Survey

NeuronAI [1] has proposed a solution to the PlantCLEF 2021 challenge to assess how automated identification of flora in data-poor regions can be improved by using herbarium collections. The team used an ensemble of several two-streamed Herbarium-Field Triplet Loss (HFTL) networks and several One-Streamed Mixed (OSM) networks. The results revealed that the last advances in domain adaptation enable the use of herbarium data to facilitate the identification of rare tropical species for which no or very few other training photos are available. A Mean Reciprocal Rank score of 0.2 was achieved.

Krishna et al. [2] have submitted a solution to the PlantCLEF 2020 challenge to create a classifier to identify plant species from a large collection of labeled images. The team's models were trained on Cloud TPUs and TPU Pods available on the Google Cloud Platform. The models, which were initially trained on the ImageNet Dataset, were fine-tuned to the PlantCLEF 2020 Dataset using transfer learning. The team achieved an overall MRR of 0.008 in the testing phase with the RedNet-50 models. For specifically chosen classes with fewer training samples, an MRR of 0.003 was achieved.

Borugadda et al. [3] have conducted a study to predict the optimal model among AlexNet and other machine learning models, to classify cotton diseases based on the extracted image features. An open-access cotton disease dataset, collected from the website of Kaggle is used. Since the given dataset is of imbalanced data, the optimal deployment model is chosen based on the macro F1_score. Therefore, the study concludes that the AlexNet model gives the best result among all classification models with an F1_score of 94.92%.

Yu Sun et al. [4] have proposed a deep learning model ResNet26, designed for large-scale plant classification in the natural environment. They have used the BJFU100 dataset containing 10,000 images, collected by mobile phones, of various plant species from the Beijing Forestry University. Using SGD optimization, the proposed ResNet26 model results in 91.78% accuracy. This is also seen to be significantly higher than the ResNet18, ResNet34, and ResNet50 models which yield lower test accuracies.

Forrest Sheng Bao et al. [5] employed a Probabilistic Neural Network for automated leaf recognition for plant classification. The network classifies the input vector into a specific class because that class has the maximum probability to be correct. The network is trained with 1800 leaf images sampled in Nanjing University and Sun Yat-Sen arboretum, Nanking, China.

Their model can classify 32 kinds of plants and their experimental result indicated that their algorithm is workable with an average accuracy of 90.312%.

M. A. Moid et al. [6] have developed a transfer learning-based plant disease classification system using Xception and InceptionV3 architecture. The models have been trained on the PlantVillage dataset containing 70,285 training images holding 38 different healthy and diseased plant classes. The InceptionV3-based model has achieved 96.88% accuracy and the Xception-based model has achieved 97.5% accuracy.

Ghosh S et al. [7] carried out a survey of different classification techniques such as Principal Component Analysis (PCA), Decision Tree, Naive-Bayes classifier (NBC), Bayesian Classification, Probabilistic Neural Network, Support Vector Machine, Artificial Neural Networks, k-Nearest Neighbours, Genetic Algorithm and Learning Vector Quantization. (LVQ). After exploring the features and drawbacks of each algorithm, they have concluded that a combination of SVM – as it is easy to control complexity of decision rule and frequency errors, k-NN – as it is simple and PNN – as its training is easy and spontaneous, are best suited for classifying plant images.

Table 1. Analysis of the results produced by researchers and their limitations

| Title | Methodology | Accuracy |
|--|--------------------------|------------------|
| Overview of PlantCLEF 2021: cross-domain plant identification [1] | HFTL and OSM | MRR - 0.2 |
| Plant Species Identification Using Transfer Learning - PlantCLEF 2020 [2] | ResNet | MRR - 0.008 |
| Classification of Cotton Leaf Diseases Using AlexNet and Machine Learning Models [3] | AlexNet | 94.92% |
| Deep Learning for Plant Identification in Natural Environment [4] | ResNet26 | 91.78% |
| A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network [5] | PNN | 90.312% |
| Transfer Learning-based Plant Disease Detection and Diagnosis System using Exception [6] | InceptionV3 and Xception | 96.88% and 97.5% |

From Table 1, we infer that the performance of Alexnet architecture is best suited for multi-class classification problems.

3. Task and Dataset

The given task was evaluated as a plant retrieval task based on multi-image plant observations from the given test set. The goal of the task is to retrieve the correct plant species among a ranked list of species returned by the evaluated system [8]. The metrics employed in this situation is the Macro Averaged Mean Reciprocal Rank (MA-MRR), which is a statistical measure

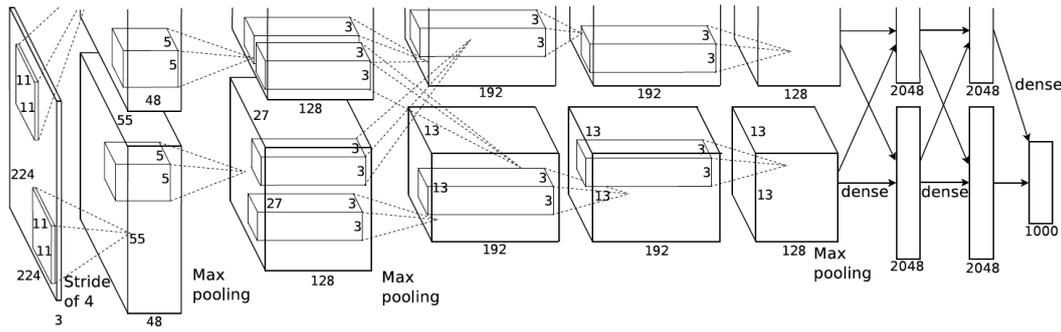


Figure 1: The AlexNet Architecture

that produces a list of possible responses for any sample of query ordered by the probability of correctness. This rank is calculated as the multiplicative inverse of the first correct answer. The training dataset used for this purpose was divided into two categories, namely trusted and web. The former is a collection of images with labels verified by human experts, whereas the latter has not been verified as such. For this venture, however, only the trusted sets of data were used, with a total of more than 2.9 million images collected from various sources such as GBIF and EOL, spanning over 80,000 plant species. This implies that there is a certain level of determination quality, with the number of images being limited to about 100 per species. Images with characteristics helpful to identification of plants, such as close ups of flowers, barks, leaves, and trunks have also been favoured. This is to limit the size of the dataset while maintaining the balance between the classes.

4. Methodology

This study employs the AlexNet architecture for the classification of different plant species. The AlexNet model was first proposed by Alex Krizhevsky et al. in the 2012 ImageNet Large Scale Visual Recognition Challenge. AlexNet is a simple and efficient Convolutional Neural Network (CNN) architecture that has around 650,000 neurons and 62.3 million learnable parameters. This model is efficient in reducing the overfitting problem with the help of maintaining dropout and data augmentation. Generally, the AlexNet architecture comprises eight layers, of which the first five layers are convolutional and maximum pooling layers, followed by three layers fully connected to the neural network. The Softmax function is used in the output layer and the ReLU non-linearity is applied to the output of every other layer. Figure. 1 illustrates the architecture of AlexNet.

5. Implementation

The implementation of this project was carried out on a system with an Nvidia RTX 3070 set up for deep learning, a Samsung 1 TB SSD onto which the dataset was loaded, and an Intel i7 core

CPU to prevent bottlenecking of the GPU. It also uses various software like Nvidia’s CUDA (Compute Unified Device Architecture), Python, and CudNN libraries.

5.1. Building the model

The standard AlexNet convolutional network was taken and modified to fit the given dataset. A pre-trained weight set for the AlexNet architecture was used to implement transfer learning and to improve the accuracy of the overall result. The pre-trained weights file was taken from a model which was trained to classify plant diseases. The model created was tested using various optimisers and loss functions and the accuracy was noted. To achieve this, a sample dataset of 135 classes taken randomly from the original dataset was used, and the model was initially trained on this dataset. Once the maximum possible accuracy was obtained using these 135 classes over 20 epochs, the best combination was taken and applied on the main dataset. Cuda and CudNN libraries were installed in order to enable the smooth execution of training and testing phases on the GPU. The dataset was transferred to a Solid State Drive and was run over 20 epochs.

6. Results and Analysis

The sample dataset previously chosen was tested out using various optimisers and loss functions, as tabulated below. The combination that gave the best results were selected, and was then subsequently applied on the main dataset.

Table 2. Results of empirical analysis done using a mini dataset.

| Epochs | Optimiser | Loss Function | Learning Rate | Loss | Testing Accuracy |
|--------|-----------|---------------------------|---------------|-------|------------------|
| 15 | Adam | Categorical Cross Entropy | 0.01 | 3.79 | 0.14 |
| 15 | SGD | Categorical Cross Entropy | 0.01 | 3.32 | 0.27 |
| 20 | SGD | Poisson | 0.01 | 0.03 | 0.1 |
| 15 | RMSProp | Categorical Cross Entropy | 0.01 | 3.6 | 0.16 |
| 15 | Adamax | Categorical Cross Entropy | 0.01 | 3.9 | 0.17 |
| 15 | Nadam | Categorical Cross Entropy | 0.01 | 7.03 | 0.17 |
| 20 | Adagrad | KL Divergence | 0.015 | 4.77 | 0.27 |
| 20 | SGD | KL Divergence | 0.01 | 3.85 | 0.28 |
| 20 | Adam | KL Divergence | 0.001 | 15.86 | 0.01 |
| 20 | AdaGrad | KL Divergence | 0.00495 | 3.79 | 0.309 |

From above test scores shown in Table 2, it is observed that the combination of Adagrad optimiser and KL Divergence loss function yielded the best results. The combination was initially observed to result in 27% test accuracy, but after further modification of the learning rate from 0.015 to 0.00495, it yielded the best result of 30.9% test accuracy. This was closely followed by SGD optimiser and KL Divergence loss function with 28% test accuracy.

Based on these results, AdaGrad optimizer and KLDivergence loss function were then implemented on the main dataset, and run for 20 epochs. Once the training phase was complete, the testing data was provided to the model, and the MRR rank could be calculated. It was noted that the accuracy of the model was around 20%, and the MRR for the same was around 0.00029.

7. Conclusion

Despite continuous development in the fields of Deep learning and machine learning, a concrete solution is still yet to be found in the case of the classification of plant species on a widespread scale. One way to solve this issue, as attempted in this paper, would be to use Convolutional Neural Networks to create a model that classifies plants accurately, despite the shortcomings of the provided dataset. After testing various loss functions and optimisers, a model was created using the combination of loss function and optimiser that yielded the best results. After choosing the optimal deployment combination of Adagrad optimiser and KL Divergence loss function, the final result obtained had an accuracy of 20.0% and a MRR score of 0.00029 on the Trusted dataset. To further increase the accuracy of this system, the data sparsity in certain classes of the dataset should be addressed using various image augmentation techniques.

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A. Online Resources

- PlantCLEF2022 Image-based plant identification at global scale - ImageCLEF
- Plant Disease Classification using AlexNet - Kaggle