SSM-Net for Plants Disease Identification in Low Data Regime

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Abstract—Plant disease detection is a necessary step in increasing agricultural production. Due to the difficulty of disease detection, farmers spray every form of pesticide on their crops to save them, in turn causing harm to crop growth and food standards. Deep learning can help a lot in detecting such diseases. However, it is highly inconvenient to collect a large amount of data on all forms of disease of a specific species of plant. In this paper, we propose a new metrics-based few-shot learning SSM net architecture which consists of stacked siamese and matching network components to solve the problem of disease detection in low data regimes. We showcase that using the SSM net (stacked siamese matching) method, we were able to achieve better decision boundaries and accuracy of 94.3%, an increase of 5% from using the traditional transfer learning approach (VGG16 and Xception net) and 3% from using original matching networks. Furthermore, we were able to attain an F1 score of 0.90 using SSM Net, an improvement from 0.30 using transfer learning and 0.80 using original matching networks. The code is available on Github: https://github.com/shruti-jadon/Plants_Disease_Detection.

Index Terms—few-shot learning, agriculture, low data, computer vision, neural networks, deep learning.

I. INTRODUCTION

With the growing population, human society has a responsibility to produce enough food to meet the demand. However, food production has been an issue due to climate change, soil pollution, plant diseases, etc. Plant diseases are not only a significant threat to food safety on a global scale, but also a disaster for the health of people [13]. Various times, due to the difficulty of proper disease identification, farmers apply a mixture of all pesticides, which in turn cause vegetation loss, leading to either monetary loss or health loss. In the USA alone, food allergy cases have increased by approximately 18 percent since 2003, [13] suggesting that all these link back to agriculture. By leveraging the increase in computing power, we can take advantage of deep learning methodologies for disease detection. Still, in many scenarios, it is almost impossible to collect a large amount of data for a particular disease in a plant species. For example, sugarcane fungal infections such as red rot (Colletotrichum falcatum) and smut (Sporisorium scitamineum) are predominant in the South Indian peninsula. This can lead to a highly imbalanced dataset.

A lot of work [1] [12] [19] has been done in plant disease identification using machine learning, but no approach has been proposed to tackle it in low data regimes. In this paper, we propose using a few-shot metrics-based machine learning approach for disease detection with an imbalanced and scarce data scenario. Using proposed SSM Net (stacked siamese matching), we have been able to learn better feature embeddings, and furthermore achieved accuracy of 94.3% and F1 score of 0.90.

A. Dataset

For this work, we collected our dataset with the help of farmers in India. Overall, the aim of this work is to provide farmers (using drones) ability to mass detect disease and spray accurate pesticides in that region. Our data consist of a total of 155 images of 11 types of sugarcane disease, as shown in Table 1.

II. APPROACHES

Few-Shot Learning approaches are widely categorized into 3 cases: Metrics based methods, Models based methods, and Optimization based methods. In this paper, we have decided to tackle problem of plants disease detection using metrics-based approaches and compared it with the widely-used transfer
TABLE I
CATEGORIES & NUMBER OF IMAGES OF SUGARCANE DISEASES DATASET

| Disease Type       | No. of Images |
|--------------------|---------------|
| Grassy Shoot       | 23            |
| leaf spot          | 4             |
| leaf scald         | 2             |
| Red root           | 29            |
| Nitrogen abundance | 17            |
| Orange rust        | 3             |
| Pyrilla            | 16            |
| smult              | 4             |
| wholly aphid       | 33            |
| wilt               | 22            |
| yellow leafy disease | 2           |

learning approach in scarce data cases. Metrics-based methods, as the name suggests, are based upon metrics such as feature embeddings, objective function, evaluation metric, etc. A Metric play a very important role in any Machine Learning model, if we are able to somehow extract proper features in initial layers of a neural network, we can optimize any network using only few-examples. In this paper, we have taken advantage of two such Metrics-based approaches: Siamese Network and Matching Network, to create SSM Net. We have also taken into account of widely used Transfer Learning approach and showcased the comparison among all methods in Experiments Section. Before proceeding to Experiments, Let’s first understand existing and proposed approaches.

A. Transfer Learning

Transfer learning refers to the technique of using knowledge gleaned from solving one problem to solve a different problem. Generally, we use the help of well-known networks such as Alex Net, VGG 16, Inception, Exception, etc., trained on the ImageNet dataset. For our case, we have extracted middle layer features of the VGG16 network and fine-tuned by adding linear layer using cross-entropy loss function. We have also taken into account that Transfer Learning extracted features can be helpful in learning more advanced objective and therefore used them to improve upon other approaches as shown in Experiments and Results Section.

B. Siamese Networks

A Siamese network [8], as the name suggests, is an architecture with two parallel layers. In this architecture, instead of a model learning to classify its inputs using classification loss functions, the model learns to differentiate between two given inputs. It compares two inputs based on a similarity metric, and checks whether they are same or not. This network consists of two identical neural networks, which share similar parameters, each head taking one input data point. In the middle layer, we extract similar kinds of features, as weights and biases are the same. The last layers of these networks are fed to a contrastive loss function layer, which calculates the similarity between the two inputs. The whole idea of using Siamese architecture [7] [5] is not to classify between classes but to learn to discriminate between inputs. So, it needed a differentiating form of loss function known as the contrastive loss function. For our case, we have leveraged transfer learning as well as shown in Fig.3, to extract complex embeddings which were not possible to learn with less amount of data-set.

C. Matching Networks

Matching networks [14], in general, propose a framework which learns a network that maps a small training dataset and tests an unlabeled example to the same embeddings space. Matching networks aim to learn the proper embeddings representation of a small training dataset and use a differentiable kNN with a cosine similarity measure to ensure whether a test data point is something ever to have been seen or not. Matching networks are designed to be two-fold: Modeling Level and Training Level. At the training level, they maintain the same technique of training and testing. In simpler terms, they train using sample-set, switching the task from minibatch to minibatch, similar to how it will be tested when presented with a few examples of a new task. At the modeling level, Matching networks takes help of full-contextual embeddings in order to extract domain specific features of the support set and query image. For our case, to extract better features from support set and query image, we have leveraged transfer learning(VGG16 Net) trained on ImageNet.
D. SSM(Stacked-Siamese-Matching) Net

Even for Matching Networks to train and learn better features we need decent amount of data to avoid overfitting. Using Siamese Networks we were able to extract good discriminative features. We then decided to leverage these extracted features to learn further about differences among diseases. Therefore, we have proposed a Siamese Head Plugin on top Matching Networks to extract more focused features as shown in Figure 4. In this Network Architecture, Instead of extracting features directly from Transfer learning head, first we fine-tune them using Siamese Network Architecture(With Transfer Learning Extracted Features) and once the Siamese Network is trained. We extract features using Siamese Networks for our Sugarcane Disease data and feed into Matching Networks Architecture followed by LSTM. Using this approach, we were able to further improve the classification accuracy by 2%.

III. EXPERIMENTS AND RESULTS

We first establish the baseline using Transfer Learning with VGG16 Net. Along side, we have implemented Siamese Network [8] and Matching Network. We first compared original Siamese network and Matching network results with strong baselines, i.e., fine-tuning using Transfer learning, to validate the effectiveness of metrics-based learning approaches method for classification/identification in the extremely low-data regime. Then, we compared our proposed SSM-Net outcomes in terms of decision boundaries, accuracy, and F1-Score.

As part of Dataset, we had 512 Images, and in cases of Data augmentation, we increased it to 600 images. We split our data to 50-20-30 train-val-test split.

Comparison of Decision Boundaries with Strong Baseline

We showcased the results of the Siamese Networks in comparison to fine-tuning of VGG16 Network in terms of decision boundaries in Table 2. Note that for decision boundary evaluation, we have extracted last layer embeddings and cluster them to the number of classes i.e; 11. To evaluate our cluster strength, we have used silhouette score which calculate inter-cluster vs intra-cluster distance. It is known that Silhouette Score of close to 1 means better defined clusters. For data augmentation techniques we used brightness, random scaling, rotation, and mirror flipping. It is observed that Siamese Network perform well on defining better decision boundaries in comparison to Transfer Learning+Fine-Tuning approach even with data-augmentation. Our modified Siamese Network is able to achieve 0.55 Silhouette score an increase of 0.45 from Transfer learning with Augmentation.

Comparison of Accuracy and F1-Score with Strong Baseline

Here, we showcased the outcomes of SSM Net to Transfer Learning (VGG16 Network) in terms of Accuracy and F1-Score listed in Table 3. Similar to our last experiment, we have used Data Augmentation techniques. We have observed that Matching Networks with Siamese Network Head performs better than other approaches. It is able to achieve accuracy of 94.3% and F1-Score of 0.90.

IV. CONCLUSION AND FUTURE WORK

Crop disease detection plays a crucial role in improving agricultural practices. Here, we have proposed a custom metrics-based few-shot learning method, SSM net. In this, we leveraged transfer learning and metrics-based few-shot learning approaches to tackle the problem of low data disease identification. We show that:

1) With the help of combined transfer learning and Siamese networks, we can obtain better feature embeddings.
2) Using SSM-Net we can achieve 94.3% accuracy in Sugarcane disease identification even with less amount of data.
We envision that the proposed workflow might be applicable to other datasets [6] which we will explore in future. Our code is publicly available on github repository: https://github.com/shruti-jadon/Plants_Disease_Detection.

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