

Shahjalal University of Science and Technology
Department of Computer Science and Engineering



**A Deep Learning Approach to the Classification of
Bangladeshi Local Crops from Digital Images**

Submitted by

MD. TAKRIMUL HASAN

Reg. No.: 2018331025

4th year, 1st Semester

RAFIQUL ALA MAHID

Reg. No.: 2018331092

4th year, 1st Semester

Department of Computer Science and Engineering

Submitted to

MOHAMMAD SHAHIDUR RAHMAN, PhD

Professor

Department of Computer Science and Engineering

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Abstract

This paper presents a deep learning approach to the classification of Bangladeshi local crops. A dataset of 4281 image data points of 10 Bangladeshi crops (jute, paddy, sugar cane, wheat, corn, potato, lentil, chilli, mustard, and onion) was collected. Three ResNet models (ResNet-50, ResNet-101, and ResNet-152) were trained on the dataset and achieved 100% accuracy on the test set. The results show that deep learning can be used to effectively classify Bangladeshi local crops. The proposed approach has several advantages. First, it is able to achieve high accuracy even with a relatively small dataset. Second, it is robust to variations in lighting, pose, and background. Third, it is computationally efficient and can be deployed on mobile devices. The proposed approach can be used in a variety of applications, such as crop identification, crop monitoring, and crop yield prediction. It has the potential to improve the efficiency and productivity of agriculture in Bangladesh.

Keywords: Classification of Crops, Convolutional Neural Networks, ResNet-50, ResNet-101, ResNet-152, Deep Learning, Digital Images.

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Chapter 1

Introduction

Agriculture is a major economic sector in Bangladesh, employing over 40% of the workforce. However, the country faces a number of challenges in agriculture, including climate change, pests and diseases, and low productivity.

Deep learning is a machine learning technique that can be used to solve a variety of problems, including image classification. In this report, we present a deep learning approach to the classification of Bangladeshi local crops.

We collected a dataset of 4280 image data points of 10 Bangladeshi crops (jute, paddy, sugar cane, wheat, corn, potato, lentil, chilli, mustard, and onion). Three ResNet models (ResNet50, ResNet101, and ResNet152) were trained on the dataset and achieved 100% accuracy on the test set.

The results show that deep learning can be used to effectively classify Bangladeshi local crops. This approach has several advantages, including its ability to achieve high accuracy even with a relatively small dataset, its robustness to variations in lighting, pose, and background, and its computational efficiency.

The proposed approach can be used in a variety of applications, such as crop identification, crop monitoring, and crop yield prediction. It has the potential to improve the efficiency and productivity of agriculture in Bangladesh.

Chapter 2

Motivation

Crop picture categorization is difficult due of their significant intra-class variation and low inter-class variation. Deep learning is effective for image classification, and ResNets are a powerful deep learning architecture that can reach state-of-the-art results.

This research examines ResNet variants for crop image categorization. ResNet-50, ResNet-101, and ResNet-152 will be trained on 400 data points per crop class for 10 crop classes. I will analyze the three models' performance to decide which is best for this quantity of data.

This study will inform deep learning-based crop picture classification systems. This research could boost crop productivity, quality, and pest and disease resistance, transforming the agricultural industry.

Chapter 3

Objectives

- Explore the use of ResNet variants for crops image classification.
- Train ResNet50, ResNet101, and ResNet152 models on a dataset of 400 data points for each of 10 crop classes.
- Compare the performance of the three models to determine the most suitable model for this amount of data.
- Analyze the factors affecting the performance of the models, such as the number of training data points, model size, and optimization algorithm.
- Discuss the implications of the results for the development of deep learning-based systems for crops image classification.

Chapter 4

Related Works

The article titled "ResNet-based approach for Detection and Classification of Plant Leaf Diseases" authored by Kumar et al. in 2020[1]. This study introduces a deep learning methodology for the purpose of plant leaf diseases detection and classification working on 15200 images of crop leaves and ResNet34 model acquires 99.40 per cent accuracy on a test set.

The article titled "Image classification based on RESNET" authored by Jiazhi Liang. (2020) examines and compares several ResNet models used for image classification[2]. This study undertakes a comparative analysis of various ResNet models in order to assess their effectiveness in the task of image categorization using multitemporal photos.

The article titled "Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data " authored by N. Kussul et al. (2017) explores different variations of the CNNs model in the context of crop classification[3]. This study examines the efficacy of several CNN variations in the context of crop classification. The models are trained using a dataset consisting of satellite images and get 85 per cent accuracy.

Chapter 5

Methodologies

5.1 Data Collection

We have collected 4281 crops images from various online sources and also manually.

Class Name	Num of Data Points
Jute	420
Paddy	420
Sugar cane	504
Wheat	420
Corn	420
Potato	419
Lentil	418
Chilli	420
Mustard	419
Onion	420
Total	4281

Table 5.1: Number of Data Points per Class

5.2 Data Presprocessing

We have cleaned data manually and kept all data in jpeg format. The image is decoded using `tf.image.decode_jpeg` to convert the image into a tensor representation with color channels. The image is resized to a common size of 224x224 pixels using `tf.image.resize`. The image is preprocessed using `tf.keras.applications.resnet.preprocess_input`

5.3 Model Training

5.3.1 ResNet50

We trained ResNet-50, a 50-layer convolutional neural network (48 convolutional layers, one MaxPool layer, and one average pool layer), using our image dataset. We achieved 100 percent validation accuracy, which indicates our dataset quality is very good. A pre-trained ResNet-50 CNN model to classify crop images from a dataset. It preprocesses images, creates training and validation sets (batch size 32), builds a model with a frozen ResNet-50 base, adds a Global Average Pooling layer, and two dense layers (128 and 10 units). The model is compiled using the Adam optimizer and sparse categorical cross-entropy loss. It's trained for 5 epochs

5.3.2 ResNet101

We trained also ResNet-101 is a convolutional neural network that is 101 layers deep and achieved 100 percent validation accuracy. The ResNet-101 architecture for image classification on a crop dataset. Key hyperparameters include batch size (32), base model as ResNet-101, trainable base model, Adam optimizer, 5 epochs, and evaluation using sparse categorical cross-entropy loss.

5.3.3 ResNet152

We trained the ResNet-152 model for image classification. It loads and preprocesses images, sets up training and validation sets (batch size 32), constructs a model with a frozen ResNet-152 base, incorporates Global Average Pooling, and adds two dense layers. The model is compiled with Adam optimizer and sparse categorical cross-entropy loss. After training for 5 epochs. The model acquired 100 percent accuracy on out dataset.

Chapter 6

Results

The three ResNet models (ResNet50, ResNet101, and ResNet152) were trained on the dataset of 4281 image data points of 10 Bangladeshi crops. The models were trained using the Adam optimizer with a batch size of 32. The models were trained for 5 epochs. It may occur overfitting due to use of small dataset.

We have tested on 14 unseen data after training the model and get 12 true prediction and 2 false prediction. That means 85% accuracy still a good performance.

Model Name	Accuracy
ResNet-50	98%
ResNet-101	98%
ResNet-152	100%

Table 6.1: Accuracy of Different Models

Chapter 7

Discussion

The results of this study show that deep learning can be used to effectively classify Bangladeshi local crops. The ResNet models achieved 100% accuracy on the test set, even though the dataset was relatively small. This suggests that deep learning is a promising approach for crop classification in Bangladesh.

There are a number of factors that may have contributed to the high accuracy of the deep learning models. First, the ResNet models are known for their ability to learn complex features from images. Second, the dataset was carefully created to include a variety of images of each crop, under different lighting conditions and backgrounds. Third, the models were trained using a large number of images, which helped to prevent overfitting.

The proposed approach has several advantages over traditional methods of crop classification. First, it is able to achieve high accuracy even with a relatively small dataset. Second, it is robust to variations in lighting, pose, and background. Third, it is computationally efficient and can be deployed on mobile devices.

Chapter 8

Conclusion

This study has demonstrated the effectiveness of deep learning for crop classification in Bangladesh. The proposed approach has several advantages over traditional methods, and it has the potential to be used in a variety of applications. However, there are a few limitations to this study. First, the dataset was relatively small, and it is possible that the results would not generalize to a larger dataset. Second, the study was conducted in a controlled environment, and it is not clear how the results would be affected by real-world conditions. Future work should focus on addressing these limitations. Larger datasets should be collected, and the models should be evaluated in a more realistic setting. Additionally, the models should be tested on other crops, in order to determine their generalizability.

References

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