Rice Grain Identification using Deep Neural Networks

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Introduction

- Attempt to identify specific types of rice grain using deep neural networks.
- Used five different types of rice, Jasmine, Basmati, Karacadag, Ipsala, and Arborio. With one thousand images each for a total sample size of five thousand images.
- Shows the concept of deep-learning models to accurately identify classify specific types of rice.
- Results: We were able to construct a model that delivered 98.30% classification accuracy.

Motivation

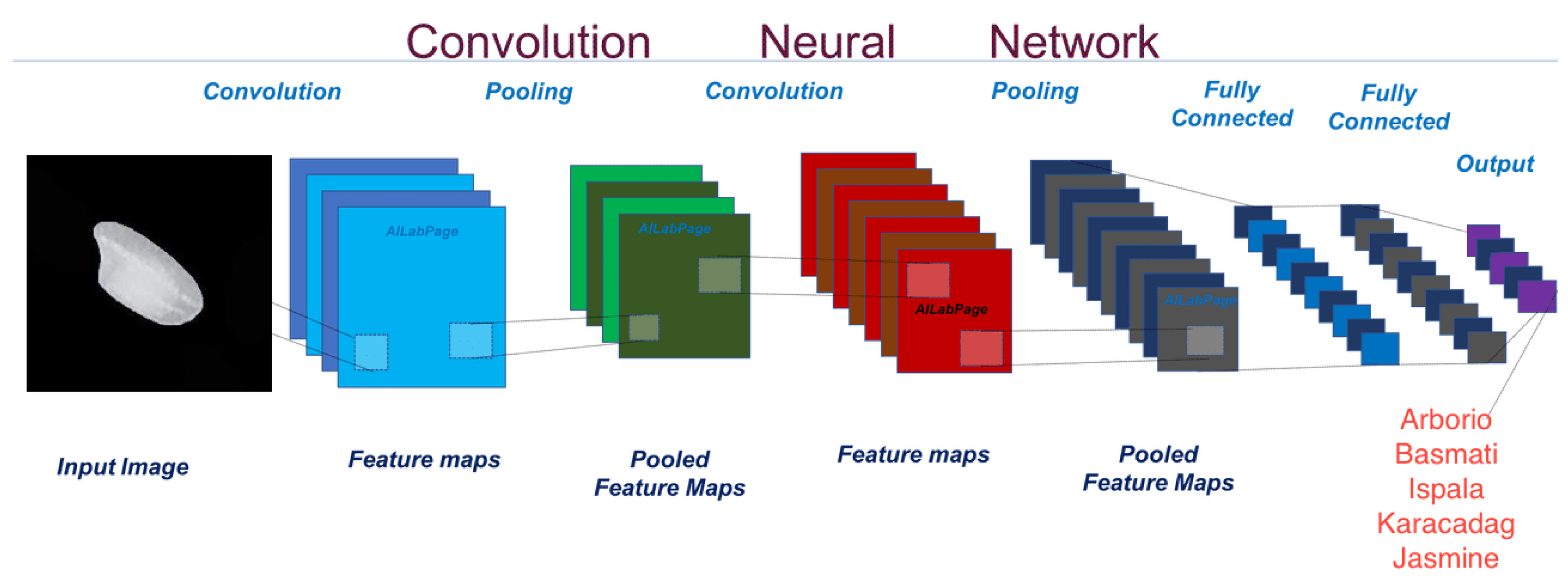
- Proof-of-concept for applications of deep neural networks for image classifications in applications such as facial recognition and automated driving software
- This software could be adapted to scan food for quality, looking for imperfections, disease, or pests to prevent ecological damage and help create better agricultural products

Data Exploration

Arborio, Basmati, Ispala, Karacadag, Jasmine

- We used 5,070 different images of rice. All images were color images.
- We used a test data size of 30 percent. We had 3,549 images in our training data, and 1,521 images in our test data.

CNN Model



`https://becominghuman.ai/beginners-guide-cnn-image-classifier-part-1-140c8a1f3c12`

In order to create our rice classification model we needed to use a type of deep learning called a Convolution Neural Network or CNN. This model sets up digital neurons and uses them to see the image, almost like humans would. As you can see from the image above the model first starts by inputting a image into the neural network. After that the model will use convolution layers to develop multiple feature maps of the image. Then it takes these maps and pools them. it does this by breaking them down into only there essential features. This will allow the model to use less computing power while still maintaining its accuracy. Then these convolution layers and pooling layers are connected to a dense layer through the neural network. The model will then output five nodes for each classification of rice.

Experimental Results

Hyperparameter Tuning

- We first tested to see the amount of epochs we should use. We decided to use 20 epochs

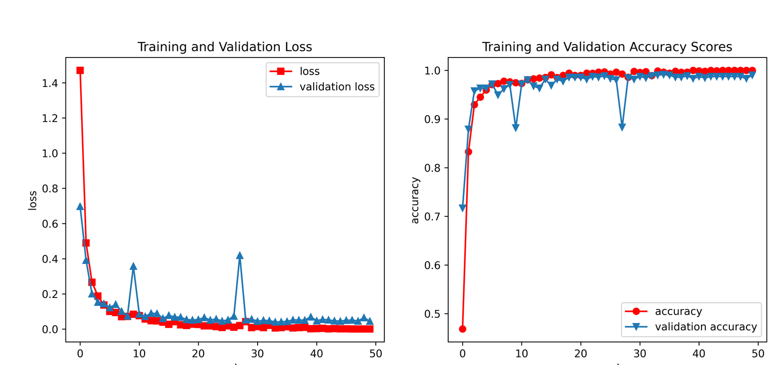


Figure 1:Validation Loss and Accuracy Charts

- We performed hyperparameter tuning on 3 models with 8,16,32 filters.
- The optimizers we used were Adam and Adagrad with learning rates of .01 and .001
- We built the models and compared the average accuracy scores

Table 1:**Best Hyperparameters for each Model**

Model	Parameters
Model 1	Conv Layers(32), Dense Layers(20), Optimizer=Adam, Learning Rate(.001)
Model 2	Conv Layers(32,16), Dense Layers(20,10), Optimizer=Adagrad, Learning Rate(.01)
Model 3	Conv Layers(32,16,8), Dense Layers(20,10,) Optimizer=Adam, Learning Rate(.001)

Model Evaluation

Table 2:**Average Accuracy of each Model**

Model	Accuracy
Model 1	.983
Model 2	.968
Model 3	.971

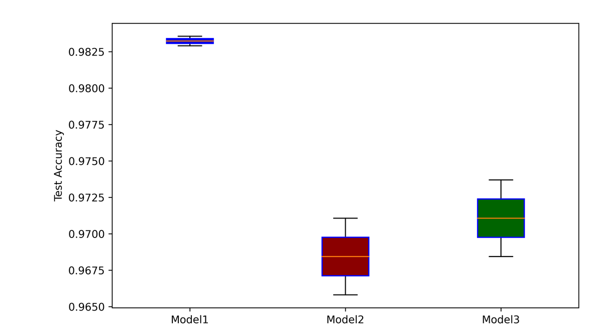


Figure 2:Distribution of each model

Remarks: All of our models were pretty good. All above .95 but this shows that model 1 was clearly the more consistent model.

Conclusion

Our CNN models were able to classify rice grains with a very high level of accurate and very few incorrect identifications. Accurately classifying objects with such minute differences such as tiny variations in grain shape and size is the fundamental accuracy needed for real world application of this technology. Our best model was using the Adam optimizer with .001 learning rate and this gave us a 98.3 percent accuracy.

- Facial recognition software will need to differentiate very small details in facial structures and features to make accurate classifications
- Self driving cars will need to navigate convoluted road conditions and make distinctions between similar objects such as traffic lights and other random lights.

Related Works

- `https://dl.acm.org/doi/abs/10.1145/2986035.2986039`
- `https://dl.acm.org/doi/abs/10.1145/`