Rice Grain Identification Using Deep Neural Networks

Aidan Ventresca^a, Alex Cole^b, Chris Cline^c, Hank Bailey^d, Hum Nath Bhandari^{e,*}

 ^a Department of Engineering, Roger Williams University, Bristol, RI, USA
^b Department of Business, Roger Williams University, Bristol, RI, USA ^c Department of Business, Roger Williams University, Bristol, RI, USA

 ^d Department of Computer Science, Roger Williams University, Bristol, RI, USA
^e Department of Mathematics, Roger Williams University, Bristol, RI, USA

^{*}Corresponding author

 $^{{\}it Email~addresses:}~ {\tt aventresca974@g.rwu.edu}~({\tt Aidan~Ventresca}),~ {\tt acole246@g.rwu.edu}$ (Alex Cole), ccline616@g.rwu.edu (Chris Cline), hbailey746@g.rwu.edu (Hank Bailey), hbhandari@rwu.edu (Hum Nath Bhandari)

Abstract

This study attempts to develop deep-learning neural networks to accurately identify and classify specific types of rice grains. This simple problem is a representation of a much larger field of image classification using machine learning algorithms including facial recognition and automated driving software to name a few. For this project we used five different types of rice; Jasmine, Basmati, Karacadag, Ipsala, and Arborio. We collected one thousand images of each grain totaling five thousand total images to use for our classification model. We were able to successfully create a model with 98.30% accuracy, allowing us to very accurately classify different types of rice even though variations in physical characteristics were minimal. The success in the creation and accuracy of this model proves meaningful for further development and implementation of deep-learning neural networks.

Keywords: Computer Vision, Image Recognition, Classification Models, CNN Models, Deep Learning, Data Science

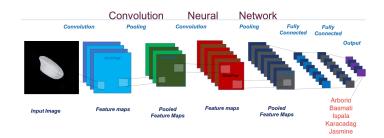
1. Introduction

- Deep learning and neural networks have become a large focus in the scientific
- and computer science communities. The ability to predict and classify trends
- 4 and images has always been a desired yet hard task. Through deep learning
- 5 models, we decided to see if we could accurately classify different types of grains
- 6 of rice with very small differences.
- We gathered our data from Kaggle's online data set library. It consisted of
- 8 five different folders with thousands of images in each of five different types of
- ⁹ rice. These types were Arborio, Basmati, Ipsala, Jasmine, and Karacadag.
- Although identifying classifications of rice doesn't have many applications
- in the real world, it serves as a proof-of-concept for Deep Neural Networks to
- show that these models can classify minute details with high accuracy. As we
- move towards a world of self-driving cars and things of the like, the accuracy of
- 14 image detection models is becoming increasingly important, so proof-of-concept
- projects like this one are necessary to show that these models can be accurate
- 16 if used correctly.

2. Related work

- https://dl.acm.org/doi/abs/10.1145/2986035.2986039
- https://dl.acm.org/doi/abs/10.1145/2986035.2986042
- https://www.sciencedirect.com/science/article/pii/S0924224403002711?
- casa_token=VWIkeOh4X-gAAAAA:tv_kvUQK3c1_x1jNcoCvI5Qy4d7sp_JOGbS7RJLUIa4_
- LVcWeMpkIdLoPNkryvKd_POcWXTPWg

3. Modelling approach



https://becominghuman.ai/beginners-guide-cnn-image-classifier-part-1- $140c8a1f3c12 \label{eq:cnn-image-classifier}$

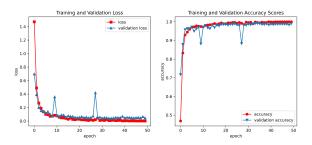
In order to create our rice classification model we needed to use a type of 24 deep learning called a Convolution Neural Network or CNN. This model sets up 25 digital neurons and uses them to see the image, almost like humans would. As you can see from the image above the model first starts by inputting a image into 27 the neural network. After that the model will use convolution layers to develop 28 multiple feature maps of the image. Then it takes these maps and pools them. 29 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. 31 Then these convolution layers and pooling layers are connected to a dense layer 32 through the neural network. The model will then output five nodes for each 33 classification of rice.

4. Data exploration and input preparation

We used 5070 different images of rice. All images were in color. We had 3,549 images in our training data and then 1,521 images in our test data. We then trained and split our data using a train-test-split model. We came to the conclusion that 20 epochs were best because as you can from the figure below the validation accuracy barely changed after 20.



Arborio, Basmati, Ispala, Karacadag, Jasmine



Validation Loss and Accuracy Charts

5. Experimental results

- Model one used 32 filters, single convolution layer, and 20 neurons single
- dense layer CNN Model. Model 2 used 32-16 filters, two convolution layers,
- and 20-10 neurons two dense layers CNN Model. Model 3 used 32-16-8 filters,
- three convolution layers, and 20-10 neurons two dense layers CNN Model. After
- testing epochs we found that 20 epochs was good enough for us to test our
- 47 models. After training and hyper parameter tuning we found that our best
- model was Model 1 using the Adam optimizer with a .001 learning rate. This
- 49 model produced a 98.3 percent accuracy rate.

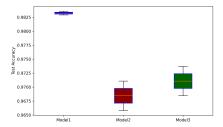
Table 1: Best Hyperparameters for each Model

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)

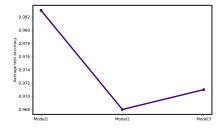
Table 2: Average Accuracy for Each Model

CNN Model	Accuracy
Model 1	98.30%
Model 2	96.80%
Model 3	97.10%

50 Distribution of Each Model



51 Average Accuracy of Each Model



- Remarks: You can see that model 1 had the best average accuracy score.
- Not only that but you can see it was the most consistent.

6. Conclusion

- We found that we were able to classify rice grains with a high level of accu-
- $_{56}$ racy and very few incorrect identifications. Our best model was Model 1 with

- an accuracy of 98.30%. This software could be further adapted to scan grain
- harvest samples for quality, looking for imperfections, disease, or pests to pre-
- vent ecological damage and help create better agricultural products. It could
- also be used to identify infestations of unwanted species of grain by classifying
- a sample of harvests. The use of this technology is limitless and this model is a
- proof of concept for the applications of this technology.

⁶³ 7. Ethics and implications

- There are minimal ethical implications for this work. This study has very
- limited use in the real world and was used to show that deep neural networks
- can perform with extreme accuracy. There are very serious ethical implications
- of the extension of this technology, most notably in the use of facial recognition
- 68 software by law enforcement.

69 8. Acknowledgment

- Roger Williams University. The Math and Computer Science Department.
- 71 Murat KOKLU for his rice image Data set on Kaggle.

9. References

- https://www.kaggle.com/code/ahmederaky/rice-classification-with-cnn-99-acc
- https://www.kaggle.com/code/sumon9300/99-75-rice-image-dataset
- https://becominghuman.ai/beginners-guide-cnn-image-classifier-part-1-140c8a1f3c12