Rice Grain Classification using Convolutional Neural Networks

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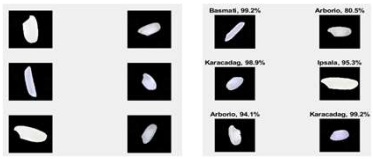
ABSTRACT

KRBL Limited is India's largest exporter of Basmati rice. They seek to expand into larger & new rice markets such as exporting Ipsala to turkey for example. By understanding the distinguishing traits of different rice varieties, it will help ensure the exportation of only the highest quality of rice to new potential geographical markets. By improving quality of rice, this allows KRBL Limited to excel and dominate in new rice markets.

Rice comes in various different varieties, each with its own unique characteristics. The ability to accurately classify rice grains is very important for quality control and agricultural research. In this project, we introduced a Convolutional Neural Network (CNN) model developed to classify rice varieties based on segmented grain images. By utilizing MATLAB's Deep Learning Toolkit, we have achieved successful rice grain classification with quick training times.

By utilizing a provided Rice Image Dataset, containing 75,000 individual segmented rice grain images, consisting of 15,000 images per rice class – Arborio, Basmati, Ipsala, Jasmine, and Karacdag. We have implemented different methodologies to train and test the CNN model in the hopes of achieving outstanding results.



The image dataset was preprocessed to enhance the features and reduce possible noise being generated. I did this by incorporating techniques such as image augmentation (reflection, resizing & rotation).
For the network architecture, AlexNet was chosen. Extensive experimentation was conducted by testing & optimizing numerous combinations of parameters to enhance the model's classification accuracy.

Upon convergence of the RGCNN model, we achieved exceptional average accuracies of 98.5% on testing dataset. This highlights the robustness and efficiency of the model in effectively distinguishing between rice images belonging to the 5 rice classes.

Average Accuracy (%) for Individual Rice Grains	
Arborio	98.80%
Basmati	97.80%
Ipsala	98.90%
Jasmine	97.50%
Karacdag	99.60%

Introduction

Rice is one of the most consumed foods globally. It plays a very crucial role in ensuring food security and nutrition for billions of people worldwide (3.5 billion total). The abundance of rice varieties highlights the importance of precise classification for agricultural research, crop management & quality assurance.

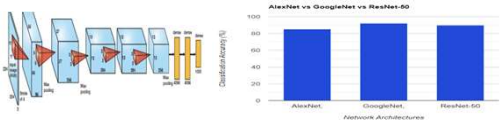
The project aims to develop & evaluate a convolutional neural network (CNN) tailored specifically to classify rice grains effectively. By exploring various network architectures like GoogleNet & training techniques such as Adam optimization, we aim to identify the optimal parameters for accurate classification with fast training & testing times allowing it to be suitable in industry use.

Accurate & precise classification of rice varieties not only provides valuable insights into the unique characteristics but also helps KRBL Limited in expanding into new markets. The RGCNN Model equips KRBL Limited farmers and their agricultural scientists with a reliable tool for crop management. By successfully distinguishing between rice such as Arborio, Basmati, Ipsala, Jasmine & Karacdag, the farmers can enhance cultivation/farming practices & ensure high quality rice therefore helping KRBL Limited's expansion into new emerging geographical rice markets by providing exceptional faultless rice.

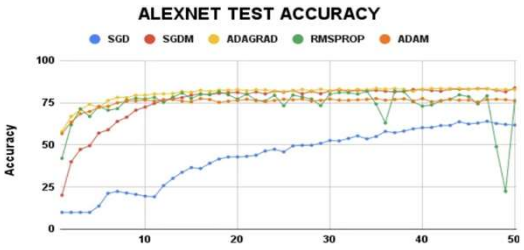
Methodology

Firstly, we determined the optimal number of images to utilize. After extensive experimentation, we found that using 1,500 total rice grain images resulted in exceptional accuracy results and lightning quick convergence times. Achieving a good balance in image selection is important to obtain robust and stable training & validation illustrated by the graphs while maintaining rapid training & testing timings. Which is very desirable for industry use.
Data set was split into 3 ways. The training set (70%) of the images, is crucial for the network to learn and identify patterns. Validation (15%) is crucial to minimize any potential overfitting from occurring. Testing (30%) which ensures unbiased evaluation of the RGCNN models performance on unseen rice images which is crucial in improving the model's overall classification performance.

In terms of the model's network architecture, AlexNet was chosen due to its simplicity and effectiveness for handling simpler datasets like rice grain images. Due to its shallower architecture compared to GoogleNet & ResNet-50, AlexNet demonstrated optimal performance while still minimizing the possible risk of overfitting in quick convergence time. Due to GoogleNet's deeper & more complex architecture, it is more prone to overfitting & providing unstable chaotic graphs. In terms of accuracy & precision classification results, utilizing AlexNet obtained still excellent generalization results, therefore making it the preferred choice for the RGCNN model.



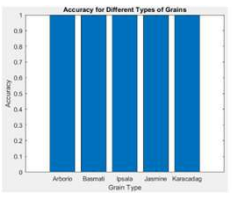
After extensive training & testing, two training options were chosen for evaluation: SGDM & ADAM. ADAM emerged as the preferred method due to its outstanding average accuracy & precision values, averaging at 98.9% as compared to SGDM's 94.6%. However, it is worth taking note that ADAM requires more memory for testing and exhibits slightly longer convergence times compared to SGDM, with ADAM converging in 76.4 seconds compared to SGDM's 43 seconds.



After extensive experimentation with multiple different parameter configurations, including Epochs, Learning Rate, and miniBatchSize, the model underwent testing to enhance rice grain classification accuracy and reduce processing time. Following an average of 20 runs, various parameter combinations were evaluated to optimize RGCNN model performance. The best parameters were:

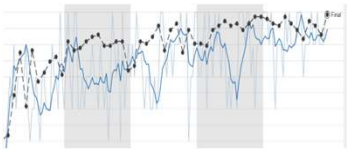
Best Optimal Paramaters for RGCNN Model		
Epochs = 10	Learning Rate = 1e-4	MBZ = 180
Accuracy (%) = 98.87%		
Precision (%) = 98.55%		
Time Taken (s) = 74.49 seconds		

Selected evaluation metrics include average Accuracy and Confusion Matrix. Accuracy measures the model's overall correctness, while the confusion matrix provides an extremely detailed insight into the true/false predictions. It helps with understanding which rice grain classes are correctly classified and which ones are being confused with each other. RGCNN model provides excellent visualization of the classification results.

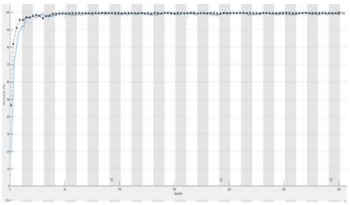


Results

Pre – Tuned RGCNN Model



Fully Optimized RGCNN Model



Final Optimised RGCNN Model

Results after 20 runs	Accuracy (%)	Precision (%)	Time Taken(s)
AVERAGE Results	98.95%	98.90%	76 seconds

Conclusions

The 2 graphs above demonstrate the before/after affects of optimal image, parameter, training options & network architecture combination. The final optimized graph shows extremely stable & non-chaotic training and validation behavior which is a very desirable trait to have.

In summary, the RGCNN model showcases impressive performance, with average accuracies & precisions of 98.95%. These results highlight the model's robust generalization to unseen rice grain images during testing, confirming its efficiency and accuracy in classifying the 5 rice classes.

A notable advantage of the RGCNN model is its quick convergence times, with an average of 74 seconds making it very suitable to be implemented & used in industry as well as its ability to minimize overfitting from occurring.

However, identified limitations include lower precision results for Basmati & Jasmine, indicating increased confusion between the 2 rice grain classes due to their similarities in appearance/features as demonstrated by the confusion matrix.

Moving forward, we aim to enhance the models' capabilities in differentiating rice images to reduce confusion. One approach may be to involve hyperspectral imaging techniques, allowing us to capture more complex details beyond the human visual perception. We'll also conduct thorough scans to identify and address potential outliers, including images affected by noise, such as blurred or low-resolution images, as well as images that may feature unusually sized grain shapes. Implementation of SAM (segment anything model) could also be integrated into the model to help make segmentation method of rice grains much easier & effective process.

Additionally, enhancing training & testing times could be achieved through the investment of more powerful GPU's.