White Maize Classification and Grading

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Background

Maize is a staple food all over the world and accounts for a significant share of South Africa's agricultural exports [5]. It is used to produce syrups, alcohols and breakfast cereals. It remains the most important feed for livestock in the country and for many of the people forms part of their staple diet. Attaining the highest quality in the industry is essential, as it ensures the most favourable market value for grain. Additionally knowing the quality of the maize is also beneficial for farmers, since this tells them how to properly store and preserve the batch.

The typical grading system to determine defective kernels is as follows. According to the South African department of agriculture [1], a 150g sample, or about 380 kernels is taken from the maize consignment and this sample is examined by hand by a qualified inspector. The inspector will sum the portions of each type of defect and then assign an overall grade to the batch. The traditional methods are slow and prone to inaccuracies. The project goal is thus to test alternative ways in which to grade defective maize kernels.

Objectives of project

In order to solve the above mentioned problem the system should be able to perform the following objectives:

1. Having a camera system that will be able to take a top and bottom images of a 150g samples with sufficient quality to distinguish defects.
2. Perform image processing to properly separate each of the kernels.
3. Use the labeled kernels to train a machine learning model.
4. Test the system with the labelled test set to determine the robustness of the system.
5. Optimize the system so that the process is relatively fast. So that multiple batches can be analyzed quickly.
6. Test and compare results with other methods of grading technologies.
7. Use graded batches that are independently sourced to test the model on.

The typical grading process

According to the South African Department of Agriculture, white maize is categorized into3 classes: WM1, WM2, WM3, with WM1 being the most pure and WM3 the least [1]. To grade the maize, a percentage of deviations, discolorings, and foreign materials in a sample is assessed according to the RSA grading regulations. The following table is a snippet from the Department of Agriculture report which shows the percentages used to place the sample of maize into each of the above mentioned categories.

Table 1. Regulations relating to the Grading, Packing and Marking of Maize intended for sale in the Republic of South Africa as published in the Government Gazette No. 32190, Regulation No. R. 473 of 8 May 2009. [1]

	Proportions allowed per deviation (%)	Grade		
		WM1	WM2	WM3
#1	Foreign matter	(0 - 0.3]	(0.3 - 0.5]	(0.5 - 0.75]
#2	Defective kernels, above and below the 6.35 mm	(0 - 7]	(7 - 13]	(13 - 30]
#3	Other coloured kernels	(0 - 3]	(3 - 6]	(6 - 10]
#4	Combination of deviations #1, #2, #3	(0-8]	(8-16]	(16-30]

The deviations chosen were those which were believed being quite difficult to see with naked eye compared to others. Thanks to the SAGL we managed to obtain enough samples of the following kernels for training.

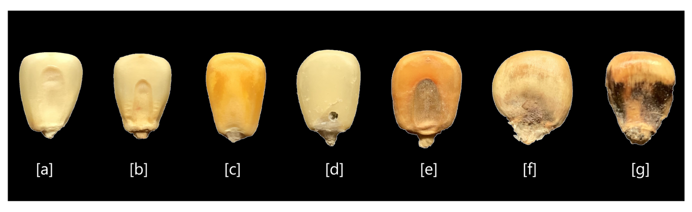


Figure 1. Visual representation of each maize category as provided by the SAGL

Where we have: (a) White maize; (b) Discolored white maize; (c) Yellow maize; (d) Insect damaged white maize; (e) Heat damaged white maize; (f) Fusarium; (e) Severe fusarium.

Previous related studies

There have been a few approaches in solving this problem of classification, with the two main approaches being, using multi-spectral and hyper-spectral cameras. This allows one to detect all wavelengths of light in a specific range. These methods also involved using principal component analysis coupled with partial least squares discriminant analysis to classify the kernels. The studies using these systems are documented in [3] and [2] respectively. These studies were conducted on behalf of the Department of Food Science at Stellenbosch University. The main issue with these solutions is that the price of these cameras are quite high. Processing images across a wide spectrum is also computationally intensive. Additionally setting up the cameras and taking images is a lengthy process.

Table 2. Benchmark accuracy from previous studies

Available categories	Benchmark Accuracy %	
	Hyperspectral Camera	Multispectral Camera
Sound White Maize	88.3	-
Discolored White Maize	-	-
Yellow Maize	75.0	100
Insect Damaged	95.8	88.57
Heat Damaged	95.0	100
Fusarium	100	88.57

Camera system

To design a camera system we decided to use the Raspberry Pi 4 Model B coupled with the Raspberry Pi Camera Module 3. A "photo-booth" type design was built which allows one to capture images of both sides of kernels. The diagram and figures below show the basic layout of the design.

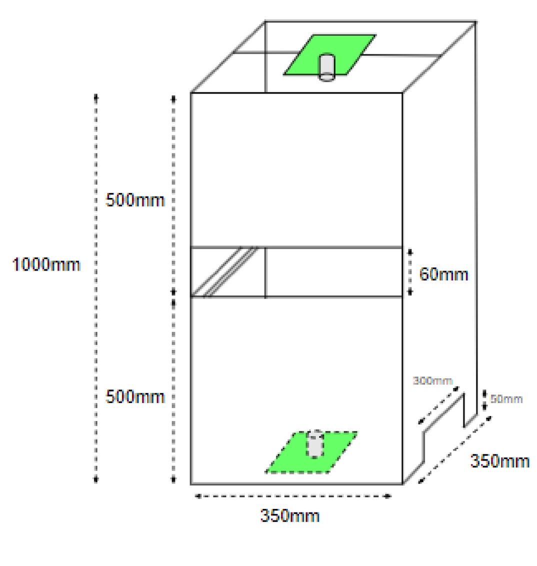


Figure 2. Photo box design

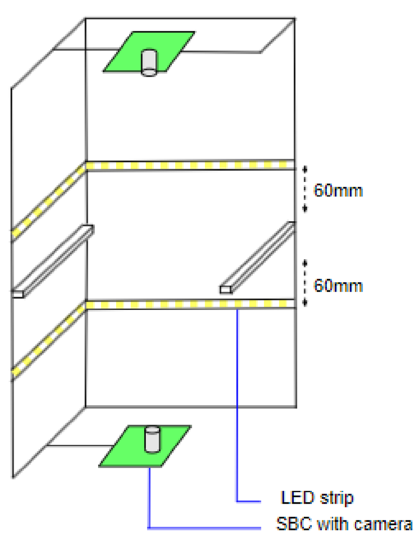


Figure 3. Inside view

The process for capturing photos

1. Activate LEDs and position the camera in place.
2. Place 150 g batch into a smaller container and make sure the kernels are well spaced.
3. Slide a black covering within the box.
4. Slide kernel container above the covering.
5. Take the top photo.
6. Slide the covering from out the bottom and place it on top of the kernel container.
7. Take the bottom image.

Figure 4. Glass container

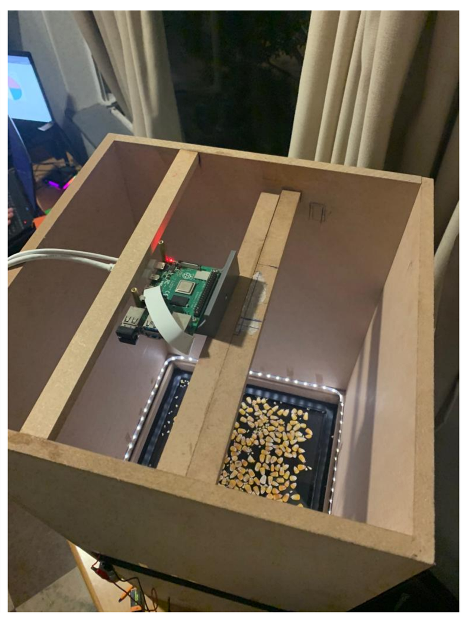


Figure 5. Top view setup

Image processing flow diagram

After the images are taken they undergo a image processing stage as follows:

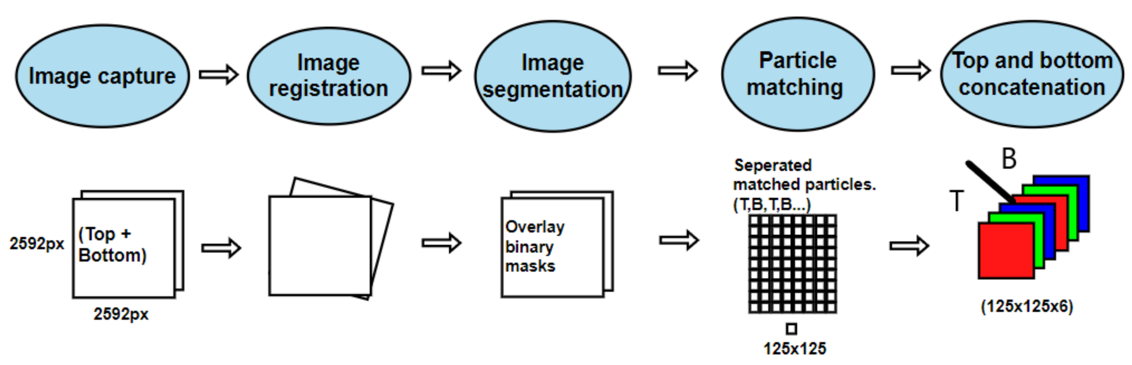


Figure 6. Image processing flow diagram.

Image registration

Initially, the top and bottom images are slightly misaligned. To fix this image registration techniques are used.

Figure 7. Before and after effect of image registration. Left: (Original images of top and bottom). Right (Top and bottom images after registration script).

Image segmentation

To extract kernels a image segmentation script is run which consists of different types of image processing techniques. Below is a example snapshot of each step of the process.

(a) Original (b) Color thresholding (c) Binary mask and eroding

(a) Original (b) Color thresholding (c) Binary mask and eroding

Figure 9. Visual examples of each image segmentation step.

Particle matching

Implementing these image segmentation steps does not always yield perfect results. Two checks have been added to decrease the chance incorrect kernel detection namely: "A size check" and a "spacial check". This eliminates all small unwanted particles. Additionally using the centers of the top and bottom kernels, pairs are only matched if they are within a certain distance range of each other.

Model architecture

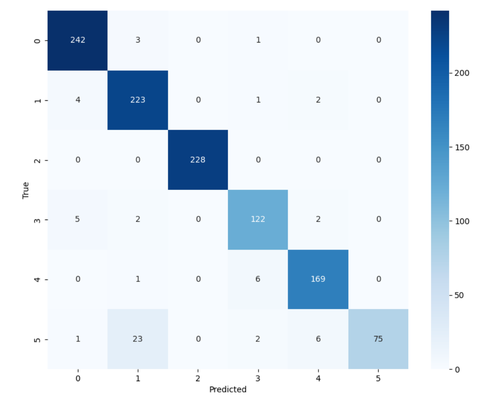
A well designed structure that has been used in the past for image recognition is LeNet-5. This architecture was used as a baseline to build our model off. Our input format after image processing is (125x125x6) so some slight adjustments had to be made to the architecture. The final architecture was designed with 5 convolutional layers and having additionally, a dropout layer and batch normalization throughout each convolution.

Image segmentation results

In general, the script that extracts kernels performs reasonably well but never perfectly. On average around 1% to 5% of kernels are not extracted cleanly and are thrown out by the validation script. The primarily factor influencing how much are missed seems be in direct correlation to the spread of kernels on the platform. These misses should be addressed in further research.

Training results

0 White Maize = 98.35%
1 Discolored Maize = 96.96%
2 Yellow Maize = 100.00%
3 Insect Damage = 93.13%
4 Heat Damage = 95.78%
5 Fursarium = 70.09%



The biggest concern when looking at the above results is the poor performance of the fusarium category. From visual inspection is was clear that fusarium kernels shared striking visual similarities to the discolored kernels themselves. With the naked eye it was extremely difficult to distinguish.

Testing results

The SAGL had provided five samples of graded maize batches for us to test the model on. These include a mixture of different types of kernels and in most cases, the proportions of each kernel type are provided as percentages. Any foreign materials and small shaving found in the batches have been removed and the original percentages given by the SAGL had to be adjusted accordingly. Below in Table 3 shows an example of how the batch comparisons look like.

Table 3. An example of a sample batch graded by the SAGL, being compared to our models performance.

Batch 5	SAGL Grade (%)	Model Grade (%)	Error
White Maize	92.65	89.68	2.97
Discolored Maize	*	2.10	*
Yellow Maize	*	1.61	*
Insect Damage	0	0.97	0.97
Heat Damage	4.39	5.48	1.09
Fusarium	0	0.16	0.16
Sprouted	0.22	-	-
Defective above 6.35mm	4.61	6.61	2
Other coloured	2.74	3.71	0.97
Combined deviations	7.35	10.32	2.82
Class and Grade	WM1	WM2	-

Summary test batches

From the test batches the overall error percentage of each category were as follows:

Table 4. Average batch error of each regulation category.

Category	Average error across batches
Defectives above 6.35mm [#2]	3.04
Other Colored kernels [#3]	3.39
Combination of deviations [#4]	3.27

It is important to note that the reports given to us by the SAGL are not perfect and should not be seen always as the absolute ground truth. There is always somewhat human error induced. All in all the model however still performed reasonably well in normal classification standards. However when comparing the performance to the regulation margins it still suggests clear room for improvement.

Speed

Given that we were using two cameras, the image capturing process took around 2 minutes. If there was a dual camera system in place this image capturing process would be done in practically an instant. After the images have been captured the program scripts runs and the entire process from start to finish around 90 seconds on the Raspberry Pi. This time is quite fast compared to the time it would take to manually grade the kernels. Additional note: (As of 3 November 2023, Raspberry Pi has recently release the new Raspberry 5 which claims to run 2-3x fast than its predecessor)

Summary

Image capture
The overall box design performs well and creates a consistent environment for the images to be taken. Images through the glass also remain high quality. Some drawbacks of this system is that the glass platform tends to get dirty when used frequently. The size of platform is limited to 150 g samples of maize at a time. Glare on the corners of the image also pose an impact on the overall quality, however this can be easily mitigated.

Training results
The high validation accuracies in training process is promising and it proves is that it is very possible to achieve similar levels of accuracy using images from ordinary cameras.

Unseen batches
When testing on the unseen batches the system was met with some challenges. Primarily involving issues with shavings, misclassifying insect damage on yellow maize and tendency for the over-classification of heat damage. The error rate was higher than expected, after having high validation results. When compared to the regulation margins, only two out of the five batches had been given the correct final grade. The others batches were off by one grade level. The performance of the model should however not be solely reflected by these results as the given samples are not the absolute ground truth and some of the batches went through somewhat inconsistent particle removals.

Final thoughts

The model could be fine-tuned slightly more. However, it is believed to be unlikely that this will drastically change the performance on unseen cases. The primary obstacle to better performance is with better image segmentation techniques and different experimental batches. What the current system does prove however, is that the principal of image grading is possible. There is significant promise, and with a bit of refinement, such a system could one day able to live up to industry standards.

References

[1] .
Grading Regulations for Maize, Government Notice No. R.473 .
Technical report, Department of argiculture, 2009.

[2] Kate Sendin and Marena Manley and Federico Marini and Paul J. Williams.
Hierarchical classification pathway for white maize, defect and foreign material classification using spectral imaging.
Microchemical Journal, 162:105824, 2021.

[3] Kate Sendin and Marena Manley and Paul J. Williams.
Classification of white maize defects with multispectral imaging.
Food Chemistry, 243:311–318, 2018.

[4] Claude E. Shannon.
A mathematical theory of communication.
Bell System Technical Journal, 27(3):379–423, 1948.

[5] Tinashe Kapuya and Wandile Sihlobo.
South Africa's maize exports: A Strategic Export Market Analysis model approach.
Argicultural bussiness center.

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