Corn Quality Assessment

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GrainTrust.org Overview

We are the part of the GrainTrust.org, an organization that prioritizes the value return on quality of the grains for sales; supporting farmers and businesses together.

Our mission is to deliver quality services for grain industry depending on the food grade quality with aim to help both farmers and buyers get benefits from the medium to premium quality produce.

Project Objective:
Overview of the Problem

To provide the farmer with decisive information to accurately ascertain the quality of his corn or maize harvest

Motivation and Opportunity

- Corn or maize is a major cereal crop, with global food consumption being the third highest after rice and wheat
- Global human food consumption of maize amounts to 18.5 kg/capita/year, 11% of the average annual cereal human consumption of 175 kg globally (2014–18, excluding beverages – FAOStat, 2021).
- In India it contributes to ~9% of the grain production. Production of maize has been growing at an average CAGR of at least ~2.5% since 2010 yet the yield is still half of the global average.
- Extreme changes in climate causing drought or flooding.
- Excess spread of disease and insects, inadequate irrigation
- Lack of right agro-technology such as single-cross hybrid

Dataset Introduction & Quality Handling

- Manual selection for representative samples
- Eliminating edge cases and corner cases
- Rebalancing of the dataset to avoid bias
- Manual annotation
- Finding wrongly labeled samples

Corn Dataset Introduction

The corn dataset consists of two broad categories: pure versus impure corn kernels. It has been divided into train, validation, test sets in a 70-20-10 split.

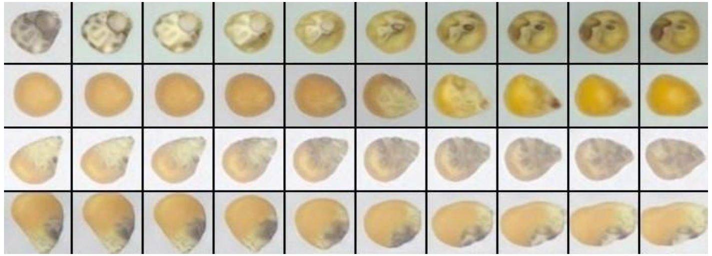
	Images	
	Pure Kernels	Impure Kernels
Train	10,502	10,325
Validation	1500	1475
Test	3001	2951

Image on the left shows impure corn kernels and on the right pure kernels

Corn Dataset: Image Sources

1. Our Dataset primarily consists of dataset from IIIT H Corns Seeds Dataset. This dataset has 4 classes:

❖ Pure: 14202 images
❖ Broken: 5670 images
❖ SilkCut: 1751 images
❖ Discolored: 3115 images



1. Our secondary dataset contains corn seed images from Kaggle.
2. We augmented and annotated the dataset with cases for impure class using Roboflow.

Corn Dataset: Image Source & Annotation

Our Dataset primarily consists of annotated dataset from Roboflow.

The various sources listed below had following classifications of the corn kernels:

1. Data Source 1- has classes belonging to Fusarium rotation, Healthy rotation, Others rotation
2. Data Source 2 - has classes Broken, Damage, Healthy, Immature, Shriveled, Weeveled, Fm-inorgnic, Fm-organic
3. Data Source 3 - has classes Broken, Damage, Fm-inorganic, Fm-organic, Fungus, Healthy,Immature, Shriveled, Weeveled
4. Data Source 4 - has classes Bad, Good
5. Data Source 5 - has classes Broken, Corpos Estranhos, Damage-Discolor, Danificado, Fungus, Healthy, Immature, Inorganic foreign material, Inteiro, Não Canjicado, Não Degerminado, Organic foreign material, Other Edible Seeds, Padrão, Película, Ponto Preto, Shriveled, Trincado, Weeveled, bad, broken, damage, fm-inorganic, fm-organic, fungus, fusarium rotation, good, healthy, healthyrotation, immature, shriveled, weeveled
6. Data Source 6 - has classes Chana-Desi, Inorganic Foreign Material, Inorganic foreign material, Maize-Yellow Maize, Organic Foreign Material, Organic foreign material, Rice-Basmati, Wheat, fm
7. Data Source 7 - has classes fusariumrotation, healthyrotation

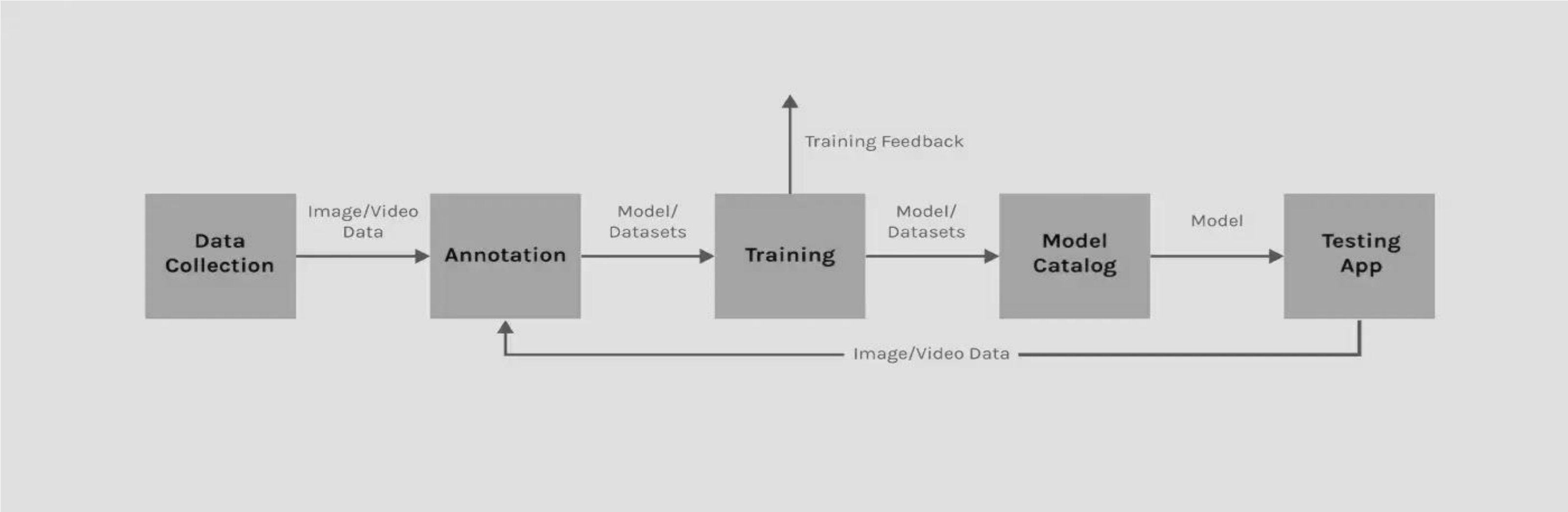
Dataset Transformation & Modeling Approach

Our data transformation and modeling approach includes manual data annotation using Roboflow and transformation using the functions for training the model.

The approach on involved series of trials and errors with cycles of testing over the annotated data to come up with the quality dataset for best results for corn kernel detection.

The transformation functions used are discussed in next slides.

Data Transformation & Modeling Approach



Data Transformation & Modeling Approach

We applied a series of transformation steps to the dataset for training.
The below data transformations were applied:

- ❏ Rotation_range = 20
- ❏ Width shift range = 0.1
- ❏ Height shift range = 0.1
- ❏ Shear range =0.2
- ❏ Zoom range =0.2
- ❏ Horizontal flip =True
- ❏ Vertical flip = True
- ❏ Brightness range = [0.5, 1.5]
- ❏ Channel shift range = 20

Greyscale Contouring

Methodology Overview

Our Corn Quality Assessment System methodology approach has the form of two major components.

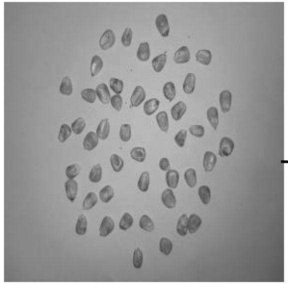
First, the Object detection module which used Roboflow and YOLOv8 model for development.

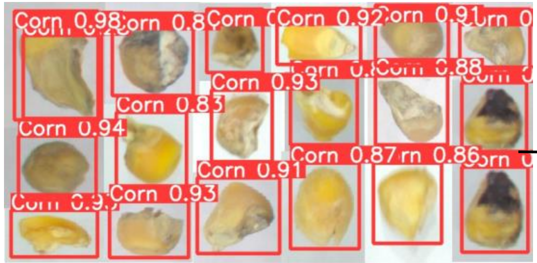
Second, the feature extraction module and classification which was developed using various models such as ResNet50, VGG16, MobileNet, Xception, Inception, and EfficientNet.

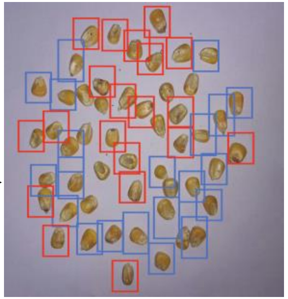
Third, an integration module used the best model as MobileNet and compiled it to get the predictions on the test corn images.

A detailed workflow of the methodology is described in the next slide.

Workflow for corn kernel detection and classification







Input Data

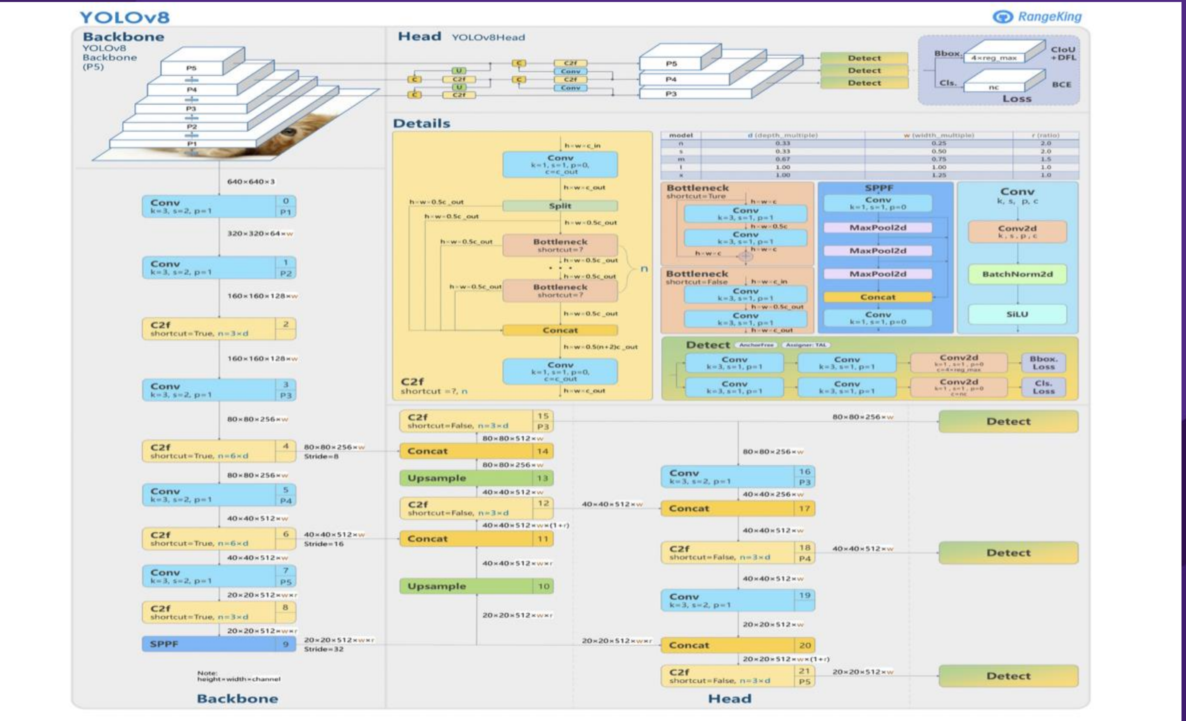
Object Detection using YOLO V8

Augment Data

Image Classification

Object Detection: YoloV8 Overview

We developed object detection model using YOLOv8 architecture.



YOLOv8 Architecture, visualisation made by GitHub user RangeKing

Object Detection: YOLO v8n

- YOLO (You Only Look Once) is a series of object detection models. YOLOv8 was launched on January 10th, 2023
- More suited for real time object detection. Its backbone network DarkNet-53 (53 deep layers) surpasses YOLOv7 in speed and accuracy.
- Yolov8 makes bounding box predictions by pixels through an anchor free detection head.
- YOLOv8 uses feature pyramid networks (different scales of feature maps), which helps to better recognize objects of different sizes, which improves its overall accuracy.

Object Detection

- Examples of correctly detected corn kernels from the original image on the left to the bounding boxes created and cropped on the right
- Images with different background and different spread of kernels was used

Image Classification: Models Overview

We developed various models for feature extraction module and classification like ResNet50, VGG16, MobileNet, Xception, Inception, and EfficientNet which were compared for various parameters during our initial analysis like:

- ❖ Training Time
- ❖ Model Size
- ❖ Model Efficiency F1 Score
- ❖ Model Accuracy & Precision

Let’s see some highlights of same in next slides to understand how we chose our best model for final deployment.

Image Classification: Test Data Results

		Impure			Pure		
Model Name	**Accuracy**	**Precision**	**Recall**	**F1 score**	**Precision**	**Recall**	**F1 score**
Baseline CNN	0.89	0.88	0.86	0.89	0.86	0.87	0.87
EfficientNet	**0.97**	**0.96**	**0.98**	**0.97**	**0.98**	**0.96**	**0.97**
MobileNet	**0.97**	**0.96**	**0.98**	**0.97**	**0.98**	**0.96**	**0.97**
VGG16	0.60	-	-	-	0.50	1.00	0.67
ResNet50	0.87	0.92	0.80	0.85	0.83	0.93	0.87
InceptionNet	0.96	0.96	0.97	0.96	0.97	0.96	0.96
VGG19	0.93	0.93	0.93	0.93	0.93	0.93	0.93
ExceptionNet	0.96	0.98	0.95	0.96	0.98	0.96	0.97

Pre-trained MobileNet and EfficientNet are among the most accurate models with a F1 score of 97% each for testing dataset.

Image Classification: Model Test Results

Distribution of Loss versus Accuracy for all Models over Test Data

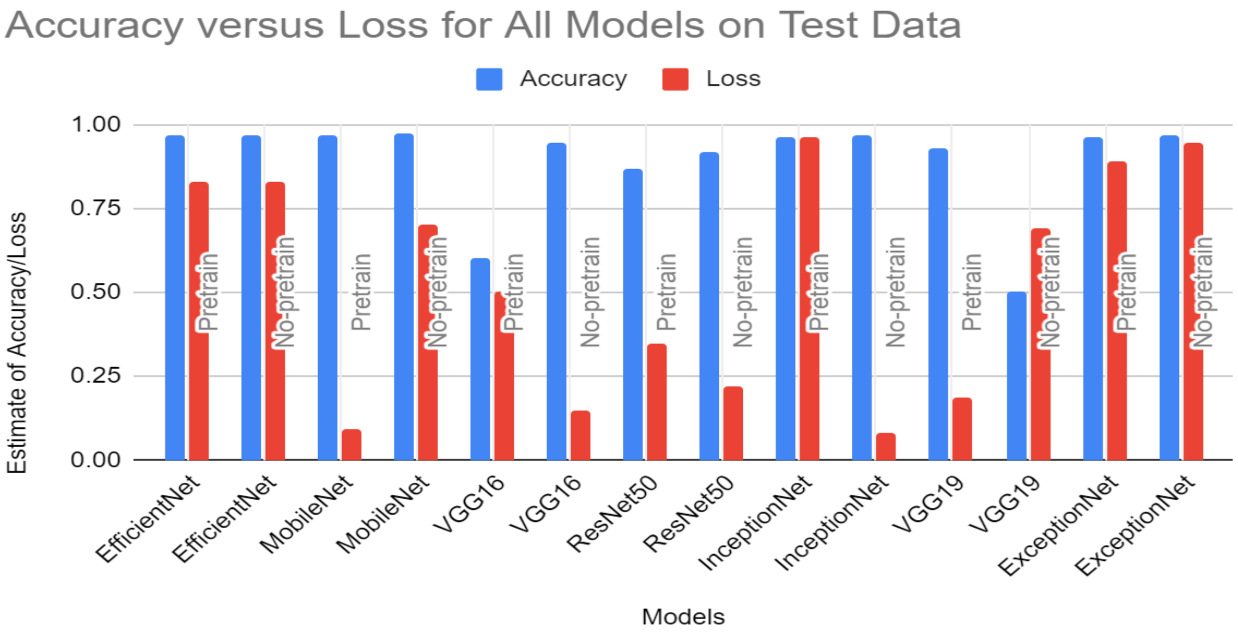


Image Classification: Model Validation Results

Distribution of Loss versus Accuracy for all Models

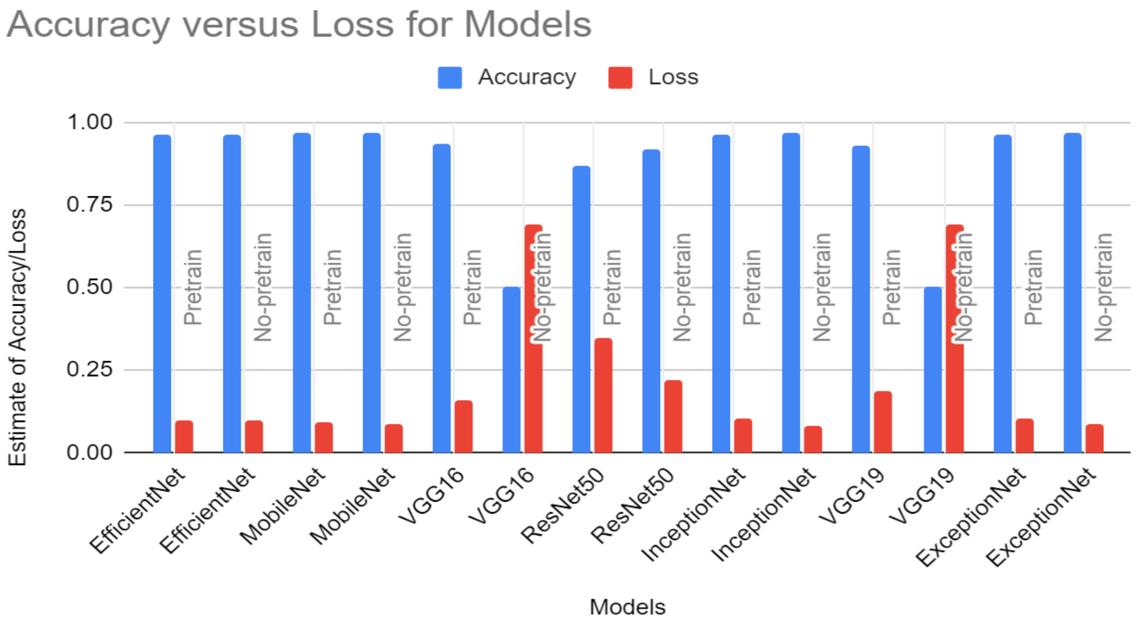
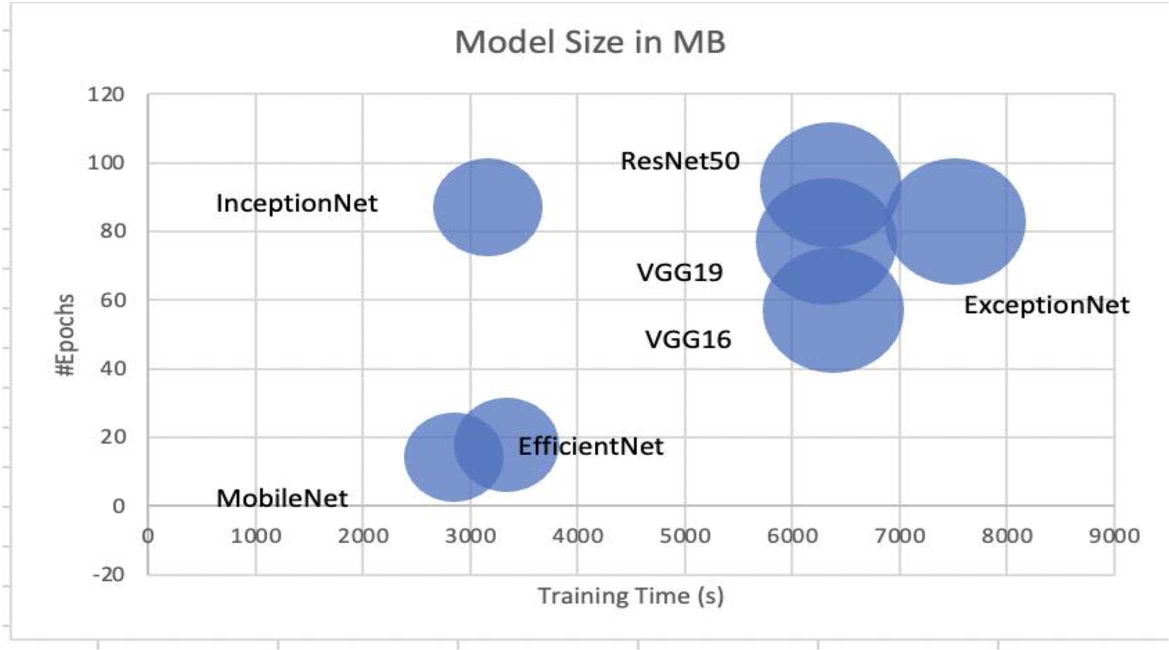
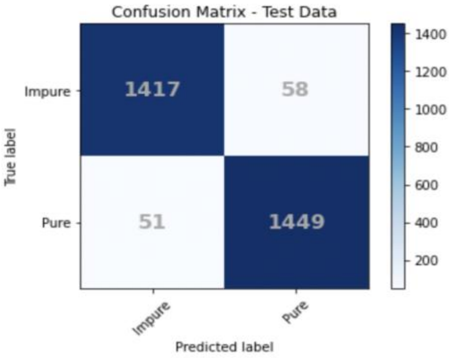


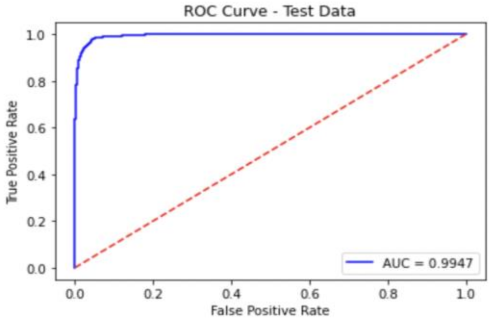
Image Classification: Model Parameters



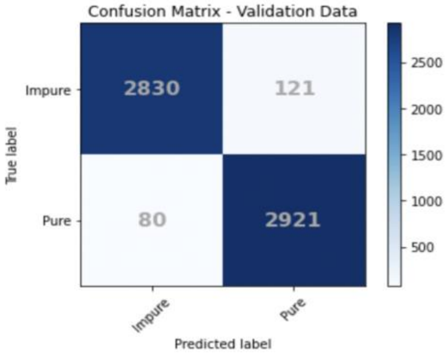
The chart above shows time taken against the number of epochs. The size of each bubble is representative of the model size. A lighter model would be easier to deploy hence we can conclude that the best model would be MobileNet

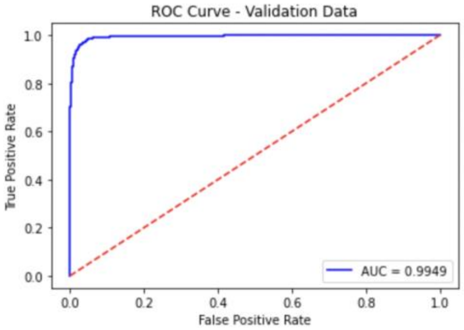
MobileNet: Test & Validation Data Results





Confusion Matrix – Validation Data:



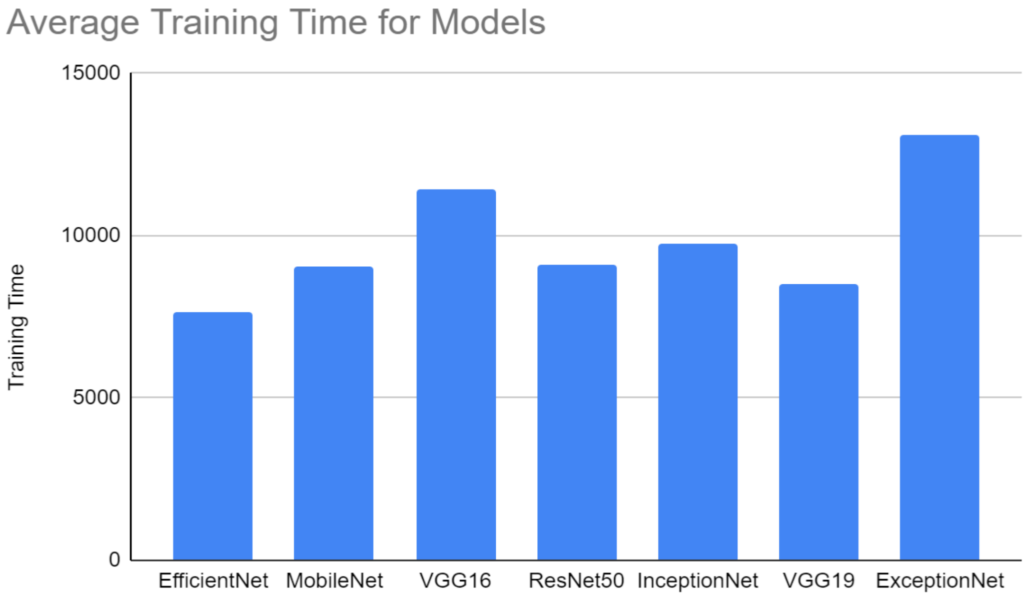


The validation and test ROC curves and the confusion matrices for illustrated on the left.

The model achieved an AUC of 0.99 for test with majority classes identified accurately.

Image Classification: Model Training Time

Distribution of Average Model Training Time for Various Models



Demo: App Deployment

Snapshots of corn kernels were taken with a mobile phone and the model was deployed on it. It took less than 2.5 seconds for the model to run

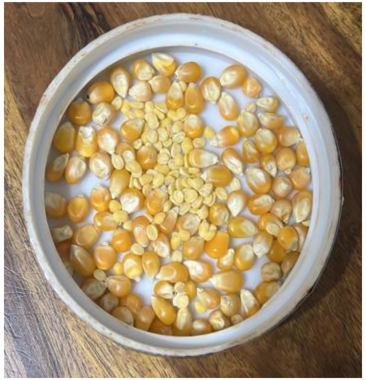
Test Data

Total grains:128

Impure: 38

Pure:90

Actual total: 145



Total grains:236

Impure: 70

Pure:166

Actual total: 245

- The model was able to identify foreign objects well
- Inaccuracies stemmed when the corn kernels were overlapping - feature extraction should be more nuanced

Conclusion

- Limitation in accuracy from YOLOv8n is bolstered by MobileNet CNN classifier
- Complete pipeline to execute took less than 2.5 seconds
- Due to the effectiveness of the YOLOv8n + pretrained MobileNet CNN classifier, this approach does not make any assumptions on the lighting conditions, orientation of kernel or the background quality or the number of kernels.
- A limitation in the approach was when multiple kernels were overlapping and perhaps enhancing the YOLOv8n with a sliding window segmentation would help. A Faster RCNN could also be tried
- This approach could be extended for disease detection and quality assessment of varieties of corn with additional data sources (multispectral, hyperspectral, geometric data etc)