Hybrid Deep Learning Model for road defects detection

El Hassan Outlaouait

~ November 24, 2022 ~

Methodology

- ⚠️ Adoption of the transfer learning concept for feature extraction.
- ⚠️ The extracted deep features are then evaluated by several machine learning classifiers.
- ⚠️ The best performing hybridization between the pre-trained deep convolutional neural networks and the machine learning classifiers is selected and then introduced to predict the final output.

Proposed method

- We propose a hybridization between pre-trained deep convolutional neural networks and machine learning classifiers :

Feature Extraction:

- ResNet-50,
- DenseNet121, DenseNet-169
- VGG-16
- EfficientNet.

Image classification:

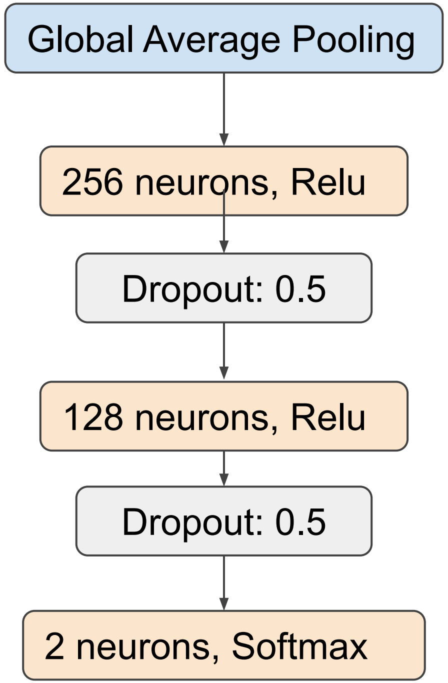
- Fully Connected Layers
- **Boosting Algorithms** : Gradient Boosting Machine (GBM), Extreme Gradient Boosting Machine (XGBM), LightGBM, CatBoost
- **Ensemble Learning** : Random forest
- SVM

Achievement & Results

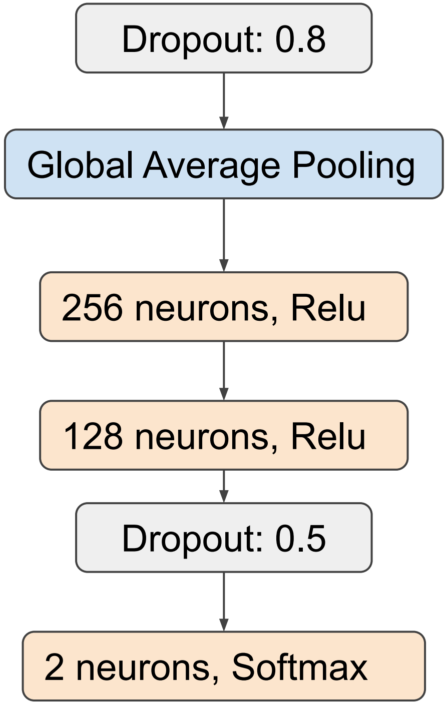
For both dataset :

- The deep feature of **EfficientNetB0** architectures outperforms the deep features of other pre-trained CNNs.
- **Fully connected layers** (FC) outperforms other ML classifiers on our dataset.

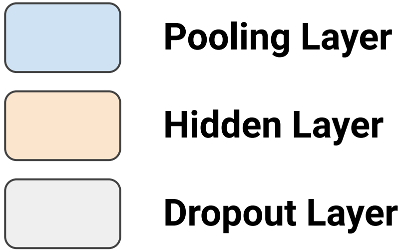
Optimal architecture of Fully connected layers



Cracks and Grooves Dataset



Rut and Subsidence Dataset



EfficientNet architecture

- **EfficientNet** architecture, is based on the compound scaling method which aims to balance the width, depth and resolution dimensions of the array by scaling with a constant ratio. Thus, if the input image is large, the array needs more layers to increase its receptive field and more channels to capture finer patterns i

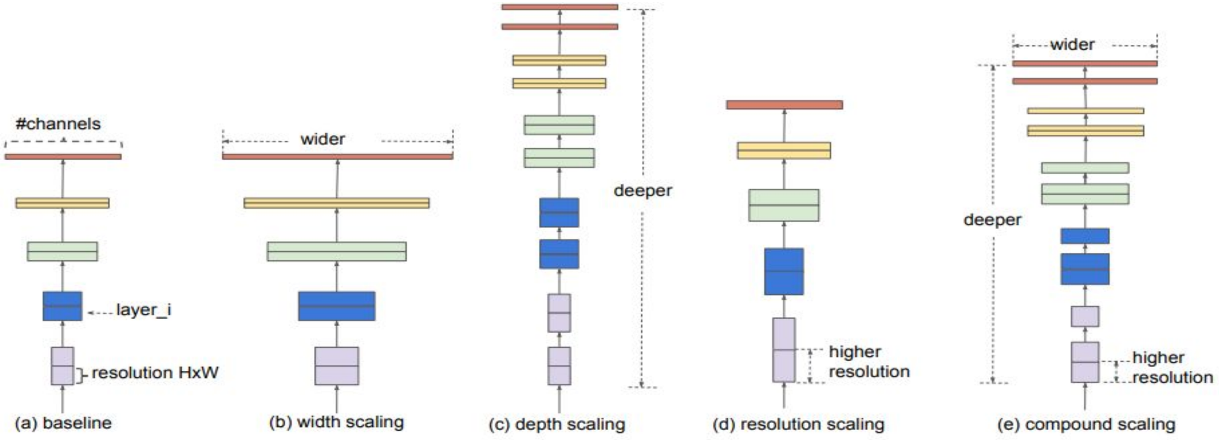
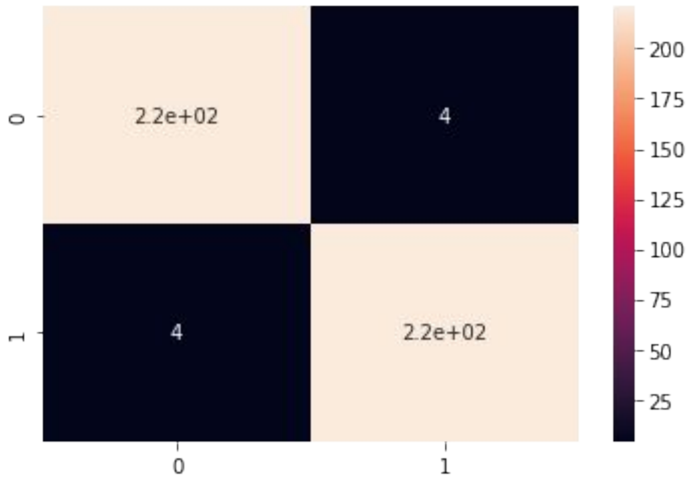


Figure 2. **Model Scaling.** (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

EfficientNetB0
Empirical results (Cracks and Grooves Dataset)

- Confusion matrix :



Metrics:

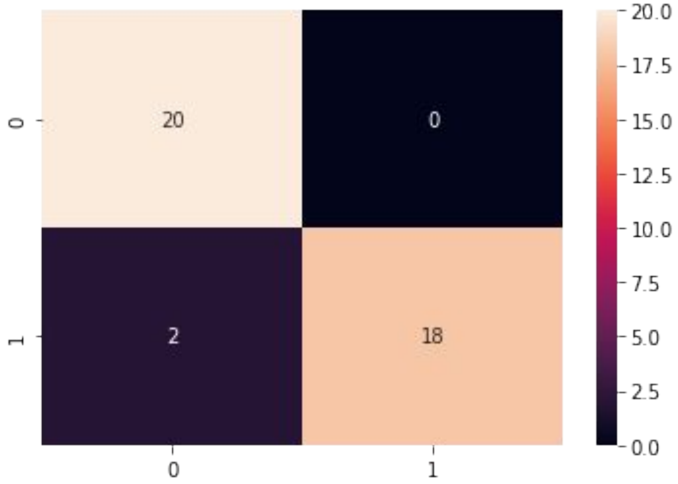
Précision	Recall	F1-score
0.9823	0.9823	0.9823

Precision = Recall = F1-score because False Positive **=** False negative **= 4**

→ The proposed technique achieved an overall accuracy of **98.23%**

EfficientNetB0
Empirical results (Rut and Subsidence Dataset)

- Confusion matrix :



Metrics:

Précision	Recall	F1-score
1.0	0.9	0.9473

→ The proposed technique achieved an overall accuracy of **95%**

Conclusion

- The hybridization of pre-trained models and classical machine learning models overcomes the limitations of a single CNN model and produces superior and robust performance.
- This hybridization allows to reach high accuracy, which could help to improve decision making.

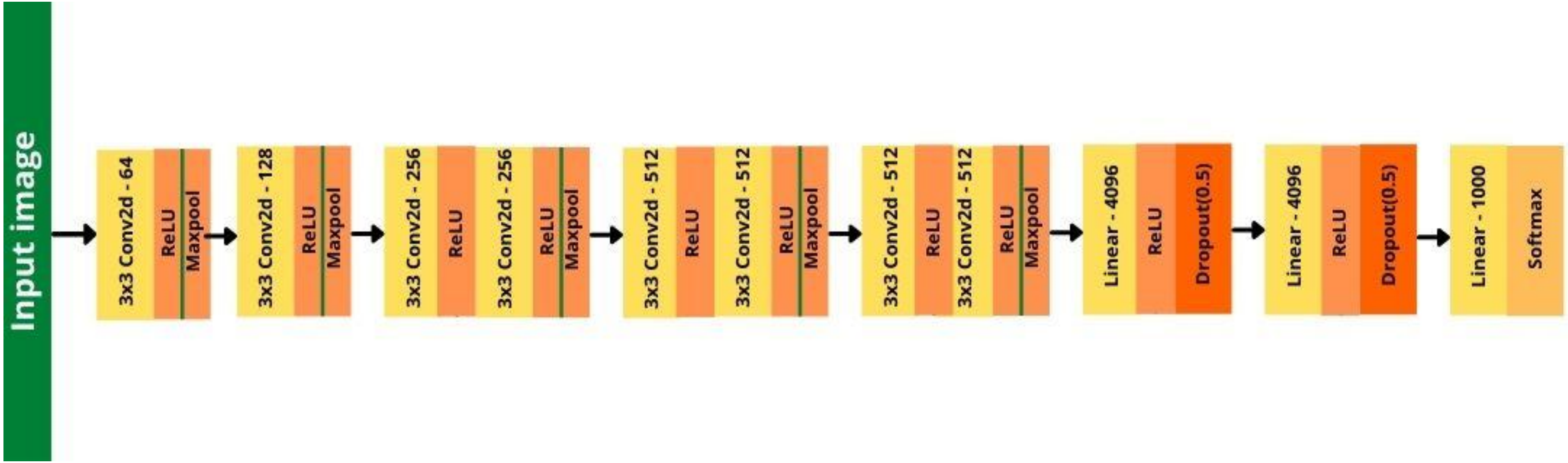
VGG-11 Model for road defects detection

Ahmed Khaled

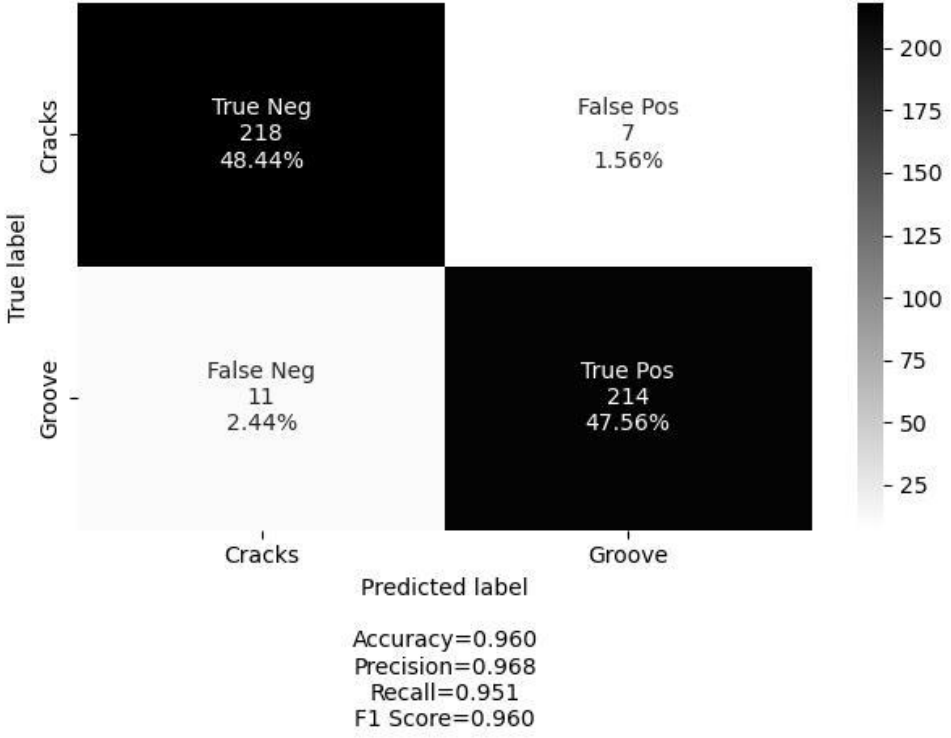
~ November 24, 2022 ~

VGG11-BN Architecture

- VGG architecture is based on using very-small convolution filters (i.e. 3x3) with increasing depth along the layers instead of having large filters. Here we used VGG11 which consists of 11 layers (8 convolutional and 3 fully-connected) with batch normalization applied before activation functions.



VGG11-BN
Empirical Results(Crack vs Groove Dataset)



Précision	Recall	F1-Score
0.968	0.951	0.960

The proposed technique achieved an overall accuracy of **96.00%**

Inception V3 Model for road defects detection

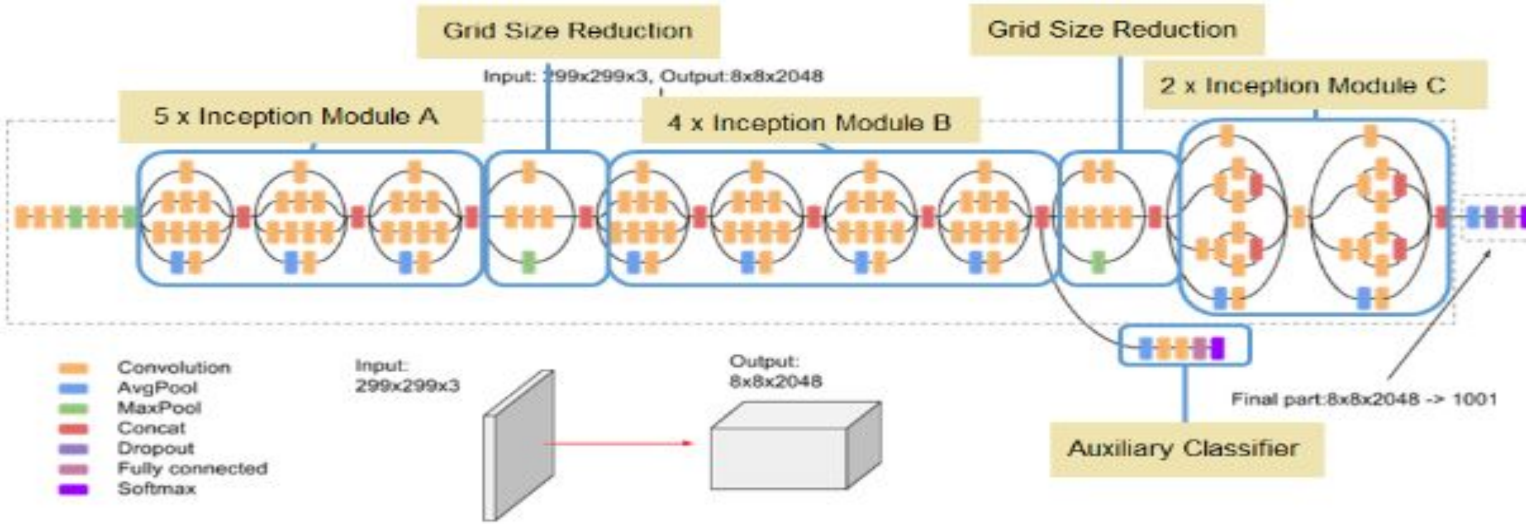
Efrem Assefa

~ November 24, 2022 ~

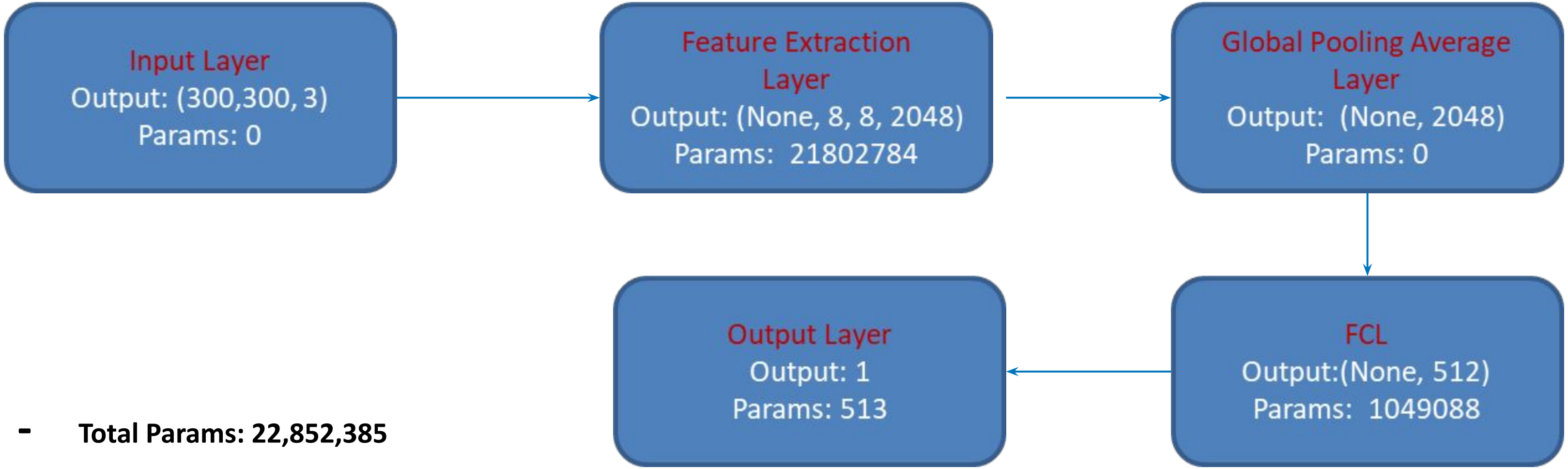
Inception V3

- Inception v3 is an image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset.

Architecture



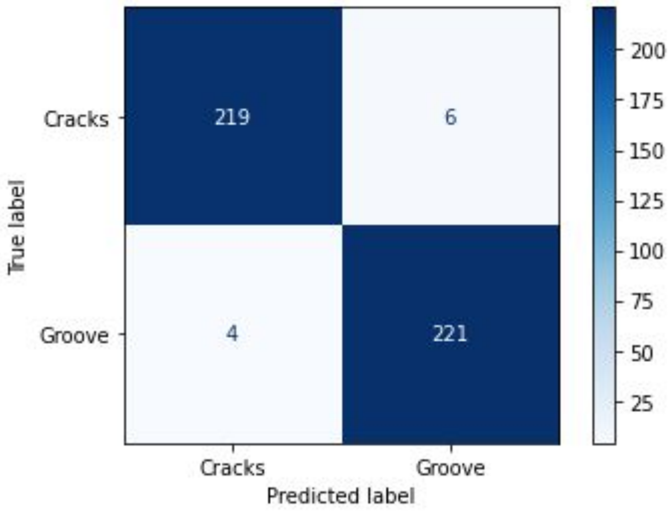
Model Summary



- **Total Params: 22,852,385**
- **Trainable Params: 22,817,953**
- **Non-trainable Params: 34,432**

Inception V3
Empirical Results(Crack vs Groove Dataset)

Classification Matrix :



Classification Report:

	precision	recall	f1-score
Cracks	0.98	0.97	0.98
Groove	0.97	0.98	0.98

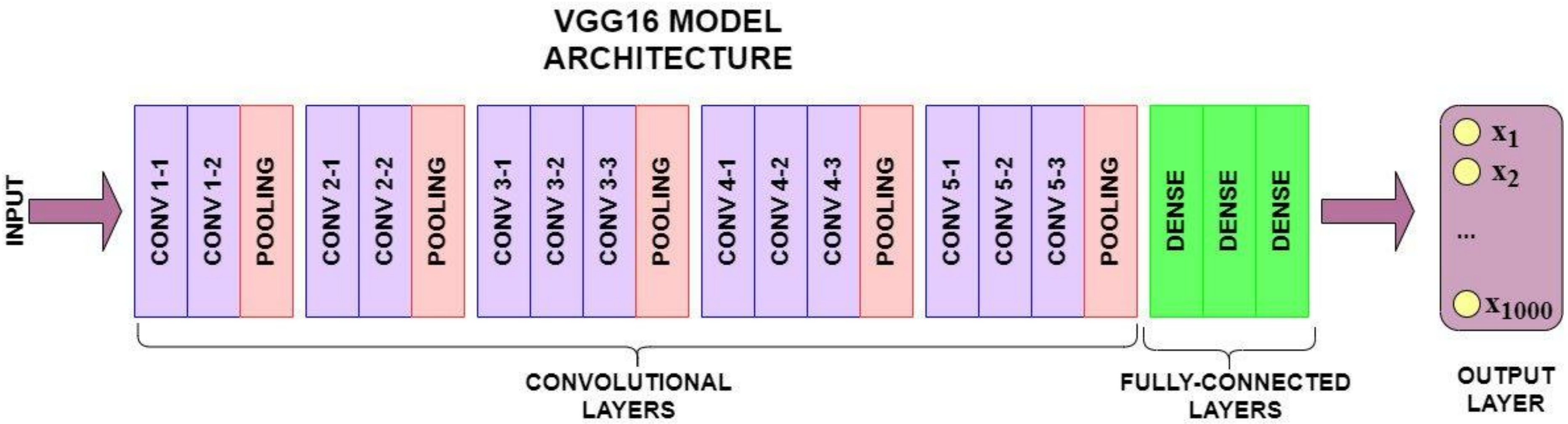
- **Train Accuracy: 98.99%**
- **Val Accuracy: 97.58%**
- **Test Accuracy: 97.78%**

Transfer Learning with VGG16 for road defects detection

Chithra Priya Janardhana

~ November 24, 2022 ~

- VGG16 is **object detection and classification algorithm** which is able to classify 1000 images of 1000 different categories with 92.7% accuracy.

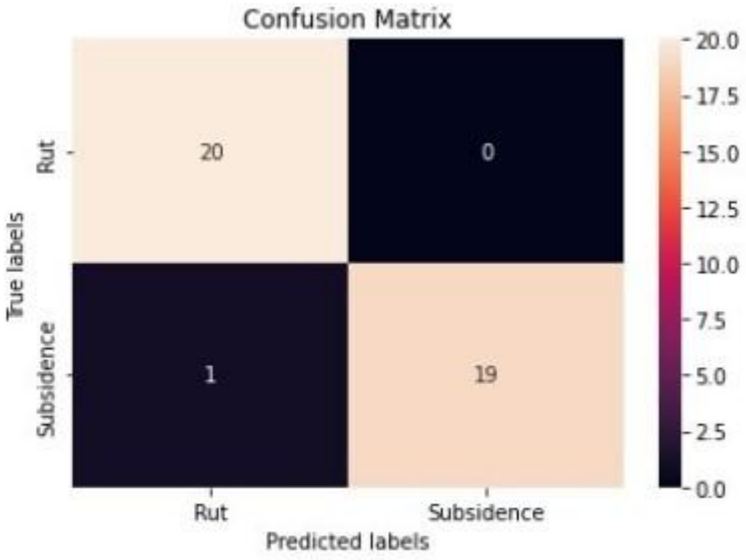


- A Transfer Learning approach is applied by using the pretrained convolutional base of the VGG16 model stacking a number of densely connected neural network layers on top and training these densely layers on the (Rut and Subsidence) and (Crack and Groove) dataset for our binary classification task.

- The accuracy of the model was then further improved by fine-tuning the convolutional base for our specific binary classification task. The final 3 convolutional layers were un-frozen and trained on the training dataset. This enabled the updated model to achieve an higher accuracy on the testing dataset.

VGG16
Empirical results (Rut and Subsidence Dataset)

Confusion Matrix:



Confidence Score:

	precision	recall	f1-score
Rut	0.95	1.00	0.98
Subsidence	1.00	0.95	0.97

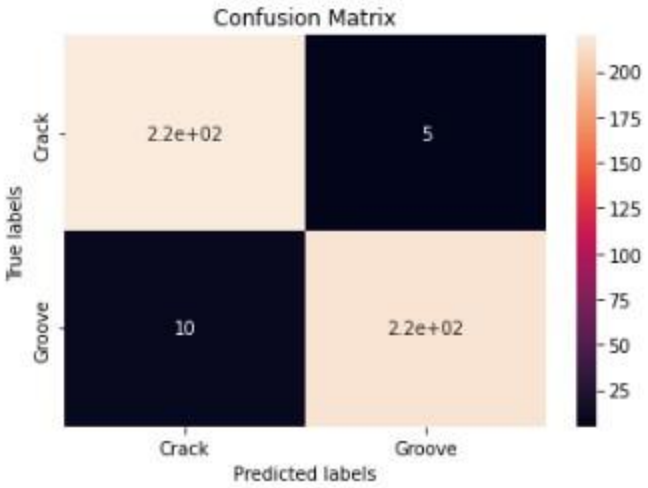
Model Results:

- Train Accuracy: 100%
- Val Accuracy: 95%
- Test Accuracy: 97%

VGG16
Empirical results (Crack and Groove Dataset)

Confusion Matrix:

```
[[220   5]
 [ 10 215]]
```



Confidence Score:

	precision	recall	f1-score
Crack	0.96	0.98	0.97
Groove	0.98	0.96	0.97

Model Results:

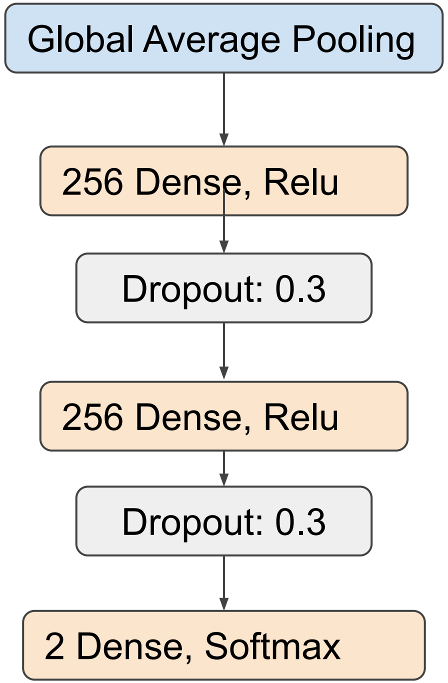
- Train Accuracy: 96.28%
- Val Accuracy: 95.70%
- Test Accuracy: 97%

ResNet and MobileNet for Road Defects Recognition

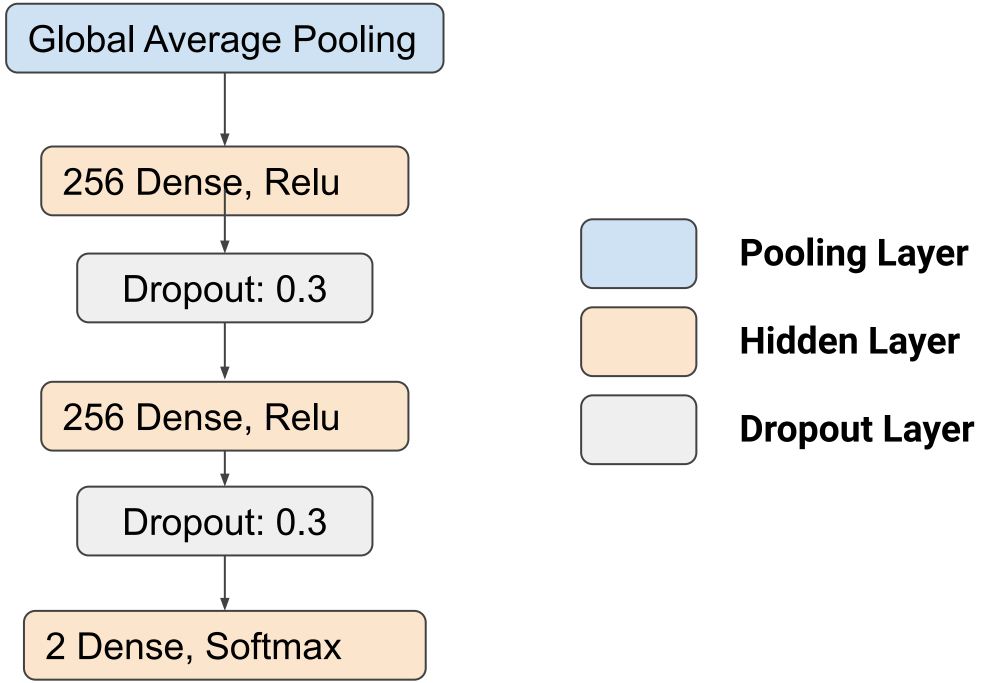
Chandler Timm Doloriel

~ November 24, 2022 ~

Transfer Learning (pre-trained with ImageNet)



Cracks and Grooves (**ResNet152v2**)



Rut and Subsidence (**MobileNetv2**)

ResNet152V2
Empirical Results (Crack + Groove Dataset) 450 test samples

Confusion Matrix:

PREDICTED

TRUE	Crack	Groove
Crack	221	4
Groove	7	218

Confidence Score:

	precision	recall	f1-score	support
crack	0.97	0.98	0.98	225
groove	0.98	0.97	0.98	225

Model Results:

- Train Accuracy: 97.16%
- Val Accuracy: 90.74%
- Test Accuracy: 97.56%

MobileNetV2
Empirical Results (Rut + Subsidence Dataset) 40 test samples

Confusion Matrix:

PREDICTED

	Crack	Groove
Crack	19	1
Groove	0	20

TRUE

Confidence Score:

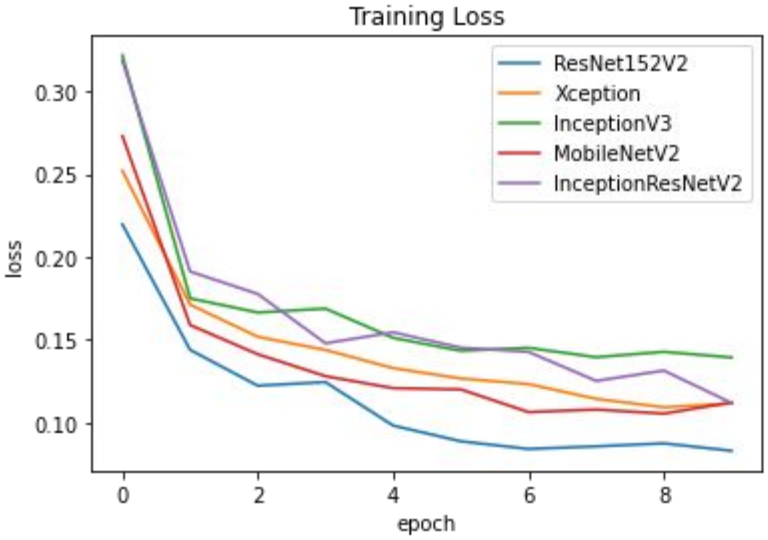
	precision	recall	f1-score	support
Rut	1.00	0.95	0.97	20
Subsidence	0.95	1.00	0.98	20

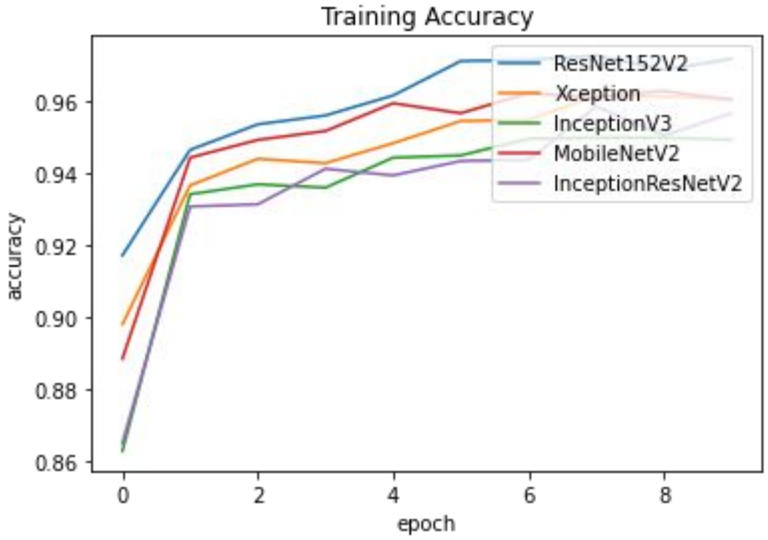
Model Results:

- Train Accuracy: 98.25%
- Val Accuracy: 90.28%
- Test Accuracy: 97.50%

Learning Curve (Crack + Groove)

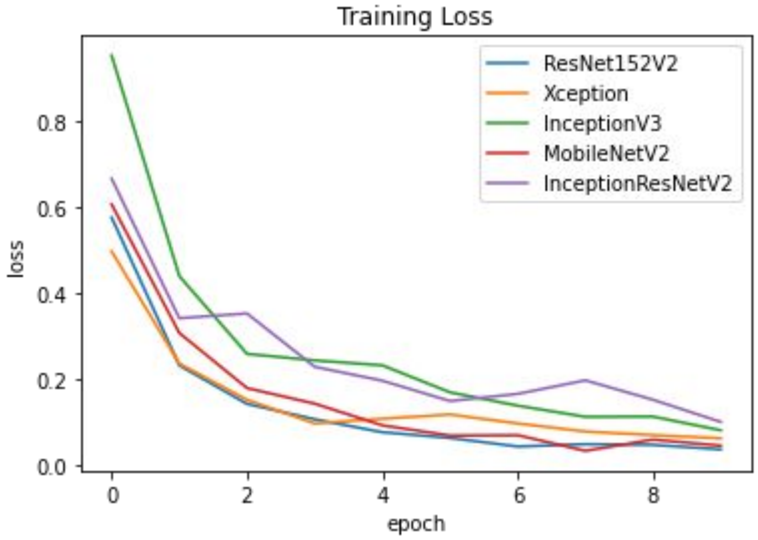
ResNet152V2 obtained the best result for crack + groove dataset

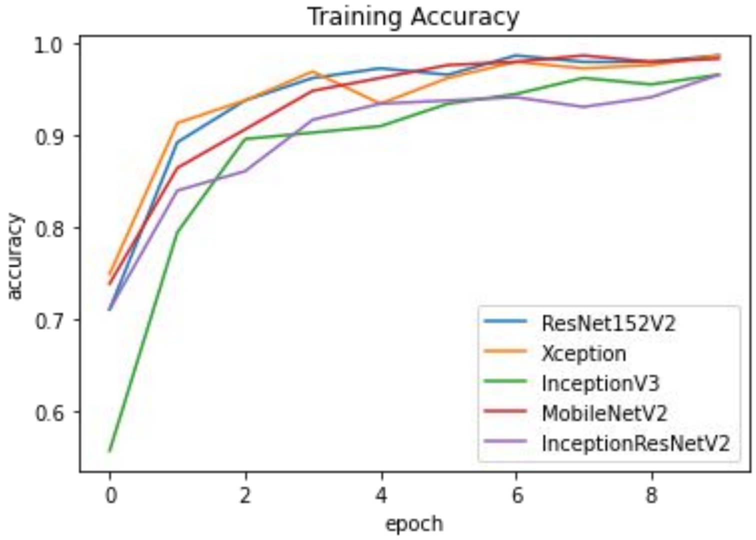




Learning Curve (Rut + Subsidence Dataset)

MobileNetV2 obtained the best result for rut + subsidence dataset





Models for Image Classification

Crack and Groove Dataset

- EfficientNetB0
- VGG11-BN
- Inception V3
- VGG16
- ResNet152V2
- Xception
- InceptionResNetV2

Rut and Subsidence Dataset

- EfficientNetB0
- VGG16
- ResNet152V2
- Xception
- Inception V3
- MobileNetV2
- Inception ResNetV1

Best Models chosen for Deployment

Crack and Groove Models:

1. ResNet152V2
2. EfficientNetB0

Rut and Subsidence Models:

1. MobileNetV2
2. EfficientNetB0

Conclusion

- Two Best Models out of 8 Models for Crack and Groove dataset were picked for Deployment.
- Two Best Models out of 7 Models for Rut and Subsidence dataset were picked for Deployment.
- Model Weights and Notebooks of every model is submitted to their respective folders in the below google drive link.

https://drive.google.com/drive/folders/1yCByBZkscwKdNZzzcJrkgSGvpuwA9Tqm