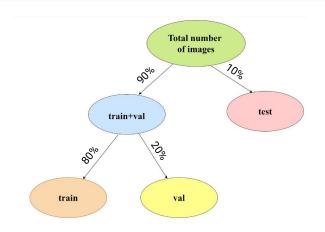
Dataset (Crack and Groove)

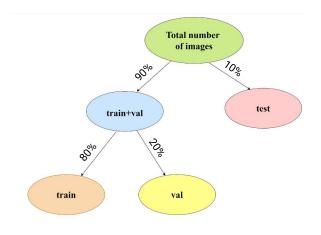
<u>Class</u>	No. of images
Crack	2250
Groove	2250



<u>Category</u>	<u>Total number of images</u> (<u>T)</u>	No. of training images (0.8*0.9*T)	No. of validation images (0.2*0.9*T)	No. of testing images (0.1*T)
Crack	2250	1620	405	225
Groove	2250	1620	405	225

Dataset (Rut and Subsidence)

<u>Class</u>	No. of images
Rut	199
Subsidence	199



<u>Category</u>	<u>Total number of images</u> <u>(T)</u>	No. of training images (0.8*0.9*T)	No. of validation images (0.2*0.9*T)	No. of testing images (0.1*T)
Rut	199	143	36	40
Subsidence	199	143	36	40



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:

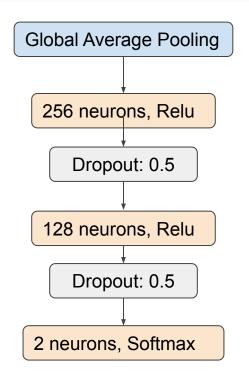
- Fully Connected Layers
- **Boosting Algorithms**: Gradient Boosting Machine (GBM), Extreme Gradient Boosting Machine (XGBM), LightGBM, CatBoost
- **Ensemble Learning**: Random forest
- SVM

Achievement & Results

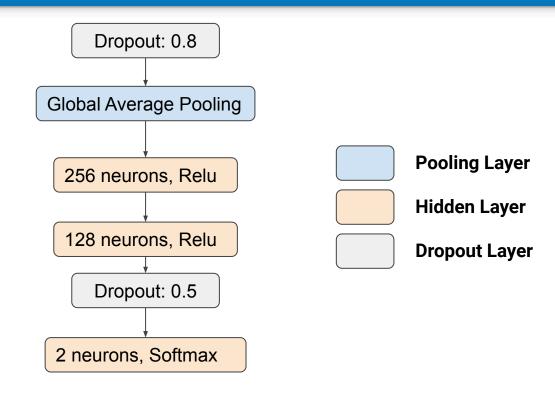
For both dataset:

- 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



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 in

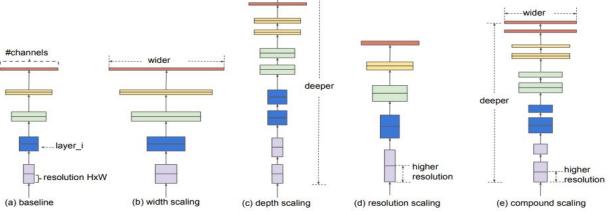
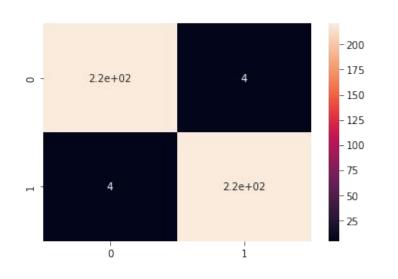


Figure 2. Model Scaling. (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

EfficientNetB0 Empirical results (Cracks and Grooves Dataset)

Confusion matrix :



Metrics:

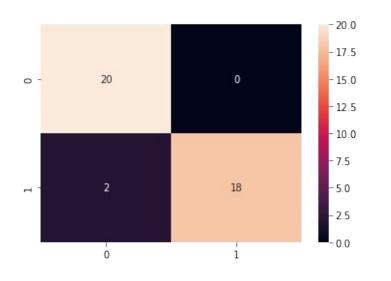
Précision	Recall	F1-score
0.9823	0.9823	0.9823

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



EfficientNetB0 Empirical results (Rut and Subsidence Dataset)

Confusion matrix :



Metrics:

Précision	Recall	F1-score	
1.0	0.9	0.9473	



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.



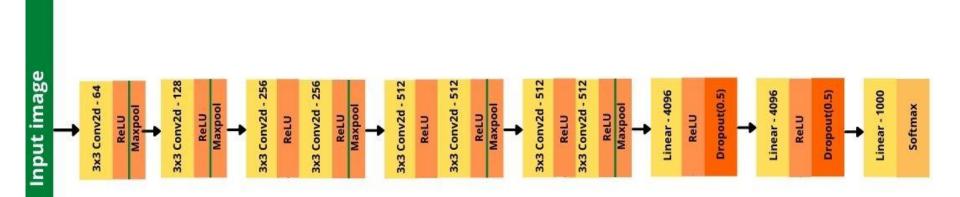
VGG-11 Model for road defects detection

Ahmed Khaled

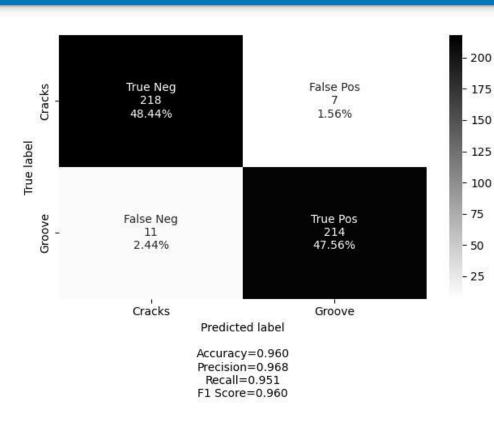
~ November 24, 2022 ~

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**%



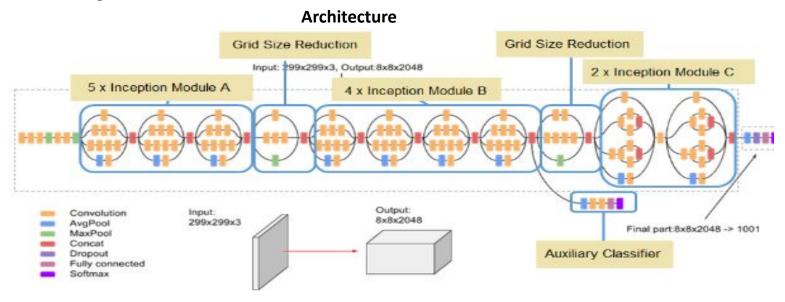
Inception V3 Model for road defects detection

Efrem Assefa

~ November 24, 2022 ~

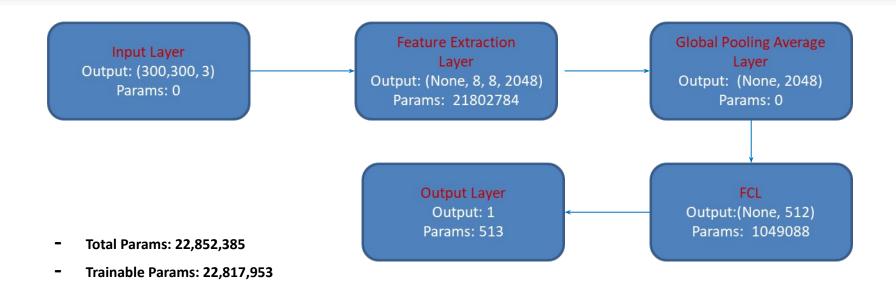
Inception V3

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



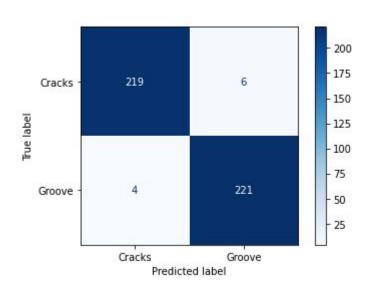
Model Summary

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%

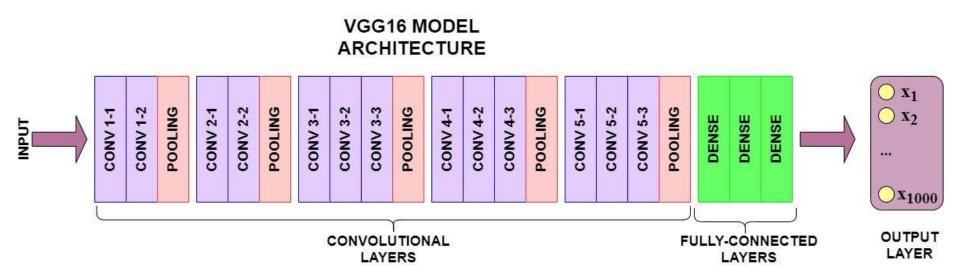


Transfer Learning with VGG16 for road defects detection

Chithra Priya Janardhana

~ November 24, 2022 ~

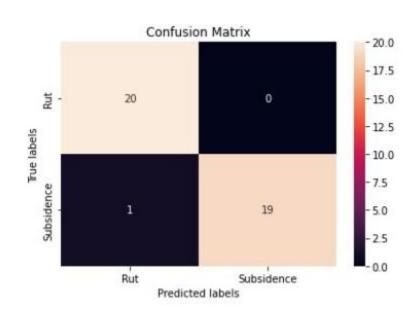
VGG16 is object detection and classification algorithm which is able to classify 1000 images of 1000 different categories with 92.7% accuracy.



- 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%

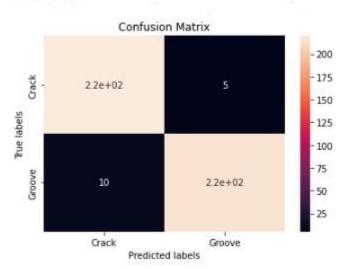
- Test Accuracy: 97%

VGG16

Empirical results (Crack and Groove Dataset)

Confusion Matrix:





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%

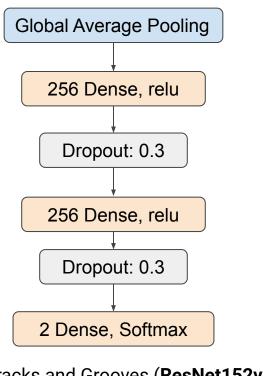


ResNet and MobileNet for Road Defects Recognition

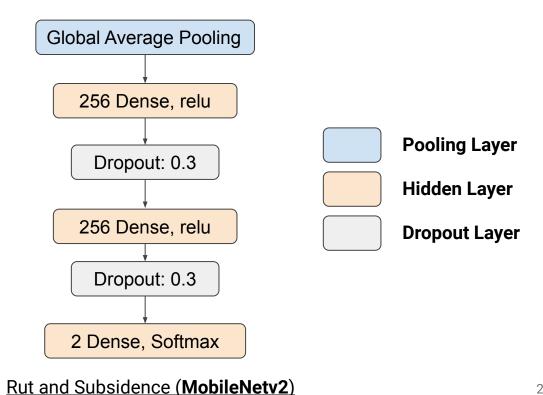
Chandler Timm Doloriel

~ November 24, 2022 ~

Transfer Learning (pre-trained with ImageNet)

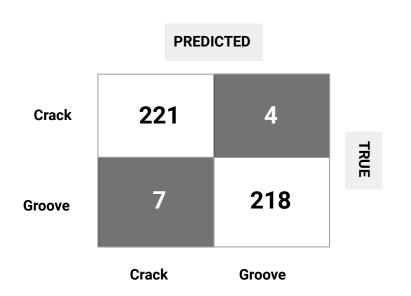


Cracks and Grooves (ResNet152v2)



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

Confusion Matrix:



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:

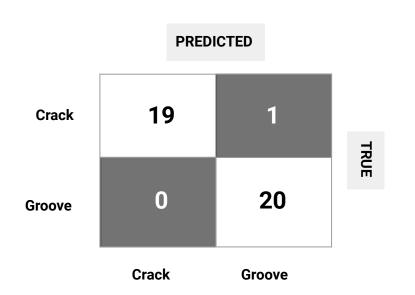
- Train Accuracy: 97.16%

- Val Accuracy: 90.74%

- Test Accuracy: 97.56%

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

Confusion Matrix:



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:

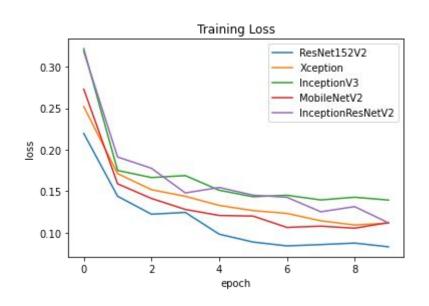
- Train Accuracy: 98.25%

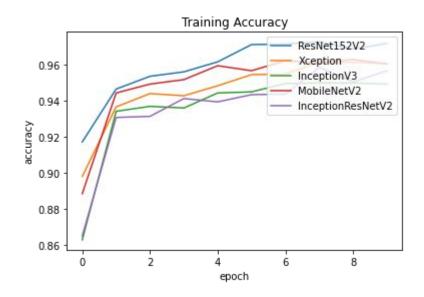
- Val Accuracy: 90.28%

- Test Accuracy: 97.50%

Learning Curve (Crack + Groove)

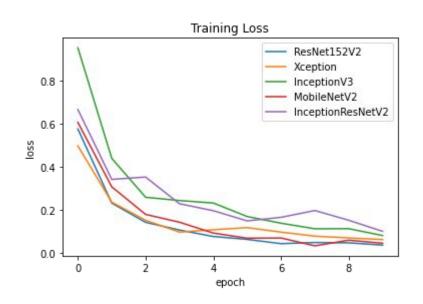
ResNet152V2 obtained the best result for crack + groove dataset

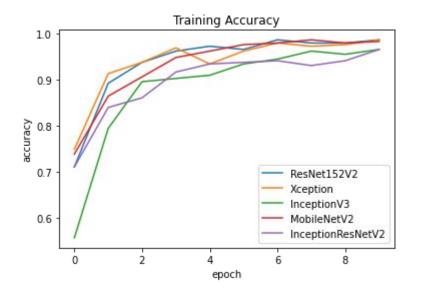




Learning Curve (Rut + Subsidence)

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
- 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.
- Datasets used for the Modeling can be found in the link below.

https://drive.google.com/drive/folders/1V04yMqTuOUdiD4Iid6IYLj964tffFiFh

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/1yCByBZkscwKdNZzzcJrkgSGypuwA9Tqm

Details of every model can be found in the link below.
 https://docs.google.com/spreadsheets/d/1GC9cmltGG00hMTZ9FCJeM1XIDnaqHEb2YssFDalruhE/edit#gid=0