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Fala: An intelligent mobile application for safe driving

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Abstract

Studies have shown that researchers have proposed various applications for Safe driving using different driving activities and events. This research considered pothole as one of the challenging factors for safe driving therefore it looked into deploying a mobile application for monitoring potholes as an important tool for safe driving. Automating pothole detection will go a long way in providing safe driving for road users and intelligent transportation systems. This paper presents a safe driving application that assists drivers by detecting and predicting potholes while on the road to curb road accidents in Nigeria. The datasets used in this research were potholes images extracted from kaggle which were classified into two; potholes and normal roads. The object detection algorithm that was used to evaluate the model is YOLOv5. The results proved that our model was not perverse. We deployed the model to the mobile application, the mobile application when launched activates the camera by default enabling the system to detect and predict between normal roads and potholes. The predicted values were all positive. The two classifiers were all detected perfectly in real-time while testing without being perverse. The system presents its predicted value in percentage, therefore showing the level of adherence to each of the classes detected.

Keywords: Safe driving; Object detection; YOLO 5; Pothhole detection; Mobile application

1. Introduction

Safe driving are categorized by many researchers and as such many researchers has looked into driving events and activities that encourages safe driving. Pothole is one of the challenging effects of safe driving as it portrays a lot of dangers to road users. A pothole is a natural cave or a hollow on the road surface formed due to erosion or aging of asphalt [1]. Potholes pose a lot of dangers for road transport users in many developing countries, especially in Nigeria. The task of maintaining roads and removing these road anomalies is an expensive and tedious one, due to the nature of landmass and climate conditions in Nigeria. It is reported that pothole is the second largest cause of accidents in Nigeria apart from overspeeding and reckless driving with annual reported accidents surpassing 45% [2]. The problem of potholes in Nigeria cannot be eradicated completely by the government but rather how to manage it and drive safely. The roads have been a concern of authorities to avoid unwanted circumstances. These roads are vulnerable to traffic load, weather conditions, age, poor material used for construction, and miserable drainage system, exhibiting two major road failures such as cracks and potholes. Potholes are essentially concave-shaped depressions in the road surface that require attention as they induce awful circumstances such as accidents, unpleasant driving experiences, and malfunctioning of vehicles. Potholes should be dealt with on a priority basis to minimize their contribution towards unfortunate scenarios.

According to the prediction by WHO (World Health Organization), road accidents will become the fifth leading cause of death in 2030 [3]. The significance of potholes created conspicuous interest for the researchers of the civil community. The developing nations use manual inspection methods to recognize the potholes leading to inaccurate estimation as it

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is highly dependent on individual experience. These manual inspection methods require human interventions that are time-consuming and costly. Many technical solutions exist for pothole detection such as scanning based with 3D reconstruction [4], vibration sensor-based, thermal imaging, and computer vision based.

2. Materials and Methods

In this section, we described the materials and methods used for the development of a safe driving application for pothole detection. We adopted the classification results from Anigbogu et al., (2023), they trained their model with YOLOv5 and we will adopt their model in training our safe driving application. The model results and analysis are presented hereunder:

Epoch	**GPU_mem**	**box_loss**	**obj_loss**	**cls_loss**	**Instances**	**Size**	
0/24	6.09G	0.09652	0.04241	0.02531	44	640: 100% 34/34 [00:34<00:00, 1.03s/it]	
	Class	Images	Instances	P	R	mAP50	**mAP50-95**: 100% 3/3 [00:02<00:00, 1.28it/s]
	All	67	157	0.173	0.0877	0.0513	0.0151
Epoch	**GPU_mem**	**box_loss**	**obj_loss**	**cls_loss**	**Instances**	**Size**	
1/24	7.99G	0.07188	0.04532	0.01243	53	640: 100% 34/34 [00:35<00:00, 1.03s/it]	
	Class	**Images**	**Instances**	**P**	**R**	**mAP50**	**mAP50-95**: 100% 3/3 [00:01<00:00, 1.80it/s]
	All	67	157	0.2	0.451	0.148	0.0474
Epoch	**GPU_mem**	**box_loss**	**obj_loss**	**cls_loss**	**Instances**	**Size**	
2/24	7.99G	0.06824	0.0401	0.005949	32	640: 100% 34/34 [00:33<00:00, 1.02it/s]	
	Class	**Images**	**Instances**	**P**	**R**	**mAP50**	**mAP50-95:** 100% 3/3 [00:01<00:00, 2.03it/s]
	All	67	157	0.148	0.317	0.126	0.0417
Epoch	**GPU_mem**	**box_loss**	**obj_loss**	**cls_loss**	**Instances**	**Size**	
3/24	7.99G	0.06281	0.03964	0.003697	27	640: 100% 34/34 [00:36<00:00, 1.08s/it]	
	Class	**Images**	**Instances**	**P**	**R**	**mAP50**	**mAP50-95**: 100% 3/3 [00:02<00:00, 1.49it/s]

	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:02<00:00, 1.49it/s]
	All	67	157	0.433	0.424	0.386	0.141
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size	
4/24	7.99G	0.05793	0.03653	0.002606	41	640: 100% 34/34 [00:34<00:00, 1.03s/it]	
	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:01<00:00, 2.07it/s]
	All	67	157	0.355	0.53	0.344	0.149
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size	
5/24	7.99G	0.05444	0.03919	0.002354	34	640: 100% 34/34 [00:34<00:00, 1.02s/it]	
	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:01<00:00, 1.91it/s]
	All	67	157	0.421	0.464	0.411	0.183
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size	
6/24	7.99G	0.05078	0.03765	0.001724	45	640: 100% 34/34 [00:31<00:00, 1.07it/s]	
	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:01<00:00, 2.04it/s]
	All	67	157	0.548	0.566	0.525	0.217
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size	
7/24	7.99G	0.04866	0.03694	0.001718	41	640: 100% 34/34 [00:32<00:00, 1.06it/s]	

	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:02<00:00, 1.49it/s]
	All	67	157	0.433	0.424	0.386	0.141
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size	
4/24	7.99G	0.05793	0.03653	0.002606	41	640: 100% 34/34 [00:34<00:00, 1.03s/it]	
	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:01<00:00, 2.07it/s]
	All	67	157	0.355	0.53	0.344	0.149
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	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:01<00:00, 1.91it/s]
	All	67	157	0.421	0.464	0.411	0.183
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size	
6/24	7.99G	0.05078	0.03765	0.001724	45	640: 100% 34/34 [00:31<00:00, 1.07it/s]	
	Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:01<00:00, 2.04it/s]
	All	67	157	0.548	0.566	0.525	0.217
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size	
7/24	7.99G	0.04866	0.03694	0.001718	41	640: 100% 34/34 [00:32<00:00, 1.06it/s]	

Figure 1 Performance evaluation of the model

Table 1 presents a log output YOLOV5 model that is being trained on pothole and normal road for object detection.

Overall, this log output provides a summary of the training progress and performance of the object detection model.

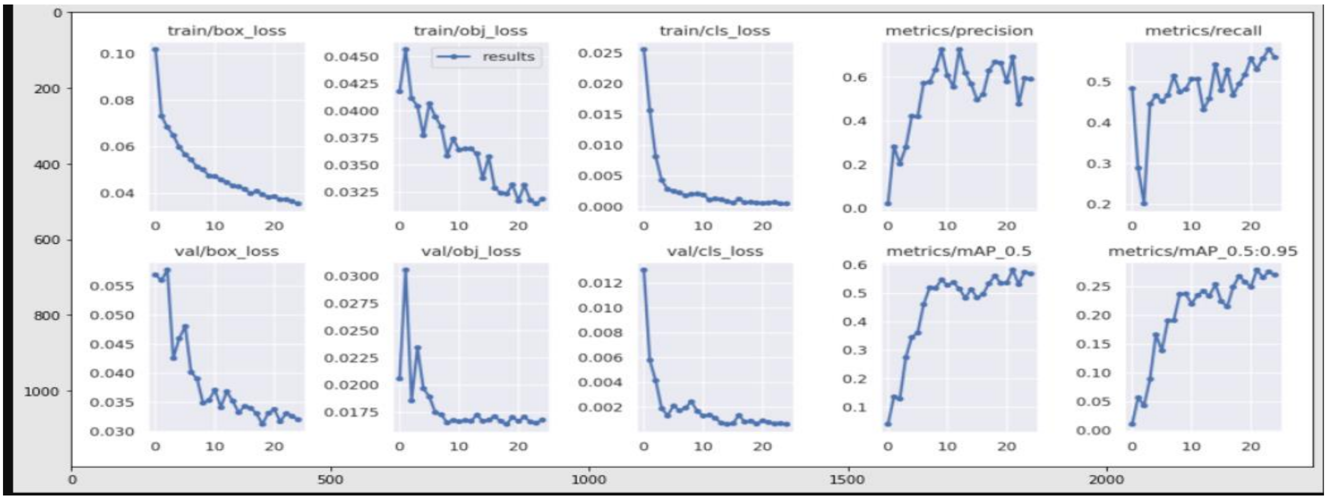

Figure 2 Model Performance for over all Results

2.1. Classification Report for model evaluation metrics with YOLOV5

Table 1 Details by categories of classification model

Class	Images	Instances	P	R	mAP50	mAP50-95: 100% 3/3 [00:01<00:00, 1.65it/s]
All	67	157	0.594	0.57	0.568	0.28
Normal	67	33	0.525	0.576	0.525	0.276
Pothole	67	124	0.663	0.565	0.612	0.287

3. Results and Discussions

3.1. Falanfa Driving Mobile Application

- After a successful training with YOLOv5 with a total loss at a converging point, evaluation was performed again from the checkpoint.
- From the checkpoint the trained model was converted into an inference graph and this inference graph ends with an extension .pb (portable binary format)
- The inference graph is being taken to the mental model, the mental model tries to check the relationships and then increase the brightness of our model. The inference graphs are image blots and cant be used for immediate detection.
- The mental model is now converted to .tflite, the application when launched analyzes, detects and predict the potholes and normal roads based on the trained model. This enabled us to deploy the model to a mobile application. In that tflite, we tested our results again (each of the classes) using Jupyter notebook and it was still able to give us encouraging results.
- From the tflite we now take the Tensorflow object detection API for the mobile application to the android studio for configurations and modifications of the code to suit our system and make sure we don't encounter an error.

3.2. Fala pothole detection application

Launching the mobile application turns up the camera automatically and then gets ready to detect and predict.

Figure 3 User Interface of the application

Figure 4a Real time result for camera

Here the mobile application detected the pothole correctly with 74.25% prediction.

Figure 4b Real-time result from the camera

Here the mobile application detected the pothole correctly with 72.64% prediction and normal road at 49.69 which is still good.

Figure 4c Real-time result from the camera

Here the mobile application detected the pothole correctly with 77.86% prediction.

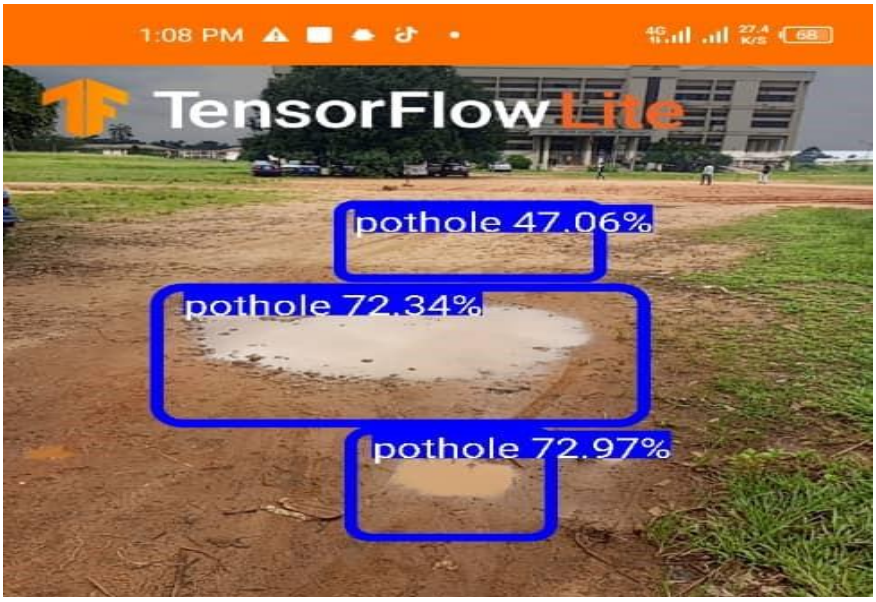

Figure 4d Real-time result from the camera

Here the mobile application detected the potholes correctly with 47.06%, 72.34% and 72.97% prediction.

Figure 4e Real-time result from the camera

Here the mobile application detected the normal road correctly with 57.98% prediction.

4. Conclusion

This research presented safe driving with a unique driving activity called pothole. Different pothole images were extracted from Kaggle and trained. The trained model was used to deploy the real-time application for safe driving. These can be adopted by researchers working on intelligent transport systems and safe driving applications to build their systems like vehicle security, embedded systems for recent automobiles, road safety systems, and many other systems related to safe driving. This research can go a long way in reducing the dangerous implications of road accidents caused by potholes because the singular act of having a pre-information on the status of the road while driving in real-time will go a long way in changing the driver's unsafe and unhealthy behaviour's while driving. More driving events can be looked into as this would also introduce more related information about intelligent transport systems.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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