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Driver behavior model for healthy driving style using machine learning methods

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Abstract

Driving is a complex and dynamic task requiring drivers not only to make accurate perceptions and cognitions about the information on the driver's driving skill but also to process this information at a high speed. This paper compared three major image processing/machine learning algorithms viz; Single Shot Multibox Detection (SSD), Convolutional Neural Networks (CNN), and support vector machine (SVM) to find the fastest and most efficient of the three with regards to the dataset from driving events (braking, speeding and safe driving) collected from Nigeria. The results analyzed showed that in an identical testing environment, Support Vector Machine outperformed Single Shot Detection and Convolutional Neural Networks.

Keywords: Machine learning; Driving events; Convolutional Neural Network; Support Vector Machine; Single Shot Multibox Detection.

1. Introduction

Machine learning is a branch of artificial intelligence that aims at enabling machines to perform their jobs skillfully by using intelligent software [1]. Such jobs involve recognition, diagnosis, planning, robot control, prediction, etc. These concepts involve the ability of the machine models to learn by themselves and improve their own performance from training example. They do not rely on rule-based programming, but on algorithms that identify patterns in data and then predict similar patterns in new data. Importantly, the software can continually improve the quality of the predictions they make as time goes on. Therefore, machines have been originally created to help humans in their daily lives. It is necessary for the machines to think, understand to solve problems, and take suitable decisions akin to humans. In other words, we need smart machines. In fact, the term smart machine is symbolic to machine learning success stories and its future target. Driving is one of the major forms of transportation.

The ability to drive is one of the most important activities of daily living. Modeling and recognizing human driving behavior have been of interest to researchers from many different disciplines like psychology, physiology, and ergonomics for more than half a century. It is commonly known that driving is a complex and dynamic task requiring drivers not only to make accurate perceptions and cognitions about information pertaining to the driver's own driving skill, driver state, vehicle performance, and traffic, but also to process all these information at a high speed. Hence, the researchers noted that models that capture both high-level cognitive processing and low-level operational control are needed. For practical applications, these models must capture the behavior of the overall population and also have facilities to adapt to a particular person or driver. Automating safe driving in vehicles and artificial transportation systems require enhanced understanding of the human driver behavior [2]. This is not only necessary to guarantee safe and adequate performance, but also to adjust to the drivers' needs, potentiate their acceptability and ultimately meet

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drivers' preferences in a safe environment. Therefore, recognition of driving style and driver inference for the integration and development of these systems is essential.

Industries have taken further steps to influence driver driving style through active and passive corrective feedback towards safer and eco-friendly practices. These were done by intervening into the driving task directly through generating haptic inputs, whilst the second is only advisory and targets to improve drivers' awareness through visual or audio advice [3]. These systems are being embedded in the newly manufactured vehicles to assist in one form or the other in cautioning and assisting the driver as the case maybe. However these set of vehicles are very expensive that transportation companies and most individuals in Nigeria might not be able to afford them. Nevertheless, better understanding of driving style is required to ensure appropriate and consistent recognition and to effectively promote safety driving. Many of the vehicle dynamic and vehicle control systems are designed by engineers, and they generally put their emphasis and interest on the vehicle itself. Recently, high-performance vehicle cannot meet the needs of customers who require more human-friendly vehicle and also acquiring those high-performance vehicles is very expensive that majority of drivers in this part of the world cannot afford such vehicles. Thus, human driving skill and characteristics is needed to be encouraged and add into the vehicle dynamic systems to improve the vehicle's drivability, maneuverability, and safe driving.

The rate of road crashes is also high in Africa as they cost about 2% of GDP [4]. The victims are mostly the vulnerable road users, which are pedestrians, cyclists and motorcyclists. These constitute largely young people who are in the productive brackets of the economy. Road accident has taken its toll heavily on economies and have also adversely impacted on the social lives on the continent.

For instance, National Bureau of Statistics / Federal Road Safety Corps (FRSC) road transport data report of 2020 showed that 2,080 road crashes occurred in 2020. Speed violation was reported as the major cause of road crashes in 2020 and it accounted for 47% of the total road crashes reported; wrongful overtaking followed closely as it accounted for 10% of the total road crashes recorded while dangerous overtaking recorded the least of the total road crashes reported. The report further stated that a total of 855 Nigerians got killed in the road traffic crashes recorded in 2020. Out of that number that got killed, 788 were adults representing 92% of the figure while the remaining 67 Nigerians were children representing 8%. 694 male Nigerians, representing 81% were killed in road crashes in 2020 while 161 female Nigerians, representing 19% got killed [5].

Therefore, the objective of this paper was to apply machine learning algorithms to the local data from Nigeria road domain for the driving events (braking, speeding, and safe driving) to check if it's trainable and then to compare the three algorithms in terms of performance. The primary dataset files stored in google June 2022 were collected for Nigeria driver behaviour. Image data from Google search engine for Nigeria domain were used to perform the analysis.

2. Related Works

This section reviewed the relevant works of an intelligent system done using machine learning model. The three types of machine learning algorithms are supervised learning, unsupervised learning and reinforcement learning respectively [6]. The supervised learning algorithm consist of a dependent variable which is to be predicted from a given independent variables. Using these set of variables, they generate a function that map inputs to desired outputs. Supervised Learning algorithm are Regression, Decision Tree, Random Forest, KNN, Logistic Regression etc. The unsupervised learning algorithm does not have any dependent variable to predict. It is used for clustering population in different groups, which is widely used for segmenting data in different groups for specific intervention. Unsupervised Learning algorithms are; A priori algorithm, K-means. In reinforcement learning the machine is trained to make specific decisions. The machine is exposed to an environment where it trains itself continually using trial and error. This machine learns from past experience thereby trying to capture the best possible knowledge to make accurate decisions. Example of Reinforcement Learning: Markov Decision Process.

The human perception has the capability to acquire, integrate and interpret all the many visual information around us. It is not an easy task to impact such capabilities to a machine in other to interpret the visual information embedded in the images, graphics, and video or moving images in our sensory world. It is therefore important to understand the techniques of storage, processing, transmission, recognition, and finally interpretation of such visual scenes of image process.

3. Conceptual Framework

In [7], their work was on combining big data machine learning to support eco-driving behaviour that described a prototype with the aim of optimizing the consumption of energy battery in electric vehicles, exploiting big data gathered from in-vehicle sensors and components. They employed a neural network to predict the activation of the friction brake in order to visualize this information in the human machine interface, and foster eco-driving behaviour.

In [8] the researchers developed a driving style recognition method based on vehicle trajectory data extracted from the surveillance video. They selected three rear end collision surrogates, Inversed Time to Collision, Time-Headway, and Modified Margin to Collision to evaluate the collision risk level of vehicle trajectory for each driver. In their research, they adopted I-80 trajectory dataset to study driving style. The trajectory data was collected on a segment of I-80 freeway in Emeryville, California. The segment contains 6 lanes, where lane 1 is a high occupancy vehicle (HOV) lane.

In [9] the researchers proposed a multilayer model for assessing driving risk. The proposed Dynamic Multilayer Model consists of identifying instant aggressive driving behavior that can be visited within specific time windows and calculating individual driving risk using Deep Neural Networks based classification algorithms. Validation results showed that the proposed methods are particularly effective for identifying driving aggressiveness and risk level via real dataset of 2129 drivers' driving behavior. Their research collected real driving behavior data from an OBD device and their data sets are all collected from the vehicles in Mainland China and Hong Kong. They evaluated the effectiveness of their behavior-centric driving risk level classification model by employing Support Vector Machine and Random Forest as the baseline for classifying driving risk. Their comparison results showed that DNN based classification with Trip-based driving behavior analysis (TDBA) performs better than SVM and RF in general. Their experimental results indicate that the proposed behavior centric model is an appropriate method for driving risk level classification.

In [10], the work centered on investigating how machine learning-based methods can be used to estimate driver behavior pattern, and how contextual variables affect these behavior patterns. They proposed two machine learning methods for estimating driver behaviour patterns. One approach is based on deep learning, and the other one is based on driver norms. The data they used consist of trips made on a daily basis by 1634 unique drivers from all continents of the world. The drivers provided accelerometer, gyroscope and GPS information from their smartphone. The sensor data were used to derive different driving events. Their results showed that both methods yielded similar results for data without taking contextual factors into account

In [11], the research was on Driver's behavior profiling: An investigation with different smartphone sensor and machine learning. They presented an investigation with different android smartphone sensors and classification algorithm in order to asses which sensor/method assembly enables classification with high performance. Their goal was to identify the best combination of motion sensor (and its area), learning algorithm (and its parameters), and numbers of frames in the sliding window (NF) to detect individual driving event types.

In [12] their study was on driving style recognition for intelligent vehicle control and advanced driver assistance they provided a survey on driving style characterization and recognition algorithm, with particular emphasis on machine learning approaches. They also differentiated between influencing factors and the actual input signals implemented. These inputs were understood as influencing factors that can be controlled and are chosen to characterize driving style. The researchers offered a review of recent researches and development efforts on driving style characterization and recognition as well as their application to intelligent vehicle control. Their design process was theologically followed from input signal identification and classification policy definition to the algorithm selections and implementation. They presented all driving style influencing factors and classification strategies which were presented in relationship to the targeted applications and implementation constraint.

This study [13] followed the guidelines of using machine learning methods to analyze and predict driving risk, thus laying a foundation for improving driver's behavior. They used real-word data to validate their method. They divided their raw data into two parts: Infantries data records and trajectory data. Infantry's data records such as the time, speed and distance traveling in the process of vehicle moving. The trajectory data records the time and GPS information during vehicle moving. They used GPS data to locate the vehicle trisecting in real time, which is important in calculating the turning data that cannot be calculated only when the instantaneous data is available. In their research, they used the data of vehicles' violation records as a criterion to judge the driving risk. They got 260 violation data and 359 non-violation data. They started from the driving data, and the data is preprocessed and combined to get the route data. Then from the route data, feature engineering is employed to get more features. Finally, they put the features into the classifier to build the model based on vehicles' records to check whether it violates traffic rules.

This study [14] provided a model that provides feedback to drivers by offering quantitative driving improvement instructions. They used k-means clustering to classify the safe driving level and the non-linear principal component analysis (NLPCA) model was trained by the classified low-risk data to analyze arbitrary driving data and provide feedback. To evaluate the proposed model, they collected sensor data while driving the vicinity of Daejon Metropolitan city in Korea and analyzed the principal component extracted using NLPCA. The researchers classified the collected data into low, moderate, and high-risk using K-means clustering method and labelled the collected data. They trained the NLPCA based feedback model by only using the data labelled with low risk to obtain the analysis mode for low risk which is considered safe driving.

In this research [15] they designed a personalized driver model by using a locally designed neural network and the real-world Vehicle Test Data (VTD). An abnormality index was proposed to quantitatively evaluate the abnormal driving behavior. The parameters used were speed, hard brake and hard acceleration. The researchers also explained that blood pressure and the blood alcohol level are also useful physiological signals for indicating abnormal behavior. The importance of using behavioral, psychological, environmental, and emotional factors to detect abnormal driving behavior was discussed in detail. Lack of real-time driving data was considered to be the drawbacks of VTD based system. The proposed system for personalized premium calculation explored the possibility of including emotional factors along with the behavioral factors for driving behavior detection.

4. Methodology

This section focused on the concept of an intelligent feedback model for healthy driving style using machine learning techniques. The approach was based on the sample of driver driving events activities or driving style data that was scraped from online platforms using Google search engine, and this sample was categorized with respect to their class label.

The sample of the driver physical behavioral images of driver driving style scraped from online platforms using Google search engine was restricted to Nigeria driving event settings. The driving events adopted for this research are braking, speeding and safe driving respectively. Figure 1 presents the frame work of the data flow diagram.

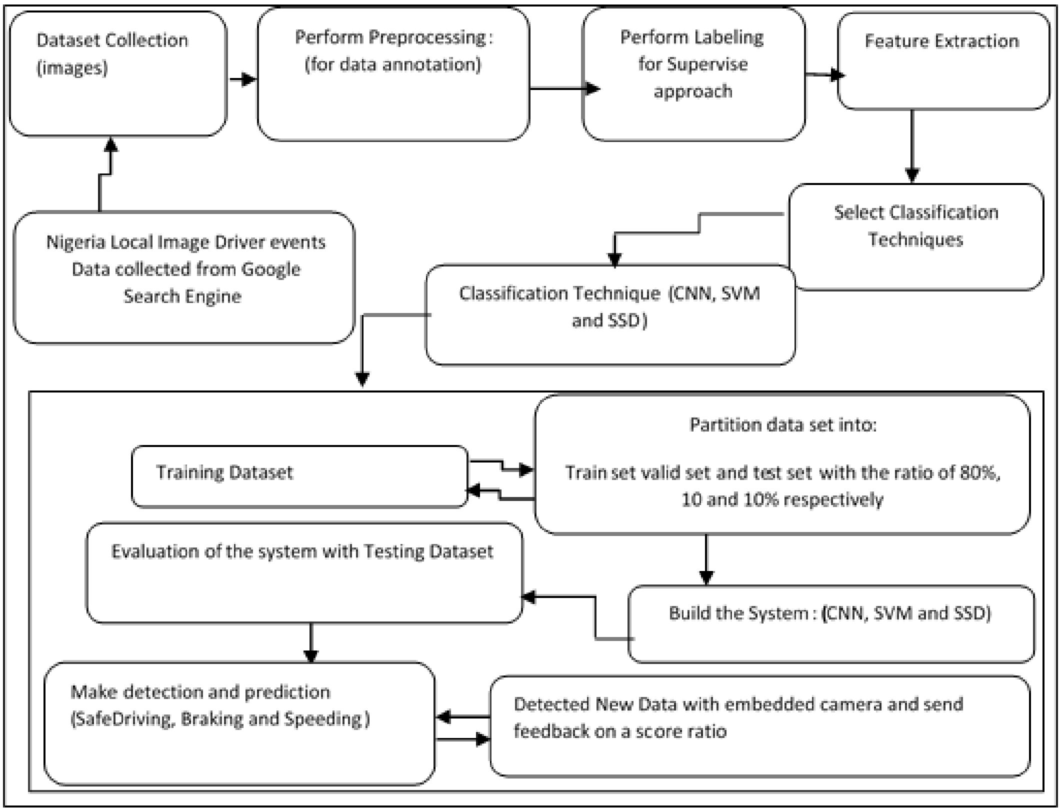

Figure 1 Working/Data flow of an intelligent feedback model

4.1. Data Source and Collection

The dataset used in this paper was scraped from online platforms using Google search engine restricted to Nigeria driving event settings and this was used for the analysis. This dataset consists of feature and instances. The feature i.e., class value has three possible values: braking, speeding and safe driving which are nothing but class labels. The dataset containing a total of 3423 instances was used in this study.

4.1.1. Experimental Set Up

The total sample data collected for this research is three thousand four hundred and twenty-three (3423). The dataset were divided into 70% for the training set and 30% for the testing set. Based on the foregoing, the total number for the training set is two thousand three hundred and ninety six (2396) and that of the testing set is one thousand and twenty seven (1027) respectively, the sample test data for braking driving event is two hundred and forty nine (249), while safe driving event has five hundred and forty four (540) and speeding driving event has two hundred and thirty four (234) for test data

4.2. Experimental Tools

All the experiments carried out are computed using open- source python library and python programming language with Jupyter notebook IDE. The Jupyter notebooks is well suited for combined software code, computational output, explanatory text, and rich content in a single document. Notebooks allow in- browser editing and execution of code and display computation results. Jupyter notebook was used to build the model.

4.2.1. Machine learning Approach

- Collect the sample data (driver driving event image)
- Pre-processing (that is the data were annotated with three labels, braking, speeding, and safe driving; and since it is a supervised learning approach, then it is a multiclass classification.
- Apply feature extraction with python scripts library (to convert the dataset into a multiclass classification analysis)
- Resizing the sample data into training set, validation set and testing set during the system implementation design.

Develop the model with python script. We used python programming language with Jupyter notebook IDE environment to implement the system and then used the proposed algorithms to develop a classification model and perform the model evaluation and report.

4.2.2. Convolutional Neural Network (CNN)

Convolutional neural networks are mainly composed of these types of layers: input layer, convolutional layer, ReLU layer, pooling layer, and fully connected layer (the fully connected layer is the same as the conventional neural network).By superimposing these layers, a complete convolutional neural network can be constructed.

In practical applications, the convolutional layer and the ReLU layer are often collectively referred to as the convolutional layer, so that the convolutional layer also passes through the activation function after the convolution operation.

Specifically, when the convolutional layer and the fully connected layer perform transformation operations on the input, not only the activation function will be used, but also many parameters, namely the weight and the deviation of the neuron; and the ReLU layer and the pooling layer perform a fixed function operation.

The parameters in the convolutional layer and the fully connected layer will be trained as the gradient drops so that the classification score calculated by the convolutional neural network can match the label of each image in the training and this was adopted in this research study. Convolutional neural network have the concepts of local receptive fields, sparse weights, and parameter sharing. These three concepts make convolutional neural networks have a certain translation and scale invariance compared with other neural networks, and are more suitable for image data learning.

Here is how a CNN system is trained

- The convolutional layer is the core layer to construct a convolutional neural network, which generates most of the calculations in the network. Note that the amount of calculation is not the number of parameters.

- The convolution operation can effectively reduce the training complexity of the network model and reduce the network connection and parameter weights, which makes it easier to train than a fully connected network of the same scale.
- Common convolution operations are as follows: ordinary convolution, transposed convolution, hole convolution and depth separable convolution.
- Activation Function is a function added to artificial neural networks to help the network learn complex patterns in data. Similar to the neuron-based model in the human brain, the activation function ultimately determines the content to be emitted to the next neuron.
- Common activation functions include: Rectified Linear Unit (ReLU), Randomized LeakyReLU (RReLU), Exponential Linear Units (ELU) and so on.
- The linear rectification function ReLU is one of the most significant unsaturated activation functions.
- The pooling layer was first seen in the LeNet article, called Subsample, and named after the publication of the AlexNet paper. It is one of the commonly used components in current convolutional neural networks

4.2.3. Support Vector Machine (SVM)

The concept is to use an SVM to classify the different domains specific challenges. Support vector machine (SVM) classifier is based on structural risk minimization. It searches for a hyperplane in an N-dimensional space that can separate the data of different classes; that is, patches with and without exudates in our case. Support vectors are points lying on the hyperplane that support the optimal classification surface. The classifier with a linear kernel function was trained using the features extracted from a Resnet-50 pre-trained on the ImageNet dataset.

4.2.4. Single Shot Multibox Detector (SSD)

This presented an object detection model employing a single deep neural network combining regional proposals and feature extraction. A set of default boxes over various aspect ratios and scales were used and applied to the feature maps. The feature maps were computed by passing an image through an image classification network; thus, the feature extraction for the bounding boxes were extracted in a very single step. Scores were generated for every object category in every of the default bounding boxes. To better fit the bottom truth boxes, adjustment offsets were calculated for every box.

Different feature maps within the convolutional network correspond with different receptive fields that were utilized to naturally handle objects at different scales. Since all the computation were enclosed in a single network, fairly high computational speeds were achieved (example, for 300 × 300 input 59 FPS). For the usage, we investigated the various sample configuration files for SSD. Several parameters were important when leveraging the SSD architecture.

The Real-time object detection and tracking on video streams is a very crucial topic of surveillance systems in field applications. The study implemented SSD with the MobileNet detection tracking method. This algorithm works well for detection and tracking. A high accuracy object detection procedure has been achieved by using the MobileNet and the SSD detector for object detection.

4.3. Pre-processing

In this step, complete geometric correction and filtering was done. The preprocessing uses the output of the classifier to take the required action to improve the performance.

5. System Design

The system was trained with the selected algorithms that can predict the output label with regards to which class it belongs. Using the labeled data, the algorithm learns the relationship between the feature sets and the output, and then classifies the categories data from the learned relationship. Shown in figure 2 is the conceptual framework of the model.

5.1. Supervised Classification

Supervised classification requires the prior information which is gathered by the analyst. The analyst must have sufficient known dataset to generate representative parameters for each class. Algorithms are used to determine decision boundaries. This process is known as training step. Once the classifier is trained, it categorizes according to the trained parameters.

The core advantage of supervised classification is that, the operator can easily detect an error and try to fix it. The disadvantage is that it becomes costly and time consuming to set a training data. Sometimes the selected training data may not represent the conditions all over the image. The analyst can commit errors in the selection of training sets

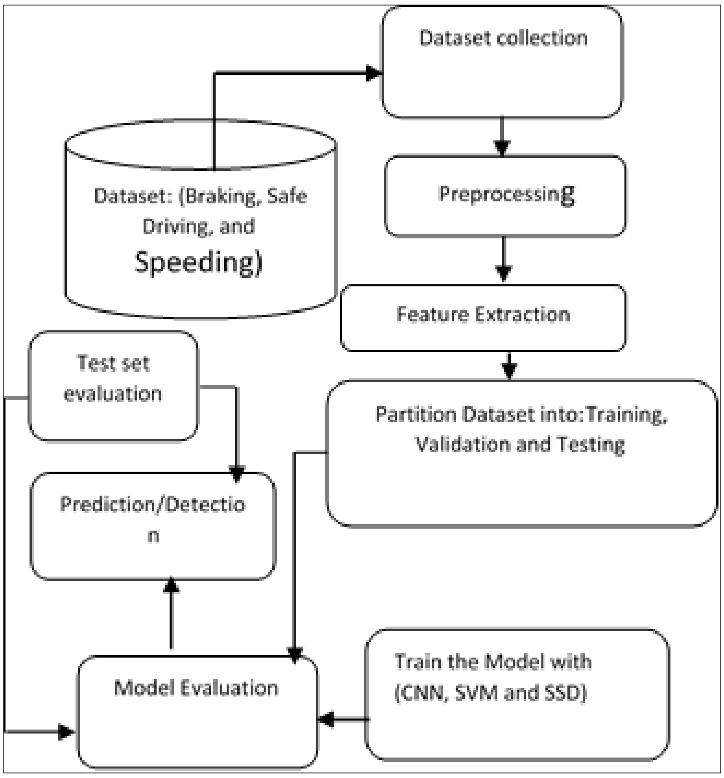

Figure 2 Overview of the Proposed System Design

5.2. Unsupervised Classification

In unsupervised classification, there is no need to have the prior knowledge of the classes. There is no interference of human as it is fully an automated process. Some clustering algorithms are used to classify an image data. The basic idea is that values within a given data type should be close enough in the measurement space. The result of the unsupervised classification is the spectral classes that are based on the natural grouping of image value.

The main advantage of unsupervised classification is time taken which is less. It minimizes the possibility of human error since there is no need of prior knowledge. The disadvantage is that sometimes the clusters in spectral region may not match to our perception of classes.

5.3. Model Implementation

This section focused on discussion and results obtained in this paper. The system was designed with three class labels which were used to predict/detect and also to analyze the driver event driving style with the proposed techniques. The evaluation was done on Jupyter notebook where the program was executed, the module provided a space for variety of activities such as sample dataset, unstructured/structure dataset, preprocessing dataset/label training set, test set, braking, safe driving and speeding label/dataset which were performed on the basis of the evaluation analysis. This model was implemented with the feature set or attributes to distinguish their performance when those factors were loaded into the python library with the use of python programming language that was used to implement this concept of object detection in driver driving event behaviour

6. Results and discussion

Experiment of classification model was done with the training set, which was used to build the model. The test set now used for detecting and predicting the result with class label as well as predicting a new class label with their respective class. The individual model results and analysis are presented hereunder.

6.1. Model evaluation of CNN.

Table 1 Results and Analysis with CNN

Class	Precision		Recall	f1-score	Support
Braking	0	0.88	1.00	0.94	274
Safe driving	1	0.96	0.95	0.96	517
Speeding	2	0.98	0.84	0.90	236

The table1 provided the classification details of CNN model with the acurracy of 99%, the loss is 0.03 %. Figure 3 and 4 are graphs of both training and loss respectively; as well as the result of confusion matrix showing the capture of image testing data set. Figure 5 show the confusion matrix for CNN.

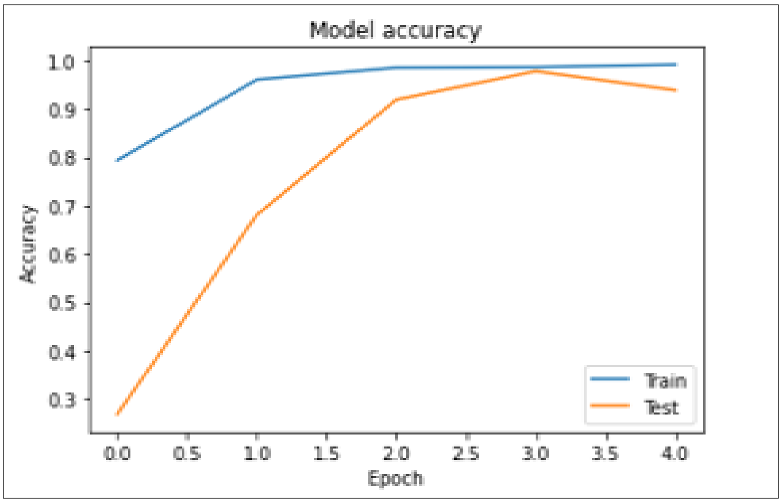

Figure 3 CNN training acurancy graph for train and test

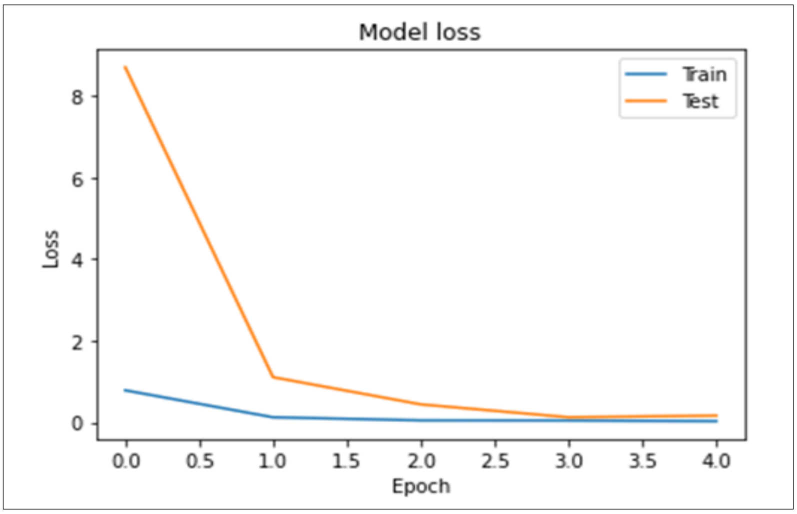

Figure 4 CNN Loss graph for train and test

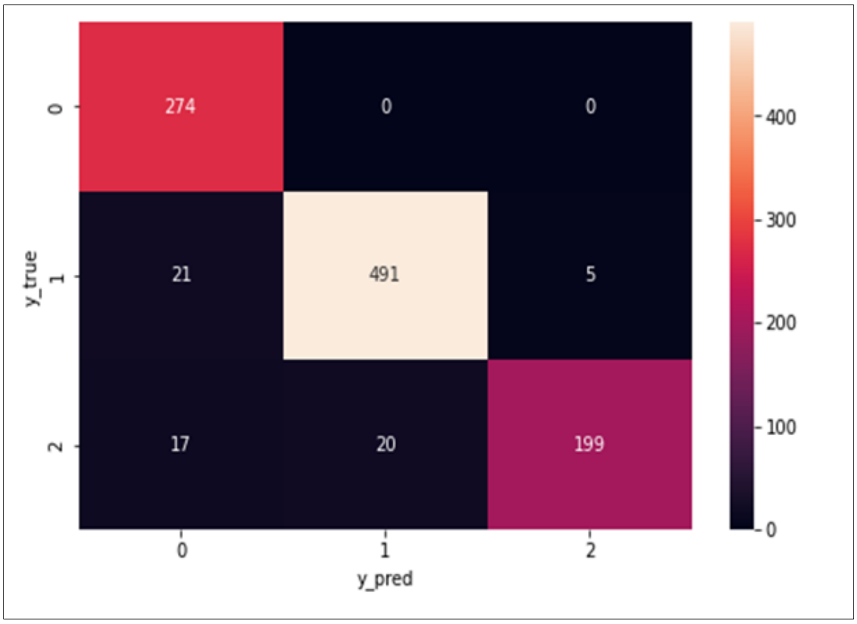

Figure 5 Confusion matrix for CNN

6.2. Classification Results for SVM

Table 2 Results and Analysis with SVM

Class	Precisson		Recall	f1-score	Support
Braking	0	1.00	1.00	1.00	249
Safedriving	1	1.00	1.00	1.00	544
Speeding	2	1.00	1.00	1.00	234

The table 2 provided the classification details of SVM model with the acurray of 100% on the evaluation of image test set; Support vector machine (SVM) classifier is based on structural risk minimization. Figure 6 presented the result of confusion matrix which captured all the details in the testing images.

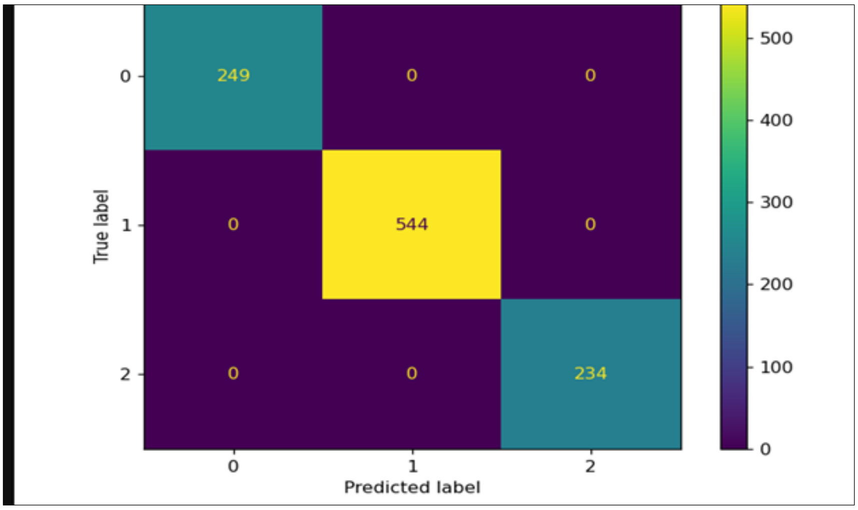

Figure 6 Confusion matrix SVM

6.3. Model Evaluation of SSD Mobilenet

Table 3 Results and Analysis with SDD

Average Precision (AP)	@[IoU=0.50:0.95	| area= all	| maxDets=100	] = **0.023**
Average Precision (AP)	@[IoU=0.50	| area= all	| maxDets=100	] = 0.091
Average Precision (AP)	@[IoU=0.75	| area= all	| maxDets=100	] = 0.003
Average Precision (AP)	@[IoU=0.50:0.95	| area= small	| maxDets=100	] = 0.000
Average Precision (AP)	@[IoU=0.50:0.95	| area=medium	| maxDets=100	] = 0.031
Average Precision (AP)	@[IoU=0.50:0.95	| area= large	| maxDets=100	] = 0.026
Average Recall (AR)	@[IoU=0.50:0.95	| area= all	| maxDets= 1	] = **0.059**
Average Recall (AR)	@[IoU=0.50:0.95	| area= all	| maxDets= 10	] = 0.267
Average Recall (AR)	@[IoU=0.50:0.95	| area= all	| maxDets=100	] = 0.386
Average Recall (AR)	@[IoU=0.50:0.95	| area= small	| maxDets=100	] = 0.000
Average Recall (AR)	@[IoU=0.50:0.95	| area=medium	| maxDets=100	] = 0.342
Average Recall (AR)	@[IoU=0.50:0.95	| area= large	| maxDets=100	] = 0.426

The table 3 presented the classification analysis of average precision and average recall respectively. The model showed the intersection over union with average precision of 0.023 or 23% with respect to 0.091 or 91%; and average recall of 0.059 or 59%. The result of elevation of the model is presented in figure 7 and 8 respectively as model training evaluation matrix and model evaluation result of SSD.

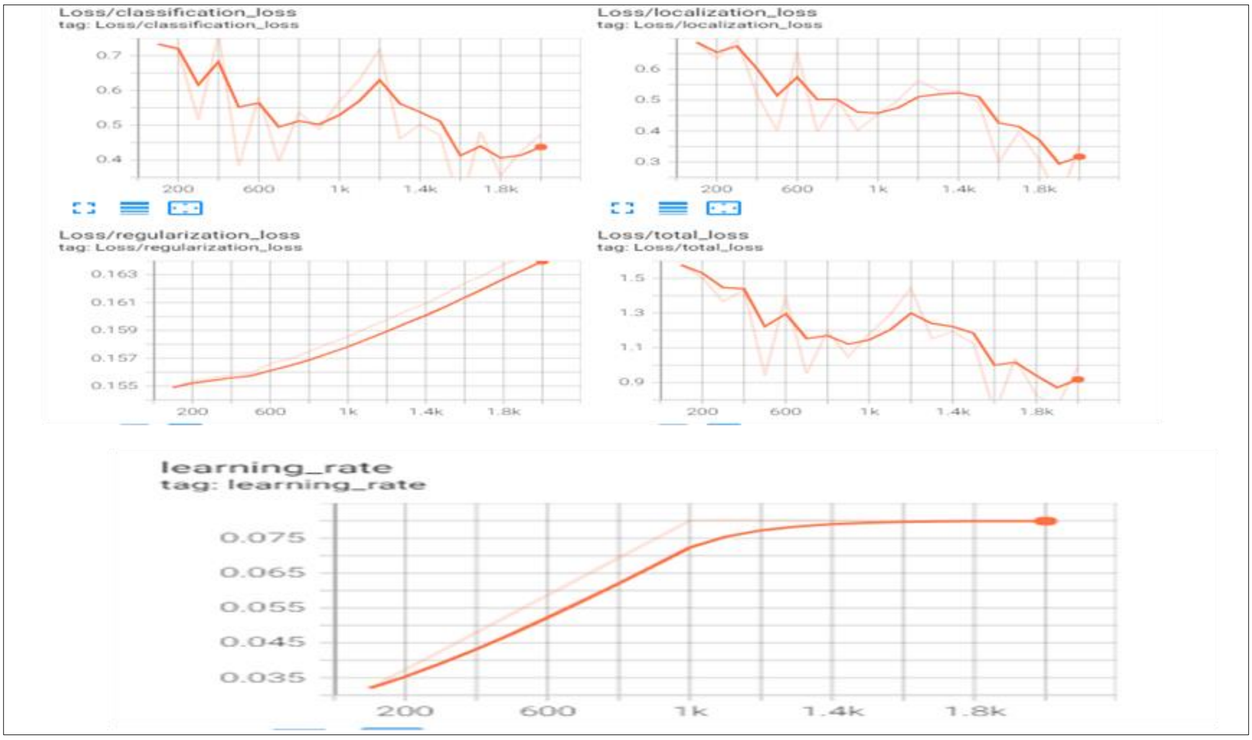

Figure 7 Model tranining evaluation metrics

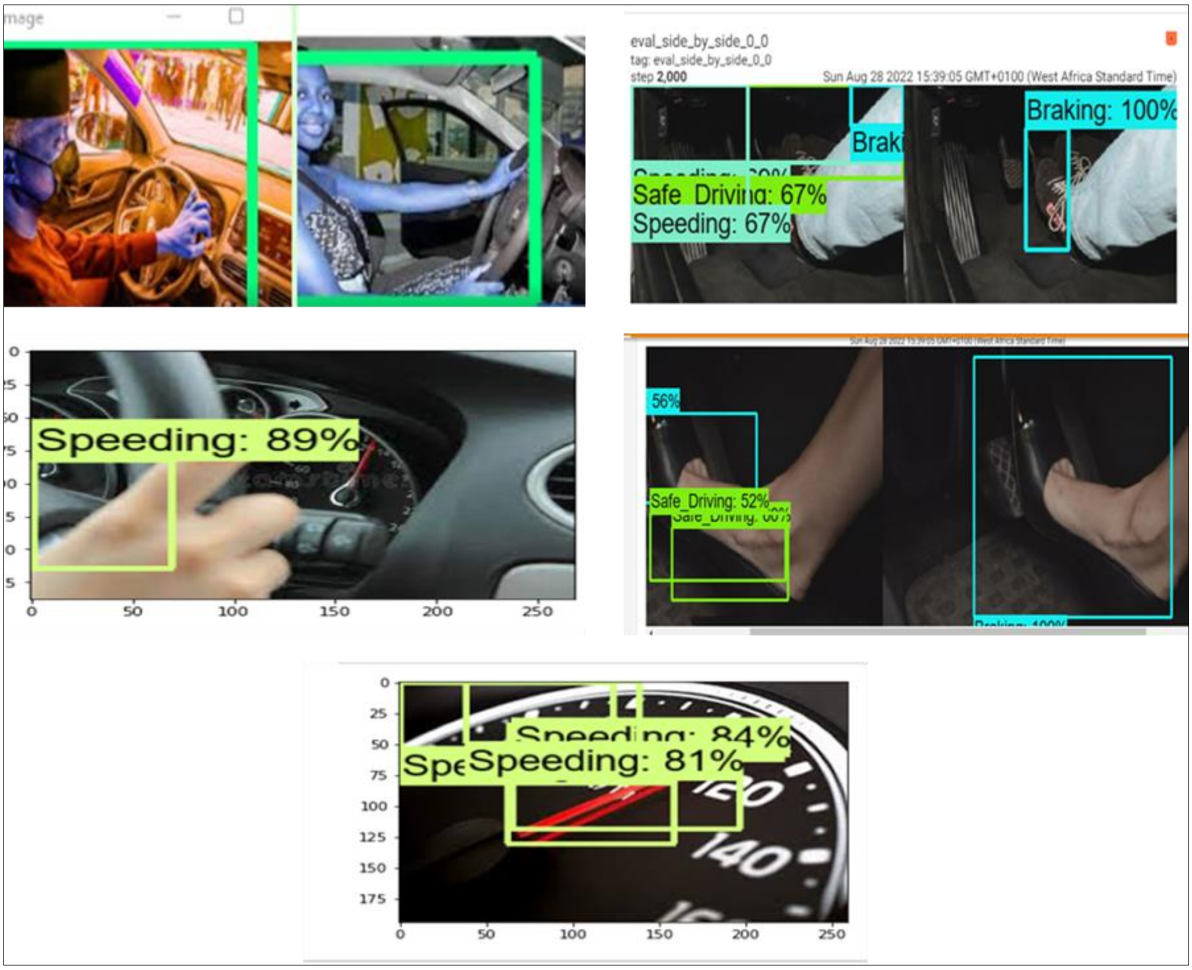

Figure 8 Model evaluation results of SSD

Table 4 Comparison Performance of the three models

Evaluation on Test data		
Model	**Support**	**Accuracy**
CNN	1027	94%
SVM	1027	100%
SSD	1027	91%

Table 4 presented the comparison performance of the three models. The work achieved the desired results in the comparison table with regard to accuracy by the algorithms with 100% in SVM, 94% in CNN and 91% SSD respectively.

7. Conclusion

Recent studies have shown that researchers have proposed various techniques for safe driving style using data collected from different parts of world. This work presented a unique set of data from Nigeria in West Africa which is now proven to be trainable with good predictions that can be adopted by researchers working on intelligent transport systems and safe driving systems in Nigeria and indeed Africa,

Compliance with ethical standards

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Disclosure of conflict of interest

All authors of this manuscript agreed and contributed significantly to the success of this research without conflict of interest.

References

[1] Mohssen M., Muhammad B., and Eihab B. (2016). Machine Learning: Algorithms and Applications. Publisher: CRC press. ISBN: 9781498705387, edition 1. DOI: 10.1201/9781315371658

[2] Liu A. and Salvucci D. (2001). "Modeling and prediction of human driver behavior," in Proceedings of the 9th International Conference on Human-Computer Interaction, New Orleans, La, USA, 2001.

[3] Martinez C. M., Mira H., Wang F., Gao B. and Dongpu C. (2018). Driving style Recognition for intelligent vehicle control and advanced driver assistance. IEEE Transactions on intelligent transportation systems, volume: 19, Issue: 3, March 2018, pp 666-676. DOI: 10.1109/TITS.2017.2706978.

[4] Olagunju K. (2018): The Implementation of the Nigeria Road Safety Strategy and Road Traffic Crashes: An Evaluation. An Individual Research Project Submitted to the National Institute for Policy and Strategic Studies, NIPSS Kuru.

[5] Olagunju K. (2018): The Implementation of the Nigeria Road Safety Strategy and Road Traffic Crashes: An Evaluation. An Individual Research Project Submitted to the National Institute for Policy and Strategic Studies, NIPSS Kuru.

[6] Mohssen M., Muhammad B., and Eihab B. (2016). Machine Learning: Algorithms and Applications. Publisher: CRC press. ISBN: 9781498705387, edition 1. DOI: 10.1201/9781315371658.

[7] Delnevo G., Lena P., Mirri S., Prandi C. and Salomoni P. (2019). On combining big data machine learning to support eco-driving behaviors. Journal of Big data. Delnevo et al. J Big Data (2019) 6:64 https://doi.org/10.1186/s40537-019-0226-zHossin, M.,

[8] Xue Q., Wang K., Jian J. and Liu Y., (2019). Rapid Driving Style Recognition In Car Following Using Machine learning and vehicle trajectory data. Hindawi Journal of Advanced Transportation Volume 2019, Article ID 9085238, 11 pages https://doi.org/10.1155/2019/9085238.

[9] Bian Y., Lee C., Wang Y. and Zhao J., (2019). A Deep Learning Based Model for Driving Risk Assessment. Proceedings of the 52nd Hawaii International Conference on System Sciences | 2019

[10] Iranzamini A. and Lindström J. (2018). Driver Behavior Profiling on Smartphone Data using Machine Learning Methods: Algorithms, Languages and Logic. Department of Electrical Engineering Chalmers University of Technology Gothenburg, Sweden 2018 Ex017/2018

[11] Jair F., Bruno F., Eduador C., and Cleidson S., (2017). Research on Drivers behavior profiling: An investigation with different smartphone sensor and machine learning. Article in PLoS ONE· April 2017. DOI: 10.1371/journal.pone.

[12] Martinez C. M., Mira H., Wang F., Gao B. and Dongpu C. (2018). Driving style.Recognition for intelligent vehicle control and advanced driver assistance. IEEE Transactions on intelligent transportation systems, volume: 19, Issue: 3, March 2018, pp 666-676. DOI: 10.1109/TITS.2017.2706978.

[13] Wang Y., Xu W., Zhang Y., Qin Y., Zhang W. and Wu X. (2017). Machine Learning Method for Driving Risk Prediction. EM GIS' 17, November 7-10, 2017, Redondo beach, CA, USA, Association for computing Machinery. ACM ISBN978-1-4503-5493-6/17/11. https://doi.org/10.1145/3152465.3152476

[14] Jeon et al. (2017). A Determinist Feedback Model For Safe driving Based On Nonlinear Principle Analysis Scheme

[15] Hu J, Xu L, He X & Meng W. (2017). Abnormal driving detection based on normalized driving behaviour. IEEE Trans Veh Technol. 2017:66(8):6645-52