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# Enhancing Road Traffic Safety in-Kenya using Artificial Neural Networks

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### 6 Abstract

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The world loses a human live in every 24 second due to Road Traffic Accidents (RTAs). In 7 Kenya approximately 3000 lives are lost annually due to RTAs. The interventions to improve 8 road traffic safety (RTS) failed because they were not informed by any scientific research. In 9 this paper we employed the multi-layer feed forward perceptron neural network model to 10 classify the road traffic safety status (RTSS) as:-excellent, fair, poor or danger states which 11 model?s output are. We considered the vehicle internal factors that contribute to RTAs as 12 model?s inputs which included:-inside-vehicle-condition, entertainment, safety-awareness, 13 passager?s (attention, criminal-history, health-history, movement inside vehicle, body posture, 14 frequency of journey, drunkenness?, drug-influence, use-of-mobile-phone and load), 15 luggage-type and the safetybelt. 16

17

18 Index terms—traffic, safety, neural-network, policy, model, MSE.

## <sup>19</sup> 1 Introduction

ccording to ((K.N.B.S), 2017) road traffic accident statistical abstracts,3000 persons die while approximately
14,000 persons are injured annually due to RTAs. The vehicles involved on RTAs are approximately 9,000. The
levels of disability caused by RTAs are on rise. Economically Kenya incurs a loss of approximately US\$50 million
annually according to (Mutune Peter Kasau, Prof. Eng. G. N. Mang'uriu, Dr.

Stephen Diang'a, 2017), due to RTAs. in all PSV's and commercial vehicles whose weight limit should not 24 25 exceed the 3,048 kilograms, speed limit of 80 kilometers per hour, fitting of seat belts on all vehicles, employment 26 of drivers and conductors on permanent basis, indication of route details and painting of a yellow band on Matatus (a passenger Vehicle) for purposes of easy identification, re-testing of drivers after every two years and 27 approval of all driver's identification by the police and also ban on night travelling. It also launched a six-month 28 Road Safety Campaign in 2003 and declared war on corruption, which contributes and indirectly to the country's 29 unacceptably high levels of RTAs. These policies failed to deliver the expected results which compelled the 30 government to resort to intermitted crackdown on the public service vehicles in an attempt to reduce the RTAs. 31 The crackdown increased the level of corruption which led to increased RTAs. The traffic act was amended to 32 introduce the safety belt and blood alcohol level laws. The aim was to enhance the safety of passengers and 33 ensure the drivers were always sober while driving. The inspection of road vehicles was also introduced. The 34 government enacted the National Transport Safety Authority (NTSA) Act in 2012. The NTSA was mandated to 35 36 ensure the safety of the roads was enhanced and managed well. This was to be achieved through registration 37 road vehicles, licensing of drivers, testing the drivers, regulating the driving schools and also conducting research 38 on road safety to provide the advice to the government on the RTS policies and also implementing of road safety policies. Under the NTSA people are still losing lives, the properties destroyed due to RTAs. This is attributed 39 to the implementations of policies which are not informed by a scientific research. 40

An accurately classification of RTSS of inside the vehicle conditions using the artificial neural network can ultimately enhance the RTS and prevent the loss of human lives. By knowing the current safety state of vehicle, the necessary precautions can then be taken in advance to prevent an occurrence of RTA. According to (Maja Urosevic,2018), the trained neural network is an expert in the category of information it has been given to analyze,

this expert can then be used to classify the RTSS of vehicle dynamically and give alerts in real time averting an 45 impending occurrence of RTA in case of poor or danger safety state of vehicle. According to (Antonio Celesti, 46

Antonino Galletta, Lorenzo Carnevale, Maria Fazio, Aime Lay-Ekuakille and Massimo Villar), Year 2 019() D 47 48 © 2019 Global Journals

Enhancing Road Traffic Safety in-Kenya using Artificial Neural Networks modern vehicles have inbuilt sensors, 49 control devices and micro-controller chips. By leveraging this emerging technologies in automobile industry 50 compounded by the artificial neural network as the expert while sensors as input devices and control devices as 51 RTS regulator, the RTA can be reduced. 52

In this study we applied a multi-layer perceptron feed-forward trained neural network with forty three selected 53 input variables to model and to classify RTSS outcomes to determine the safety state of vehicle to inform the 54 RTS vehicular policies and decisions in Kenya. The purpose of this study was to examine patterns of vehicular 55 accidents, design and develop a neural network model and evaluate the model performance on classifying RTSS. 56

#### II. $\mathbf{2}$ 57

#### Materials/Tools 3 58

Materials used in study were data, statistical programming software i.e. R, database management system i.e. 59 Oracle Database, Neural Network Framework i.e. Neuroph Studio. 60

#### a) Data Requirements 4 61

In this research data was collected from RTAs Reports from NTSA daily and fatal reports and KNBS statistical 62 abstracts. This data is readily available in websites. The categorical data was collected from experts in RTSA 63

which included:-traffic police, NTSA, drivers, St John's ambulance and the public via guided questionnaires. We 64

primarily considered the factors that contributed to RTAs as models inputs and RTS status as model's output 65

as shown in This was due to their easy to handle aspect by the riders making them ideal for busy towns to ease 66 67 traffic congestion.

#### The Neural Network Model for Enhancing Road Traffic Safety 5 68

In this research we utilized a multi-layer neural network with one hidden layer of neurons. After preprocessing 69 70 of classical data, there were 43 model inputs and 4 model outputs. The classical data was converted into binary 71 number format as shown in Table 1 in

#### **Evaluation of Neural Network Architectures** 6 72

The training data set was divided into 70% training, 15% testing and 15% validation to facilitate neural 73 network model development, experimentation and performance assessment. The results of Evaluation of various 74 75 neural network architectures are shown in Table ?? in the appendices. The best neural network architecture was Backpropagation, Momentum 0.7, Maximum error 0.01, learning rate 0.5, number of epochs 1, had 76 77 a MSE 000166. The Resilient Backpropagation and Dynamic Backpropagation were not able to learn. The overall classification accuracy for the best model was 76.0%, it had the precision of 1.0, and the recall of 78 79

#### Conclusion 7 80

In this research we employed a multi-layer feedforward neural network with backpropagation learning rule to 81 classify the Road Traffic Safety Status of Vehicle based on vehicle internal factors that contributed to RTAs. The 82 model was trained, tested, and validated using 20,000data samples compiled from categorical data collected from 83 experts in RTSA which included:traffic police, NTSA, drivers, St John's ambulance and the public via guided 84 questionnaires. Forty three input variables consist of categorical data elements including: inside-vehicle-condition, 85 entertainment, safetyawareness, passager's (attention, criminal-history, health-history, movement-inside-vehicle, 86 body-posture, frequency-of-journey, drunkenness', drug-influence, use-of-mobile-phone and load), luggage-type 87 88 and the safety-belt. These inputs and the multi-layer neural network model were used to classify road traffic 89 safety state as: excellent, fair, poor or danger state. The multilayer perceptron feed forward neural network 90 model with one hidden layer of fifteen neurons, variable learning rate of backpropagation, momentum value of 91 0.7, learning rate of 0.5 and weighted summation and sigmoid hidden activation functions achieved the best performance. 92

The Resilient Backpropagation and Dynamic Backpropagation were not able to learn. 93

Classification accuracy in most model architectures exceeded 74%. This model may be used to inform Road 94 Traffic Safety policies and decisions. Model can be adopted in emerging vehicle automation technologies such as 95

sensors, control devices, and micro controller chips as a safety measure hence saving loss of human lives on roads. 96



Figure 1:

Oracle database 11g Express Edition with RTAs Data from N.T.S.A Daily Fatal Reports

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The prefix NTSA from NTSA\_TRAFFIC\_ACCIDENT show it's a table of RTA Data uploaded into oracle

database from MS Excel Reports of NTSA Daily fatal reports





R version 3.5.1 (2018-07-02)

 $\mathbf{2}$ 





Figure 4: Fig. 3 :



vehicles involved in accidents

 $\mathbf{4}$ 

Figure 5: Fig. 4 :



Figure 6: Fig. 5 :



Figure 7: Fig. 6 :

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RTS_NET2.nnet II Total Network Error Graph II Test Results I		8
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MeanSquare Error: 7.089388282930669E-5 Confusion matrix: True False True 322 98 False 0 0		Accuracy of
Classification metrics		network
Class: True		
Total items: 420.0		
True positive: 322.0	1	
False positive:0.0		
False negative:98.0		
Accuracy (ACC): 0.7666666666666666667-		
Sensitivity or true positive rate (TPR): 0.766666666666666667		
Specificity (SPC) or true negative rate (TNR): NaN Eal-out or faire portifice rate (EDD): NaN		
False negative rate (FNR): 0.233333333333333333		
Precision or positive predictive value (PPV): 1.0		
Recall: 0.76666666666666666		
F-measure: 0.8679245283018869		
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Figure 8:

Appendices 97 **8** 98 <sup>1</sup>

 $<sup>^{1}(</sup>$ ) D © 2019 Global Journals Enhancing Road Traffic Safety in-Kenya using Artificial Neural Networks

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No	.Variable	Description	Data Type	Locati	on (	Code	
1	Inside vehicle condition	Inside vehicle condition	categorical	input	Worse 1 0 0 0 Poor Fair (	) 1 0	
					Good	L 0 D 0 0	
					Low 1	l 100	
2	Entertainment	Entertainment	categorical	input	High ( Excess high 0.0.1	)10	
3	Safety awareness	Safety awareness inside vehicle	categorical	input	Lack Few Many 1	L 0 0 ) 1 0 ) 0 1	
					Sleeping 1 0 0		
4	Passenger atten- tion	Passenger atten- tion	categorical	input	Dozing	)10	
					Alert	0 1	
		Criminal history			law breaker		1
		of					0
							0
5	Criminal history	passenger	categorical	input	ever broken law		0
							1
							0
					law abiding		0
							0
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0	Passenger nealth	Fassenger nearth	Categoricamput	Input	no nealth issue have health	issue	1
	mstory	mstory					0
							1
7	Movement inside vehicle	Movement inside vehicle	categorical	input	Minimal movement Much m	loveme	nt Excessive 1
8 9	Body posture Frequency of passenger journey	Body posture	categorical	input	Improper sitting position 1	0 Prop	er sitting 0 1

Figure 9: Table 1 :

# 8 APPENDICES

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