Development of a Safety System for Intelligent Cyclist modelling

Faheem Ahmed Malik
Mechanical and Construction Engineering
Northumbria University
Newcastle upon Tyne, UK
faheem.malik@northumbria.ac.uk

Laurent Dala
Mechanical and Construction Engineering
Northumbria University
Newcastle upon Tyne, UK
laurent.dala@northumbria.a.uk

Krishna Busawon
Mechanical and Construction Engineering
Northumbria University
Newcastle upon Tyne, UK
krishna.busawon@northumbria.ac.uk

***Abstract*— This paper is concerned with the modelling of cyclist road traffic crashes by considering multiple factors affecting the safety of cyclists. There are very few works in the literature dealing with such a problem. The available models in the literature are only based upon the probabilistic function of human error. In this study, we propose an intelligent safety system for modelling cycling infrastructure. The historic crash dataset for the Tyne and Wear County, north-east of England is used as a case study. There are five predictive road safety models develops using the Artificial Neural Network, with the output for the riskiest road type infrastructure. The study demonstrates that infrastructure, spatial variables, personal characteristics, and environmental conditions affect safety, which can also be used for predicting safety. These identified variables are modelled both individually and in combination with each other, and a plausible high accuracy is achieved in all the five models (> 85% accuracy). This demonstrates the benefit of using ANN for effective and efficient modelling of the safety variable for infrastructure design and planning. It is hoped that the proposed model can help in designing better cyclist infrastructure and contribute towards the development of a sustainable transportation system.**

Keywords*— *cycling safety, artificial neural network, infrastructure, real-time safety modelling.

I. Introduction

The cyclist account for only 2% of the trip share and 1% of the distance travelled in Great Britain. However, they account for 10%, 14.3% and 19.5% of the slight, killed or seriously injured (KSI) and fatalities respectively. Presently, the risk faced by the cyclist is 12.5 times higher compared with the car users for the same distance traversed [1]. The economic growth of 7-22 per cent in the per capita GDP over 24 years can be achieved through the reduction in the road injuries in line with the set out United Nations target [2]. Presently, in the European region, societal costs associated with a road crash vary from 0.6% to 5.8% of the GDP with a median of 1.4% [3]. Nationally the road traffic collisions cost the UK economy more than £ 35 billion per year [4].

It is imperative that cycling is made safer and an attractive mode of travel. Currently, road safety analysis is mostly performed using fatality and injury rate. The sole usage of statistics is insufficient to achieve a thorough understanding of road safety and developments over time [5], [6]. The current modelling is based upon the complex human factors believed to be directly or indirectly responsible for most of the crashes (Sabey, and Taylor, 1980, postulated that in 95% of the crashes, the human element is a main or complementary contributory factor. The same is then validated by TRL, 2011) [7]–[9]. The output of these prediction models gives prediction over a long-term with the main aim to forecast the yearly crash, their seasonal variation and identification of the major black spots. The main assumptions in these models are that instantaneous traffic flow data are a direct representation of the human factors responsible for these crashes. As the flow increase, the probability of the interaction increases, and so does the probability of a crash. All the major crash prediction models British [10], USA /Canada Model [11], Danish Model [12], Swedish Model [13], Finnish Model [14], etc. are all based on this assumption.

However, from the literature, the cyclist is found to be susceptible to the different infrastructural environmental parameters it is subjected to (see [15]–[17]). The preference and requirements of cyclists are different from other road users [18]. The present road safety theories are unable to model the special needs of the cyclist [19]. They are mostly constructed and validated for motorized travel only [20]. On the other hand, Peltola & Kulmala, 2010 [21] work on crash models led them to conclude that more complicated/detailed models are required for understanding the relationship between flow, road conditions and expected number of crashes. They recommended that, for proper estimates of the exposure and risk estimation, detailed crash safety models need to be developed. There is adequate information available in the literature [20], [22] while investigating motor vehicles. However, for vulnerable road users, there are very few exposure models which can be utilized for the investigation [21]. The main drawback with current safety models is their inability to quantify the effect of safety performance functions and evaluate how safety is affected by various underlying dynamic variables such as varying environmental, infrastructural, and personal attributes of the trip maker which vary temporally and spatially. These may not be a governing variable for the motorist, but the cyclist is susceptible to these externalities. Therefore in the present literature, it is essential to incorporate, evaluate, and model these dynamic variables. The research aims to 'develop a safety system for intelligent cycling infrastructure modelling incorporating infrastructural, environmental, personal attributes, and spatial variables'; with the following objectives:

1. Develop a framework for infrastructure safety modelling
2. Test the Hypothesis that the cyclist's infrastructure safety is dependent upon the variable infrastructure, environmental conditions, personal attributes of the rider, and the spatial variables.

3. To develop an accurate safety model with the output for the riskiest 'road type' infrastructure.

4. Identify the most important variable affecting the unsafeness of an identified group of riders.

There are several mathematical techniques explored for infrastructure safety analysis. Fuzzy logic and neural network are the two most popular techniques in artificial intelligence; considered as a proper tool for decision support and development [23]. They enable the modelling of a complex system through verbal data and the intuitive process [24]. This is essential for modelling uncertainties encountered in infrastructure planning issues.

In this work, we propose a safety system framework by using Artificial Neural Network (ANN), while as considering multiple factors affecting the safety of cyclists. We use historic crash data on a case study in Tyne and Wear County, north-east of England, shown in Figure 1.

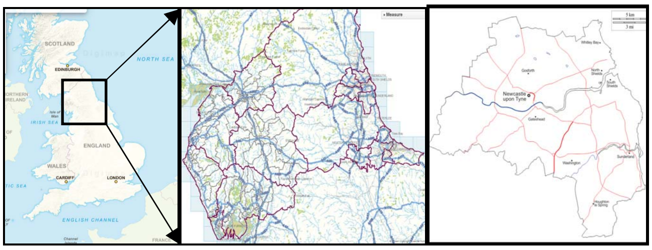

Fig 1: Location and Boundaries of the study area

It is one of the nine official regions of England, encompassing an area of 3,317 sq. miles, housing five boroughs with a population of 1.13 million. The Department for Transport (DfT) houses the database for road crashes in the United Kingdom. The police forces record the information relating to a particular crash and forward to DfT for storage. For each road traffic collision, a trained road crash investigator visits the crash site and records the crash in a document, known as "STATS 19". It consists of four sections, i). Accident Statistics, ii). Vehicle Record, iii). Casualty Record and IV). Contributory Factors. For this study, we were provided access to the crash database Traffic and Data Unit (TADU) available with the Gateshead city council. The accessed dataset includes i) Type of severity, ii) Time, date and location of the crash, iii) Environment conditions such as lighting conditions, weather, road surface condition, type of infrastructure and number of vehicles involved, iv) Sociodemographic information such as age and gender of the cyclist. The severity of the crash is categorised into i) Fatal ii) Serious and iii) Slight through DfT criterion.

In the next section, a general background on ANN is presented, followed by the proposed intelligent safety system in section III. The results and discussion are presented in section IV, and conclusion in section V.

II. Background on ANN in Transportation

The neural networks were introduced in transportation research in the 1990s. The ANN for transportation infrastructure is a multi-layer method involving traditional inputs. It is a promising mathematical approach for its modelling, as infrastructure problems have interconnectivity between the physical and tangible assets, required for developing and supporting a nation [25]. It is widely applied as a data analytic method, for modelling due to its generic nature; resulting in accurate and convenient mathematical models while simulating numerical model components [27]. This is due to its ability to work with the large multi-dimensional data, modelling flexibility, learning and generalization ability, adaptability and excellent predictive ability [27], [28]. Although there exist other algorithms and ANN is not a new concept, however, its ability to solve the complex and the interchangeable system problems, which the transportation system is characterized, is the main advantage of this technique. [25].

III. Proposed Intelligent Safety System

The following real-time modelling system is proposed (Fig 2).

A. Data Collection Unit

To investigate the safety, a holistic and correct picture of the circumstances leading to the crash needs to be investigated. In this case study application on Tyne and Wear, this is achieved through analysing and modelling the detailed collision report for each crash. As crashes are a rare phenomenon, therefore we have used the historic crash datasets.

B. Data Transmission/ Storage Unit

The data collected needs to be transmitted to the main database/server, where it can be stored safely and securely. This allows the aggregation of the data for model construction, development and regular updating. (TADU crash database for the case study)

C. Knowledge Processing Unit (KPU).

The raw data collected can only be used to get a macro picture of the area under investigation. In the Knowledge Processing Unit (KPU) model development is performed through the Artificial Neural Network. It receives details of the crash and develops a correlation between various parameters and causation based upon historic data.

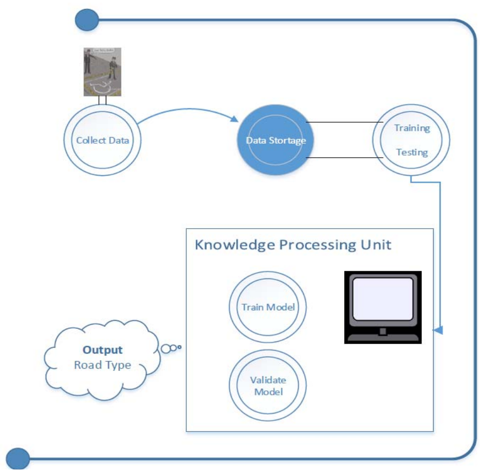

Fig 2: Proposed Safety Analysis System

A base file is constructed for the study area having detailed information regarding each crash from 2005-2018 (Table 3). Firstly, the data set is randomly divided into training (2/3) and testing (1/3). This is the recommended division from the literature (see [26]), which ensures sufficient data is provided for the network to learn properly and efficiently. This also provides enough data for a proper assessment of the trained model. To obtain the random division of the data, Bernoulli distribution is used, with the probability parameter of 0.67. The crashes modelled 1 by Bernoulli distribution are used for training, and 0 for testing.

A multilayer perceptron feedforward neural network with backpropagation error function is used to develop the predictive model. The output of the model is the riskiest road type. The output will help the planners/designers in selecting the safest road type depending upon the dynamic prevalent conditions. Also, it can be used for selecting the safest route out of the route set. From the literature (see [19], Dublin cycling route choice model), it is concluded that the cyclists select the safest route rather than use the minimum path algorithm for route selection, and their route selection can vary both spatially and temporally for the same journey. As the input variables are a random variable, therefore the riskiest road type output will also change depending upon these dynamic variables. Therefore, route X_1 can be the safest for Y_1 conditions, and route X_2 for Y_2 conditions, for the same journey between a-b. The network structure for developing the predictive model is described in Fig 3.

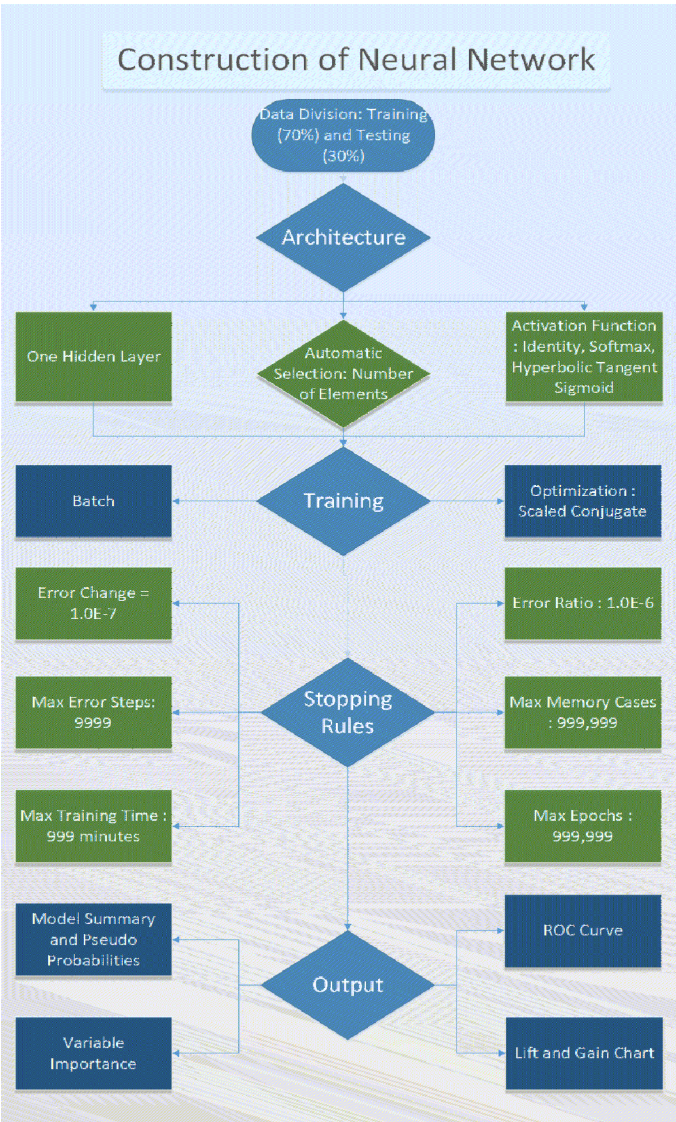

Fig 3: Methodology for Constructed Neural Network

The input variables are divided into four categories. There are five predictive models developed based upon each variable category, and a combination of all the variables.

Table 1: Input variable's for constructed road safety models

No.	Variable	Type	Values
1.	**Infrastructure**		
a).	Speed limit	Scale	20-70
b).	1st Road Class	Ordinal	A,B,C,E,U
c).	Junction Detail	Nominal	Crossroad, Mini Roundabout, Multiple Junction, Straight Road, Roundabout, Slip Road, T or Staggered, Private Drive
d).	2nd Road Class	Scale	A,B,C,E,U
e).	Junction Control	Nominal	No Control, Traffic Signal, Give way or uncontrolled, Stop sign
2.	**Spatial**		
a).	Journey Hour	Scale	0-23
b).	Number of vehicles	Scale	1-5
c).	Month of Journey	Nominal	Jan-Dec
3.	**Personal attributes**		
a).	Gender	Nominal	Male, Female and Unknown
b).	Age Group	Ordinal	0-87
c).	Purpose	Nominal	Commuting, work trip, School Journey by Pupil, taking pupil to school, other, Unknown
4.	**Environmental**		
a).	Lighting conditions	Ordinal	Daylight /Darkness- No Street Lighting, Street Lighting Unknown, Street Lights present and lit, Street Lights present but unlit,
b).	Meteorological	Ordinal	Fine/Rain/Snow-with high winds, without high winds, fog or Mist Hazard, Other.
c).	Road Surface Condition	Ordinal	Dry, Frost/ice, Wet/damp, Snow
5.	**Combined** = Infrastructure + Spatial + Personal attributes + Environmental		

After the model development, the critical input variables are identified, and their importance estimated through variable importance and normalized importance of each variable concerning the most critical variable. The independent variable importance is a measure of how much the predicted output value changes viz a viz change in the input variable. The normalized importance of each of the input variable is their respective importance value divided by the largest importance value, expressed as a percentage.

IV. Results and Discussion.

There are 3,325 bicyclist crashes recorded in the study area between 2005 and 2018. Out of this 79.3 % (2638) are slight, 19.9% (661) serious and 0.8% (26) fatal crashes. The following crash distribution is obtained for the predicted output, i.e., road type.

Table 2: Crash Distribution for different road types.

Road Type	Frequency	Cumulative Percent
Dual Carriageway	141	4.2
One-way street	62	6.1
Roundabout	224	12.8
Single Carriageway	2866	99
Slip Road	18	99.6
Unknown/unclassified	14	100

The ANN-based predictive model is constructed with the following accuracy, and importance and normalized importance (Fig 4) of the input variables are presented in Table 3.

Table 3: Variable importance in different models.

	Variable	Incorrect prediction	Importance	Normalized Importance
1.	**Infrastructure Parameters**	7.2%		
a).	Junction Detail		0.237	100.0%
b).	1st Road Class		0.232	97.9%
c).	Speed limit		0.22	93.0%
d).	2nd Road Class		0.178	75.1%
e).	Junction Control		0.133	56.1%
2.	**Spatial Variable's**	14.30%		
a).	Journey Hour		0.375	100.0%
b).	Number of vehicles		0.324	86.4%
c).	Month of Journey		0.3	80.0%
3.	**Personal attributes**	11.90%		
a).	Age Group		0.372	100.0%
b).	Purpose		0.319	85.9%
c).	Gender		0.309	83.2%
4.	**Environmental Conditions**	12.00%		
a).	Lighting conditions		0.4	100.0%
b).	Meteorological Conditions		0.318	79.6%
c).	Road Surface Condition		0.283	70.7%
5.	**Combined (1+2+3+4)**	6.70%		
i).	Junction Detail		0.117	100.0%
ii).	Age Group		0.111	94.5%
iii).	Speed limit		0.104	89.2%
iv).	Journey Hour		0.102	87.1%
v).	Month of Journey		0.087	74.3%
vi).	Lighting conditions		0.069	58.6%
vii).	Purpose		0.066	56.5%
viii).	1st Road Class		0.064	54.2%
ix).	2nd Road Class		0.061	52.1%
x).	Meteorological Conditions		0.058	49.8%
xi).	Road Surface Condition		0.057	49.0%
xii).	Number of vehicles		0.044	37.7%
xiii).	Junction Control		0.034	29.0%
xiv).	Gender		0.026	22.0%

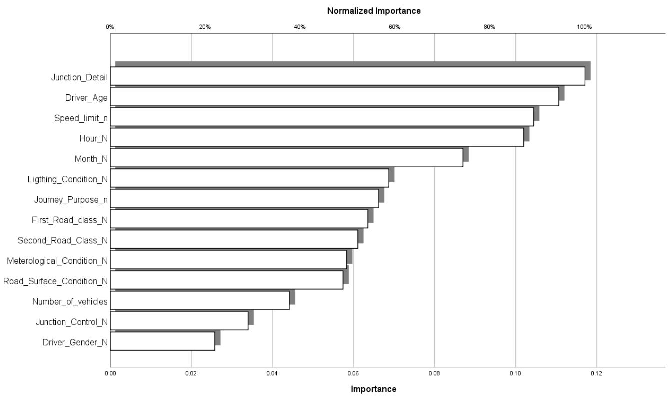

Fig 4: Normalized Importance of different variables in the 5th model concerning Junction Detail (100%).

The first predictive model, i.e., Infrastructure variable based model is developed with the highest accuracy. Therefore, this model is explained in detail. The network details of this model are presented in Table 4.

Table 4: Network Information for the First variable model.

			N	Per cent
Sample	Training		2339	70.4%
	Testing		985	29.6%
Valid			3324	100.0%
Total			3324	
Network Information				
Input Layer	Factors	1	Speed Limit	
		2	1st Road Class	
		3	Junction Detail	
		4	Junction Control	
		5	2nd Road Class	
	Number of Units		30	
Hidden Layer(s)	Number of Hidden Layers		1	
	Number of Units in Hidden Layer 1		15	
	Activation Function		Hyperbolic tangent	
Output Layer	Dependent Variables		1	Road Type
	Number of Units		6	
	Activation Function		SoftMax	
	Error Function		Cross-entropy	
Training	Cross-Entropy Error		485.446	
	Percent Incorrect Predictions		7.30%	
	Stopping Rule Used		Relative Error criterion achieved	
Testing	Percent Incorrect Predictions		7.20%	
Dependent Variable: Road Type				

The accuracy for the training and testing is approximately the 0same, therefore suggesting that the model is not overstrained. The following accuracy matrices are obtained for Training and Testing.

$$W = \begin{bmatrix} \boldsymbol{a_{D,D}} & a_{C,D} & a_{R,D} & a_{S,D} & a_{L,D} & a_{U,D} \\ a_{D,O} & \boldsymbol{a_{C,O}} & a_{R,O} & a_{S,O} & a_{L,O} & a_{U,O} \\ a_{D,R} & a_{C,R} & \boldsymbol{a_{R,R}} & a_{S,R} & a_{L,R} & a_{U,R} \\ a_{D,S} & a_{C,S} & a_{R,S} & \boldsymbol{a_{S,S}} & a_{L,S} & a_{U,S} \\ a_{D,L} & a_{C,L} & a_{R,L} & a_{S,L} & \boldsymbol{a_{L,L}} & a_{U,L} \\ a_{D,U} & a_{C,U} & a_{R,U} & a_{S,U} & a_{L,U} & \boldsymbol{a_{U,U}} \end{bmatrix}$$

where D= Dual Carriageway, O= One-way street (O), R = Roundabout, S= Single Carriageway, L = sLip Road, U = Unknown. The positive value represents the correct prediction proportions.

$$W^{Training} = \begin{bmatrix} \mathbf{0.45} & 0.00 & -0.08 & -0.47 & -0.01 & 0.00 \\ -0.04 & \mathbf{0.08} & -0.02 & -0.86 & 0.00 & 0.00 \\ 0.00 & 0.00 & \mathbf{0.94} & -0.05 & -0.01 & 0.00 \\ 0.00 & 0.00 & -0.02 & \mathbf{0.98} & 0.00 & 0.00 \\ -0.18 & 0.00 & 0.00 & 0.00 & \mathbf{0.82} & 0.00 \\ 0.00 & 0.00 & 0.00 & -0.64 & 0.00 & \mathbf{0.36} \end{bmatrix}$$

$$W^{Testing} = \begin{bmatrix} \mathbf{0.29} & 0.00 & -0.13 & -0.58 & 0.00 & 0.00 \\ 0.00 & \mathbf{0.09} & 0.00 & -0.91 & 0.00 & 0.00 \\ 0.00 & 0.00 & \mathbf{0.93} & -0.07 & 0.00 & 0.00 \\ -0.01 & 0.00 & -0.02 & \mathbf{0.97} & 0.00 & 0.00 \\ 0.00 & 0.00 & -0.57 & -0.14 & \mathbf{0.29} & 0.00 \\ 0.00 & 0.00 & 0.00 & -1.00 & 0.00 & \mathbf{0.00} \end{bmatrix}$$

The predicted pseudo probability for each of the output variable is evaluated through the boxplot (Fig 5)

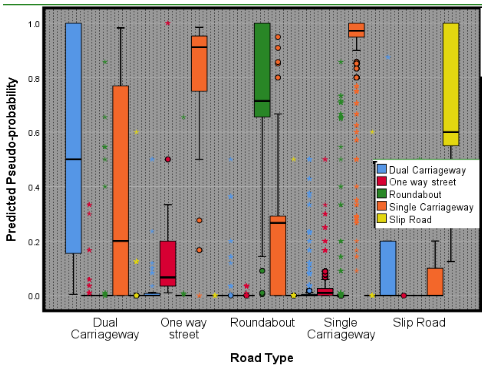

Fig 5: Predicted Pseudo-probability vs observed.

In each of the plots, values above 0.5 represent the correct probabilities for each output class. The first box plot from the left represents the predicted probability of the calculated road type to be a dual carriageway to the observed in the training dataset, whereas the second one is the predicted one-way street to the observed dual carriageway. To estimate the distinguishable power of the network for identifying the riskiest road type, Receiver Operating Characteristics (ROC) curve (Fig 6) is developed, which gives the visual display of the sensitivity and the specificity for all the possible cut-offs.

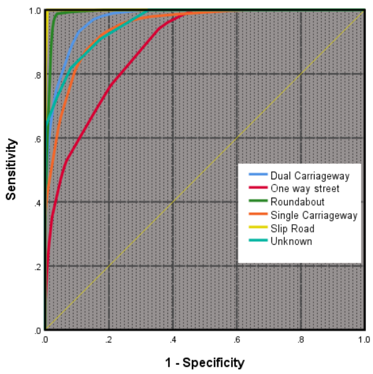

Fig 6: ROC curve for the Infrastructure variable based model.

The numerical evaluation of the ROC curve is performed through the Area under the ROC curve (AUROC); evaluation matrices utilized for checking the networks' classification performance. ROC is a probability curve, and AUROC represents the measure of the separability power of the network. The following AUROC values are obtained for the output (Table 5), which depicts a plausible high accuracy. The average and median accuracy in distinguishing between the riskiest road type and other is 0.96. This distinguishable power develops the requisite confidence in the constructed model for further use in the planning and design of the cycling transportation network.

Table 5: Area under the curve for the Infrastructure variable based model

Area Under the Curve		Area
Road Type	Dual Carriageway	.972
	One-way street	.885
	Roundabout	.992
	Single Carriageway	.945
	Slip Road	.999
	Unknown/ unclassified	.959

To undertake the benefit of the predictive model, with the simple probability-based investigation, gain and lift charts are constructed (Fig 7). In both cases, the model performance is higher than the baseline, which indicates the benefit of using ANN modelling. An average overall lift of 3 is achieved. Indicating that the model's performance is 3 times higher than the probability-based model.

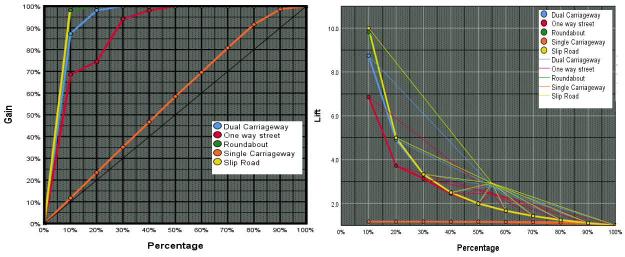

Fig 7: Gain and Lift Chart for the Infrastructure variable based model.

The independent variable importance of each of the input variable is presented in Table 6, and Fig 8. The most critical variable affecting the unsafeness of a particular road type is dependent upon the junction details, the first road class, and the speed limit. Therefore, any change in any of these can negatively affect safety. We can infer that the particular combination of the infrastructure variables affects safety differently.

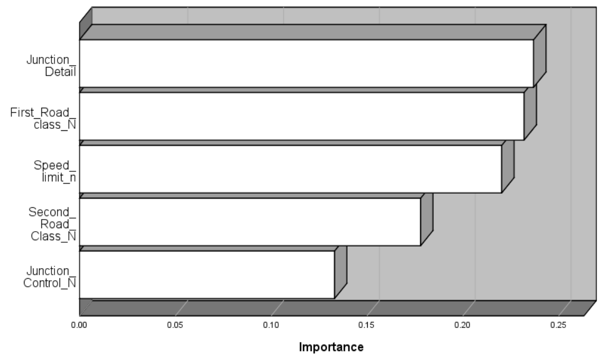

Fig 8: Independent variable Importance.

Table 6: Independent variable Importance for the Infrastructure variable based model

Independent Variable Importance		
	Importance	Normalized Importance
Junction Detail	0.237	100.0%
1st Road Class	0.232	97.9%
Speed limit	0.22	93.0%
2nd Road Class	0.178	75.1%
Junction Control	0.133	56.1%

V. CONCLUSION

In this work, we have proposed an intelligent safety system for modelling cycling infrastructure, consisting of a) Data collection unit, b) Data transmission /storage unit, and c) Knowledge processing unit. Modelling of the historic crash dataset is performed on the study area of Tyne and Wear county in north-east England. Five different predictive models are developed using a) Infrastructure, b) Spatial, c) Personal attribute of the rider, d) Environmental conditions, and e) Combination of all the variables. These models have a significantly high accuracy (> 85%), with the most accurate model being developed using the infrastructure variables.

This model is described in-depth in the paper. The model's accuracy is evaluated through the accuracy matrix; distinguishable power to distinguish between the riskiest road type, and other through the ROC curve and AUROC values. An average AUROC value of 0.96 is achieved, which establishes the requisite confidence in the model for practical application.

The infrastructure variables model has the highest accuracy of 93%. The inaccuracy of 7%, can be attributed to the dynamic nature of crashes. It is demonstrated that the unsafeness of infrastructure is dependent upon a variety of dynamic variables in the following descending order: a) Infrastructure variables (Type of Junction, Hierarchy of the road infrastructure, and speed limit), b) Personal Characteristics (Age and Journey Purpose), c) Spatial variables (Hour and Month of the travel), and d) Environmental (lighting conditions). The hour and month of travel are the representation of the traffic flow regime.

The results of the study can have a significant impact on the route choice, modelling and planning of infrastructure. The constructed model can assess with certainty regarding the type of infrastructure required to increase safety. The remedial/recommendation measures can thus be knowledge-driven. The limitation of the study is the inability to develop an understanding of the underlying mechanism in which the variables interact with each other. This is due to the black-box nature of the neural network.

Acknowledgement: We would like to thank Northumbria University for sponsoring the research (Research Development Fund) and Gateshead city council for providing access to crash data

REFERENCES

[1] Department for Transport, "National Travel Survey : England 2017," London, United Kingdom, 2018.

[2] World Bank Group, "The high toll of traffic injuries : Unacceptable and Preventable," Washington, D.C, 2017.

[3] Jackisch, J., D. Sethi, F. Mitis, T. Szyma~nski, and I. Arra, "European Facts and Global Status Report On Road Safety," p. 12, 2015, doi: 978 92 890 0297 4.

[4] Department for Transport, "Road accidents and safety statistics," 2019. [Online]. Available: https://www.gov.uk/government/collections/road-accidents-and-safety-statistics.

[5] E. Hauer and A. S. Hakkert, "Extent and some implications of incomplete accident reportingNo Title," Transp. Res. Rec., no. 1185, pp. 1–10, 1998.

[6] S. Meade and K. Stewart, "Vulnerable Road Users on Irish Roads , 2006-2012 : An Analysis of CT68 Data," in STAR Conference, Glasgow, 2015, no. May.

[7] O. M. J. Carsten, M. R. Tight, M. T. Southwell, and B. Plows, "Urban accidents: why do they happen.," Basingstoke, 1989. [Online]. Available: https://trid.trb.org/view/349471.

[8] B. Sabey and H. Taylor, "The known risk we run: The Highway," Berkshire, 1980. [Online]. Available: https://trl.co.uk/sites/default/files/SR567.pdf.

[9] N. Guthrie, G. Davies, D, and G. Gardner, "Cyclists ' assessments of road and traffic conditions : the development of a cyclability index," 2001.

[10] R. D. Connors, M. Maher, A. Wood, L. Mountain, and K. Ropkins, "Methodology for fitting and updating predictive accident models with trend," Accid. Anal. Prev., vol. 56, pp. 82–94, 2013, doi: 10.1016/j.aap.2013.03.009.

[11] AASHTO, Highway Safety Manual, 1st ed. Washington. USA: American Association of State Highway and Transportation Officials, 2010.

[12] P. Greibe, "Accident prediction models for urban roads," Accid. Prev. Prev., vol. 35, pp. 273–285, 2003.

[13] T. Jonsson, "Predictive models for accidents on urban links - A focus on vulnerable road users," Lund University, 2005.

[14] H. Peltola, "Evaluating road safety and safety effects using Empirical Bayes Method," in 4th IRTAD Conference, 2009, pp. 307–314.

[15] M. Wardman, R. Hatfield, and M. Page, "The UK national cycling strategy: Can improved facilities meet the targets?," Transp. Policy, vol. 4, no. 2, pp. 123–133, 1997, doi: 10.1016/S0967-070X(97)00011-5.

[16] D. G. Kim, Y. Lee, S. Washington, and K. Choi, "Modeling crash outcome probabilities at rural intersections: Application of hierarchical binomial logistic models," Accid. Anal. Prev., vol. 39, no. 1, pp. 125–134, 2007, doi: 10.1016/j.aap.2006.06.011.

[17] D. Delen, R. Sharda, and M. Bessonov, "Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks," Accid. Anal. Prev., vol. 38, no. 3, pp. 434–444, 2006, doi: 10.1016/j.aap.2005.06.024.

[18] J. Parkin, M. Wardman, and M. Page, "Estimation of the determinants of bicycle mode share for the journey to work using census data," Transportation (Amst)., vol. 35, no. 1, pp. 93–109, 2008, doi: 10.1007/s11116-007-9137-5.

[19] A. R. Lawson, V. Pakrashi, B. Ghosh, and W. Y. Szeto, "Perception of safety of cyclists in Dublin City," Accid. Anal. Prev., vol. 50, pp. 499–511, 2013, doi: 10.1016/j.aap.2012.05.029.

[20] A. Lawson, "An Analysis of Cycling Safety and development of a bicycle trip assignment methodology," Trinity College Dublin, 2015.

[21] H. Peltola and R. Kulmala, "Accident models," VTT, Technical Research Centre of Finland, Espoo, Finalnad (2010).H

[22] J. C. Calvey, J. P. Shackleton, M. D. Taylor, and R. Llewellyn, "Engineering condition assessment of cycling infrastructure: Cyclists' perceptions of satisfaction and comfort," Transp. Res. Part A Policy Pract., vol. 78, pp. 134–143, 2015, doi: 10.1016/j.tra.2015.04.031.

[23] O. Selvi, "Traffic Accident Predictions based upon fuzzy logic approach for safer Urban Environments, Case Study : IZMIR Metropolitan area," İzmir Institute of Technology, 2009.

[24] M. Driss, T. Saint-Gerand, A. BenSaïd, K. Benabdeli, and M. A. Hamadouche, "A fuzzy logic model for identifying spatial degrees of exposure to the risk of road accidents (Case study of the Wilaya of Mascara, Northwest of Algeria)," 2013 Int. Conf. Adv. Logist. Transp. ICALT 2013, pp. 69–74, 2013, doi: 10.1109/ICAdLT.2013.6568437.

[25] K. Gharehbaghi, "Artificial neural network for transportation infrastructure systems," MATEC Web Conf., vol. 81, 2016, doi: 10.1051/matecconf/20168105001.

[26] S. Haykin, Neural Networks, A Comprehensive Foundation, Second Edi. Pearson Education (Singapore) Pte.Ltd, 2005.

[27] M. G. Karlaftis and E. I. Vlahogianni, "Statistical methods versus neural networks in transportation research: Differences, similarities and some insights," Transp. Res. Part C Emerg. Technol., vol. 19, no. 3, pp. 387–399, 2011, doi: 10.1016/j.trc.2010.10.004.

[28] T. Pamuła, "Neural networks in transportation research-recent applications," Transp. Probl., vol. 11, no. 2, pp. 27–36, 2016, doi: 10.20858/tp.2016.11.2.3.