INTELLIGENT CYCLIST MODELLING OF PERSONAL ATTRIBUTE AND ROAD ENVIRONMENT CONDITIONS TO PREDICT THE RISKIEST ROAD INFRASTRUCTURE TYPE

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1. ABSTRACT

Infrastructure selection, design and planning play a pivotal role in creating a safe travel environment for road users, especially the vulnerable road user. In this work, it is aimed to develop a predictive intelligent safety model for the riskiest cyclist infrastructure, based upon the prevalent environment, traffic flow conditions, and specific users using the infrastructure; and also develop an understanding of how these factors affect safety alone and in combination with each other. The study area of Northumbria in the northeast of England is selected for investigation. A hybrid methodology is proposed: a) Crash data collection, b) Predictive model (deep learning), and c) Variable interaction model (deep learning variable importance and principal component analysis). A complex deep learning model with a neural network classifier, and backpropagation error function is used to model this complex and nonlinear relationship. An accurate model is developed with an average accuracy of 86%. Through variable interaction, it is found that critical variables affecting safety are the riders age, gender, environmental conditions, sudden change in the road hierarchy, and the traffic flow regime. It is found that the adverse environmental conditions and different traffic flow regimes complicate the cyclist interactions, having varied safety implications for different infrastructure types. The traffic flow regime poses a varying level of risk to the cyclist to which riders belonging to different genders react differently. The traffic flow conditions and the infrastructure variables alone are critical variables affecting the safety of cyclists. The study results help develop a better understanding of risk variation for different infrastructure types and predict the riskiest infrastructure type. It will contribute towards better planning of the cyclist infrastructure and thus contribute towards the development of a sustainable transportation system

Keywords: Cycling safety, infrastructure modelling, road type, deep learning.

2. INTRODUCTION

The creation of a comprehensive network for cycle traffic is imperative, which is both comfortable and attractive (Parkin, 2018). Cycling has begun to gain prominence in transportation policy due to its role in providing a sustainable transportation system. To set out to achieve a sustainable transport system, the share of cycling mode has to increase by several folds [2]. It will reduce the carbon footprint and enhance the liveability of the metropolises. However, safety concerns are associated with this mode (Elvik, 2009), which is the most commonly perceived barrier to its adoption (Aldred and Crosweller, 2015). The infrastructure selection, design, and planning play a pivotal role in creating a safe travel environment for road users, especially vulnerable road user. A rider's interaction with the variable road infrastructure can result in a varying level of physical and cognitive strains, negatively affecting its safety. Identifying these threats within the network provides essential insight into its preference and choice's (Lawson, 2015).

Road safety involves a complex interaction of factors and underlying phenomena, requiring an in-depth understanding and knowledge-driven measures to reduce crashes' frequency and impact. The overall frequency and severity of crashes are strongly correlated with the network area-wide infrastructure features (Noland and Oh, 2004), especially its geometric characteristics (AASHTO, 2010). These geometrics do not act independently, but rather in conjunction with other variables (Imprialou, 2015)to influence the safety of a specific road user. The index of infrastructure accessibility and cycling modal share have a positive relationship. The motorist mode shift study (Fyhri *et al.*, 2017), conducted through a questionnaire survey in Norway, concluded that the most frequently cited barrier for uptake of cycling as a mode is inadequate cycling infrastructure (46%), riders feeling unsafe (40%), bad weather (34%), and cycling being physically demanding (22%). The influence of infrastructure improvements on modal shift was modelled in a Canadian cycling commute study, which found that a 10% increase in the infrastructure accessibility index can result in a 3.7 % increase in ridership (Zahabi *et al.*, 2016). According to an individual preference study, riders are willing to switch to a longer journey with better facilities, such as better surface conditions, priority at junctions, and bespoke infrastructure (Tilahun, Levinson and Krizek, 2007). A similar route choice study Sener, Eluru and Bhat, 2009) concluded that cyclist route choice is determined by the attributes of the route as well as the demographics of the riders. Although travel time is a crucial attribute for cyclist mode choice, dynamic variables such as traffic volume, and street infrastructure characteristics are critically considered parameters.

The rider attributes; age, gender, and time of the day journey is undertaken (Bill, Rowe and Ferguson, 2015) are also critical safety variables. These personal attributes of the rider in combination with the infrastructure parameters pose a varying level of risk to the rider (see Dublin cycling model (Lawson *et al.*, 2013), London cyclist near miss study (Aldred and Goodman, 2018)), to which riders respond differently, which is evident in the choices of the journey including route selection. The Transport Research Lab (TRL) report (TRL, 2011), argued that although the cyclist's age and gender significantly affect the safe interaction of particular infrastructure, rider's personal attribute does not affect the quality evaluation of infrastructure, i.e. a poor infrastructure is rated poorly irrespective of riders age and gender. Another reported critical variables affecting the safe usage of the infrastructure are the varied environmental conditions of lighting and meteorology (Potoglou *et al.*, 2018), (Perrels *et al.*, 2015). The variable environment conditions can result in an additional variable for the cyclist to deal/ negotiate with while interacting with the infrastructure under different traffic flow regimes; thereby acting as a significant hazard. This phenomenon can be attributed to the safety law of complexity (Elvik, 2006); 'more the variables road user has to attend to; notable is the risk faced. The rain degrades the driving environment through various physical factors, through a possible loss of friction between the tyre and road, impaired visibility, and a spray of water from other vehicles (Jaroszweski and McNamara, 2014). These conditions also impact the cyclists riding comfort (Hong, Philip McArthur and Stewart, 2020), its cognitive capability (safety law of cognitive capacity), making it a potential safety hotspot. These can affect the safety variedly for a cyclist varying from one rider to another (Heinen, Maat and van Wee, 2011).

Subsequently, different micro infrastructure characteristics complicate the cyclist's interaction variedly in combination with other dynamic variables (Akgün *et al.*, 2021). The safety study on the number of lanes of different types, lane miles, and each road type's proportion (functional road types) found these variables correlated with crashes' probability (Noland, 2003). Similarly, the study in the United Kingdom (Noland and Quddus, 2004) found that increasing the length of 'B' type roads can increase serious crashes. A sudden change in road type is also essential variables affecting cycling safety, as they govern micro road geometrics such as camber, curvature, length of tangents, median width, sight distance's, and others (see (DMRB TD9/93, 1993; Highways England, 2016)). However, presently very few works have attempted to undertake such a modelling, and a more in-depth understanding of variable interaction for a cyclist is required. Therefore, the study aims to develop a predictive intelligent safety model and understand how different variables affect its safety. More precisely, the objectives are:

1. To develop a safety modelling methodological paradigm for cycling road infrastructure safety modeling.
2. To develop a predictive model, which can predict the riskiest road infrastructure type.
3. Test the hypothesis that it is possible to predict the riskiest infrastructure based on cyclist's attributes under specific environmental and traffic flow conditions
4. To develop an understanding of how different variables act alone and in combination to make a particular infrastructure type risky.

The primary motivation for the study is that there are very few works that have attempted to undertake such modelling. Presently, such a model is absent to predict the micro infrastructure parameter for a cyclist infrastructure. This limitation has negatively affected the planning and design of cycling networks. Such limitations need to be addressed to improve the design and planning of infrastructure. Most of the available studies in literature only report the variables without mathematically modelling or validating them. Through such modelling, requisite confidence for policy implications and knowledge-driven recommendation measures can be achieved. This study will improve the understanding of how different input parameters of different traffic flow regimes, environmental conditions, and rider personal attribute affect the safe usage of a particular infrastructure type. This paper is organised as follows: investigation area is defined in section 3, section 4 proposed hybrid methodological paradigm is described, section 5 results and discussion are presented, and the conclusions drawn in section 6.

3. INVESTIGATION AREA

The model development, can only be performed through an application on an investigation area. The Northumbria county in north-east of England is used for this purpose. It is composed of five boroughs; Gateshead, Newcastle–upon-Tyne, North Tyneside, South Tyneside, and Sunderland, containing thirteen urban and three rural districts with a population of 1.13 million, and an area of 210 sq. miles. The crash records for cyclists in the study area is held in the form of STATS19 forms, housed by the Traffic and Data Unit (TADU). The access to TADU was provided by Gateshead city council. Each crash is investigated in detail, including: I the time, date, and location of the collision; ii) the severity of the collision; iii) environmental conditions such as lighting, weather, road surface condition, type of infrastructure, and the number of vehicles involved; and iv) sociodemographic information such as the cyclist's age and gender.

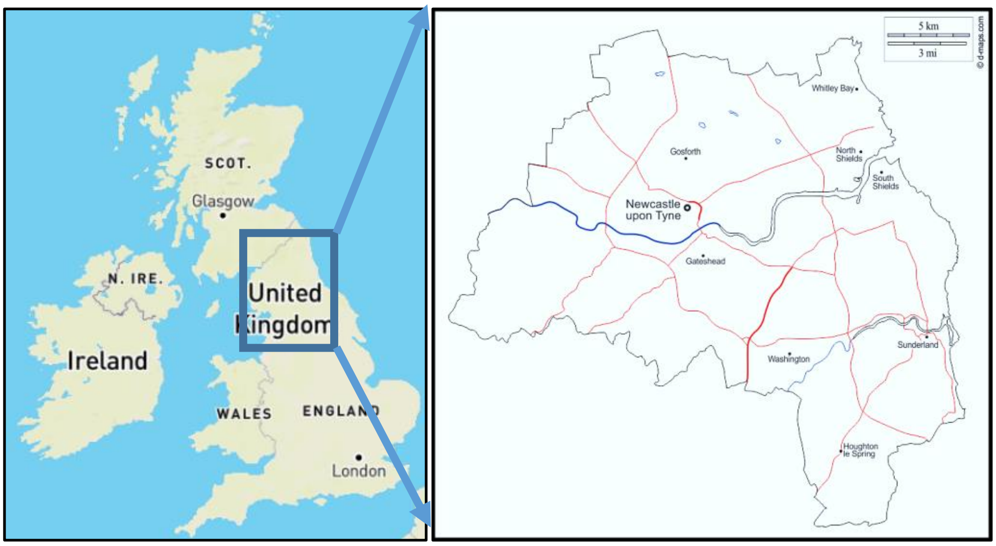

Fig. 1. Location and Boundaries of the study area Source: Traffic and Data Unit.

4. PROPOSED HYBRID METHODOLOGY

A hybrid intelligent methodology is proposed, illustrated in Fig 2. To begin, details of each crash in the study area from 2005 to 2014 are documented (TADU). Following data cleaning, a base input crash file is created. This serves as an input for the predictive models. Then, exploratory data analysis is used to determine the governing variables and their impact on safety.

4.1. Data learning predictive models

Deep learning is a data-driven, robust flexible computational method that captures and simulates nonlinear and complex underlying relations with high accuracy. A base crash input file is developed for the investigation area, and input data is randomly divided into training, validation and testing in the division of : 65:30:5. The Bernoulli distribution is used for random division. The constructued predictive model's output predicts the riskiest road type.

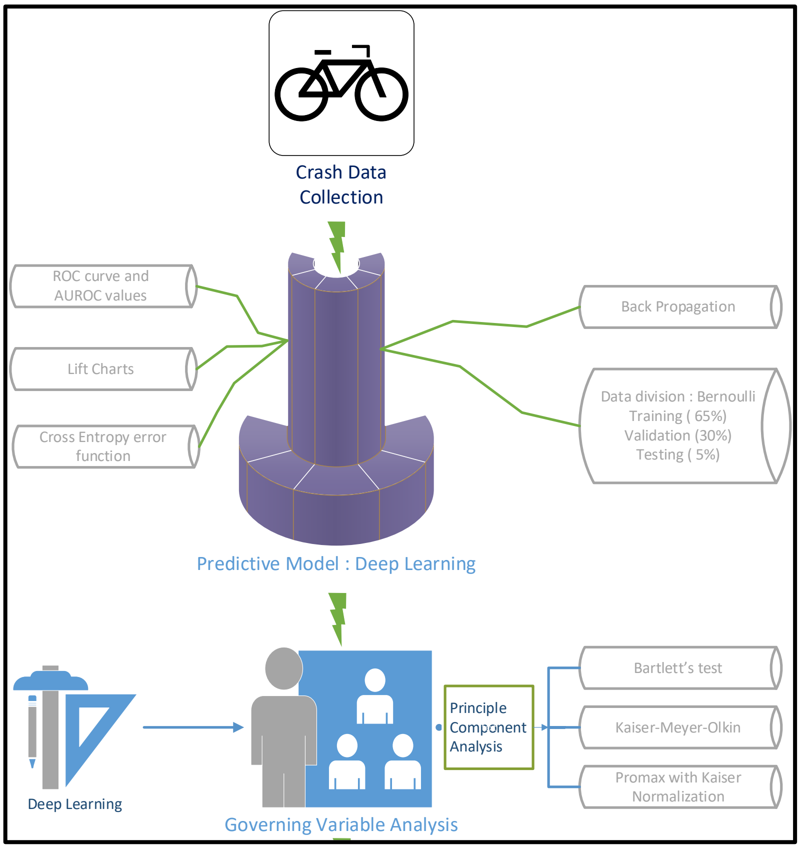

Fig. 2. Hybrid intelligent framework for safety analysis.

Deep learning trains itself on the training data to map the input with the output through weighted connections between different layers, similar to the normal functioning of a neuron in the human brain. The signal is transmitted within the network through the activation function, which is identical to the signal transmission between two brain neurons in the synaptic cleft (Fig 3.). Initially, random weights are assigned between the input and hidden, between hidden layers, and hidden and output layer. As weights are randomly assigned, an expected error is modelled using the cross-entropy (*C*) error function. The initial weights (*w*) are then updated based upon this error through the backpropagation algorithm (eq 1). The weighted connection w_{hi} (eq 2 and eq 3) is updated in every new training epoch by adding it to the previously updated weight. This process is iterated using scaled conjugate gradient optimisation (eq 4-9).

$$C = -\sum_{i=1}^{k} t_i \ln E_i \qquad (1)$$

$$\Delta\, w_{hi} = -\mu \frac{\partial C}{\partial w_{hi}} \qquad (2)$$

$$\Delta\, w_{hi+1} = w_{hi} + \Delta\, w_{hi} \qquad (3)$$

where E_i is the actual output value of the output node$i$, t_i is the largest value i, and k is the number of output nodes, and μ is the learning rate.

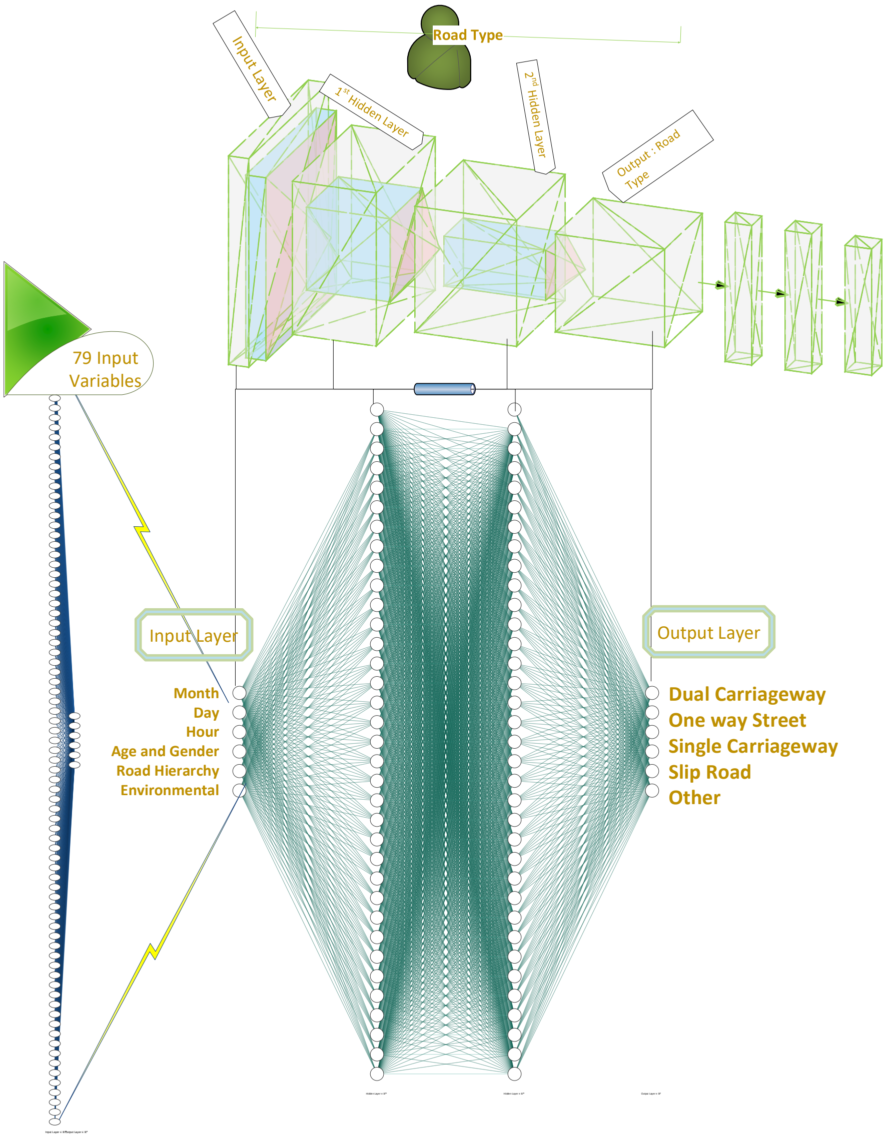

Fig.3. Framework for the development of predictive models

Iteration (scaled conjugate gradient): Weights are updated iteratively until either the minimum change in training error or the maximum number of these iterations (epochs) are reached.

$$d_0 = r_0 = b - Ax_o \tag{4}$$

$$\alpha_i = \frac{{r_i}^T r_i}{{d_i}^T A d_i} \tag{5}$$

$$x_{i+1} = x_i + \alpha_i d_i \tag{6}$$

$$r_{i+1} = r_i - \alpha_i A d_i \tag{7}$$

$$\beta_{i+1} = \frac{{r_{i+1}}^T r_{i+1}}{{r_i}^T r_i} \tag{8}$$

$$d_{i+1} = r_{i+1} + \beta_{i+1} d_i \tag{9}$$

where a, and b are constants.

The performance of the model is assessed through the receiver operating characteristic (ROC) curve, and its efficiency is measured by gain and lift charts compared to the probability-based model. To measure the models' separability power, the area under the receiver operating characteristic curve (AUROC) curve is used, an evaluation matrices, to check network classification performance. The critical variables that affect cyclists' safe use of infrastructure are identified through literature review and fed as input variable in the data learning model. The input and the output of the predicted model are tabulated in Table 1. The cyclist flow in terms of trips is not used as an input variable since the goal is to develop the nanoscopic model for cyclists rather than for overall generalised infrastructure usage at a city or county level.

Table 1. Input and output variables of the constructed predictive model

	Input	Output
Riskiest road type predictive model	Month	Dual Carriageway
	Day	One way street
	Hour	Roundabout
	Road Hierarchy level and direction	Single Carriageway
	Age and Gender	Slip Road
	Environment Light Road surface condition	n/a

Given the extremely nonlinear and intricate interaction between the input and output variables (Elvik, 2009), two hidden layers are utilised. The batch training, cross-entropy error function, and scaled conjugate gradient optimisation are used. Table 2 illustrates the network structure explicitly.

Table 2. The network structure of the constructed predictive model

Network Information		
Input Layer	Number of Units	79
Hidden Layer(s)	Number of Hidden Layers	2
	Number of Units in Hidden Layer 1	35
	Number of Units in Hidden Layer 2	35
	Activation Function: Hyperbolic tangent	
Output Layer	Dependent Variables	Road Type
	Number of Units	6
	Activation Function : Softmax	
Error Function	Cross Entropy Error	637.6
Training	Type	Batch
	Optimisation	Scaled conjugate gradient
	Initial lambda, sigma, and offset	1.0 E – 10
	Initial Centre	0
Stopping and	Maximum iterations without an error change	9.9 E 5
	Maximum training epochs	9.9 E 5

Memory Criterion	Minimum change in the training error (relative)	1.0E – 6
	Minimum change in the training error ratio (relative)	1.0E – 6

B. Variable interaction model

Firstly, in the variable interaction model, the importance of each input variable in the data-learning model is identified through variable importance. This is measured by measuring how the predicted output value changes viz a viz change in the input variable and then calculating each variable's normalised importance in relation to the most critical governing variable, expressed as a percentage. The second is the use of exploratory data processing, i.e., the principal component analysis (PCA). The input variables are clustered together, and a value curve determines the number of classes. The factor classes having eigenvalues greater than one are selected since they can explain significant variation in the variance. A matrix of correlations is constructed to verify the relationship between the variables, and for further study, the corresponding variables at a 95% confidence interval are used. Crashes are a multi-factor occurrence, and input variables are thought to be associated (tested by KMO) such that the use of the Promax oblique rotation with Kaiser normalisation is prompted. The rotation maximises the loading of each vector on one of the derived variables while minimising the load on all other factors. The PCA is based on two hypotheses (a) that multicollinearity does not exist and (b) correlations exist within the input variables. For testing multicollinearity, the determinant of the correlation matrix is used (to be > 00001). The sampling adequacy (eq 10) and the sphericity test Bartlet (eq. 11) is used to degust the association (shall > 0.5) by Kaiser-Meyer-Olkin (KMO).

$$KMO = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} a_{ij}^2} \tag{10}$$

$$\chi^2 = \frac{(N-k)\ln V_a^2 - \sum_{i=1}^{k}(n_i-1)\ln V_i^2}{1+\frac{1}{3(k-1)}(\sum_{i=1}^{k}\left(\frac{1}{n_i-1}\right)-\frac{1}{N-k})} \tag{11}$$

where, r_{ij} is the correlation matrix, and $a_{ij}$is the partial covariance matrix, k is the number of samples with a sample size $n_i$and sample variance V_i^2, $N = \sum_{i=1}^{k} n_i$, and $V_a^2 = \frac{1}{N-k}\sum_i (n_i-1)\,V_i^2$, i.e. the pooled estimate of the variance.

5. RESULTS AND DISCUSSION

There are 3,325 bicyclist crashes recorded in the study area from 2005 to 2018; 79.3 % slight, 19.9% serious and 0.8% fatal crashes. In the first section, the predictive model is described, followed by the governing variable model, including exploratory data analysis.

5.1. Predictive models

The predictive road infrastructure model is developed, with its characteristics described through ROC curves (Fig. 4). The curves are towards the top left-hand corner for each output variable, depicting a significantly high accuracy. To numerically quantifying the distinguishable power of the models, between riskiest and non-risky infrastructure type, AUROC values are presented in Table 3. Significantly high accuracy is achieved for all the output variables with an average and median accuracy of 86% and 88%, respectively. Thereby validates the hypothesis that it is possible to predict the riskiest infrastructure based on a particular cyclist's specific input variable under the specific environmental and traffic flow conditions. It is well established in the literature that the present safety models cannot be used to model cyclist infrastructure due to their inability to model their safety accurately (Calvey *et al.*, 2015; Lawson, 2015). To validate the use of a complex computational methodology, such as deep learning compared with the simple probability-based model, a lift chart for the model is developed. The lift achieved in model is 5-9 times is significantly high, implying that the model can better undertake prediction five to nine times higher than the probability-based model.

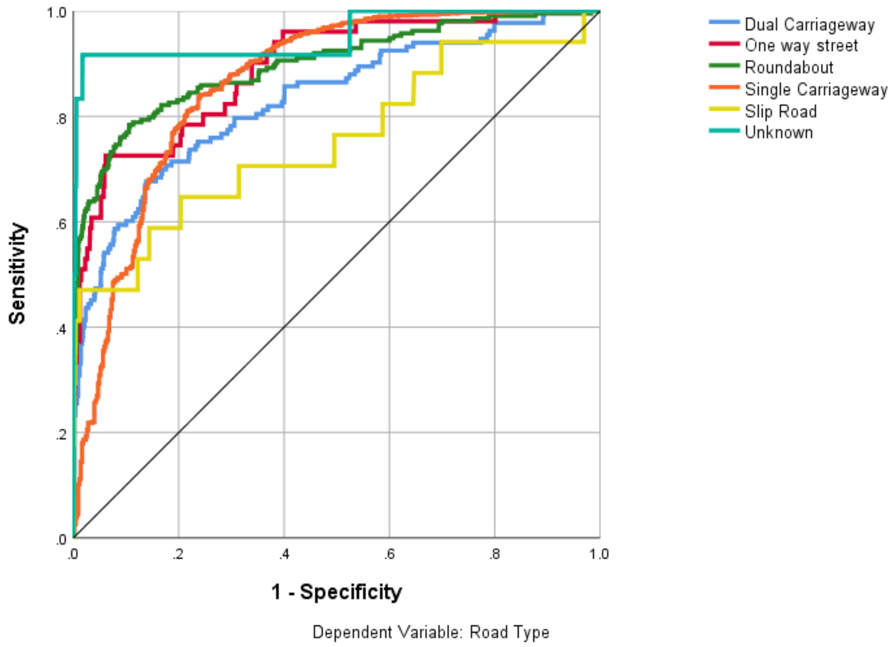

Fig. 4. ROC curve for the constructed model predictive model.

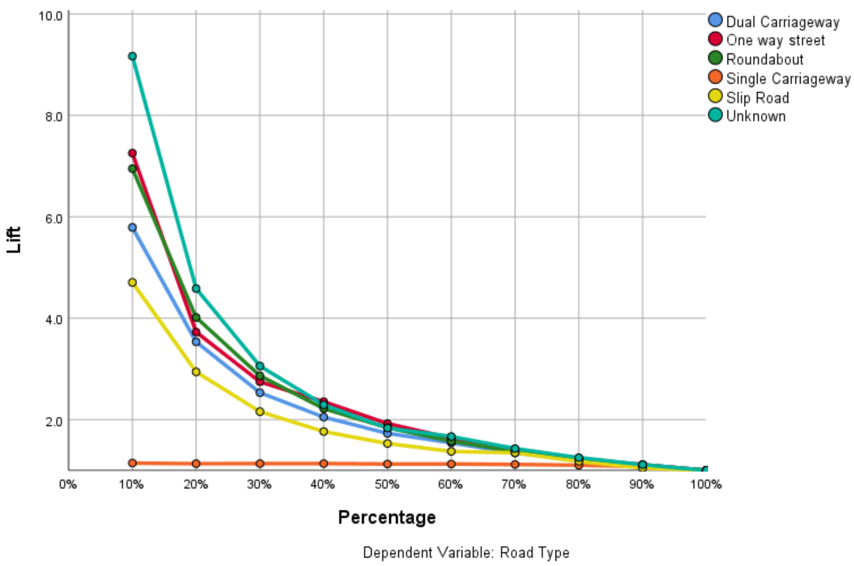

Fig. 5. Lift chart for the constructed predictive model.

Table 3. AUROC values for the constructed predictive model

Riskiest road type predictive model		
Output variable	Road Type	AUROC
	Dual Carriageway	0.83
	One way street	0.89
	Roundabout	0.9
	Single Carriageway	0.86
	Slip Road	0.75
	Other	0.95
	Mean	0.86
	Median	0.88

4.2. Governing Variable analysis

The critical variable identification from the input of the deep learning model is presented in Table 4. The critical variables affecting the riskiest road type are the environmental conditions, the hour of journey and the difference in the functional road hierarchy level. The environmental conditions have a varied effect on safety; however, their impact on safety varies depending upon the infrastructure parameters. The adverse environment complicates the interactions that a cyclist performs, compounded by the different road infrastructure types. Similarly, the hour of the journey, a representation of the traffic flow regime during the journey's entire trip, and a sudden change in the road hierarchy affect the safe interaction and have a varied effect on safety. As the number of variables that the cyclist has to adhere to increases, the interactions get complicated, negatively affecting different infrastructure types. However, the motorist benefits from a closed and secure machine at their disposal, contrary to the cyclist. The micro infrastructure parameters are designed as per the motorists' requirements (see (DMRB TD9/93, 1993; DMRB TD 42/95, 1995)). Therefore, infrastructure poses a unique risk to the cyclist, which gets compounded as the interaction with infrastructure and motorists is perplexed. There is a need for the planning and design to move toward a cyclist centric approach rather than the present motorists focussed

Table 4. AUROC values for the constructed predictive model

Variables	Imp.	Normalized Imp.
Month	0.14	72%
Day	0.13	65%
Hour	0.18	91%
Age and Gender	0.16	82%
Road Hierarchy level and direction	0.18	90%
Env. (Light and Road surface condition)	0.20	100%

The principal component analysis with orthogonal rotation (Promax with Kaiser normalisation) is used to determine the combined influence of safety variables. The determinant value is 0.87 >> 0.00001. As a result, the multicollinearity assumption is met. The Kaiser-Meyer-Olkin verifies the sampling adequacy for analysis, KMO value = 0.51, which is acceptable for PCA analysis. There needs to be some correlation between the variables, and if R is an identity, then the correlation within the variables will be equal to zero. The assumption is verified using Bartlett's test's, with the null hypothesis that the correlation matrix is an identity matrix; B = 566, df = 28, and $p < 0.0001$. Therefore, both the assumptions of the PCA are met.

The initial analysis is performed on eigenvalues for each variable in the data. Five factors have eigenvalues greater than Kaiser criteria of one, and in combination, explain 63 % of the variance. The variables from clusters on the same factors suggest that factor 1 represents environment, factor 2 mixed variable, factor 3 infrastructural, factor 4 represents gender and month, and factor 5 represents the traffic flow conditions. The statistically significant variables at 99.9% confidence interval are determined through the pattern matrix in Table 5 for each factor.

Table 5. Pattern matrix

	1	2	3	4	5
Rider age	-.694				
Road Type	.678				
Environment Condition		.775			
Hour of journey	.311	-.751			
Junction Detail and Control			.803		
Sudden change in road hierarchy	.343		-.708		
Gender				.742	
Month				.677	
Day					.953

The environmental conditions and hour of the journey are associated together in the first factor. Therefore, the riskiest environmental conditions get compounded by the plying traffic flow regime and act as a significant hazard for the cyclist to deal with. Factor two is characterised by rider age, road type and a sudden change in road hierarchy. Thereby suggests that infrastructure variables and rider age act combined to make a particular situation risky for cyclists. We can deduce that infrastructure variables pose a varying risk to which the riders belonging to different age groups react differently through inverse analysis. The third component is a combination of the infrastructure variables, inferring that the infrastructure variables alone significantly affect the safety of the cyclists. The fourth component has variables of gender and month. Therefore, the traffic flow regime poses a varying risk to the cyclist to which riders belonging to different genders react differently, affecting their infrastructure's safe usage. The final component is comprised of a single variable, the day of the journey. This being a single variable in the component, therefore explains a higher proportion for the variance, leading us to conclude that traffic flow conditions are alone significant variable affecting the safety of the cyclist.

6. CONCLUSION

The selection, construction, and planning of infrastructure are critical in creating a safe travel environment for road users, particularly vulnerable road users. Increasing cycling safety is a critical step in developing intelligent and efficient transportation infrastructure. This paper developed an intelligent hybrid modelling paradigm for predicting the riskiest road type, estimating each input variable's effect, and evaluating the combined effect of the safety variables for a cyclist in its natural road environment. The study area of Northumbria in the northeast of England is selected for investigation. The methodological framework combines a) Crash data collection, b) Predictive model (deep learning), and c) Variable interaction model (deep learning variable importance and principal component analysis).

An accurate predictive model is developed with an average and median accuracy of 86% and 88%, respectively. The understanding of the personal attributes, spatial, temporal, personal, and environmental variables, and how they affect the safe usage of the infrastructure is developed. It is found that the critical variables affecting the riskiest road type are the environmental conditions, the hour of journey and the difference in the functional road hierarchy level. The adverse environment complicates the interactions that a cyclist performs, compounded by the different road infrastructure types. Similarly, the hour of the journey, a representation of the traffic flow regime during the journey's entire trip, and a sudden change in the road hierarchy affect the safe interaction and have a varied effect on safety. As the number of variables that the cyclist has to adhere to increases, the interactions get complicated, negatively affecting different infrastructure types. The infrastructure variables and rider age act combined to make a particular situation risky for cyclists. The riskiest environmental conditions get compounded by the plying traffic flow regime and act as a significant hazard for the cyclist to deal with.

The efficacy of an intelligent hybrid paradigm is demonstrated by its application, which resulted in an accurate model and investigation of valuable insights on fault manoeuvres. This knowledge-driven approach can be used to develop V-V (motorists - cyclists) interaction algorithms and plan and design cycling infrastructure. The widespread usage of navigation systems has paved the way for intensive use of technology in the daily travel, augmented by possible car and infrastructure automation. As a result, the potential of real-time intelligent route choice modelling for a bicycle, choosing the safest route for a given journey for a specific cyclist, is now being explored.

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