European Transport \ Trasporti Europei (2021) Issue 85, Paper n° 8, ISSN 1825-3997

https://doi.org/10.48295/ET.2021.85.8

Capacity of deep learning algorithms on modelling pedestrian behaviour at crossings with countdown signal timer installations

Aristomenis Kopsacheilis*, Marios Fourkiotis, Chrysanthi Kazaklari, Ioannis Politis

Transport Engineering Laboratory, Department of Civil Engineering Aristotle University of Thessaloniki, Thessaloniki, GR-54124, Greece

Abstract

This paper attempts to investigate the capacity of different techniques in the modelling of pedestrian crossing behaviour in an urban signalised intersection with a Countdown Signal Timer (CST). Initially, two (2) models were used for the estimation of the average pedestrian crossing speed. The first model was a Linear Regression (LR) model, while the second one was a Deep Learning (DL) model. The R^2 value of 0.56 for the DL model indicated a significant improvement in performance, in contradiction to the R^2 of 0.22 for the LR model. Afterwards two (2) more models were exploited for the classification of pedestrians in terms of their crossing behaviour. At first, a Multinomial Logistic Regression (MLR) model was used as baseline, achieving an overall accuracy of 98.2%. A DL was then fit, which reached an accuracy of 99.6% and managed a better classification for the minority classes compared to the base model.

Keywords: pedestrians; countdown signal timer; crossing behaviour; artificial neural network; machine learning; road safety.

1. Introduction

The continuous development of technology over the years tends to fundamentally change modern people's reality. Nowadays smart cities, where technology has a vital role, are becoming not only a priority but also a necessity. The core of all societies are their citizens, who constitute the cornerstone around which all decisions are taken and every infrastructure is designed and organized in order to improve the provided quality of life.

A significant factor that affects the quality of life, is the sustainability of transportation systems and the conditions that exist in the different modes of transport, in terms of safety, comfort, reliability, security etc. The increased frequency of cases associated with problematic operation of the transport system in urban areas, has led researchers and policy makers in the search for ways to make transport systems more sustainable. More to the point, practitioners have investigated traffic congestion under a plethora of different

* Corresponding author: Aristomenis Kopsacheilis (kopsacheilis@civil.auth.gr)

conditions, the operation of the public transport system (e.g. quality of service, mode's occupancy according to its capacity, etc.), road accidents due to their alerting increase, and all the characteristics that form a transport system in general. In their effort, a variety of technological tools have been applied, in order to address the problems at hand in the most efficient way.

In particular, many studies have been carried out in the transportation domain based on innovative techniques and state-of-the-art methods. Lately, advances in the processing capacity of computer systems, have given researchers the advantage of adding Artificial Neural Networks (ANNs) in their modelling arsenal. The ability of ANNs to process complex data and achieve high predictive accuracy in addition to their unsupervised learning capabilities have made them a popular option among researchers in many cases. Additionally, the application of Deep Learning (DL) models is ever more common as the complexity of these models contributes to the estimation of nonlinearities and the identification of underlying latencies in datasets.

In this paper, an attempt was made to investigate and examine the efficiency and contribution of DL models to transport problems, in terms of exploiting their predictive capacity, in the interests of appropriate design and improvement of transportation systems. More in detail, the scope of the research was to examine the crossing and kinematic behaviour of pedestrians in an intersection with a Countdown Signal Timer (CST). Apart from the purpose of eliciting useful information with respect to the classification of pedestrians' behaviour, the research aimed to extract promising findings for the improvement of road safety for pedestrians. In this respect, traditional mathematical regression techniques that have extensively been used for decades in the transport domain, such as linear regression modelling and multinomial logistic regression modelling are compared against the predicting capability of DL models. The analysis is performed in a scale (pedestrian speed) and a nominal (pedestrian behaviour) variable respectively.

The paper is structured as follows; in the following section a concise literature review of past research is presented, denoting the innovative and efficient use of ANN techniques in a wide range of mobility problems in contemporary cities. In section 3, the theoretical background is presented to display some details for the models developed for the purposes of this research. In section 4, the case study is analysed, describing the collection and the processing of the data, as well as the development of the models. At the end of this section, the results of the paper are summarized, followed by the conclusions, in section 5.

2. Literature Review

ANNs have been a promising method for estimating difficult problems in transportation engineering over the past years. The adaptability of the models along with their high potential accuracy have led researchers in applying them in a variety of domains in the transport sector.

Traffic congestion is an issue that affects the quality of people's everyday life. Li and Lu, carried out a study for traffic forecasting, in which no conventional ANNs were used (Li and Lu, 2009). Instead, two different network structures were developed. The survey was conducted for the 3rd Beijing Ring Road. A Self-organizing Feature Map Neural Network (SOFM) model, or Kohonen, was chosen, which was applied for the classification of traffic conditions. The second model was an Elman Neural Network. The

only difference from conventional Multilayer Perceptrons (MLP), is that all hidden neurons' outputs are fed back to the input layer.

The World Health Organization ranks road crashes as one of the leading causes of death, as the number of deaths worldwide exceeds 1 million, while many are injured (WHO, 2018). As a consequence, actions to make transport safer are ever more intense, with researchers focusing their efforts on the application of new tools, in an attempt to predict phenomena more efficiently and avert accidents.

In this context, Çodur and Tortum (Çodur and Tortum, 2015) developed an accident prediction model, which took into account accident data and road design features for highway sections of a major city in Eastern Turkey. For the needs of the paper, a MLP ANN was developed, for which the Levenberg-Marquardt algorithm was exploited. Results of the analysis showed that road vertical curvature was the most influencing parameter for the occurrence of accidents.

A more introspective view of the issue of road crashes was a study by Pradhan and Sameen (Sameen and Pradhan, 2017), who examined the performance of several types of ANNs in the prediction of road accident severity. The researchers developed a Recurrent Neural Network (RNN), which was compared to a MLP and a Bayesian Logistic Regression (BLR) model. The results of the comparison showed that the RNN model was more efficient.

ANN applications have been also used in the field of public transport. In 2009 an attempt was made to predict the volume of commuters on a railway in Taiwan (Tsai et al., 2009). At first a MLP model was developed as reference and was compared against two different neural network models. The first model was a Multiple Temporal Units Neural Network (MTUNN) and the second one was a Parallel Ensemble Neural Network (PENN). Regarding the MLP model, MTUNN showed 8.1% and 4.4% better performance in terms of Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) respectively. On the other hand, PENN showed improvements by 10.5% and 3.3% in terms of the two metrics.

Significant research has also been done on the estimation of public transport operational characteristics, such as arrival time and commercial speed. Yu et al, developed several travel time forecasting models, using multiple bus line route data (Yu et al., 2011). Results indicated that ANN and Support Vector Machine (SVM) models were the most accurate. Jeong and Rilett compared the performance of simple regression models against ANNs for the estimation of bus travel time, using Automatic Vehicle Location Data as input and reached the conclusion that ANNs were the most efficient choice (Jeong and Rilett, 2004). In terms of bus speed prediction, Julio et al, applied ANN and SVM models, which were trained on both historical and real time data (Julio et al., 2016). Except from the prediction of bus speed and arrival time, researchers have looked into the factors that affect these variables in an effort to improve the provided level of service. Research by Chen et al focused on the influence of several parameters on bus arrival time through the use of ANNs. Results showed that dwell time was the most determinant factor (Chen et al., 2007). Dwell time was also among the most important factors influencing bus speed between successive bus stops, according to a DL model developed by Kopsacheilis et al. Stop spacing and the number of traffic lights were also factors that affected speed (Kopsacheilis et al., 2021).

Advanced algorithms have been also used for the management of urban mobility through the optimization of traffic lights cycle. In this context, a research was carried out by R.A. Gonzalez et al, in 2020 (Gonzalez et al., 2020). The aim of the research was to

improve transport, through the application of smart traffic lights in order to save energy and better control traffic. A Multilayer Feedforward network was used in the research. Results indicated an unsatisfactory efficiency, which led to the conclusion that neural networks require detailed and reliable data in order to deliver satisfactory results.

Another signal cycle optimization study was conducted by A. A. Zaid et al, in Jordan (Zaid et al., 2017). In this research, traffic data at an intersection were collected through recordings. Through the application of a DL model with 4 hidden layers and a fuzzy logic controller, the traffic light cycle is optimised based on the occurring traffic conditions.

Last but not least, ANN models have also been applied on pedestrian research. In 2015 a survey on the detection of pedestrians was conducted that used Convolutional Neural Networks (CNN) (Fukui et al., 2015). Kadali et al, in 2014, attempted to interpret the pedestrians' decision to cross the road in regard to vehicular gap acceptance in India (Kadali et al., 2014) with the implementation of a feedforward neural network. Recent research has looked into the behaviour of pedestrians and their distraction from the use of mobile devices while crossing the road (Yannis et al., 2020). Results indicate lower crossing speeds for pedestrians who were texting or web-surfing (Ropaka et al., 2020), while pedestrians that were texting or listening to music while crossing were in increased danger of getting hit by a vehicle (Schwebel et al., 2012). Research has also been made on the determination of the pedestrians' crossing behaviour by using state of the art models (Anapali et al., 2021; Zhang et al., 2020).

3. Theoretical Background

3.1 Linear Regression

Regression models are a family of statistical methods used for the determination of the value of a continuous variable *Y*, based on a set of predictors. The assumed relationship between the dependent variable *Y* and the independent variables *X*, characterizes the type of the regression model used. As a consequence, regression models are distinguished in linear and non-linear.

Linear regression (LR) (Equation 1) is the most widely used statistical model, mainly due to its simplicity. In many cases linear regression is used as a starting point in a variable estimation problem. Finally, although linear regression may be easily applicable in a variety of problems, it may not be the most suitable option, mainly due to the non-linearity of the majority of the phenomena occurring in reality.

$$Y = a_i X_i + b \tag{1}$$

where:

$Y =$ Dependent variable

$X_i =$ Independent variables

$a_i =$ Regression coefficient

$a_i =$ Intercept

3.2 Logistic Regression

Logistic Regression (Equation 2) forms a nonlinear classification model for the values of a dependent variable Y, according to probability theory. By adjusting the data of each problem to the equation of the logistic curve, it is possible to predict the probability of an event taking place. The categorical variable is mainly two-way (consisting of two possible categories) but can be used to encounter multi-class classification problems (for more than two categories). In other words, Logistic Regression can be considered as a neural network consisting of only one layer (Raschka, 2020). At the same time, the connection between neural networks and Logistic Regression is also reflected through the activation functions used in the hidden layers of neural networks, for example the Sigmoid function.

$$Y = logit(P_i) = LN(\frac{P_i}{1 - P_i}) \tag{2}$$

where:

$Y =$ Dependent variable

$P_i =$ Probability of event occurring

3.3 Artificial Neural Networks

ANNs or neural networks are computational models that try to simulate how the human brain operates. In particular, the form of these networks demonstrates their source of inspiration and the purpose of their implementation. It is a set of properly formed nodes (neurons), which are joined together by various combinations and follow the corresponding logic of biological neurons (Haykin, 2010). With regard to the architecture of ANNs, information is essentially drawn on the formation of connections between neurons and, by extension, the number and type of neurons. Neurons are organized into layers-levels. The structure and way of organising the neural network is directly related to the learning methodology in its training and is divided into three general categories (Haykin, 2010):

- The one-layer feedforward network consisting of an input layer and an output layer, which are connected directly without a two-way connection between them.
- The multi-layered feedforward networks consisting of an input layer, one or more hidden layers and the output layer. The existence of hidden layers enables the network to have higher-order exports than the input.
- Recurrent neural networks in which there is even a feedback loop, allowing information to be stored within the network.

One of the most important characteristics of ANNs is their ability to learn. The efficiency and accuracy of the outputs of an ANN is increased by the experience (training) gained by it. The learning process is carried out through the use of algorithms and contributes to the determination of synaptic weights (strength of the connection) in the absence of substantial intervention of the human factor, which makes the exported result more reliable. The main categories of learning are supervised learning, and unsupervised learning. In the second basic category there are two subcategories, where there is unsupervised and supporting learning.

During supervised learning the neural network is also fed with the desired output in addition to the input information. The performance of a network is determined based on certain metrics, such as the Mean Squared Error (MSE) (Equation 3) or the Mean

Absolute Percentage Error (MAPE) (Equation 4). One of the most common algorithms used by this method is to proceed the error backwards through the network (back propagation) (Lundberg and Lee, 2017).

$$MSE = \sum_{\iota=1}^{n} \frac{(\widehat{y_\iota} - y_\iota)^2}{n} \tag{3}$$

$$MAPE = \frac{1}{n} \sum \left| \frac{A_t - F_t}{A_t} \right| \tag{4}$$

where:

$n =$ Number of observations

$\widehat{y_\iota} =$ Predicted value

$y_\iota =$ Observed value

$A_t =$ Actual value

$F_t =$ Forecasted value

4. Case Study

4.1 Study Area

The study was carried out in the city of Kalamaria in Greece, at the intersection of Adrianoupoleos and Aegean streets (40° 35' 10.78"N, 22° 57' 20.73"E). A CST device has been installed in the pedestrians' traffic light (Figure 1), which is active only in one direction. The main road is a one-way street and is consisted of 4 lanes, while the intersecting section is a two-way street with 2 lanes in each direction. The intersection analysed has a traffic flow of 1,650 vehicles per hour, while pedestrian flow is estimated at 80 crossings per hour on average (Labrianidou P., 2010).

Figure 1: Study area intersection (CST device on the right side of the picture). (Google Maps, 2021)

4.2 Programming Environment

For the needs of data processing and model development the Python programming language (version 3.7) was chosen ("Python 3.7.12 Documentation," 2018). All processes were run through the Jupyter Notebook either locally or through the Google Colab environment. The libraries that were used for the purposes of ANN model development were the following:

- Tensorflow: mathematical library compiled by the Google group and is applicable to machine learning and neural networks
- Keras: library suitable for neural networks, with excellent results in deep learning, which has been written in Python
- Pandas: suitable for analyzing and processing data in Python programming language
- Numpy: mathematical library for the implementation of complex mathematical calculations between tables of different dimensions
- Matplotlib: graphical depictions library

4.3 Data Collection & Preprocessing

The data for the development of the models derived from a previous study, in 2017 (Mochlas Konstantinos, 2017). In order to draw valid conclusions, data were collected for three different days of a week (2 working days and on Saturday) and at three different time periods (2 hours in the morning, afternoon and evening, respectively) during it. With 18 hours of panoramic filming and monitoring of visual material, 1,412 pedestrian crossings were recorded.

In the first stage, the dataset was processed in order to be easily interpreted by the programming language, contributing to the optimal performance of the models. The dataset included rows with incomplete data, the number of which was less than 10% of the total. In this case these rows were deleted, as the absence of a small proportion of data does not significantly affect the performance of the model, as emerged from the literature review. Then, some nonnumeric (nominal-quality) variables that identified certain pedestrians' characteristics (gender, age, group, etc.) were identified and converted to arithmetic variables through dummy variable recoding.

After the preprocessing procedure, a dataset of 1,330 pedestrians and their crossing behaviour was further analysed. As a preliminary data manipulation of our study, the correlation between the independent variables was examined in order to ascertain which of them would be taken into account as input variables at each problem considered. Table 1 provides details about the attributes and the descriptive characteristics of the variables used in this study. The results of the statistical analysis between the dependent variables of each problem (*'Speed mean'* and *'Behaviour Class'*) and the independent variables are presented in Table 2.

The representativeness of the dataset was assessed in terms of the gender and age of the pedestrians of the sample. Results indicate a satisfactory representativeness regarding age (74% of adults between 19 and 60 years old in our sample against 83% in the population). Certain deviations appear in terms of gender in favour of females (61.5% against 50.9% in the population) that could potentially be attributed to the locality of the analysis (a commercial road with shops).

Table 1. Description of measured variables.

Variable Name	*Description/Attributes*	*Type of Variable*	*Min*	*Max*	*Average*	*Standard Deviation*
Gender	1: Male/2: Female	Nominal	1	2	1.61	0.49
Age	1: Children/2: Adults/3: Elderly	Nominal	1	3	1.95	0.51
Group	1: Pregnant woman/2: Shopper with bags/ 3: Disabled/4: Wheelchair companion/ 5: Parent/6: Elderly companion/7: Pet walker	Nominal	0	7	0.85	1.68
PCS Visible	1: Yes/0: No	Nominal	0	1	0.45	0.5
PCS Search	1: Yes/0: No	Nominal	0	1	0.12	0.33
Traffic Existence	1: Yes/0: No	Nominal	0	1	0.94	0.23
Waiting Spot	1: Pavement/2: Road	Nominal	1	2	1.27	0.44
Arrival	PCS's indication when pedestrian arrives at the crossing.	Scale	1	66	23.01	15.49
Entry	PCS's indication when pedestrian enters the crossing.	Scale	1	66	19.53	7.6
Exit	PCS's indication when pedestrian exits the crossing.	Scale	0	65	16.56	16.28
Reaction Time	The time that pedestrian needs to react.	Scale	0	12	1.51	1.61
Speed mean	Average speed of pedestrian (m/s).	Scale	0.66	4.41	1.39	0.34
Speed max	Maximum pedestrian's speed (m/s).	Scale	0.95	6.54	2	0.53
Speed mid	Pedestrian speed in the middle of the crossing (m/s).	Scale	0.63	5.51	1.52	0.46
Speed end	Pedestrian speed in the end of the crossing (m/s).	Scale	0.09	4.52	1.43	0.52
Behaviour Class	Characterization according to their crossing behaviour (1: Law-abiding/2: Law-compliant/3: Violator)	Nominal	1	3	1.31	0.53

Table 2. Statistical test results.

Dependent Variable	*Type*	*Independent Variables*	*Type*	*Statistical test*	*Value*	*Sig.*
Speed Mean	Scale	Arrival	Scale	Pearson's correlation	-0.77	0.005[a]
		Entry			-0.74	0.007[a]
		Exit			0.29	0.000[a]
		Reaction Time			-0.22	0.000[a]
		Gender	Nominal (2 categories)	Independent Samples t Test	9.46	0.002[a]
		PCS Visible			0.11	0.738
		PCS Search			1.89	0.170
		Traffic Existence			0.38	0.539
		Waiting Spot			12.76	0.000[a]
		Age	Nominal (k categories)	One way ANOVA	65.87	0.000[a]
		Group			11.07	0.000[a]
Behaviour Class	Nominal (k categories)	Arrival	Scale	One way ANOVA	3.42	0.000[a]
		Entry			10.31	0.000[a]
		Exit			5.85	0.000[a]
		Reaction Time			6.12	0.000[a]
		Gender	Nominal (2 categories)	Chi-squared test	6.18	0.045[b]
		PCS Visible			13.11	0.001[a]
		PCS Search			40.49	0.000[a]
		Traffic Existence			199.19	0.000[a]
		Waiting Spot			1242.02	0.000[a]
		Age	Nominal (k categories)		5.70	0.223
		Group			40.31	0.000[a]

[a] *Significance at 1%*
[b] *Significance at 5%*

4.4 Estimation of pedestrian crossing speed

For the needs of estimating the average crossing speed of pedestrians, we employed two models. At first a LR model was developed as base model. Afterwards, a DL model was developed in order to examine potential improvements in forecasting accuracy.

The independent variables of the regression model were chosen based on the results from the statistical tests, as presented in Table 2. Thus, the variables *'PCS Visible', 'PCS Search', 'Traffic Existence'*, were excluded from the analysis. However, model results indicated a p-value (sig.) of 0.563 for the variable '*Arrival'* and as a consequence the variable was excluded from the model. Results of the ANOVA test indicate a statistical significance of the model ($p<0.001$), while the R^2 value of 0.216 suggests an adequate fit of the dependent variable.

The DL model that was chosen for this analysis was a feed-forward neural network, whose weights were optimised according to the backpropagation algorithm. The input layer of the model was comprised of the variables that were statistically significant according to the statistical analysis (Table 2). For the needs of the model, all nominal independent variables were transformed into dummy variables. In order to achieve optimum performance, several different network architectures were tested in terms of the number of hidden layers and neurons. Ultimately the network configuration of 2 hidden layers with 48 neurons each operated best (Figure 2.a). In terms of the model's hyperparameters, the batch size was set to 128, while the value of 0.01 was chosen for the learning rate. The activation of the neurons of both layers was achieved through the Recertified Linear Unit (ReLu) function. The model was trained at 70% of the dataset and tested on the remaining percentage, while the duration of the training was set to 400 epochs.

The results of the model indicate a satisfactory performance overall. More to the point, according to the learning curves (Figure 2.b) the algorithm converges very quickly and reaches minimum loss at the end of the 400th epoch. The training was stopped at this point, as the slope of the curves indicates that the cost function has reached a minimum. Although some overfitting is observed throughout the training of the model, results indicate an admirable performance, according to the MSE value. In addition, the R^2 value of 0.56 indicates a satisfactory fit to the data, outperforming the based model (Table 3).

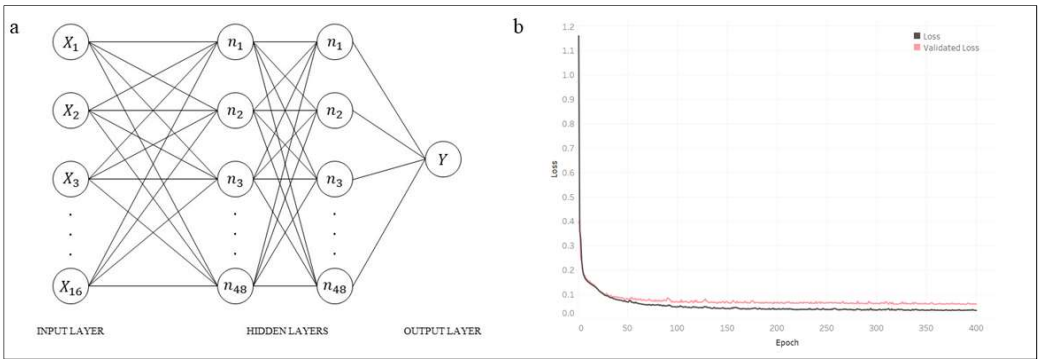

Figure 2: (a) ANN architecture, (b) Model learning curves.

Table 3. Average crossing speed-Model comparison.

	R^2	*Mean Square Error (MSE)*
Linear Regression Model	0.216	0.092
Deep Learning Model	**0.557**	**0.060**

4.5 Classification of pedestrian crossing behaviour

The second model attempts at classifying pedestrians based on their crossing behaviour. The classification is done according to three possible classes: law-abiding (crossed during the green phase), law-compliant (crossed during the green phase, but waited on the street and not on the sidewalk), violator (crossed during the red phase).

Initially, a Multinomial Logistic Regression (MLR) model was fit as the base model of the analysis. The independent variables of the model were determined based on the results from the statistical analysis (Table 2), with only the variable *'Age'* being excluded from the model as statistically insignificant. Additionally, since pedestrian behaviour was also influenced by kinematic characteristics during the crossing, data regarding the pedestrians' mean speed was also considered based also on the results of the one-way ANOVA test ($F(2,1327)=21.673$, $p=.000$).

Results showed that the model classified pedestrian behaviour with satisfactory precision, as the overall percentage of the correctly classified cases rose to 98.2% (Table 4). According to the confusion matrix (Table 4), cases in the law-abiding and law-compliant classes were classified mostly correct. On the other hand, although the majority of the violator cases are correctly classified, the number of false positives from the other two classes (8 and 3 respectively) indicate a weakness in identifying violating crossing behaviour. Overall, the model achieved a satisfactory accuracy of 98.2%, despite the smaller accuracy observed in the 'Violator' class.

Table 4. Confusion Matrix - Logistic Regression model.

Observed Values	Predicted Values			
	Law-abiding	Law-compliant	Violator	Percentage Correct
Law-abiding	948	5	4	99.1%
Law-compliant	1	324	3	98.8%
Violator	8	3	34	75.6%
Overall Percentage	72.0%	25.0%	3.1%	98.2%

For the prediction of pedestrians' crossing behaviour a DL model was also developed, which used as input the same independent variables as the base model. In order to determine the most suitable architecture for the network, several trials were made. The optimum combination of neurons and layers was determined in terms of the achieved accuracy, while all other hyperparameters were kept to their default values. As can be surmised from Figure 3, the final model was comprised of 3 hidden layers, with 64 neurons each.

Layer 1	Layer 3							Layer 2
	0	2	4	8	16	32	64	
2	0.970	0.970						2
4	0.970	0.970	0.970					4
8	0.972	0.970	0.970	0.970				8
16	0.985	0.966	0.970	0.966	0.972			16
32	0.979	0.966	0.967	0.964	0.979	0.986		32
64	0.990	0.967	0.964	0.975	0.980	0.989	0.991	64

Figure 3: Determination of optimum network architecture based on accuracy.

The model was trained at 80% of the total dataset and tested on the remaining set. Regarding the hyperparameters of the model, several values were tested for batch size and learning rate. Finally, the model achieved its best performance when batch size was set at 32 and for a learning rate of 0.1. In terms of the training epochs, the learning curves presented in Figure 4 appear to converge at the 450th epoch. At the same time, their horizontal slopes indicate that the cost function has reached a minimum, thus the training process was halted at this point.

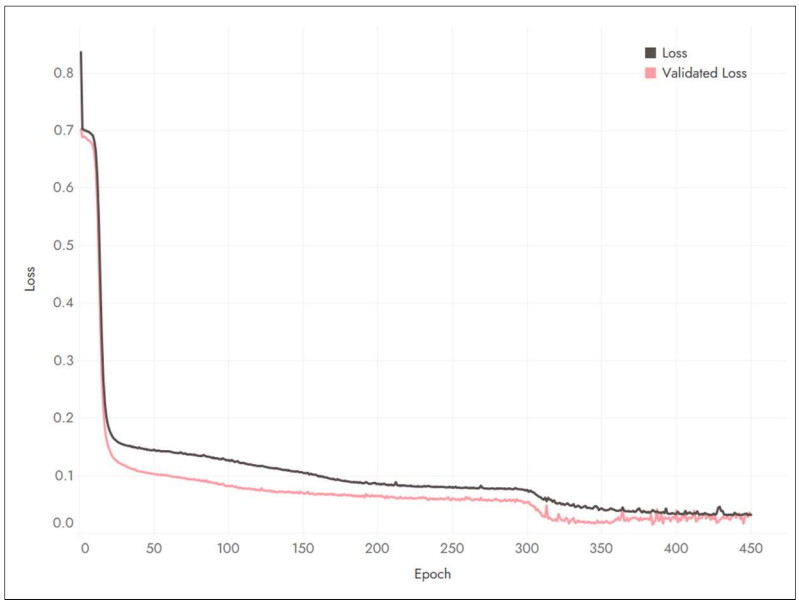

Figure 4: Model learning curves.

The results of the model as presented in Table 5 and 6, indicate a very good predictive capacity in terms of classifying pedestrian behaviour in the 3 classes of the dependent variable. More to the point, according to the accuracy metric (Table 6) the model achieved an overall accuracy of 99.6%. Although the increase in accuracy in comparison to the base model seems marginal, the results presented in the confusion matrix (Table 5) indicate an almost faultless classification process. Specifically, only one predicted case from the 'Law-abiding' class was misclassified, while all the cases in the 'Law-compliant' and 'Violator' classes were classified correctly.

Table 5. Confusion Matrix – Deep Learning Model.

Predicted Values	Actual Values		
	Law-abiding	Law-compliant	Violator
Law-abiding	191	0	1
Law-compliant	0	66	0
Violator	0	0	8

Table 6. Classification Metrics – Deep Learning Model.

Characterization	Precision	Recall	F1 Score	Support
Law-abiding	1.00	0.99	1.00	192
Law-compliant	1.00	1.00	1.00	66
Violator	0.89	1.00	0.94	8
Accuracy		0.99624		

5. Conclusions

The present research focused on the investigation of pedestrians' crossing and kinematic behaviour at a signalised crossing, which utilised a CST device. The kinematic behaviour of pedestrians was determined based on their average speed while their crossing behaviour was determined according to their characterization as 'law-abiding', 'law-compliant' and 'violators'. In the framework of the paper, four models were developed. Regarding the prediction of pedestrians' average crossing speed one Linear Regression (LR) and one Deep Learning (DL) model were developed, whereas for the classification of pedestrians according to their crossing behaviour, one Multinomial Logistic Regression (MLR) model along with a DL model were developed.

Overall, both models perform satisfactory in terms of predicting the average crossing speed of the pedestrians. Although the LR model is statistically significant, it is outperformed by the DL model, which achieved a considerably higher R^2 value. This can be attributed to the nonlinear nature of the problem examined, which can be depicted more accurately from an ANN model. However, both models seem to predict the average crossing speed with adequate accuracy, as indicated by the MSE values of 0.092 and 0.060 for the LR and the DL model respectively.

Regarding the classification of pedestrians according to their crossing behaviour both models perform very well. Although, the MLR model achieved a satisfactory accuracy overall, it encountered issues when classifying cases in the two minority classes. On the other hand, the DL model outperformed the base model by a small margin in terms of overall accuracy. Additionally, it performed substantially better in classifying cases across all classes, with only one misclassified case overall. The shortcoming of the MLR model could be allocated to the considerably smaller number of pedestrians with violating behaviour in our sample, which led to an insufficient pattern detection process by the model. By comparing the results of the pedestrians' crossing behaviour against relevant research, our model performs on a satisfactory level overall.

Results of this paper could assist researchers, transport planners and policymakers in the process of making infrastructure safer for pedestrians. The proposed models could be applied in the evaluation of the safety level of existing infrastructure, as well as in the framework of feasibility studies focusing on the upgrade of crossings. Installation of such

types of Information and Communication Technologies (ICT) as well as their enrichment with innovative applications like the one described in this study, can provide an overall improvement of the road safety levels at urban intersections where the majority of accidents occur.

The main limitations of the paper lie upon the size of the dataset, although it is considered representative for the existing conditions in the area. A more detailed on-field survey that would result in a more balanced dataset in terms of the pedestrians' behaviour, could possibly improve predictive capacity. Future research could focus on the performance assessment of more complex algorithms. Furthermore, the determination of the impact of each independent variable on pedestrian behaviour could provide insight in the factors that affect crossing patterns.

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