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Investigation of pedestrian jaywalking behaviour at mid-block locations using artificial neural networks

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ABSTRACT

This research presents a framework based on artificial neural networks (ANNs) to predict jaywalker's trajectory while crossing the road. In this process, different causal and conditional variables related to jaywalking, such as, gender, direction of crossing, walking or running, cell phone use, roadway lane number, etc. are taken as input variables. The dataset comprises of 2504 samples which is collected under non-lane based heterogeneous traffic conditions. Through testing predictive performance of several ANN architectures based on correlation coefficient and mean square error, the best ANN architecture to predict jaywalker's movement is determined. The optimal ANN architecture comprises of 9 input nodes, 10 hidden nodes and 1 output node. This study also determines the microscopic variables, i.e., speed, flow and density, associated with jaywalking. The results indicate that the average speed of male jaywalkers is higher than female jaywalkers. The density is found to be higher in the last lanes of the crossing paths. In addition, this research develops jaywalker trajectories in order to understand their position shifting strategies. Findings suggest that 'median to sidewalk' movement trajectories tend to move closer to the foot-over bridge, whereas, the 'sidewalk to median' movement trajectories tend to move further away from foot-over bridge. The outcome of this research is expected to assist driver assistance technology as well as Connected and Autonomous Vehicle (CAV) technologies by allowing vehicles to safely navigate through both clustered and individual jaywalkers.

1. Background

Pedestrians are among the most vulnerable road users, accounting for 65% of road crash fatalities worldwide (Xu et al., 2013). According to the National Highway Traffic Safety Administration (NHTSA) report in 2019, 6205 pedestrians were killed in traffic crashes in the USA which is 17.1% of total traffic crash fatalities (National Highway Traffic Safety Administration, 2019). Additionally, nearly 181,599 pedestrians were treated in emergency rooms for non-fatal crash-related injuries (Centers for Disease Control and Prevention, 2019). In terms of crash location and time, most of the fatal crashes had occurred at urban non-intersection locations where pedestrians were involved in jaywalking (National Highway Traffic Safety Administration, 2019). Jaywalking can be defined as a pedestrian activity that involves ignoring or disobeying road rules near crossings (Shiwakoti et al., 2017). Jaywalking activities also have detrimental impacts on the vehicle flow which include increased delays, reduced capacity, and resulting in harmful influences, such as, excessive fuel consumption and induced emissions due to more inconsistent flow and stop-and-go motion (Liu et al., 2018). Yet, jaywalking is an under-explored and often neglected area in pedestrian research as it is considered a violation of traffic rules (Wang et al., 2010).

Existing research on pedestrian safety has focused on their route choice modeling, flow characteristics, walking behavior analysis, pedestrian protection methods; whereas the recent studies focus on pedestrian detection for enhancing pedestrian safety, and pedestrian dynamics (Anik et al., 2020). The studies on jaywalking have mostly been focused on unveiling the factors responsible for jaywalking, its safety hazards and the street environment allowing jaywalking. Xu et al. (2013) explored the predictors of pedestrians' intention to jaywalk based on a dual-process model, which categorized the intention formation process into controlled and automatic processes. The results postulated that a pedestrians' intention to jaywalk is driven more by the frequency of past behavior, i.e., habit, and less by the cognitive components of the extended theory of planned behavior (TPB) model. Li

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et al. (2014) conducted a survey involving 128 Chinese undergraduate students to explore the effects of situational factors on pedestrian intention to jaywalk. The study included eight scenarios to manipulate three situational factors, namely, time pressure, descriptive norm, and official supervision. The results indicated that hypothetical high time pressure, unsafe descriptive norm, and unsupervised effect can significantly increase pedestrian jaywalking intention. Apart from that, Kadali et al. (2014) examined the pedestrian gap acceptance behavior by employing an artificial neural network (ANN) model for understanding the decision-making process of pedestrians, i.e., acceptance or rejection of vehicular gaps at a mid-block location. More recently, Aden et al. (2021) conducted a comparative analysis of jaywalking behavior in Dalian (China) and Djibouti (Djibouti). Their objective was to investigate the effects of sensation seeking and conformity tendency on the intention to violate traffic rules while crossing. The authors used the TPB model coupled with structural equation modeling (SEM) to analyze jaywalking behavior. Results showed that the instrumental attitude, the subjective norm, and perceived behavioral control positively affect the behavioral intention to violate traffic rules. Besides, divergent illegal road crossing behavior was found among pedestrians in those two cities. Based on the results, the authors recommended designing road infrastructures fitting the pedestrians' characteristics.

Jaywalking on mid-block locations are riskier than jaywalking on marked or signalized crosswalks Thus, it is crucial to have a clear understanding of jaywalking behavior where there are no legal crossings provided (Shaaban et al., 2019). Studies exploring this topic are rare. Shaaban et al. (2018) examined jaywalking behavior on a mid-block location of a six-lane divided arterial road in downtown Doha, Qatar. Jaywalking data were collected at different stages of crossing, including before, during and after crossing to analyze the effects of obstacles, vehicular traffic, and peer effects on the crossing behavior. Results revealed that male pedestrians are more inclined to jaywalk than female. Time taken by the jaywalkers to cross the road was found to be affected by age, gender, mobile phone use, type of clothing, clustered jaywalking, crossing point, the path of crossing, and presence of a vehicle. Ravishankar and Nair (2020) examined jaywalking behavior at midblock crossings in two south Indian cities: Thiruvananthapuram and Warangal. They used a combination of both questionnaires and video graphic surveys to collect data on jaywalking. They found that men are more likely to take risks by accepting small gaps between the vehicles. Acharya and Marsani (2019) used Multi Linear Regression (MLR) model to ascertain the effects of various parameters on jaywalking at mid-block locations. They took Kathmandu city, Nepal as the study area. The authors found that the volume of jaywalkers at these locations depends upon the traffic speed, rather than the traffic volume. This finding is analogous to the findings of Ravishankar and Nair (2020). Another interesting outcome was that the jaywalkers were reluctant to search for a nearby legal crossing facility while deciding to cross the road illegally. In recent times, Kadali and Vedagiri (2020) conducted video graphic surveys at selected uncontrolled crosswalk locations in Mumbai, India to collect data on jaywalking. Their goal was to understand pedestrian risk-taking behavior considering the effect of pedestrian behavior and different roadway characteristics at uncontrolled mid-block. The authors identified that pedestrian risk-taking behavior increases with the increased number of lanes. They suggested controlling pedestrian behavioral characteristics to reduce the risky jaywalking behavior at midblock locations.

The above discussion suggests that understanding jaywalking behavior at mid-block locations (outside the crosswalk) is crucial for designing road infrastructures and controlling peoples' intention to jaywalk at these high-risk zones. Microscopic flow parameters, associated with jaywalking such as, jaywalkers flow, speed and density are critical factors to consider while designing for roadways and crossing facilities (Anik et al, 2020). However, research works analyzing these variables are quite limited. Furthermore, with the advancement in the Connected and Autonomous Vehicle (CAV) technologies, a new branch of experimental research has emerged which investigates vehicular-pedestrian interactions. Fejes and Földes (2020) examined vehicle–pedestrian conflict points in Budapest, Hungary, intending to develop methods to prevent pedestrians from being hit by an AV. The authors found that road crossing behavior is highly affected by gender. Moreover, pedestrians' movements approaching a crossing point are heavily decided by the surrounding environment. The authors concluded that their results can be utilized in the design and planning process of autonomous vehicles. Ackermans (2019) evaluated designs of external human–machine interface (eHMIs) to an autonomous vehicle (AV) to improve communication between pedestrians and AVs. The author took Netherlands as the study area. The author corroborated research showing that the primary task an eHMI should accomplish is to communicate the vehicle's intended behavior to the crossing pedestrian, which can be best achieved by utilizing asymmetrical light animation placed on the front bumper of the AV. Wang et al. (2020) evaluated the adaptability of AVs to pedestrians in urban China. Their results suggested that the adaptability of AVs depends on the compliancy of detection, interaction, as well as the reception. They also argued that AVs detecting and safely maneuvering through jaywalkers is a complex phenomenon and needs more attention. The authors suggested the governments to take more efficient and stringent approaches for limiting pedestrians to cross illegally. However, these studies have mostly been conducted in the context of developed countries having decently designed and maintained roads, strict enforcement and pedestrians with sufficient knowledge on basic rules of the road. Self-driving vehicular research examining CAV- jaywalker interactions are rare though there have been major accusations on CAV technologies failing to identify jaywalkers which have led to road crashes (Combs et al., 2019). Although not yet prominent as a research topic, there is widespread excitement that advanced algorithms in CAVs may in the future legalize jaywalking as such vehicles or human-driven vehicles equipped with driver assistance technologies can assist vehicles to ply through jaywalkers safely. This triggers an urgent need to have a clearer theoretical and empirical understanding of jaywalking behavior to utilize the know-how as an input to modern vehicular technologies to enhance pedestrian safety. Additionally, with time, the CAV technologies may also get adopted by the developing countries, where the predominance of jaywalking is much higher compared to developed countries (Prabhu and Sarkar, 2016). Hence, a microscopic model for jaywalking to comprehend jaywalking behavior more incisively, especially in the context of developing countries needs to be researched. Having a model that can mathematically analyze jaywalking behavior and predict movements of jaywalkers can establish a broader understanding of jaywalking phenomena both for human-driven and self-driven vehicles. In addition, the findings generated from that research can stimulate further jaywalking-related studies, such as impacts of jaywalking on heterogeneous traffic flow, impacts of a jaywalker's behavioral factors on jaywalker-vehicle crashes, among others.

Taking these gaps in the literature into consideration, this research examines jaywalking behavior in a growing megacity, Dhaka, Bangladesh where jaywalking is a common phenomenon. After collecting data on pedestrians' illegal road crossing through video graphic survey, traffic data extractor software is used to extract variables related to jaywalking, such as, gender, mobile phone use, walking or running, the direction of movement, as well as factors on the surrounding environment, such as the presence of vehicles, lane number. Jaywalkers' each second positional coordinates are also extracted from the videos. After that, using the collected data, artificial neural network (ANN) models are developed to predict jaywalkers' instantaneous movement on the road. In addition, microscopic parameters associated with jaywalking, such as density, flow, and speed of jaywalkers concerning each lane on the road are also analyzed. Besides, to investigate jaywalkers' position shifting strategy while crossing, jaywalking trajectories are developed and examined. The objectives of this study can be summarized as follows: 1) to identify different geometric and microscopic traffic flow parameters associated with jaywalking strategy, 2) to derive jaywalking trajectories and use that to investigate jaywalker's position shifting strategy while crossing the road under mixed traffic conditions, 3) to develop a microscopic model for jaywalking which can predict each movement of jaywalkers on the roads based on different causal and conditional factors, and, 4) to examine the influence of various contributing input variables on the pedestrians' movement while crossing.

2. Study area

This research selects Dhaka, the capital city of Bangladesh as its study area. Dhaka is situated in the middle part of Bangladesh covering 1463.60 sq. km. of which the metropolitan area occupies 302 sq. km. (Bangladesh Bureau of Statistics Report, 2001, 2011–2016). According to United Nations' report, the city exhibited a staggering 3.6% average annual rate of increase of population from 2000 to 2018, eventually reaching 19,578,000 in 2018 (United Nations, 2018). The traffic system in Dhaka is heterogeneous due to the wide variation in the operating and performance characteristics (motorized, non-motorized, slow-moving, fast-moving) of vehicles (Karim et al., 1998). Across all modes of travel, the average trip time is about 15 min which indicates that most of the trip destinations are within walking distance and highlights the possibilities of 'walking' as a sustainable travel mode for the city (Rahman, 2010). Complying with the statistics, it is expected that the policymakers will provide the highest priority to the pedestrians. However, only 400 km footpath is available for the pedestrians of which 40% are being encroached by vendors and others. Most of the intersections in Dhaka city are operated manually and the signalized pedestrian crossing facilities are often non-existent. Rather, zebra crossings and foot-over bridges are available but inadequate in number. Most of the foot-over bridges are also not covered keeping the pedestrians exposed during the long rainy season, encroached by street hawkers and at times pose a security threat that discourages the pedestrians to use them (Aowsaf, 2018). Lack of pedestrian-friendly infrastructures coupled with ineffective enforcement encouraged the city commuters into jaywalking leading to high pedestrian casualty and traffic congestion. People of all ages and gender are seen to cross the busy city streets amid traffic when in most cases foot-over bridges are just a few steps away. Jaywalkers crossing the road where there is no zebra crossing while using their phones is a common phenomenon here. Even though jaywalking is equally dangerous for the jaywalker and nerve-wracking for the motorist, it is an offense that is rarely penalized by the authorities in Dhaka (Rayhan, 2018). Hence just like many other developing cities, jaywalking has emerged as an acute problem for the Dhaka traffic system making the city a suitable candidate to assess the complex behavior of jaywalkers.

3. Methodology

This study is divided into the following parts: data collection, extraction and processing, analysis and prediction. First, video data of jaywalking is collected using a video recording device at one location of Dhaka city where jaywalking is predominant. The data is collected for the afternoon peak time (4.30 PM to 5.30 PM) on a typical weekday. The weather was sunny with no sign of rain. The road users' behavior did not get influenced by the presence of the video recording device as the devices were placed at ample distance and road users were unable to see it. Video graphic survey showed that vehicle composition at the road for which jaywalking is observed is approximately 40% private vehicles, 30% public bus, 12% motorcycles, and 18% other vehicles (compressed natural gas (CNG) vehicles, vans). Video recording is conducted from foot-over bridges located facing the roadway sections having four lanes (approximately 10 feet wide) at each direction. The road is located in front of the Shyamoli foot-over bridge (right side of the road facing Kallyanpur. The road has lane markings and does not have provisions for shoulders. The pedestrian walkway along the road is 6 feet in width, however, they are mostly encroached by hawkers. The road is set with no functioning traffic signals or pedestrian signals. The rectangular area for which jaywalking is observed in this study accounts for both 'median to sidewalk' and 'sidewalk to median' movement. Next, using Traffic Data Extractor software (Munigety et al., 2014), the co-ordinates of jaywalkers, as well as these jaywalking parameters: gender, walking/running, cell phone using/not, direction of travel, lane number, starting/middle/ end of crossing, front vehicle present/not, back vehicle present/not, rear threat, and existing threat, next threat, are extracted from the videos. These variables are selected from an in-depth literature review on jaywalking, focus group discussions (FGDs) involving jaywalkers and expert counsel of academicians, practitioners, vehicle drivers and policymakers. After that, using the extracted coordinates of jaywalkers, trajectories are traced and analyzed. Finally, using all the extracted variables as inputs at time t-1 s and jaywalker's position on the road at t second as output, a mathematical model for jaywalking is developed. This model can be used to predict instantaneous jaywalker's movement, and to predict jaywalker's trajectory. Furthermore, the relative importance of the input variables considered in this study can be evaluated using the same model. Fig. 1 shows the workflow of the methodology.

3.1. Artificial neural network (ANN) model for jaywalking

Jaywalker movement or trajectory forecasting is a time series forecasting where the past observations on the jaywalking factors are gathered and analyzed to form a model describing the underlying relationships among them. The model can then be used to extrapolate the time series into the future, which in this case, jaywalker's position for each successive second (Zhang, 2003). Attempts have been made over the last several decades to develop and improve these time series forecasting models. Traditional statistical models that are used in this regard are linear in that predictions of the future values and are associated with several restrictions. To overcome the restrictions of the linear models as well as to account for specific nonlinear patterns observed in a real-life scenario, several classes of nonlinear models have been evaluated, such as the bilinear model, the threshold autoregressive (TAR) model and the autoregressive conditional heteroscedastic (ARCH) model. Despite the improvements noticed with these non-linear models compared to linear models, the benefits of using them for general forecasting problems are limited as they are not capable of modeling all types of nonlinearity in time series. Artificial neural networks (ANNs) have been suggested as an alternative to time series forecasting more recently (Kadali et al., 2014; Zhang, 2003). The main strength of the ANNs over the classical statistical approaches is their flexible nonlinear modeling capability for which they have been extensively studied and used in time series forecasting in recent time. ANNs are universal approximates which are capable to approximate a large class of functions with a high degree of precision (Zhang, 2003). This study uses time-series data representing a jaywalker's behavior taken in the form of location data successively extracted for each second and employs the ANNs to analyze jaywalking behavior.

An ANN consists of three layers which are input, hidden and output layer. The input layer consists of the initial data provided for the neural network model. The hidden layer is the intermediate layer between input and output layers where all the computation is done. The output layer produces the results for given inputs. Each layer consists of a different number of nodes that are connected to each of its adjacent layer nodes mimicking a biological neural network that constitutes the animal brain. Each connection has a weight and a bias value to calculate the weightage value of its following node to finally obtaining the output layer. For this study, the input layer consists of these input variables (X_1 - X_{12}):

X_1 = jaywalker's position at t-1 s (resultant vector calculated from x-y coordinates)

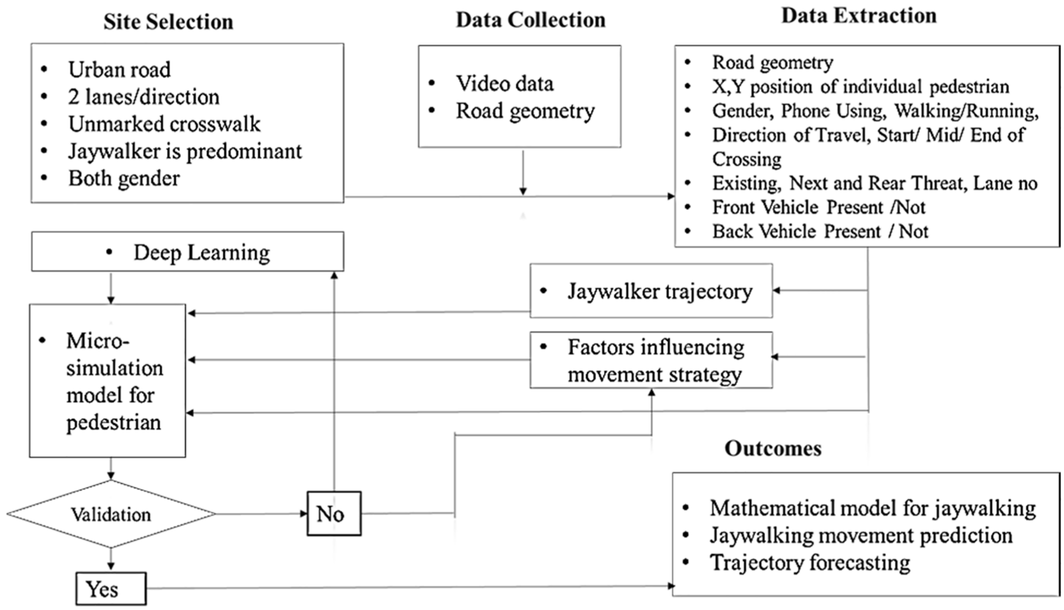


Fig. 1. Workflow of the methodology.

X_2 = gender (male:1/female:0)

X_3 = direction of travel (median to sidewalk movement:1/ sidewalk to median movement:0)

X_4 = cell phone use (using:1/not using:0)

X_5 = lane number (lane 1–4: leftmost lane to the rightmost lane)

X_6 = stage of crossing (starting:0/middle:1/ end of crossing:2)

X_7 = front vehicle presence (present:1/not present:0)

X_8 = back vehicle presence (present:1 /not present:0)

X_9 = existing threat (0–1-2–3: no threat-low threat-high threat-extreme threat)

X_{10} = next step threat (0–1-2–3: no threat-low threat-high threat-extreme threat)

X_{11} = rear step threat (0–1-2–3: no threat-low threat-high threat-extreme threat)

X_{12} = status (running:1/ walking:0)

X_9, X_{10}, X_{11} are fixed by the following principle: no threat = jaywalker will get hit in 4 s; low threat = jaywalker will get hit in 3 s; high threat = jaywalker will get hit in 2 s; extreme threat = jaywalker will get hit in 1 s provided that the jaywalker makes her/his move and the vehicle is not taking any evasive move. The output layer is the jaywalker's position (resultant vector of x-y coordinates) at t second. The steps involving the development of a microscopic model for jaywalking in ANN are as follows. Step 1–3 are for training the model using available data whereas step 4 is for predicting from new data using the trained model outlined as follows:

Step 1: Jaywalker's position at present, gender, walking/running, threats, vehicle presence, etc. are set as input layer in the ANN model. In the beginning, the node connections are initiated with random integers as weights. Jaywalker's position after 1 s is set as the output layer.

Step 2: Through the process of forwarding propagation, using the input layer (jaywalking variables) and hidden layers (different layer architectures are tested while training the model), the ANN model calculates the cost function, which is the difference between the actual x-y co-ordinates of jaywalker and the predicted x-y co-ordinates of jaywalker after 1 s. The model with the least amount of cost is considered the best fit to represent jaywalking behavior.

Step 3: After calculating the cost function, the model calculates the gradient descent/slope for all the connections between the nodes. Through this process, it updates and optimizes the weight values to reduce the difference between actual and predicted jaywalker x-y co-ordinates (reducing the cost/loss). This step is called backward propagation. Once this step is accomplished, the model is ready to predict position from new jaywalking data.

Step 4: The trained model accuracy can be evaluated and then used to predict the test data. Using the trained model's node connection weights, the interrelationships between the jaywalking variables are evaluated.

The dataset comprises over 2504 positions of 156 jaywalkers (109 males, 46 females) on the road. The code divided 70% of the data to be used for training, 20% for validating the model and the remaining 10% for making predictions.

3.2. Tools used

The video data is collected using a high-definition video recording device. To extract the coordinates of jaywalkers as well as other input variables from the video data, Traffic Data Extractor software is used (Munigety et al., 2014). To develop the ANN model, the Python programming language is used. The packages that are used in Python are 'numpy' for scientific computing, 'pandas' for data frame handling, 'tensorflow', sci-kit learn and 'keras' for ANN algorithms. Fig. 2 shows the locations as well as the cross-sections of the road in Traffic Data Extractor software for the study site. The next section presents the analysis and the results of the study.

4. Analysis and results

4.1. Speed, flow, and density

This section starts with analyzing gender-based jaywalking behavior, followed by examining the microscopic parameters associated with jaywalking. Comparison between male and female jaywalker's general road crossing characteristics in terms of mode of movement, cell phone use and risky situations are illustrated in Fig. 3.

Fig. 3 shows that male jaywalkers are less hesitant to run to avoid collisions with vehicles than female jaywalkers while crossing. Besides, the tendency of talking over the phone while crossing is more evident in men than women. One-way ANOVA analysis is conducted to examine whether there are significant differences in running, phone using and risk-taking behavior across male and female jaywalkers. Phone using (p-value: 0.185; Fig. 3) and running behavior (p-value: 0.417; Fig. 3) is found to be not statistically significant at a 95% confidence interval

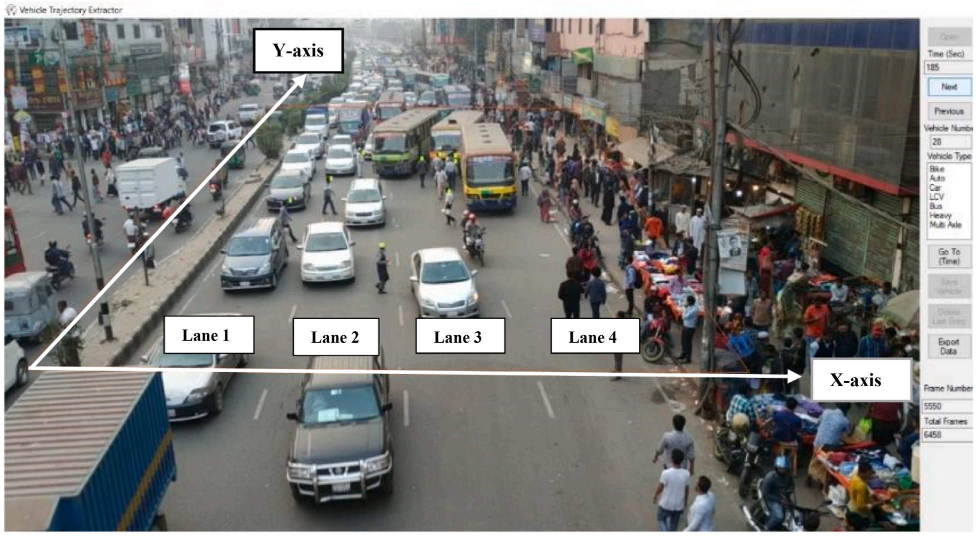


Fig. 2. Data Extraction using Traffic Data Extractor Software.

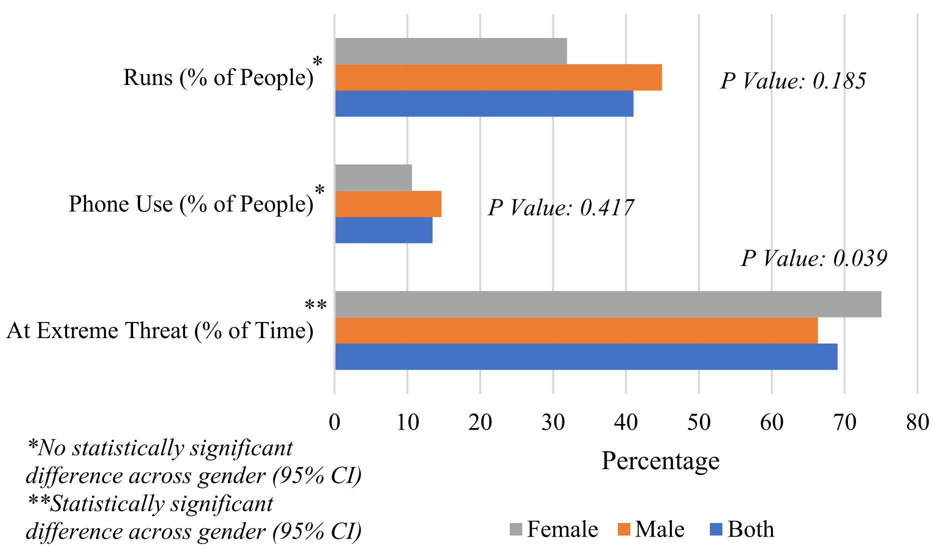


Fig. 3. Male and female jaywalker's road crossing characteristics.

across gender. Considering jaywalker's position and his/her nearest vehicle position on the road, it can be observed that women jaywalkers often get exposed to collision threat (will get hit in 1 s if they do not move and the vehicle heading towards them do not take evasive action), 75.06% of their crossing time, as compared to men (66.32%). This result is found to be statistically significant at a 95% confidence interval across gender (p-Value: 0.039; Fig. 3). This indicates that women are more involved in near-miss crashes exhibiting a higher level of risky jaywalking behavior while crossing the road than men.

The combined average speed of a jaywalker is found to be 2.487 feet/second where the male jaywalkers on an average walk at 2.568 feet/second and the female jaywalkers at 2.314 feet/second speed, i.e., the male jaywalkers are quicker than female jaywalkers. Two-way ANOVA is carried out to examine the effects of jaywalking-related factors on the speed of jaywalkers. Also, to determine whether there are any statistically significant differences in crossing speed across gender, lane number, crossing direction, and walking/running. The results are shown in Table 1. Two-way ANOVA analysis showed that there is a statistically significant difference in jaywalking speed between male and female jaywalkers (p-value 0.008; 95% confidence interval; Table 1). Besides, a statistically significant difference is found in jaywalkers' speed across crossing directions (p-Value: 0.026; 95% confidence interval; Table 1). However, the effects of interaction between gender and crossing direction on speed came out as non-significant (p-value: 0.913; 95% confidence interval; Table 1**).**

Further analysis is conducted to determine lane-based jaywalkers' speed concerning different criteria, such as, gender, the direction of crossing (sidewalk to median/median to the sidewalk), and state of crossing (walking/running). The results (on average for a jaywalker) are shown in Fig. 4.

Fig. 4 illustrates significant findings on the behavior of jaywalkers. Fig. 4 **(a)** shows the speed of the jaywalkers accounting for both 'median to sidewalk' and 'sidewalk to median' movement. The figure indicates that men are faster than women in lane 1, lane 2 and lane 3 but slower in lane 4. Considering both gender, jaywalkers move fastest in lane 2 (2.64 feet/second). In the two-way ANOVA analysis, no statistically significant difference in lane-based speed is found across gender. Fig. 4 **(b)** shows that for the 'median to sidewalk' crosses, men are approximately 0.5 feet/second faster than women on lane 1, lane 2, and lane 3 but slower by 0.17 feet/second in lane 4. The reason behind this can be male jaywalker's behavior of spending much time at the end-lane of their crossing. This behavior was affirmed by inspecting the videos while data

Table 1
Two-Way ANOVA analysis to examine effects of jaywalking-related factors on crossing speed of jaywalkers.

Dependent Variable: Speed; Independent Variables: Gender, Crossing Direction

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	6.410[a]	3	2.137	6.440	0.000	0.113
Intercept	418.870	1	418.870	1262.480	0.000	0.893
Gender	2.404	1	2.404	7.247	0.008	0.046
Crossing Direction	1.667	1	1.667	5.023	0.026	0.032
Gender * Crossing Direction	0.004	1	0.004	0.012	0.913	0.000
Error	50.099	151	0.332			
Total	1127.630	155				
Corrected Total	56.510	154				

a. R Squared = 0.113 (Adjusted R Squared = 0.096)

Dependent Variable: Speed; Independent Variables: Crossing Direction, Walking/Running

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	5.407a	3	1.802	5.326	0.002	0.096
Intercept	762.327	1	762.327	2252.557	0.000	0.937
Walking/Running	3.511	1	3.511	10.375	0.002	0.064
Crossing Direction	1.558	1	1.558	4.604	0.033	0.030
Walking/Running * Crossing Direction	0.964	1	0.964	2.848	0.094	0.019
Error	51.103	151	0.338			
Total	1127.630	155				
Corrected Total	56.510	154				

a. R Squared = 0.100 (Adjusted R Squared = 0.082)

Dependent Variable: Speed; Independent Variables: Lane, Crossing Direction

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	144.083a	7	20.583	6.132	0.000	0.066
Intercept	7839.804	1	7839.804	2335.509	0.000	0.795
Lane	31.174	3	10.391	3.096	0.026	0.015
Crossing Direction	44.820	1	44.820	13.352	0.000	0.022
Lane * Crossing Direction	89.167	3	29.722	8.854	0.000	0.042
Error	2027.499	604	3.357			
Total	11552.000	612				
Corrected Total	2171.582	611				

a. R Squared = 0.066 (Adjusted R Squared = 0.056)

Dependent Variable: Speed; Independent Variables: Lane, Walking/Running

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	75.320a	7	10.760	3.100	0.003	0.035
Intercept	8193.914	1	8193.914	2360.929	0.000	0.796
Lane	7.089	3	2.363	0.681	0.564	0.003
Walking/Running	50.109	1	50.109	14.438	0.000	0.023
Lane * Walking/Running	14.742	3	4.914	1.416	0.237	0.007
Error	2096.262	604	3.471			
Total	11552.000	612				
Corrected Total	2171.582	611				

a. R Squared = 0.035 (Adjusted R Squared = 0.023)

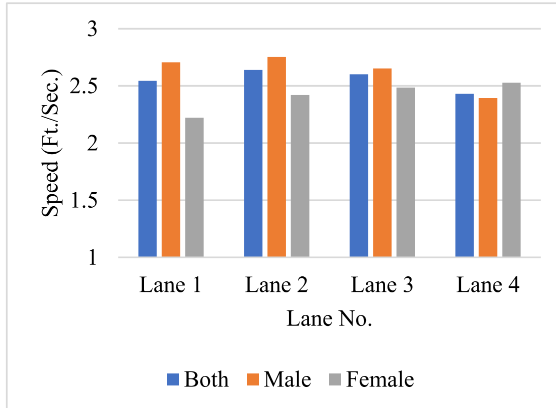
extraction. Another interesting behavior of men observed is their tendency to practice parallel jaywalking. This behavior is also present in women but not as evident as in men. Parallel jaywalking is mostly seen on lane 4 (the last lane of 'median to sidewalk movement'). As indicated by Fig. 4 **(c)**, the speed of jaywalkers in the 'sidewalk to median' movement shows that both men and women pass the final lane of their crossing (lane 1) at the fastest speed. In this directional movement, men are faster than women in each lane except lane 2. It has been found that jaywalkers who run to cross the road are at higher speed in all lanes and in both directional movements than jaywalkers who walk to cross. One significant finding is the high speed of the running jaywalkers (3.667 feet/second) in 'sidewalk to median movement' on lane 1. The difference in jaywalkers' speed across lanes for crossing direction came out as statistically significant (p-value: 0.000; 99% Confidence Interval; Table 1). Fig. 4 **(d)** and Fig. 4 **(e)** show that in 'median to sidewalk' movements, there is not that much speed difference between running and walking jaywalkers whereas in 'sidewalk to median' movements the difference is quite clear. Two-way ANOVA results show that there is a statistically significant difference in walking and running jaywalkers' speed (p-value 0.094; 90% Confidence Interval; Table 1) in the directional movement. The difference in speed in different lanes came out as statistically significant (p-value 0.026; 95% Confidence Interval; Table 1). The interaction effects of the lane and walking/running variable on speed came out as not significant (p-value 0.237; Table 1).

The calculation for the density of jaywalkers shows that lane 4 has the highest density, 1248 jaywalker-movements/hour followed by lane 1 (1214 movements/hour), lane 3 (1180 movements/hour), and lane 2 (1172 movements/hour) (Fig. 5). This suggests that the pedestrians tend to gather together at the initial and final stage of jaywalking while crossing the road. Fig. 5 also indicates that jaywalkers cross lane 2 quicker than other lanes.

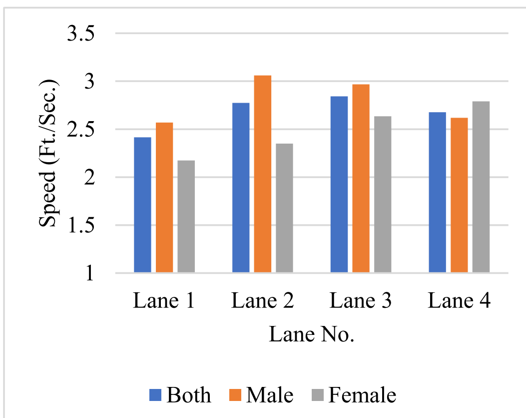
4.2. *Jaywalker trajectory and movement analysis*

This section presents the trajectory analysis of jaywalkers' movement while crossing. Jaywalker trajectories have been traced to analyze their road crossing strategies and patterns as demonstrated through Fig. 6.

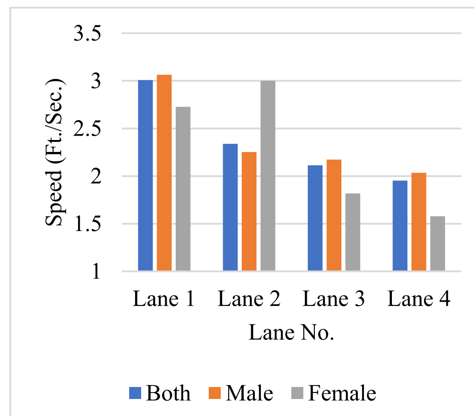
The trajectories can be divided into three parts along its length which are the start, the crowding (middle) and the end. Fig. 6 indicates that the jaywalkers start from similar points, get dispersed in the middle and merge towards the same points at the end part of jaywalking. The



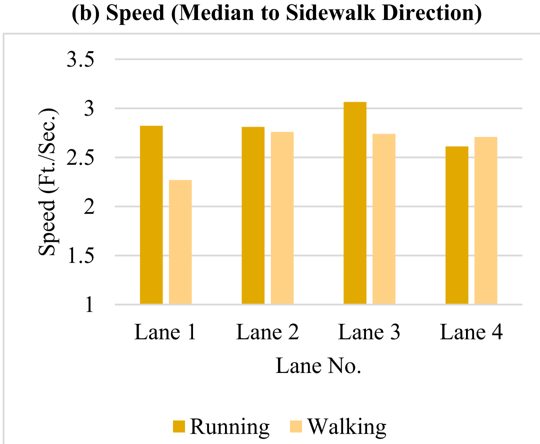
(a) Speed (Both Direction)



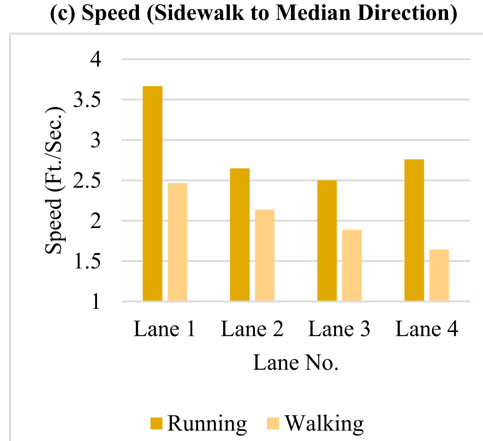
(b) Speed (Median to Sidewalk Direction)



(c) Speed (Sidewalk to Median Direction)



(d) Speed (Median to Sidewalk Direction)



(e) Speed (Sidewalk to Median Direction)

Fig. 4. Jaywalker's speed on different lanes of the crossing road.

'median to sidewalk' movement trajectories show that jaywalkers tend to move closer to the foot-over bridge. On the other hand, the 'sidewalk to median' movement trajectories tend to move further away from the foot-over bridge. Inspection of video graphic survey data showed that the tendency for herd jaywalking is more vigilant among the female jaywalkers than the male. It is also observed that women follow men, when present, while crossing though they are not together at the initial stage of their crossing. It is noticed from the video data that though most men and women had no physical disabilities to use the foot-over bridge, they would rather choose risky jaywalking over safe passage through the foot-over bridge.

4.3. *Artificial neural network model results*

Different Artificial neural network (ANN) architectures are applied to the data to find out the most optimal set of input and hidden nodes that can accurately forecast jaywalkers' movement. The best ANN architecture for predicting jaywalker's movement is determined following a trial-and-error process by altering the number of input nodes as well as hidden nodes in the hidden layers corresponding to the performance criteria of co-efficient of determination (R^2) and mean square error (MSE). R^2 indicates information about the model fit; the larger value indicating a better model fit. The most commonly used error function in neural networks is the MSE. A lower MSE value indicates a better

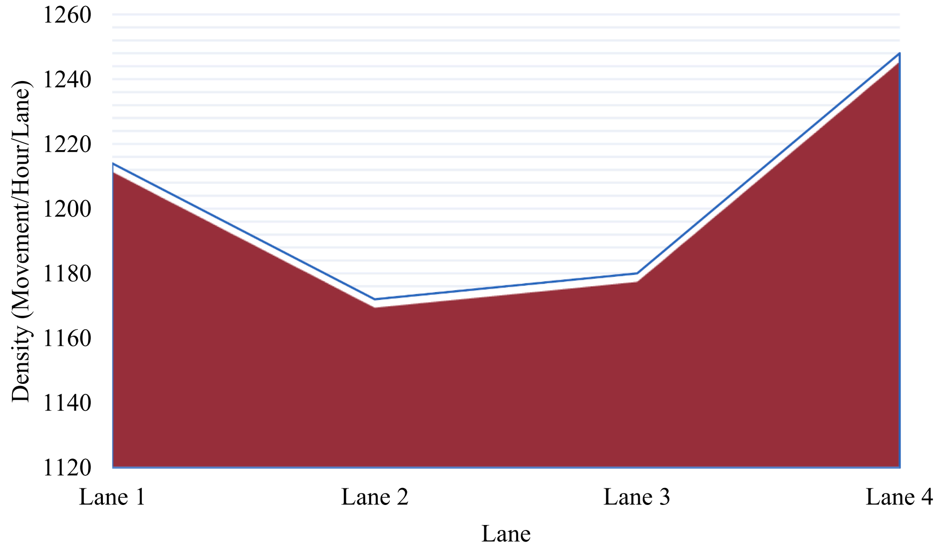


Fig. 5. Density of Jaywalkers across the road.

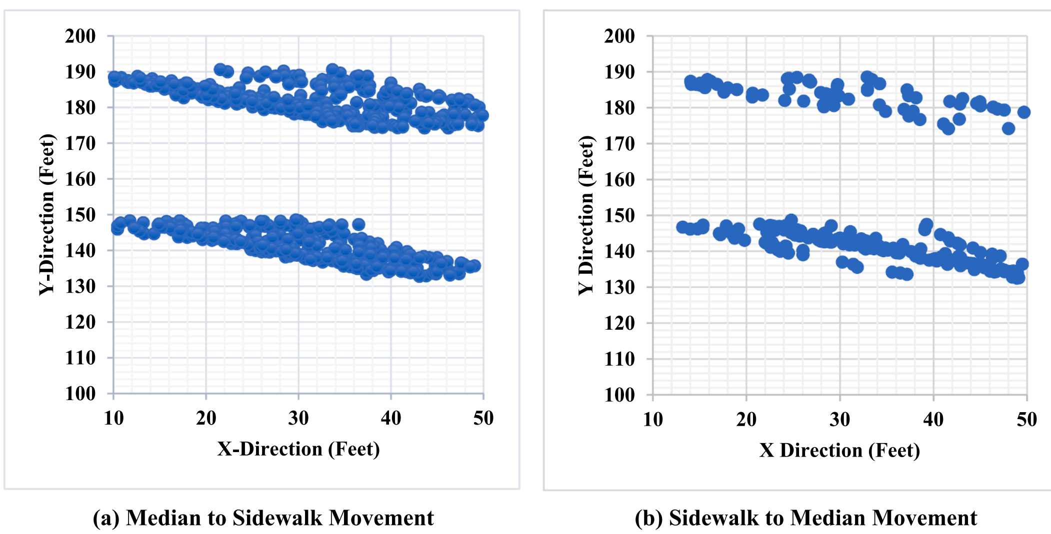


Fig. 6. Jaywalker Road Crossing Points.

predictive capacity of the model. Several ANN models are developed with increasing order of both input and hidden nodes. In each case, the output node is 1 (jaywalkers next-second position). The ANN architectures that performed well in terms of R^2 and MSE are listed in Table 2 (the best ones are in bold). For the best-performed architectures, the R^2 value is highest among the models indicating a good model fit. For these models, MSE values are quite low indicating the models' high accuracy in predicting jaywalkers' movement. Table 2 shows that the best performed ANN models have R^2 value of 0.66 and MSE value around 37.

Sensitivity analysis is conducted to find out the effects of input variables over the output and to generate a ranking of importance for the variables. For that, irrespective of the best-performed architectures in Table 2, the optimum number of hidden nodes are determined. The experiment is repeated 5 times for each hidden neuron to reach the optimal number of hidden nodes (Kadali et al., 2014). A plot is drawn between the co-efficient of determination and the number of hidden neurons as shown in Fig. 7.

Fig. 7 demonstrates that the model performance is the best with 10 hidden nodes. Therefore, further analysis is conducted with 10 nodes in the hidden layer assuming that model performance improvement beyond this value is negligible. The sensitivity analysis results of ANN models consisting of varied input nodes (6–12) across 12 input nodes, 10 hidden nodes, and 1 output node are shown in Table 3.

From the sensitivity analysis, it is found that 9-10-1 is the best ANN model to predict jaywalker's instantaneous movement. Input variables considered in this architecture are: jaywalker's position at t-1s (X_1), gender (X_2), direction of travel (X_3), cell phone use (X_4), lane number (X_5), existing threat (X_9), next step threat (X_{10}), rear step threat (X_{11}), status (X_{12}) – indicating that these variables significantly contribute to jaywalkers' movement while crossing. The three left-out variables of the 9-10-1 model are the stage of crossing (X_6), front vehicle presence (X_7), and back vehicle presence (X_8) – postulating that these three variables are not significant to jaywalkers' road crossing behavior.

5. Discussion

Jaywalking is one of the most critical problems of traffic systems across cities, particularly in rapidly growing developing areas. With the arrival of connected autonomous vehicles on the horizon, it is important to have a clear understanding of jaywalking dynamics in these contexts where jaywalking is predominant. Very few research works have examined lane-based microscopic parameters related to jaywalking for

Table 2
Performance of ANN architectures to predict jaywalker's movement (best performing ones are in bold).

Sl. No.	ANN Model	Coefficient of Determination (R^2)	MSE	Architecture
1	7-4-1	0.63	40.66	$X_1, X_2, X_3, X_4, X_5, X_9, X_{12}$
2	10-20-1	0.64	39.64	$X_1, X_2, X_3, X_4, X_5, X_6, X_9, X_{10}, X_{11}, X_{12}$
3	11-15-1	0.61	42.66	$X_1, X_2, X_3, X_4, X_5, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}$
4	9-12-1	0.62	42.08	$X_1, X_2, X_3, X_4, X_5, X_9, X_{10}, X_{11}, X_{12}$
5	9-18-1	0.64	39.3	$X_1, X_2, X_3, X_4, X_5, X_9, X_{10}, X_{11}, X_{12}$
6	12-10-1	0.66	38.6	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}$
7	12-20-1	0.66	37.96	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}$
8	10-22-1	0.66	37.96	$X_1, X_2, X_3, X_4, X_5, X_6, X_9, X_{10}, X_{11}, X_{12}$
9	**10-30-1**	**0.66**	**37.79**	$\mathbf{X_1, X_2, X_3, X_4, X_5, X_6, X_9, X_{10}, X_{11}, X_{12}}$
10	10-10-1	0.65	38.21	$X_1, X_2, X_3, X_4, X_5, X_6, X_9, X_{10}, X_{11}, X_{12}$
11	9-10-1	0.66	37.95	$X_1, X_2, X_3, X_4, X_5, X_9, X_{10}, X_{11}, X_{12}$
12	11-10-1	0.65	38.22	$X_1, X_2, X_3, X_4, X_5, X_7, X_8, X_9, X_{10}, X_{12}$
13	**11-19-1**	**0.66**	**37.67**	$\mathbf{X_1, X_2, X_3, X_4, X_5, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}}$
14	8-10-1	0.64	39.92	$X_1, X_2, X_3, X_4, X_9, X_{10}, X_{11}, X_{12}$
15	7-10-1	0.66	37.95	$X_1, X_2, X_3, X_4, X_5, X_9$
16	**7-17-1**	**0.66**	**37.52**	$\mathbf{X_1, X_2, X_3, X_4, X_5, X_9, X_{12}}$
17	6-10-1	0.63	40.89	$X_1, X_2, X_3, X_4, X_9, X_{12}$
18	6-17-1	0.64	39.6	$X_1, X_2, X_3, X_4, X_9, X_{12}$

densely developing areas. Furthermore, the advancement of predictive modeling capacity of machine learning methods has enabled to development of forecasting models with more accuracy. This paper takes Dhaka, Bangladesh as a study area to examine jaywalking behavior under mixed non-lane-based heterogeneous traffic conditions. Results show that jaywalkers move fastest in lane 2 (2.64 feet/second). Though the speed of the jaywalkers seems quite low, it is understandable from the fact that the mean walking speed of an average Bangladeshi pedestrian is 3.60 feet/second, and it is found to be slower as compared to the United States, Europeans and Asian countries but higher than the pedestrian of Saudi Arabia and Indonesia (Nazir, 2014). This indicates that pedestrians walk slower while crossing the road than usual walking. The reason behind this behavior can be the fact that while crossing the road, pedestrians are under threat from approaching vehicles, and they have to make instant decisions whether they should move forward, stop, or go in the backward direction. If they are at a slower speed, it is easier to make these decisions. It is a global phenomenon that female pedestrians walk slowly compared to their male counterparts (Chandra and Bharti, 2013; Fruin, 1971; Polus et al., 1983; Montufar et al., 2007). According to the results of this paper, this behavior is reflected while they are crossing the road, as male jaywalkers are found to be faster than female on average. This result is similar to the findings of Tarawneh (2001) as well as Chandra and Bharti (2013). Results of this study also suggest that females are at more risk while road crossing since they encounter more near-miss events than men. Difference in risky road-crossing or walking behavior in men and women have also been observed in other studies (Haghighi et al., 2021; Useche et al., 2021; Holland and Hill, 2010). Psychosocial predictors of risky walking such as, road misbehaviors observed in other users, interactions with ICTs, road distractions, sensation seeking and risk perception can play major roles in aberrant road behaviors across gender (Useche et al., 2021). Age-level of jaywalkers which was not considered in the study can contribute to risky road-crossing behavior. Herd jaywalking or grouping behavior is observed among jaywalkers (especially among females) while analyzing the video-graphic survey data. Crossing alone or with children may also affect adult jaywalkers road-crossing strategy – as hypothesized in the work of Yu et al. (2020) that calls for considering

Table 3
Sensitivity of ANN models with various input variables.

Sl. No.	ANN Model	Coefficient of Determination (R^2)	MSE	Architecture
1	12-10-1	0.66	38.60	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}$
2	11-10-1	0.65	38.22	$X_1, X_2, X_3, X_4, X_5, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}$
3	10-10-1	0.65	38.21	$X_1, X_2, X_3, X_4, X_5, X_6, X_9, X_{10}, X_{11}, X_{12}$
4	**9-10-1**	**0.66**	**37.95**	$\mathbf{X_1, X_2, X_3, X_4, X_5, X_9, X_{10}, X_{11}, X_{12}}$
5	8-10-1	0.64	39.92	$X_1, X_2, X_3, X_4, X_9, X_{10}, X_{11}, X_{12}$
6	7-10-1	0.66	37.96	$X_1, X_2, X_3, X_4, X_5, X_9, X_{12}$
7	6-10-1	0.63	40.89	$X_1, X_2, X_3, X_4, X_9, X_{12}$

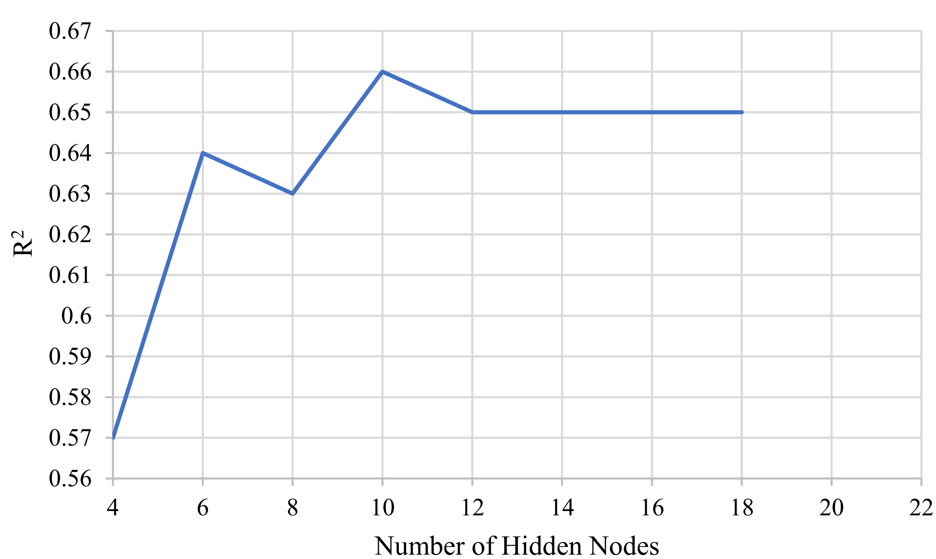


Fig. 7. Variation in coefficient of determination (R^2) with hidden neurons.

age differences in risk perception and responsibility attribution when planning and implementing strategies to improve pedestrian safety. An interesting behavior of male jaywalkers observed is their tendency to practice parallel jaywalking. This behavior is also present in women but not as evident as in men. Parallel jaywalking is mainly practiced on the lane that is beside the sidewalk. Safety posters on the sidewalk can be established to highlight the risks of jaywalking to change jaywalkers' intention to do jaywalking, in particular, parallel jaywalking. This fear-based road safety poster strategy is also suggested by Shiwakoti et al. (2020) as they have found positive changes in jaywalkers' behavior after adopting this measure. Also, to account for the safety of vulnerable female pedestrians, gender-specific risk-reduction interventions may promote safer crossing behaviors (Haghighi et al., 2021).

Results indicate that in 'sidewalk to median' movements the difference in speed between running and walking jaywalkers is quite evident. A possible reason behind this behavior is people take higher risks while crossing from 'sidewalk to median' than crossing from 'median to sidewalk'. Moreover, it has been found that jaywalkers use the phone mostly at the end-lane of their crossing. The propensity of jaywalkers for using cell phones on their last crossing lane is probably because they perceive a feeling of greater safety as they have almost reached their destination, however, the outermost lane is supposed to exhibit higher vehicle safety and lesser visibility for an incoming crossing pedestrian from the perspective of a vehicle driver. It has been found that hawker encroachment on the footpaths forces people to jaywalk causing serious hindrance to the traffic flow. Few jaywalkers are seen to board the buses before reaching the sidewalk, i.e., jaywalking initiated for boarding a bus before it reaches a stop (designated or undesignated) rather than crossing the road. This may be due to the lack of designated bus stops and their tendency to on-load/off-load passengers without completely stopping or even in the mid lanes of the streets (Anik et al., 2018). Because of this behavior of bus drivers coupled with the absence of passenger queuing behavior at stops, pedestrians are forced to jaywalk to board the buses or in case of alighting to get to the sidewalk after getting off the buses. Results of this paper show that around 30% of the jaywalkers on an average run to avoid collisions with other vehicles while crossing. This puts them at more risk of getting into an accident. Cell phone using behavior while crossing is also observed, especially among men. Publicity and awareness campaigns can be carried out to inform people about the risks and negative impacts of jaywalking. Different psychophysiological states could result in different jaywalking behaviors – as shown in the work of Oviedo-Trespalacios et al. (2021) that perceived risk influences intention of walking when impaired by alcohol. Road safety planners may consider these issues while designing for the pedestrian-safety promotional campaigns. Mass media can be utilized to carry out these campaigns. Formulation and enforcement of laws for discouraging jaywalking behavior can be considered as strict measures to adopt by the road safety planners. Results indicate that, on the sides lanes (lane 1 and 4), jaywalkers' speed is low, but density is high. On the other hand, speed is high on mid-lanes (lane 2 and 3), but density is low. Further analysis of video data showed that most of the near-miss events occur on the mid-lanes, rather than the side-lanes. This is a significant piece of information to consider while designing safety campaigns for vehicle drivers as well as pedestrians. This outcome will also assist in planning for connected autonomous vehicles (CAVs) in these areas.

ANNs developed in this study are found to be satisfactory with acceptable fit measures to forecast jaywalkers' movement on the road. ANN model results show that stage of crossing, front vehicle presence, and back vehicle presence do not significantly contribute while predicting jaywalkers' movement when crossing, whereas, current position, gender, the direction of travel, cell phone use, lane number, existing threat, next step threat, rear step threat, walking/running are significant for predicting jaywalkers' next second position. Previous research studies have shown that these variables significantly affect road crossing behavior (Anik et al., 2020; Holland and Hill, 2007; Tiwari et al., 2007).

Despite several merits, this study has some limitations. Some of the pedestrian positions were not considered while data extraction from the video due to obstruction caused by vehicular movement. The pedestrian trip purpose was also an unknown factor in this study that might influence pedestrian behavior. Furthermore, this study did not consider potential variables, such as gap acceptance. Considering this paper as an introductory research in this field, the authors have examined the mid-block location first. As future scopes of this study, the authors are planning to extend it to include variables like gap acceptance, and the context of intersections. Nevertheless, the developed optimal ANN model may come in handy in predicting jaywalker behavior under mixed traffic conditions. Results from this paper can be utilized as input while developing predictive models or tools for CAVs to forecast jaywalkers' position shifting while crossing the road. These results may also help reduce pedestrian and vehicular conflicts by control measurements at undesignated crosswalks.

6. Conclusions

This study proposes a framework based on artificial neural networks (ANNs) to predict jaywalker's instantaneous movement while crossing the road. It also determines the microscopic variables, such as speed, flow, and density of jaywalkers to get a clearer idea of jaywalking behavior under non-lane-based heterogeneous traffic conditions. Furthermore, it develops jaywalker trajectories and analyses to understand jaywalker's position shifting strategy. This study fills gaps in the understanding of jaywalking behavior on non-lane-based mixed traffic– since little is known about illegal road crossing in these contexts. This paper takes Dhaka, Bangladesh as a study area where jaywalking is predominant and causes severe disruptions to vehicular traffic movement. Knowledge extracted by this paper offers critical insights on pedestrians' illegal road crossing behavior that can be beneficial while planning for connected autonomous vehicles in the context of rapidly growing and densely populated developing cities. Results reveal the existence of a substantial difference in jaywalking behavior between men and women. Findings show that the average speed of men is higher than women considering both directional crossing. Another interesting finding is that women encounter more near-miss events with vehicles than men indicating that women display more risky jaywalking behavior. Besides, the density of jaywalkers is highest on lane 4, followed by lane 1, lane 3, and lane 2. Besides, women are more likely to show grouping behavior but less likely to use a cell phone while crossing than men. Jaywalkers in general are found to be running mostly at the end of their crossing stage. Several feed-forward backpropagation ANN models are used to simultaneously predict jaywalker's instantaneous movement, using pedestrian behavioral, demographic, and roadway characteristics as inputs. The developed ANN models based on performance criteria (co-efficient of determination and mean square error) show positive results in correctly predicting jaywalker's position under mixed traffic conditions and non-lane-based traffic. Sensitivity analysis is used to evaluate the importance of input variables. The optimal ANN architecture with the best performance in predicting jaywalker's position is found to be 9-10-1 (9 input nodes, 10 hidden nodes, 1 output node). The three left-out variables of the 9-10-1 model are the stage of crossing, front vehicle presence, and back vehicle presence. This indicates that the jaywalker's current position, gender, the direction of travel, cell phone use, lane number, existing threat, next step threat, rear step threat, walking/running significantly affect the jaywalker's next second position. The framework proposed in this study can be utilized in the future to investigate individual jaywalker's behavior keeping in an account that individual's socio-economic and demographic characteristics. The findings of this study on jaywalking behavior extend the understanding of the complex road crossing strategies of pedestrians. The insights from this paper can be useful to develop tools for autonomous, connected or self-driven vehicles, accounting for safety considerations for jaywalkers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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