future transportation

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Modeling and Evaluating the Impact of Mobile Usage on Pedestrian Behavior at Signalized Intersections: A Machine Learning Perspective

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Abstract: Pedestrian safety is a growing global concern, particularly in urban areas, where rapid urbanization and increased mobile device usage have led to an increase in distracted walking. This study investigates the impact of technological distractions, specifically mobile usage (MU), on pedestrian behavior and safety at signalized urban intersections. Data were collected from 11 signalized intersections in New Delhi, India, using video recordings. Key inputs to the modeling process include pedestrian demographics (age, gender, group size) and behavioral variables (crossing speed, waiting time, compliance behaviors). The outputs of the models focus on predicting mobile usage behavior and its association with compliance behaviors such as crosswalk and signal adherence. The results show that 6.9% of the pedestrians used mobile phones while crossing the road. Advanced machine learning models, including Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Recurrent Neural Networks (RNN), have been applied to analyze and predict MU behavior. Key findings reveal that younger pedestrians and females are more likely to exhibit distracted behavior, with pedestrians crossing alone being the most prone to mobile usage. MU was significantly associated with increased levels of crosswalk violation. Among the machine learning models, the CNN demonstrated the highest prediction accuracy (94.93%). The findings of this study have a practical application in urban planning, traffic management, and policy formulation. Recommendations include infrastructure improvements, public awareness campaigns, and technology-based interventions to mitigate pedestrian distractions and to enhance road safety. These findings contribute to the development of data-driven strategies to improve pedestrian safety in rapidly urbanizing regions.

Keywords: pedestrian safety; distraction; mobile usage; machine learning; violation behavior

Academic Editor: Luigi dell'Olio

Received: 6 December 2024
Revised: 14 January 2025
Accepted: 24 January 2025
Published: 1 February 2025

Citation: Haque, F.; Kidwai, F.A.; Thapa, I.; Ghani, S.; Mtapure, L.M. Modeling and Evaluating the Impact of Mobile Usage on Pedestrian Behavior at Signalized Intersections: A Machine Learning Perspective. *Future Transp.* **2025**, *5*, 11. https://doi.org/10.3390/futuretransp5010011

1. Introduction

Road user safety and well-being are prominent global issues. Approximately 1.19 million people die each year, and more than 20 million are left with nonfatal injuries as a result of road accidents. The number of fatalities and injuries is significantly higher in low- and middle-income countries (LMICs) [1]. In 2022, 6364 road accident deaths were reported in Vietnam [2]. Developing countries face unique challenges owing to rapid urbanization, high population densities, and less stringent traffic regulations. India ranks first in terms of road accident fatalities, followed by China [3]. Compared with rural areas, urban cities are emerging as critical hotspots for road accidents. For instance, Delhi leads in terms of accidental deaths, followed by Bengaluru [4].

Among road users, pedestrians are particularly vulnerable to road accidents. This can be established by the fact that the number of pedestrian deaths has increased by 53% since 2009 [5]. The exposure of pedestrians to moving traffic, combined with the lack of protective barriers, makes them more susceptible to serious injuries in the event of a collision. Worldwide, pedestrians account for 23% of the total fatalities due to road accidents [1]. India is no exception to this global trend, as pedestrians comprise 19.5% of the total accidental deaths [4].

In recent years, there has been an exponential increase in mobile phone usage, particularly among smartphone users around the world. Although mobile phones are the most preferred and convenient choice for people to communicate, they result in inadvertent traffic safety issues owing to the distraction caused by their use. More than five billion people currently own a mobile phone, which is 70% of the total world population [6]. The use of mobile devices and other technological gadgets has led to an increase in distracted walking, posing significant risks to pedestrian safety globally [7,8]. This behavior not only endangers the individuals using the devices but also poses significant hazards to drivers and other road users. The National Highway Traffic Safety Administration (NHTSA) estimated that distracted driving claimed around 3308 people by 2022 in the United States [9]. Recent statistics have revealed that pedestrian distractions caused by technology are contributing to a growing number of accidents and fatalities. Investigations on crash data statistics in the USA reported that 74% of pedestrian victims listened to music at the time of crashes [10]. The majority of these fatalities are linked to distractions caused by mobile device use with activities such as talking, listening to music, texting, or browsing.

Figure 1 visually presents the consequences of mobile phone usage and the benefits of awareness at traffic intersections through illustrations. Figure 1a: A pedestrian is distracted by a smartphone while crossing the road, illustrating a common safety hazard leading to accidents. Figure 1b: An accident involving a pedestrian hit by a car due to distracted walking, emphasizing the dangers of mobile phone use while crossing. Figure 1c: A traffic intersection with an "Avoid Mobile Phone" sign, highlighting the importance of adhering to safety protocols to prevent accidents. Figure 1d shows a harmonious traffic intersection with attentive pedestrians, cyclists, and drivers, demonstrating the positive outcomes of avoiding mobile phone use on roads and promoting road safety awareness.

Figure 1. Illustrations depicting the risks of mobile usage and benefits of awareness at traffic intersections: (**a**) a distracted pedestrian using a mobile phone while crossing, (**b**) the consequence of distraction—a road accident, (**c**) the role of "avoid mobile phone" signs in promoting safety, and (**d**) the harmony and order achieved by avoiding mobile phone distractions.

To provide a strong theoretical foundation for the study, an understanding of established behavioral frameworks to contextualize pedestrian safety and distraction behaviors is required. The Theory of Planned Behavior (TPB), has been widely utilized in traffic safety research to understand the factors influencing individuals' decision-making processes. It highlights that attitudes, subjective norms, and perceived behavioral control are critical determinants of behavior. For pedestrians, this theory can explain how personal attitudes toward mobile phone usage, societal norms regarding its acceptability, and perceived control over safe crossing influence compliance and distraction behaviors. The TPB has been successfully applied in studies to demonstrated its utility in predicting safety-related behaviors in traffic contexts [11].

The Health Belief Model (HBM) provides a framework for understanding health-related behaviors by emphasizing the role of perceived susceptibility, severity, benefits, and barriers. In the context of pedestrian distraction, this model can elucidate how individuals perceive the risks associated with distracted walking and the potential benefits of adhering to safe crossing practices. For instance, interventions like awareness campaigns or environmental cues can serve as triggers for behavioral change by enhancing perceptions of risk and the benefits of safe behavior. Social dynamics significantly affect pedestrian behaviors, as peer presence and group size influence risk-taking tendencies. Studies have highlighted the impact of social contexts on adolescent pedestrian safety, demonstrating that group settings can either mitigate or exacerbate risky behaviors [12,13]. This perspective is particularly relevant in urban settings, where pedestrian interactions are frequent and varied.

Researchers have attempted to study the effect of pedestrian demographics, such as age and gender, on distracted behavior. Age has a significant impact on how people react to distractions. Older pedestrians are more cautious when it comes to road crossings [6,14]. Research shows that approximately 40% of younger pedestrians are seen and have admitted to using a phone while crossing the street, and it was discovered that they are

60% more likely to cross the street unsafely than people in older age groups [6,15]. Another study showed that 14% of adults in America admit to bumping into something due to mobile distraction [16]. It was observed that those below the age of 20 were 2.7 times more likely to use mobile devices and behave unsafely when crossing intersections [8]. This is supported by another study, which reported that young adults are more likely to use mobile phones while crossing the road [17].

Gender differences significantly influence pedestrian behavior at intersections, with men and women exhibiting distinct patterns of distraction. Men are more likely to engage in risky behaviors such as crossing streets in non-designated areas or against traffic signals, often while distracted [6,18]. One study found that men were 70% more likely to put themselves in these dangerous situations [19]. In another paper, the researcher claimed that women tend to be more distracted than men, which contradicts the previous statement [20]. Females are more likely to use mobile devices while crossing the road [17]. One study showed that females using mobile phones are less likely to look at traffic before and during crossing, and are also less likely to wait for traffic to stop [7]. Females were found to be less likely to look at traffic signs or signals at both un-signalized and signalized intersections [16]. Women were found to multitask more, resulting in increased levels of distractions, and women were more likely to engage in conversations while crossing compared to men [21].

Several studies have examined how mobile phone use affects pedestrian road crossing behavior. It has been observed that smartphone-distracted pedestrians are less likely to wait for a crossing light [16]. Distracted pedestrians are less likely to exhibit safe crossing behavior [22]. Mobile phone use while crossing is associated with reduced situational awareness and increased unsafe crossings, which may increase the risk of accidents [23]. Pedestrians committing crosswalk violations are more likely to talk on their phones while walking [24]. Technological distraction also affects other types of unsafe behaviors, such as not looking left or right before crossing [25]. Basch et al. (2015) performed one of the largest studies to understand technologically distracted walking behavior and found that 42% of the total signal-violating pedestrians were distracted [26]. Pedestrians were more likely to use mobile phones at signalized intersections, as they felt safer than at unsignalized intersections, where they are forced to pay attention [8]. Mobile phone activities significantly distract pedestrians, leading to unsafe crossing behaviors and contributing significantly to traffic accidents. Among distracted behaviors, texting has the highest odds of showing unsafe behavior [25]. Smartphone activities, particularly texting, have been identified as critical in reducing pedestrian safety, as they lead to risky behaviors [18]. Text distraction is associated with the highest level, whereas music distraction has the lowest level of impairment in the crossing performance of pedestrians [27]. Various studies have been conducted to gauge the effects, causes, and possible solutions to this problem. Some studies have attempted to explore the implications of these psychological factors on pedestrian safety, suggesting that interventions addressing mobile addiction and boredom could mitigate distracted walking risks and potentially enhance awareness of pedestrian safety [28].

Machine learning (ML) methods have been extensively employed in pedestrian safety research to model and predict risky behaviors, evaluate compliance with traffic rules, and understand the factors influencing pedestrian safety. These methods offer high predictive accuracy and the ability to analyze complex, high-dimensional datasets. Several studies have demonstrated the effectiveness of ML techniques in pedestrian safety applications [29–31]. In one study, Support Vector Machine (SVM) and Random Forest (RF) were used to predict pedestrians' red-light crossing behavior [32]. Deep learning approaches have further enhanced the predictive performance of pedestrian safety studies. For example, Long Short Term Memory (LSTM) and Recurrent Neural Network (RNN) have been used to classify pedestrian behavior and detect violations at signalized intersections [33].

Despite their effectiveness, these ML methods often operate as “black-box” models, providing little insight into how input variables contribute to the predictions. In safety-related research, this lack of transparency limits the ability to identify causal relationships, which are critical for designing targeted interventions and preventive measures. Explainable artificial intelligence (XAI) addresses this limitation by providing interpretability and transparency in ML models. XAI techniques, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), help quantify the contribution of individual features to model predictions, enabling researchers to understand the underlying factors driving the results. Recent studies have demonstrated the utility and effectiveness of XAI in transportation safety research [34,35]. Thus, integrating XAI into pedestrian safety research can bridge the gap between predictive accuracy and interpretability, offering deeper insights into how demographic, behavioral, and situational factors influence distracted behaviors.

Pedestrian distraction due to technology is a significant safety concern, contributing to numerous traffic accidents and fatalities worldwide. The integration of mobile devices into daily life has increased the likelihood of pedestrians engaging in risky behaviors such as ignoring traffic signals and stepping into the road without proper attention. Addressing this issue requires targeted interventions, including public awareness campaigns, improved infrastructure, and personalized safety protocols. Building on the discussion regarding the adverse effects of mobile device usage on pedestrian safety, this study aimed to investigate the impact of technological distractions on pedestrian behavior and safety. It further explored the influence of demographic and behavioral factors that contribute to distracted walking. Additionally, this study examined the application of advanced machine learning algorithms to model the behavior of technologically distracted pedestrians. This study seeks to enhance road safety and protect vulnerable road users by identifying and mitigating the factors that lead to pedestrian distraction. Ultimately, this study aimed to deepen the understanding of pedestrian compliance behavior and develop effective models to improve road safety measures, particularly in rapidly urbanizing areas.

2. Methodology

The major steps involved in this research include selecting a suitable study site, data collection, data extraction and compilation, and the analysis phase, which involves examining pedestrian behavior using various statistical hypothesis testing and modelling techniques. The steps are explained and discussed in the following sections. The flow of the research methodology is shown in Figure 2.

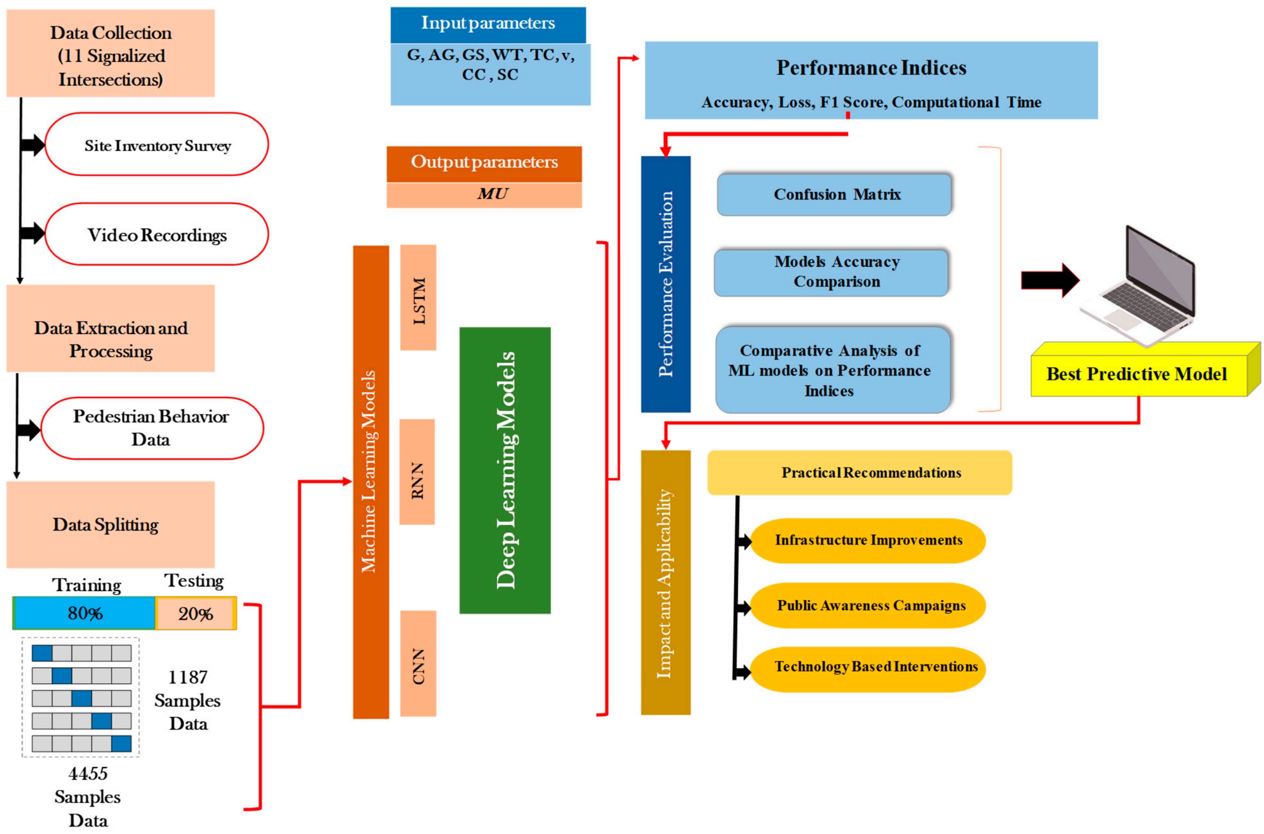


Figure 2. Flow of research methodology.

2.1. Study Site

To obtain a basic idea of possible research sites, a reconnaissance assessment of a number of crossings in New Delhi, India, was first conducted. Several locations were eliminated based on different physical, transportation, and pedestrian criteria. Following a thorough analysis of these filtered locations, 11 signalized intersections with a sizable number of vehicles and pedestrians were chosen for the study. The selected crossings showed a variety of built environments, signal phases, physical attributes, and pedestrian amenities. These crossings are also located in locations with a variety of land uses and are spatially well separated. The details of the study sites are presented in Table 1.

Table 1. Details of the study locations.

Intersection No.	Intersection Type	Land Use	Vehicle Volume (veh/h)	Signal Violation (%)	Crosswalk Violation (%)	Mobile Usage (%)
1	T	Residential	7582	7.75	56.46	4.97
2	4-Legged	Mixed	1472	17.33	72.44	6.67
3	T	Commercial	3142	28.44	56.16	7.4
4	4-Legged	Commercial	3250	2.68	59.3	6.29
5	4-Legged	Commercial	1510	7.24	62.15	4.63
6	4-Legged	Commercial	1602	14.28	32.33	4.14
7	4-Legged	Commercial	1329	17.3	28.74	10.12
8	T	Commercial	3180	21.27	65.28	2.45
9	T	Residential	4332	46.28	73.83	7.58
10	4-Legged	Commercial	1964	26.8	71.53	9.8
11	T	Commercial	2071	11.93	70.34	4.89

2.2. Data

Road inventory surveys and video recordings were conducted to gather detailed information on intersections and pedestrian activities. Data were collected on weekdays under normal weather conditions to ensure sufficient traffic and pedestrian volume. A comprehensive format was prepared to record various physical and built environment features, including road geometry, signal phases, pedestrian facilities, and the surrounding land use. To capture pedestrian demographics and behaviors, two or more cameras were installed at each study site based on site conditions. These cameras were strategically placed to cover the entire intersection, including the sidewalks, medians, and crosswalks. Video recordings were performed during peak hours (9–10 AM and 5–6 PM) without disrupting the normal traffic flow. Pedestrians were unaware of the cameras, ensuring that their natural behaviors were recorded. The cameras were adjusted to ensure a clear field of view, covering the ends of the carriageway and a few meters on both sides. The recordings were played in ultra-slow motion (2–3 frames per second) using the AVS video editor 9.8 software, and the data were manually extracted by trained volunteers. Each crossing instance was manually analyzed, with demographic (e.g., age, gender, group size) and behavioral attributes (e.g., crossing speed, waiting time, compliance behaviors) recorded. Mobile usage (MU) was classified based on observed interactions, such as texting, calling, or browsing, during the crossing period. The final dataset comprised 5642 individual pedestrian observations, representing diverse behaviors and contexts. The extracted data were coded and entered into preset Excel formats.

Gender is categorized as "Male" and "Female". Since the exact age of a pedestrian cannot be determined from video footage, age is estimated by grouping individuals into three categories: "Young", "Middle-aged", and "Old". The age group was estimated based upon factors such as physical characteristics, including facial features, overall appearance, hair color, walking style, and clothing type [31]. Group size is classified based on the number of pedestrians crossing together: "Single", "Pair", or "More than two". Technological distraction is identified as "Yes" if a person is clearly observed using a mobile phone, talking on the phone, or wearing headphones; otherwise, it is labeled as "No". The arrival time is recorded when a pedestrian reaches the sidewalk or median, and the departure time is noted when they step onto the carriageway. After crossing the road, the end time is recorded when the pedestrian reaches the opposite sidewalk or median. The waiting time is calculated as the difference between the departure time and the arrival time, while the crossing time is determined as the difference between the end time and the departure time. Crossing speed is defined as the width of the carriageway divided by the crossing time. Pedestrian crosswalk compliance behavior is defined as "Yes" if the individual crosses the road within the crosswalk or within 0.5 m on either side of it. This 0.5 m margin is included to account for pedestrians in large groups, some of whom may be slightly outside the marked crosswalk. Crossing at any other location is considered non-compliant, labeled as "No". If a pedestrian crosses the road during the vehicle green phase or red phase for pedestrians, it is noted as a signal violation. The variable descriptions and coding are presented in Table 2. Typical mobile usage while crossing a road is shown in Figure 3.

Table 2. Variable description and coding details.

Pedestrian Characteristics	Category	Description (Coding)	Value
Mobile Usage (MU)	No	Using mobile, talking over phone, and using headphones: Yes (1), No (0)	93.10%
	Yes		6.90%
Gender (G)	Male		76.92%

	Female	Male (0), Female (1)	23.08%
Age Group (AG)	Young	Since exact age of pedestrian cannot be found from video, it is estimated by grouping them into Young (0), Middle (1), and Old (2) age groups	45.56%
	Middle		46.60%
	Old		7.84%
Group Size (GS)	Single	Pedestrian group size while crossing: Single (0), Pair (1), More than 2 (2)	65.42%
	Pair		20.34%
	>2		14.24%
Waiting Time (WT)	Mean waiting time	Difference between pedestrian's arrival time at sidewalks or medians and their departure time (s)	5.543 s
Crossing Time (TC)	Mean crossing time	Time required by the pedestrian to cross the carriageway (s)	10.067 s
Crossing Speed (v)	Mean crossing speed	Width of carriageway divided by crossing time of pedestrian (m/s)	1.284 m/s
Crosswalk Compliance (CC)	No	If pedestrian uses designated crosswalks: Yes (1), No (0)	59.40%
	Yes		40.60%
Signal Compliance (SC)	No	If pedestrian cross road during pedestrian's green phase: Yes (1), No (0)	20.12%
	Yes		79.90%

Figure 3. Typical mobile usage at study site.

2.3. Analysis and Modeling

Descriptive statistical analysis was initially performed to obtain a general idea about pedestrian demographics and behaviors. Further detailed analyses and modelling of pedestrian mobile usage were performed. Mobile usage is modeled against several predictor variables, such as gender (G), age group (AG), group size (GS), waiting time (WT), crossing time (TC), crossing speed (v), crosswalk compliance (CC), and signal compliance (SC). The dependent variable is a categorical dichotomous (yes/no) variable, and classification algorithms are best suited to model it. This study models technologically distracted pedestrian behavior using CNN, RNN, and LSTM due to the sequential and high-dimensional nature of the data. The choice of these models was motivated by the nature of the problem and the data structure, specifically owing to the sequential and high-dimensional data in the dataset that include temporal and behavioral sequences, such as crossing speeds, waiting times, and compliance behaviors. These are inherently sequential and require capturing patterns over time, and simpler models such as logistic regression or decision trees may not be adequately handled. RNN and LSTM are specifically designed for sequential data, enabling them to model time-dependent behaviors effectively. CNN was chosen for its ability to extract hierarchical and spatial features from input data. Although CNNs are traditionally used in image analysis, their utility in extracting complex patterns from structured tabular data has been established in recent studies. In this study, convolutional layers facilitated the detection of nuanced relationships between pedestrian behaviors and mobile usage. Preliminary experiments with simpler models, such as logistic regression and decision trees, revealed a significantly lower accuracy and predictive performance. These models struggled to capture the intricate nonlinear relationships within the data. For instance, logistic regression assumes a linear relationship between the independent and dependent variables, which is unsuitable for this multifaceted problem. Decision trees, while interpretable, tend to overfit small datasets and fail to generalize well for complex, high-dimensional data [36]. These deep learning models also provide better generalizability and robustness, which are critical for real-world applications. This study aimed not only to predict distracted pedestrian behavior but also to analyze and understand the intricate associations between demographic, behavioral, and compliance factors. Advanced models such as CNN, LSTM, and RNN are capable of achieving both high predictive accuracy and deeper insights into data. In total, 80% was used for training, and 20% for testing. The details of these models are presented below.

2.3.1. Convolutional Neural Network (CNN)

CNN is a strong deep learning model for tasks such as binary digit prediction in image classification applications. The model uses convolutional layers to extract hierarchical features from the input data, followed by classification using dense layers. Binary digit prediction aims to classify an image into one of two categories: 0 or 1. The initial component of the basic CNN architecture is an input layer, usually in the shape of a 2D matrix that displays the pixel values of the image. Convolutional layers utilize the input along with a set of filters (also known as kernels) to generate feature maps, which reveal detected patterns, such as textures or edges. Mathematically, this is expressed as

$$Y_{ij} = (X * W)_{ij} + h \quad (1)$$

where h is the bias, X is the input, W is the filter, and * is the convolution procedure. The output Y represents the feature map generated by applying convolution, followed by the use of nonlinear activation functions such as a Rectified Linear Unit (ReLU) after convolutional layers:

$$f(x) = \max(0, x) \quad (2)$$

By adding nonlinearity, the network can detect complex connections in data. Pooling layers typically utilize Max Pooling to decrease the spatial dimensions of the feature maps and down-sample them, retaining vital characteristics while reducing computational costs. In mathematical terms, this is expressed as

$$R_{ij} = \max(m, n) \quad (3)$$

where R_{ij} denotes the pooling area. The feature mappings that emerge were transformed into a 1D vector and passed through fully connected (dense) layers. To achieve classification, the layers initially calculate the weighted sums and then activate them with functions. Typically, the last dense layer for binary classification contains a single unit that utilizes a sigmoid activation function.

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (4)$$

The value produced by the sigmoid function falls within the range of 0 to 1 and represents the likelihood of being part of a specific category. During training, the goal was to minimize the binary cross-entropy loss function as follows:

$$L = -(y\log(p) + (1-y)\log(1-p)) \tag{5}$$

where y represents the actual label and p is the predicted probability. The weights are adjusted to minimize loss and enhance the classification accuracy by optimizing the model with stochastic gradient descent or its variations.

2.3.2. Recurrent Neural Network (RNN)

An RNN is a type of neural network designed for handling sequential data, making it well suited for tasks such as predicting binary digits. Unlike traditional feedforward networks, RNNs have loops that allow them to retain information from the previous time points. Because of this memory, RNNs are perfect for tasks that require the order of data to be important, such as predicting binary digits in a sequence. In an RNN, each time step in the input sequence is sequentially processed. At each time step t, the network calculates a hidden state h_t by merging the information from the previous hidden state h_{t-1} and the current input x_i. This can be mathematically expressed as follows:

$$h_t = \tanh(W_h x_i + U_h h_{t+1} + b_h) \tag{6}$$

where *tanh* serves as the activation function that brings nonlinearity, b_h represents the bias vector, and W_h and U_h represent the weight matrices. The procedure for binary digit categorization includes sending hidden states through a dense layer with a sigmoid activation function. This layer generates a result that shows the probability that the input sequence belongs to either of the two categories. In the final time step T, the ultimate prediction is given by

$$y_T = \sigma(W_y h_T + b_y) \tag{7}$$

The weight matrix is represented as W_y, the bias term is denoted b_y, and the sigmoid function $\sigma(z)$ produces a probability ranging from zero to one.

2.3.3. Long Short-Term Memory (LSTM)

A type of RNN known as the LSTM network was developed to address issues such as the vanishing gradient problem faced by conventional RNNs. LSTMs are ideal for tasks that involve sequences, such as predicting binary digits, because of their ability to effectively grasp long-term relationships. The information flow inside the network is controlled by three gates: the input, forget, and output gates, which are present in an LSTM unit. The input gate regulates the amount of new data that will be used to update the cell state, whereas the forget gate manages how much of the previous cell state C_{t-1} is retained. The mathematical expression for the forget gate can be formulated as

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{8}$$

W_f and b_f represent the weights and bias, respectively, h_{t-1} is the prior hidden state, and x_t corresponds to the present input. The input gate was responsible for modifying the cell state.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{9}$$

$$C_t = \tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{10}$$

The updated new cell state is expressed as

$$C_t = f_t * C_{t-1} + i_t * C^{\sim}{}_t \tag{11}$$

Ultimately, the output gate creates an updated hidden state, which is utilized for forecasting the binary class with a sigmoid activation function:

$$h_t = o_t * \tanh(C_t) \tag{12}$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{13}$$

The binary forecast is computed at the final period T through the following calculation:

$$y_T = \sigma(W_y h_T + b_y) \tag{14}$$

Training the model involves using binary cross-entropy loss and optimizing it with Backpropagation Through Time (BPTT). LSTMs are proficient in categorizing sequential binary information by efficiently understanding the relationships between different time points. The hyperparameters of the classification models are listed in Table 3.

Table 3. Hyperparameters of classification models.

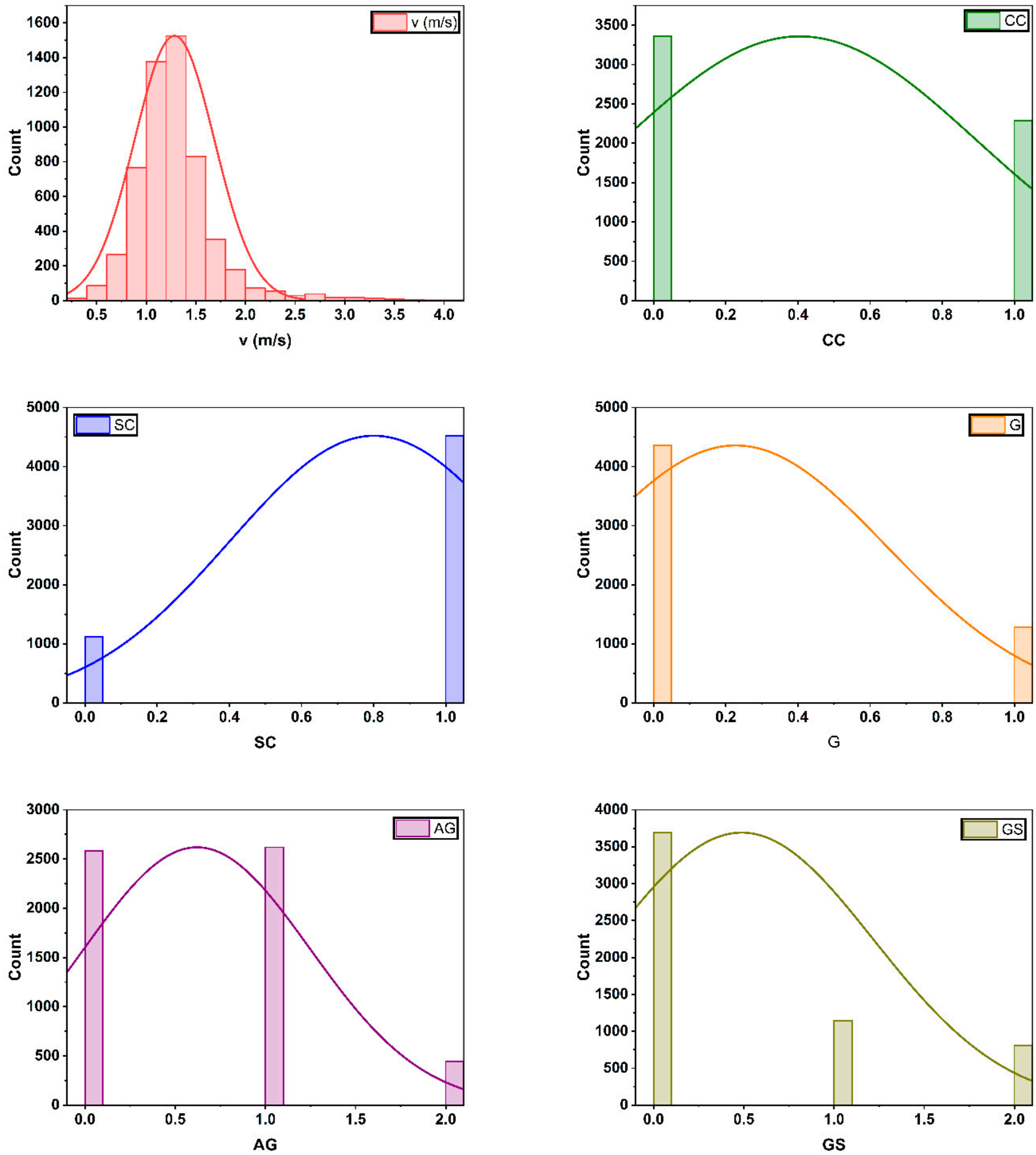
Models	Epoch	Batch
CNN	15	50
LSTM	10	35
RNN	25	40

3. Result and Discussion

The statistical and histogram distributions of the overall dataset are presented in Table 4 and Figure 4, respectively. Pedestrian mobile usage (MU) at each study location is listed in Table 1. This shows that the MU varies significantly across different locations, and, overall, 6.9% of pedestrians are found to be using mobile phones while crossing the road.

Table 4. Statistical distribution of overall dataset (count = 5642).

Parameters	Input Parameters								Output Parameter
	v (m/s)	CC	SC	G	AG	GS	TC (s)	WT (s)	MU
Max	4.08	1.00	1.00	1.00	2.00	2.00	51.10	111.66	1.00
Min	0.24	0.00	0.00	0.00	0.00	0.00	2.79	0.00	0.00
Mean	1.28	0.40	0.80	0.23	0.62	0.49	10.07	5.54	0.07
Median	1.24	0.00	1.00	0.00	1.00	0.00	9.30	0.00	0.00
Std	0.40	0.49	0.40	0.42	0.63	0.73	4.03	10.64	0.25
Variance	0.16	0.24	0.16	0.18	0.39	0.54	16.28	113.18	0.06


v (m/s)
Count
CC
SC
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GS

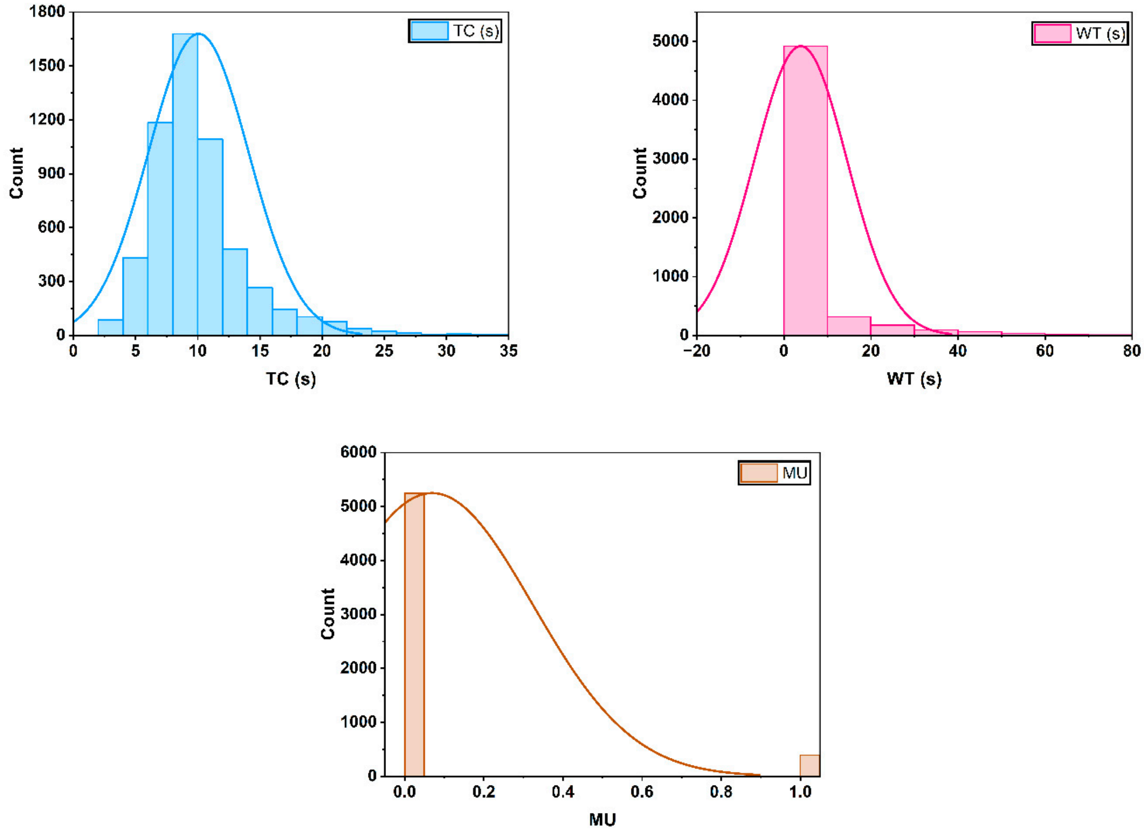


Figure 4. Histogram distribution of input and output variables.

To obtain a comprehensive understanding of the effect of pedestrian demographics on the MU, a detailed analysis was performed, as shown in Figure 5. These findings indicate that MU is slightly higher among females than among males, consistent with previous studies suggesting that females are more prone to distraction than males [17]. Regarding age groups, young pedestrians were found to be the most distracted, whereas elderly pedestrians were the least distracted when crossing roads. Similar patterns have been reported in other studies [15,22]. This behavior among younger pedestrians can be attributed to their higher risk-taking tendencies, enhanced cognitive and sensory abilities, and frequent smartphone use for social media interactions. The analysis also revealed that the percentage of MU was significantly higher among pedestrians crossing alone than among those crossing in pairs or groups. Previous studies corroborated these findings [24,31]. Pedestrians in pairs or groups are more likely to engage in conversations, reducing their mobile usage while crossing. In contrast, individuals crossing alone often interact with their smartphones to remain engaged and combat feelings of boredom.

The impact of MU on pedestrian compliance behavior while crossing roads is illustrated in Figure 6. The findings revealed that approximately 58% of the distracted pedestrians failed to use designated crosswalks. Conversely, more than 75% of mobile users comply with traffic signals. This indicates that distracted pedestrians often overlook crosswalks and opt to cross at more convenient locations while waiting for a pedestrian green signal. Similar patterns have been observed in other studies, supporting these findings [24,37]. As shown in Figure 7, pedestrians using mobile phones had significantly longer waiting times.

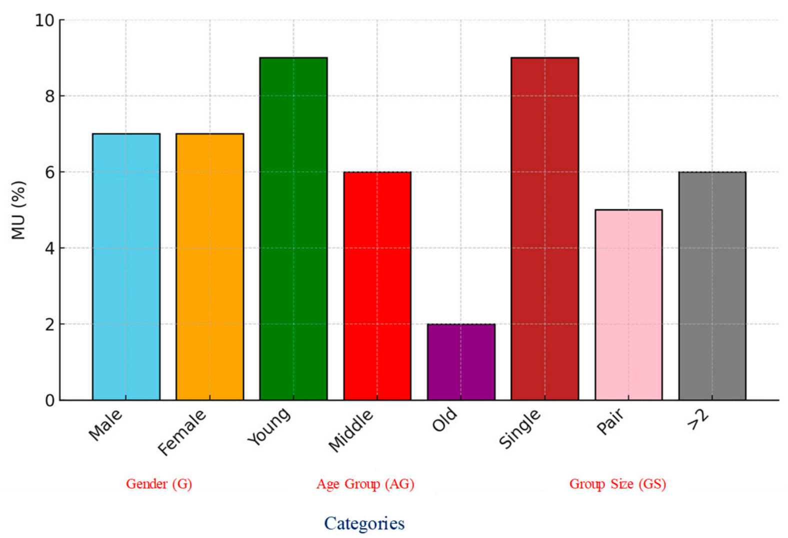


Figure 5. Mobile usage with respect to pedestrian demographics.

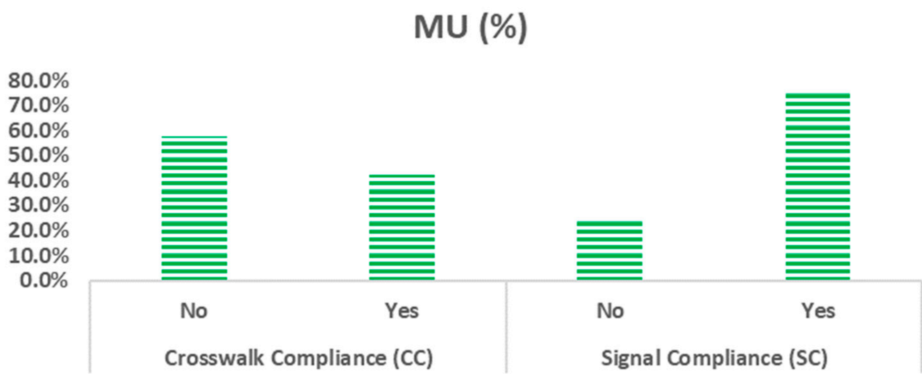


Figure 6. Mobile usage with respect to compliance behavior.

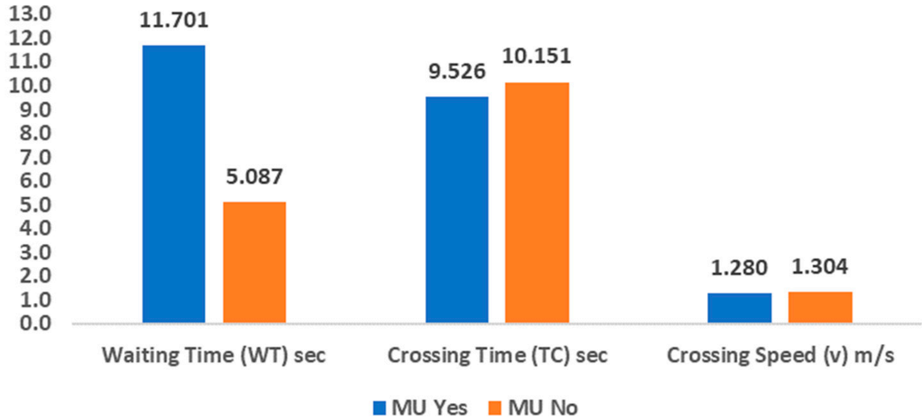
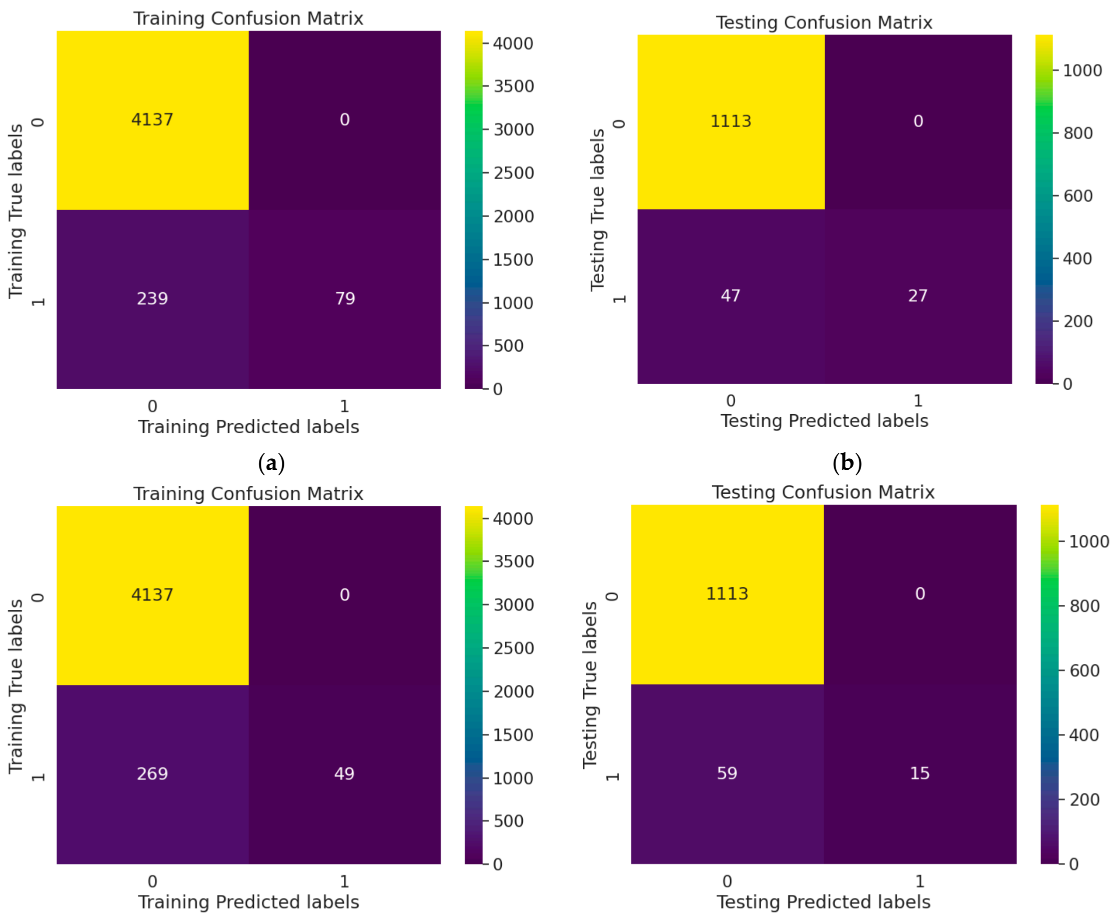


Figure 7. Mobile usage with respect to crossing behavior.

Finally, the MU behavior of pedestrians while crossing the road was modeled against the predictor variables, as defined in Section 2.3. Prediction using a classification model involves analyzing the accuracy, loss, confusion matrix, and F1 score. Table 5 illustrates the accuracy and loss outcomes of the classification models. The CNN model exhibited the highest accuracy (0.9493) and lowest loss (0.2233), whereas the RNN model exhibited the lowest accuracy (0.9364) and highest loss (0.2241). Figure 8 illustrates the confusion matrix graphs that compare the effectiveness of different models—CNN, LSTM, and RNN—with CNN being the most successful model. The dataset is highlighted in yellow for the maximum value and in purple for the minimum value. The dataset number is located in the upper-right corner of the figures, labeled from yellow to purple. The training and testing predicted labels were on the X-axis, whereas the training and testing true labels were on the Y-axis. The datasets positioned at (0,0) and (1,1) in the confusion matrix correctly predicted traffic in both the training and testing stages. In Figure 8a,b, the CNN model makes accurate predictions, as indicated by the sum of the diagonal elements from the top-left corner to the bottom-right corner. More precisely, out of the 4455 datasets in the training dataset, the model accurately predicted 4216 datasets (sum = 4137 + 79), showing poor predictions for 239 datasets. Similarly, out of 1187 datasets in the testing set, the CNN model makes accurate predictions for 1140 datasets (1113 + 27), but inaccurately predicts only 47 datasets. The CNN model demonstrated excellent performance with high accuracy in making predictions during both training and testing phases. In addition, Figure 8c,d show how well the LSTM model performed by making 4186 correct predictions in the training set out of 4455 and accurately predicting 1128 out of 1187 datasets in the testing set. Similarly, Figure 8e,f display the performance of the RNN model, with 4159 correct predictions out of 4455 in the training set and 1124 out of 1187 in the testing set.

Table 5. Accuracy and loss of classification models.

Models	Accuracy	Loss
CNN	0.9493	0.2233
LSTM	0.9419	0.2237
RNN	0.9364	0.2241



(a) (b) (c) (d)

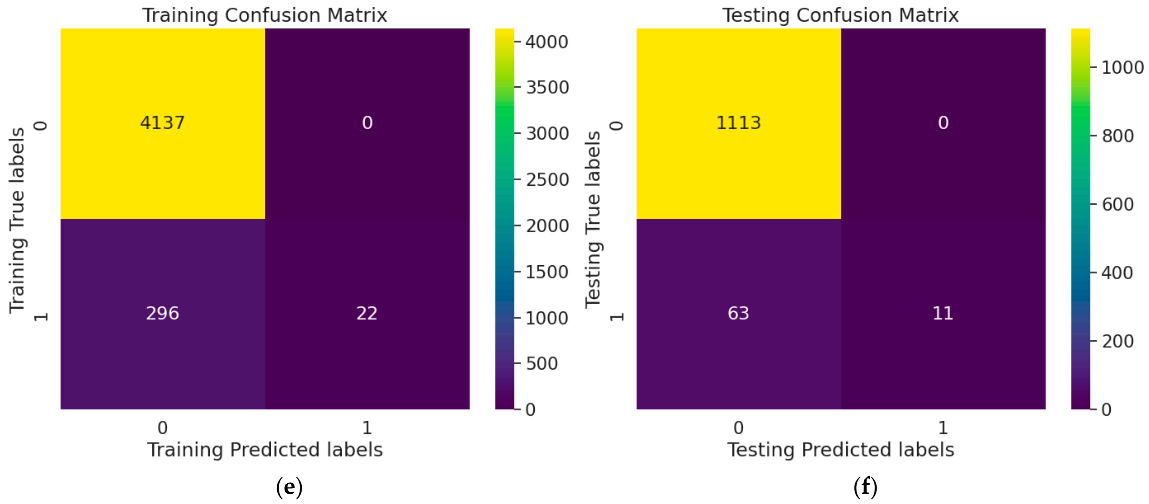


Figure 8. Confusion matrix of classification models: (**a**,**b**) CNN, (**c**,**d**) LSTM, and (**e**,**f**) RNN.

The F1 scores of the classification models are listed in Table 6. The F1 score of the CNN model is highest in both the training and testing phase, with 0.68 and 0.75, followed by the LSTM model, with 0.61 and 0.65 in the training and testing phase, respectively. The CNN model's computational time of 10 s was the shortest among all models, followed by RNN and LSTM, with 12 and 37 s, respectively, as shown in Table 7. Ultimately, CNN was observed to be the top performer of all these models.

Table 6. F1 score of classification models.

Models	Training	Testing
CNN	0.68	0.75
LSTM	0.61	0.65
RNN	0.54	0.61

Table 7. Classification model computational time.

Models	Computational Time (Seconds)
CNN	10
LSTM	37
RNN	12

The relative importance of each predictor variable to predict MU was assessed by performing sensitivity analysis. Figure 9 shows the sensitivity analysis of the input parameters with the output parameters. This shows that MU is highly sensitive to v (m/s), TC (s), and SC, with values of 0.252, 0.232, and 0.222, respectively. This indicates that the signal compliance and crossing speed are significantly related to the MU. AG, G, and CC, with values of 0.129, 0.145, and 0.178, respectively, were moderately sensitive to MU. This indicates that pedestrian demographics, such as gender and age group, considerably affect the mobile usage of pedestrians. Lastly, MU sensitivity is poor, with WT (s) and GS represented by sensitive values of 0.081 and 0.1, respectively.

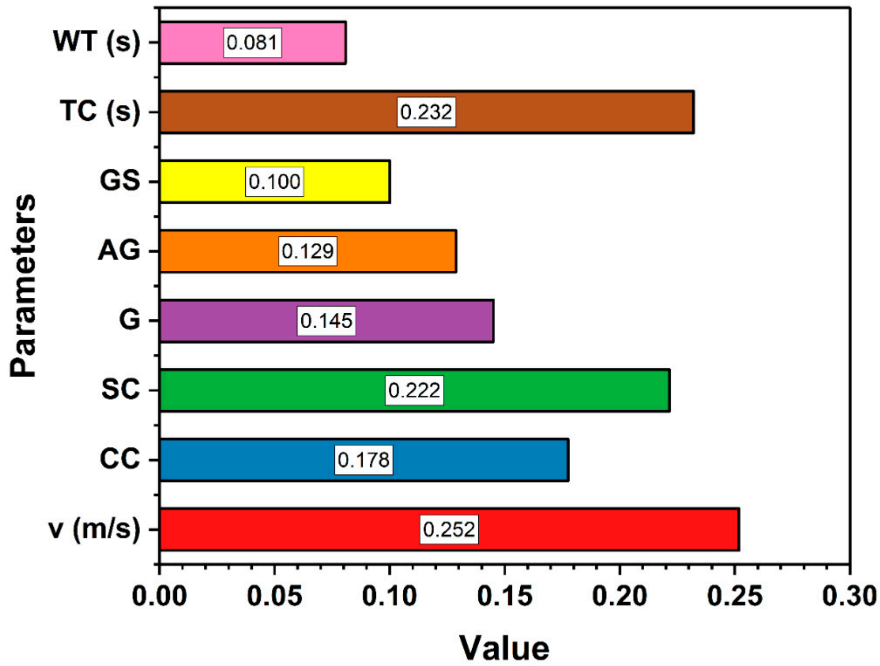


Figure 9. Sensitivity analysis.

4. Model Validation Using Cross-Validation

To validate the robustness and generalizability of all models utilized in this study, CNN, LSTM, RNN, and others, a 5-fold cross-validation was performed. In this approach, the dataset was divided into five subsets. For each fold, four subsets were used for training and one subset was reserved for testing, ensuring that every data point was included in both the training and testing phases throughout the validation process. This methodology allowed for a comprehensive evaluation of model performance across different partitions of the dataset. The mean accuracy, standard deviation, and additional metrics, such as F1 score and loss, were calculated across all folds to assess the consistency and reliability of each model. The results of the 5-fold cross-validation conducted for various models are summarized in Table 8, highlighting key performance metrics, such as mean accuracy, standard deviation, mean F1 score, mean loss, and computational time. These metrics provide a comprehensive evaluation of the capabilities of the models to effectively predict and generalize. Additionally, Figure 10 effectively highlights the strengths and weaknesses of each model, providing a clear basis for decision-making, depending on whether accuracy or efficiency is prioritized.

CNN achieved the highest mean accuracy of 94.93%, with a low standard deviation of ±0.57%, demonstrating consistent performance. It also attained a mean F1 score of 0.75 and a mean loss of 0.2233, indicating effective error minimization. Despite its high accuracy, the computational time of the CNN was efficient at 10 s. The LSTM network had a mean accuracy of 94.19%, with a standard deviation of ±0.62%, demonstrating its stability. The mean F1 score was 0.65, which was slightly lower than that of the CNN, and a mean loss of 0.2237. However, the computational time for LSTM was notably higher at 37 s, reflecting the complexity of processing the sequential data. RNN achieved a mean accuracy of 93.64%, with a standard deviation of ±0.68%, showing slightly higher variability. The mean F1 score is 0.61, which is the lowest among the three models, and the mean loss is 0.2241. The computational time of 12 s was slightly higher than that of CNN, but significantly lower than that of LSTM, making it a feasible alternative with reasonable accuracy. In conclusion, CNN emerged as the most accurate and efficient model overall, combining superior performance with reduced computational time. The LSTM network demonstrated its efficacy in processing sequential data, albeit at the expense of increased computational demand. The RNN provided a satisfactory balance, but exhibited a lower accuracy and F1 score, indicating the potential for further optimization.

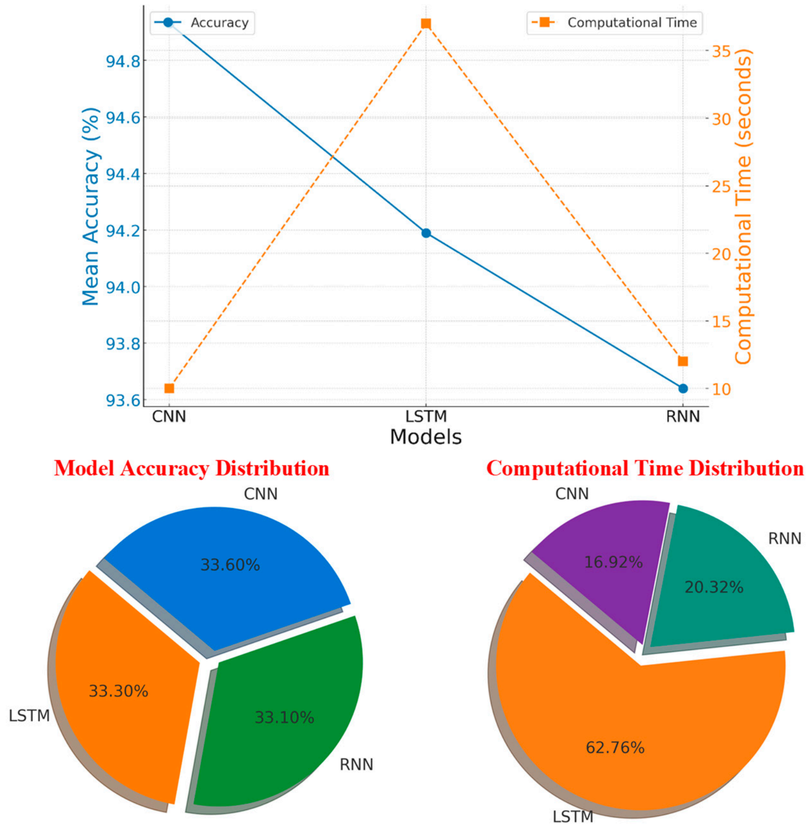


Figure 10. Comparison of accuracy and computational time across models.

Table 8. Results of 5-fold cross-validation for all models.

Model	Mean Accuracy (%)	Standard Deviation (%)	Mean F1 Score	Mean Loss	Computational Time (s)
CNN	94.93	±0.57	0.75	0.2233	10
LSTM	94.19	±0.62	0.65	0.2237	37
RNN	93.64	±0.68	0.61	0.2241	12

5. Conclusions

This study addresses the critical issue of pedestrian safety in the context of rising technological distractions, particularly mobile phone usage, which pose significant risks to road users globally. This study explores the extent and impact of mobile usage (MU) among pedestrians and examines how demographic factors, such as age, gender, and group size, influence distracted behaviors. Detailed observational data were collected from urban signalized intersections in New Delhi, India, capturing pedestrian behaviors under real-world conditions.

Advanced machine-learning techniques, including Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Recurrent Neural Networks (RNN), have been employed to model and predict distracted pedestrian behavior. The analysis highlights the relationship between mobile device usage and key behaviors, such as compliance with crosswalks and traffic signals, as well as demographic and situational factors influencing distraction levels. This comprehensive approach not only identifies the behavioral patterns of distracted pedestrians, but also demonstrates the effectiveness of machine learning in predicting and understanding these behaviors. The major findings of this study are as follows:

- MU was observed in 6.9% of the observed pedestrians, with significant variations across the different intersections.
- Females and younger pedestrians exhibited higher levels of distraction, and pedestrians crossing alone were more likely to use mobile devices than those in groups.
- Distracted pedestrians showed lower compliance with crosswalk usage (58%), but higher compliance with traffic signals (75%).
- All models have far superior performance compared to the conventional ANN. The CNN model demonstrated the best performance among the tested machine-learning algorithms, achieving the highest accuracy (94.93%) in predicting distracted behavior.
- Sensitivity analysis revealed that signal compliance and crossing speed were the most significant predictors of MU, followed by demographic factors, such as gender and age.

Based upon the above findings, the following recommendations are proposed:

- Because the majority of distracted pedestrians exhibit crosswalk violations, the installation of tactile surfaces and clearly marked crosswalks at crossing locations would certainly guide the distracted pedestrians. Audible warnings and flashing lights should be installed to alert distracted pedestrians at intersections.
- As young pedestrians are found to be most distracted, awareness of the dangers of distracted walking using social media, schools, and public platforms should be provided.
- To reduce the share of distracted crossings, strict enforcement, similar to that for drivers, should be implemented for pedestrians.
- To minimize distraction, technology can be used to provide real-time tactile feedback and temporarily block notifications while approaching an intersection.

This study underscores the urgent need for targeted interventions to mitigate the risks associated with distracted walking, particularly in rapidly urbanizing regions with high pedestrian activity and traffic density. By focusing on both behavioral patterns and technological solutions, this study aims to contribute to safer urban environments for vulnerable road users. This study contributes to the existing body of knowledge by comprehensively analyzing pedestrian behavior influenced by technological distractions in urban settings. It introduces applying advanced machine learning models to predict technologically distracted pedestrian behaviors. Furthermore, it offers insights into the demographic and behavioral factors contributing to pedestrian safety risks, thereby guiding targeted interventions.

The current study focuses on a limited number of intersections in New Delhi, which may restrict the generalizability of the findings to other regions. Further, the study focused only on individual pedestrian attributes. Future research should consider integrating environmental factors, such as crosswalk width, road traffic volume, and lane width, to provide a holistic understanding of pedestrian behavior. Including these variables could improve model performance and offer richer insights into the interplay between individual and environmental factors influencing mobile usage behavior. Moreover, in future research, a comparative analysis of ensemble models with deep learning architectures with XAI models would help identify the most suitable models based on accuracy, computational efficiency, and generalizability for similar contexts. The transferability of the models to other geographical locations has also not been explored. In the future, this study can be expanded to include a broader geographical scope and diverse urban settings to enhance the generalizability of the results. Simulation-based studies can be used to understand real-time behavioral observations and refine predictions. Finally, the long-term effectiveness of interventions such as educational campaigns and technology-based solutions in mitigating pedestrian distractions should also be studied.

Author Contributions: F.H.: conceptualization, data curation, methodology, investigation, formal analysis, writing—original draft preparation. F.A.K.: conceptualization, methodology, writing—reviewing and editing, supervision. I.T.: software, formal analysis, visualization. S.G.: software, visualization, writing—reviewing and editing. L.M.M.: data curation, formal analysis, writing—original draft preparation. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data is available on request.

Conflicts of Interest: The authors declare no conflict of interest.

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