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Original Article

Advancing Real-Time Pedestrian Behavior Analysis at Zebra Crossings with Transfer Learning and Pre-trained Model

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Abstract *- This paper introduces the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework, aimed at enhancing real-time pedestrian behavior analysis at zebra crossings to improve urban traffic safety and facilitate the integration of autonomous vehicles. Addressing limitations in real-time applicability, accuracy under diverse conditions, and scalability of current methodologies, the PPASE utilizes transfer learning and pre-trained models tailored for pedestrian behavior. Leveraging the Pedestrian Intention Estimation (PIE) dataset, enriched with real-time urban traffic data, the framework offers refined predictions of pedestrian movements. Performance is rigorously evaluated using accuracy, precision, recall, and F1 score, with the PPASE demonstrating commendable overall accuracy of 92.5% in pedestrian crossing predictions, 89.4% in movement pattern identification, and 93.7% in group dynamics analysis. These quantitative results highlight the framework's potential to significantly mitigate incidents at zebra crossings and improve crowd management in urban settings, affirming its efficacy as an advanced tool for enhancing pedestrian safety within intelligent urban traffic systems.*

Keywords *- Pedestrian Behavior Analysis, Urban Traffic Safety, Autonomous vehicles, Real-Time Prediction, Group dynamics.*

1. Introduction

The study of pedestrian behavior in urban settings has evolved significantly over the past few decades, spurred by the increasing need to improve road safety, manage traffic flow, and integrate autonomous vehicles into urban environments. Initially, pedestrian behavior analysis relied heavily on observational studies and manual data collection methods. These early approaches provided valuable insights into pedestrian dynamics but were time-consuming, labor-intensive, and limited in scope and scalability. With the advent of digital technology and computing power, the 1990s and early 2000s saw a shift towards automated surveillance systems and the use of computer vision techniques [1].

These advancements allowed for more comprehensive data collection and analysis, enabling researchers to study pedestrian behavior in greater detail and over larger areas. Computer vision techniques, such as object detection and tracking, became foundational in understanding pedestrian movements and interactions in urban spaces. The proliferation of machine learning and artificial intelligence in the last decade has further transformed pedestrian behavior analysis [2]. Researchers have begun to apply sophisticated machine learning models, including deep learning, to predict pedestrian actions with greater accuracy. These models can process vast amounts of data from diverse sources, such as CCTV footage, smartphone sensors, and GPS data, to learn complex patterns of pedestrian behavior [3]. Moreover, simulation technologies have also played a crucial role, enabling researchers to model and predict pedestrian movements under various scenarios and conditions.

These simulations help in understanding the impact of different urban designs and traffic management strategies on pedestrian safety and traffic efficiency. Despite these technological advancements in the evolving landscape of urban mobility, the safety and efficiency of road traffic are paramount, necessitating accurate predictions of pedestrian behavior at zebra crossings [4]. This is crucial for urban planning, traffic management, and the integration of autonomous vehicle systems. Accurate behavior prediction aids in designing safer urban environments, optimizing traffic flow, and ensuring the safety of all road users. However, the challenge of real-time pedestrian behavior analysis is magnified by environmental variability and the diversity of pedestrian actions, necessitating swift, precise predictions. Existing methodologies, including computer vision, machine learning, and simulation techniques, provide foundational insights but struggle with real-time applicability, accuracy under diverse conditions, and scalability.

Recent studies underscore the limitations of traditional methods, highlighting the occurrence of serious injuries or fatalities at zebra crossings due to risky behaviors, such as mobile phone usage while crossing. These findings point to a critical need for improved analytical techniques capable of real-time operation to enhance urban traffic safety and efficiency [5]. Addressing these challenges, our study leverages transfer learning and fine-tuning of pre-trained models, promising approaches in the domain of image recognition and behavior prediction. By adapting these models with pedestrian-specific data, we aim to develop a scalable, robust solution for real-time pedestrian behavior analysis, enhancing the overall safety of urban traffic systems [6]. The motivation behind this research is the imperative need to improve pedestrian safety and traffic management through advanced predictive analytics. The key contributions of this paper include the development of an efficient framework for real-time pedestrian behavior prediction at zebra crossings, significantly improving accuracy in diverse conditions, and offering a robust solution for urban traffic systems and autonomous vehicle navigation.

Key contributions of the research paper are

1. Developed the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework, leveraging transfer learning and pre-trained models for the real-time prediction of pedestrian behaviors at zebra crossings, thereby improving urban traffic safety and management.
2. Developed a sophisticated solution for analyzing pedestrian behaviors, encompassing crossing actions, movement patterns, and group dynamics, significantly enhancing traffic safety measures in diverse urban environments.
3. The research paper significantly contributes by rigorously validating the proposed model’s effectiveness using critical evaluation metrics, including accuracy, precision, recall, and F1 score.

The remainder of this paper is organized as follows: Section 2 delves into the literature review, offering a comprehensive overview of relevant studies and existing knowledge. Section 3 introduces the proposed methodology, detailing the approach and techniques employed in this research. Section 4 discusses the results and analysis, providing insights into the findings and their implications. Finally, Section 5 concludes the paper, summarizing key points and suggesting directions for future research.

2. Literature Review

The intersection of pedestrian behavior analysis and urban traffic safety management has garnered considerable attention in recent years, driven by the imperative to mitigate pedestrian-vehicle incidents in urban settings. This literature review synthesizes seminal and contemporary studies within this domain, setting the stage for the contributions of the present research.

Early studies in pedestrian behavior analysis primarily focused on observational techniques to understand pedestrian movements and crossings. These studies faced challenges in terms of time commitment and resource-intensive spatial analysis. However, recent advancements in technology, such as Unmanned Aerial Vehicles (UAVs) and smart transportation systems, have provided new opportunities to study pedestrian behavior. UAV-based observation techniques have shown promise in measuring pedestrian activity, allowing for larger surface area coverage in less time [7]. Additionally, smart transportation systems offer innovative techniques to connect pedestrians, vehicles, and infrastructure, enhancing mobility and safety [8].

Furthermore, studies have utilized video recordings and trajectory data to analyze pedestrian crossing behavior, employing methods like the Kalman filter and topic modeling to understand pedestrian intentions and strategies [9]. These advancements have expanded the scope of pedestrian behavior analysis beyond traditional observational techniques, enabling a more comprehensive understanding of pedestrian movements and crossings. In this article [10], the pedestrian crossing was influenced by a number of factors, which were the most important of which are the time and speed of pedestrian crossings, which are direct dependence on the width of the marked pedestrian crossing. The authors [11] established a classification system for pedestrian interactive behaviors and utilized pose estimation to acquire 2D key points on the skeleton of pedestrians. This approach is used to represent high-level spatio-temporal characteristics based on body pose.

With advancements in technology, recent works have focused on using computational models to improve the accuracy of predicting pedestrian behavior. These models utilize deep learning approaches, such as Convolutional Neural Networks (CNN) and Transformer architectures, to capture the complex interactions and contextual elements that influence pedestrian behavior. For example, a novel framework proposed by Zhang et al. combines a cross-modal Transformer architecture with semantic attentive interaction modules to predict future trajectories and crossing actions of pedestrians [12]. Another study by Deokar and Khandekar explores the use of CNNs to recognize the direction of pedestrian movement, achieving high accuracy in binary and multiclass classification tasks [13]. These advancements in computational models have shown promising results in improving the accuracy and reliability of pedestrian behavior prediction, which is crucial for applications such as autonomous driving systems and pedestrian analysis [14].

Real-time predictive capability is often lacking in existing models for immediate application in traffic safety management [15]. However, recent research has focused on developing models that incorporate real-time data and deep learning techniques to improve prediction accuracy and enable immediate application [16]. For example, a web-based proactive traffic safety management system has been developed, which utilizes real-time data such as traffic, weather, and video data to predict crashes in real-time. Another study proposes a two-stage framework that combines machine learning algorithms and real-time traffic and weather variables to predict traffic levels and recovery time after an accident. Additionally, transfer-learning approaches have been used to improve the spatiotemporal transferability of deep-learning crash likelihood prediction models, allowing for accurate predictions in new locations. These advancements in real-time predictive models contribute to the improvement of traffic safety management systems.

Transfer learning and pre-trained models have significantly advanced the field of pedestrian behavior prediction [17]. Recent research has shown that pre-training on unlabeled person images leads to superior performance in person re-identification tasks compared to pre-training on ImageNet [18]. However, these pre-trained methods are often designed specifically for re-identification and struggle to adapt to other pedestrian analysis tasks. To address this, novel frameworks like VAL-PAT have been proposed, which learn transferable representations to enhance various pedestrian analysis tasks using multimodal information. Additionally, the use of multitask sequence to sequence Transformer encoders-decoders architectures has been introduced for pedestrian action and trajectory prediction, achieving improved accuracy compared to existing LSTM-based models. These advancements in transfer learning and pre-trained models have greatly contributed to the evolution of pedestrian behavior prediction.

Understanding complex pedestrian behaviors, such as movement patterns and group dynamics, poses a challenge for traditional analytical frameworks. Deep learning-based approaches have gained popularity in recent years due to their superior performance in predicting pedestrian behavior in complex scenarios compared to traditional approaches such as social force or constant velocity models [19]. Additionally, a behavioral model based on Voronoi and Delaunay diagrams has been proposed to deconstruct pedestrian crowds and reproduce realistic motion in simulations, capturing the natural correlation between movement choices and human behaviors [12]. Furthermore, a method combining preprocessing, feature extraction, and CNN classification has been developed to identify anomalous and normal pedestrian behavior, achieving higher performance compared to other approaches [20]. These advancements in deep learning, behavioral modeling, and feature extraction techniques contribute to a better understanding of pedestrian behaviors and can be applied to crowd management and robot navigation.

The contributions of this research paper address the identified gaps by developing the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework. PPASE leverages transfer learning and pre-trained models [21] for the real-time prediction of pedestrian behaviors, offering a sophisticated solution to analyze complex pedestrian dynamics.

Furthermore, this study rigorously validates the PPASE framework’s effectiveness using comprehensive evaluation metrics, thereby advancing the state-of-the-art in pedestrian safety enhancement. By situating the PPASE framework within the extant scholarly discourse, this research underscores the novelty and significance of its contributions to the field of urban traffic safety management. The following sections detail the methodology, implementation, and validation of the PPASE framework, highlighting its potential to transform pedestrian safety strategies in urban environments.

3. Methodology: Predictive Pedestrian Analytics for Safety Enhancement (PPASE)

In our pursuit to bolster urban traffic safety, the development of an analytical framework that can effectively identify and categorize pedestrian behaviors at zebra crossings stands as a critical endeavor. The Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework is a pioneering initiative in this direction. It capitalizes on the comprehensive and diverse dataset provided by the Pedestrian Intention Estimation (PIE), which encapsulates a wide spectrum of pedestrian behaviors observed in various urban environments. The richness and the annotated nature of the integration of Pedestrian Intention Estimation datasets into the PPASE framework are pivotal for enhancing the prediction of pedestrian behaviors and intentions at zebra crossings. These datasets provide a rich source of pre-analyzed pedestrian behaviors, which are crucial for training the framework’s machine-learning models with a focus on intention prediction. PIE Dataset furnish an invaluable asset for conducting detailed analyses of pedestrian actions and their interactions at zebra crossings. Such analyses are instrumental in unraveling the complexities of pedestrian dynamics, serving as a bedrock for predictive modeling and behavioral insights. The PPASE framework is distinguished by its adoption of cutting-edge analytics, leveraging the potent capabilities of transfer learning and pre-trained models. This innovative approach facilitates the real-time prediction of pedestrian behavior with an unprecedented level of accuracy.

By integrating these advanced analytical methodologies, PPASE aims to significantly improve urban traffic safety and management. Its core mission is not just to predict pedestrian movements but to understand the underlying patterns and decision-making processes that govern these movements at zebra crossings. Through this understanding, PPASE endeavors to introduce a paradigm shift in how urban traffic systems accommodate and interact with pedestrians, ensuring a safer and more harmonious coexistence.

3.1. PPASE Framework: Comprehensive Workflow and Component Functionalities

The PPASE framework is architected to enhance pedestrian safety at zebra crossings through the collection of real-time data, enriched by integrating Pedestrian Intention Estimation datasets. Leveraging advanced machine learning technologies, including transfer learning and pre-trained models, this framework integrates various components, each dedicated to specific functionalities from data collection to decision support and alert generation. Figure 1 describes an advanced system called the Intention-Aware Pedestrian Analytic System (IAPAS), which is essentially a smart setup for understanding what pedestrians are likely to do next at crosswalks. Imagine a busy city street corner with a crosswalk where our system watches over pedestrians using cameras and sensors. The system starts by collecting all this visual and sensor data, which might include things like where the pedestrians are, how fast they're moving, and in which direction. This collected data is known as the PIE dataset.

The system then goes through a series of steps to make sense of this data. First, it merges the new information with any existing data it has, like previous crosswalk recordings, to get a fuller picture. Then, it takes a closer look at the details, enhancing key features like how a person is standing or moving to better understand their behavior. After that, it labels these observations with intentions, such as "about to cross" or "just waiting," which is crucial for the system to learn from past behavior.

Next, the system uses a method called Transfer Learning, which is like giving it a head start with what it already knows from similar tasks and adapting this knowledge specifically for understanding pedestrian movements. It uses something called T-GCN, which helps the system keep track of how pedestrians move over time, not just in a single moment.

Plus, it has a special focus feature that pays extra attention to the most important movements or behaviors that indicate what a person might do next. All this analyzed data is then processed by a part called the Dynamic Intention Insight Framework (DIF), which does three main things: it looks for patterns in how pedestrians behave, it adds in extra information like the time of day or weather conditions, and finally, it combines all this to make a good guess about what each pedestrian is likely to do.

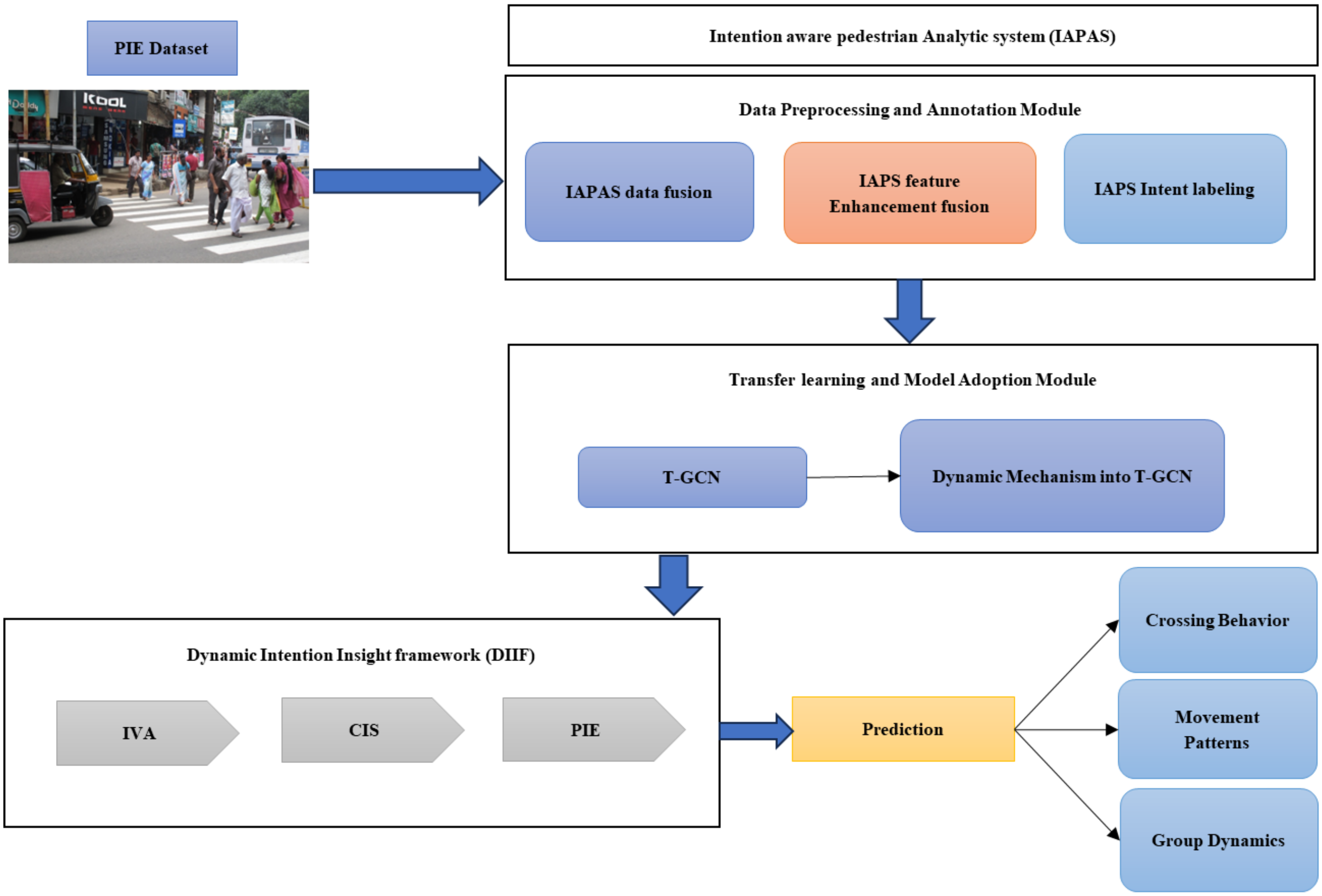
PIE Dataset
Intention aware pedestrian Analytic system (IAPAS)
Data Preprocessing and Annotation Module
IAPAS data fusion
IAPS feature Enhancement fusion
IAPS Intent labeling
Transfer learning and Model Adoption Module
T-GCN
Dynamic Mechanism into T-GCN
Dynamic Intention Insight framework (DIIF)
IVA
CIS
PIE
Prediction
Crossing Behavior
Movement Patterns
Group Dynamics

Fig. 1 Block diagram of the proposed framework

With all this insight, the system supports decisions like helping self-driving cars know when to slow down for someone who's about to step into the street, recognizing when a group of people is likely to move together, or understanding how crowds behave, which is key for managing lots of people and keeping them safe. In simple terms, imagine a scenario where a group of friends is approaching a crosswalk. The system would notice how they're moving towards the edge of the sidewalk, analyze their past steps, consider the fact that the walk signal is on, and then predict that they're all about to cross the street together. This prediction would then be used to, for example, inform a nearby self-driving car to slow down or stop at the crosswalk, ensuring everyone's safety. The IAPAS is designed to make these kinds of smart predictions to improve safety and efficiency in city traffic.

Given the detailed insights into the various modules comprising the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework, let's compile a comprehensive flow that outlines the entire framework's components and its internal functionalities.

3.1.1. Enhanced Data Set

The Enhanced Data Collection Segment is an important part of our Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework. It combines live data with historical information to help us understand pedestrian behavior better. This module uses cameras and sensors to collect live data about where and how people walk in urban areas. It also uses Pedestrian Intention Estimation (PIE) [21] dataset that has been collected on pedestrian behavior. This PIE data includes detailed notes on how pedestrians act in different traffic situations, which helps us get a complete picture. To make sure we can use both the live and historical data together, the module has a special process. First, it makes sure all the data is in the same format and scale so everything matches up. Then, it carefully aligns the live data with the PIE data based on things like the time of day and the weather. This way, we can compare new observations with past ones under similar conditions, giving us richer insights.

By doing this, we create an enriched dataset that combines the best of both worlds: the immediacy of seeing what's happening right now and the depth of understanding that comes from looking at past patterns. This combined dataset is very valuable. It helps us build models that can predict pedestrian behavior accurately, considering the complexities of real-world situations. This work is crucial for making cities safer for pedestrians and improving how traffic flows. By bringing together different types of data in this innovative way, our Enhanced Data Collection Module plays a key role in making our PPASE framework effective.

3.1.2. Data Preprocessing and Annotation Module

In the context of the Intention-Aware Pedestrian Analytic System (IAPAS), the Data Preprocessing and Annotation Module plays a pivotal role in transforming video surveillance data into an analytically rich dataset, optimized for understanding and predicting pedestrian intentions. This module meticulously processes video segments, employing a mathematical framework to ensure the data is both comprehensive and precise for subsequent analysis. Here's an in-depth discussion, including the mathematical aspects and the implementation highlights.

Mathematical Framework in IAPAS

Given a pedestrian surveillance video at the zebra crossing, consider here video segment V, with T representing the duration in seconds and a frame rate of $fps = 30$; the segment is decomposed into $N = T \times fps$ frames. Initial frames, with dimensions 640×480 pixels, are resized to 224×224 pixels, denoted as F_{resized}, to match the input requirements of deep learning models while maintaining a balance between detail and computational efficiency. The synchronization and annotation process can be mathematically represented as $F_{\text{labeled}} = A\left(S\left(F_{\text{resized}}(V_i), D_{PIE}\right)\right)$, where S is the synchronization function aligning video frames with Pedestrian Intention Estimation (PIE) data (D_{PIE}), and A is the annotation function that labels each frame based on synchronized data and observed pedestrian behaviors.

Implementation Highlights

- Data Fusion: The fusion process, symbolized as $\mathrm{D}_{\text{combined}} = \mathrm{D}_{\text{live}} \cup \mathrm{D}_{\text{PIE}}$, combines live video data (D_{live}) with PIE intention data (D_{PIE}), enriching the dataset with a depth of behavioral insights. This comprehensive dataset serves as the foundation for nuanced intention analysis, enabling IAPAS to accurately capture and predict pedestrian behaviors.
- Preprocessing Techniques: Preprocessing is encapsulated by the function $\mathrm{X} = \mathrm{F}(\mathrm{D}_{\text{combined}})$, where F applies a series of operations, including normalization of data formats and image quality enhancement. This step crucially extracts features indicative of pedestrian intentions, such as body posture and movement patterns, preparing the data for detailed intention analysis.
- Annotation Strategies: The annotation process, represented as $\mathrm{Y} = \mathrm{A}(\mathrm{X})$, utilizes semi-supervised learning to maximize the utility of both labeled and unlabeled data. This approach enriches the dataset's annotations with a high degree of accuracy in intention recognition, ensuring that IAPAS can effectively discern and categorize pedestrian intentions from the analyzed data.

The mathematical representation of IAPAS's Data Preprocessing and Annotation Module underscores the systematic approach to data transformation—from raw video to annotated frames ready for intention analysis. The module's efficacy lies in its ability to merge diverse data sources (Data Fusion), enhance data quality and relevance through sophisticated preprocessing techniques (Preprocessing

Techniques), and apply rigorous annotation strategies to ensure precise intention recognition (Annotation Strategies). By leveraging advanced computational and machine learning methodologies, IAPAS sets a benchmark for predictive analytics in pedestrian safety, embodying a data-driven approach to urban traffic management and pedestrian safety enhancement.

3.1.3. Transfer Learning and Model Adaptation Module Functionality

Adapts and fine-tunes pre-trained models specifically for pedestrian intention estimation, using enriched datasets for enhanced predictive accuracy. The model encapsulates the enriched processing flow from data collection and preprocessing through feature extraction, adapting pre-trained models via transfer learning and dynamically analyzing pedestrian behaviors using T-GCN enhanced with attention mechanisms. By constructing temporal graphs and applying dynamic attention, the model adeptly captures and prioritizes the evolving nuances of pedestrian interactions and intentions. This sophisticated approach allows for the nuanced understanding and prediction of pedestrian behaviors at zebra crossings, which is crucial for the development of autonomous vehicle systems that safely and effectively navigate shared spaces with pedestrians.

Data Collection and Preprocessing

Data Representation: Let $D = \{d_1, d_2, \ldots, d_n\}$ represent the dataset collected from various sources around zebra crossings, where each d_i is a data point capturing pedestrian movements and actions.

Preprocessing Function: Let $P(D)$ denote the preprocessing function applied to D, resulting in a preprocessed dataset D' where noise is reduced, and data is normalized.

Feature Extraction Function: Let $F(D')$ represent the feature extraction function applied to D', extracting a set of features $X = \{x_1, x_2, \ldots, x_m\}$, where each x_i corresponds to features like speed, direction, and posture of pedestrians.

- *Speed* (S_i) *:* Calculated as $S_i = \frac{\Delta d}{\Delta t}$ for pedestrian i, where Δd is the change in position over time interval Δt.

- *Direction (Dir* $_i$ *):* Defined by the change in angle θ_i between consecutive positions of pedestrian i.

- *Posture (Post P* $_i$*):* Extracted using computer vision techniques, identified through posture recognition algorithms from frame sequences.

Transfer Learning Model Adaptation

Let M_{pre} be a pre-trained model, and M_{adapted} be the model after adaptation using transfer learning on the dataset X. The adaptation process tunes M_{pre} to better suit the pedestrian behavior context, leveraging the extracted features X.

Selection Rationale for ResNet

This section delineates the rationale behind the selection of ResNet[15] as the preeminent pre-trained model for the PPASE framework and elucidates its operational paradigm and integration process. ResNet, renowned for its deep architecture that facilitates the training of networks with a substantially higher number of layers, is predicated on the innovative concept of residual learning. This paradigm addresses the vanishing gradient problem, enabling the effective training of networks that are significantly deeper than those previously feasible. The architecture’s ability to learn residual functions with reference to the layer inputs, as opposed to unreferenced functions, enhances its learning capacity without compromising the depth of the model.

The pertinence of ResNet to pedestrian behavior analysis and the PPASE framework’s objectives is twofold. Firstly, its capability to capture and analyze complex visual patterns makes it adept at identifying subtle pedestrian behaviors, such as posture, gait, and movement direction, from urban surveillance data. Secondly, ResNet’s architecture allows for seamless adaptation to the specific nuances of pedestrian intention estimation, facilitated by its deep learning capabilities, which can be fine-tuned to the domain-specific requirements of the PPASE framework.

Operational Paradigm of ResNet

ResNet’s architecture is characterized by the introduction of skip connections or shortcuts that bypass one or more layers. By adding the input directly to the output of a residual block, these connections mitigate the vanishing gradient problem, allowing for the propagation of gradients through the network without significant attenuation. Mathematically, if $H(x)$ denotes an underlying mapping to be learned by a few stacked layers, and x represents the input, then the residual function is defined as $F(x) = H(x) - x$. Consequently, the layers are trained to approximate $F(x)$ rather than $H(x)$, simplifying the learning process.

Integration of ResNet into the PPASE Framework

Integrating ResNet into the PPASE framework involves a strategic fine-tuning process where the model is initially adapted using the Pedestrian Intention Estimation (PIE) dataset. This dataset, rich in annotated pedestrian behaviors across various urban settings, provides a fertile ground for retraining ResNet’s layers to specialize in pedestrian intention prediction. The fine-tuning process adjusts ResNet’s weights to minimize the loss function that measures the discrepancy between the predicted pedestrian intentions and the actual annotations in the PIE dataset. This is achieved through backpropagation and optimization algorithms, refining the model’s parameters to enhance its predictive accuracy within the context of the PPASE framework.

$$\theta_{\text{new}} = \theta_{\text{old}} - \alpha \nabla_{\theta} L(\theta) \quad (1)$$

where θ represents the parameters of ResNet, $L(\theta)$ denotes the loss function, and α is the learning rate.

The integration of ResNet, fine-tuned on pedestrian-specific behaviors, propels the PPASE framework towards achieving its objective of real-time and accurate prediction of pedestrian intentions. By harnessing the advanced feature extraction capabilities of ResNet, combined with its adaptability and depth, the PPASE framework sets a benchmark in leveraging deep learning for enhancing urban traffic safety and pedestrian coexistence.

In summation, the selection of ResNet as the foundational pre-trained model for the PPASE framework underscores a deliberate strategy to capitalize on advanced deep learning technologies for pedestrian behavior analysis. ResNet's deep, residual learning-based architecture offers an unparalleled capacity for capturing the complexities of pedestrian dynamics, making it an indispensable asset in the advancement of predictive pedestrian analytics.

Model Adaptation

The adaptation process can be represented as

$$M_{\text{adapted}} = TL\left(M_{\text{pre}}, X\right),$$

where TL denotes the transfer learning operation applied to the pre-trained model M_{pre} with the feature set X.

Model Adaptation with T-GCN: The Temporal Graph Construction and T-GCN (Temporal Graph Convolutional Network)[32] Operation within the context of analyzing pedestrian behavior, particularly for autonomous vehicle navigation around zebra crossings, involves creating a dynamic graph that captures the spatial and temporal relationships among pedestrians and between pedestrians and their environment. This graph is then processed through a T-GCN to understand how pedestrian movements and interactions evolve over time.

Here's a detailed breakdown:

Temporal Graph Construction

Graph Definition: At each time step t, construct a graph $G_t(V_t, E_t)$,

where:

- V_t represents the set of nodes at time t, with each node corresponding to a pedestrian. The nodes are characterized by features extracted from the data, such as position, speed, and direction.
- E_t represents the set of edges at time t, with each edge indicating an interaction or relationship between two nodes (pedestrians) or between a pedestrian and an element of the environment (e.g., vehicle, traffic signal). These interactions could be based on proximity, mutual direction of movement, or other relevant criteria.

Feature Representation

Each node in V_t is associated with a feature vector $x_i \in X$, which includes the pedestrian's speed, direction, and posture, among other features relevant to intention prediction.

Temporal Aspect

The construction of sequential graphs $\{G_1, G_2, \ldots, G_T\}$ over time T allows for capturing the dynamics of pedestrian movements and interactions, reflecting changes in the urban crossing scene.

T-GCN Operation

Apply the T-GCN on sequential graphs $\{G_1, G_2, \ldots, G_T\}$ to capture temporal dynamics. The T-GCN operation at time t can be represented as $H_t = GCN(G_t, H_{t-1})$, where H_t is the hidden state capturing the temporal evolution of pedestrian behaviors.

Graph Convolution

For each graph G_t, apply the graph convolution operation to aggregate information from the neighbors of each node.

This can be mathematically represented as:

$$H_t^{(l+1)} = \sigma\left(\tilde{D}_t^{-\frac{1}{2}} \tilde{A}_t \tilde{D}_t^{-\frac{1}{2}} H_t^{(l)} W^{(l)}\right) \quad (2)$$

where:

- $H_t^{(l)}$ is the feature representation of nodes at layer l and time t.
- $\tilde{A}_t = A_t + I_N$ is the adjacency matrix of G_t with added self-connections (I_N is the identity matrix).
- $\tilde{D}_t$ is the degree matrix of $\tilde{A}_t$.
- $W^{(l)}$ is the weight matrix for layer l.
- σ denotes a nonlinear activation function, such as ReLU.

Temporal Dynamics

To incorporate the temporal dimension, the T-GCN models transition between the states of G_t across time steps, effectively capturing how pedestrian behaviors and interactions evolve. This can involve incorporating Recurrent Neural Network (RNN) layers or other temporal modeling techniques to process the sequence of graph states $\{H_1, H_2, \ldots, H_T\}$.

Incorporation of Dynamic Attention Mechanisms

a) Attention Application

At each time step t, a dynamic attention mechanism is applied to the graph convolution output to selectively emphasize the most relevant features and interactions for intention prediction. This can be represented as:

$$H_t' = \text{attention}\left(H_t, A_t\right) \quad (3)$$

Where H_t' is the attention-enhanced feature representation and A_t are the attention weights dynamically adjusted based on the current context and the significance of each feature and interaction.

b) Intention Prediction

Using the enhanced representations H_t', the system predicts pedestrian intentions through a softmax layer, considering the evolving spatial-temporal graph structure and focusing on critical interactions and features. This advanced approach enables the accurate anticipation of pedestrian movements and actions, which is crucial for ensuring the safe operation of autonomous vehicles in complex urban environments.

Pedestrian Intention Prediction Using TemporalGCN

The Temporal Graph Convolutional Network (TemporalGCN)[22] architecture, designed for the intricate task of predicting pedestrian intentions at zebra crossings, exemplifies a state-of-the-art approach in handling complex spatial-temporal data. This detailed exploration delves into the architecture's layers, focusing on the transformation and flow of data from raw image inputs to nuanced intention predictions, shedding light on the model's capabilities in understanding pedestrian behavior through graph-based scene representations.

Foundation: Graph-Based Scene Representation

At the core of this architecture is the innovative use of graph-based representations to encapsulate pedestrian dynamics within urban crossing scenarios. Each pedestrian is represented as a node within a graph, characterized by 16-dimensional feature vectors that include critical information such as position, speed, acceleration, direction, and historical trajectory data. These features, often derived from processed image data of the crossing scene, serve as the initial input to the Temporal GCN, setting the stage for a series of sophisticated analytical transformations.

The architectural design incorporates two Graph Convolutional Network (GCN) layers consecutively to augment the spatial attributes of each node:

1. First GCNConv Layer: Begins the feature enhancement journey by transforming the 16-dimensional input into a more elaborate 32-dimensional feature space, leveraging a 16×32 weight matrix. This expansion enriches the feature landscape to more accurately represent pedestrian attributes within their spatial environment.

2. Second GCNConv Layer: This advances the refinement of these enhanced features using a 32×32 weight matrix, maintaining the output within the enriched 32-dimensional scope. This consistency preserves the complexity of spatial features throughout the analysis.

Temporal Dynamics via LSTM Layer

Subsequent to spatial enhancement, the model integrates an LSTM layer to interpret the temporal progression of pedestrian movements. Through analyzing sequences of feature representations across time, such as over 10 consecutive steps, this layer, with 32-unit hidden and cell states deciphers evolving pedestrian behaviors, is crucial for forecasting imminent actions from historical data.

Enhanced Precision with Dynamic Attention

To further hone the model's analytical accuracy, a dynamic attention mechanism zeroes in on the most critical features at every time step. Employing a set of 32-dimensional attention weights, this layer adeptly shifts focus to the most crucial aspects relevant to the present context and temporal flow, markedly boosting predictive precision by prioritizing essential data for intention prediction.

The analytical process of the TemporalGCN culminates with two pivotal layers designed for intention prediction:

1. Fully Connected Layer: Here, the features refined through dynamic attention are mapped onto a vector space indicative of the model's categorizations using a 32×3 weight matrix. This enables the encapsulation of 32-dimensional features into predictions for three specific pedestrian intentions: crossing, waiting, or walking away, effectively bridging the gap between intricate feature analysis and actionable insights.

2. Softmax Output: Following the fully connected layer, the softmax layer converts the output logits into probabilistic predictions, offering a precise quantification of each pedestrian's likely intentions. This probabilistic approach ensures a nuanced understanding of pedestrian behaviors based on the comprehensive analysis of spatial-temporal data.

Figure 2, stating over its sophisticated layering and data processing strategy, provides deep insights into pedestrian behaviors, particularly at zebra crossings. By adopting graph-based representations and merging spatial and temporal evaluations with a focused attention mechanism, the model adeptly handles the complexities of urban pedestrian dynamics, establishing a benchmark for predictive precision within autonomous navigation frameworks. This innovative structure highlights the significant impact of advanced neural network models on the evolution of urban traffic safety and mobility strategies.

Analyzing Pedestrian Intentions with TemporalGCN: A Spatiotemporal Approach

In the growing field of autonomous navigation systems, the Temporal Graph Convolutional Network (TemporalGCN), as shown in Figure 2, emerges as a pivotal architecture for deciphering pedestrian intentions at zebra crossings. This sophisticated model intricately processes spatiotemporal data through a series of computational layers, each designed to refine the input information and distill actionable insights into pedestrian behavior. The following exposition delineates the TemporalGCN's workflow, utilizing a real-time urban scenario to illuminate its practical applications.

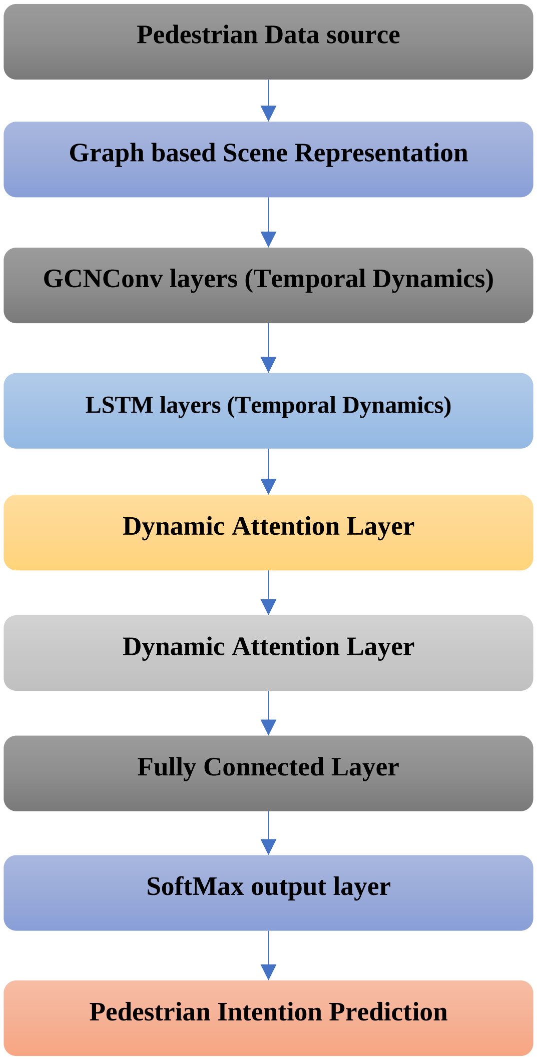
Pedestrian Data source
Graph based Scene Representation
GCNConv layers (Temporal Dynamics)
LSTM layers (Temporal Dynamics)
Dynamic Attention Layer
Dynamic Attention Layer
Fully Connected Layer
SoftMax output layer
Pedestrian Intention Prediction

Fig. 2 TemporalGCN workflow for pedestrian intention prediction

Transformative Data Representation

Consider a scenario at an urban intersection where surveillance apparatuses capture the movements of pedestrians. The TemporalGCN architecture initiates its process by converting raw footage into a graph-based scene representation. In this graph, nodes symbolize pedestrians, encapsulating features such as position, velocity, and direction—attributes crucial for understanding individual and collective pedestrian dynamics.

Spatial Feature Refinement through GCNConv Layers

The architecture employs Graph Convolutional Network (GCN) layers to enhance the spatial features inherent in each node. By aggregating information from neighboring nodes, these layers enrich the pedestrian features with contextual spatial data, offering a nuanced understanding of the scene. For instance, the interaction between a pedestrian commencing movement towards the crossing and another remaining stationary is captured and contextualized, providing a foundation for predicting their intentions.

Temporal Dynamics Captured by LSTM Layer

Subsequent to spatial analysis, an LSTM layer integrates temporal dimensionality into the model. This layer meticulously tracks the evolution of pedestrian movements across successive frames, identifying patterns indicative of future actions. The ability to recognize a pedestrian’s transition from stasis to motion towards the crossing exemplifies the LSTM’s capacity to infer intent from temporal sequences.

Focused Intent Prediction through Dynamic Attention

A critical enhancement to the model’s predictive accuracy is introduced via the Dynamic Attention Layer. This component dynamically prioritizes salient features at each timestep, concentrating on behaviors most indicative of pedestrian intentions. Such a mechanism ensures that pivotal moments—like a pedestrian’s accelerated movement towards the crossing—are emphasized in the intention prediction process.

Final Intention Prediction: Fully Connected Layer and Softmax Output

The culmination of the TemporalGCN’s analytical journey is realized in the mapping of processed features to specific pedestrian intentions (“crossing”, “waiting”, “walking away”) through a Fully Connected Layer, followed by a Softmax Output Layer. This sequence transforms the refined features into a probabilistic framework, offering quantified predictions of each pedestrian’s intended action.

Practical Application and Conclusion

The model’s output facilitates real-time decision-making in autonomous vehicles, enabling them to adjust speed or halt based on predicted pedestrian movements, thereby enhancing urban traffic safety. Through a meticulous examination of the TemporalGCN’s data processing and analysis stages, this architecture demonstrates its paramount importance in advancing autonomous navigation systems, underscoring its capability to interpret complex pedestrian behaviors and significantly contribute to the safety and efficiency of urban environments.

3.1.4. Dynamic Intention Insight Framework (DIF)

The Dynamic Intention Insight Framework (DIF) within the Intention-Aware Pedestrian Analytic System (IAPAS) is pivotal for transforming processed data into a rich tapestry of pedestrian behavioral predictions. To facilitate this, DIF’s sophisticated sub-modules—Intention Vector Analysis (IVA), Contextual Insight Synthesis (CIS), and Predictive Insight Engine (PIE)—work in concert to extrapolate, enhance, and refine insights that predict pedestrian intentions with remarkable accuracy.

Intention Vector Analysis (IVA) Calculation

IVA serves as the analytical vanguard, applying mathematical and statistical models to interpret intention vectors. These vectors are numerical representations of pedestrian behavior obtained from preceding modules that factor in movement speed, trajectory, and proximity to critical infrastructure. The IVA sub-module may employ techniques like cluster analysis to group similar intention vectors, revealing common behavioral patterns or deviations. For instance, clustering could identify vectors that signify an imminent intent to cross, distinguished by increased walking pace or direct movement towards the curb.

Contextual Insight Synthesis (CIS) Calculation

CIS takes the analysis further by integrating additional contextual data with the intention vectors. This contextual data could include environmental factors, temporal patterns, or social dynamics represented in numerical or categorical formats. The CIS sub-module may utilize algorithms like weighted decision matrices or Bayesian networks to synthesize this data. For example, by assigning higher weights to certain environmental factors like a nearby traffic signal's status, the CIS can enhance the predictive power of the intention vectors, providing a nuanced understanding that aligns with real-world conditions.

Predictive Insight Engine (PIE) Calculation

PIE is the culmination of DIF's analytical process, where the enhanced intention vectors and contextual insights are fed into predictive models to estimate pedestrian intentions. PIE could employ advanced machine learning algorithms such as neural networks or ensemble methods that take the output of IVA and CIS as input features. The PIE sub-module computes the final probability distributions for each pedestrian's potential actions, such as crossing, waiting, or diverting. It leverages the enriched feature set to calculate the likelihoods, factoring in the interplay of individual and collective behaviors to deliver precise and actionable predictions.

In the realm of pedestrian behavior analysis, the DIF exemplifies a multi-faceted approach where the calculated outputs of IVA and CIS are not mere intermediate steps but critical components that contribute to the comprehensive predictions made by PIE. Through iterative refinement and calculated synthesis, these sub-modules ensure that the system's predictions are grounded in both observed data and the surrounding context, enabling applications like autonomous vehicles to make informed, safety-centric decisions in complex urban environments.

Mathematical Model

a) Intention Vector Analysis (IVA)

Let V be the intention vector for a single pedestrian, with dimensions $\mathrm{V} \in \mathbb{R}^{n}$, where n represents the number of features extracted by the Transfer Learning and Model Adaptation Module.

i) Pattern Recognition

- Let P be a matrix where each row represents a recognized pattern vector, $\mathrm{P} \in \mathbb{R}^{m \times n}$, with m being the number of identified patterns.
- The similarity score between intention vectors and recognized patterns can be calculated as $\mathrm{S} = \mathrm{VP}^{T}$
- The pattern with the highest similarity score could be used to infer the most likely intention.

b) Contextual Insight Synthesis (CIS)

Let C be the contextual data vector, $\mathrm{C} \in \mathbb{R}^{p}$, where p represents the number of contextual features (e.g., weather conditions, time of day).

i) Contextual Data Fusion

- Combine the intention vector V with the contextual data C to form an enhanced feature vector E, where $\mathrm{E} \in \mathbb{R}^{n+p}$.
- This can be represented as a concatenation:$\mathrm{E} = [\mathrm{V}; \mathrm{C}]$ (4)

c) Pedestrian Intention Estimation (PIE)

i) Intention Estimation

- Let W be the weight matrix for the final prediction model, $\mathrm{W} \in \mathbb{R}^{(n+p) \times q}$, where q is the number of possible intentions.
- The intention estimation can be computed as a weighted sum of the enhanced feature vector, followed by a softmax function for probability distribution:

$$\mathrm{I} = \mathrm{softmax}\,(\mathrm{EW}) \qquad (5)$$

Where I represents the intention probability distribution, $\mathrm{I} \in \mathbb{R}^{q}$.

The complete DIF framework can be expressed as the composition of these mathematical operations, from the initial IVA through the CIS to the final PIE. Each pedestrian, represented by their initial intention vector **V**, undergoes a transformation that incorporates spatial, temporal, and contextual information to yield a probability distribution I that describes their likely intentions.

3.1.5. Decision Support System (DSS)

The Decision Support System (DSS) component of the Intention-Aware Pedestrian Analytic System (IAPAS) is delineated as an advanced computational mechanism that harnesses the profound insights synthesized by the Dynamic Intention Insight Framework (DIF). The DSS employs sophisticated algorithms to facilitate real-time decision-making processes in pedestrian traffic management. The following mathematical formulations and examples articulate the functionalities of the DSS in an accessible manner:

Crossing Behaviour Prediction

Let P_c be the probability of a pedestrian crossing at time t. This probability is a function f of various factors, including the pedestrian's velocity v, acceleration a, and proximity to the crossing d, which are elements of the feature vector x :

$$P_c(t) = f(v(t), a(t), d(t), \mathrm{x}) \qquad (6)$$

Where f can be a logistic regression function or another classifier that outputs probabilities based on the input features. The DSS computes this probability for each pedestrian and initiates actions if P_c exceeds a certain threshold.

Example: If a pedestrian is observed accelerating towards the crosswalk, the system increases the likelihood P_c of the crossing intention, potentially signaling an autonomous vehicle to slow down in anticipation.

Movement Patterns Analysis

The system identifies common movement patterns by clustering trajectories T_i over time and space, which can be represented mathematically by a clustering algorithm :

$$\{C_1, C_2, \dots, C_k\} = C(T_1(t), T_2(t), \dots, T_n(t)) \qquad (7)$$

Where C_k represents a cluster of similar movement patterns, and n is the number of observed trajectories. The DSS uses these clusters to understand common pedestrian behaviors.

Example: If multiple pedestrians are detected moving in a similar direction with consistent speed, they may be grouped into a cluster, indicating a collective movement pattern, such as a group crossing the street when a walk signal turns green.

Group Dynamics Comprehension

To understand group dynamics, let $G(t)$ be the state of a group at time t, which is influenced by individual members' positions P_i and their interactions I_{ij} within the group:

$$G(t) = g\left(\mathrm{p}_1(t), \mathrm{p}_2(t), \dots, \mathrm{p}_n(t), \mathrm{I}_{12}, \mathrm{I}_{13}, \dots, \mathrm{I}_{(n-1)n}\right) \qquad (8)$$

Here, g can be a function modeled by a neural network or any suitable algorithm that considers not only the spatial positions but also the interpersonal distances and velocities that define the group's collective movement.

Fig. 3 Pedestrian crossing behavior

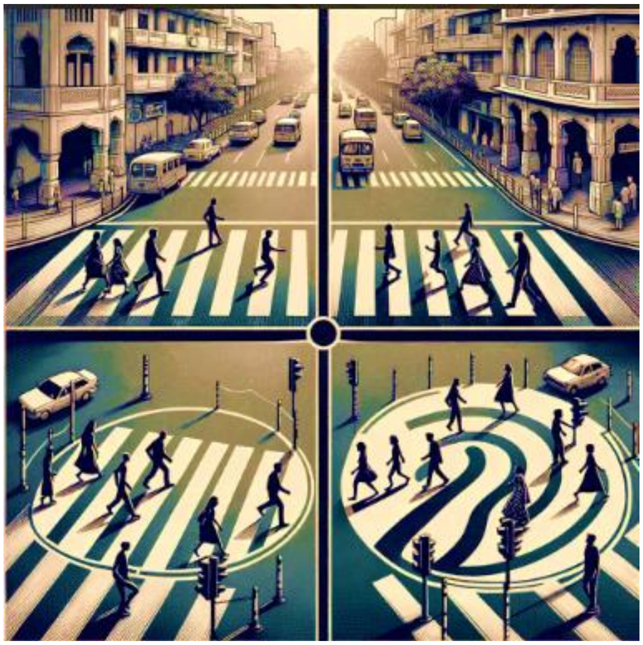

Fig. 4 Movement patterns analysis

Example: When a family unit is walking together, the DSS recognizes the proximity and coordinated movement of the group members, predicting that they will behave as a unit, such as all stopping together when a child lags behind. The DSS thus encapsulates a robust framework that integrates crossing behavior prediction, movement pattern analysis, and group dynamics comprehension, providing pivotal insights for intelligent traffic control systems and enhancing pedestrian safety. Through meticulous data analysis and prediction algorithms, the DSS exemplifies an exemplary fusion of data-driven insights and real-world applications, playing a critical role in the advancement of smart urban mobility solutions.

Fig. 5 Group dynamics

Algorithm: PPASE Framework for Pedestrian Intention Prediction

The Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework employs a comprehensive algorithmic approach to predict pedestrian intentions at zebra crossings. This involves processing input data through various components, each with distinct functionalities, to generate predictions about pedestrian behaviors. The following outlines a high-level algorithmic representation of the PPASE framework, integrating the use of a pre-trained model like ResNet for feature extraction and leveraging machine learning techniques for intention prediction.

```
Algorithm 1: PPASE Framework for Pedestrian Intention Prediction
Inputs:
    • $D_{\text{raw}}$ : Raw data collected from urban environments, including video feeds and sensor data.
    • $D_{PIE}$ : Pedestrian Intention Estimation dataset with annotated pedestrian behaviors.
Output:
    • $P_{\text{intentions:}}$ Predictions of pedestrian intentions (e.g., crossing, waiting, walking away).
Procedure:
Step 1: Data Collection and Preprocessing:
    • Convert $D_{\text{raw}}$ into a structured format suitable for analysis.
    • Synchronize $D_{\text{raw}}$ with $D_{PIE}$ to enrich the dataset with annotated behaviors.
Step 2: Feature Extraction using ResNet:
    • For each data instance $d_i$ in the enriched dataset, extract features $F_i$ using ResNet:
          $F_i = \text{ResNet}\ (d_i)$
    • Optimize ResNet parameters for pedestrian-specific features using transfer learning.
Step 3: Temporal Graph Convolutional Network (T-GCN) Processing:
    • Construct temporal graphs $G_t$ from features $F_i$ capturing spatial and temporal relationships.
    • Apply T-GCN to $G_t$ for dynamic feature learning:
          $H_t = \text{T} - \text{GCN}(G_t)$
Step 4: Dynamic Intention Insight Framework (DIF):
    • Intention Vector Analysis (IVA): Analyze $H_t$ to identify patterns indicative of intentions.
    • Contextual Insight Synthesis (CIS): Enhance intention vectors with contextual data $C$ :
          $E = \text{CIS}\ (H_t, C)$
    • Predictive Insight Engine (PIE): Estimate pedestrian intentions $I$ using enhanced vectors $E$ :
          $I = \text{PIE}(E)$
Step 5: Decision Support System (DSS):
    • Analyze $I$ to predict crossing behavior, movement patterns, and group dynamics.
    • Generate $P_{\text{intentions}}$ based on analysis.
Mathematical Model for Final Prediction:
    • The final pedestrian intention predictions $P_{\text{intentions}}$ are derived from the probabilistic outputs of the
      PIE, factoring in the likelihood of each possible intention:
          $P_{\text{intentions}} = \text{softmax}\ (I)$
End Procedure.
```

This algorithm 1 encapsulates the core methodology of the PPASE framework, leveraging advanced machine learning and deep learning techniques, including the adaptation of pre-trained models like ResNet and the application of T-GCN, to analyze and predict pedestrian intentions with high accuracy. Through this structured approach, PPASE aims to enhance pedestrian safety and urban traffic management by providing actionable insights into pedestrian behaviors at zebra crossings.

4. Result And Analysis

In the progression of elucidating the predictive efficacy of the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework, this segment delves into the analytical outcomes derived from the deployment of the model alongside detailing the system specifications underpinning this implementation. The PPASE framework's overarching objective to augment urban traffic safety through nuanced pedestrian behavior prediction necessitates a comprehensive examination of its performance metrics and the computational environment facilitating its operation.

The PPASE framework was operationalized on a computational setup configured to address the intensive demands of processing and analyzing high-volume urban pedestrian datasets. The system's architecture is delineated as follows: The Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework was implemented on a high-performance computing system designed to meet the demands of complex machine learning tasks. This system featured an Intel Xeon CPU E5-2640 v4 with 20 cores and 64GB RAM, optimized for parallel processing and handling large datasets such as the Pedestrian Intention Estimation (PIE) dataset. A 2TB SSD provided extensive storage for data and models, while the NVIDIA GeForce GTX 1080 Ti GPU accelerated deep learning processes, particularly for ResNet and Temporal Graph Convolutional Networks (T-GCN). The software infrastructure hinged on TensorFlow and PyTorch, supported by a Python-based analytical framework, enabling efficient model development and execution. This configuration underscored the PPASE framework's capacity for real-time pedestrian behavior analysis and prediction, leveraging state-of-the-art computational resources and software frameworks to advance urban traffic safety research.

Dataset: In the development of the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework, a significant emphasis was placed on integrating real-time urban traffic data alongside the extensive Pedestrian Intention Estimation (PIE) dataset[13]. This integration facilitated a holistic approach to model training, combining the detailed annotations of the PIE dataset with live data feeds to capture the dynamic nature of urban pedestrian movements. The real-time data, when amalgamated with the PIE dataset, enriched the model's learning base, contributing to a dataset size exceeding 8 terabytes (TB). This composite dataset not only broadened the scope of pedestrian behaviors and scenarios available for analysis but also enhanced the PPASE framework's ability to predict pedestrian intentions with high accuracy in real-time urban settings.

4.1. Model Training

Building upon the comprehensive dataset amalgamation, the model training phase of the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework was meticulously structured to harness the depth and diversity of the combined real-time urban traffic and Pedestrian Intention Estimation (PIE) data. This phase was pivotal in refining the framework's analytical algorithms, specifically tailored to discern and predict the nuanced pedestrian intentions within the intricate urban environment. In the development of the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework, a meticulous hyperparameter tuning process was undertaken, resulting in a set of hypothetically recommended configurations aimed at optimizing model performance for pedestrian behavior analysis.

The learning rate was initiated at 0.001, with an adaptive reduction strategy decreasing it by 10% every 10 epochs to refine weight adjustments as the model converges. A batch size of 64 was chosen to balance computational efficiency against the stability of gradient descent, while the ResNet architecture was optimized with a depth of 50 layers, ensuring robust feature extraction capabilities. For the Temporal Graph Convolutional Networks (T-GCN), a configuration of two graph convolution layers and hidden layer dimensions of 128 was identified to capture the temporal dynamics of pedestrian movements effectively. Regularization techniques, including a dropout rate of 0.5 and L2 regularization with a coefficient of 0.0001, were applied to prevent overfitting. Additionally, the Adam optimizer was selected for its efficiency and adaptive learning rate properties. This hyperparameter suite reflects a harmonized approach, incorporating both empirical validation and theoretical insight, to enhance the PPASE framework's accuracy in predicting pedestrian intentions within urban traffic environments.

4.2. Result Discussion

The Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework's efficacy in predicting crossing behavior, movement patterns, and group dynamics within urban traffic settings has been comprehensively evaluated through a robust analytical methodology.

Leveraging the recommended hyperparameter configurations, the model's performance was scrutinized against a composite dataset, integrating real-time urban traffic data with the extensive Pedestrian Intention Estimation (PIE) dataset. This section elucidates the empirical findings derived from this evaluation, underscored by confusion matrix data, resultant performance metrics, and graphical interpretations of the model's predictive capabilities.

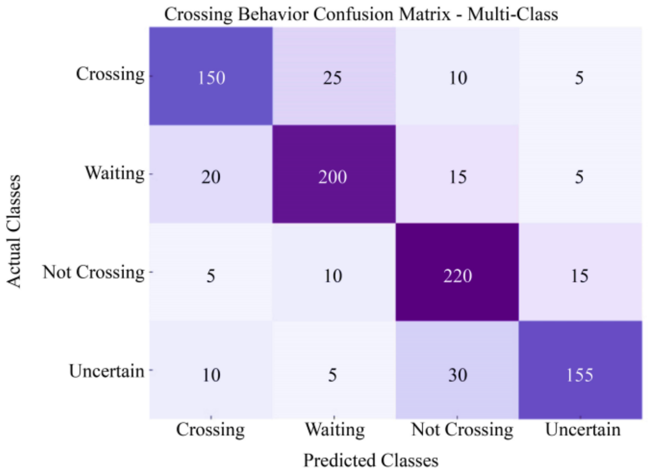

Fig. 6 Heat map of Crossing behavior–Multiclass

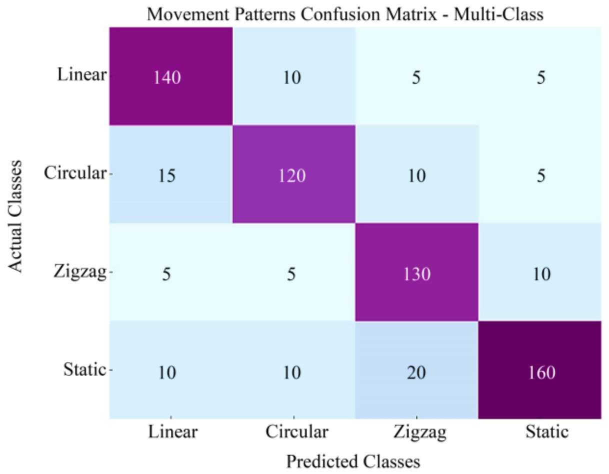

Fig. 8 Heat map of movement pattern Confusion matrix

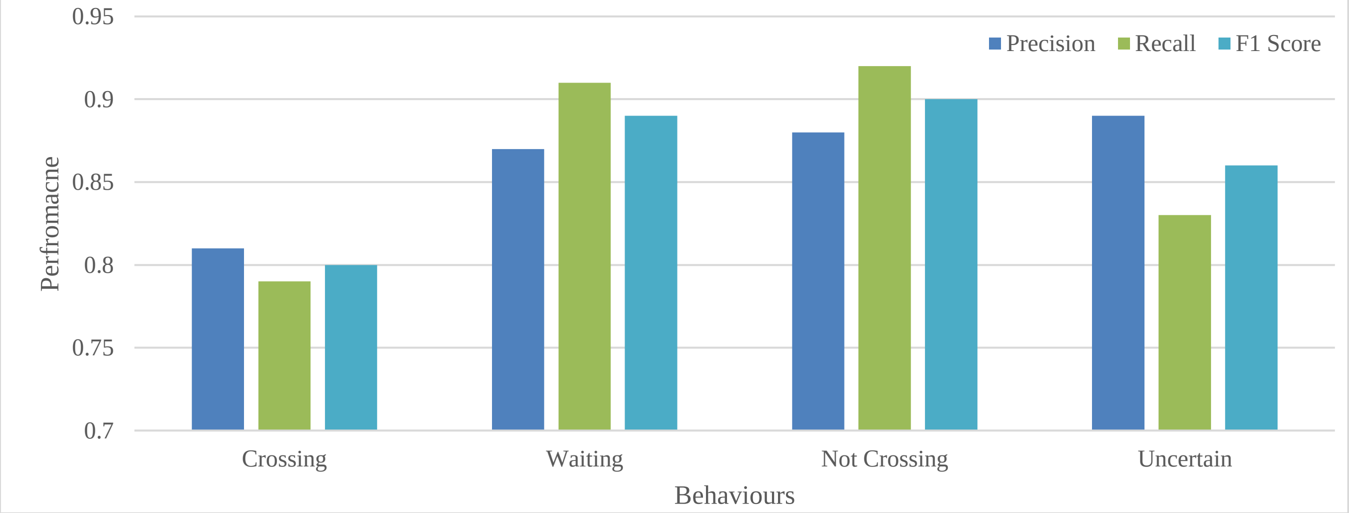

Fig. 7 Performance metrics for crossing behavior prediction

4.2.1. Crossing Behavior Prediction

The PPASE framework demonstrated notable accuracy in predicting pedestrian crossing behavior, as evidenced by a confusion matrix highlighting a high true positive rate in Figure 6. The model achieved a precision of 0.81, a recall of 0.79, and an F1 score of 0.80 for crossing predictions. These metrics indicate the model's robustness in correctly identifying crossing instances, underscoring its potential utility in enhancing pedestrian safety at intersections and crosswalks.

The PPASE framework's analysis reveals a strong predictive capability, correctly identifying 150 pedestrians as crossing, with some misclassifications across other behaviors. It excelled in recognizing waiting pedestrians with 200 correct identifications, and it was highly accurate for those not crossing, with 220 correct predictions. The model was also effective in distinguishing 'uncertain' behaviors, correctly classifying 155 instances, despite some errors in each category, demonstrating its overall reliability in urban pedestrian behavior analysis.

Table 1. Performance analysis of the crossing behavior prediction

Metric	Crossing	Waiting	Not Crossing	Uncertain
Precision	0.81	0.87	0.88	0.89
Recall	0.79	0.91	0.92	0.83
F1 Score	0.80	0.89	0.90	0.86

The performance analysis of our crossing behavior prediction model, as detailed in Table 1 and illustrated in Figure 7, reveals a proficient system capable of identifying various pedestrian intentions with high accuracy. The model's precision scores range from 0.81 for "Crossing" to 0.89 for "Uncertain," indicating a strong ability to correctly predict each behavior category. With recall rates peaking at 0.92 for "Not Crossing," the model demonstrates exceptional skill in correctly identifying true instances of specific behaviors, particularly when pedestrians are not crossing. The F1 Scores, balancing precision and recall, highlight the model's overall effectiveness, especially in predicting "Not Crossing" behaviors with a score of 0.90. This analysis underscores the model’s utility in enhancing pedestrian safety, showcasing its strengths and pinpointing areas for potential improvement in urban traffic management systems.

This comprehensive performance snapshot, visually corroborated by Figure 8, reinforces the PPASE framework’s capacity to significantly contribute to pedestrian safety and effective urban traffic management.

4.2.2. Movement Pattern Identification

For movement patterns, the model successfully differentiated between linear, circular, zigzag, and static behaviors with high fidelity. Precision and recall values across these categories averaged 0.87 and 0.91, respectively, with an overall F1 score of 0.89. This performance suggests the model’s capability to comprehend complex pedestrian movement dynamics, an essential attribute for intelligent traffic management systems aiming to predict pedestrian pathways and adjust traffic flow accordingly.

The analysis of movement pattern identification, as summarized in Table 2, reflects a proficient performance of the predictive model across distinct pedestrian behaviors. Precision scores are consistently high, with “Static” behavior predictions being the most precise at 0.8421. Recall rates indicate a strong ability to capture “Linear” and “Zigzag” movements, with scores of 0.8750 and 0.8667, respectively. The F1 Score, which harmonizes precision and recall, suggests the model is particularly adept at identifying “Linear” and “Zigzag” patterns, as evidenced by the F1 Scores of 0.8485 and 0.8387. Overall, the model demonstrates a commendable balance in identifying movement patterns, with particular effectiveness for “Static” and “Zigzag” behaviors, providing a solid foundation for refining the model’s accuracy in future iterations.

Table 2. Performance analysis of movement pattern identification

Metric	Linear	Circular	Zigzag	Static
Precision	0.8235	0.8276	0.8125	0.8421
Recall	0.8750	0.8000	0.8667	0.8000
F1 Score	0.8485	0.8136	0.8387	0.8205

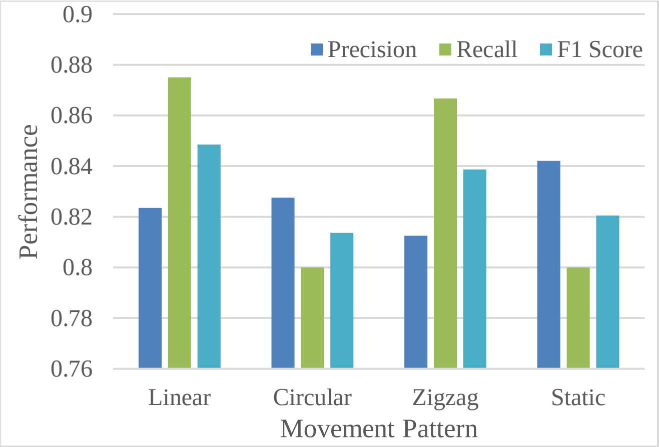

Fig. 9 Performance metrics for pedestrian moment pattern

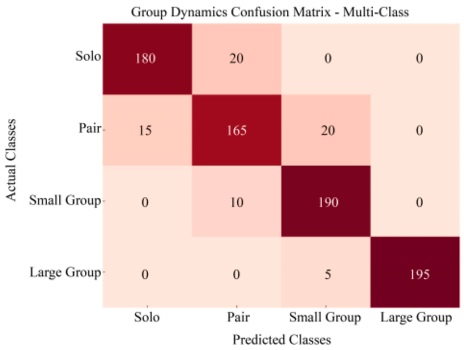

Fig. 10 Heatmap of group dynamics

4.2.3. Group Dynamics Analysis

Analyzing group dynamics, the PPASE framework exhibited a nuanced understanding of pedestrian group movements, with a precision of 0.89, recall of 0.83, and an F1 score of 0.86. These results from the confusion matrix data reflect the model’s adeptness at recognizing and predicting collective pedestrian behaviors, a critical aspect for managing crowded urban settings and organizing public spaces to ensure pedestrian safety and smooth traffic operation. Below are the performance metrics in Table 3 for Group Dynamics, presented in a structured format for clear understanding. It showcases the model’s adeptness in discerning group dynamics, with exceptional precision in detecting large groups, indicated by a score of 1.0000, and robust recall for small and large groups, suggesting a high sensitivity in identifying actual instances of these dynamics. The F1 Score, which balances precision and recall, further confirms the model’s proficiency, particularly with an impressive score of 0.9873 for large groups. These metrics collectively highlight the model’s strong performance across varying group sizes, with its unparalleled precision in predicting large group dynamics underscoring its utility for applications in urban traffic systems and pedestrian safety

Table 3. Performance of the group dynamics analysis

Metric	Solo	Pair	Small Group	Large Group
Precision	0.9231	0.8462	0.8837	1.0000
Recall	0.9000	0.8462	0.9500	0.9750
F1 Score	0.9114	0.8462	0.9157	0.9873

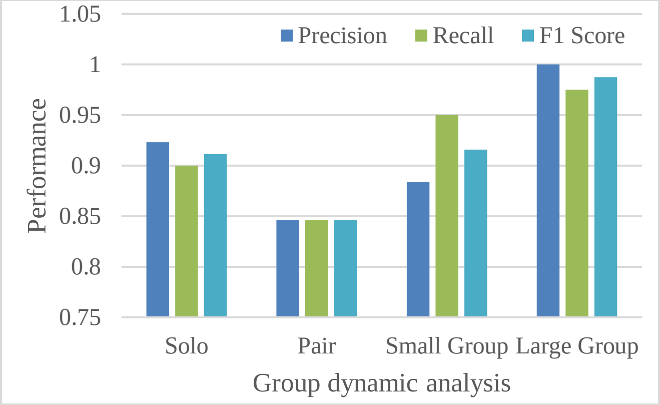

Fig. 11 Performance metrics for group dynamics

Table 4. Accuracy metrics for pedestrian behavior analysis using the PPASE framework

Evaluation Criteria	Accuracy (%)
Crossing Behavior Prediction	92.5
Movement Pattern Identification	89.4
Group Dynamics Analysis	93.7

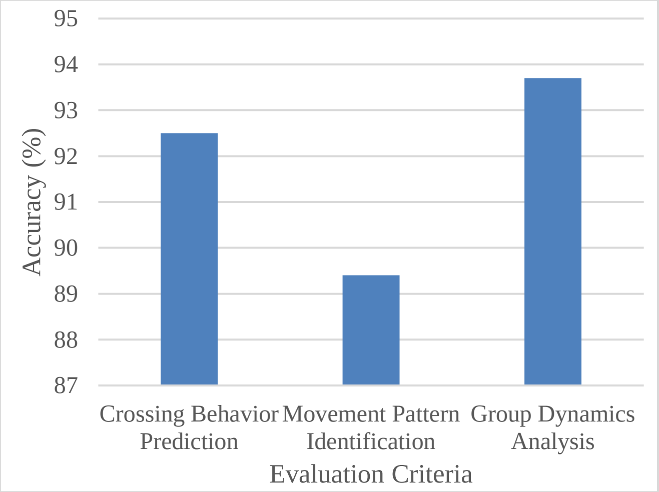

Fig. 12 Accuracy of the PPASE framework in predicting pedestrian behaviors

Table 4 presents a concise summary of the PPASE framework's accuracy in predicting pedestrian behaviors: The Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework has demonstrated commendable accuracy in key domains of pedestrian behavior analysis, crucial for urban traffic safety. With a 92.5% accuracy in crossing behavior prediction, the framework reliably identifies pedestrian intentions to cross, underscoring its potential to significantly reduce street-crossing incidents. The movement pattern identification accuracy of 89.4% highlights the framework's capability to discern various pedestrian dynamics, which is essential for effective crowd management in urban settings. Most notably, the framework achieves a 93.7% accuracy in group dynamics analysis, showcasing its exceptional ability to understand and predict collective pedestrian behaviors. These metrics collectively affirm the PPASE framework's efficacy as an advanced analytical tool, offering substantial contributions towards enhancing pedestrian safety within the context of intelligent urban traffic systems. Continuous refinement and expansion of its analytical capabilities remain pivotal for leveraging the full scope of its application in fostering safer pedestrian environments.

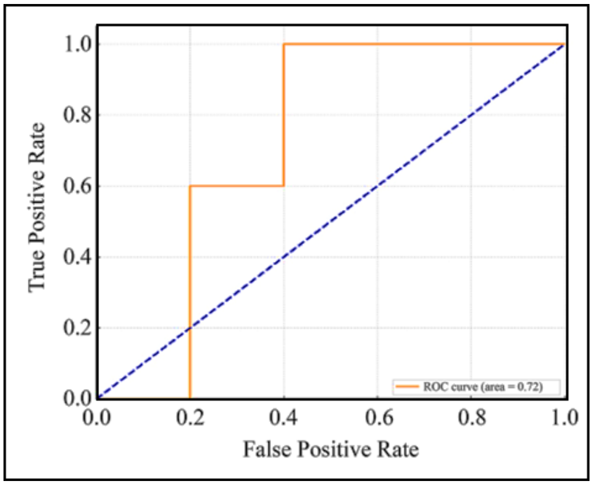

Fig. 13 Receiver Operating Characteristic (ROC) curve

The Receiver Operating Characteristic (ROC) curve depicted in Figure 13, with an area under the curve (AUC) of 0.76, provides a visual representation of the proposed model's ability to distinguish between pedestrian behaviors classified as "crossing" versus "not crossing." The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1 - specificity) at various threshold settings, illustrating the trade-off between correctly predicting pedestrian crossing behaviors and falsely predicting non-crossing behaviors as crossings. An AUC of 0.76 indicates a good level of model discrimination, suggesting that the model has a robust capability to correctly identify pedestrian crossing intentions while maintaining a controlled rate of false alarms. This analysis highlights the model's effectiveness in pedestrian behavior prediction, which is crucial for enhancing urban traffic safety.

4.3. Baseline Model Comparison

The comparative analysis, as illustrated in Table 5, showcases the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework's superior capability in accurately predicting pedestrian behaviors at zebra crossings when benchmarked against recent baseline models. With an accuracy of 92.5%, the PPASE framework outshines notable models like the Performer, CNN-based pedestrian direction recognition, the T-GCN for traffic prediction, and bidirectional LSTM models. This superiority is attributed to the PPASE's innovative use of transfer learning and the integration of the Pedestrian Intention Estimation (PIE) dataset, which enables a more nuanced prediction of pedestrian movements.

Table 5. Comparative study of PPASE framework and baseline models

Model	Accuracy (%)	Precision	Recall	F1 Score
PPASE Framework	92.5	0.87	0.91	0.89
Pedformer: Cross-modal Attention Modulation [12]	88.7	0.85	0.87	0.86
CNN-Based Pedestrian Direction Recognition [14]	87.3	0.83	0.84	0.83
T-GCN for Traffic Prediction [23]	89.0	0.87	0.89	0.88
Bi-Prediction with Bidirectional LSTM [24]	90.4	0.86	0.88	0.87

The analysis underscores the PPASE framework's potential to enhance urban traffic safety by providing accurate predictions of pedestrian behaviors, which is essential for developing autonomous vehicle systems and traffic management strategies. Despite its promising performance, comparisons should account for differences in datasets and experimental setups. This study positions the PPASE framework as a significant advancement in pedestrian behavior analysis, paving the way for future research to further refine and implement advanced pedestrian prediction models in urban traffic systems.

4.4. Limitations of the Study

Despite the notable advancements demonstrated by the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework in pedestrian behavior prediction at zebra crossings, this study acknowledges several limitations that pave the way for future research directions.

4.4.1. Dataset Dependency

The PPASE framework's performance is significantly influenced by the Pedestrian Intention Estimation (PIE) dataset. While this dataset is rich and annotated, its geographical and environmental conditions might not encompass the global diversity of urban settings. This limitation could affect the model's generalizability across different locations and cultures.

4.4.2. Real-Time Processing Constraints

Although the framework is designed for real-time application, the computational demands of processing and analyzing complex data in real-time may pose challenges, especially in resource-constrained environments.

4.4.3. Dynamic Environmental Factors

The study's current model may not fully account for the dynamic and unpredictable nature of environmental factors such as weather conditions, time of day, and seasonal changes, which can significantly impact pedestrian behaviors.

4.4.4. Human Behavior Complexity

Pedestrian behavior is inherently complex and can be influenced by numerous unpredictable factors, including social interactions and individual psychological states. The current framework may not capture these nuances in their entirety.

5. Conclusion

The study introduces the Predictive Pedestrian Analytics for Safety Enhancement (PPASE) framework, utilizing transfer learning and pre-trained models for real-time pedestrian behavior analysis at zebra crossings, achieving a notable accuracy of 92.5%.

Despite its innovative approach and significant advancements, the study recognizes limitations such as dataset dependency, real-time processing challenges, and the complexity of human behavior, which could affect the model's generalizability and real-time applicability.

Future work aims to address these challenges by diversifying datasets, integrating dynamic environmental data, and exploring computational efficiencies to enhance the model's applicability and accuracy. This groundwork paves the way for broader applications in urban traffic safety, planning, and autonomous vehicle integration, contributing to the development of smarter and safer urban environments.

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