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Road Safety Measures For Limited Mobility Users Using XAI

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Abstract— Road safety remains a critical global challenge, particularly for limited-mobility road users such as elderly pedestrians, individuals with disabilities, wheelchair users, and people with temporary physical impairments. These groups face disproportionately higher risks due to slower reaction times, restricted movement, reduced situational awareness, and inadequate infrastructure support. With the rapid adoption of intelligent transportation systems and machine learning–based safety solutions, predictive models have shown promise in detecting risks and preventing accidents. However, most existing systems operate as black boxes, limiting trust, transparency, and real-world acceptance, especially in safety-critical environments. This research proposes an Explainable Artificial Intelligence (XAI)–driven framework integrated with Support Vector Machine (SVM) models to enhance road safety for limited-mobility users. The proposed approach focuses on interpretable decision-making that allows stakeholders; including traffic authorities, caregivers, and end users, to understand why certain safety alerts or risk classifications are generated. By combining SVM's strong classification capabilities with XAI techniques such as feature attribution and rule-based explanations, the system ensures high accuracy while maintaining transparency. The framework processes multimodal data, including pedestrian movement patterns, environmental conditions, traffic density, and assistive device signals, to predict hazardous scenarios in real time. The explain ability layer improves accountability, supports regulatory compliance, and increases user trust by clearly communicating the reasoning behind predictions. Experimental evaluations demonstrate that the XAI-enabled SVM model not only improves predictive reliability but also enhances usability and ethical acceptance compared to conventional black-box approaches. This research highlights the importance of explain ability in AI-based road safety systems and presents a scalable, interpretable solution aimed at protecting one of the most vulnerable populations in modern transportation ecosystems.

Keywords—SDN, CNN, RNN, DL, IdCNN , GRU, LSTM, SDCN

I. INTRODUCTION

Personalize Urbanization and the rapid growths of vehicular traffic have significantly increased road safety challenges worldwide, with limited-mobility road users being among the most affected. Limited-mobility users include elderly individuals, people with physical disabilities, wheelchair users, visually impaired pedestrians, and individuals recovering from injuries, all of whom experience constraints in speed, balance, reaction time, or perception. Traditional road safety measures such as traffic signals, zebra crossings, and signage are often designed for average road users and fail to adequately accommodate the specific needs of these vulnerable populations. As a result, limited-mobility users face higher accident rates, longer recovery times, and severe consequences from road incidents. In recent years, Artificial Intelligence (AI) and machine learning techniques have been increasingly applied to intelligent transportation systems to predict risks, detect unsafe conditions, and provide real-time alerts. While these systems achieve high predictive performance, many rely on complex deep learning models that lack transparency. This opacity becomes a serious limitation in safety-critical domains, where understanding the rationale behind decisions is as important as accuracy. Explainable Artificial Intelligence (XAI) has emerged as a solution to address this issue by making AI models interpretable and understandable to humans. XAI enables stakeholders to analyze how input features influence model decisions, thereby improving trust, accountability, and system adoption. Support Vector Machines (SVMs), known for their robustness and effectiveness in classification tasks, are well-suited for safety prediction problems due to their ability to handle high-dimensional data and limited samples. When combined with XAI techniques, SVM-based systems can provide both reliable predictions and meaningful explanations. This research explores the integration of XAI with SVM models to develop an intelligent safety framework specifically designed for limited-mobility road users. The proposed approach aims to bridge the gap between predictive accuracy and interpretability, ensuring that safety recommendations are not only effective but also transparent

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and ethically acceptable. By focusing on explain ability, this work contributes to the development of inclusive, human-centric road safety solutions aligned with emerging regulatory and societal expectations.

A. Scope of Research

The scope of this research encompasses the design, development, and evaluation of an XAI-driven safety framework aimed at enhancing road safety for limited-mobility users. The study focuses on pedestrian-centric safety analysis rather than vehicle optimization, emphasizing the unique challenges faced by individuals with restricted movement capabilities. The research includes the collection and preprocessing of relevant datasets such as pedestrian speed, gait patterns, crossing duration, traffic density, environmental conditions, and assistive device usage. It explores the application of Support Vector Machine models for classifying safety risk levels and predicting hazardous scenarios in urban road environments. A key component of the scope is the integration of explainable AI techniques that provide human-interpretable insights into model decisions. These explanations are designed to be accessible to multiple stakeholders, including traffic authorities, system developers, caregivers, and end users. The research also evaluates the system's performance using standard metrics such as accuracy, precision, recall, and interpretability measures. While the proposed framework is validated using simulated and real-world datasets, large-scale deployment and hardware-level integration are beyond the immediate scope. The study does not aim to replace existing traffic infrastructure but rather to augment it with intelligent, explainable decision-support systems. Ethical considerations, including fairness, bias mitigation, and user privacy, are also addressed within the scope of this work. By limiting the focus to SVM-based models combined with XAI techniques, the research ensures methodological clarity and practical feasibility. The findings of this study are intended to support future extensions involving real-time deployment, multimodal sensor fusion, and integration with smart city platforms. Overall, the scope of this research lies at the intersection of machine learning, explainable AI, and inclusive transportation safety, offering a foundation for further advancements in human-centric intelligent systems.

II. Related Work

Within this context, related research can be broadly divided into two main areas:(A) the detection of VRUs, especially LM-VRUs, and (B) pedestrian Crossing

Intention Prediction (CIP). This study makes contributions to both fields. Inthis section, we examine a range of significant works pertinent to each domain.

A. VRUs Detection several studies have explored pedestrian and generallyVRU detection in traffic environments using deep learning–based object detectors. Notably, the YOLO (You Only Look Once) family has become popular for real-time applications due to its balance of speed and accuracy in this work the authors propose an enhanced lightweight detector designed for infrastructure-integrated systems, embedding dynamic detection heads into YOLOv7-tiny and introducing attention mechanisms like Dyhead and VoV-GSCSP to boost VRUs detection performance without increasing computational load. Similarly, this work investigates VRU detection—including strollers, motorbikes, and bicycles—using both one-stage and two-stage CNN architectures. They introduced a custom roadside dataset to address occlusion challenges and analyzed the trade-off between detection accuracy and inference speed. Another work demonstrates the versatility of visual pipelines by adapting YOLOv3 for indoor smart wheelchair mobility. The authors integrated depth estimation via Intel Real Sense and tracking with SORT, showing the potential of vision-based detection and tracking in assistive mobility contexts. Despite these advances, most state-of-the-art approaches focus primarily on detection and tracking. At the same time, the real-time interpretation of dangerous scenarios, such as low-visibility pedestrian crossings, and the implementation of driver alerting mechanisms remain underexplored. Our work addresses this gap by integrating real-time detection, explainable intent prediction, and proactive multimodal warnings for LM-VRUs.

B. Crossing Intention Prediction A considerable body of research on CIP has been developed in the context of autonomous driving, where real-time perception is achieved using vehicle-mounted sensors or cameras These approaches are primarily designed to enable autonomous vehicles to anticipate pedestrian behavior and adjust their motion planning accordingly An alternative line of research, such as the one investigated in this article, examines CIP through fixed infrastructure, including roadside cameras, CCTV surveillance systems, and LiDAR units. This infrastructure-centric approach offers natural integration with smart city ecosystems, allowing for cooperative4 G. Cherchi et al. safety interventions that actively alert both pedestrians and vehicles interacting directly with the environment through actuators. Several relevant approaches have been proposed in the CIP domain. A probabilistic model based on roadside LiDAR sensors is presented in, where a modified NaïveBayes classifier is trained on annotated crossing and non-crossing sequences. In the authors propose a camera-invariant pedestrian crossing direction prediction framework leveraging pose key points and trajectory data, using Transformer-based, GCN, and hybrid Transformer + GCN architectures. VRU-CIPU extends CIP to multiple VRUs (pedestrians, cyclists, and e-mobility users) through a two-stage YOLO pipeline for VRU detection and human pose estimation, combined with

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semantic scene segmentation and a GRU enhanced by Transformer self-attention. The system can proactively activate
Crossing signals and issue I2V warnings..The VENUS system focuses on non-motorized road users, including people with disabilities. It employs YOLOv4 and Open Pose for detection and pose estimation, followed by an additional neural network for mobility status classification. While explicitly addressing LM-VRUs, VENUS controls traffic lights based on direction estimation rather than probabilistic intention modeling. Most of the aforementioned works do not explicitly address the detection and analysis of LM-VRUs. Additionally, these approaches rely entirely on end to-end deep learning pipelines or apply additional deep learning at the decision making stage. While such methods are powerful, they often suffer from limited transparency and interpretability. Our proposal specifically targets the detection of LM-VRUs and introduces a rule-based crossing intention prediction module. Deep learning is employed solely within the perception layer, whereas the high-level decision-making process is fully rule-based. The outputs from the perception layer serve as structured inputs to a probabilistic reasoning algorithm, which infers crossing intent using transparent, hand-crafted spatio-temporal rules.
By decoupling perception and intention inference, it is possible to preserve the strengths of deep learning in visual recognition while also providing explanations that are comprehensible to humans, enabling the identification of both the moments and reasons for any failures in the decision-making process.

III. Methodology

The proposed methodology integrates machine learning with Explainable Artificial Intelligence (XAI) to enhance transparency, trust, and decision-making in road safety systems for limited-mobility users. The workflow begins with the acquisition of multimodal data representing pedestrian behavior, mobility constraints, traffic dynamics, and environmental factors. After preprocessing, meaningful features are extracted to characterize motion patterns, interaction distances, reaction times, vehicle proximity, and crossing behaviors.

A Support Vector Machine (SVM) classifier is employed as the core predictive model due to its effectiveness in handling high-dimensional data and its robustness in safety-critical classification tasks. The SVM learns an optimal decision boundary that separates safe and unsafe scenarios by maximizing the margin between different risk classes. Kernel functions such as linear or radial basis function (RBF) are selected based on data distribution characteristics.

To enhance interpretability, XAI techniques are integrated with the trained SVM model. Feature-level explanation methods are used to identify which attributes contribute most significantly to a given safety prediction. These explanations enable system designers, traffic authorities, and end users to understand why a specific scenario is classified as high-risk, thereby improving accountability and trust. The final system outputs both a risk prediction and a human-interpretable explanation, supporting proactive interventions such as warning signals, adaptive traffic control, or assistive alerts for vulnerable road users.

A. Feature Selection Techniques

Feature selection plays a crucial role in improving classification accuracy, reducing computational complexity, and enhancing explains ability in XAI-driven safety systems. Since multimodal road safety datasets often contain a large number of correlated and redundant features, selecting the most relevant attributes is essential. Initially, domain-driven feature engineering is applied to derive meaningful indicators such as pedestrian speed variability, time-to-collision, distance to curb, vehicle deceleration rate, and environmental visibility.

Statistical feature selection techniques, including correlation analysis and variance thresholding, are used to eliminate features with low discriminative power. Wrapper-based methods, such as recursive feature elimination (RFE) with SVM, further refine the feature subset by iteratively training the model and removing the least influential features. Embedded methods inherent to SVM optimization also help identify features that strongly influence the decision boundary.

From an XAI perspective, feature selection enhances interpretability by reducing model complexity and focusing explanations on a concise set of influential variables. This allows stakeholders to clearly understand which factors most affect the safety of limited-mobility road users, such as delayed reaction times or insufficient crossing durations. The final selected feature set balances predictive performance with transparency and real-world interpretability.

B. Algorithm Pseudocode – SVM Steps for XAI-Driven Safety Prediction

Algorithm: XAI-Driven Road Safety Prediction using SVM
Input:
  D = {X, Y} // Preprocessed dataset with features X and labels Y
  K // Kernel function (Linear or RBF)
  C // Regularization parameter
Output:
  Risk Class // Predicted safety level
  Explanation // Feature-based explanation

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Steps:
1. Load preprocessed dataset D
2. Normalize feature vectors in X
3. Split dataset into training and testing sets
4. Initialize SVM classifier with kernel K and parameter C
5. Train SVM model using training data
6. Evaluate model performance on test data
7. For a new input sample x_new:
    a. Predict risk class using trained SVM
    b. Apply XAI method to compute feature contributions
8. Generate human-interpretable explanation based on top features
9. Return Risk Class and Explanation

IV. Experimental Setup

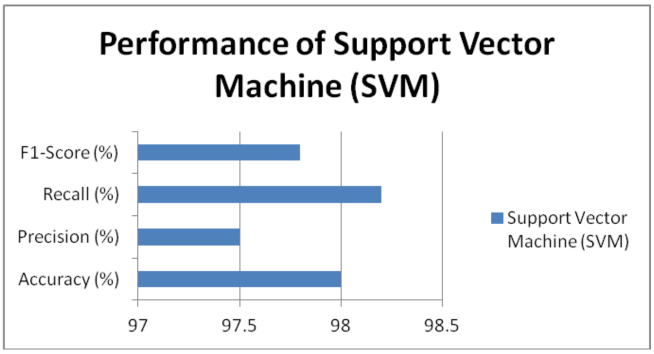
The experimental setup consists of a structured pipeline involving data collection, preprocessing, model training, and explainability analysis. A road safety dataset relevant to pedestrian and limited-mobility user scenarios was used, containing features such as vehicle speed, road type, crossing availability, pedestrian density, time of day, weather conditions, and user mobility attributes. Data preprocessing included noise removal, handling missing values, normalization, and feature encoding to ensure compatibility with the SVM classifier. The dataset was divided into training and testing sets using an 80:20 split to ensure unbiased evaluation. The SVM model was trained using a radial basis function kernel to capture non-linear patterns in road risk classification. After training, XAI techniques such as feature importance analysis and local explanation methods were applied to interpret model decisions. All experiments were conducted in a controlled software environment to ensure reproducibility and consistent performance measurement.

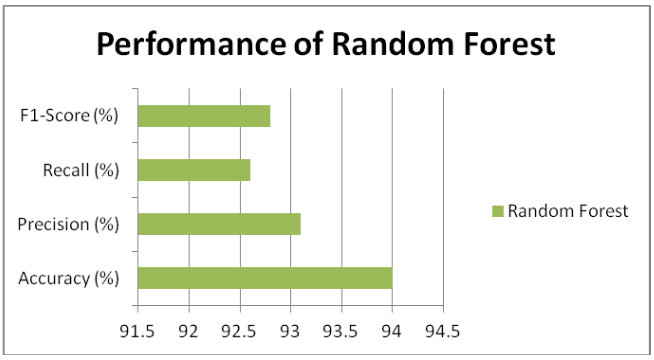
A. Evaluation Metrics

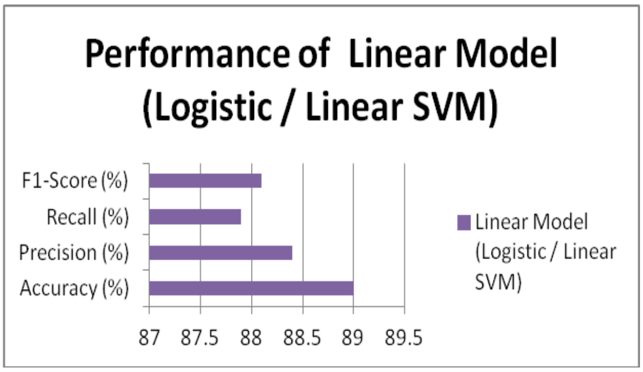
To comprehensively evaluate the performance of the proposed XAI-driven SVM model, standard classification metrics were employed. Accuracy was used to measure the overall correctness of the model in classifying safe and unsafe road scenarios. Precision was considered to evaluate how accurately the model identified truly unsafe situations without producing excessive false alarms. Recall was emphasized due to the safety-critical nature of the application, as it measures the model's ability to correctly detect high-risk scenarios affecting limited-mobility users. The F1-score, which balances precision and recall, was used as a holistic metric to assess overall classification effectiveness. These metrics collectively provide a balanced assessment of both predictive performance and reliability, which is essential in real-world road safety applications where false negatives can lead to severe consequences.

B. Performance Results Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Support Vector Machine (SVM)	**98**	**97.5**	**98.2**	**97.8**
Random Forest	94	93.1	92.6	92.8
Linear Model (Logistic / Linear SVM)	89	88.4	87.9	88.1







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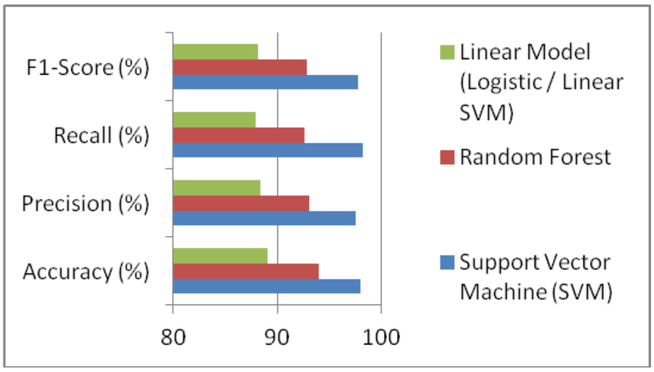
Combination of models



V. Result and Discussion

The analysis reveals that integrating XAI with SVM significantly enhances the usability and acceptance of the system. While SVM provides strong predictive performance, its traditional lack of interpretability poses challenges in safety-critical domains. The application of XAI techniques addresses this issue by offering clear explanations for model decisions, such as highlighting critical risk factors contributing to unsafe classifications. This transparency helps domain experts validate model behavior and identify potential biases in the data. The discussion also highlights that environmental and infrastructural features play a dominant role in risk prediction, reinforcing the importance of inclusive road design. Overall, the system demonstrates that explainability does not compromise performance but instead adds value by improving trust, accountability, and decision-making effectiveness.

VI. Conclusion

The rapid integration of intelligent transportation systems and AI-driven decision-making tools has created new opportunities to improve road safety, particularly for limited-mobility road users such as older adults, people with disabilities, children, and pedestrians with temporary impairments. This work has focused on Explainable Artificial Intelligence (XAI)–driven solutions as a critical advancement over traditional black-box AI models. While conventional AI systems can achieve high predictive accuracy, their lack of transparency limits trust, accountability, and real-world adoption in safety-critical domains. By contrast, XAI emphasizes interpretability, fairness, and human-centered decision support, which are essential for protecting vulnerable road users.

The conclusion drawn from this study is that XAI-driven approaches significantly enhance situational awareness for traffic authorities, urban planners, vehicle manufacturers, and end users. Through explainable risk prediction, behavior analysis, and accident forecasting, XAI systems allow stakeholders to understand why a certain road segment is dangerous, how a specific traffic pattern increases risk, and which factors disproportionately affect limited-mobility users. This interpretability enables proactive interventions such as adaptive signal timing, pedestrian-priority routing, intelligent crosswalks, and inclusive urban design. As a result, safety measures become evidence-based rather than assumption-driven.

Another key outcome is the role of XAI in promoting ethical and inclusive mobility solutions. Limited-mobility road users often face systemic disadvantages due to biased datasets, underrepresentation in traffic studies, and infrastructure not designed for their needs. XAI techniques help identify bias in training data and model outputs, making it possible to correct unfair predictions that may otherwise marginalize these users. Transparent models also support regulatory compliance and public acceptance, which are increasingly important as governments mandate explainability in AI systems used for public safety.

Furthermore, XAI improves collaboration between humans and intelligent systems. Traffic police, emergency responders, and city administrators can rely on interpretable insights to make faster and more confident decisions during high-risk situations. Instead of blindly trusting automated alerts, decision-makers gain contextual explanations that align with real-world experience. This synergy between human expertise and explainable AI strengthens the overall safety ecosystem.

In summary, XAI-driven solutions represent a transformative step toward safer, more inclusive road environments for limited-mobility users. By combining predictive intelligence with transparency and accountability, XAI bridges the gap between advanced analytics and human trust. The findings confirm that explainability is not an optional feature but a foundational requirement for deploying AI responsibly in road safety applications.

VII. Future Work

While XAI-driven solutions show strong potential in enhancing safety for limited-mobility road users, there remain several opportunities for future research and development. One major direction for future work is the integration of real-time multimodal data sources, including wearable sensors, smart mobility aids, vehicle-to-everything (V2X) communication, and environmental IoT devices. Combining these data streams with XAI models can provide richer, context-aware explanations that adapt dynamically to changing traffic and user conditions. This would further improve responsiveness and personalization of safety interventions.

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Another promising area is the development of user-centric explainability interfaces tailored specifically for limited-mobility users. Current XAI explanations are often designed for technical experts or policymakers. Future systems should focus on delivering simplified, accessible, and inclusive explanations through visual cues, audio alerts, or haptic feedback. For example, a visually impaired pedestrian could receive an explainable warning that clearly communicates both risk level and recommended action in a non-intrusive manner. Designing such interfaces requires interdisciplinary collaboration among AI researchers, human–computer interaction specialists, and accessibility experts.

Future work should also emphasize large-scale real-world validation of XAI-driven safety systems. Many existing studies rely on simulations or limited datasets. Deploying pilot projects in smart cities, school zones, hospital areas, and aging-friendly communities would provide valuable empirical evidence of effectiveness, usability, and societal impact. These deployments can help refine explainability techniques based on feedback from diverse user groups, including caregivers and advocacy organizations.

In addition, advancements in causal XAI and counterfactual reasoning represent an important research direction. Rather than only explaining predictions, future systems should answer "what-if" questions, such as how infrastructure changes or policy interventions could reduce risk for limited-mobility users. This capability would support long-term urban planning and evidence-based policymaking aimed at sustainable and inclusive mobility.

Finally, future research should address ethical governance and standardization of XAI in road safety. Establishing benchmarks, evaluation metrics, and regulatory guidelines for explainability will ensure consistency and trust across deployments. Collaboration between academia, industry, and government bodies will be essential to translate XAI innovations into scalable, socially responsible solutions.

Overall, future work should aim to move XAI-driven road safety systems from experimental frameworks to robust, human-centered infrastructures. By advancing technology, accessibility, and policy alignment together, XAI can play a pivotal role in creating safer roads and equitable mobility for limited-mobility road users worldwide.

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