XAI-V2X-Driven Decision Support for Safe and Efficient Transport of Parkinson's Patients in Healthcare Systems

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***Abstract*—Vehicle-to-Everything (V2X) communication systems are central to the development of intelligent urban infrastructures, enabling seamless interaction between vehicles, infrastructure, personal devices, and pedestrians. This paper proposes a novel integration of V2X technologies with wearable health monitoring and machine learning to improve emergency response for Parkinson's disease patients. Each patient is monitored using clinical scores UPDRS I, II, and III, which respectively capture cognitive, functional, and motor impairment. These indicators are analyzed using a Support Vector Machine (SVM) model trained to classify emergency conditions in real time. SHAP-based interpretability is applied to provide transparency and support medical decision making. The proposed framework was evaluated using a synthetic dataset of 20 simulated Parkinson's patients. Alerts are transmitted via V2P to Roadside Units (RSUs), which coordinate with ambulances using V2V and V2I protocols. The system's performance was assessed via SUMO and OMNeT++ simulations. Results demonstrate feasibility in reducing delays and improving emergency interventions.**

***Index Terms*—Healthcare, Parkinson's disease, Patient routing management, Explainable Artificial Intelligence (XAI), Vehicle-to-Everything (V2X) technology, Simulation**

I. Introduction

Patients with Parkinson's disease (PWP) is a progressive neurodegenerative disease that affects both motor and non-motor functioning, making quick emergency care necessary for patients going through sudden crises like falls, unexpected motor shutdowns, or freezing of gait. Let us imagine a scenario in which a Parkinson's patient experiences a sudden fall in the street or a severe freezing episode at home, unable to move or call for help. Time has become importance in these moments. A wearable sensor or smartphone detects the abnormal event, triggering an automatic emergency alert. But how can we make sure that the patient gets the appropriate and urgent help as soon as possible, particularly in crowded urban areas or remote locations?

Vehicle-to-Everything (V2X) communication technologies have the potential to revolutionize this problem. V2X systems can establish a perfect connected emergency response network by enabling easier real-time communication between emergency vehicles like roadside infrastructure (RSUs) , ambulances and personal devices. Also To be able to get to the patient as soon as possible, ambulances can be alerted instantly, guided along the most efficient short routes, and given traffic signal priority. To ensure early, timely, and informed care, medical teams can access real-time patient data before to their arrival at the location of the incident.

The integration of V2X communication and machine learning has been investigated recently in a variety of fields, including mobile health monitoring, emergency vehicle prioritization, and autonomous driving. by adjusting traffic lights dynamically, V2V and V2I systems have been used to optimize emergency vehicle routing and reduce response time significantly [1]. meanwhile, wearable IoT devices that use ECG and inertial sensors have shown guarantee in identifying Parkinson's disease symptoms like falls or freezing of gait [2]. However, the majority of current methods concentrate on either health monitoring or smart mobility separately. To facilitate coordinated, real-time emergency response, there is still a gap in the integration of patient specific health alerts into vehicular networks specifically for PWP.

Most existing research on V2X communication in healthcare and emergency response addresses only isolated components of the problem. For instance, without integrating patient health data, Arikumar et al. [3] suggest a system in which ambulances utilize V2X to control traffic lights and warn nearby cars. Similarly, Kumar et al. [4] design a DSRC based system to optimize ambulance routing through V2I communication, focusing solely on vehicle coordination. Concerning healthcare, Kaur et al. [5] present "IoV-Health," a system that uses wearable technology to track drivers' vital signs and sends out alerts to hospitals and other nearby vehicles. yet this is limited to in vehicle health monitoring. Likewise, Thirugnanam and Ghalib [6] propose a vehicular network for heart disease monitoring, but it does not support real time routing or personalized traffic management. These systems do not address chronic conditions like Parkinson's disease, nor do they combine wearable emergency detection with full V2X based emergency response. Our proposed method is the first to integrate real time wearable monitoring of Parkinson's patients with V2X communication (including V2P and V2I) for ambulance coordination, while also leveraging explainable

AI (SHAP) to clarify the emergency classification. This end-to-end, health to traffic pipeline enables rapid, interpretable, and location aware responses to medical emergencies, setting our approach apart from existing literature.

In this paper, we propose a novel V2X enabled emergency support system tailored for Parkinson's patients. Our architecture bridges wearable health monitoring and smart transportation networks to create a unified real time pipeline: from emergency detection using Support Vector Machines (SVM) to ambulance dispatch and dynamic traffic coordination via V2X. Furthermore, we employ SHAP (SHapley Additive Explanations) to enhance the interpretability of medical alerts, increasing trust and transparency for healthcare professionals.

The added value of our work lies in its integrated, cross domain architecture. While existing systems often focus either on emergency detection through wearable health monitoring or using XAI/machine learning to help the medication teams, or on optimizing vehicle routing via V2X communication, our approach brings these domains together into a cohesive, real-time emergency management framework. When a critical health event is detected, the system generates an alert, processes it through cloud infrastructure, and coordinates ambulance dispatch using V2V, V2I, and V2P communication to minimize response time. To assess patient condition with clinical precision.

We rely on the Movement Disorder Society–Unified Parkinson's Disease Rating Scale (MDS-UPDRS), a standardized tool composed of four parts; in our case, only Parts I, II, and III are used to capture non-motor symptoms, daily motor function, and clinician rated motor impairments, respectively [7]. A case is considered *Urgent* when the patient presents a severe score in any of the three parts: Score $\geq$ 22 (Part I), Score $\geq$ 30 Part II, or Score $\geq$ 59 Part III ; otherwise, the case is considered *non-urgent*. These thresholds are based on severity levels defined in the literature [8], since there is no an standardized score to establish the need for emergency attention in a Parkinson's patient. Moreover, we incorporate Support Vector Machines (SVM) for event classification, and enhance interpretability through SHAP (SHapley Additive Explanations) values [9], enabling medical professionals to better understand which sensor inputs influenced the decision. By combining wearable sensing, explainable AI, cloud based processing, and smart mobility coordination, the proposed system aligns multiple technologies toward a unified goal: improving the emergency response for Parkinson's patients in both urban and remote settings.

Our primary objective is to ensure a rapid response for PWP in the event of a fall or any emergency situation. To successfully attain these objectives, we address in this paper the following three key challenges:

- How can an integrated system combining real-time wearable monitoring and V2X communication (V2V, V2I, V2P) enable early detection and quick management of emergency events in Parkinson's disease patients?
- How does the combination of wearable health data with V2X infrastructure improve coordination among patients, emergency services, and urban mobility networks, particularly in complex environments such as crowded cities or remote areas?
- How can doctors use explainable AI to better understand alerts from machine learning systems that combine wearable, vehicle, and infrastructure data?

This paper is structured in four sections: in the second section, we introduce the most important related work about the problem addressed in this paper. In Section III, we give the proposed methodology and architecture. Section IV addresses the study environment. Obtained results and discussions are given in Section V. The last section concludes the paper and gives some perspectives.

II. Literature Review

A. V2X Communication Technologies and Emergency Response

V2X communication refers to the information exchange between vehicles and other entities, typically to improve road safety and efficiency. Its components include V2V (vehicle-to-vehicle) [10], V2I (vehicle-to-infrastructure), and V2P (vehicle-to-pedestrian or person) [11]. V2X has been applied to traffic safety scenarios for instance, enabling cars to broadcast their position and speed to avoid collisions, or allowing traffic signals to communicate with approaching vehicles. With the maturation of intelligent transportation systems, as shown in [12], the *Bgestion* system enables communication between accident vehicles, RSUs, and ambulances to speed up emergency response. In our case, we adapt this idea by replacing accident vehicles with Parkinson's patients, using V2P technology to connect them to the emergency network. This helps ensure faster medical intervention and improves patient safety in real time. In addition, these technologies can communicate with smart traffic lights to turn them green in its path, and send alerts to nearby vehicles to yield the right of way. These capabilities form the foundation on which a health focused V2X system for Parkinson's patients can be built by treating a patient's medical emergency as an event that the transportation network must be aware of and respond to in real time.

B. Wearable and Mobile Sensors for Parkinson's Patients

Continuous health monitoring through wearables is a cornerstone of modern mobile health, particularly for chronic conditions like Parkinson's disease. Wearable sensors (such as smartwatches, accelerometer equipped pendants, and smart shoes) can track a patient's motion, gait, and vital signs, detecting anomalies that may indicate an emergency situation—for example, a hard fall or a prolonged freeze [13]. Various wearable Internet of Things (IoT) devices have emerged for detecting, diagnosing, and quantifying Parkinson's disease symptoms, predominantly using inertial motion sensors and advanced algorithms. These wearables enable remote, real time assessment of a patient's condition and can automatically trigger alerts. For instance, a wrist worn device [14] might sense a fall and immediately notify a caregiver or call an emergency service. Studies in continuous monitoring of PD patients demonstrate that such systems can reliably capture events like falls or freezing of gait in home and community settings, which is essential for timely intervention. However, wearable devices raise challenges like connectivity, privacy, and energy use. To address this, we use a cloud based system that collects and processes sensor data in real time. In case of an emergency, the data is analyzed using Support Vector Machine (SVM) algorithms to detect critical events and alert hospitals or caregivers instantly—ensuring faster, more accurate intervention.

Furthermore, recent studies have emphasized the importance of interpretability in AI-driven medical alerts. Techniques such as SHAP (SHapley Additive Explanations) [9] have been applied to health prediction models to provide transparency into feature importance and support clinician trust. In our approach, we adopt SHAP to clarify SVM based decisions and ensure that health professionals can understand which sensor inputs triggered the emergency classification, addressing a key limitation in many black box wearable systems.

III. Methodology: Proposed Architecture

The main goal of our Parkinson's patient management system, as seen in the figure (1), is to ensure that emergency teams can reach Parkinson's patients locations as quickly as possible, no matter where the incident occurs. It also focuses on detecting obstacles along the routes and creating smooth, real time communication between ambulances, patients, and healthcare centers. This allows the system to adapt to changing environments and respond effectively regardless of the situation. Ultimately, the aim is to significantly reduce ambulance response time and improve outcomes for Parkinson Disease in critical condition.

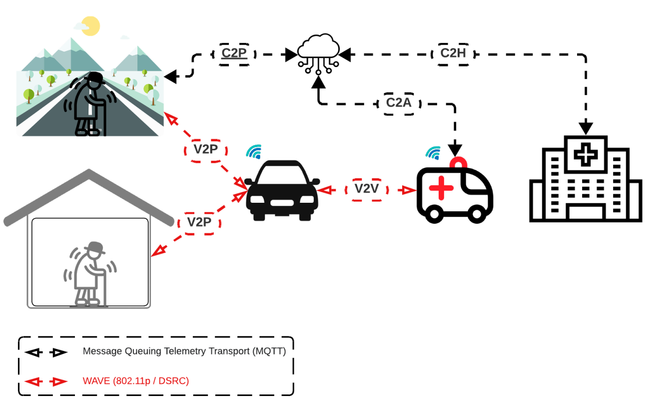

Fig. 1. The system architecture

Our system architecture is designed to detect emergency situations in Parkinson's patients as soon as they occur. When a problem is detected such as a fall or a sudden loss of mobility wearable sensors collect; as shown in Figure (2), the patient's data and send it to the cloud. There, the system performs variable selection and pre processing to organize the data clearly for medical analysis. At the same time, a machine learning algorithm, specifically SVM [15] [16], is used to predict the severity of the situation.

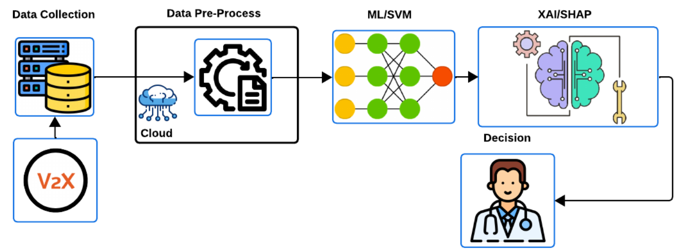

Fig. 2. Proposed Framework

After the analysis is performed, the cloud system sends a structured alert to the hospital or caregiver (emergency service), allowing them to make an informed decision. If the case is classified as urgent, the system communicates with the nearest ambulance via Roadside Units [10]. The RSUs help locate the closest available emergency vehicle, which is then dispatched immediately using V2V communication.

In urban public areas, V2P communication plays a key role in ensuring patient safety. When a Parkinson's patient experiences an emergency, the system sends alerts to nearby vehicles through their onboard communication units. These vehicles then share information with others in the vicinity, creating a local awareness network. If an ambulance is approaching road (localization X/Y) , nearby cars automatically send updates about the current road conditions such as obstacles or traffic that could help the ambulance find a quicker or safer route. At the same time, vehicles close to the patient location are warned to stay alert, as someone in medical distress is nearby. This entire communication loop is made possible through Roadside Units, which act as key intermediaries between the patient, nearby vehicles, the ambulance, and the cloud system ensuring real time coordination for a faster and safer emergency response.

A. Dataset and Experimental Setup

To evaluate the proposed system, we created a synthetic dataset simulating 20 patients with Parkinson's disease. Each patient record includes three clinical severity scores—UPDRS I, UPDRS II, and UPDRS III—which reflect cognitive, functional, and motor symptoms, respectively. The design of this dataset is inspired by real data collected from the roche PD Mobil application [17], a tool commonly used by Parkinson's patients for monitoring their condition. We extracted a representative sample of 20 patients and concentrated on three key variables to test the framework. Additionally, each record is annotated with a binary emergency status (0 = normal, 1 = emergency), simulating real time alerts triggered by critical events such as sudden falls or freezing episodes.

The dataset was split into two sets: 10 patients for training and 10 for testing. A Support Vector Machine (SVM) classifier

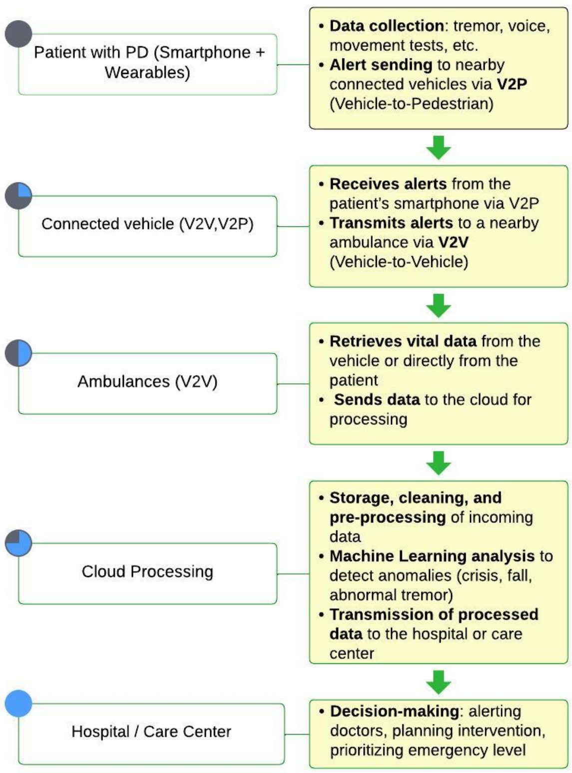

Fig. 3. The key steps of decision making

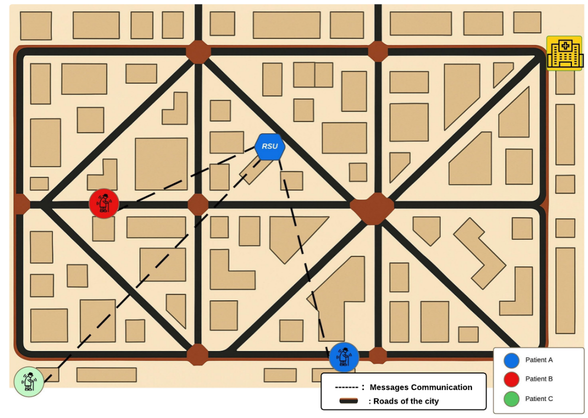

Fig. 4. Map of the urban scenario used for ambulance and patient coordination

with a linear kernel was trained on the normalized training data. Predictions on the test set were then compared against the ground truth. To improve interpretability of the model's outputs, SHAP like explanations were computed using the model coefficients, identifying the contribution of each UPDRS score to the emergency decision. For example, patients with high UPDRS II and low UPDRS I were more likely to be flagged as emergencies.

To simulate a full system, we extended the dataset with artificial V2X features including the patient's geolocation, timestamp, and list of nearby ambulances. This information would be collected via vehicle-to-everything (V2X) infrastructure and used by the decision support system to trigger and route emergency response services. In our implementation, the ambulance closest to the GPS coordinates of the patient is selected and guided to the scene using V2I/V2V messages.

All processing steps including data collection, emergency detection (SVM), and explainability (SHAP) were performed in a simulated cloud environment. The final decision is sent to medical professionals, enhanced with transparent explanations to ensure human oversight.

IV. Evaluation Environment

To simulate and evaluate the studied scenario, we developed a graphical model using SUMO [18], incorporating key elements such as road networks, ambulances, traffic congestion, and simulated patients. To emulate realistic V2X communication, we integrated SUMO with OMNeT++ via the TraCI interface, enabling the simulation of V2V, V2I, and V2P interactions. This entire setup operates within the VIENS framework (Vehicular Network Integration Environment based on OMNeT++ and SUMO) [19], offering a powerful and flexible platform to assess how vehicles, infrastructure, and personal devices communicate and respond in real time emergency situations.

Figure (3) illustrates the key steps of our proposed system. As shown, Parkinson's patients wear a wrist sensor capable of communicating with both the hospital's cloud platform and nearby Roadside Units (RSUs). In our simulation, we consider a scenario with 10 patients, three patient were in an urgent stage of Parkinson's as shown in Figure (4), meaning they were at high risk of experiencing a shutdown or emergency episode.

To evaluate the system, we collected various types of data voice patterns, movement tests, and a history of shutdown events. This data is then uploaded to the cloud, where it is framed and preprocessed. When an emergency is detected, the patient device can also communicate with nearby vehicles via V2P to alert drivers and help locate the nearest ambulance. In urban areas, cars near the patient receive real time alerts from the RSU, warning them to proceed with caution because a vulnerable patient is nearby. Simultaneously, the ambulance receives the exact location of the patient and waits for hospital confirmation before proceeding, ensuring a rapid and coordinated response.

An important feature of our system is its ability to predict emergencies using machine learning, specifically Support Vector Machines. We chose SVM to highlight the critical role of predictive modeling in this context. This capability allows hospitals to proactively reach out to patients when early signs of a shutdown are detected sometimes even before it happens enabling timely intervention and improved patient safety.

In our simulation environment, we created a scenario with 10 patients, including three in critical condition. One of these patients was intentionally placed outside RSU coverage to evaluate how the V2V system handles communication gaps.

TABLE I
CONFUSION MATRIX FOR EMERGENCY DETECTION (TEST SET)

	Predicted: No urgent	**Predicted: Urgent**
Actual: No Urgent	13	0
Actual: Urgent	4	3

TABLE II
SVM PERFORMANCE SUMMARY (EMERGENCY CLASS)

Metric	**Value**
Accuracy	80%
Precision (Emergency)	100%
Recall (Emergency)	42.9%
F1-Score (Emergency)	60.0%

We also modeled three ambulances: One ambulance is assigned to a care task within the city, while the other two are stationed at the hospital, ready to be dispatched in case of an emergency.

Table (IV) summarizes the standard parameters used in the studied scenario, which includes diverse conditions such as low and high traffic densities, and both highway and urban settings.

V. RESULTS AND DISCUSSION

A. Classification Performance

The SVM model trained on simulated Parkinson's patient records was evaluated on a test set of 20 patients. It achieved a reasonable overall accuracy of 80% as shown in Table II, effectively identifying non emergency cases while exhibiting conservative emergency detection.

Table I shows that the model accurately classified all non-emergency cases, with No urgent-No urgent (True Positive). However, it only detected 3 of Urgent-No Urgent (True Negative) and missing 4 No urgent-Urgent patients (False Positive). This results in high precision (100%) but low recall (42.9%) for the emergency class.

Table III shows that UPDRS II had the most significant positive impact on the emergency prediction, highlighting the role of functional impairment in clinical alert generation. Although UPDRS III (motor symptoms) was elevated, its negative contribution reduced the overall urgency score, indicating that motor severity alone may not imply emergency. This demonstrates that the model aligns with clinical reasoning and provides interpretable outputs that can support informed decision making by healthcare professionals.

B. Communication Performance

To evaluate the performance of the proposed solution, we simulated several scenarios, each designed to assess different

TABLE III
SHAP LIKE CONTRIBUTIONS FOR ONE PATIENT

Feature	**Stand-Value**	**Model-Coef**	**Contribution**
UPDRS_I	-1.12	-0.67	+0.75
UPDRS_II	+2.54	+0.24	+0.61
UPDRS_III	+0.75	-0.74	-0.56

TABLE IV
SIMULATION PARAMETERS

Parameters	**Values**
Simulation time	500 s
Protocol suite	DSRC
Protocol	IEEE8021.11p
Number of RSUs	1
Speed of the cars	0-80 km/h
Beacon Interval	1 s
Beacon Length	256 bit
Data Length	1024 bit
Number of patient	3
Number of ambulances	3
Channel frequency	5.89 GHz
Channel bandwidth	10 MHz
Mobility model	Traci Model
Backoff slot time	13 μs

key metrics. These include total CO_2 emissions there a part of enery of the ambulance and claud , travelled distance, and overall time taken. We also measured communication performance, focusing on Wave Short Messages (WSMs) broadcast messages exchanged between entities at a frequency of 2–10 Hz to share real time status—and Basic Safety Messages (BSMs), which are used to communicate critical situations. Additionally, we analyzed network performance, particularly looking at packet loss, to understand the reliability of data transmission within the V2X environment.

- **Environmental Impact:** As shown in Figure 5, Ambulance 3 recorded the highest CO_2 emissions due to its distant position from both the hospital and RSU. Ambulance 2, located near the patient, emitted only 310 mg/s. Although Ambulance 1 was nearby, traffic congestion increased its emissions despite the shorter route.
- **Communication:** Figure 6 shows that Patient A had stable connectivity (10 lost packets), while Patient B experienced moderate loss (50 packets). Patient C suffered major communication issues, with 150 lost packets, likely due to RSU coverage gaps. It should be noted that the current simulation does not incorporate buffering mechanisms or signal interference due to obstacles; therefore, intermittent connectivity and message recovery in real-world conditions are not reflected in these results.

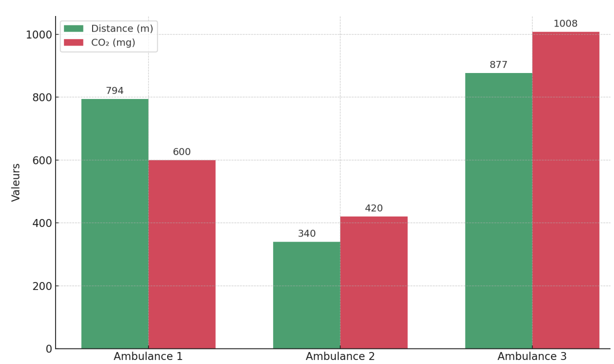

Fig. 5. Environmental Impact

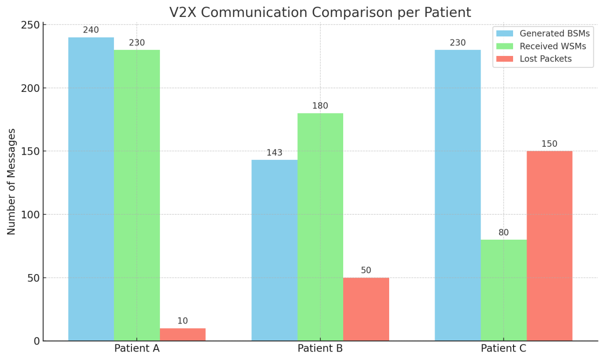

Fig. 6. Generated BSMs,Received WSMs,Total-Lost-Packets

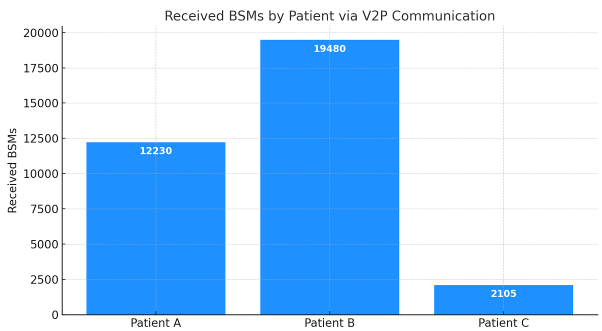

Fig. 7. Received BSMs

Figure (7), shows the number of Basic Safety Messages (BSMs) received by each patient through V2P communication. Patient B received the highest number of BSMs (19,480), indicating excellent communication coverage and strong V2P connectivity. Patient A received 12,230 BSMs, showing stable but slightly lower performance. In contrast, Patient C received only 2,105 BSMs, suggesting weak communication possibly due to poor RSU coverage or limited vehicle presence around the patient. These results highlight the importance of consistent V2P signal availability, especially for patients in vulnerable or isolated environments.

VI. Conclusion

This paper presented an integrated decision support system for emergency management in Parkinson's disease, combining wearable health monitoring, machine learning, and V2X (V2V, V2I, V2P) communication technologies. Using UPDRS I, II, and III scores as input features, a Support Vector Machine (SVM) model was developed to detect emergency situations in real time, with SHAP values providing interpretability of predictions. The proposed architecture enables immediate alert transmission from patients to Roadside Units and ambulances, ensuring optimized routing and reduced response time.

Future work will focus on implementing the framework in real time using complete data and more variables from the Roche Parkinson's Disease application. We also plan to integrate OpenStreetMap in order to operate on real-world geographic maps. Also, we aim to compare the performance of alternative machine learning models, and further investigate practical deployment challenges such as obstacle detection and DNS-related connectivity issues in order to face the issue of the lost packets.

References

[1] Y. Chen, H. Lin, S. Wang, Z. Zheng, and J. Wu, "Emvlight: Multi-agent reinforcement learning for emergency vehicle routing and traffic signal control," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 5438–5450, 2022.

[2] X. Huang, H. Liu, W. Zhang, and T. Wu, "Wearable devices for parkinson's disease: A systematic review," *Frontiers in Aging Neuroscience*, vol. 15, p. 1119956, 2023.

[3] K. Arikumar, S. Prathiba, S. Basheer, R. Moorthy, A. Dumka, and M. Rashid, "V2x-based highly reliable warning system for emergency vehicles," *Applied Sciences*, vol. 13, no. 3, p. 1950, 2023.

[4] N. Kumar, H. Shukla, and P. Rajalakshmi, "V2x enabled emergency vehicle alert system," *arXiv preprint arXiv:2403.19402*, 2024. [Online]. Available: https://arxiv.org/abs/2403.19402

[5] K. Kaur and H. Verma, "Iov-health: an intelligent integrated emergency health monitoring and alert generation system," *Soft Computing*, 2023.

[6] T. Thirugnanam and M. Ghalib, "A new healthcare architecture using iov technology for continuous health monitoring system," *Health Technology*, vol. 10, pp. 289–302, 2020.

[7] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, and N. LaPelle, "Movement disorder society–sponsored revision of the unified parkinson's disease rating scale (mds-updrs): scale presentation and clinimetric testing results," *Movement Disorders*, vol. 23, no. 15, pp. 2129–2170, 2008.

[8] P. Martínez-Martín, C. Rodríguez-Blázquez, M. Alvarez, T. Arakaki, V. Arillo, P. Chaná, M. Merello *et al.*, "Parkinson's disease severity levels and mds-unified parkinson's disease rating scale," *Parkinsonism & Related Disorders*, vol. 21, no. 1, pp. 50–54, 2015.

[9] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[10] S. Ma, F. Wen, X. Zhao, Z. M. Wang, and D. Yang, "An efficient v2x based vehicle localization using single rsu and single receiver," *IEEE Access*, vol. 7, pp. 46 114–46 121, 2019.

[11] R. Q. Malik, K. N. Ramli, Z. H. Kareem, M. I. Habelalmatee, A. H. Abbas, and A. Alamoody, "An overview on v2p communication system: Architecture and application," in *3rd International Conference on Engineering Technology and its Applications*. IEEE, 2020, pp. 174–178.

[12] Y. Amadiaz, A. Nait Sidi Moh, and S. Kharraja, "Decision support for patient transport efficiency based on v2x communications in healthcare systems," in *2024 IEEE Symposium on Computers and Communications (ISCC)*. IEEE, 2024, pp. 1–6.

[13] M. D. Xames and T. G. Topcu, "A systematic literature review of digital twin research for healthcare systems: Research trends, gaps, and realization challenges," *IEEE Access*, vol. 12, pp. 4099–4126, 2024.

[14] S. Pardoel, J. Kofman, J. Nantel, and E. D. Lemaire, "Wearable-sensor-based detection and prediction of freezing of gait in parkinson's disease: a review," *Sensors*, vol. 19, no. 23, p. 5141, 2019.

[15] B. R. Senapati, P. M. Khilar, T. Dash, and R. R. Swain, "Vehicular network based emergency data transmission and classification for health care system using support vector machine," *Journal TBD (unspecified)*, 2022, please update with full journal details if available.

[16] L. A. Claude, J. Houenou, E. Duchesnay, and P. Favre, "Will machine learning applied to neuroimaging in bipolar disorder help the clinician? a critical review and methodological suggestions," *Bipolar Disorders*, vol. 22, no. 4, pp. 334–355, 2020.

[17] F. Lipsmeier, K. I. Taylor, R. B. Postuma, E. Volkova-Volkmar, T. Kilchenmann, B. Mollenhauer, M. Lindemann *et al.*, "Reliability and validity of the roche pd mobile application for remote monitoring of early parkinson's disease," *Scientific Reports*, vol. 12(1), p. 12081, 2022.

[18] "Veins - vehicles in network simulation (last visit : 26/05/2025)." [Online]. Available: https://arxiv.org/abs/2403.19402

[19] "Sumo - simulation of urban mobility (last visit : 26/05/2025)." [Online]. Available: https://sumo.dlr.de/docs/Demand/Dynamic-User-Assignment.html/