Low-cost animal and pedestrian crossing detection in rural roads using WiFi sensing and deep learning

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Abstract. *Road traffic accidents involving animals cause great health, environmental, and monetary costs every year, specially on rural areas. Current animal detection systems suffer from either cost, scalability or accuracy issues, which prevent their effective use in a more extensive manner. In our research, we explore WiFi sensing to monitor events in rural roads, using low-cost IoT devices to collect WiFi data, publishing the first open CSI dataset of animal crossings and applying machine learning techniques to detect and classify them. Event detection runs on ESP32-S3 devices, while classification runs on Raspberry Pi 4 devices, both with accuracy of at least 95%. Our system enables a scalable and cost-effective solution for monitoring multiple kilometers of roads.*

1. Introduction

Traffic accidents are the leading cause of death among persons aged 5 to 29 years old, accounting for more than 1.35 million fatalities every year [(WHO) 2018]. A significant portion of these accidents is caused by collisions between vehicles and wildlife, which incur in great environmental, monetary and public health damages to communities in both developed and developing countries. In Brazil, tens of millions of vertebrate animals are ran over and killed every year, impacting wildlife to such an extent that studies [Abra et al. 2021] indicate that traffic accidents could be a bigger threat to some endangered species than illegal hunting. In the United States, government agencies estimate that animal-vehicle collisions cause over 26,000 human injuries, 365 million vertebrate animal deaths and over 8 billion dollars in damages every year [(FHWA) 2008]. More than 89% of these accidents occur on rural, two-lane roads, which have limited infrastructure and operational budget due to their extensiveness and low amount of traffic when compared to highways closer to large cities.

A commonly employed method of reducing the likelihood of accidents is using animal detection systems to monitor animal crossings on the roadway and alert incoming drivers by lighting up warning signs placed along the road. There have been many technologies employed for this purpose, including LiDAR sensors [Chen et al. 2019] and imaging cameras [Sharma and Garg 2022], but they are often not scalable and cost-effective enough for covering large distances. Recently, new sensing methods using WiFi signals have been proposed, allowing to effectively monitor events by analyzing WiFi Channel State Information (CSI) data using just the embedded antennas of low-cost IoT devices, without the need for expensive equipment or additional sensors. However, these studies are often conducted on highly controlled environments, not encompassing the challenges of monitoring wildlife crossings in rural roads.

In this dissertation [Ducca et al. 2024], we bridge this gap by proposing and developing a low-cost road monitoring system based on WiFi sensing to monitor events in rural roads that could not otherwise be monitored by more expensive methods. We create the first open WiFi CSI dataset containing animal, pedestrian and vehicle crossings, and apply machine learning techniques to detect and classify them. Our models are executed in real time using low-cost IoT hardware such as ESP32-S3 and Raspberry Pi 4 boards, achieving over 95% accuracy in detection and classification tasks.

2. Related Work

There are many proposed animal detection systems in the literature which enjoy high accuracy (e.g. computer vision and LiDAR), but fail to prove cost-effective and scalable enough to be deployed over the long distances of rural highways. For instance, LiDAR sensors achieve over 99% accuracy in monitoring animals, vehicles and people, but have a limited range of 30 meters and cost up to US$ 3,900 per unit [Chen et al. 2019]. Likewise, less expensive and more scalable systems have also been proposed (e.g. Doppler radars, infrared), but they do not classify the type of crossing detected and are not accurate enough for reliable monitoring. Thus, in this research, we focus on solving both of the aforementioned challenges, proposing and developing a system which is scalable, cost-effective and accurate.

Table 1 summarizes the state of the art regarding traffic, animal and pedestrian detection systems for road safety, including their suitability for use in low-light conditions. To the best of our knowledge, there is no proposed work in the literature that is able to conduct both detection and classification tasks with high accuracy and low cost.

Table 1. Summary of existing sensing methods for animal, vehicle and pedestrian detection on roads.

Work	Method	Subjects	Detection Accuracy	Classification Accuracy	Low Cost	Operates in Low Light
[Sharma and Garg 2022]	Camera	Vehicles, animals, people	98%	97 - 99%	-	-
[Singh et al. 2022]	Camera	Animals	98%	-	-	-
[Chen et al. 2019]	LiDAR	Vehicles, animals, people	$>$ 99%	$>$ 99%	-	✓
[Agafonovs et al. 2014]	PIR	Vehicles, people	76 - 94%	-	✓	✓
[Viani et al. 2016]	Doppler	Animals	80%	-	✓	✓
[Maus and Brückmann 2020]	Bluetooth	Vehicles	98%	-	✓	✓
[Won et al. 2019]	WiFi	Vehicles	$>$ 99%	91%	-	✓
Ours [Ducca et al. 2024]	**WiFi**	**Vehicles, animals, people**	$>$ **95%**	$>$ **95%**	✓	✓

3. Method

In order to achieve ours goals and develop this low-cost, IoT-based system for monitoring rural roads, we focus on three different aspects: (i) the wireless sensor network architecture, (ii) the data collection process and machine learning models and finally (iii) the optimization of such models for execution using low-cost devices.

The first aspect involves guaranteeing that data is properly sent and received in a timely manner over dozens of kilometers of roads monitored by hundreds of sensors with limited network and energy infrastructure available. In this context, we simulate both cloud and edge data processing architectures for the sensor network using the COOJA simulator [Österlind et al. 2006], considering factors such as traffic volume, node density, overall road distance monitored and processing delays from low-cost hardware. By analyzing metrics such as Packet Delivery Rate (PDR) and Round Trip Time (RTT), we evaluate which architecture better provides both timely and reliable data transfer over a rural road monitoring scenario. We also employ the OMNeT++ [omn 2024] simulator to analyze the coexistence between our wireless sensor network and the IEEE 802.15.4 wireless communication protocol, ensuring that both sensing and communication tasks have a high packet delivery rate. These simulations serve as basis to design our system architecture, presented in Section 4.

The second aspect involves using WiFi Sensing — a novel sensing method based on WiFi Channel State Information — to detect dangerous roadway crossings using only the built-in antennas of inexpensive IoT devices. We adapted the traffic monitoring methodology available [Won et al. 2019] to collect WiFi CSI data from small and large animals (illustrated in Figure 1), people, cars and ambient background noise in a variety of environments, using ESP32 boards instead of laptops. We then use the CSI amplitude data to train a Transformer deep learning model capable of detecting and classifying among these different types of events. We evaluate the model using several quantitative metrics, in order to verify its ability in identifying potentially dangerous situations on the road.

The third and last aspect involves optimizing the model previously trained so that we can execute it using inexpensive IoT commodity hardware. Due to compatibility issues and resource constraints, we developed an additional lightweight MLP (Multi-Layer Perceptron) model for the detection of roadway crossings on the ESP32 sensing devices, while delegating classification tasks to the Transformer model running on a Raspberry Pi edge processing node. We employed feature engineering and dimensionality reduction techniques in order to reduce the models' memory footprint and inference time; thereby, we can execute both models in real time given the constraints of the target hardware.

4. Architecture

We employ low-cost ESP32 devices for the detection of roadway crossings using WiFi sensing (ESP32-S3) and IEEE 802.15.4 communication (ESP32-H2), while delegating the classification of the type of crossing and handling of eventual false positives to a more powerful Raspberry Pi 4 edge processing node. The ESP32 sensing nodes are placed in pairs every 50 meters in both sides of the road, within range of WiFi and IEEE 802.15.4, whereas one edge processing node is placed per kilometer, allowing for low latency when communicating with the sensing nodes. In this topology, even if one of the nodes fails the overall data communication of the system is not compromised due to other neighboring nodes also being in range of IEEE 802.15.4, allowing for alternative routing of packets containing data from detected events. Depending on the local geography, the distance between sensing nodes should be reduced to properly reflect curvature and elevation changes on the road.

Our proposed system architecture (illustrated in Figure 2) enables the detection and classification of roadway crossings with high accuracy and low number of false negatives through a three-step process:

1. Roadway crossings are detected using WiFi sensing and a lightweight MLP model

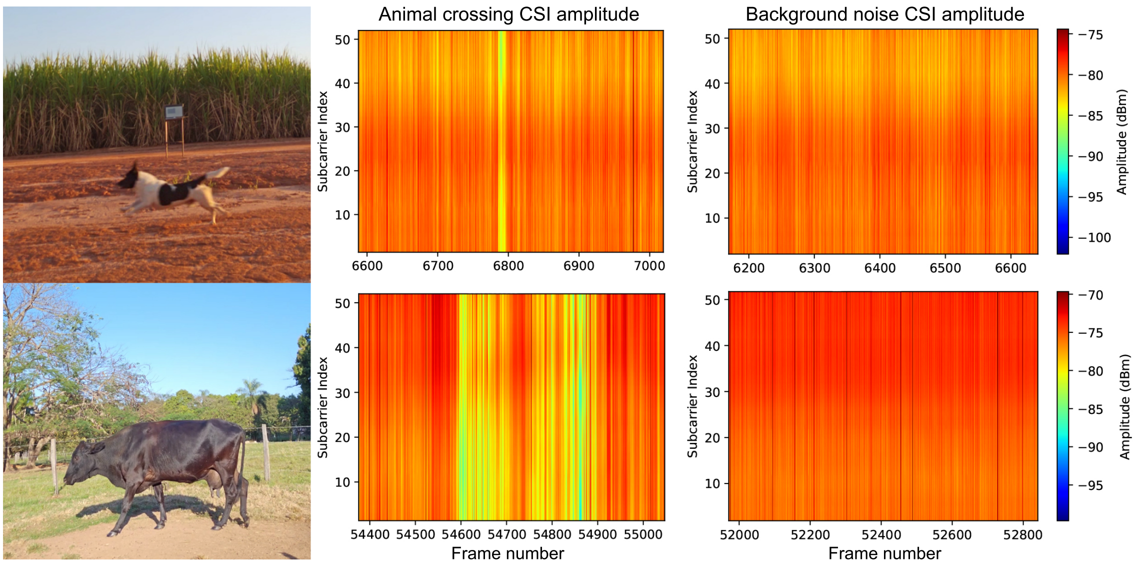


Figure 1. CSI amplitude heatmap for animal crossing events and background data from the corresponding environment, collected a few seconds prior to the event. Top: data from a dog crossing and dirt road background. Bottom: data from a cow crossing and pasture background. [Ducca et al. 2023] © 2023 IEEE.

executed locally in the ESP32-S3 board. The model is optimized for minimizing the number of false negatives, as any false positives can be re-evaluated later by the sink node. An early warning system such as dynamic LED lighting can be enabled to alert incoming drivers in real time;

2. Once a crossing is detected, the data is forwarded towards a sink node by the ESP32-H2 board, which acts as a radio co-processor for the ESP32-S3 [ope 2024], allowing the use of ad-hoc communication and the IEEE 802.15.4 protocol without hampering sensing;
3. Equipped with a Raspberry Pi 4 Model B board, the sink node uses a more accurate and complex Transformer model for classifying the received data to determine whether the event was a vehicle, an animal or a pedestrian crossing the road. If the received data is a false positive, the sink node can quickly send a message back to the respective sensor node to disable the early warning system. In case of a real crossing, the alert can be forwarded to notify the road operator using available networking infrastructure such as satellite or cellular internet.

4.1. Cost Analysis

In this section, we compare our WiFi sensing solution for detection of dangerous roadway crossings to the commonly employed camera-based monitoring systems. The total cost of implementing an animal detection system is comprised of many factors, such as equipment, infrastructure, installation and maintenance expenses — which can vary substantially on a case-by-case basis. Therefore, we limit our analysis to three main factors: (i) equipment cost, (ii) power consumption and (iii) bandwidth usage, presented in Table 2. A more detailed cost breakdown is available in the dissertation manuscript [Ducca et al. 2024].

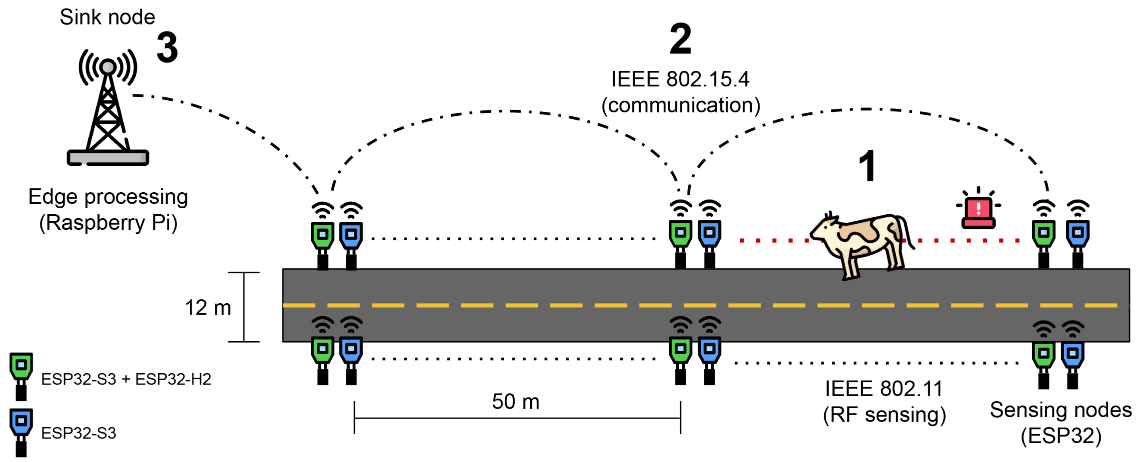


Figure 2. Diagram illustrating our system architecture for the (1) detection, (2) data transmission and (3) classification of roadway crossings using WiFi sensing.

Our WiFi sensing system costs 7.3 times less than surveillance cameras (US$ 407 vs US$ 3000 per km, respectively), while using approximately the same amount of power and requiring no connection to the internet. It is very likely that other infrastructure costs associated with video surveillance would make our cost advantage even more pronounced, as cameras often need to be installed on high poles that cost hundreds of dollars and require additional networking equipment that our WiFi sensing system does not.

Table 2. Total power consumption, internet bandwidth usage and cost per kilometer for each sensing method

Method	Power Consumption (W/km)	Internet Bandwidth (kbps/km)	Cost (USD/km)
Video Monitoring	64	8650	3000
WiFi Sensing (ours)	68.28	<1	407.4

5. Results

In this section, we present a summary of the results obtained for the networking and animal detection aspects of our work. We encourage reading Chapters 5 and 6 of our dissertation [Ducca et al. 2024] for an in-depth presentation and analysis of the results.

5.1. Networking

Implementing large-scale roadway monitoring systems based on IoT devices brings up new challenges, as this type of low-cost hardware may not be able to fully execute the data processing and classification algorithms required for a real-time application. Thus, it is necessary to evaluate alternatives such as processing the data in the cloud or in local processing nodes through edge computing. We conducted simulations in COOJA representing an IoT monitoring system covering up to a 10 km stretch of road, in three different topologies (illustrated in Figure 3): (i) cloud processing, in which the nodes must forward the collected data to a sink node with access to the internet, (ii) edge processing, wherein the nodes send the data to the nearest local processing nodes and (iii) cloud processing with retransmission, which uses retransmitter nodes with more powerful antennas to aggregate and forward data from the sensor nodes to the sink in a smaller number of hops.

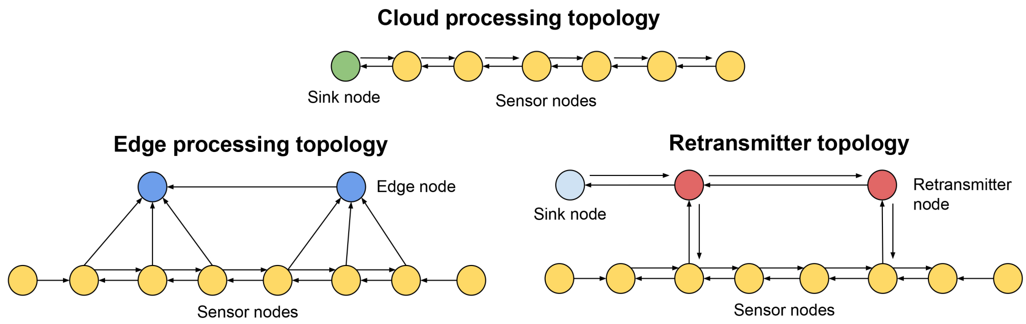


Figure 3. Diagram illustrating the cloud, retransmitter and edge processing network topologies. Adapted from [Ducca and Margi 2022] © 2022 IEEE.

In this manuscript, we focus our evaluation on the most challenging scenario and metric from our simulations, which was the packet delivery ratio while monitoring over a 10 km distance. Summarized results are shown in Figure 4. Even though the retransmitter topology presents a substantially better upstream packet delivery than the cloud topology, achieving over 77% PDR, it practically does not improve downstream PDR, which is still at less than 12%. Our results show that an edge processing topology is a more scalable and robust solution for a wireless sensor network in this context, achieving over 99% PDR in both upstream and downstream directions. However, these simulations did not factor in the physical layer interference between WiFi sensing and IEEE 802.15.4 communications, which is addressed in our next set of simulations.

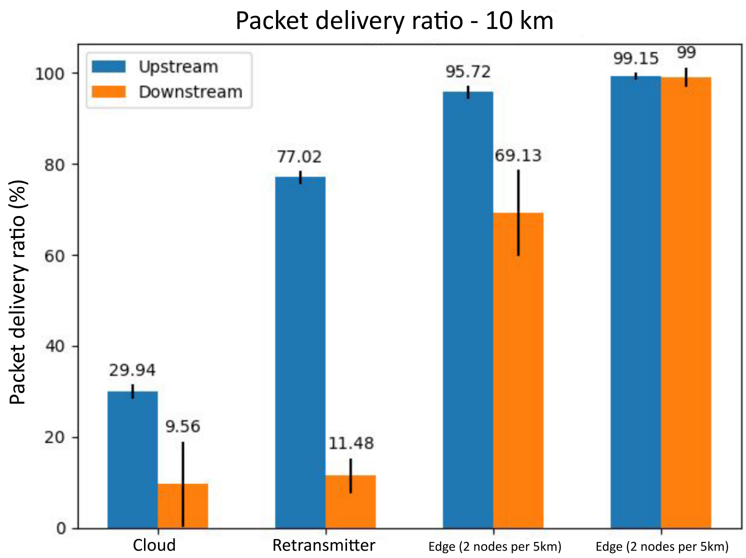


Figure 4. Packet delivery ratio for cloud, retransmitter and edge topologies.

As IEEE 802.15.4 and IEEE 802.11 (WiFi) share an overlapping 2.4 GHz frequency range , the two protocols may have degraded performance when operating in coexistence due to cross-technology interference. We implemented a series of simulations in OMNeT++[1] to evaluate this interference and ensure that both protocols can be used with the network topology described in our architecture in Section 4.

In summary, the IEEE 802.15.4 PDR was substantially impacted when operating in the same frequency band as WiFi, staying below 40%. WiFi PDR, on the other hand, was not impacted by IEEE 802.15.4 interference, maintaining close to 49% PDR in all frequencies. Using a non-overlapping frequency for WiFi sensing dramatically improves IEEE 802.15.4 PDR to over 99%, as cross-technology interference is avoided, but WiFi PDR is not affected. The low WiFi PDR was caused by all sensors operating in the same frequency, leading to saturation of the IEEE 802.11 network and evidencing the need for distributing sensing over a larger frequency range.

For the last set of simulations, we distributed the WiFi sensing channels sequentially from 1 to 11 throughout the sensors, as to avoid saturation of a single frequency and improve WiFi PDR. We also shifted the IEEE 802.15.4 frequency to 2480 MHz (channel 26) to prevent cross-technology interference. The results shown in Figure 5 present a marked improvement, with WiFi PDR higher than 94% and IEEE 802.15.4 PDR still close to 99%. Not only did the average PDR improve, but also the overall standard deviation in PDR values among the WiFi sensors was reduced, which indicates a more consistent performance across the whole network.

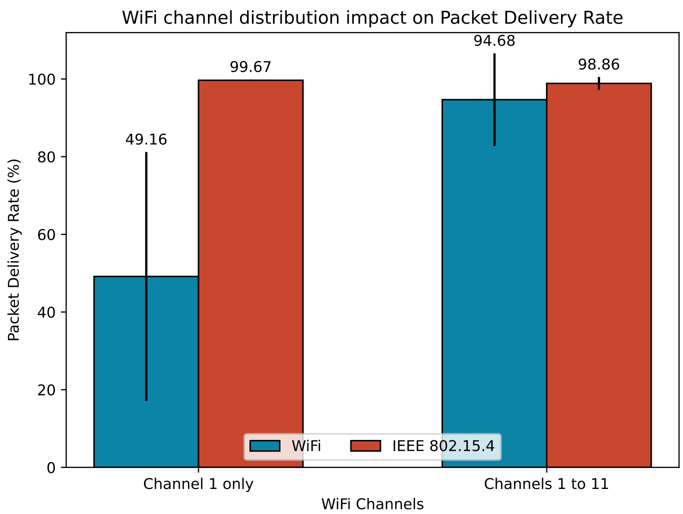


Figure 5. WiFi and IEEE 802.15.4 packet delivery rate with and without distribution of WiFi sensing over multiple channels

5.2. Detection and classification of roadway crossings

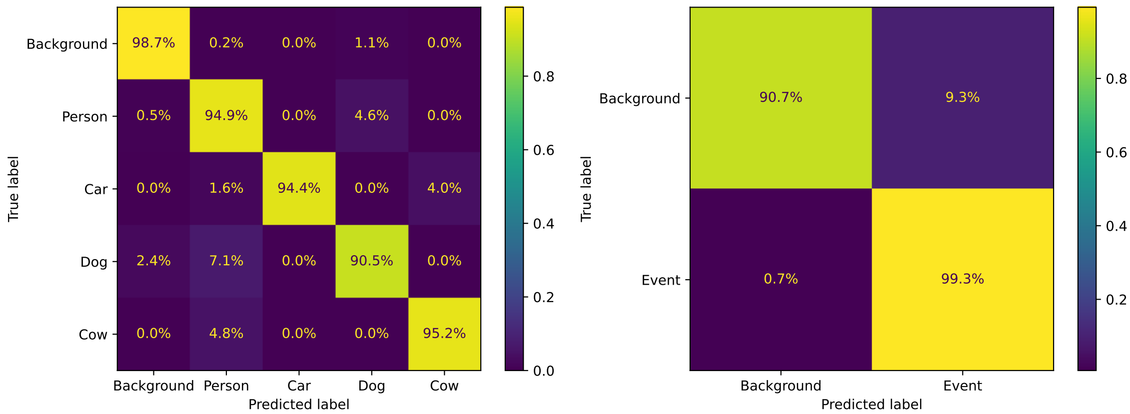
We employ two different machine learning models for ascertaining roadway crossings, as described in our architecture (Section 4). The first model is only responsible for detecting if something has passed in front of the ESP32 boards. It is a lightweight MLP, comprised of 5 layers with 35, 16, 8, 4 and 1 neurons, interleaved with 20% dropout layers. The hidden layers use ReLU activation, while the output layer employs sigmoid activation due to the binary classification nature of the detection task. The second model is a more complex Transformer network, responsible for classifying what kind of object corresponds to that

[1] Simulation parameters available at: https://github.com/SamuelDucca/csi-animal-crossing

crossing event, such as an animal or a vehicle. Our Transformer model has four layers consisting of 64, 32, 16 and 8 self-attention modules (i.e., components in the multihead attention), respectively.

We trained both models with the Tensorflow framework, using the same dataset[2] and a 80/20 train/test split. We then optimized the models for execution in low-cost IoT hardware using the LiteRT (formerly Tensorflow Lite Micro) library and post-training quantization techniques, as well as employed feature engineering techniques to reduce the model input size and improve performance.

Figure 6 shows the confusion matrices for both Transformer (a) and MLP (b) models. In summary, the MLP detection model presented a false negative rate of only 0.7%, while maintaining a moderate 9.3% false positive rate and overall detection accuracy of over 95%. As for the Transformer model, even the least accurate class (dog) is correctly identified in over 90% of cases. Dogs and persons are the most confounded classes due to similar CSI signal characteristics, but still have a low rate of misclassification. Overall, the Transformer model provides a false positive rate of only 1.3%, proving its ability to control the number of false positives that may arise from the MLP detection model, while maintaining a low false negative rate of 1.0% and general classification accuracy of over 95.8%.



(a) Transformer classification model **(b) MLP detection model**

Figure 6. Confusion matrix for the Transformer classification model (a) and the MLP detection model (b), normalized by true labels. Non-normalized matrices are available in the full dissertation manuscript.

The inference metrics for all developed models are shown in Table 3. With our optimization techniques, we were able to execute both models in their respective target hardware in real-time, maintaining a high accuracy of over 95%.

6. Conclusion and contributions

In this dissertation, we explored novel WiFi sensing techniques that enable sensing using CSI data collected from low-cost IoT devices, renouncing the need for costly sensing hardware for monitoring rural roads. Given the absence of available datasets, we collected data from hundreds of crossings of pedestrians, cars, small and large animals in several

[2]Open dataset available at: https://doi.org/10.5281/zenodo.8266462

Table 3. Inference metrics for the standard Transformer classification model (executed on a laptop), the optimized version (executed on a Raspberry Pi) and the detection MLP model (executed on the ESP32-S3).

Device	Task	Optimized?	Average Inference Time	Model Size	Accuracy
Laptop (Ryzen 7 5800H)	Classification	No	3.00 ms	43 MB	95.35%
Raspberry Pi 4	Classification	Yes	2.19 ms	2199 KB	95.88%
ESP32-S3	Detection	Yes	0.17 ms	5.6 KB	95.17%

distinct environments, publishing the first open CSI dataset in this domain[3]. Leveraging this data, we developed Transformer and Multi-Layer Perceptron machine learning models capable of correctly detecting and classifying roadway traversals in over 95% of cases, with a false negative rate of only 0.7%. Finally, we demonstrated that our approach is suitable for large-scale monitoring of rural roads, conducting network simulations to determine the best sensor topology in this scenario and mitigating the interference between WiFi sensing and IEEE 802.15.4 communications. Our simulation setup code, as well as the data processing scripts, are openly available at the author's Github[4].

We proposed techniques and developed a system for detecting dangerous animal and pedestrian roadway crossings that is accurate, scalable and more cost-effective than the alternatives. Our research is an important step towards developing affordable monitoring solutions for traffic safety on rural roads, with the potential to help preserve the local fauna, reduce economical damage and save human lives.

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