WIP: A First Look At Employing Large Multimodal Models Against Autonomous Vehicle Attacks

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***Abstract*—As the advent of autonomous vehicle (AV) technology revolutionizes transportation, it simultaneously introduces new vulnerabilities to cyber-attacks, posing significant challenges to vehicle safety and security. The complexity of these systems, coupled with their increasing reliance on advanced computer vision and machine learning algorithms, makes them susceptible to sophisticated AV attacks. This paper* explores the potential of Large Multimodal Models (LMMs) in identifying Natural Denoising Diffusion (NDD) attacks on traffic signs. Our comparative analysis show the superior performance of LMMs in detecting NDD samples with an average accuracy of 82.52% across the selected models compared to 37.75% for state-of-the-art deep learning models. We further discuss the integration of LMMs within the resource-constrained computational environments to mimic typical autonomous vehicles and assess their practicality through latency benchmarks. Results show substantial superiority of GPT models in achieving lower latency, down to 4.5 seconds per image for both computation time and network latency (RTT), suggesting a viable path towards real-world deployability. Lastly, we extend our analysis to LMMs' applicability against a wider spectrum of AV attacks, particularly focusing on the Automated Lane Centering systems, emphasizing the potential of LMMs to enhance vehicular cybersecurity.**

I. Introduction

In the past few years, autonomous vehicle (AV) systems witnessed great success of deep neural networks (DNNs) in a variety of computer vision tasks, such as image classification, object detection, etc. These advanced models have become increasingly robust against a multitude of AV attacks. For instance, techniques that use shadows [1] or stickers [2] to deceive traffic sign detection systems in autonomous vehicles have been effectively countered by the enhanced capabilities of DNNs [3]. The evolution of DNNs has improved traffic sign recognition accuracy, significantly boosting autonomous vehicles' safety and efficiency.

However, with the advancement of diffusion models in image generation, they reveal new vulnerabilities that could be a challenge for the robust detection capabilities of the existing DNN models [4]. For example, innovations, such as OpenAI's DALL-E [5], Adobe Firefly [6], Google Imagen [7], and the VQ-GAN + CLIP [8] combination have redefined image generation, seamlessly converting text descriptions into detailed, photorealistic images. Images from these models pose a threat to AV systems, especially with Natural Denoising Diffusion (NDD) attacks [9], a new cybersecurity challenge for AVs.

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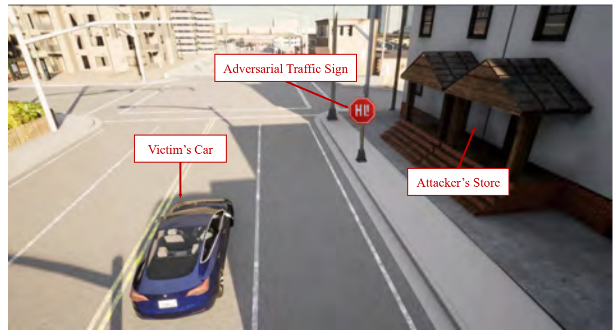


Fig. 1. The victim's car is approaching a pole in front of the attacker's store with an adversarial traffic sign depicting the word *'HI!'*. In our experiments, this sign has been classified as a *stop sign* by ResNeXt with a confidence score of 95%.

Attackers can use diffusion models to create images that, while not actual traffic signs, deceive AV perception systems' DNNs into recognizing them as real traffic signs. Since it is illegal to use, alter, or replicate official traffic signs [10], attackers can use NDD attacks to manipulate AV behavior without legal risks associated with physically tampering or using authentic road signs. An attacker could generate a fake *Stop* sign, visually distinct yet recognized by an AV's perception system, avoiding law enforcement attention but potentially causing the AV to stop unexpectedly, leading to confusion or accidents.

The advent of Large Language Models (LLMs) [11] marks a significant milestone in Artificial Intelligence and Large Multimodal Models (LMMs) [12] expand the capabilities of LLMs by incorporating visual signals. LMMs excel not only in handling and generating substantial textual-only tasks, but also demonstrate impressive performance in various multimodal tasks, such as video recommendations [13] and image understanding [14], amongst others. This paper presents an in-depth analysis of the robustness of LMMs against NDD attacks and their integration into AV systems. Given the success of generative pretraining in vision-language modeling, we use combined visual and textual data such as multimodal GPT-4V [15] and LLaVA [16]. This paper further discusses how the use of instruction tuning in LMMs was key in identifying NDD attack sample images. In summary, we make the following contributions:

- We conduct comprehensive evaluation of large multimodal models (LMMs) in identifying traffic signs com-

promised by NDD attacks. Our findings show that LMMs, such as GPT-4V and Google Bard showed accuracies of 84.06% and 85.42% respectively, outperforming state-of-the-arts models such as ResNeXt and MobileNet, which had much lower accuracies (below 18.67%). [†]
- We integrate LMMs into constrained computing environments, which are common in AVs, to demonstrate their potential feasibility in real-world scenarios. Our results illustrate that the latency was significantly high when these models were run locally. Conversely, server-run models like GPT-4V reduced latency to about 4.5 seconds, enhancing their practicality in AV systems.

II. Threat Model

An attacker can get the same Traffic Sign Recognition (TSR) module as in the victim's vehicle to comprehend its implementation fully. This can involve buying or leasing the same car model as the victim's and then reverse engineering it, a method proven feasible with Tesla's Autopilot [17]. Additionally, it's worth noting that some TSR module algorithms used in production are open-source [18]. Using the white-box knowledge, the attacker creates and places an adversarial traffic sign with the text *'HI!'* on a pole across from their store, as illustrated in Figure 1. The victim's vehicle which is headed towards the store will recognize the fake traffic sign as a *stop sign* and come to a halt.

The goal of the adversary is to minimize the *obviousness* of the generated traffic sign to increase stealthiness. To achieve this, context-aware adversarial example generation is recommended. For instance, the adversary might want to install an adversarial traffic sign resembling the image of a vegetable near a grocery store. We assume the attacker exclusively targets the Traffic Sign Recognition (TSR) module using AI-generated signs, without considering patches or alternative threats.

III. Datasets and Models

A. Dataset

To systematically assess the effectiveness of LMMs in identifying these NDD samples as adversarial, we first use the Adobe Firefly diffusion model [6] to generate a small-scale dataset containing NDD adversarial examples. We used text prompts aimed to disrupt the fundamental properties that humans typically use to identify these signs. For example, we focused on altering the most important visuals of traffic signs, changing their shape, texture, and color. These elements are crucial for how objects are typically recognized, as emphasized in existing research [19]. To generate a diverse set of samples, we created combinations such as altering both shape and text, shape and pattern, alongside other combinations, as depicted in Table I. Subsequently, two of the authors filtered the dataset manually to ensure that the generated images do not reflect actual traffic signs.

[†]The implementations codes of this work and generated dataset are available at https://anonymous.4open.science/r/LMM_on_AV-118E.

(a) No Entry (b) Priority Sign (c) Stop Sign (d) Yield Sign

Fig. 2. The Selected Traffic Signs

The generated dataset features images of four common traffic signs from the German Traffic Sign Recognition Benchmark (GTSRB) [20],namely *no entry* 2a, *priority road* 2b, *stop sign* 2c, and *yield* 2d, 40 variations were generated from each of the 4 real signs, resulting in a total of 160 signs. Each sign was changed in 4 features, resulting in 10 variations for each feature. We validated the adversarial effectiveness of our NDD dataset by testing with the ResNeXt model, including only images predicted as traffic signs with over 80% confidence, to assess the risk of NDD attacks misleading autonomous driving systems.

B. Models

To thoroughly evaluate the generated NDD dataset, we employed a different set of models. Our selection includes state-of-the-art models from conventional deep neural networks paradigms, such as pre-trained ResNeXt model that had been trained on GTSRB dataset [21], and manually trained MobileNet [22], VGG16 [23], YOLOv5 [24], serving as a baseline for our comparisons. On the other hand, we incorporated Large Multimodal Models (LMMs) such as GPT-4V [15], LLaVA-7B, LLaVA-13B [16], as well as Google Bard [25]. For the testing process, all LMMs were employed in their pre-trained state without any further fine-tuning to assess their out-of-the-box efficacy against the NDD dataset.

LMMs are notably computationally intensive and memory-demanding, posing challenges in environments with limited hardware, such as autonomous vehicles. Quantization [26] emerges as a vital technique to reduce the precision of weight values, thereby conserving memory and accelerating the inference process, all with minimal impact on the performance of the model [27], as will be discussed in Section V. Therefore, we first convert the LLaVA models to a *fp16* binary format. The focal point of our quantization process is reducing the number of bits used to represent each weight in the model to *4-bits*.

IV. Task 1: NDD Attack Discovery

A. Goal

In this task, LMMs are asked to discover if images in the generated NDD dataset are related to actual traffic signs to evaluate their practical applicability in real-world scenarios. AVs, for example, use traffic sign recognition models as part of their navigation systems. Through this comprehensive evaluation, we aim to understand how different models react to the NDD attack and assess the robustness of the LMMs model against NDD attacks.

TABLE I
A DETAILED BREAKDOWN OF HOW WE GENERATE THE NDD DATASET. WE ELIMINATE OR MODIFY SOME OR ALL OF THE FOUR FEATURES. THE RESNEXT MODEL IS USED TO CALCULATE THE PREDICTED CLASS AND CONFIDENCE SCORE.

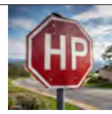
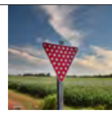
Features	Generated Sample	Predicted Class + Confidence	Combination Features	Generated Sample	Predicted Class + Confidence
Shape		Prediction: No Entry Confidence: 99.7%	Shape & Text		Prediction: Stop Sign Confidence: 98.9%
Color		Prediction: No Entry Confidence: 99.3%	Shape & Pattern		Prediction: Stop Sign Confidence: 99.9%
Text		Prediction: Stop Sign Confidence: 99.9%	Color & Pattern		Prediction: No Entry Confidence: 93.44%
Pattern		Prediction: Yield Confidence: 95.5%	Shape & Text & Color & Pattern		Prediction: Yield Confidence: 85.07%

TABLE II
COMPARISON OF LLMS AND TRADITIONAL MODELS AGAINST NDD ATTACK SAMPLES

Type	Model	Accuracy	F1-Score	Precision	Recall
LLMs	GPT-4V	84.06%	**86.73%**	**92.42%**	84.06%
	Bard	**85.42%**	85.94%	86.82%	**85.42%**
	LLaVA-7B	79.80%	79.93%	80.88%	79.80%
	LLaVA-13B	80.81%	83.48%	88.70%	80.81%
Traditional Models	ResNeXt [21]	17.17%	6.34%	3.99%	17.17%
	MobileNet [22]	18.67%	22.41%	62.50%	15.01%
	YOLOv5 [24]	44.12%	43.57%	65.11%	38.22%
	VGG16 [23]	**71.05%**	**66.56%**	**71.10%**	**78.88%**

B. Experimental setup

We formulate NDD attack discovery as a binary-class classification task. Given an NDD sample image from the dataset, we ask the LMM model via prompt whether the image corresponds to actual traffic sign. Here is the prompt used in this scenario: *"**Q1**: Is the traffic sign displayed a real-world traffic sign that has the same shape, color, pattern and text as real world traffic sign ? Answer with 'yes' or 'no'."*. Then, we enumerate the AE images in the dataset, systematically presenting each to the LMMs for classification.

Similarly, we evaluate traditional traffic sign detection models, ResNeXt, MobileNet, YOLOv5, VGG16 in identifying traffic signs within the NDD dataset. To thoroughly assess each model's performance, we not only obtained the inference results from each image in the dataset but also focused on acquiring the confidence scores of each classified image since a high confidence score in classifying a NDD sample can reveal the model's susceptibility to such attacks. For instance, if a model wrongfully classifies a non-actual traffic sign (from our generated NDD dataset) as a legitimate traffic sign with high confidence, it indicates a potential vulnerability in the model's detection capabilities.

C. Results

Table II presents the overall detection results of all four signs in the generated NDD dataset. Rather than measuring the misclassified traffic sign class, the table evaluates if each model identifies NDD signs as a legitimate traffic sign or not. For example, the accuracy in Table II reflects the model's capability to identify samples in the NDD dataset as non-actual traffic signs. We observe GPT and Bard to exhibit the highest accuracy achieving 84.06% and 85.42%, respectively. LLaVA-7B and LLaVa-13B also demonstrate noteworthy performance with accuracies of 79.80% and 80.81%, respectively. While the LLaVA models are effective in identifying NDD samples as non-actual traffic signs, they are slightly outperformed by GPT and Bard. On the other hand, traditional DNN models such as ResNeXt and MobileNet and YOLOv5 show significantly lower accuracy in identifying NDD samples, with accuracies of 17.17%, 18.85% and 44.12%, respectively. Nonetheless, VGG16 emerges as an exception among traditional models, achieving a noteworthy accuracy of 71.05% and the highest F1-Score in its category, indicating a relatively better but still not comparable performance to LMMs.

This notable success in LLMs is largely due to the their ability to handle complex visual patterns due to their extensive training on diverse datasets. LMMs have an advanced understanding of context. This means they are better at interpreting the broader meaning or implications of the data they process, rather than just focusing on specific features. This capability makes them more effective at identifying anomalies or irregularities in data, which is crucial for detecting and responding to attacks, where data might be intentionally altered to mislead the model. On the contrary, traditional DNN models rely heavily on visual cues or specific features in the data they are trained on such as shape, color, and text. These models have been optimized to identify these features with high accuracy under normal conditions. In the case of NDD attacks, these visual features are subtly manipulated so that traditional models still continue to predict the presence of traffic signs with high confidence. This overconfidence is likely due to the altered signs still retaining enough of the original features to trigger recognition by the model. The LLMs vary in false positive rates, with Bard at 8.33%, LLama-7b at 10.10%, GPT

TABLE III
COMPARISON OF LMMS AND TRADITIONAL MODELS AGAINST NON-AES

Type	Model	Accuracy	F1-Score	Precision	Recall
LMMs	GPT-4V	**79.04%**	**84.79%**	**95.06%**	**79.04%**
	LLaVA-7B	73.00%	69.91%	80.92%	73.00%
	LLaVA-13B	70.00%	62.39%	59.66%	70.00%
Traditional Models	ResNeXt [21]	**99.50%**	**99.50%**	**99.51%**	**99.50%**
	MobileNet [22]	93.50%	96.44%	99.99%	93.50%
	YOLOv5 [24]	54.80%	56.86%	94.67%	52.81%
	VGG16 [23]	99.00%	99.20%	99.22%	99.20%

at 14.49%, LLama-13b at 16.16%, and Resnex with the highest rate at 82.83%.

Despite the strong performance of Google Bard, integrating it was tough due to no official API. We used an unofficial API [28], which worked but had limits, especially handling lots of images. It couldn't process batches over 30 images well, even with delays. So, we only used this method for Task 1, leaving Bard out of Table III and in Task 2.

V. TASK 2: LMM INTEGRATION IN AUTONOMOUS PERCEPTION

A. Goal

Building upon the insights gained from Task 1, where LMMs demonstrated a notable proficiency in identifying the images within our generated NDD dataset as non-actual traffic signs, the goal of this task is to explore the feasibility of integrating LMMs into the perception systems of autonomous vehicles to enhance decision-making and environmental understanding. We examine how the integration of LMMs, with their significant computational requirements, aligns with the operational capabilities of AVs, aiming to strike an optimal balance between enhanced cognitive processing and the computational efficiency of onboard vehicle systems.

B. Method

In the **first** phase, we integrated ZED BOX [29], designed for running sophisticated neural networks and processing voluminous 3D sensor data in real-time, which is crucial for the complex decision-making processes of autonomous vehicles. One of the major tasks in perception systems is object detection, which is essential for safe navigation without collisions. To achieve this, we employ a stereo camera system, the ZED X – an IP66-rated stereo camera powered by the Neural Depth Engine 2, designed for next-generation robotics and ideally suited for industrial environments. This camera employs triangulation to construct a three-dimensional understanding of the scene, thereby significantly improving our perception of space and motion within the test environment.

In the **second** phase, we utilize the Raspberry Pi as an Electronic Control Unit (ECU) to simulate an autonomous vehicle's perception system, particularly focusing on its response to NDD dataset. We chose the Raspberry Pi 4 Model B, which features 8GB RAM and 64GB ROM, a Broadcom BCM2711, Quad-core Cortex-A72 (ARM v8) 64-bit SoC running at 1.8GHz, due to its similar specifications to comparable autonomous driving ECUs. For instance, while not as advanced as the high-computing Tesla HW3 or HW4, the Raspberry Pi 4's processing capabilities and system architecture offer a modest parallel to early versions of Tesla's Autopilot hardware, such as HW1. Specifically, Raspberry Pi 4 provide a sufficient platform for handling tasks such as image recognition and processing sensor data, similar to the capabilities of the Mobileye EyeQ3 chip in Tesla's HW1 Moreover, it allows us to create a controlled environment where LMMs can be tested on their ability to process environmental data, including images from the NDD dataset.

Traditional traffic sign detection models based on DNNs have proven to be effective in accurately recognizing non-adversarial traffic signs, as shown in Table III. Meanwhile, LMMs demonstrate promising capabilities in identifying NDD attack examples. Therefore, we deploy LMMs in our system as a verification layer, and the workflow of this approach is illustrated in Figure 3. This integration forms a comprehensive perception system for street view analysis in AVs. Initially, a traffic sign recognition model scans the street to locate and identify traffic signs then models such as ResNeXt are utilized to classify the specific type of traffic sign detected. When the vehicle approaches within a proximity of 7 meters to the traffic sign, LMMs are activated as a verification layer to confirm whether the identified sign is non-adversarial. Based on the outcome of the LMM verification, the system either warns the driver if the sign is deemed adversarial or allows the vehicle to continue driving if the sign is verified as legitimate.

To determine this operational range of 7 meters for LMM activation, we conducted a series of tests at varying distances. These tests were designed to identify the threshold distance at which the LMMs reliably and accurately identified traffic signs as adversarial or legitimate. We initiated our testing process by capturing images (via ZED stereo camera) of traffic signs from a close distance of 2 meters. LMMs were capable of accurately identifying NDD signs in a short-range scenario. Following that we tested at 5, 7, and finally 10 meters. The accuracy of the LMMs in identifying NDD signs was high up until 7 meters. However, beyond this threshold, it dropped significantly, leading us to set 7 meters as the optimal activation range for the LMMs verification layer. The observed decrease in accuracy beyond the threshold can be related to the limited capability of the camera to capture clear and detailed images at longer distances, leading to a reduction in the quality of data fed to the LMMs. The necessity for LMMs to receive high-quality images for detection constrains the deployment within AV systems, as it highlights the physical limitations of current sensory hardware (i.e., camera and lidar).

Additionally, the nature of the signs being displayed on a TV screen may have influenced the captured image quality.

This finding highlights the importance of considering both the technological capabilities and the operational environment in determining the effective range for LMM activation, ensuring optimal threat detection and adequate response time for the AV's decision-making processes.

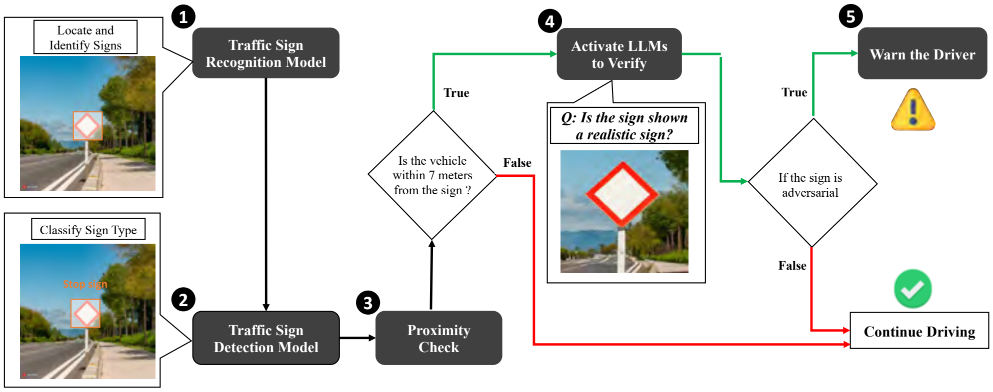


Fig. 3. Workflow of the LLM as a Verification Layer in an Autonomous Vehicle's Perception System.

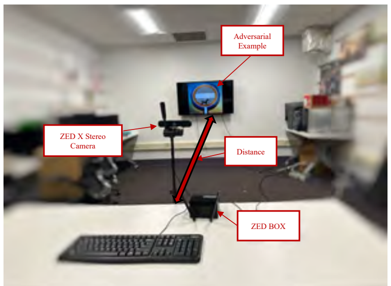


Fig. 4. Experimental Setup

C. Experimental setup

We connect the ZED BOX to the ZED X stereo camera module through its GMSL2 port to capture real-time images from the NDD dataset projected on a TV screen, providing a dynamic and realistic testing environment as depicted in Figure 4. We deployed GPT-4V on it for testing the NDD dataset. The captured images from the camera module are directly fed into the GPT-4V model as we formulate NDD attack identification with a binary classification prompt. The prompt used in this scenario is: "***Q2***: *Is the traffic sign shown a real-world sign commonly used in the physical environment, such as on roads, highways, or streets? If 'yes', name the sign in three words. If 'no', simply respond with 'no'*".

However when working with LLaVA models, we first need to quantize the models as outlined in Section III-B. This quantization is crucial for running these models on the hardware of a ZED BOX. Following this, we apply the same method used for the GPT-4V model by feeding images captured by ZED X stereo camera into the quantized LLaVA models and we employed the same binary classification prompt for NDD attack identification. This direct approach enables us to evaluate the model's performance in real-time, mirroring potential real-world applications in autonomous vehicles.

In a parallel experiment, we replicated this setup using a Raspberry Pi 4 Model B. This experiment aimed to assess the portability and efficiency of our approach on more constrained hardware environments. It is worth noting that the Raspberry Pi does not have the GMSL2 port to connect ZED stereo camera. Therefore, we utilized the images that were previously captured using the ZED BOX setup and then fed directly into the Raspberry Pi. This approach ensured consistency in the testing environment across different hardware platforms.

TABLE IV
COMPARISON OF RPI AND ZED BOX AGAINST AES

Device	Model	Accuracy	F1-Score	Precision	Recall
ZED BOX	GPT-4V	77.27%	48.28%	35.00%	77.78%
	LLaVA-7B	59.09%	18.18%	12.50%	33.33%
	LLaVA-13B	53.03%	34.04%	21.05%	88.89%
Raspberry Pi	GPT-4V	74.24%	45.16%	31.82%	77.78%
	LLaVA-7B	59.10%	30.08%	20.00%	66.70%
	LLaVA-13B	48.48%	29.16%	17.94%	77.77%

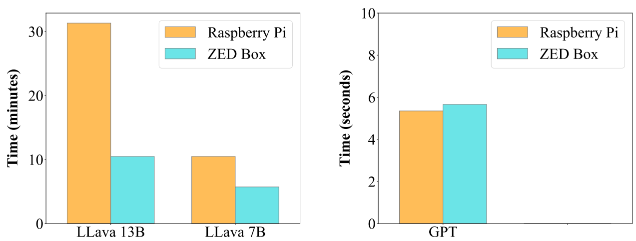
D. Results

Table IV illustrates the comparative performance of the Raspberry Pi and ZED BOX in handling LMMs to detect NDD attack samples. Notably, the GPT models on the ZED BOX and Raspberry Pi demonstrate higher accuracy of 77.27% and 74.24%, respectively. This observation aligns with the outcomes presented in Task 1, as illustrated in Table II, where GPT models emerge as the superior among other LMMs. Despite using the same GPT environment and images as deployed on the ZED BOX, the GPT model on Raspberry Pi shows a slight decline in its performance.

Meanwhile, the LLaVA models displayed varying performances, with LLaVA-7B surprisingly outperforming the more robust LLaVA-13B model. This unexpected outcome may stem from the inherent complexity and quantization tolerance of each model. LLaVA-7B, being less complex than LLaVA-13B, might be more resilient to the precision loss from quantization, retaining more effectiveness. This means that when the models are converted to a lower precision format (such as *fp16* binary format) for deployment in environments with limited hardware and memory capacity such as in AVs, the less complex LLaVA-7B model retains more of its effectiveness compared to the more complex LLaVA-13B.

Figure 5 analyzes the latency in processing LMMs to detect NDD attack samples. GPT-4V shows the shortest processing time among the three models for both devices averaging around 4.5 seconds per image. One the other hand, LLaVA-13B shows a significant latency on the Raspberry Pi, with processing times exceeding 30 minutes per image, while the ZED BOX processes the same model in roughly 10 minutes per image. LLaVA-7B demonstrates considerably lower latency on both devices, with the Raspberry Pi taking around 10 minutes per image and the ZED BOX about 5 minutes.

The substantial latency difference between the LLaVa and GPT models is associated with the computational complexity of LMM. The latency observed in GPT models is mainly network round-trip time (RTT) latency, where data is transmitted to and from the server for processing. In this scenario, the actual computation is being carried out on OpenAI servers. Unlike GPT, the LLaVA models require heavy computations to be performed directly on local hardware, leading to higher computational latency, especially in resource-constrained environments such as the Raspberry Pi or ZED BOX. Hence, this latency becomes a critical bottleneck, particularly in time-sensitive applications in AV, underscores the need for optimization strategies focused on reducing computational overhead on LMMs.



(a) (b)

Fig. 5. Comparative Performance Analysis: Processing Times of ZED Box vs. Raspberry Pi

VI. Discussion

A. Implications

Numerous studies show AV attacks on Object Tracking [30], Traffic Light Detection, Camera Localization and Object Detection [30], These attacks can cause malfunctions in perception systems, leading to severe consequences. Adversarial training, adversarial detection, input reconstruction, input denoising, network verification, and a combination of multiple models, such as defensive distillation and ensembling, are some popular defense methods against perception attacks [31]. While the performances of these methods in attack scenarios can increase the resilience of machine learning and deep learning models, they are often not comparable to non-attack scenarios and are still vulnerable to unknown attacks [32].

Due to the relative novelty of LMMs, only few studies [33] have demonstrated the application of LMMs in AVs. However, none have specifically utilized LMMs as an in-vehicle tool for helping the perception system with recognizing adversarial attacks. By leveraging the strengths of LMMs in environmental perception and decision-making and combining them with AVs' perception system to identify and react to road markers, these vehicles are becoming more adept at navigating complex driving scenarios. The result is a more robust and intelligent system that adapts to road challenges, potentially increasing autonomous vehicles' safety and efficiency.

B. Limitations

Simulating a real-world environment and accurately showing the AV's performance with LMM integration was challenging. Directly deploying LMMs in real cars for detecting adversarial traffic signs, as tested in Section V, was impractical due to the limited power and hardware of current AVs. In this context, Tesla's HW4 system, an advanced update to the Autopilot ECU, is specialized for autonomous driving with features like 20 ARM cores, 2 GPUs, three neural network processors, and 16GB RAM, all optimized for this purpose. In contrast, the ZED Box, a powerful AI computer with spatial computing capabilities, comes with 16GB RAM and an AI performance of 100 TOPS, making it well-suited for versatile, high-performance AI tasks, including running LMMs.

The second limitation involved using varied prompts for dataset generation and human perception evaluation of real signs. Generating AEs varied significantly across traffic signs, with the *Stop Sign* being easier than the other three groups. This led to tedious experimentation with prompts for each sign type to generate the dataset. In future work, we aim to address these challenges by evaluating advanced prompting strategies like the 'chain of thoughts' method and conducting a user study to see if users can identify these AEs as real traffic signs.

VII. Related Work

Mao *et al.* [34] integrated OpenAI's GPT-3.5 with a vehicle's motion planner, treating it as a language modeling problem. This method allows the GPT model to act as a planner that explains decisions in natural language. Tests on the nuScenes dataset confirm its effectiveness and interpretability, showing its potential to advance autonomous driving with language model features. Yang *et al.* [35] discussed using LLMs to enhance human-centric autonomous systems for interpreting user commands, focusing on complex and emergency scenarios in autonomous vehicles. Chen *et al.* [33] show that LMMs are utilized in autonomous driving for enhancing context understanding and decision-making through a novel object-level multimodal architecture that merges vectorized modalities with pre-trained language models. Zarzà *et al.* [36] show improved traffic accident prediction using deep learning and introduce real-time interventions with compact large language models. Our exploration of LMMs in the realm of AVs marks a significant advancement in automotive technology.

VIII. Conclusion

Our work revealed LMMs' potential to enhance AV perception systems in adversarial scenarios. We created a small-scale NDD attack dataset to evaluate LMMs' detection abilities against diffusion model attacks. We refined this dataset using the ResNeXt model, choosing images predicted with over 80% confidence as non-representative of real-world traffic signs, highlighting their applicability strictly in adversarial tests. This highlights the potential for sophisticated NDD attacks to mislead autonomous driving systems. In detecting NDD samples, our comparative analysis shows the superior performance of LMMs with an average accuracy of 82.52% across the selected models compared to 37.75% for state-of-the-art deep learning models. Finally, we discuss the implications and limitations of our research. We hope that our study and dataset will inform the autonomous vehicle community about the potential of LMMs in detecting adversarial attacks, thus enhancing vehicle safety and security.

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