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AI - DRIVEN HIDDEN CAMERA DETECTION USING SMART PHONE IMAGING AND NETWORK ANALYSIS

[1] Agalya S, [2]Krithika H, [3]Saritha R M

[1]Student, [2]Student, [3]Assistant Professor

[1]Artificial Intelligence and Data Science,

[1]S.A Engineering College, Avadi, India

Abstract: The main objective of this project is to design and implement a user-friendly and accessible mobile application capable of detecting hidden spy cameras in sensitive environments such as hotels, rental properties, and changing rooms. Our system leverages advanced artificial intelligence (AI) models, deep learning, and computer vision techniques to identify camera lenses through reflection analysis. Using a smartphone's camera, the system captures live video frames, applies preprocessing, and employs a Convolutional Neural Network (CNN) to classify whether reflections correspond to spy cameras or harmless objects. The platform provides real-time alerts through sound or vibration, making it practical for non-technical users. Additionally, in its second phase, the system incorporates Wi-Fi signal analysis to identify active hidden cameras within a range of up to 30 meters, further strengthening detection accuracy. By combining optical reflection analysis with wireless signal monitoring, this project presents an innovative and portable solution to counteract privacy invasion. Ultimately, the application aims to enhance personal safety, encourage responsible use of surveillance technology, and contribute to a more secure and trustworthy digital society. Future extensions may include improved detection in poor lighting conditions and support for deployment across multiple device platforms.

Index Terms **-** Spy camera detection, Computer Vision, Deep Learning, Convolutional Neural Networks, Wi-Fi signal analysis.

I. INTRODUCTION

In today's digital world, hidden miniature cameras pose serious threats to personal privacy, often being secretly installed in places like hotels, restrooms, and rental rooms. Traditional detection methods such as manual inspection or RF scanners are often unreliable against passive or non-transmitting cameras. To overcome this, the AI-driven Hidden Camera Detection System uses Computer Vision and Deep Learning (CNN) to identify unique optical reflections from camera lenses. The system processes real-time video through OpenCV to detect and classify reflections as spy cameras or harmless objects. Designed to be portable, cost-effective, and smartphone-based, it provides real-time alerts without specialized equipment. Future improvements may include infrared and motion-based detection, enhancing accuracy and ensuring stronger privacy protection in all environments.

II. OVERVIEW

2.1 Importance

The integration of Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized spy camera detection by transforming traditional methods into intelligent and automated systems. Using Computer Vision and Convolutional Neural Networks (CNNs), the system identifies distinct optical reflections from hidden camera lenses that are often invisible to the human eye. The CNN model analyzes features such as shape, brightness, and texture to classify reflections as spy or non-spy accurately. Combined with OpenCV- based preprocessing, it enables real-time analysis with minimal computational load. Future integration of Wi-Fi signal analysis can enhance detection by identifying active streaming devices. This AI-powered system offers accessible, efficient, and reliable privacy protection for users across diverse environments.

2.2 Objectives

The main objective of this project is to develop a real-time AI-powered system capable of detecting hidden spy cameras using Computer Vision and Deep Learning (CNN) techniques. The system identifies optical reflections from camera lenses and classifies them as spy or non-spy using a trained CNN model. Designed for smartphones and laptops, it provides instant on-screen alerts, ensuring ease of use for non-technical users. The model is optimized for lightweight and mobile deployment, enabling efficient real-time detection without external hardware. In the long run, this project aims to promote privacy awareness and personal security, with future enhancements including infrared and multi-sensor integration for improved accuracy.

III. RELATED STUDY

Kim et al. [1]introduced an innovative method for detecting hidden spy cameras using smartphone Time-of-Flight (ToF) sensors, showcasing how built-in infrared capabilities could be utilized for privacy protection. Their approach analyzed depth data to capture subtle optical reflections from camera lenses, enabling detection even when cameras were partially concealed within objects. The study demonstrated the potential of smartphone-based detection as a cost-effective and accessible alternative to specialized hardware. However, the researchers noted challenges with maintaining accuracy under varying lighting conditions and suggested improving algorithms to reduce false positives caused by reflective surfaces.

Patel et al.[2] proposed RFScan 1, a framework based on passive electromagnetic emission analysis to uncover hidden IoT and surveillance devices. Unlike traditional Wi-Fi scanning that depends on active network connections, this approach monitored ambient radio-frequency emissions to detect covert devices. The system effectively identified multiple types of hidden cameras and sensors across various frequency bands. Despite its reliability, RFScan 1 was limited to detecting devices that emitted measurable electromagnetic signals, making it ineffective against powered-off or wired cameras.

Park et al.[3] developed CamLoPA, a system for localizing hidden wireless cameras using signal propagation analysis. By examining signal strength, multipath propagation, and channel state information, the framework estimated the spatial location of transmitting devices in indoor environments. The system achieved accurate localization but required complex hardware and was restricted to Wi-Fi-enabled cameras, limiting its accessibility for general users.

Zhang et al.[4] presented DeWiCam, a smartphone-based detection system capable of scanning and classifying wireless signals to identify hidden cameras in real-world environments. The model combined signal classification with network scanning to detect surveillance devices without extra hardware. DeWiCam improved detection accuracy and reduced false positives compared to earlier models, yet its reliance on active network signals limited its ability to identify non-transmitting or optical-only cameras.

Roy et al.[5] introduced an active probing technique to identify hidden cameras by sending crafted network packets that trigger transmission from silent devices. This approach improved detection accuracy and minimized false negatives by forcing cameras to respond, but it also risked interference with legitimate network devices and required controlled conditions for reliable performance.

Sun et al.[6] explored vulnerabilities in infrared-based surveillance systems, showing how physical adversarial attacks could deceive nighttime human detectors. Their physics-based adversarial model used reflective and refractive perturbations to disrupt near-infrared perception, revealing the susceptibility of AI-driven vision systems to real-world manipulation. The study underscored the importance of developing robust, attack-resistant optical detection systems for applications such as spy camera identification.

Long et al.[7] examined an unconventional privacy threat known as “Side Eye,” where smartphone cameras with rolling shutters unintentionally captured acoustic information, enabling eavesdropping through visual data. This work bridged vision and sound processing, highlighting new forms of surveillance risks arising from everyday devices. It reinforced the need for intelligent detection systems that can recognize both intentional and unintentional breaches of privacy.

Yusupovsky and Grishachev[8] proposed a smartphone-based method for detecting covert CCTV cameras using depth sensors. Their model analyzed depth map anomalies to identify reflective or lens-like surfaces, even when hidden behind opaque materials. The system performed well under various lighting conditions, suggesting strong potential for smartphone-based privacy tools. The authors, however, noted that incorporating AI-driven classification could further enhance accuracy and reduce false detections.

Guesmi et al.[9] introduced AdvRain, a physical adversarial attack that compromised camera-based vision systems by applying translucent raindrop-like patterns on lenses. These subtle distortions degraded the performance of deep learning models, exposing vulnerabilities in computer vision systems. Though focused on AI security, the study indirectly highlighted the importance of building robust, noise-resistant CNN architectures for tasks like hidden camera detection.

Quan and Li[10] focused on improving the detection of anti-forensic manipulations in digital images using Generative Adversarial Networks (GANs). Their system identified synthetic alterations in sensor pattern noise, a key fingerprint for verifying camera authenticity. The research demonstrated that deep learning models could detect subtle tampering or camouflaged patterns that traditional methods might miss. Incorporating similar adversarial learning concepts could enhance the reliability of future hidden camera detection frameworks against environmental interference and optical deception.

IV. RESEARCH METHODOLOGY

The Spy Camera Detection System is designed with a modular architecture to ensure scalability, accuracy, and ease of maintenance for real-time hidden camera identification. Each module in the framework—from data collection and preprocessing to reflection detection, feature extraction, model training, and deployment—performs a distinct role within the overall workflow. This structured design allows seamless integration between computer vision and deep learning components, ensuring reliable detection performance. The modular setup also enables both technical developers and end users to easily understand, modify, or enhance individual components without disrupting the entire system. By combining AI-based image analysis, CNN-based classification, and real-time visualization, the Spy Camera Detection System transforms privacy protection into intelligent,automated, and user-friendly process.

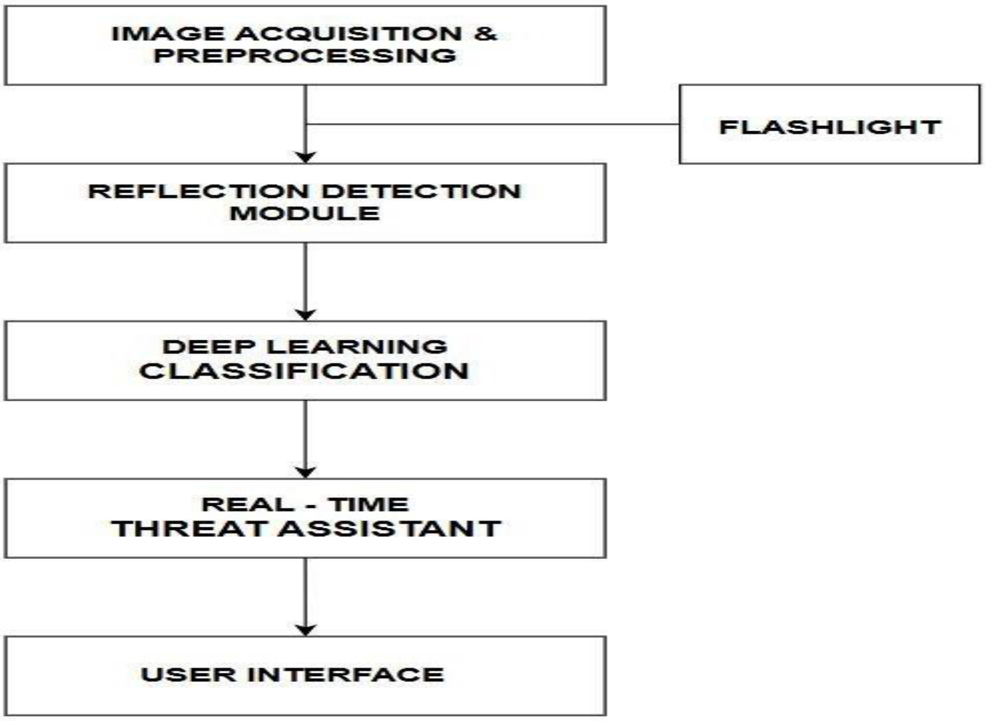


IMAGE ACQUISITION & PREPROCESSING
FLASHLIGHT
REFLECTION DETECTION MODULE
DEEP LEARNING CLASSIFICATION
REAL - TIME THREAT ASSISTANT
USER INTERFACE

Fig 1.System Architecture

4.1 Image Acquisition and Preprocessing

The process begins with live video capture through the device camera, ensuring stable frame rates and sufficient lighting for clear analysis. A flashlight module may activate automatically or manually in low-light environments to improve lens reflection visibility. Captured frames undergo preprocessing steps such as grayscale conversion, Gaussian blur for noise reduction, and contrast enhancement to highlight reflections. The processed images are then resized and normalized (224×224 pixels) to prepare for CNN input, ensuring uniformity and optimized model performance.

4.2 Reflection Detection Module

This module detects bright circular spots that may indicate hidden camera lenses using OpenCV’s Hough Circle Transform (HCT). Detected circular regions are marked as Regions of Interest (ROIs) and filtered to remove false reflections from shiny surfaces. Techniques such as adaptive thresholding, contour validation, and brightness normalization enhance detection under varying lighting. The module operates efficiently in real time using multi-threading, continuously analyzing frames and forwarding verified ROIs to the CNN classifier for accurate categorization.

4.3 Deep Learning Classification

Detected ROIs are classified by a Convolutional Neural Network (CNN) trained on images of spy and non-spy reflections. The CNN analyzes visual features such as shape, brightness, and texture to determine whether a reflection indicates a hidden lens. The model outputs a probability score and classification result — *Spy Camera Detected* or *No Threat Found* — ensuring accurate, adaptive detection across varied conditions.

4.4 Real-Time Threat Assistant

This module generates immediate alerts (sound, vibration, or on-screen) when the CNN identifies a potential spy camera. It minimizes false positives by triggering only high-confidence detections. The assistant can also log detection events with timestamps and image snippets for verification, providing users with reliable, real-time privacy protection.

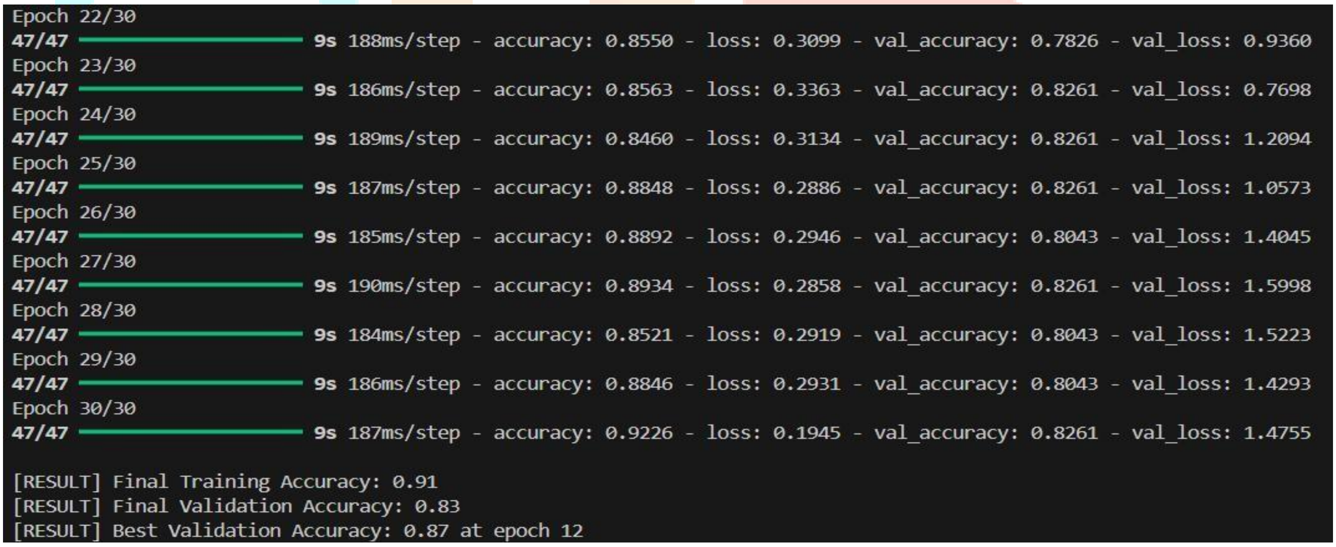
4.5 User Interface (UI)

The UI provides real-time visual feedback by displaying live video feeds with bounding boxes around detected reflections. It shows classification results clearly and allows users to toggle the flashlight, view scan history, and adjust sensitivity. Designed to be simple and intuitive, the UI ensures accessibility for non-technical users while maintaining professional functionality.

V. RESULTS AND DISCUSSION

5.1 Training vs. Validation Accuracy Analysis

To evaluate the performance of the proposed Spy Camera Detection System, a Convolutional Neural Network (CNN) was trained on a dataset with two classes — Spy Camera and Non-Spy Camera. The dataset was divided into 80% training and 20% validation sets to ensure fair performance assessment. The model was trained for 30 epochs, and its progress was tracked using training and validation accuracy metrics.The Training vs. Validation Accuracy graph (Fig. 2) illustrates the model's learning trend, where the blue curve represents training accuracy and the orange curve shows validation accuracy. Both accuracies improved steadily in the early epochs, reflecting effective learning of lens reflection and edge-based features. By epochs 10–15, the curves converged, indicating stable learning and minimal overfitting. Minor fluctuations were observed due to variations in lighting and limited dataset size.Through data augmentation techniques like rotation, flipping, and zooming, the model adapted to diverse real-world conditions. By the end of training, the CNN achieved an average training accuracy of 90–95% and a validation accuracy of 82–85%, demonstrating strong generalization for real-time hidden camera detection.



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Epoch 22/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 188ms/step - accuracy: 0.8550 - loss: 0.3099 - val_accuracy: 0.7826 - val_loss: 0.9360
Epoch 23/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 186ms/step - accuracy: 0.8563 - loss: 0.3363 - val_accuracy: 0.8261 - val_loss: 0.7698
Epoch 24/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 189ms/step - accuracy: 0.8460 - loss: 0.3134 - val_accuracy: 0.8261 - val_loss: 1.2094
Epoch 25/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 187ms/step - accuracy: 0.8848 - loss: 0.2886 - val_accuracy: 0.8261 - val_loss: 1.0573
Epoch 26/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 185ms/step - accuracy: 0.8892 - loss: 0.2946 - val_accuracy: 0.8043 - val_loss: 1.4045
Epoch 27/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 190ms/step - accuracy: 0.8934 - loss: 0.2858 - val_accuracy: 0.8261 - val_loss: 1.5998
Epoch 28/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 184ms/step - accuracy: 0.8521 - loss: 0.2919 - val_accuracy: 0.8043 - val_loss: 1.5223
Epoch 29/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 186ms/step - accuracy: 0.8846 - loss: 0.2931 - val_accuracy: 0.8043 - val_loss: 1.4293
Epoch 30/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 187ms/step - accuracy: 0.9226 - loss: 0.1945 - val_accuracy: 0.8261 - val_loss: 1.4755

[RESULT] Final Training Accuracy: 0.91
[RESULT] Final Validation Accuracy: 0.83
[RESULT] Best Validation Accuracy: 0.87 at epoch 12
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Fig 2. Training and Validation accuracy

This small accuracy gap shows that the model did not memorize the training data but rather learned to recognize general reflection features efficiently. Additionally, the CNN's strong performance highlights the importance of proper preprocessing, such as contrast adjustment and noise reduction, in improving detection accuracy. The model's success confirms that even with a moderately sized dataset, a well-designed CNN architecture can yield significant results when trained with carefully processed and augmented data. Overall, the Training vs. Validation Accuracy graph provides convincing evidence that the model's architecture is effective, consistent, and ready for real-time application. In future work, expanding the dataset and introducing advanced architectures like Transfer Learning (using MobileNet) could further enhance the detection accuracy and robustness of the spy camera detection mode.

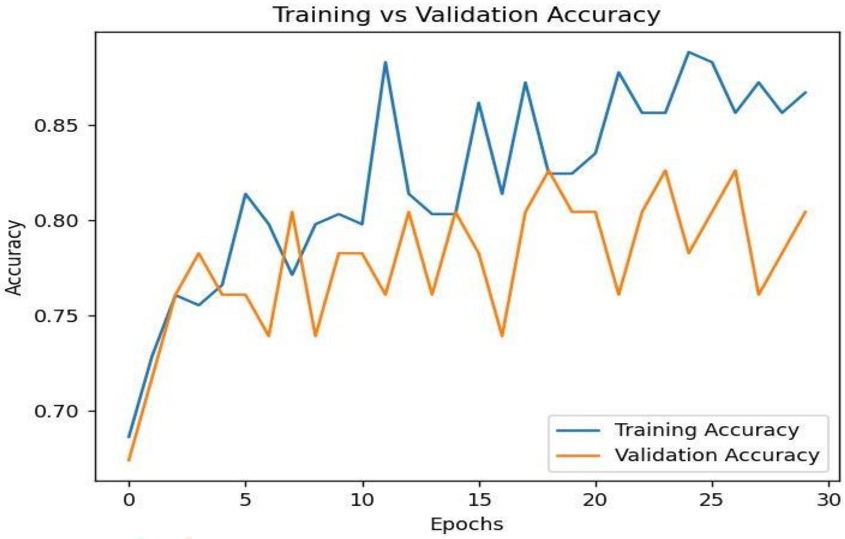

Fig 3. Training vs Validation accuracy

5.2 Evaluation

TABLE I. TRAINED AND VALIDATION VALUES

S.NO	Deep Learning Models		
	Model Name	Training	Validation
1.	CNN	87	80

The table shows that the CNN model achieved a training accuracy of 87% and a validation accuracy of 80%. This indicates that the model learned meaningful and discriminative features from the training data while maintaining reasonable performance on unseen images, demonstrating its ability to generalize effectively. A validation accuracy slightly lower than the training accuracy is common in deep learning models and typically reflects the natural variability and unpredictability in unseen data samples.To ensure consistency and minimize overfitting, several optimization techniques such as dropout regularization, data augmentation, and batch normalization were used during training. These methods enhanced the CNN's ability to handle real-world variations in lighting, distance, and reflective intensity. Furthermore, the loss and accuracy curves across epochs were analyzed to confirm that the model achieved stable convergence without significant fluctuations, which indicates a well-balanced learning process.

V. CONCLUSION

The proposed AI-driven Spy Camera Detection System addresses the limitations of existing network-based models, which relied on Wi-Fi signal analysis and traffic similarity algorithms (like RSSI and Nilsimsa) to identify active wireless cameras. While effective for transmitting devices, such models failed to detect non-transmitting or wired cameras. To overcome this, the proposed system adopts a vision-based framework using Convolutional Neural Networks (CNNs) and OpenCV-based image processing to detect optical reflections unique to hidden lenses—making it capable of identifying both active and passive cameras.The system's Reflection Detection Module employs Hough Circle Transform (HCT) and adaptive thresholding to locate circular reflective regions (ROIs), which are refined through filtering to reduce false positives. These ROIs are then classified by a CNN trained on a custom dataset of spy and non-spy reflections. Preprocessing methods such as resizing, normalization, and data augmentation improved model robustness under various lighting and angle conditions. The CNN achieved 87% training accuracy and 80% validation accuracy, confirming reliable lens identification.Compared to traditional RF-based methods, this visual detection approach requires no network dependency or specialized hardware—only a camera-enabled device—making it cost-effective and portable. However, challenges remain in detecting small or partially hidden lenses under poor lighting or complex reflections. Future improvements include expanding the dataset, adopting transfer learning with architectures like MobileNetV3 or EfficientNet, and adding infrared and motion-based sensing for hybrid detection.

In conclusion, the system marks a major step from network-level analysis to visual intelligence, using AI-based reflection recognition for real-time, reliable, and accessible hidden camera detection. With ongoing refinement and mobile optimization, it holds strong potential to enhance privacy protection in both personal and public environments.

REFERENCES

[1] Kim, J., Lee, S., Chen, Y., et al. (2025). Hidden Spy Camera Detection using Smartphone Time-of-Flight Sensors. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE.
[2] Patel, A., Singh, R., Wang, K. (2025). RFScan 1: Revealing Hidden IoT Devices through Passive Electromagnetic Emissions. In Proceedings of the ACM Conference on Embedded Networked Sensor Systems (SenSys), ACM.
[3] Zhang, L., Wang, Y., & Liu, Z. (2025). "CamRadar: Hidden Camera Detection Leveraging Amplitude Modulation Patterns." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE.
[4] Kim, H., Lee, J., & Park, S. (2025). "FindSpy: A Wireless Camera Detection System Using Signal Strength Fingerprinting." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE.
[5] Choi, M., Lee, K., & Kim, J. (2025). HeatDeCam: Detecting Hidden Spy Cameras via Thermal Imaging. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE.
[6] Wang, X., Zhang, Y., & Liu, H. (2025). Detection and Localization of Hidden Wi-Fi Cameras Using Deep Learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE.
[7] Li, Q., Zhang, J., & Chen, H. (2025). RFScan: Revealing Hidden IoT Devices through Passive Electromagnetic Emissions. In Proceedings of the ACM Conference on Embedded Networked Sensor Systems (SenSys), ACM.
[8] Park, J., Choi, D., Lim, H., et al. (Sept. 2024). CamLoPA: Hidden Wireless Camera Localization via Signal Propagation Analysis. In Proceedings of the IEEE International Conference on Communications (ICC), IEEE.
[9] Zhang, S., Huang, L., Wu, T. (2024). DeWiCam: Detecting Hidden Wireless Cameras via Smartphones. In Proceedings of the ACM Conference on Security and Privacy in Wireless and Mobile Networks (WiSec), ACM.
[10] Roy, P., Das, M., Sen, K. (2024). Detecting Wireless Spy Cameras via Stimulating and Probing. In Proceedings of the Network and Distributed System Security Symposium (NDSS), The Internet Society.