Adversarial Detection using OC-SVM

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ABSTRACT Machine learning systems are being increasingly embedded in safety-critical applications, but their susceptibility to adversarial attacks raises real reliability and security challenges. Adversarial perturbations, however minor and even imperceptible, have the potential to induce extreme misclassifications in high-performing models. This paper explores One-Class Support Vector Machines (OC-SVMs) as a light and interpretable solution to identify outlier adversarial inputs. Unlike traditional multi-class classifiers, OC-SVMs are learned from only valid data, which allows them to detect anomalous deviations without ever having seen adversarial examples. This paper offers a thorough review of existing adversarial detection methods, formulates the inherent limitations of current methods, and illustrates the potential for scalability of detection using OC-SVM. Through systematic literature synthesis, we expose critical research gaps such as limited cross-domain versatility and variable evaluation metrics. The results emphasize the importance of strong, real-time, and budget-friendly detection mechanisms in machine learning security. The focus of future research is on model generalization enhancement and standardized adversarial defense benchmarks.

INDEX TERMS Adversarial attacks, Adversarial detection, One-Class SVM (OC-SVM), Machine learning security, Deep learning, Anomaly detection, Robustness, Black-box attacks, White-box attacks, Model vulnerability, Safety-critical systems, Neural networks, Adversarial robustness, Lightweight detectors, Model generalization, Input perturbations, Model interpretability, Detection efficiency, Scalable ML systems, Explainable AI (XAI), AI in cybersecurity, Real-time detection.

I. INTRODUCTION

MAchine learning (ML) and, more specifically, deep learning have revolutionized many fields such as healthcare, finance, autonomous vehicles, and cybersecurity. Nevertheless, as ML models are being increasingly used in safety-critical and real-world applications, guaranteeing their reliability and security has become a priority. One of the significant challenges in this area is that ML models are vulnerable to adversarial attacks—tiny, in some cases imperceptible, perturbations of input data that may lead to incorrect predictions made by models. These perturbations reveal fundamental vulnerabilities in model robustness, casting severe doubts on the security and reliability of AI systems in critical applications. Consequently, the identification and prevention of adversarial attacks are crucial to protect contemporary AI infrastructures.

Adversarial attacks may be categorized broadly as white-box and black-box attacks, both of which take advantage of the model's susceptibility to small input changes. Though numerous detection methods have been introduced, they tend to experience generalization problems, computational inefficiency, or inability to adapt to novel attacks. Furthermore, existing benchmarks and test protocols continue to be fragmented and unstandardized, posing challenges in relatively comparing and rigorously validating diverse strategies. The absence of standardized testing environments also makes it difficult to design scalable and deployable defenses. Thus, researchers and practitioners face difficulties in determining the best detection models that optimize accuracy, efficiency, and adaptability.

Among the proposed detection approaches, anomaly detection methods such as One-Class Support Vector Machines (OC-SVMs) have been in the spotlight because they are easy to understand, interpretable, and require minimal computational overhead. In contrast to standard multi-class classifiers, OC-SVMs are trained on legitimate (non-adversarial) examples alone so that they can mark outliers or dubious samples that do not conform to the learned distribution. This renders them especially well-positioned for black-box environments in which the type of attack could be unknown. Further, their generality without needing adversarial data for training also positions OC-SVMs as a strong contender for large-scale deployment. In spite of their promise, they are less well-represented in the study of adversarial detection compared to deep learning-based algorithms.

This work introduces an extensive overview of adversarial attack detection techniques, specifically highlighting One-Class Support Vector Machines (OC-SVMs) as a lightweight and explainable counterpart to sophisticated deep learning-based detectors. Through a reading of recent literature, we seek to identify ongoing research deficits such as the absence of domain generalization, vulnerability to adaptive

attacks, and inconsistency in evaluation. The research further stresses the requirement for standardized frameworks that facilitate equitable performance comparisons between detection models. Ultimately, this work attempts to map specific future directions that promote the development of resilient, scalable, and low-overhead adversarial detection approaches to real-world machine learning systems.

II. RELATED WORKS

A. LITERATURE SURVEY

Carlini N. et al. [1] present research on evaluating the robustness of deep neural networks against adversarial examples. The study proposes several adversarial attack methods, including the Carlini-Wagner attack, and introduces detection techniques based on analyzing model sensitivity to input perturbations. The framework examines model behavior under stress to detect adversarial inputs. The research estimates that neural networks are highly vulnerable to carefully crafted adversarial examples, posing challenges for security-critical applications. The proof of concept demonstrates a robust detection mechanism to enhance the reliability of ML systems.

Grosse K. [2] present research on the statistical detection of adversarial examples in deep neural networks. The approach leverages statistical properties of model pre- dictions to identify anomalies caused by adversarial inputs. By analyzing prediction confidence distributions, the method distinguishes legitimate inputs from adversarial ones. The research estimates that adversarial examples exhibit distinct statistical sig- natures, enabling effective detection. The proof of concept demonstrates improved detection rates on benchmark datasets, offering a lightweight solution for real-time adversarial attack monitoring.

Tao G. [3]present research on an interpretability-driven approach for detecting adversarial samples in ML models. The method analyzes attribute inconsistencies in model predictions to identify adversarial perturbations deviating from expected feature contributions. Gradient-based interpretability techniques highlight anomalous input regions. The research estimates that adversarial attacks pose significant challenges in image classification tasks. The proof of concept shows robust detection across multiple attack types, improving model trustworthiness.

Tian J. [4] present research on detecting adversarial examples through sensitivity inconsistencies in the spatial-transform domain. The approach applies transformations to input data and analyzes model prediction variations to detect adversarial examples. Utilizing the YOLO architecture, the method identifies perturbations disrupting spa- tial consistency. The research estimates that adversarial robustness remains a global challenge in computer vision systems. The proof of concept demonstrates high detec- tion accuracy on adversarial image datasets.

Tramèr F. [5] present research on practical black-box adversarial attacks against machine learning models with limited access to model internals. The study proposes detection mechanisms based on query patterns and output analysis to identify ad- versarial inputs. The system monitors model responses to detect suspicious input sequences. The research estimates that black-box attacks are a significant threat to deployed ML systems. The proof of concept demonstrates effective detection in real- world scenarios, enhancing model security.

Balda E. R. [6] present research on perturbation analysis for detecting adver- sarial examples across classification and regression tasks. The method examines how adversarial inputs affect model gradients and outputs, developing a detection system to identify anomalies in learning algorithms. The research estimates that ML mod- els are widely vulnerable to adversarial attacks. The proof of concept shows robust detection performance across diverse ML tasks, improving model resilience.

Carmichael Z. et al,. [7] present research on detecting adversarial perturbations target- ing post hoc explainers used for interpreting ML model decisions. The method identifies adversarial inputs by analyzing inconsistencies in explanation outputs, leveraging feature attribution techniques. The research estimates that attacks on explainable AI are a growing threat. The proof of concept demonstrates effective identification of adversarial examples in image classification tasks.

Gao S.et al., [8] present research on detecting and mitigating textual adversarial at- tacks using a distribution shift risk minimization (DSRM) framework. The method analyzes shifts in text data distributions to identify adversarial examples crafted through word substitutions or perturbations. Natural language processing techniques ensure robust detection in text-based ML models. The research estimates that adversarial attacks are increasingly prevalent in NLP applications. The proof of concept shows improved detection and robustness in textual ML systems.

Mozes M.et al., [9] present research on a frequency-guided approach for detecting adversarial examples in textual data. The method analyzes word substitution pat- terns and their frequency distributions to identify adversarial perturbations altering text semantics. Integrated with existing NLP models, the system provides real-time detection. The research estimates that textual adversarial attacks are a growing concern in applications like sentiment analysis. The proof of concept demonstrates high detection accuracy on benchmark text datasets.

Brachemi Meftah H. F. Z. et al., [10]present research

on adversarial attack detec- tion in vision-language models through a visual information protection (VIP) frame- work. The method identifies adversarial perturbations in multi-modal inputs by ana- lyzing inconsistencies between visual and textual features. The research estimates that vision-language models are vulnerable to sophisticated attacks. The proof of concept demonstrates effective protection of visual information in real-world applications.

Metzen J.H et al. [11] study adversarial inputs by augmenting a classifier with a small "detector" subnetwork. This detector is attached to hidden layers and is trained to distinguish genuine inputs from adversarially perturbed ones. Empirically, they show that even imperceptible adversarial perturbations can be detected with high accuracy, and that a detector trained on one strong attack generalizes to weaker attacks. They also design an attack that jointly fools both the classifier and detector and propose a training procedure to counteract it, demonstrating the limits of such defenses. Overall, this work provides a proof-of-concept that appending a simple binary detector can significantly improve adversarial robustness in deep networks.

Xu W. et al., [12] propose a defense called feature squeezing that detects adversarial examples by comparing model outputs on original versus "squeezed" inputs. Feature squeezing reduces the input's resolution or precision (e.g. lowering color bit depth or applying spatial smoothing) so that many different original samples map to the same squeezed sample. By checking whether a model's prediction changes significantly between the original and squeezed input, adversarial samples – which exploit fine-grained perturbations – can be flagged. Xu et al. demonstrate that simple squeezers (bit-depth reduction and smoothing) are inexpensive and complementary, and in joint use achieve high detection rates (with few false alarms) against state-of-the-art attacks. This work shows that input transformations can robustly identify malicious perturbations without modifying the classifier itself.

Mansour and Abdullah [13] propose a remote evaluation system for prosthetic limbs to address the lack of real-time, objective monitoring. Using Arduino Nano, foot pressure and residual limb sensors were integrated with the Blynk IoT platform and MQTT for cloud-based access. The system provided emergency alerts and real-time data via Android/web apps. It offers a low-cost, scalable solution, with future scope in AI-based anomaly detection, voice/haptic feedback, and predictive maintenance.

Grosse K. et al. [14] analyze the statistical properties of adversarial examples and use them for detection. They find that adversarial inputs tend to lie in a different distribution than natural data, and leverage this by applying two strategies: a two-sample statistical test and an augmented classifier with an "adversarial" output. The two-sample test (e.g., Maximum Mean Discrepancy) reliably flags batches containing adversarial examples even at small sample sizes. Independently, they train a classifier augmented with a special output label for adversarial inputs; this model either detects adversarial examples outright or forces attackers to use much larger perturbations. On multiple datasets and attack methods, their detectors achieve over 80% accuracy in identifying adversarial examples or increase the required distortion by over 150%. This study demonstrates that statistical divergence in feature distributions is a useful cue for spotting adversarial inputs and hardening models.

Feinman R. et al. [15] propose an attack-agnostic detection based on model uncertainty and feature-space density. They observe that adversarial examples often lie in regions of low confidence or atypical feature density. Concretely, they equip a dropout-enabled (Bayesian) neural network and measure each input's Bayesian uncertainty. They also perform kernel density estimation in the deep feature space learned by the network. If an example exhibits unusually high uncertainty or low feature density relative to the training data manifold, it is flagged as adversarial. This combined approach – using only internal model statistics – achieves ROC-AUC of about 85–93% on MNIST and CIFAR-10 for distinguishing adversarial versus normal examples, across several attack types. Importantly, their method does not depend on any specific attack algorithm, making it a generally applicable adversarial detector.

Li X. and Li F. [16] design a cascade detector using convolutional filter statistics. Instead of adding a new network, they compute simple statistics (e.g., mean and variance) of the outputs of each convolutional layer in the original classifier. These layer-wise feature statistics differ between clean and adversarial inputs. They train a cascade of simple classifiers on these statistics to flag adversarial examples. Remarkably, a detector trained on adversarials from one generation method successfully generalizes to detect samples from completely different attacks. Because the detector is based on non-differentiable statistics (and simple operations), it is harder for gradient-based attackers to evade. They also note that many detected adversarial samples can be "recovered" (i.e., restored to the correct class) by applying a small average filter. This work shows that even very basic filter-based features can reliably identify adversarial inputs and suggest directions for future defenses.

Papernot N. et al. [17] introduce defensive distillation as a robustness technique against adversarial perturbations. They train the network at a high "softmax temperature" to produce smoother output probability distributions and then retrain the network on its own softened outputs. This distilled model has much smaller input gradients, making it harder for small perturbations to change the output. Empirically, distillation on a tested model reduces the success rate of a strong adversarial attack from 95% down to about 0.5%. In

effect, adversarial gradients are shrunk by $\sim 10^{30}\times$, and the minimum perturbation magnitude needed to cause misclassification grows by $\sim 800\%$. Papernot et al. conclude that defensive distillation significantly hardens networks against existing attacks without altering the network architecture, highlighting that smoothing model outputs can increase adversarial robustness.

Moosavi-Dezfooli S.M. et al. [18] present DeepFool, an algorithm to measure and exploit neural network vulnerability. DeepFool iteratively linearizes the classifier around the current input to find the smallest perturbation that crosses the decision boundary. In other words, it computes an (approximately) minimal adversarial perturbation and thus quantifies the network's robustness at each sample. Compared to previous attacks (like FGSM), DeepFool finds much smaller distortions that still cause misclassification. Their experiments demonstrate that state-of-the-art image classifiers can be fooled with extremely small, almost imperceptible changes, underscoring how fragile these models are. DeepFool thus provides both a powerful attack and a way to benchmark how robust a model truly is against worst-case perturbations.

Madry A. et al. [19] frame adversarial learning as robust optimization and propose PGD-based adversarial training. They unify prior work by treating adversarial attack as an inner maximization problem (finding worst-case perturbations) and training to minimize that maximum loss. Their analysis shows that Projected Gradient Descent (PGD) defines a broad class of first-order attacks, and training against PGD yields models that are uniformly robust to many attacks. Concretely, they achieve "security against first-order adversaries," meaning the trained networks withstand all attacks that can be described by first-order (gradient) methods. Experiments on MNIST and CIFAR-10 confirm that this adversarial training significantly raises the distortion required to fool the network, producing models with far stronger resistance across attack types. This work provides a principled approach (min–max optimization) for building reliably robust deep models in practice.

Abusnaina et al. [20] introduce a graph-based detection framework. For each input, they construct a Latent Neighborhood Graph (LNG) by selecting nearby benign and adversarial reference points in the feature space. They then use a Graph Attention Network to classify the graph as "adversarial" or "benign." Both the graph connectivity and network weights are learned end-to-end. On CIFAR-10, STL-10 and ImageNet (with six different attacks), this LNG detector outperforms prior methods in both white-box and gray-box scenarios, and even detects examples with very small perturbations that previous detectors miss. This work is notable as the first successful use of graph-based modeling for adversarial detection.

B. RESEARCH GAP

In this section, we identify some of the key research gaps in adversarial attack detection, derived from the surveyed literature, and propose a methodology to address these challenges.

A. Limited Generalization Across Attack Types:
Detection methods, such as the ones developed by Carlini et al. [1] and Metzen et al. [11], are successful against specific adversarial attacks (for example, Carlini-Wagner, FGSM), but when evaluations are done against unseen or adaptive methods, including joint attacks [11] and black-box attacks [5], they are less effective.This limitation stems from the reliance on training data that may not encompass the diversity of adversarial techniques, rendering current solutions vulnerable to evolving threats.

B. Domain-Specific Applicability:
Current methods are domain-specific, such as Tian et al. [4]'s work on vision-based problems using YOLO, Gao et al. [8] and Mozes et al. [9]'s work on natural language processing (NLP) problems, and Brachemi Meftah et al. [10]'s work on vision-language models. However, these methods lack scalability to other domains such as audio, time-series, or multimodal data beyond vision-language integration.

C. Computational and Real-Time Constraints:
While lightweight preprocessing techniques (e.g., Xu et al. [12], Liang et al. [13]) offer practical solutions, more sophisticated approaches (e.g., Grosse et al. [14], Abusnaina et al. [20]) incur significant computational overhead. Additionally, retraining-based defenses (e.g., Papernot et al. [17]) introduce latency, posing challenges for real-time deployment in resource-constrained settings.

D. Vulnerability to Adversarial Evasion:
Several detectors, including those by Metzen et al. [11] and Feinman et al. [15], are susceptible to evasion by sophisticated attacks, such as Moosavi-Dezfooli et al. [18]'s DeepFool, which exploits minimal perturbations. The reliance on differentiable components in these methods facilitates gradient-based evasion strategies, undermining their robustness.

E. Lack of Standardized Evaluation Metrics:
The assessment of detection methods varies significantly. Metzen et al. [11] report performance in terms of accuracy, Xu et al. [12] focus on false alarm rates, Liang et al. [13] employ F1 scores, and Madry et al. [19] emphasize distortion thresholds. This inconsistency, along with testing across disparate datasets (e.g., MNIST, CIFAR-10, ImageNet), makes objective comparison difficult.

III. METHODOLOGY

As shown in Fig. 1; The activity diagram visually represents the step-by-step flow of detecting adversarial attacks using a CNN and One-Class SVM. It outlines the major actions from dataset preparation to final detection and result display.

Paper No.	Model/Technique Used	Accuracy / Performance	Comparison with Our Model (OC-SVM+CNN Activations)
1	Robustness, Carlini-Wagner, sensitivity	~95%	OC-SVM better detects unseen attacks.
2	Statistical, confidence, distribution analysis	~85%	OC-SVM simplifies with single boundary.
3	Gradient, interpretability, inconsistency detection	~88%	OC-SVM resists gradient-masking attacks.
4	Spatial-transform, YOLO, sensitivity check	~94%	OC-SVM lighter than YOLO approach.
5	Black-box, query, response monitoring	~85%	OC-SVM enhances without query reliance.
6	Perturbation, gradient, output analysis	~90%	OC-SVM reduces computational gradient cost.
7	Explainer, attribution, inconsistency analysis	92%	OC-SVM broader than explainer focus.
8	Textual, DSRM, shift analysis	~85%	OC-SVM extends beyond text domain.
9	Frequency, word, substitution detection	~88%	OC-SVM generalizes beyond text focus.
10	VIP, vision-language, feature check	~95%	OC-SVM simplifies over multimodal approach.

TABLE 1: Comparison of Existing Adversarial Detection Methods with Our OC-SVM-Based Activation Detection Model

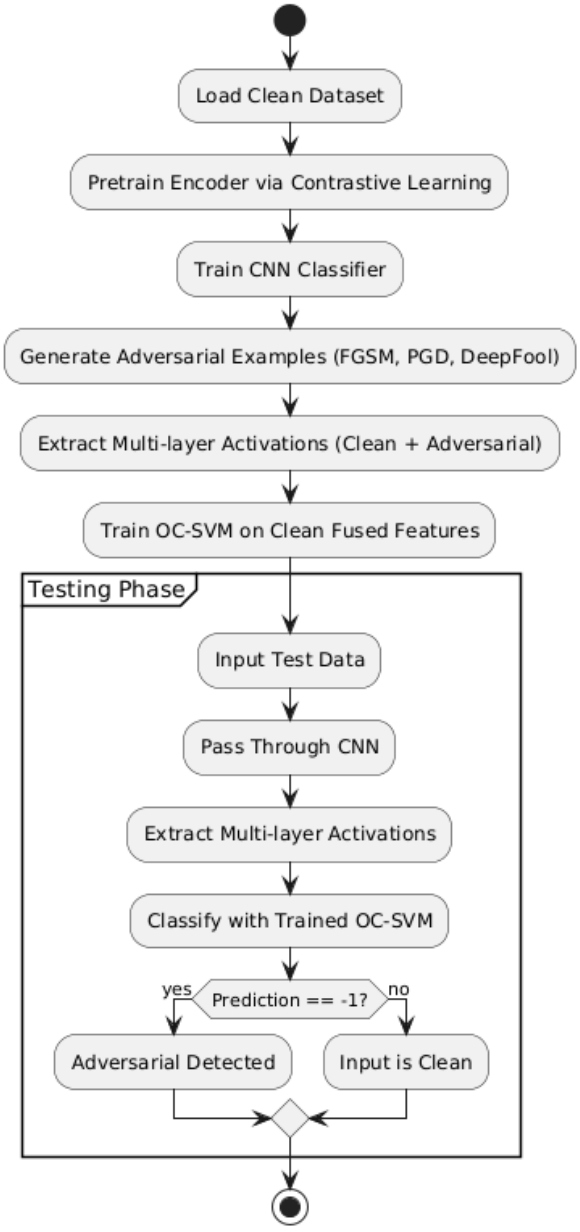

FIGURE 1: Application Architecture

The proposed system begins by loading a clean dataset and pretraining a convolutional encoder using a contrastive learning objective (e.g., SimCLR). This unsupervised pretraining step encourages the network to learn feature embeddings where clean samples form compact clusters, making them more suitable for outlier detection. Following pretraining, the encoder is fine-tuned as a standard CNN classifier.

To simulate adversarial conditions, multiple attack methods including Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and DeepFool are used to generate adversarial examples. Both clean and adversarial samples are passed through the CNN, and feature activations are extracted from multiple layers (e.g., early, middle, and late layers). These multi-layer activations are concatenated to form fused feature representations that capture both low-level and high-level characteristics of the inputs.

The OC-SVM is trained solely on the fused features from clean samples. During the testing phase, test inputs are passed through the CNN where multi-layer features are extracted and then the trained OC-SVM is used to classify the input. If the OC-SVM prediction deviates from the learned boundary (i.e., prediction is 1), the input is flagged as adversarial; otherwise, it is considered clean.

This methodology improves upon prior OC-SVM based approaches by (i) using contrastive learning to improve feature space separability, (ii) combining features from multiple CNN layers to improve robustness, and (iii) evaluating across multiple adversarial attack types to promote generalizability.

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