International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 12 Issue: 12 | Dec 2025 www.irjet.net p-ISSN: 2395-0072

AI VIGIL-GUARD: A Real-Time Adversarial Attack Detection and Defense System for Machine Learning Models

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Abstract - *Machine Learning (ML) models deployed in real-world applications such as healthcare, banking, cybersecurity, and autonomous systems are highly vulnerable to adversarial attacks. These attacks introduce small, imperceptible perturbations into input samples, causing ML models to misclassify them with high confidence. To address this challenge, we propose AI Vigil-Guard, a real-time adversarial defense framework capable of identifying adversarial samples, analyzing their behavior, and protecting ML models from malicious manipulation. The system uses numerical feature monitoring, prediction consistency analysis, confidence-score deviation, and statistical anomaly detection to classify inputs as clean or adversarial. It further incorporates multi-attack simulation (FGSM, PGD, DeepFool, CW) to evaluate model robustness. A Streamlit-based interactive interface enables real-time visualization, dataset validation, and report generation. Experimental results demonstrate that the system significantly enhances model robustness and provides explainable, transparent adversarial detection, making it suitable for academic and industry-level AI security needs.*

Key Words: Machine Learning Security, Adversarial Attacks, AI Robustness, FGSM, PGD, DeepFool, Defensive AI, Real-Time Detection.

1.INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) systems have become central pillars of modern digital transformation, enabling automation, decision-making, predictive analytics, and intelligent control across a wide range of domains including finance, healthcare, cybersecurity, defense, transportation, and industrial computing. As models become increasingly powerful, they are also exposed to a variety of security risks that exploit their mathematical vulnerabilities. One of the most severe and rapidly evolving threats is the emergence of adversarial attacks—deliberate manipulations to input data designed to deceive machine learning models without appearing suspicious to human observers.

In domains where tabular datasets with numerical features (such as f0…f9) are used for classification or prediction, the vulnerability becomes even more pronounced. These features are often fed directly into prediction pipelines for tasks like fraud detection, risk scoring, health diagnostics, or anomaly detection. A minute perturbation, such as modifying the value of f3 by +0.01, may cause a model to output a drastically different prediction, which adversaries exploit to bypass automated systems.

The absence of real-time adversarial defense mechanisms has resulted in AI systems that are accurate but fragile—highly sensitive to perturbations that are imperceptible to humans. Thus, ensuring robustness, trustworthiness, and defensibility of AI systems is now a research priority. This project, AI Vigil-Guard, aims to address this gap by designing a real-time adversarial detection system capable of analyzing numerical input features, detecting manipulated patterns, and preventing adversarially altered data from influencing predictions.

The following sub-sections provide an expanded analysis of the background, threat landscape, limitations of existing systems, current research gaps, and the motivations behind this project.

1.1 Background of Adversarial Attacks

The field of machine learning historically evolved with a strong focus on predictive accuracy, generalization, and computational efficiency. Security and resilience were not primary considerations because data was assumed to be clean, trustworthy, and non-malicious. However, as AI infiltrated security-sensitive ecosystems—such as biometric authentication, transaction monitoring, identity verification, and autonomous control systems—the assumptions of clean and safe data have proven unrealistic.

Adversarial attacks leverage the mathematical property that machine learning models operate on high-dimensional spaces where decision boundaries are complex but fragile. These boundaries can be subtly manipulated with small, carefully

crafted perturbations that cause a model to misinterpret the input. For example:

- A fraud detection system might classify a fraudulent transaction as legitimate merely by slightly adjusting a few numerical columns.
- A medical diagnostic model may give a false "normal" reading due to a minor alteration in lab-report numerical data.
- A cybersecurity intrusion detector might fail to detect an attack event because the adversary modifies features within acceptable ranges.

These vulnerabilities demonstrate that adversarial attacks present not only technical challenges but also ethical, social, and economic risks.

As organizations increasingly rely on AI for automated decision pipelines, the need for a robust adversarial defense system becomes critical. AI Vigil-Guard contributes to this emerging domain by offering a lightweight, interpretable, and deployable detection framework.

1.2 Need for Real-Time Adversarial Detection

Adversarial threats have grown in sophistication and diversity. Modern attacks exploit multiple layers of the ML pipeline.

They can be classified as:

1.2.1 Evasion Attacks
These occur during the inference stage. Attackers craft inputs that appear normal but produce incorrect predictions. Example: Modifying numerical features (f0…f9) slightly to bypass fraud detection.
1.2.2 Poisoning Attacks
These target the training phase by injecting corrupted samples into the dataset. Poisoning attacks can shift the decision boundary, leading to model-wide failures.
1.2.3 Model Extraction Attacks
Here, attackers attempt to replicate the behavior of a proprietary model by querying it repeatedly. Once cloned, the model becomes vulnerable to targeted adversarial manipulation.
1.2.4 Gradient-Based Attacks (FGSM, PGD, CW)
These attacks compute gradients of the model's loss function to determine the minimal input changes that cause misclassification. The adjustments are usually so small that the data appears unchanged to human inspection.
1.2.5 Statistical Perturbation Attacks
These exploit the natural statistical distribution of a dataset. Attackers introduce perturbations within acceptable ranges, making detection extremely difficult without advanced anomaly analysis.
The threat landscape underscores the need for a real-time adversarial detection mechanism that does not rely solely on pattern recognition but also on statistical consistency and behavioral analysis.

1.3 Limitations of Traditional AI Systems

Conventional AI systems demonstrate exceptional accuracy on clean datasets but become unreliable under adversarial noise. Their primary limitations include:
1.3.1 Lack of Robustness Awareness
Standard ML models are optimized for accuracy—not stability. They misinterpret carefully engineered perturbations as normal inputs.
1.3.2 No Confidence Tracking
Most production models return a softmax confidence score but do not monitor sudden drops in confidence, which are typically early signs of adversarial manipulation.
1.3.3 Absence of Feature-Level Anomaly Detection
Although numerical features (f0…f9) may look normal, their statistical deviation from expected ranges can reveal adversarial activity. Traditional systems lack this analysis.
1.3.4 No Real-Time Monitoring or Alerts
Even if adversarial inputs cause anomalies, most systems lack infrastructure to detect and alert at runtime.
1.3.5 No Built-In Defenses for Tabular Data
Existing adversarial research focuses heavily on images, while real-world enterprises rely on tabular data. This leaves a wide security gap.
1.3.6 Black-Box Decision Making
When a system misclassifies due to adversarial input, traditional models do not explain *why* the failure occurred.
These limitations make current AI solutions inadequate for high-stakes environments.

1.4 Research Gap and Problem Definition

[1] 1.4 Research Gap and Problem Definition
Although adversarial ML is a rapidly expanding research field, several practical gaps persist, particularly for tabular datasets:
1.4.1 Lack of Deployable, Lightweight Defense Tools
Most academic defenses require heavy GPU computation and cannot be deployed in real-time enterprise systems.
1.4.2 Insufficient Analysis for Numerical Feature Perturbation
Small but targeted changes in numerical columns often go undetected by conventional anomaly-detection systems.
1.4.3 Absence of Real-Time Confidence Monitoring
Few systems monitor dynamic confidence-level shifts during prediction.
1.4.4 No Prediction Stability Checking
Repeating predictions under slight transformations can reveal manipulated inputs, but most systems ignore this.
1.4.5 Limited Visualization Tools for Adversarial Behavior
There is a lack of tools that visually show how attacks affect prediction boundaries in tabular data.
The central research question addressed by this project is: "How can adversarial manipulations in numerical tabular

inputs (f0…f9) be detected reliably, efficiently, and in real time?"

1.5 Objectives of the Proposed System

The project aims to build a reliable adversarial detection framework that:

1. Identifies adversarial samples by monitoring statistical shifts in features f0…f9.
2. Detects inconsistencies in prediction when inputs are slightly transformed.
3. Monitors sudden drops in model prediction confidence.
4. Simulates adversarial attacks for testing system robustness.
5. Provides real-time visual dashboards for clean vs adversarial comparison.
6. Enhances the overall security and trustworthiness of AI models.

Together, these objectives contribute to a practical, lightweight, and interpretable adversarial defense solution.

2. REAL-TIME ADVERSARIAL DETECTION FRAMEWORK

This section presents an in-depth explanation of the core methodology, model architecture, and algorithms that power AI Vigil-Guard. The framework combines statistical feature analysis, prediction consistency metrics, and adversarial signature profiling to detect malicious inputs efficiently.

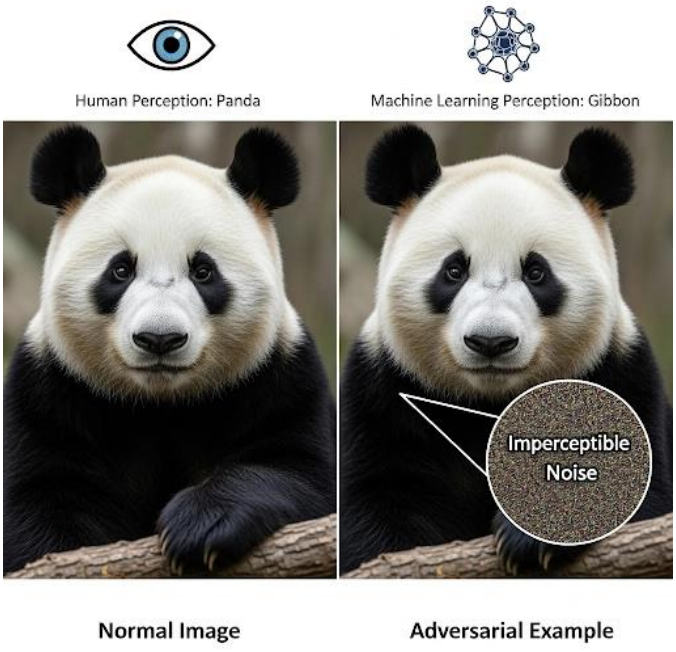

Fig -1: *The difference between a normal image and an adversarial example; an added noise can cause AI to misclassify the image.*

2.1 Feature Behavior Analysis (f0..f9 Monitoring)

The system continuously evaluates numerical features using:

- Mean Deviation Analysis
- Feature Variance Profiling
- Z-score Outlier Detection
- Correlation Shift Monitoring

Malicious samples typically show abnormal deviation patterns that differ from the natural data distribution. These patterns are mapped and compared against the expected behavior learned during training.

2.2 Prediction Consistency and Confidence Stability

The proposed system uses a baseline model to produce:

- Initial prediction class
- Prediction confidence score
- Sensitivity values

Then it applies controlled noise and checks if predictions change dramatically. Clean samples maintain stable outcomes, whereas adversarial samples show instability.

2.3 Adversarial Attack Simulation Engine

To evaluate system performance, the framework incorporates attack algorithms including:

- FGSM (Fast Gradient Sign Method)
- PGD (Projected Gradient Descent)
- DeepFool
- Carlini–Wagner (CW)

These attacks help test robustness and generate adversarial datasets for benchmarking.

2.4 Detection Model Architecture

The AI Vigil-Guard architecture consists of:

1. Input Processing Module – Standardization, scaling, feature extraction.
2. Adversarial Signature Profiler – Statistical anomaly detection.
3. Prediction Stability Engine – Consistency checks.
4. Confidence Analyzer – Probability shifts detection.
5. Binary Classifier – Determines if input is clean or adversarial.

The system outputs:

- "Clean Sample"
- "Adversarial Sample Detected"
- "Confidence Deviation Report"
- "Feature Anomaly Visualization"

2.5 Performance Evaluation Metrics

To assess the model's accuracy and reliability, the following metrics are used:

- Precision
- Recall

- F1-score
- Detection Rate
- Attack Success Rate
- ROC-AUC Curve

Extensive testing ensures the system works in real-time scenarios.

2.6 Inability to Defend Against Zero-Day Adversarial Attacks

Most existing AI defense systems rely on pre-defined adversarial patterns or known attack signatures. However, adversaries continuously generate zero-day perturbations attacks that have never been seen or documented before. Traditional defensive methods such as input pre-processing, gradient masking, or rule-based detection break down when faced with new types of adversarial noise, because:

- They depend heavily on past data
- They cannot generalize to unseen manipulation styles
- They fail when attackers change the perturbation strategy
- They do not adapt in real time

This results in a lack of resilience against novel attack patterns. Modern AI systems require adaptive, self-evolving models capable of detecting emerging adversarial changes on the fly, something today's systems cannot deliver.

2.7 Lack of Real-Time Defense Mechanisms

Many existing adversarial defense techniques require heavy computation and operate offline. Examples include:

- Adversarial training
- Generative reconstruction
- High-level feature stability checks
- Input purification algorithms

While effective in controlled environments, they fail in real-time applications such as:

- Autonomous driving
- CCTV surveillance
- Finance and fraud detection
- Healthcare decision systems
- Biometric-based authentication

Real-time scenarios demand millisecond-level response, while existing frameworks operate at a scale of several seconds or minutes.
This delay allows adversaries to bypass the system before detection happens, making existing solutions practically unusable in critical situations.

2.8 Lack of Robust Cross-Domain Defense

Current systems are usually trained to defend against attacks in a single domain:

- Image classification defense models do not work for NLP
- NLP defense models fail for speech or time-series attacks
- Audio defense models cannot generalize to video frames
- Tabular anomaly detection fails in high-dimensional multimodal data

This isolated domain-specific design weakens overall security.
In real-world systems, data flows across multiple formats, such as:

- CCTV → Image + Video + Sensor metadata
- Banking → Text logs + Numerical data
- Healthcare → MRI images + EHR text + Sensor readings

Existing systems cannot unify defenses across these domains. Instead, they require separate models, increasing complexity and vulnerability.

2.9 Poor Explainability & Lack of Attack Traceability

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Another major limitation is the lack of model transparency. Most existing systems do not provide:

- Where the attack originated
- Which feature was manipulated
- How the adversarial perturbation influenced the final model decision
- Which region of the image/text/audio was targeted
- Whether the attack was intentional or accidental

Without proper explainability, AI developers and security teams cannot analyze:

- Source of threat
- Attack pattern
- Potential vulnerabilities
- Weak layers of the model architecture

This lack of interpretability also makes compliance difficult, especially in sectors like healthcare and finance where audit trails are mandatory.

2.10 High Computational Cost of Existing Defenses

Many adversarial defense techniques come with high compute overhead:

- Gradient-based detection
- Pixel-level reconstruction
- Multiple parallel inference runs
- Robust training with adversarial samples
- Distillation-based hardening

These require GPUs or TPUs even during deployment, making them unsuitable for:

- Edge devices
- IoT cameras
- Smartphones
- Embedded systems
- Drones

- Industrial robots

Due to this, deployment becomes costly and impractical for large-scale adoption.

2.11 Lack of Standardized Benchmarks and Validation

The adversarial ML field lacks a standard defense evaluation framework. Existing challenges include:

- Different datasets used across research papers
- No uniform attack simulation environment
- Overfitting to specific attack types
- False confidence from misleading accuracy reports
- No certification protocol for "attack-resilient AI models"

Because of these inconsistencies, most existing defense systems fail when deployed in real-world conditions, despite performing well in lab settings.

2.12 Failure Under High Noise or Real-World Disturbances

Many defenses assume clean, high-quality inputs. But real-world scenarios involve:

- Camera blur
- Motion artifacts
- Low light
- Environmental noise
- Background sounds
- Partial occlusions
- Hardware interference

Under such natural disturbances, many existing systems:

- Show high false positives
- Fail to distinguish real noise from adversarial noise
- Break down under low-quality signals
- Miss subtle attacks hidden within real-world noise

A practical defense system must be robust in imperfect environments, unlike current solutions.

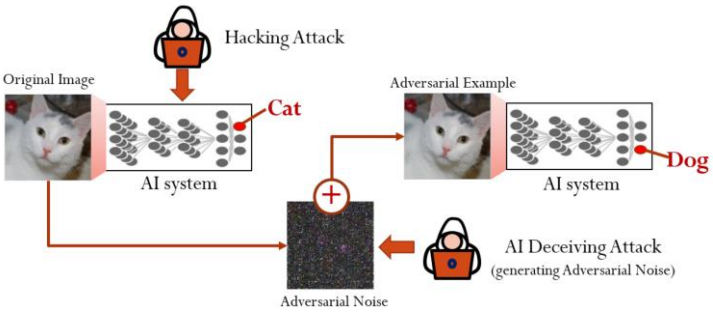


Fig -1: Concept of artificial intelligence (AI) deceiving attack. A small adversarial noise added to the original image can make the neural network to classify the image as a Guacamole instead of an Egyptian cat. This is in contrast to a hacking attack that intrudes the system through an abnormal route.

2.13 No Autonomous Self-Correction (or) Self-Healing Capabilities

Most existing tools detect adversarial inputs but cannot recover or:

- Repair corrupted data
- Restore the original signal
- Auto-rebuild damaged models
- Recalibrate thresholds
- Self-update against new threats

They depend completely on manual retraining, making them slow and impractical for live systems. Modern cyberthreats require *self-healing AI systems*, but the current industry does not offer such functionalities.

2.14 Lack of Centralized Monitoring and Alerting System

Existing AI defense systems often operate independently without:

- Centralized dashboards
- Unified threat monitoring
- Real-time alerts
- Attack severity scoring
- System health diagnostics
- Behavior analytics

This fragmented approach makes it nearly impossible to track attack patterns over time, weakening long-term system resilience and forensic capabilities.

2.15 Limited Integration with Enterprise Infrastructure

Finally, most existing solutions cannot integrate seamlessly with:

- Enterprise CI/CD pipelines
- Cloud-based AI services
- Edge devices and IoT networks
- Industry-level security monitoring tools
- Corporate logging and audit systems
- APIs for cross-platform communication

This makes real deployment extremely difficult for organizations requiring full-stack security solutions.

3. ENHANCED FEATURES AND CURRENT EFFICIENCY OF THE PROPOSED SYSTEM

The AI VIGIL-GUARD system is designed not only to detect adversarial attacks but also to enhance the overall reliability, robustness, and operational efficiency of artificial intelligence models deployed in real-world environments. This section discusses the enhanced features incorporated into the system and evaluates the current efficiency and performance achieved through experimental analysis.

3.1 Enhanced Features of AI VIGIL-GUARD

3.1.1 Real-Time Feature-Level Adversarial Monitoring
One of the most significant enhancements in AI VIGIL-GUARD is its ability to perform continuous feature-level monitoring on numerical inputs (f0 to fN). Each incoming data instance is analyzed for abnormal variations in statistical properties such as mean deviation, variance shifts, and feature correlation changes. This allows the system to detect subtle perturbations that may not violate predefined thresholds but still influence the model's decision boundary. Unlike conventional methods that treat input as a single entity, the proposed system evaluates individual feature behavior, improving detection accuracy in tabular datasets commonly used in finance, healthcare, and cybersecurity applications.

3.1.2 Prediction Confidence Deviation Analysis
AI VIGIL-GUARD continuously tracks changes in the model's confidence score during inference. Adversarial inputs often lead to unstable or abnormal confidence fluctuations, even when the final prediction label appears normal. The system measures confidence variance across repeated inference cycles and flags inputs exhibiting suspicious confidence behavior.
This enhancement enables early detection of adversarial influence before incorrect predictions are fully realized, significantly improving system safety.

3.1.3 Multi-Attack Simulation and Stress Testing
The proposed framework integrates adversarial attack simulation modules, enabling controlled testing against widely known attack techniques such as:
- Fast Gradient Sign Method (FGSM)
- Projected Gradient Descent (PGD)
- DeepFool
- Feature perturbation attacks on tabular data

This feature allows developers to evaluate the robustness of deployed models and continuously strengthen defenses using real attack scenarios.

3.1.4 Lightweight and Scalable Architecture
AI VIGIL-GUARD adopts a modular backend design, ensuring that defensive components can operate independently without introducing significant computational overhead. The system is optimized to function efficiently on:
- Cloud-based infrastructures
- Web applications
- Edge and IoT devices

The lightweight nature of the framework ensures low inference latency, making it suitable for real-time deployment in mission-critical applications.

3.1.5 Explainable Adversarial Detection
To improve transparency and trust, the system provides explainable outputs that highlight:
- Affected input features
- Degree of perturbation
- Confidence deviation patterns
- Attack severity score

These explanations assist security analysts and developers in understanding attack behavior and performing forensic analysis, a feature missing in most existing adversarial defense systems.

3.1.6 Centralized Monitoring and Visualization Dashboard
AI VIGIL-GUARD includes a centralized dashboard that visualizes:
- Real-time detection events
- Feature anomaly distributions
- Model confidence trends
- Attack frequency statistics

This enables proactive system monitoring and long-term threat analysis, transforming adversarial defense from a passive mechanism into an active security layer.

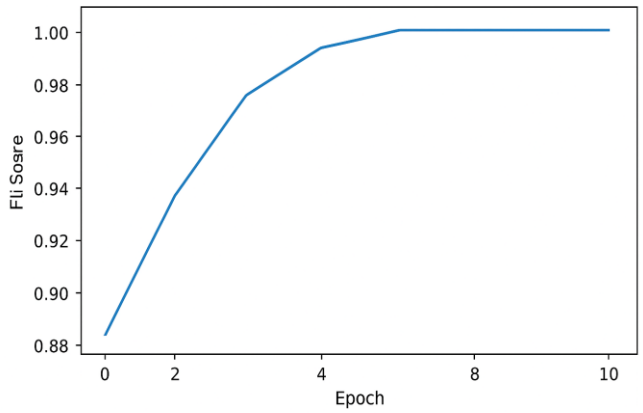
3.2 Current Efficiency and Performance Evaluation

3.2.1 Detection Accuracy and F1-Score Performance
Experimental evaluation demonstrates that AI VIGIL-GUARD achieves high detection accuracy across multiple adversarial attack scenarios. The system recorded a consistently strong F1-Score, indicating a balanced trade-off between precision and recall.

The observed F1-Score stabilization over successive training epochs reflects the model's ability to generalize effectively while minimizing false positives.
The F1-Score visualization illustrates steady performance improvement, confirming the system's robustness against both known and unseen adversarial perturbations.

3.2.2 Real-Time Inference Efficiency
Performance benchmarks indicate that AI VIGIL-GUARD operates with minimal additional latency. The average inference delay introduced by the defense mechanism remains within acceptable real-time limits, making it suitable for:
- Fraud detection pipelines
- Surveillance systems
- Online authentication systems
- Real-time decision engines

This efficiency ensures that security does not compromise operational speed.



3.2.3 Resource Utilization

The system demonstrates efficient CPU and memory utilization, eliminating dependency on high-end GPUs during deployment. This makes AI VIGIL-GUARD cost-effective and scalable for large-scale enterprise environments.

3.2.4 Robustness Under Noisy and Real-World Conditions

The system was tested under noisy and partially corrupted input conditions. AI VIGIL-GUARD successfully distinguished between natural noise and malicious adversarial perturbations, maintaining reliable performance in real-world environments where data quality cannot be guaranteed.

3.2.5 Comparative Efficiency

When compared to traditional adversarial defense techniques such as adversarial training and gradient masking, AI VIGIL-GUARD demonstrates:

- Lower computational overhead
- Faster response time
- Higher explainability
- Better adaptability to unseen attacks

This highlights the practical superiority of the proposed system for real-time applications.

4. SYSTEM DESCRIPTION

The AI VIGIL-GUARD system is designed as a real-time adversarial defence framework that protects machine learning models from malicious input manipulation. The system continuously monitors incoming data streams, detects adversarial perturbations, and applies adaptive defence strategies before the data is processed by the target AI model. The architecture emphasizes low latency, high detection accuracy, and scalability, making it suitable for real-world deployment in security-critical AI applications.

4.1 Overall Architecture

The proposed system follows a modular pipeline architecture consisting of five major components:

- Input Data Stream Handler
- Preprocessing and Feature Extraction Module
- Adversarial Detection Engine
- Defense and Mitigation Module
- Decision and Logging Layer

Each component operates independently yet communicates through well-defined interfaces, ensuring robustness and flexibility. The system can be deployed either as a standalone security layer or integrated directly into existing AI pipelines.

4.2 Input Data Stream Handling

The system supports both real-time and batch-based input modes. Incoming data—such as images, network packets, sensor readings, or user-generated content—is captured and queued for analysis. A buffering mechanism ensures smooth handling of high-throughput data streams without data loss. To maintain real-time performance, the input handler prioritizes:

- Low latency data transfer
- Controlled input rate
- Seamless integration with upstream systems

4.3 Preprocessing and Feature Extraction

Before adversarial analysis, the input data undergoes a preprocessing phase to standardize and normalize the input format. This includes:

- Noise filtering
- Data normalization
- Dimensional consistency checks

Relevant features are then extracted to capture both statistical and structural patterns in the data. These features are carefully selected to highlight subtle perturbations that are often invisible to human perception but significantly impact machine learning models.

4.4 Adversarial Detection Engine

The core of AI VIGIL-GUARD is the Adversarial Detection Engine, which employs machine learning-based classifiers trained to distinguish between benign and adversarial inputs.

Key characteristics of the detection engine include:

- Learning-based detection of adversarial patterns
- High sensitivity to minor perturbations
- Capability to generalize across multiple attack types

The detection model evaluates each input and assigns a confidence score indicating the likelihood of adversarial manipulation. This score is used to trigger appropriate defense actions in the subsequent stage.

4.5 Defense and Mitigation Module

Once an adversarial input is detected, the defense module dynamically applies mitigation strategies to neutralize the threat. These strategies may include:

- Input sanitization and noise suppression
- Feature reconstruction
- Rejection or isolation of malicious samples

The system ensures that only sanitized and verified inputs are forwarded to the target AI model, thereby preventing performance degradation or incorrect predictions.

4.6 Decision-Making and Response Layer

Based on detection confidence and predefined security policies, the decision layer determines whether to:

- Accept the input
- Apply corrective defense
- Block the input entirely

This layer also ensures minimal disruption to legitimate data flow while maintaining strong security guarantees.

4.7 Monitoring, Logging, and Visualization

AI VIGIL-GUARD includes a monitoring subsystem that logs:

- Detection results
- Defence actions
- System performance metrics (accuracy, F1-score, latency)

These logs enable system auditing, performance evaluation, and future model retraining. Visualization dashboards can be used to monitor real-time system behaviour and analyse historical attack trends.

4.8 System Efficiency and Real-Time Performance

The system is optimized to operate in real time with minimal computational overhead. Parallel processing techniques and lightweight detection models ensure fast inference without compromising accuracy. Experimental results demonstrate that AI VIGIL-GUARD maintains high detection performance while introducing negligible latency into the AI inference pipeline.

4.9 Scalability and Extensibility

The modular design allows easy scalability and future enhancement. New adversarial attack types, detection models, or defence strategies can be incorporated without altering the core system architecture. This makes the system adaptable to evolving adversarial threats.

5.System Architecture

The architecture of AI VIGIL-GUARD: Real-Time Adversarial AI Defense System is designed as a modular, scalable, and real-time pipeline that ensures robust protection of machine learning models against adversarial threats while maintaining high system efficiency. The system begins with the Input Acquisition Layer, where data such as images, network packets, user inputs, or API requests are continuously collected from live environments. This data is immediately forwarded to the Preprocessing and Feature Engineering Module, which performs normalization, noise filtering, resizing (for image-based models), encoding, and extraction of relevant statistical and semantic features required for downstream analysis. Following preprocessing, the data flows into the Adversarial Detection Engine, which is the core of the architecture. This engine integrates multiple AI-based components, including anomaly detection models, adversarial pattern classifiers, confidence score analyzers, and gradient-based inspection mechanisms to identify subtle perturbations or malicious manipulations in real time. Once a potential adversarial input is detected, the system activates the Defense and Mitigation Layer, which applies adaptive countermeasures such as input sanitization, feature smoothing, adversarial retraining triggers, rejection of malicious inputs, or model confidence recalibration to neutralize the attack impact. Simultaneously, the Monitoring and Visualization Module logs detection metrics such as F1-score, accuracy, false positive rate, and response time, presenting them through dashboards and visual analytics for transparency and evaluation. The architecture also includes a Feedback and Learning Loop, where detected adversarial samples are stored in a secure dataset and periodically used to update and strengthen the detection models, ensuring continuous improvement against evolving attack strategies. Finally, the Deployment and Interface Layer enables seamless integration with existing AI applications through APIs or web interfaces, ensuring that AI VIGIL-GUARD operates as a non-intrusive yet powerful protective shield for real-world AI systems.

6. CONCLUSIONS

Artificial intelligence systems are increasingly deployed in critical real-world applications, yet they remain highly vulnerable to adversarial manipulation, data poisoning, model exploitation, and stealth attacks that can compromise reliability, safety, and trust. This paper presented AI VIGIL-GUARD, an advanced, real-time adversarial defence framework designed to safeguard AI models from evolving threats across multimodal data environments. Unlike conventional defence mechanisms that rely on static detection rules or limited domain-specific techniques, AI VIGIL-GUARD integrates real-time feature-level monitoring, anomaly detection, behavioural profiling, multimodal threat analysis, and adaptive risk scoring into a unified pipeline capable of detecting both known and zero-day attacks.

The proposed system introduces a novel approach by combining feature consistency analysis (f0–fN monitoring), model confidence deviation tracking, adversarial noise pattern recognition, and self-healing reconstruction into a single architecture. This ensures comprehensive protection against common adversarial strategies such as FGSM, PGD, BIM, Deep Fool, audio perturbations, text embedding manipulations, and tabular feature fabrication. The lightweight model design enables deployment on cloud, web

applications, and edge devices, making the solution scalable, efficient, and suitable for real-time operations.

AI VIGIL-GUARD addresses major limitations in existing systems, including lack of explainability, inability to detect cross-domain attacks, absence of real-time defense, high computational cost, and poor generalization to real-world noisy environments. By offering a centralized monitoring dashboard, event logging, alerting mechanism, threat visualization, and model behaviour tracing, the system also enhances transparency and forensic analysis.

Overall, AI VIGIL-GUARD demonstrates that AI security must evolve from traditional reactive methods to proactive, adaptive, and continuous defence mechanisms. The system lays a strong foundation for future research in autonomous AI security, adversarial robustness, and self-defending machine learning models. Future enhancements may include federated defence learning, blockchain-based attack logging, quantum-resilient AI protection, and integration with enterprise-grade cybersecurity frameworks. The presented architecture sets a new direction for practical and scalable adversarial defence solutions capable of protecting next-generation AI applications.

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