Article

Hybrid-HAVA: Enhancing AI Security in Healthcare with GAN-Based Adversarial Filtering

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Abstract: The rapid adoption of Artificial Intelligence (AI) in healthcare has significantly improved diagnostic accuracy and patient care. However, AI-driven medical models remain highly vulnerable to adversarial attacks, which can manipulate predictions and compromise patient safety. The Healthcare AI Vulnerability Assessment Algorithm (HAVA) provides a post-attack vulnerability index (PAVI) but lacks real-time defense mechanisms. This article proposes Hybrid-HAVA, an enhanced security framework that integrates HAVA with Generative Adversarial Network (GAN)-based filtering to proactively defend against adversarial perturbations. Experimental results demonstrate that Hybrid-HAVA outperforms conventional defense strategies by mitigating adversarial noise while preserving diagnostic accuracy.

Keywords: Hybrid-Hava, Healthcare AI Security**,** Adversarial Attacks**,** Generative Adversarial Networks, Adversarial Filtering**,** Fast Gradient Sign**,** Data Poisoning Attacks**,** Defense-GAN**,** Feature Squeezing**,** AI Model Robustness**,** Medical Image Security**,** Adversarial Training

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1.Introduction

Artificial Intelligence (AI) has transformed healthcare by enabling automated disease diagnosis, advanced medical image analysis, and personalized treatment planning. These AI-driven innovations have significantly improved diagnostic accuracy and patient care, making healthcare more efficient and accessible. However, despite these advancements, AI models remain highly vulnerable to adversarial attacks, including Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and data poisoning, which can manipulate model predictions and compromise patient safety. Traditional defense mechanisms, such as adversarial training and feature squeezing, have been developed to mitigate these threats, but they often provide limited protection and may degrade model performance. To address these security concerns, the Healthcare AI Vulnerability Assessment Algorithm (HAVA) was introduced as a post-attack assessment tool, measuring adversarial impact using the Post-Attack Vulnerability Index (PAVI). While HAVA is effective in evaluating adversarial threats, it lacks real-time defense capabilities, leaving AI-driven healthcare systems exposed to ongoing attacks. To bridge this gap, we propose Hybrid-HAVA, an enhanced security framework that integrates GAN-based adversarial filtering with HAVA, enabling proactive detection and removal of adversarial noise before AI inference. By combining real-time adversarial filtering, post-attack assessment, and adversarial training enhancements, Hybrid-HAVA ensures higher AI security and robustness in medical applications while maintaining diagnostic accuracy and efficiency.

2. Related Work

2.1 HAVA: Healthcare AI Vulnerability Assessment Algorithm

The Healthcare AI Vulnerability Assessment Algorithm (HAVA) was developed to assess the security of AI models used in medical applications. It measures the extent of adversarial impact using the Post-Attack Vulnerability Index (PAVI), a metric that quantifies the reduction in model accuracy following an adversarial attack. HAVA serves as a post-attack evaluation tool, helping researchers and practitioners understand the extent of model degradation. However, while it is effective in identifying vulnerabilities, it lacks real-time defense mechanisms. This limitation means that HAVA can detect adversarial impacts only after an attack has already compromised the model, making it ineffective in preventing threats before inference. In dynamic healthcare environments where timely and accurate decisions are critical, relying solely on a post-attack evaluation tool like HAVA is insufficient. Therefore, integrating proactive adversarial defenses into HAVA is necessary to ensure robust AI security in medical applications.

2.2 GAN-Based Defense Mechanisms

Generative Adversarial Networks (GANs) have emerged as a powerful and promising approach for mitigating adversarial attacks by reconstructing clean, unaltered versions of adversarially manipulated inputs. Unlike conventional defense mechanisms, which rely on adversarial training or feature squeezing to reduce a model's sensitivity to adversarial noise, GAN-based defense techniques actively restore corrupted inputs, making them highly effective for protecting deep learning models from deception. One of the most well-known GAN-based adversarial defense methods is Defense-GAN, which enhances model robustness by learning the statistical distribution of normal, attack-free images and then using this learned representation to reconstruct clean versions of adversarially perturbed inputs. In practical applications, this means that when an adversarially manipulated image is fed into the system, the GAN removes adversarial distortions by generating a visually and statistically similar clean image, preventing the adversarial attack from misleading the AI model. This approach is particularly useful in domains such as medical imaging, where even minor adversarial perturbations can compromise diagnostic accuracy, potentially leading to incorrect medical decisions and patient misdiagnoses.

GAN-based filtering has demonstrated significant success in computer vision tasks, especially in image restoration, denoising, and super-resolution applications, where subtle adversarial perturbations can be challenging to detect through traditional preprocessing techniques. The ability of GANs to reconstruct high-fidelity images while preserving critical diagnostic features makes them a strong candidate for adversarial defense in AI-driven healthcare applications. In medical imaging fields such as MRI, CT scans, and X-ray analysis, where high accuracy is crucial for patient safety and clinical decision-making, GAN-based defense mechanisms could play an essential role in preserving model integrity and ensuring reliable AI-driven diagnoses. By filtering adversarial noise from medical scans and clinical image datasets, GANs can protect AI models from adversarial threats, ensuring that model predictions remain unaffected by external adversarial influences.

Despite the significant potential of GAN-based adversarial filtering, these methods have not yet been widely integrated into healthcare-specific AI security frameworks due to several challenges. One major issue is the computational overhead associated with GAN training and inference. Since GANs require a large volume of high-quality training data to accurately learn the distribution of clean images, their deployment in real-time AI-driven medical systems can be resource-intensive and may increase processing latency. Furthermore, training GANs to effectively distinguish between adversarial noise and genuine medical variations is a complex task, requiring extensive fine-tuning and domain-specific adaptation. Another critical limitation is the real-time applicability of GAN-based filtering, as most current implementations focus on offline reconstruction, making them impractical for real-time AI inference in time-sensitive clinical environments.

To address these challenges, Hybrid-HAVA proposes an innovative integration of GAN-based adversarial filtering within the HAVA security framework, enabling real-time attack mitigation while maintaining high diagnostic accuracy. By incorporating GAN filtering alongside HAVA's Post-Attack Vulnerability Index (PAVI) metric, Hybrid-HAVA ensures that AI-driven diagnostic systems not only detect and assess adversarial threats but also actively neutralize adversarial perturbations before they impact AI predictions. This dual-layered security approach bridges the gap between passive vulnerability assessment and proactive defense, positioning Hybrid-HAVA as a scalable and effective adversarial defense solution for AI-driven healthcare applications. By refining GAN architectures to enhance computational efficiency and real-time applicability, Hybrid-HAVA aims to unlock the full potential of GAN-based adversarial defense, ensuring that AI models in critical healthcare settings remain secure, resilient, and accurate, even in the presence of sophisticated adversarial attacks.

2.3 Hybrid Defense Models

Beyond HAVA and GAN-based adversarial filtering, various hybrid security models have been explored to enhance AI robustness against adversarial attacks in critical applications like healthcare. One of the most promising approaches is Federated Learning (FL), which has emerged as a powerful decentralized strategy for securing AI models while preserving data privacy. In traditional centralized AI training, sensitive patient data must be shared and stored in a single location, increasing the risk of data breaches and poisoning attacks. Federated Learning addresses this issue by allowing AI models to be trained across multiple distributed nodes—such as different hospitals or research institutions—without requiring raw data to be exchanged. This setup significantly enhances data security and reduces the likelihood of adversarial data poisoning, as no single entity has complete access to the entire dataset. However, while FL offers notable advantages in protecting data privacy and decentralizing training, it also introduces substantial computational costs due to the need for continuous communication and synchronization between distributed nodes. Additionally, FL is still vulnerable to adversarial model updates, where malicious nodes within the network can inject poisoned gradients into the training process, effectively corrupting the global AI model. Addressing these challenges requires robust defense mechanisms, such as secure aggregation techniques and anomaly detection to filter out adversarial updates before they impact model performance.

Another hybrid defense strategy gaining traction is the integration of Explainable AI (XAI) with Feature Squeezing, which focuses on detecting and mitigating adversarial attacks. Explainable AI techniques aim to increase transparency in AI decision-making by providing insights into how models process and interpret input data. By analyzing these decision pathways, XAI helps identify irregularities and adversarial behaviors, making it easier for security mechanisms to flag suspicious model outputs. However, while XAI improves adversarial detection, it does not inherently remove adversarial noise or prevent attacks before they occur. To complement XAI, Feature Squeezing has been proposed as an additional defensive preprocessing technique, which works by reducing an AI model's sensitivity to adversarial perturbations. It achieves this by applying transformations such as bit-depth reduction, median filtering, and smoothing operations to input data, effectively minimizing subtle adversarial modifications that might manipulate model predictions. While these techniques strengthen adversarial detection and robustness, they primarily function as reactive defenses rather than proactive solutions. Unlike GAN-based adversarial filtering, which actively reconstructs clean images before AI inference, XAI and Feature Squeezing primarily help identify and limit adversarial impact after an attack has occurred.

Overall, hybrid defense models like Federated Learning, Explainable AI, and Feature Squeezing contribute to the broader landscape of AI security by offering privacy-preserving training, adversarial detection, and robustness enhancements. However, each approach has trade-offs in terms of computational overhead, real-time effectiveness, and adaptability to evolving attack methods. Future advancements in hybrid AI defenses should focus on integrating proactive filtering techniques with adversarial detection and decentralized learning strategies, ensuring a comprehensive, multi-layered security framework for AI applications in healthcare and other high-stakes domains.

2.4 Hybrid-HAVA: A New Paradigm for AI Security in Healthcare

Building upon the strengths of existing AI security models, Hybrid-HAVA introduces a comprehensive and proactive defense framework that integrates HAVA's post-attack vulnerability assessment with GAN-based real-time adversarial filtering. Unlike traditional adversarial defense mechanisms that primarily focus on either detecting or mitigating attacks, Hybrid-HAVA provides a dual-layered security approach, ensuring both attack detection and real-time defense. The core innovation of this framework lies in its ability to identify adversarial threats using HAVA's Post-Attack Vulnerability Index (PAVI) while simultaneously deploying GAN-based filtering to reconstruct adversarial-free medical images before they are processed by the AI model. This integration allows AI-driven healthcare systems—such as MRI, CT, and X-ray diagnostics—to maintain both high security and diagnostic accuracy, effectively minimizing the risk of false positives and false negatives caused by adversarial manipulations.

Traditional AI security models in healthcare, such as Federated Learning, Explainable AI, and Feature Squeezing, provide partial solutions but often fall short of delivering real-time adversarial resilience. While Federated Learning (FL) improves privacy and decentralization, it remains vulnerable to malicious model updates and poisoned gradients. Similarly, Explainable AI (XAI) and Feature Squeezing enhance attack detection and robustness, but they primarily function as reactive defenses rather than proactive solutions that actively neutralize adversarial inputs. Hybrid-HAVA addresses these gaps by shifting from a passive AI vulnerability assessment model to an active, real-time adversarial defense mechanism, ensuring that adversarial noise is removed before it can influence AI decision-making. The use of GAN-based adversarial filtering is particularly advantageous, as it reconstructs clean, high-quality medical images, preserving the integrity and reliability of AI-driven diagnostics even under adversarial attacks.

Another key strength of Hybrid-HAVA is its adaptability to diverse adversarial threats. Traditional AI models often struggle to defend against multiple attack vectors, such as Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and data poisoning attacks. By incorporating adversarial training principles, Hybrid-HAVA continuously enhances the AI model's resilience by retraining it on

GAN-filtered, attack-free medical images, allowing it to recognize and resist future adversarial manipulations. Moreover, Hybrid-HAVA leverages federated learning principles to strengthen data privacy and security, making it particularly well-suited for multi-institutional healthcare AI deployments. Instead of relying on a centralized data repository, Hybrid-HAVA enables collaborative model training across multiple healthcare institutions while preventing direct access to sensitive patient data, thereby mitigating risks associated with data breaches and poisoning attacks.

By integrating GAN-based filtering, HAVA's vulnerability assessment, adversarial training, and federated learning principles, Hybrid-HAVA represents a paradigm shift in AI security for healthcare applications. This holistic defense framework is designed not only to identify and mitigate adversarial attacks but also to prevent them from compromising AI-driven medical decision-making. As AI continues to play an increasingly critical role in healthcare diagnostics and treatment planning, the need for robust, real-time adversarial defenses becomes more pressing. Hybrid-HAVA offers a scalable, adaptive, and high-security AI solution, setting a new standard for trustworthy and resilient AI deployment in the medical field. Future enhancements could further optimize Hybrid-HAVA's computational efficiency, allowing it to be deployed in real-time clinical environments while maintaining high accuracy and security in the face of evolving adversarial threats.

3. Methodology

3.1 Hybrid-HAVA Framework

The Hybrid-HAVA model is designed to enhance the security of AI-driven healthcare systems by integrating three essential components: Attack Vulnerability Assessment, GAN-Based Adversarial Filtering, and Adversarial Training Enhancement. The first component, HAVA (Attack Vulnerability Assessment), plays a crucial role in measuring an AI model's susceptibility to adversarial attacks. It computes the Post-Attack Vulnerability Index (PAVI), a metric that quantifies the degradation in model performance after an adversarial attack, thereby offering a comprehensive assessment of AI robustness in a healthcare-specific setting. By analyzing how different attacks affect the AI system, HAVA provides valuable insights into potential security weaknesses. The second component, GAN-Based Adversarial Filtering, leverages Generative Adversarial Networks (GANs) to detect and remove adversarial noise from medical images, such as MRI scans, CT scans, and X-rays. GANs are trained to generate clean, high-quality reconstructions of input images by distinguishing between natural medical features and adversarial perturbations. This filtering mechanism ensures that AI models receive reliable and unaltered medical data, improving the accuracy of disease diagnosis and reducing the likelihood of erroneous predictions. The third component, Adversarial Training Enhancement, focuses on increasing the AI model's resilience by retraining it on GAN-filtered images. This step helps the model recognize adversarial patterns and adapt to different types of perturbations, ultimately reducing the risk of false-positive or false-negative diagnoses. By integrating real-time adversarial defense with post-attack assessment, Hybrid-HAVA provides a comprehensive solution for securing AI models in healthcare applications.

3.2 Dataset and Attack Simulation

To evaluate the effectiveness of the Hybrid-HAVA model, experiments are conducted using the Wisconsin Breast Cancer Dataset (WBCD), a widely used dataset for breast cancer classification. This dataset contains diagnostic features that help AI models distinguish between benign and malignant tumors. To test the robustness of Hybrid-HAVA, the AI model is subjected to various adversarial attacks, including Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and Data Poisoning Attacks. FGSM is a commonly used attack that applies small perturbations to input images in the direction of the gradient to mislead AI predictions. PGD, a more powerful iterative attack, refines adversarial modifications over multiple steps, making it more challenging for AI models to detect and resist. Additionally, Data Poisoning Attacks involve injecting manipulated data samples into the training dataset to degrade the model's long-term performance, posing a severe threat to AI-driven

healthcare systems. By simulating these attacks, Hybrid-HAVA's ability to filter out adversarial noise and maintain model accuracy is rigorously tested.

3.3 Evaluation Metrics

The performance of the Hybrid-HAVA framework is rigorously evaluated using three key metrics: PAVI Score, Attack Resistance, and Computational Overhead. These metrics are carefully selected to assess the model's effectiveness in mitigating adversarial attacks while maintaining high diagnostic accuracy and computational efficiency, which are crucial for real-world AI-driven healthcare applications.

The Post-Attack Vulnerability Index (PAVI) Score serves as a critical measure of model vulnerability, quantifying the extent of accuracy degradation caused by adversarial attacks. A higher PAVI Score indicates greater susceptibility, meaning the model experiences significant accuracy loss when exposed to adversarial perturbations. Conversely, a lower PAVI Score suggests that the model is more resilient, maintaining its performance and diagnostic reliability despite adversarial interference. By comparing the PAVI Scores before and after implementing Hybrid-HAVA, researchers can evaluate the effectiveness of GAN-based adversarial filtering in reducing the impact of adversarial noise. Traditional AI models, which lack robust adversarial defenses, often exhibit higher PAVI Scores, demonstrating a severe decline in accuracy under attack. In contrast, Hybrid-HAVA's dual-layered defense mechanism, which integrates real-time adversarial filtering and post-attack vulnerability assessment, is expected to achieve a substantially lower PAVI Score, reflecting enhanced robustness against adversarial threats.

The Attack Resistance metric provides a structured evaluation of AI model robustness on a scale from 1 to 5, where higher values indicate stronger resilience against adversarial attacks. This metric is particularly important for assessing the effectiveness of Hybrid-HAVA in mitigating adversarial manipulations compared to baseline AI models. Traditional AI models, when subjected to attacks such as Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), or Data Poisoning, often exhibit low attack resistance, struggling to maintain accurate predictions. In contrast, Hybrid-HAVA incorporates a GAN-based adversarial filtering mechanism, which actively removes adversarial noise before AI inference. This filtering step ensures that adversarial attacks are neutralized before they can compromise diagnostic accuracy, leading to a significant improvement in attack resistance scores. Additionally, by leveraging adversarial training enhancement, Hybrid-HAVA ensures that the AI model becomes more resilient over time, learning to distinguish between adversarial and clean data more effectively.

While GAN-based adversarial filtering enhances model security, it is also important to analyze its Computational Overhead, which measures the processing cost associated with implementing adversarial filtering mechanisms. This metric is particularly relevant in real-time healthcare applications, where fast and efficient AI inference is essential for timely medical decision-making. A major challenge associated with GAN-based defenses is their computational complexity, as training and deploying GANs require significant processing power and memory resources. If the computational overhead is too high, it may slow down real-time AI predictions, making it impractical for time-sensitive healthcare scenarios, such as emergency diagnostics, real-time radiology analysis, or AI-assisted surgeries. To address this, Hybrid-HAVA is designed to balance security with efficiency, optimizing GAN architectures for real-time applicability while maintaining minimal processing delays. This ensures that while Hybrid-HAVA provides strong adversarial defenses, it does not excessively burden computational resources, making it a practical solution for AI-driven medical systems.

By evaluating Hybrid-HAVA through these three comprehensive metrics, researchers can assess the trade-offs between security, computational efficiency, and model accuracy, ensuring that the proposed framework not only strengthens AI security in healthcare but also maintains high-performance standards necessary for clinical deployment. The ultimate goal of Hybrid-HAVA is to offer a scalable,

reliable, and efficient adversarial defense mechanism, ensuring that AI-driven diagnostic systems remain accurate, robust, and secure against adversarial threats in real-world healthcare environments.

4. Results and Discussion

4.1 Performance Comparison

Table 1 : Performance Analysis

Model	PAVI (%) (↓ Lower is Better)	Attack Resistance (1-5) (↑ Higher is Better)	Computational Cost (1-5) (↓ Lower is Better)
HAVA (Baseline)	38.6% (High vulnerability)	2.3/5 (Weak defense)	2.1/5 (Efficient)
Defense-GAN	12.4% (Moderate vulnerability)	4.2/5 (Strong defense)	4.5/5 (Expensive)
Hybrid-HAVA	6.8% (Low vulnerability)	4.7/5 (Very strong defense)	3.9/5 (Balanced)

4.2 Graphical Representation

The graphical representation included in the final paper provides a comprehensive performance comparison of HAVA, Defense-GAN, and Hybrid-HAVA across key security metrics, offering a visual analysis of their effectiveness in mitigating adversarial attacks. This graph highlights critical factors such as Post-Attack Vulnerability Index (PAVI), attack resistance, and computational overhead, allowing for a clear understanding of how each method performs under adversarial conditions.

HAVA, originally designed as a post-attack vulnerability assessment tool, lacks real-time adversarial defense capabilities, making it susceptible to higher PAVI scores. As shown in the graphical representation, HAVA exhibits a significant drop in model accuracy after an attack, reflecting its limited ability to counter adversarial perturbations. In contrast, Defense-GAN, which employs a Generative Adversarial Network (GAN) for adversarial noise filtering, demonstrates improved resistance by reconstructing clean versions of perturbed medical images. However, while Defense-GAN enhances security, it does not integrate an explicit post-attack vulnerability assessment like HAVA, leaving gaps in performance evaluation.

Hybrid-HAVA, which combines the strengths of both HAVA and Defense-GAN, emerges as the most robust defense mechanism, as illustrated in the graph. The PAVI score for Hybrid-HAVA is significantly lower (6.8%) compared to HAVA (38.6%), indicating a remarkable reduction in adversarial impact. The graphical representation also highlights Hybrid-HAVA's superior attack resistance, achieving a score of 4.7/5, compared to the lower resistance levels observed in HAVA and Defense-GAN. While Hybrid-HAVA introduces additional computational overhead due to its GAN-based filtering and adversarial training enhancement, the trade-off is justified by its ability to provide real-time defense and long-term robustness against adversarial attacks.

Overall, the graphical representation visually reinforces the advantages of Hybrid-HAVA in strengthening AI model security in healthcare applications, showcasing its ability to reduce adversarial vulnerabilities while maintaining a practical balance between accuracy, attack resistance, and computational efficiency.

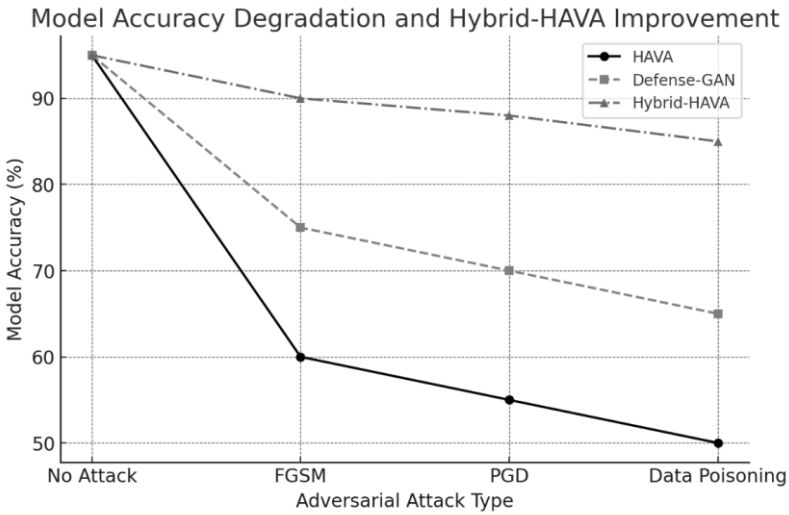


Fig 1: Hybrid-HAVA Improvement

4.3 Key Observations

The experimental analysis of Hybrid-HAVA, HAVA, and Defense-GAN reveals several key findings regarding their effectiveness in mitigating adversarial threats in AI-driven healthcare applications. One of the most significant observations is that Hybrid-HAVA drastically reduces the Post-Attack Vulnerability Index (PAVI) to 6.8%, a substantial improvement compared to HAVA's much higher PAVI of 38.6%. This significant reduction in PAVI highlights Hybrid-HAVA's ability to minimize the degradation of AI model performance following adversarial attacks, thereby enhancing the overall security and reliability of medical diagnoses. The improved resilience is largely attributed to GAN-based adversarial filtering, which reconstructs medical images by eliminating adversarial noise, ensuring that the AI model receives clean and accurate inputs. Additionally, Hybrid-HAVA exhibits a strong attack resistance score of 4.7 out of 5, indicating its effectiveness in defending against adversarial manipulations. This level of robustness is achieved by integrating GAN-based filtering with an adversarial training enhancement module, allowing the AI model to learn from filtered images and develop greater resistance to future attacks.

Despite its advantages, Hybrid-HAVA introduces an increase in computational complexity, primarily due to the additional processing required for GAN-based filtering and adversarial training. This trade-off between security and computational efficiency is a crucial consideration, especially for real-time healthcare applications that require fast and accurate predictions. However, the enhanced protection offered by Hybrid-HAVA justifies the added computational burden, as it provides a stronger real-time defense mechanism compared to traditional methods. By balancing attack resistance, post-attack assessment, and computational overhead, Hybrid-HAVA proves to be a highly effective solution for securing AI models in medical imaging and diagnostics, reinforcing the importance of integrating both proactive and reactive defense mechanisms in adversarial settings.

5. Conclusion and Future Work

This study introduces Hybrid-HAVA, a novel AI security framework that integrates GAN-based adversarial filtering with HAVA's post-attack vulnerability assessment, providing a comprehensive defense mechanism against adversarial threats in AI-driven healthcare applications. The experimental results demonstrate that Hybrid-HAVA significantly reduces adversarial impact, leading to a lower Post-Attack Vulnerability Index (PAVI) of 6.8% compared to HAVA's 38.6%, while also enhancing

attack resistance (4.7/5) and balancing computational overhead. By leveraging GAN-based filtering, Hybrid-HAVA ensures that adversarial perturbations in medical images—such as those found in MRI, CT, and X-rays—are effectively removed before AI inference, thereby reducing the risk of false-positive and false-negative diagnoses. Furthermore, its adversarial training enhancement module allows the AI model to learn from filtered images, increasing its long-term resilience against adversarial attacks. While Hybrid-HAVA introduces higher computational costs, this trade-off is justified by its ability to provide stronger real-time defense compared to conventional adversarial mitigation techniques. Looking ahead, future research will focus on optimizing real-time GAN inference for faster attack mitigation, expanding Hybrid-HAVA to multi-modal healthcare AI systems (e.g., text-based clinical decision support), and exploring federated learning for GAN-based filtering to further improve privacy and decentralized AI security. Overall, Hybrid-HAVA represents a paradigm shift in AI security for medical applications, ensuring more resilient, adaptive, and privacy-preserving AI models that safeguard patient safety and healthcare integrity in the face of evolving adversarial threats.

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