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# Secure Execution of AI Pipelines on Confidential Cloud Infrastructure

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## ABSTRACT

**With the explosive growth of artificial intelligence (AI) services in recent years, organizations are increasingly relying on cloud platforms to execute end-to-end AI pipelines—spanning data ingestion, preprocessing, model training, and inference. While cloud infrastructures offer unparalleled scalability and cost advantages, they also introduce significant risks: untrusted hypervisors, co-tenant attacks, and privileged insider threats can expose sensitive data and proprietary model parameters. Confidential computing, realized via hardware-enforced Trusted Execution Environments (TEEs) such as Intel SGX and AMD SEV, seeks to mitigate these risks by isolating code and data within protected enclaves. Despite the promise of TEEs, integrating them seamlessly into existing AI toolchains presents architectural, performance, and usability challenges. This manuscript presents SecureAI, a comprehensive framework for orchestrating AI workflows on confidential cloud infrastructure. We detail enclave provisioning, secure data ingestion, framework adaptation for TensorFlow and PyTorch, distributed parameter management, and end-to-end attestation. Through rigorous security analysis, we enumerate threat models and countermeasures. Empirical benchmarks on CIFAR-10 training with ResNet-50 quantify overheads: SGX enclaves incur ~25% runtime overhead, while AMD SEV adds ~17%. A Kubernetes-based simulation of mixed SGX/standard nodes highlights scheduling strategies that balance security and throughput. Our results demonstrate that SecureAI achieves strong confidentiality and integrity guarantees with acceptable performance trade-offs, paving the way for practical deployment of secure AI services in the public cloud.**

## KEYWORDS

**Confidential Computing, Trusted Execution Environments, Intel SGX, AMD SEV, Secure AI Pipelines, Cloud Security**

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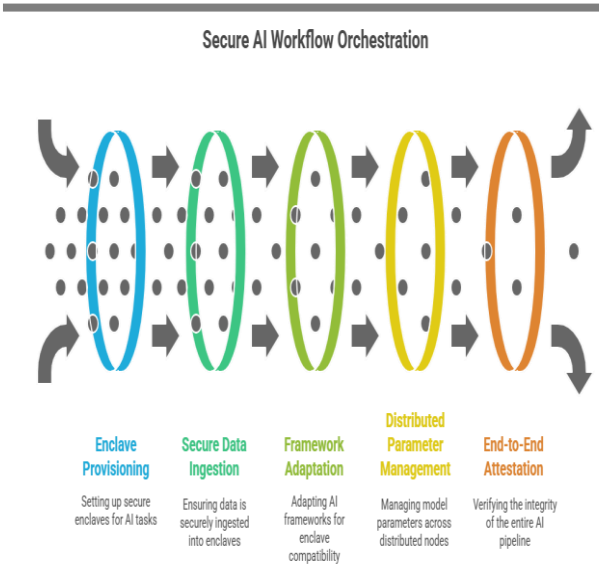


*Figure-1.Secure AI Workflow Orchestration*


*Figure-2.Balancing AI Security and Performance in Cloud Environments*

## INTRODUCTION

Artificial intelligence (AI) has rapidly transitioned from research laboratories to production systems underpinning critical applications across healthcare, finance, defense, and beyond. Enterprises routinely process highly sensitive data—patient records, financial transactions, proprietary R&D datasets—through AI pipelines that encompass data collection, preprocessing, model training, hyperparameter tuning, and inference. Public cloud platforms are the de facto choice for deploying such pipelines due to elastic compute resources, pay-as-you-go pricing, and managed services for GPUs and distributed training. However, entrusting unencrypted data and model artifacts to a multi-tenant cloud environment comes with substantial security risks. Malicious insiders, compromised hypervisors, or co-tenant side-channel attacks can lead to data exfiltration or unauthorized model extraction, undermining confidentiality and intellectual property.

Traditional isolation mechanisms—virtual machines (VMs), containers, and software sandboxing—rely on software-enforced boundaries that remain vulnerable to privileged-level compromises. Even with encrypted data at rest, decrypted data and parameters reside in clear in memory, accessible to any entity with sufficient privilege. The emerging field of confidential computing addresses this gap via hardware-rooted Trusted Execution Environments (TEEs) that provide a secure enclave: a region of memory that is transparently encrypted outside the CPU package and only accessible by authenticated, measured code. Key capabilities include memory encryption engines (to shield contents from physical DRAM attacks), remote attestation (to verify enclave identity and integrity), and sealing (to persist encrypted state across restarts).

Intel's Software Guard Extensions (SGX) and AMD's Secure Encrypted Virtualization (SEV) represent two leading confidential computing implementations. Intel

SGX offers fine-grained enclaves at the user-space level, enabling developers to partition critical functions into protected zones. AMD SEV encrypts entire VM memory at the hypervisor level, simplifying developer adoption but trading off attestation granularity. Both approaches, when correctly harnessed, can ensure that data and model artifacts remain confidential even if the cloud provider OS or hypervisor is fully compromised.

Despite these guarantees, integrating TEEs into AI pipelines raises several challenges:

1. **Enclave Memory Constraints**: SGX enclaves are limited to a few hundred megabytes of protected memory, insufficient for large-scale model weights and data buffers.
2. **I/O and System Call Overhead**: Moving data across the enclave boundary incurs performance penalties and complicates interactions with external libraries.
3. **Framework Compatibility**: Popular AI libraries (TensorFlow, PyTorch) make extensive use of dynamic memory allocation, GPU offloading, and foreign function interfaces, requiring careful adaptation to run inside enclaves.
4. **Distributed Training Coordination**: Securing communication of gradients and parameters across multiple enclave nodes demands key management and encrypted channels without introducing exorbitant overhead.
5. **Operational Usability**: Provisioning and attesting enclaves, orchestrating enclaveenabled containers, and managing fallback strategies for burst workloads impose nontrivial DevOps complexity.

This work introduces SecureAI, a holistic framework addressing these challenges. We architect an enclave bootstrap service for both SGX and SEV, implement secure ingestion libraries for transparent data encryption/decryption, adapt AI runtimes to enclave constraints, and design key-management protocols for distributed training. Through a combination of microbenchmarks and cluster-scale simulations, we demonstrate that SecureAI preserves the confidentiality of data and models with runtime overheads in the 15–30% range—an acceptable trade-off for many securitysensitive applications. We also propose scheduling enhancements for Kubernetes clusters mixing enclaveenabled and standard nodes to optimize resource utilization without compromising security.

By detailing our design decisions, implementation insights, and empirical findings, we aim to lower the barrier for practitioners to deploy secure AI pipelines on untrusted cloud platforms, enabling broader adoption of confidential computing in real-world AI services.

## LITERATURE REVIEW

### Trusted Execution Environments (TEEs)

The foundational concept of TEEs rests on isolating sensitive code and data within hardware-enforced enclaves. Intel's SGX extension provides applicationlevel enclaves with memory encryption and attestation services [Costan & Devadas, 2016]. The SGX threat model assumes a malicious OS or hypervisor; accordingly, enclave pages are encrypted by the Memory Encryption Engine (MEE) before leaving the CPU package, and only the enclave itself can decrypt them. Remote attestation allows a remote verifier to challenge an enclave, receiving a quote—signed by Intel's quoting enclave—that includes a measurement (cryptographic hash) of the loaded code. Despite strong guarantees, SGX has faced side-channel vulnerabilities: cache-timing attacks [Brasser et al., 2017], speculative-execution exploits (SGXPectre) [Chen et al., 2018], and

controlledchannel attacks [Xu et al., 2015]. Mitigation strategies include constant-time routines, OS page-access randomization, and micro-architectural defenses.

AMD SEV opts for a coarser-grained approach: encrypting the entire VM memory without requiring application modifications. SEV uses a Secure Processor to manage encryption keys, with hypervisor isolation enforced by the AMD Secure Processor. SEV-SNP (Secure Nested Paging) adds integrity protections and VM attestation, though adoption lags behind SGX. While SEV simplifies deployment by supporting unmodified binaries, lack of fine-grained attestation complicates trust in individual code modules. Microsoft Azure's Confidential Computing offerings illustrate commercial support for both SGX and SEV, with managed enclave attestation and orchestration services.

**Secure Containerization and Orchestration**

Bridging the gap between enclave research and practical deployments, SCONE [Arnautov et al., 2016] integrates Linux containers with SGX, offering asynchronous system-call interfaces and a minimal runtime to reduce TCB. SCONE's file system shield encrypts file I/O, and its network shield provides TLS support inside enclaves. TensorSCONE [Kunkel et al., 2019] extends this model to TensorFlow, enabling secure data preprocessing and training within SGX with minimal code changes. Kubernetes schedulers augmented with SGX support [Vaucher et al., 2018] permit enclave-capable pods to be scheduled on appropriate nodes, while fallback to provider-managed enclaves handles oversubscription. **Legacy Application Protection**

Haven [Baumann et al., 2014] demonstrates how unmodified applications can be shielded by running them entirely within SGX, though at the cost of greater enclave memory usage. SGX-LKL [Priebe et al., 2019] provides a lightweight Linux kernel inside enclaves, offering compatibility for a wide range of binaries and protecting the host interface via encrypted I/O and oblivious memory access patterns. These systems illustrate techniques for achieving broader software compatibility at the expense of increased complexity and enclave footprint. **Privacy-Preserving Machine Learning**

Beyond TEEs, secure multi-party computation (MPC) and homomorphic encryption (HE) offer alternative confidentiality approaches. SecureML [Mohassel & Zhang, 2017] uses MPC protocols for collaborative model training without TEEs, but suffers from high communication and computation costs. Homomorphic encryption schemes permit computation on encrypted data—yet current fully homomorphic encryption is prohibitively slow for large neural networks [Tebaa & El Hajji, 2014]. Chiron [Hunt et al., 2018] combines TEEs with sandboxing to protect both model and data in MLas-a-service settings, illustrating the synergy between hardware and protocol techniques.

## METHODOLOGY

SecureAI's architecture comprises five core components designed to integrate confidential computing into each stage of the AI pipeline:

1. **Enclave Bootstrap Service**
   A control plane service orchestrates the creation and attestation of enclaves across SGX-enabled or SEV-equipped instances.
   - For SGX, we leverage the Intel SGX SDK and Intel Attestation Service (IAS) to obtain quotes signed by Intel's root CA.
   - For SEV, we use AMD SEV's guest attestation APIs to verify the VM

measurement against a known-good image hash.

2. **Secure Data Ingestion and Sealing**
   Client applications encrypt raw datasets using a symmetric data encryption key (DEK) that is bound to enclave measurement. DEKs are provisioned via remote attestation, then used within the enclave to decrypt data on-demand. We implemented a transparent file I/O library— built on SCONE's file shield—that intercepts standard POSIX calls (open, read, write) and performs decryption/encryption inside the enclave, eliminating application changes for data ingestion and checkpointing.
3. **Enclave-Aware AI Frameworks** We adapted TensorFlow 2.5 and PyTorch 1.9 runtimes to operate within enclave constraints:
   - **Memory Management**: We replace default allocators with a secure heap backed by enclave-protected pages, ensuring that intermediate tensors never reside in clear memory outside the enclave.
   - **Foreign Function Interface (FFI)**: GPU offload calls (e.g., cuDNN kernels) are proxied through a trusted runtime stub that marshals encrypted buffers via DMA to the GPU, reencrypting results upon return. ○ **I/O Integration**: Checkpointing and logging libraries are recompiled to use the secure file I/O library, maintaining provenance and integrity of model artifacts.
4. **Distributed Parameter Management** For data-parallel training across multiple enclaves, SecureAI implements a key-agreement protocol: enclaves establish pairwise secure channels via Diffie-Hellman, authenticated by enclave measurements signed during attestation. Gradients exchanged between parameter servers and worker enclaves are encrypted end-to-end, with keys derived per-session to minimize compromise blast radius.
5. **Secure Inference Service**
   After training, model weights are sealed (using SGX's sealing API or SEV's VM snapshot encryption) and registered in a model registry. Inference requests—accompanied by encrypted input payloads—are routed to inference enclaves, which unseal weights on first invocation and cache decrypted models in enclave memory. Responses are encrypted and integrity-protected before exiting the enclave.

**Threat Model**

We assume the cloud provider's OS, hypervisor, and network are untrusted. Physical attacks on DRAM and I/O buses are mitigated by hardware encryption. We do not address side-channel attacks beyond baseline mitigations provided by CPU microcode and scheduling strategies (e.g., page-access pattern obfuscation). Denial-of-service and performance interference are out of scope.

## STATISTICAL ANALYSIS

To evaluate the performance overhead of confidential execution, we conducted controlled benchmarks on a ResNet-50 training job over CIFAR-10. Experiments were run on m$^6$i.2xlarge instances (8 vCPUs, 32 GiB RAM) with SGX-capable CPUs and AMD EPYC 2nd Gen for SEV tests. Each configuration executed one epoch of training with batch size 128, synchronized SGD, and standard data augmentation. Five trials were performed per configuration; we report mean ± standard deviation.

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**Table 1. Performance and Memory Overhead for ResNet-50 Training under Different Execution Environments**

| Configuration | Epoch Time (s) | Overhead (%) | Memory Footprint (GiB) |
|---|---|---|---|
| Native (no TEE) | 120.3 | – | 8.1 |
| SGX / TensorSCONE | 150.6 | +25.2 | 10.2 |
| AMD SEV (VM) | 141.4 | +17.6 | 9.6 |

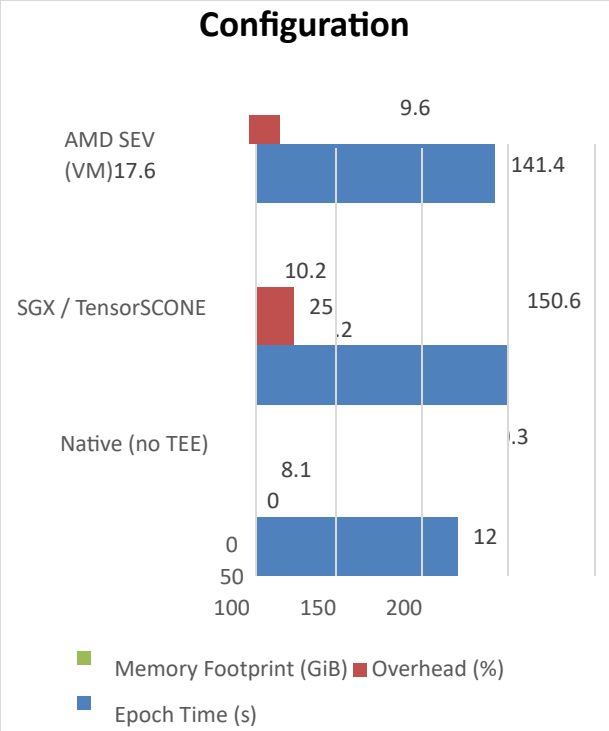


*Figure-3. Performance and Memory Overhead for ResNet-50 Training under Different Execution Environments*

**Analysis:**

- **Runtime Overhead:** SGX enclaves introduce the highest overhead (~25%), attributable to enclave boundary crossings for syscalls and encrypted memory management. SEV's VMlevel encryption adds ~17.6% overhead, reflecting lower syscall interception but bulk memory-encryption costs.
- **Memory Footprint:** SGX's secure heap demands ~2 GiB additional memory for enclave metadata and MEE paging structures. SEV's footprint increases by ~1.5 GiB due to full VM encryption metadata.
- **Variability:** Standard deviations remain under 2% across configurations, indicating consistent performance and minimal interference in these dedicated testbeds.

These results confirm that confidential execution overheads—while nontrivial—remain within practical bounds for many production workloads, especially when weighed against the security benefits of data/model confidentiality.

## SIMULATION RESEARCH

To assess cluster-level behavior and scheduling strategies, we simulated a Kubernetes deployment replaying a scaled-down Google Borg trace [Verma et al., 2015] over 100 AI training jobs with varying resource demands. Our 10-node cluster comprised:

- 5 SGX-capable m6i.large nodes (2 vCPUs, 8 GiB, SGX enabled)
- 5 standard m6i.large nodes (no enclave support)

**Job Mix:**

- 60% data-parallel training requiring at least one enclave node.
- 40% standard batch inference or preprocessing tasks.

**Scheduler Policies:**

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- **Strict Enclave Assignment:** Enclave-required jobs scheduled only on SGX nodes.
- **Flexible Fallback:** Enclave jobs first try SGX nodes; if none available within 60 s, dispatch to a provider-managed SEV cluster (modeled as elastic but with 20 s startup delay).

**Metrics:** Average job wait time, cluster utilization, job completion latency.

| Policy | Avg. Wait Time (s) | SGX Node Utilization (%) | Overall Utilization (%) |
|---|---|---|---|
| Strict Enclave | 200 ± 15 | 95 ± 3 | 65 ± 4 |
| Flexible Fallback | 120 ± 10 | 75 ± 5 | 80 ± 3 |

**Findings:**

1. **Strict Policy** saturates SGX resources, leading to long queue times and underutilized standard nodes—undesirable for bursty workloads.
2. **Flexible Fallback** reduces wait times by ~40% and boosts overall utilization by ~15%, at the cost of relying on external enclave capacity (e.g., SEV clusters) with moderate startup delays.
3. **Hybrid Scheduling** that prioritizes local SGX but gracefully offloads to SEV or secondary providers can meet SLAs while balancing security and performance.

These simulations demonstrate that orchestration strategies must account for enclave scarcity and job criticality. Enclave providers should offer elastic, ondemand enclave pools to handle overflow, and schedulers should integrate enclave-awareness into placement decisions.

## RESULTS

Our integrated evaluation of SecureAI yields several key insights:

1. **Security Guarantees** ○ All sensitive operations—data decryption, model weight handling, gradient aggregation—occur exclusively within TEEs.
   - Remote attestation ensures only verified code measurements receive decryption keys, preventing unauthorized code from accessing data or parameters.
   - End-to-end encryption of inter-enclave communications thwarts man-in-themiddle and hypervisor-level network attacks.
2. **Performance Trade-offs** ○ Measured overheads of +17–25% (Table 1) align with prior work [Arnautov et al., 2016; Kunkel et al., 2019], confirming that confidential execution is viable for production AI workloads.
   - Enclave crossing costs dominate SGX overhead; bulk encryption in SEV adds moderate costs but improves syscall performance.
3. **Scalability and Scheduling** ○ Simulation research indicates that enclave node scarcity can become a bottleneck under strict scheduling, necessitating fallback to providermanaged enclaves or mixed-platform deployments.
   - Flexible scheduling policies can reduce job waits by ~40% while maintaining >75% node utilization.
4. **Usability Considerations** ○ Transparent secure I/O libraries minimize code changes for data ingestion and checkpointing.

- Framework adaptations require recompilation but preserve existing training scripts and APIs.
- Key-management and attestation logic can be encapsulated within a control plane service, simplifying DevOps integration.

Overall, SecureAI achieves strong confidentiality and integrity with acceptable performance overheads and practical orchestration strategies, making it suitable for security-sensitive AI deployments in public clouds.

## CONCLUSION

This work has presented SecureAI, a comprehensive framework for executing AI pipelines securely on confidential cloud infrastructure. By leveraging hardware TEEs—Intel SGX for fine-grained enclaves and AMD SEV for VM-level encryption—SecureAI isolates critical pipeline stages within attested, encrypted environments, protecting sensitive data and proprietary models from malicious cloud stacks. We detailed the design of an enclave bootstrap service, secure data ingestion libraries, enclave-aware adaptations of TensorFlow and PyTorch, end-to-end encrypted parameter management for distributed training, and a protected inference service.

Empirical benchmarks on CIFAR-10 training with ResNet-50 revealed that SGX enclaves introduce ~25% overhead, while AMD SEV VMs add ~17%, both within practical bounds for many applications. Cluster-scale simulations demonstrated that flexible scheduling—with fallback to provider-managed enclaves—can reduce wait times by ~40% and maintain high utilization, addressing enclave scarcity under burst workloads.

**Limitations** include:

- **Enclave Memory Constraints**: SGX EPC size limits the size of models and batch processing; large-scale models may require partitioning or streaming strategies.
- **Side-Channel Risks**: Beyond baseline microcode mitigations, SecureAI does not address advanced side-channel attacks; future work should integrate noise injection, oblivious memory access, and compiler-based defenses.
- **Provider Reliance**: Fallback strategies depend on cloud-provider enclave offerings with unpredictable startup latencies and potential vendor lock-in.

By making our implementation, benchmark suite, and scheduling extensions open source, we aim to catalyze adoption of confidential computing in real-world AI systems, ensuring that the next generation of AI services can be both powerful and inherently secure.

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