Golden Grain: Building a Secure and Decentralized Model Marketplace for MLaaS

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Abstract—ML-as-a-service (MLaaS) becomes increasingly popular and revolutionizes the lives of people. A natural requirement for MLaaS is, however, to provide highly accurate prediction services. To achieve this, current MLaaS systems integrate and combine multiple well-trained models in their services. However, in reality, there is no easy way for MLaaS providers, especially for startups, to collect well-trained models from individual developers, due to the lack of incentives. In this paper, we aim to fill this gap by building a model marketplace, called as Golden Grain, to facilitate model sharing, which enforces the fair model-money swaps between individual developers and MLaaS providers. Specifically, we deploy the swapping process on the blockchain, and further introduce a blockchain-empowered model benchmarking design for transparently determining the model prices according to their authentic performances so as to incentivize the faithful contributions of well-trained models. Especially, to ease the blockchain overhead for benchmarking, our marketplace carefully offloads the heavy computation and crafts a trusted execution environment (TEE) based secure off-chain on-chain interaction protocol, ensuring both the integrity and authenticity of benchmarking. We implement a prototype of our Golden Grain on the Ethereum blockchain, and extensive experiments with standard benchmark datasets demonstrate the practically affordable performance of our design.

Index Terms—ML-as-a-service, Blockchain, Marketplace, Trusted execution environment.

1 INTRODUCTION

The era of big data has witnessed a rapid growth of machine learning (ML) systems and algorithms that fundamentally revolutionize the lives of people, such as face recognition [1], automated vehicles [2] and disease diagnosis [3], [4]. Among others, one important improvement for ML is ML-as-a-service (MLaaS) [5], leaded by giants, e.g., Google [6], Amazon [7] and Microsoft [8] and supported by growing startup companies [9]. MLaaS makes ML practical for everyone by easing users’ need for training ML models before they can enjoy ML services. But while MLaaS greatly facilitates users, it brings very critical requirements for MLaaS providers. For example, it is natural to ensure that the predictions given from the service should be as accurate as possible [10], [11], [12]. Toward this goal, recently several improved prediction serving systems like Clipper [10] and PRETZEL [11] are proposed, which integrate and merge predictions from multiple models, compared with TensorFlow Serving [12], improving the prediction accuracy and robustness.

Despite being very promising, they usually assume that the trained models used for accurate prediction serving are collected as a prior and that they are well-trained (i.e., they have good model accuracy). However, in reality an MLaaS provider, especially a startup company, faces a lot of challenges to securely collect well-trained models. Firstly, a few of large companies, such as Google and Amazon, might be reluctant to release their models which are trained on sensitive user data, due to protection laws [13]. Individual developers (or model owners) also may be unwilling to publicly share their trained models, since trained models contain the private personal information about the training data [14], [15], [16]. Secondly, many MLaaS startups have no access to an experienced and qualified data science team [17]. Even when they can hire individual developers, there may lack an effective mechanism for motivating developers to train really good models, so that model qualities can be varying in practice, e.g., when meeting shifted data or adversarial examples [18], [19].

On the other hand, we are aware that existing data marketplaces, such as Sterling [20] and OpenMined [21], have paved the way for training models on shared data, eliminating the obstacle of obtaining available training data. However, there still lacks a connection between trained models and realizing robust predictions for MLaaS due to the lack of incentives. Therefore, the above issues inspire this work: We build a model marketplace to bridge model owners and MLaaS startups, which leverages incentives to facilitate model sharing and motivate well-trained models, and in the meantime, fully respects the model privacy.

1 We call it as Golden Grain, since Golden Grain is regarded as a key concept used to describe a world where all participants (referred to model owners and MLaaS providers, here) are fully responsible for what they should do, learnt from “The Little Prince”.

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Building such a model marketplace, however, is a non-trivial task. To start with, it is easily understood that fairness between the model seller and the model buyer (i.e., the MLaaS provider) should be enforced \[22, 23\]. That is, a seller should reveal nothing about its model unless someone pays to purchase the model, and meanwhile, the buyer should indeed obtain the model he is interested in once the money is spent. Usually, fulfilling such a fair swapping process would require a trusted third party (TTP) to enforce the process and avoid disputes \[24\]. But the use of TTP apparently makes our marketplace hard to be deployed in real practice, and it would also bring several disadvantages, e.g., the lack of process transparency and the concern of denial-of-service (DoS) attacks \[25, 26\]. To enable a fair and secure marketplace without a TTP, blockchain is a widely adopted choice for its transparency and enforces execution correctness \[27, 28, 29\].

Besides, we also need a secure mechanism to incentivize the model sellers to provide well-trained models on the marketplace, so how to craft a satisfactory solution? Particularly, we have to address the following two challenging problems.

**Challenge 1: Correct and Privacy-Preserving Model Benchmarking.** To incentivize the sellers to provide well-trained models on the marketplace for sell, a natural idea is to determine the model price in proportion to the authentic model performance; model performance is measured via benchmarking on unrevealed datasets, by following a consensus in ML practice \[18, 19\]. By this way, sellers might be motivated to provide better models for earning more money \[30\]. At a first glance, considering a malicious seller, it might appear that we can readily put his/her model on-chain, and run the benchmarking process through crafting smart contracts to correctly record the result performance and determine its price in later monetization. However, as the model might be large, readily storing it on-chain would incur unaffordable costs. Besides, putting the model on-chain would also compromise model privacy, since the blockchain is publicly accessible.

**Challenge 2: Authenticated Benchmark Dataset Relaying.** For guaranteeing the correctness of benchmarking, we also need an unbiased benchmark dataset for correctly calculating each model’s performance. This is, however, challenging because although there are reputable benchmark datasets, e.g., provided by authorized organizations \[18, 19, 31\], they are stored outside the blockchain. Requested external benchmark datasets might be tampered before being written on the blockchain and used to evaluate models. An efficient and authenticated mechanism for relaying those requested data without bias for benchmarking is desired.

Our Result. To address the two challenges above, our design follows a widely adopted off-chain processing approach and further resorts to trusted execution environments (TEEs) to complete a correct model benchmarking process. Specifically, the correctness of the model benchmarking is two-fold. First, the benchmarking process is executed with integrity guarantees. A seller is required to first commit to his model into the locally equipped TEE before receiving the benchmark samples, which prevents the seller from forging a fake model during the execution or providing an unauthentic benchmarked result. Second, the model is benchmarked on the unbiased benchmark samples which are authentically relayed. Following a trend practice \[32\], in our case, the ready-made TEE-based infrastructure residing on the seller can help relay the required samples and record their digests on the blockchain, realizing the end-to-end authenticated samples relaying for benchmarking. Notably, our solution using TEEs can be more performant, compared with using privacy-preserving verifiable cryptography \[33\].

With the authentic result performance of a model, our marketplace transparently decides the model price on smart contracts. Additionally, our pricing mechanism simultaneously maximizes the revenue of sellers and the utility of buyers, in order to maintain the long-term running of the model marketplace. Finally, the model performance and price are correctly recorded on the blockchain. After the model benchmarking stage, a buyer can choose a model according to the recorded information (i.e., model information, model performance and model price) on the blockchain and trade with the model seller.

For building such a secure and fair model marketplace, Golden Grain, we use smart contracts to enforce a fair model-money swapping process, and meanwhile, we combine the TEEs with secure commitments to guarantee that the buyer gets the correct model which matches the recorded information on the blockchain.

By using the widely adopted Universal Composability (UC) security model, we design two on-chain off-chain interaction protocols to achieve the correct model benchmarking process and the fair model-money swapping process, during the model benchmarking stage and model monetization stage, respectively. To be specific, we adopt the UC-based security definitions for smart contract which are formalized by Hawk \[27\] and the definitions for transparent TEEs which are formalized in the SGP protocol \[28\]. Besides, we prove that our defined protocols ensure two desirable security properties including the correctness of model benchmarking and the fairness of model exchanging under the UC security framework.

In conclusion, the main contributions of our work are as follows:

- We build a secure and decentralized model marketplace to facilitate the model sharing via achieving the fair model-money swapping process, where the seller obtains the money iff the buyer can correctly and timely get the authentic model of his interest.
- We design a blockchain-empowered model benchmarking stage, where model performances are correctly evaluated on authenticated test datasets, and model prices are determined based on the authentic model performances, through which our marketplace motivates the faithful contributions of well-trained models.
- We implement a prototype of our marketplace design on the Ethereum blockchain, and the extensive experiments with three standard datasets demonstrate the practically affordable performance of our design.

2 RELATED WORK

**Decentralized Data Marketplace for Machine Learning.** Decentralized data marketplaces which help connect participants to contribute reliable data for machine learning
Involves two phases, TEEs-Based Model Evaluation, and enabling the fair monetization through the blockchain.

Service in MLaaS systems, motivating good-quality models in the machine learning community, we consider that they focus on collecting high-quality data for training models and lack connections to realize a robust prediction service in current MLaaS systems. Different from them, we focus on filling this important gap by building a decentralized model marketplace towards robust prediction behaviors [22], [36]. Although decentralized data marketplaces shed lights on how to overcome the dilemma of data scarcity and quality in the machine learning community, we consider that they focus on collecting high-quality data for training models and lack connections to realize a robust prediction service in current MLaaS systems. Different from them, we focus on filling this important gap by building a decentralized model marketplace towards robust prediction service in MLaaS systems, motivating good-quality models and enabling the fair monetization through the blockchain.

**TEE-Based Model Evaluation.** An ML pipeline generally involves two phases, i.e., model training and model evaluation, and a prediction serving system mainly focuses on the latter phase. For model privacy and integrity, model evaluation can be run by employing TEEs, e.g., Intel’s Software Guard Extensions (SGX) [37]. Recently, there exists a series of work on running the phase of model evaluation inside the TEEs. Slalom [38] for improving efficiency, does not run the entire phase of model evaluation inside the TEE which is only supported by CPUs. Instead, it executes a few of non-linear computation inside a TEE and delegates all linear computation to a co-located GPU processor combing with secure primitives. By adopting this method, it achieves more efficient evaluation, compared to the case of solely running in the TEE. In our case, we consider that the setting of TEEs coexisted with GPUs may bring constraints to sellers entering the marketplace. PRIVADO [39] particularly considers access pattern based attacks on the TEEs and leverage the oblivious constructs tool to transform any deep learning model to have data-independent access patterns, eliminating the data leakage inside the TEEs. In this work, the benchmark samples are non-private during the benchmarking stage, and thus access pattern attacks on TEEs need not be considered. Different from the aforementioned two works only focusing on the model evaluation, Chiron [40] runs both phases of model training and model evaluation. It builds a system using TEEs and Ryaan sandbox to protect data privacy and model privacy, but it has a larger Trusted Computing Base (TCB), compared to the mentioned two works. In our work, we pay the main attention to secure model evaluation by resorting to the TEEs.

### 3 Preliminaries

Here we are ready to introduce the used cryptographic primitives, smart contracts and TEEs which are employed in our design. Note that we make black-box use of the cryptographic primitives and assume that they are secure.

#### 3.1 Cryptographic Primitives

**Commitment Schemes.** A commitment scheme is generally denoted as \( \text{COM} = (\text{Setup}, \text{Commit}, \text{Opening}) \). Specifically, Setup is used to generate public parameters \( \text{pub} \). Commit takes the public parameters \( \text{pub} \), a message \( \text{msg} \) and random coins \( r \) as inputs and outputs a commitment to the message, formally denoted as \( \text{com} \leftarrow \text{Commit}(\text{pub}, \text{msg}, r) \). Opening is used to re-compute the commitment by using the same message \( \text{msg}' \) and the unveiled random coins \( r' \), and \( (\text{com}, \text{msg}, r) \) is valid if \( \text{com} = \text{Commit}(\text{pub}, \text{msg}', r') \).

**Zero-Knowledge Proofs.** A zero-knowledge proof protocol for a statement enables a potentially malicious prover to convince a honest verifier that the statement is valid without revealing any other information. This paper resorts to trusted hardware based proofs [28] to realize zero-knowledge proofs of knowledge.

#### 3.2 Smart Contracts

Smart contracts are Turing-complete programs which are automatically executed on the blockchain. One of the most popular systems implementing smart contracts is Ethereum. Ethereum users can write and deploy smart contracts for performing designated business logic, defined as a sequence of entry points. Deployed smart contracts with the entry points will be invoked by messages (i.e., transactions) sent from other contracts or non-contract users. Once smart contracts are deployed on the Ethereum, no one can modify it.

Generally, blockchain endows smart contracts with the integrity property, but smart contracts also inherit the transparency of blockchain. On one hand, smart contracts running on the blockchain ensures the integrity of the program execution, and thus enforces trust among distrustful parties. On the other hand, data stored on the smart contracts are public without confidentiality guarantees. Aim to overcome the undesirable property, a few smart contract systems [27], [41], [42] propose privacy-preserving smart contracts.

On Ethereum, the execution of each smart contract (and each transaction) associates with Gas (i.e., money) costs. Gas consumption of a smart contract depends on the computation steps and storage space this smart contract requires. Therefore, the successful execution of a smart contract needs amount of available Gas, since Gas limitation will restrict its execution. Besides, the Gas cost can bound the computation steps of a smart contract, thereby preventing DoS attacks. For example, a smart contract creator defines an infinite looping with the intention to waste the computation and storage resources within the system.

#### 3.3 Software Guard Extensions (SGX)

We use Intel's SGX [43] as a TEE, following the wide adoption [37], [38], [39], [40]. SGX provides the extended CPU instruction set to initialize a secure address space, so-called enclave. Applications executed in an enclave against eavesdropping and tampering from the outside world. More precisely, the enclave is isolated from the operating system, hypervisor, and even other enclaves created in the same host.

SGX supports remote attestation mechanism which enables (1) proving to a remote client the correctness of an enclave, and (2) creating an encrypted and authenticated communication channel between the enclave and the remote client. In addition to the identity of the created enclave, the remote client can verify that the enclave is not tampered.
with and the enclave is running on a genuine platform. Concretely, the enclave signs the contents by using a group signature scheme and generates a proof known as attestation. The attestation then can be verified by the remote client by resorting to Intel Attestation Service (IAS).

However, Intel's SGX is susceptible to well-known side-channel attacks [44], [45] and rollback attacks [46], which can destroy its properties of confidentiality and integrity. In this paper, we are fully aware of the two kinds of attacks and our concerns can be seen in Section 4.2.

Additionally, Intel's SGX has a restricted 128 MB Processor Reserved Memory (PRM), but it supports paging on Linux enabling a program inside the TEE to use more memory outside PRM while ensuring the confidentiality and integrity via extra symmetric key cryptography. Although the memory limitation is removed by SGX 2.0, SGX 2.0 has not been widely used.

4 Overview

In this section, we present an overview in terms of the system model, threat assumptions and security goals.

4.1 System Model

At a high level, our proposed decentralized marketplace consists of four major entities, i.e., model seller, model buyer, blockchain, and external benchmark datasets shown in Fig. 1. Model seller owns trained models and wants to monetize them, while model buyer is the entity who aims to purchase some trained models pertaining his interests. Meanwhile, they want to achieve such a model-money swap in a decentralized setting, where there is no trusted third party enforcing the whole swapping process.

But without the trusted third party, how to guarantee fairness for the sellers and buyers becomes challenging. First, since the sellers and buyers in our system are individuals that have no enforced regulations, both of them can cheat in the swapping process to maliciously gain extra benefits. Second, for sellers, they also demand a transparent pricing mechanism to avoid destructive price competitions in the marketplace [47].

To address the two requirements above and enable a healthy ecosystem for the marketplace, we construct the swapping process on the blockchain as a starting point, and further use model performance (e.g., accuracy and robustness) as the important factor for deciding the model price. Specifically, before a model can be sold, it is involved in a benchmarking stage where its performance will be evaluated to decide the price used in the later monetization stage. Here, for ensuring the integrity of the benchmarking process, we follow a trending practice [32] to securely relay authenticated benchmark samples inputs from the benchmarking datasets outside the blockchain, and resort to a trusted execution environment (TEE) for its correctness-enforced executions. Both the model and the relayed benchmark samples inputs will be put inside the TEE to execute the benchmarking with integrity guarantee, and finally the benchmarked performances will be anchored on the blockchain to guide later model monetization processes.

After the benchmarking stage, the model is ready to be sold, and buyers can readily browse the marketplace and choose the model of interest. The model monetization stage between a buyer and a seller begins when a buyer deposits money on the blockchain, and finalizes by finishing a fair model-money swap which ensures that the seller gets the money as rewards iff the buyer can later correctly retrieve the model of interest.

4.2 Threat Assumptions

Seller and buyer. We consider that the model seller and the model buyer are malicious, given that they are both loosely regulated. Here, the model sellers might want to forge the benchmark results for selling the model at a higher price, and they might also want to reap the money rewards without delivering the model or just delivering an incorrect model (i.e., which is inconsistent with the benchmarked one) to the buyer. While for the model buyers, they might want to repudiate the payment after obtaining the model that they are intended to purchase.

TEEs. We assume that each seller’s computer is equipped with a TEE, e.g., Intel’s SGX [37], frequently called as “enclave”. But instead of readily assuming the Intel’s SGX as a totally protected environment which perfectly guarantees confidentiality and integrity of the executions, we carefully take into account the recent side-channel attacks [44], [45] and rollback attacks [46]. Specifically, the goal of side-channel attacks is to reveal the secret inputted in the enclave via observing side-channel information during the enclave runtime, e.g., cache timing and power consumptions. We are aware that although many efforts have been devoted to conceal side-channel leakages [48], [49], [50] inside the enclave, they cannot address physical access-based attacks and still lack systematic protections that can perfectly address all side-channel leakages. Therefore, in this paper we follow the TEE security assumption in [28] and consider that the enclave only ensures the confidentiality of the attestation keys rather than sealing keys. In contrast, rollback attacks target damaging the enclave’s execution integrity by replaying old states to the enclave. Here, we consider that a malicious host of the SGX (e.g., the seller) might compromise the benchmark results by initiating rollback attacks.

In addition, we consider that the host may launch multiple enclaves at the same time, but they can be identified via a unique fresh random nonce, and meanwhile, we assume that the probability of two co-existing enclaves with the same nonce is negligible [28].

Benchmark datasets. We assume that the benchmark datasets are correctly constructed and unrevealed to model
sellers before the benchmarking stage. The assumption is following the methodology of work [18], [19], [51], that is, the models to be benchmarked are assumed not trained on the benchmark datasets.

We argue that the assumption is feasible in the real world. For example, our marketplace can make a commercial contract with the designers of the benchmark datasets. More practically, we can connect our marketplace with Kaggle [52], a currently popular data science competition platform. In Kaggle, a task organizer is able to recruit a group of competitors to build ML models and after collecting the competitors’ models, he has ability to reveal a test dataset and uses it to evaluate the competitors’ models. Here, we assume that the task organizer is honest and his/her test dataset can be stored in a system which is authentically accessed, e.g., via an HTTPS-enabled website.

Besides, we assume that a subset of data used to benchmark a model is generated by randomly sampling from the whole benchmark dataset. That means that the subset of data has the representative distribution of the whole benchmark dataset [53].

**Remark.** We additionally assume that the blockchain is trusted for integrity and availability, but not for privacy, following a widely adopted threat model of the blockchain [27].

### 4.3 Security Goals

In this paper, we want to build a secure and decentralized model marketplace that enables correct model benchmarking and fair model monetization through the blockchain. In particular, we have the following three security goals:

- **Model privacy.** The seller’s model is never revealed to anyone other than the buyer who has bought the model.

- **Model correctness.** The model for sell is correctly benchmarked using the external benchmark datasets, and the buyers will obtain the correct model which matches the generated model report on the blockchain.

- **Exchanging fairness.** The buyer should obtain the model once his money is paid to the seller, and the seller should get paid once the model is revealed to the buyer.

### 4.4 Real-world Application Scenario

Consider a real-world application scenario in an ML competition platform, such as Kaggle [52]. Our design can be applied into this real-world application scenario to achieve some desirable security goals.

In the scenario, an competition organizer has both public training set and private test set and solicits multiple model developers for solving his ML task. To start with, the competition organizer can publish an ML task along with a public training set and an unrevealed test set. Then, parties of interest compete for the task by training ML models on the public training set and submit their trained models. Lastly, to choose the best model from the submitted models with varying quality, the organizer can launch a testing process to benchmark the performance of the submitted models by using the test set that those models never see before.

Yet, it might not be easy to conduct the testing process between the competition organizer and participating parties who are mutually distrustful. The reasons are two-fold. Firstly, due to intellectual property issues, participating parties (also called as model owners) might not expect to disclose their trained models to the organizer before being paid, since they spend a lot of efforts, e.g., time and computation, to train their models. Secondly, the organizer needs to conduct a correct testing process so as to obtain the authentic performance of the models and choose the best one. Lastly, the organizer gets the model of his interest iff the model’s owner receives the money paid by the organizer.

In light of the above concerns, the organizer and participating parties can leverage our design involving the benchmarking and monetization stages to achieve two functionalities: correct model testing and fair model-money swapping. In such a setting, the benchmark data sets used in the benchmarking stage are provided by the organizer, which are revealed and authentically accessed in the testing process. Also, the benchmark data sets are trusted by the participating parties for the current ML task. For further enforcing the authenticity, we can require the organizer to commit to his benchmark data sets on the blockchain before publishing his ML task; the corresponding commitments enable checking the consistency of the benchmark data sets when the organizer reveals them during the testing process.

### 5 CONCRETE DESIGN

In this section, we present the detailed designs of the benchmarking stage and the monetization stage. We particularly pay the major attention to the benchmarking stage, since it is a crucial step serving for the monetization stage.

#### 5.1 Benchmarking Stage

**5.1.1 Intuition**

The benchmarking stage aims to correctly benchmark selling models and to transparently decide their prices, by leveraging trusted execution environments and smart contracts, as Fig. 2 demonstrated. At the high-level view, this stage benchmarks each seller’s model inside a TEE residing on the seller’s local host, by using the authentically transmitted test data randomly sampling from the benchmark data outside the blockchain. After benchmarking, each seller’s model is given a price according to the benchmarking performance. The enclave’s remote attestation mechanism enables publicly verifiable proofs of correct benchmarking. Meanwhile, the blockchain plays the role of keeping the
consistency of off-chain and on-chain data as well as states inside the enclave and offering a public interface for future buyers to purchase the benchmarked models they are interested in.

5.1.2 Design Workflow and Concerns

Suppose that a seller possesses a trained model and registers with our marketplace to sell it. The workflow of model benchmarking is as follows: (1) The seller commits to his model as Com_m on the blockchain via publishing a model report. This event of publishing invokes the execution of the Benchmarking Contract (called as BM-Contract hereafter). The BM-Contract reads Com_m from the blockchain. (2) The seller commits to and loads his model in a local TEE. Here, we do not distinguish the role of the seller and the TEE’s host. (3) The BM-Contract requests and in response receives a set of test data (referred to ‘samples’ hereafter) randomly sampling from the benchmark dataset. (4) The seller gets the samples and Com_m from the BM-Contract and relays them into the TEE. The TEE checks whether or not the loading model is indeed the one committed by Com_m before. If the checking result is true, it proceeds to run the model evaluation on the samples; otherwise, it aborts. (5) The TEE returns a proof including the evaluation outputs (i.e., model m’s performance) to the BM-Contract. (6) If the proof is verified to be true, the BM-Contract gives a price based on the evaluation outputs and then publishes the evaluation outputs and price on the blockchain. It is noteworthy that the correctness of benchmarking indicates two-fold: (1) the benchmarking process is correctly executed and returns authentic outputs; (2) the used benchmark data are authentically relayed without bias.

To securely design the above workflow, we have the following three concerns:

(a). How to guarantee that the model loaded in the TEE is the off-chain stored model? Our intuition is to ensure that the model committed inside the TEE is identical to the one committed on the blockchain, and meanwhile, the on-chain commitment to the off-chain model should be authentic. With the guarantees, this concern can be canceled.

(b). How to ensure that the benchmark samples directly imported into the TEE are authenticated while avoiding storing them on chain? This concern is not intuitive in the workflow and comes from the following two practical issues. Firstly, the benchmark samples received by the BM-Contract might not be trustworthy, suppose that the samples can be stored on the contract. Specifically, although the benchmark samples can be from an authenticated source (e.g., an HTTPS-enabled website), smart contract does not support network access and needs a message repeater, causing the lack of an end-to-end authentication for the transmitted samples. Secondly, the benchmark samples may be large that thus the samples should not be stored on smart contracts, for practicality.

(c). How to convince that the execution of benchmarking inside the TEE is indeed correct considering the TEE vulnerable to rollback attacks? This concern is caused by the TEE’s fundamental limitations that the TEE relies on the host for storing its state data. The malicious host may relay a stale state into the TEE, which can lead to the incorrect execution of the TEE, even if the TEE itself is correct.

For ease of presentation, we give a detailed design mainly taking concern (a) into consideration. We left the last two concerns in Section 5.1.7.

### TABLE 1: Notations used in our design.

| Notation | Description |
|----------|-------------|
| S        | the account address of a seller on the blockchain |
| B        | the account address of a buyer on the blockchain |
| Addr_m   | the storage address of encrypted model m |
| Prog_m   | the program binary implementing model m |
| prog     | the program executed inside a seller’s enclave during the benchmarking stage |
| ID_m     | the model identifier |
| k_m      | the symmetry secret used to encrypt model m |
| Com_k    | the commitment to secret k |
| Com_m    | the commitment to model m |
| pk_b     | a proof of proving a model indeed encrypted by k_m |
| pck_b    | a proof of proving the construction correctness of Com_k |
| pcm_b    | a proof of proving the construction correctness of Com_m |
| sid_b    | the session identifier |
| st_c     | the state on the smart contract |
| T        | time point on the smart contract |
| pk_b     | the public key of a buyer |
| mGE      | the metric describing a model’s corruption robustness |
| mFP      | the metric describing a model’s perturbation robustness |
| ce       | the metric describing a model’s nature accuracy |
| price    | the price of a model |

5.1.3 Seller Registration

Seller S registers with our model marketplace and publishes a model report to the blockchain. The model report contains some public terms which indicate the successful registration of Seller S. In addition, the model report will be appended with new terms, such as mCE, mFP and ce, price, after the benchmarking stage.

We proceed to explain the necessary terms on the model report shown in TABLE 1 as following:

- **Addr_m**: the storage address of model m; we suppose that seller S can encrypt and store his model in a decentralized storage system (e.g., IPFS).
- **Prog_m**: the program binary containing the codes corresponding to the network architecture of machine learning model m, which does not contain private model parameters.
- **prog**: not only contains the codes corresponding to the model network architecture, but also contains the codes to calculate the performance metrics and compute a commitment Com_m.
- **ID_m**: is the model identifier which is generated by hashing model m’s storage address and the respective seller’s account address; suppose that a model owns a unique model report on the blockchain, so a model report can be identified by ID_m, and the updated model does not share the same identifier.
- **k_m**: is the symmetry secret used to encrypt the model.
- **pk_b**: is the proof which proves that the remotely stored model is indeed encrypted by secret k_m by using a symmetry encryption algorithm.
- **pcm_b** and **pcm_b** are the proofs used to prove that commitments Com_k and Com_m are authentic, respectively.
It is noteworthy that $p_{k}$, $p_{ck}$ and $p_{cm}$ are asymmetry knowledge proofs, which can be generated by launching additional enclaves [28]. We omit the detailed explanation for them. Other relevant notations in TABLE 1 which are used in our design will be elaborated in the later section.

In addition, the model report also contains some useful information for sell, such as the intended use of the model and the model performances (e.g., error rate, accuracy, confidence level), by following a trending practice. Here, the model performances are evaluated on a local holdout test by the seller, which may be not reliable to buyers and should be distinguished from the benchmarked performance we introduce below.

5.1.4 Performance Metrics of Benchmarking Model

The publication of the model report invokes the execution of the BM-Contract, which means stepping into the benchmark stage. The contact interacts with the seller to evaluate the model performances fed with standard benchmark datasets. The seller would agree on the interaction if he wants to promote the sale of his model. We note that the program logic of the BM-Contract is pre-defined by a group of maintainers in the model marketplace like the blockchain miners. For simplicity of introducing the model benchmarking, we focus on the setting of object recognition. Particularly, models are used to identify the class for the objects in a given image based on its raw pixels (other settings will be discussed in Section 9).

We benchmark models using three performance metrics, namely, corruption robustness, perturbation robustness and nature accuracy. In addition to the nature accuracy, we stress that the corruption robustness and perturbation robustness separately measuring the robustness of model against corrupted and perturbed data are crucial for MLaaS, due to a sign image added by a crafted perturbation [56], we do not expect that a traffic sign classifier breaks down against corrupted and perturbed data are crucial for MLaaS, especially in the safety-critical scenarios. For example, we do not expect that a traffic sign classifier breaks down due to a sign image added by a crafted perturbation [56], [57], [58]. To achieve this, we use the standard benchmark datasets, where data are added with the common corruptions and perturbations. They include a corruption dataset—ImageNet-C, a perturbation dataset—ImageNet-P [18], [19]. [21]. Additionally, we use ImageNet validation dataset for estimating the nature accuracy. The former two datasets are derived from the ImageNet validation dataset [59] applied with 15 corruptions and 10 perturbations, respectively. Recall that the benchmark datasets are assumed unrevealed to the model sellers before their models are trained (see Section 5.2).

Specifically, the two robustness metrics include the mean Corruption Error (mCE) and the mean Flip Rate (mFP). mCE is a mean value of corruption errors on ImageNet-C, reflecting a model’s corruption robustness. mFP is a mean value of the perturbation errors on ImageNet-P, measuring a model’s perturbation robustness. The standard metric for measuring the nature accuracy of a model is denoted as clean error (ce) on the ImageNet validation dataset without containing corrupted and perturbated data. We note that 2. The error rate is estimated by the quantity of samples being incorrectly classified divided by the total quantity of samples being tested via a confusion matrix.

```plaintext
BM-Contract(S, Addr_s, ID_m, prog, Com_m, T_1, T_2, T_3)
1 Trigger: Upon receiving the publishing event of a model report:
2 assert ID_m
3 set st_1 = TRIGGERED /* st_1 is the session id */
4 send (sid, S, "install", prog, T_1) to S
5 Commit: Upon receiving transaction containing id:
6 assert T_1 < T_2
7 send (sid, S, "commit", Com_m, T_2) to S
8 Request: Upon receiving transaction tz_1:
9 assert T_1 < T_2
10 set st_2 = COMMITTED /* sampling randomness will be introduced */
11 in Section 5.1.7 /*
12 REQUEST(S, GET, URL, params)
13 wait to receive (samples)
15 Publish: Upon receiving transaction tz_2:
16 set st_3 = REQUESTED /*
17 assert T_2 < T_3
18 add (ID_m, outp) to ledger

Fig. 3: Definition of the Benchmarking Contact.
```

1.0 minus ce that equals to the nature accuracy. Notably, mCE and mFP can consistently represent a model’s robustness reliably, since the two metrics do not have a fundamental trade-off relationship and they can be enhanced together [18], [19]. Additionally, a lower value indicates a stronger robustness for both the metrics.

The aforementioned metrics are calculated inside the enclave. Concretely, the BM-Contract will require the seller to load the corresponding calculation programs and execute the programs correctly inside the enclave, so that the contract can release itself from the complex computation. We define those programs as $progmce$, $progmfp$ and $progc$, respectively. They can be wrapped as the programs embedded in program $prog$. In such a way, the contract finally obtains the computed statistics, i.e., mCE, mFP and ce, over the corresponding benchmark data. As demonstrated above, estimating the three metrics needs different benchmark datasets, ImageNet-C, ImageNet-P and ImageNet validation dataset, respectively. It implies that there occurs a multi-step interaction between the host and the enclave, since the host needs to relay the requested samples from different benchmark datasets into the enclave for running the process of model evaluation. In addition, the size of the benchmark samples apparently is large, so it is impractical to store the samples on the blockchain. We optimize this issue in Section 5.1.7.

5.1.5 Model Benchmarking with Correctness Guarantees

We realize the workflow of model benchmarking with a protocol BM by utilizing a trusted hardware-based ZK proof (i.e., sealed-glass proofs, SGPs) [28] and smart-contracts in the blockchain setting. In this protocol, the seller is a prover while the BM-Contract seems like a verifier. The seller needs to prove that the process of model benchmarking is correct, which implies (1) the benchmarking process is executed with integrity guarantees; (2) the model is benchmarked on the authentically relayed benchmark samples. Note that the trusted hardware is not expected to provide the confidentiality, since the seller’s model does not leave its local device.
Fig. 4: Definition of execution programs in the enclave eid.

First of all, we leverage the functionalities of the SGPs, \( F_{SGP} \), enabling the seller to convince the BM-Contract that he correctly evaluates his model on the benchmark samples which are fetched from an authenticated source outside the blockchain and returns the evaluation results. We highlight two points when leveraging the SGPs: (1) the seller should firstly commit to his model in the enclave before receiving the test samples. (2) the enclave can bind its public key \( pk_{TEE} \) to an account \( E \) on the blockchain, and meanwhile, the respective private key of \( pk_{TEE} \) is protected to generate attestations (e.g., Intel’s EPID signatures). To be specific, the first point aims at preventing the seller from faking his model by observing the verifier’s inputs. The second point enables the attestations of the seller’s enclave to be regarded as the blockchain transactions and to be verified via the transaction verification protocol of the underlying blockchain, thereby eliminating the on-chain cost of verifying the attestation on the BM-Contract \([32]\).

Secondly, we resort to smart contract and blockchain for enforcing the execution correctness of the workflow. Here, we emphasize a vital feature, that is, a trusted clock provided by the underlying blockchain. As highlighted in the previous work \([27, 69]\), a trusted clock is crucial to achieve financial fairness and computational fairness. Although a TEE also owns a clock source, we do not rely on it due to its timer failures \([41]\). We define a trusted clock \( T \) in the smart contract, and any party can read it. The clock is incremented when a new block is created, meaning a new round starts, and smart contract is executed in rounds. We also preserve other generic features on the blockchain, such as authenticated messages, message batches and money (see \([27]\)).

As demonstrated in Fig. 5 \( \text{Prot}_{BM} \) shows that the seller who uses the enclave interacts with the BM-Contract. Formally, we define in Fig. 5 the execution program inside the enclave by combining with the transparent TEE ideal functionality which is formalized by the SGPs protocol \([28]\). We also define the program logic of the BM-Contract demonstrated in Fig. 5 by using the blockchain functionality which is defined under the UC framework \([27]\). For simplicity, we add a wrapper \( G \) on the BM-Contract, representing messages read from the BM-Contract. The interactive procedures are as follows:

(a) Seller \( S \) receives the message to install programs \( prog \) with deadline \( T_1 \). With the input messages by the seller, the enclave then installs \( prog \) and returns its identifier \( \text{id} \).

(b) Seller \( S \) commits his model before \( T_2 \). \( S \) then loads the model into the enclave memory. The enclave receives \( Com_{m} \) and checks whether or not it is identical to \( Com'_{m} \), which is generated later inside the enclave, and outputs \( \sigma_c \). Similarly, seller sends \( \sigma_c \) as transaction \( tx_2^c \). If the \( tx_2^c \) is true, it sends a request with a URL for sampling the benchmark data.

(c) Seller \( S \) gains the benchmark samples and delivers them into the enclave. The enclave executes the programs and returns the execution output. The execution output finally contains the evaluation results with respect to three performance metrics. Attestation transaction \( tx_2^c \) can be verified to assert the correctness of the execution output.

(d) The BM-Contract then determines a price for the model based on the evaluation results. Note that the evaluation results and price will be published on the blockchain, linked with the model’s model report.

5.1.6 Model Pricing

Table 2: Notations used in the model pricing mechanism.

| Notation | Description |
|----------|-------------|
| \( q_{EC} \) | value of the corruption robustness metric |
| \( q_{EP} \) | value of the perturbation robustness metric |
| \( C \) | cost of generating a model |
| \( c \) | marginal cost of generating a model |
| \( q \) | model quality |
| \( W \) | willingness of buying a model |
| \( l_1, l_2 \) | marginal willingness of buying a model |
| \( R \) | seller revenue |
| \( U \) | buyer utility |
| \( p \) | model price |

With the obtained model performances, the BM-Contract transparently determines a price for the model. Guided by the market rule of high-performance models being highly valued, we leverage a quality-based pricing method which uses the performance metrics to measure the model quality. In addition, this pricing method needs to maximize two objectives which are the revenue of sellers and the utility of buyers, for maintaining the long-term running of the model marketplace.

With the considerations above, we define a performance-oriented model pricing mechanism, and this mechanism is to solve a bi-level programming problem \([61]\). Specifically,
the up-level problem is to find the optimal solutions to maximize the revenue of sellers, and the low-level problem is to find the optimal solutions to maximize the utility of buyers. Both the revenue of sellers and the utility of buyers are related to the model performance.

Additionally, we employ genetic algorithm [62] to solve the defined bi-level programming problem which is a provably NP-hard problem [61]. The reason to choose genetic algorithm is that it has been proved solving bi-level problem efficiently [63], [64], [65], [66]. Then, the solutions guide the BM-Contract to decide a price for a model with given performance. Notice that for ensuring efficiency, the process of solving the bi-level programming problem is conducted in an off-chain TEE component. Returned solutions to the BM-Contract are used to guide pricing.

Note that although the existing model-based pricing (MBP) algorithm [67] meets our market rule that better performance deserves better revenue, it may not fit our scenario well with the following reasons. First, our model marketplace sells models trained on various datasets while the MBP algorithm bids the instances of a model which are trained on the same dataset. Second, we benchmark selling models with the consistent benchmarking datasets while the MBP algorithm evaluates a model instance with the individual holdout test data. Most importantly, a well-performed model in a holdout test may have an uncertainty performance in real-world practice [18], [19], [51], meaning that the performance based on the holdout test cannot really indicate the model quality.

Now, for easy presentation of the bi-level programming problem for our performance-oriented pricing mechanism, we firstly introduce and denote the following necessary factors which also are summarized in TABLE 2.

- **Performance.** mCE and mFP are used to measure the quality of a model, which are the robustness performance metrics trustfully obtained in the model benchmarking stage. We donate them with \( q_{mCE} \) and \( q_{mFP} \). As for nature accuracy, we suppose that the market would reject the models whose nature accuracy is below a given threshold, e.g., 60.0%, since we think that buyers generally are not willing to purchase a model with low nature accuracy, regardless of robustness. Pricing depending on the quality of data has been well-studied in the community of data market [68], [69]. Follow these existing work, we use \( q_{mCE} \) and \( q_{mFP} \) measuring model quality to score another two factors cost and willingness below.

- **Cost.** It describes the expense of generating a model and varies with the model robustness, i.e., spending more cost to get higher model robustness. It has been widely investigated that, for improving model robustness, model developers usually consume more time and computation to carefully design algorithms and select additional training data [19], [70], [71]. Specifically, cost \( C \) is scored via a linear function of quality, that is, \( C = c \cdot \frac{1}{2}(w_1 \cdot q_{mCE} + w_2 \cdot q_{mFP}) \), where \( c \in (0, c_{max}) \) is the marginal cost, and \( w_1 \) and \( w_2 \) mean the relative weights with the constraint of \( w_1 + w_2 = 1 \). The reason of using an increasing linear function instead of a nonlinear one is that mCE and mFP can consistently represent the model quality, guided by [69]. We note that a model quality is \( q = \frac{1}{2}(w_1 \cdot q_{mCE} + w_2 \cdot q_{mFP}) \). In addition, \( C > 0 \).

- **Willingness.** It describes the preference of paying for a model and also varies with the model robustness. It is not hard to understand that service providers prefer robust models for providing reliable ML services [56], [57], [58]. Specifically, willingness \( W \) is scored by an increasing linear function of \( W = \frac{1}{2}(l_1 \cdot q_{mCE} + l_2 \cdot q_{mFP}) \), where \( l_1, l_2 \sim U(0, 1) \) are the marginal willingness for \( q_{mCE} \) and \( q_{mFP} \), respectively. In addition, \( W > 0 \). We treat both \( q_{mCE} \) and \( q_{mFP} \) equally essential for buyers.

With cost and willingness, we define revenue \( R \) of seller and utility \( U \) of buyer, with respect to a model in quality \( q \), when given a take-it-or-leave-it price \( p > 0 \):

\[
R(q, p, x, y) = p \cdot x \cdot (W - p) \cdot x
\]

\[
U(q, p, x) = (W - p) \cdot x \cdot y
\]

Here, \( C \) and \( W \) are related to \( q \). Note that if given price \( p \) is not higher than expense \( C \), a seller would not join the market, which indicates Individual Rationality (IR), and thus \( p > C \). We use \( x \) to express whether or not to buy the model, and \( x = 1 \) if \( W \geq p \), otherwise, \( x = 0 \) if \( W < p \). \( y \) is used to express whether or not to sell the model.

Then, the Bi-Level programming problem for Model Pricing mechanism is denoted, named as BLMP, given that the market shows \( N \) models with different levels of quality and price, and \( M \) consumers:

- the up-level problem

\[
\max \quad R(q_i, p_i, x_{i,j}, y_i) = \sum_{j=1}^{M} \sum_{i=1}^{N} p_i x_{i,j} - \sum_{i=1}^{N} C_i y_i
\]

with constraints \( p_i > C_i > 0, \; x_{i,j} = 0 \; or \; 1, \; y_i \leq \sum_{j=1}^{M} x_{i,j} \; and \; y_i = 0 \; or \; 1; \)

- the low-level problem

\[
\max \quad U_j(W_{i,j}, p_i, x_{i,j}) = \sum_{i=1}^{N} [(W_{i,j} - p_i) \cdot x_{i,j}]
\]

with constraints \( W_{i,j} \geq p_i > 0, x_{i,j} = 0 \; for \; any \; i_1 \neq i_2 \; and \; x_{i,j} = 0 \; or \; 1.

Notice that each of model at most is sold to one consumer. Solving the bi-level programming problem is not easy due to the need of solving the low-level problem at each step of an algorithm that finds solutions for the up-level problem. Specifically, the decision maker deciding \( y_i \) in the up-level should interact with the decision maker deciding \( x_{i,j} \) of the low-level to obtain the best solution [63], [69].

Lastly, we use genetic algorithm to approximately solve the above problem in finite time steps, following the works [63], [69]. Genetic algorithm is a stochastic search technique derived from natural selection and natural genetics mechanisms, consisting of the procedures of initialization, fitness evaluation, selection, crossover and mutation, in which the latter four procedures repeat successively [62]. The algorithm terminates until a preset stopping criterion is reached,
Remark. Once a model is sold, a state ‘SOLD’ is updated to its model report. Any identical model cannot be sold twice while updated models are treated as new models. Recalled that the on-chain commitments of each model can be used to filter out the model which has been on-chain before.

5.1.7 Design Refinement

Here, we seek to refine our design by reviewing the remaining two concerns mentioned in Section 5.1.2. Recall that concern (b) is how to ensure that the benchmark samples directly imported into the enclave are authenticated without the need to store them on chain; concern (c) is how to convince that the model evaluation inside the enclave is indeed correct when the enclave is vulnerable to rollback attacks. In this section, we are ready to refine our design by resolving the two concerns with the off-the-shelf techniques, namely, Town Crier [32] and the Enclave-Ledger Interaction (ELI) protocol [46].

First, we need an efficient off-chain intermediator who correctly relays the trustworthy samples into the seller’s enclave, and meanwhile leaves the digest of the samples on the blockchain. Following the instruction of Town Crier [32], we can use the ready TEE-based component to realize the intermediator. In our scenario, an intuition is to let the seller himself create an addition enclave served as the intermediator. Despite that it can work, it may be not cost saving, compared to using a common intermediator with a TEE-enabled platform. Imagine that multiple sellers’ models are benchmarked at the same time with the consistent benchmarking samples. The common intermediator can request benchmarking can cause the multi-step execution of the enclave. Suppose that a model includes program $prog^i$, the counter of the execution step and programs $prog^{mCE}$, $prog^{mFP}$ and $prog^{ce}$ with the samples of ImageNet-C, ImageNet-P and ImageNet, respectively.

The instance derived from the existing ELI protocol [46] is presented with the following constructions. The enclave $B$ encrypts/decrypts an intermediate execution state $st^E_i$ and program information $prog$ in a step $i$, using a symmetry authenticated encryption scheme $(Enc(\cdot), Dec(\cdot))$ with deterministic secret $k_i$. The encrypted states, i.e., $C_{st} \leftarrow Enc(k_i, (st^E_i, \text{Hash}(\text{prog})))$, are stored in the host. Herein, we highlight two points. First, program information $prog$ includes program $Prog_{ini}$, the counter of the execution step and programs $prog^{mCE}$, $prog^{mFP}$ and $prog^{ce}$. Second, deterministic secret $k_i$ is derived via pseudorandom function $F(\cdot)$ on $sk_{TEE}$ and a hash value $hash_b$ of the blockchain’s latest block, namely, $(k_i, r_i) \leftarrow F(sk_{TEE}, hash_b)$. Random coin $r_i$ is used by the enclave in each execution to avoid the forked execution. Notably, the digest of the samples have been persisted on the blockchain, when the enclave receives authenticated samples. The host thus cannot replay the old block with different samples into the enclave. As a result, the state data in the enclave at each step is latest.
5.2 Monetization Stage

After the benchmarking stage, buyers can purchase models according to the model performances anchored on the blockchain and then move into the monetization stage.

5.2.1 Intuition

The monetization stage introduces a fair model-exchange procedure as shown in Fig. 6. The basic idea is to achieve the exchange fairness of the seller’s symmetry secret used to encrypt his model and the buyer’s money paid for the model. By leveraging the TEE’s attestation mechanism and the self-enforcing smart contract, the seller receives the money iff the buyer obtains the symmetry secret which can correctly decrypt the encrypted model.

5.2.2 Design Workflow

Buyers can pull the model reports from the blockchain, and may decide to purchase a model based on his budget and robustness requirements. The workflow is shown as follows: ① When deciding to buy, a Buyer can initiate the Exchanging Contract (BE-Contract for short) with a deposit which is not less than the price of the model he wants to buy and public information including IDm, pk and Comk. ② The model seller commits to and loads his secret (used to encrypt the model) inside the enclave. We note that the seller can encrypt and store his model in a decentralized storage system, e.g., IPFS [73], for being retrieved by purchasers later. ③ The seller then inputs the buyer’s public key and the on-chain commitment to the secret into the enclave. ④ The seller finally returns a secret encrypting the model under the buyer’s public key. ⑤ The buyer obtains and decrypts the secret using the private key of pkB. Meanwhile, the deposit is transferred to the seller’s account. After obtaining the secret, the buyer downloads and decrypts the model. Note that the buyer should confirm what he obtain is authentic. This workflow implies a fair exchanging process, in which the component of “commit and reveal” km is used to prevent the buyer from being cheated.

5.2.3 Model-Money Swapping with Fairness Guarantees

We now present a detailed design of achieving a fair model-money swapping procedure, where the seller should give an authentic model to the buyer; the model should be consistent to the one the buyer desire to purchase by

Fig. 6: Workflow of the monetization stage.

```plaintext

5.2.3 Model-Money Swapping with Fairness Guarantees

We now present a detailed design of achieving a fair model-money swapping procedure, where the seller should give an authentic model to the buyer; the model should be consistent to the one the buyer desire to purchase by

Fig. 7: Definition of the buyer-initiated Exchanging Contact.

```
is required to present that he commits to symmetry secret $k_m$ into enclave with identifier $\text{eid}$ after the buyer has deposited sufficient money. Then, if the commitment to $k_m$ is successfully checked, the seller sends "resume" message to the enclave ingesting the buyer’s $pk_B$ as input. The enclave encrypts $k_m$ under $pk_B$ by using an asymmetric encryption scheme $\text{AEnc}$ and returns it back. After successfully verifying $tx', f_{\text{Enc}}'$, the buyer decrypts the output $\text{AEnc}_{pk_k}(k_m)$ using the respective private key of $pk_B$ and obtains $k_m$ to decrypt the model stored in the IPFS.

6 SECURITY ANALYSIS

With regard to our security goals mentioned in Section 4.3, we give the security analysis for our presented protocols Prot$_{BM}$ and Prot$_{ME}$.

6.1 Model Privacy

In protocol Prot$_{BM}$, a seller’s model is locally kept during the process of model benchmarking. Finally, the seller (or the host) only reveals statistics of the classification error rates on the given samples, without class labels and confidence levels which are used to steal model information [14]. In protocol Prot$_{ME}$, if the process of model swapping is completed as expected, only the buyer can decrypt the encrypted model via a symmetry secret $k_m$ which is transmitted under the buyer’s public key. Thus, assuming that the utilized asymmetric encryption algorithm used to encrypt secret $k_m$ (i.e., $\text{AEnc}_{pk_k}(k_m)$) is semantic secure [74], anyone excepts that the seller and buyer cannot gain any information about secret $k_m$ during the transmission, thereby failing to decrypt the model. In addition, assume that published data related to the symmetry key and model on the blockchain do not reveal their values. Specifically, commitments $\text{Com}_k$, $\text{Com}_m$, $p_{cm}$, $p_{ck}$ and $pk$ are securely constructed [75].

6.2 Model Correctness

Both of protocols guarantee model correctness. First, protocol Prot$_{BM}$ based on the SGPs protocol [28] enables a seller to prove the integrity of the execution and the authenticity of the benchmarked result. Second, protocol Prot$_{ME}$ uses the SGPs protocol to realize a “commit and reveal” component that a seller commits a model and then reveals it to a buyer, where the model is the real one this buyer wants to purchase. Note that in the cases of not considering rollback attacks and untrustworthy data feed to BM-Contract (referred to concerns (b) and (c), respectively), model correctness is ensured based on the security of the SGPs protocol. Therefore, we present security analysis for Prot$_{BM}$ in Lemma 1 following Tramer et al.’s work [28] under the Universal Composability (UC) framework. The case for Prot$_{ME}$ is similar and thus omitted.

Lemma 1. Assume that the used TEE’s signature scheme is existentially unforgeable under chosen message attacks (EU-CMA). Assume that commitment $\text{Com}_m$ is securely constructed. Assume that samples are authenticated. Then protocol Prot$_{BM}$ securely realizes an ideal functionality $f$ which ensures model correctness in the TEE model for static adversaries.

Following the UC-style proof, we construct an ideal adversary $\mathcal{S}$ against the ideal function $f$ (i.e., a simulator) in the idea model IDEAL such that the environment $Z$ as a distinguisher cannot distinguish the distribution in IDEAL from that in the $f_{\text{TEE}}$-hybrid model $f_{\text{TEE-HYBRID}}$, where a static adversary $A$ interacts with protocol Prot$_{BM}$:

$$\{ IDEAL_{f,S,z} \} \lambda \equiv c \{ f_{\text{TEE-HYBRID}}_{Prot_{BM}, A, z} \} \lambda,$$

where $\equiv_c$ means that two distributions are computationally indistinguishable, and $\lambda$ is the security parameter.

Considering seller is malicious, we prove the computational indistinguishability above by sequentially constructing six hybrids. Specifically, simulation $S$ emulates the view of $A$ in hybrids one by one, starting from the real execution of protocol Prot$_{BM}$, which makes the distinguisher $Z$ fail to distinguish the distribution between hybrids. Six hybrids are as follows: (a) In hybrid $H_1$, $S$ perfectly emulates the behaviors of TEE, and others follow the real protocol; (b) In hybrid $H_2$, $S$ proceeds as $H_1$ and it will abort, when receiving any message-signature tuple which is not generated by the TEE; (c) In hybrid $H_3$, $S$ proceeds as $H_3$ and it will abort, when receiving a commitment whose committed value is not pre-stored inside the TEE; (d) In hybrid $H_4$, $S$ proceeds as $H_3$ and it will abort, when receiving a message-signature tuple which is sent by an enclave with different identifiers; (e) In hybrid $H_5$, $S$ proceeds as $H_4$, and it will abort, when inspecting that $A$ forwards incorrect messages from the TEE to BM-Contract; (f) In hybrid $H_6$, $S$ emulates the messages that $A$ interacts with Prot$_{BM}$ and then interacts with the ideal function $f$. With the last hybrid, $S$ in IDEAL can faithfully emulate the view of the static adversary $A$ in $f_{\text{TEE-HYBRID}}$. More proof details about the case of honest seller can be referred to the proof for work [28]'s Theorem 1.

When considering the case of adaptive adversaries, where a malicious host can adaptively query the states of a enclave, our refinement design resists this kind of adversaries by introducing an instance of the ELI scheme [46] in Section 5.1.7. The instance enables stateful multiple-step execution and keeps the state freshness before each execution. The ELI scheme is provably secure, since Lemma 2 has been proved in the appendix of work [46]. Note that the inputs, i.e., the benchmark samples inputted into the enclave can be in plaintext in our case. We thus need not use a commitment with the hiding property for the inputs, but they should be committed on the blockchain in advance. Additionally, a seller entering the model marketplace should use a secure commitment mechanism to generate commitments to the model and the secret, that is, $\text{Com}_m$ and $\text{Com}_k$, respectively [75]. Meanwhile, the seller’s off-line proof $pk$ (see Section 5.1.3) can be generated based on the SGPs protocol and their security have proved in work [28].

Lemma 2. Assume a secure authenticated encryption scheme $\text{Enc}()$, a collision resistant hash function $\text{Hash}()$, a secure pseudorandom function $F()$, and the underlying blockchain is unforgeable. Then the ELI scheme is simulation secure.

6.3 Exchanging fairness

The model-money swap process is fair by leveraging SGPs protocol and BE-Contract. A buyer cannot reject to pay fees, once he receives $\text{AEnc}_{pk_s}(k_m)$ which is proved correctly
generated, since his/her deposit on the BE-Contract can be automatically sent to the seller’s account. On the other hand, the seller cannot gain the payment from the buyer only if he does not reveal $AEnc_{pk_B}(k_m)$ in time, since the buyer’s deposit can be refunded. We present the security analysis for protocol $Prot_{ME}$ in Lemma 3. More details refer to the security proof of work [28]'s theorem 3.

Lemma 3. Assume that the used TEE’s signature scheme is existentially unforgeable under chosen message attacks (EU-CMA). Assume that $AEnc()$ is semantic secure. Then protocol $Prot_{ME}$ securely realizes an ideal functionality $g$ combining an SGP and the BE-Contract which ensures fairness for static adversaries.

A simulator $S$ is constructed against the ideal function $g$ in the idea model $IDEAL$ such that the environment $Z$ cannot distinguish the distribution in $IDEAL$ from that in the $gsGP$-hybrid model $gsGP_{HYBRID}$, where a static adversary $A$ interacts with protocol $Prot_{ME}$:

$$\{IDEAL_{s,S,Z}\} = \{gsGP_{HYBRID},Prot_{ME},A,Z\},$$

where $\equiv_c$ means that two distributions are computationally indistinguishable, and $\lambda$ is the security parameter.

With the proceeding round in the blockchain setting, $S$ emulates messages between $A$ and $Prot_{ME}$ to interact with $g$ via four hybrids. Starting from the execution of the real protocol, the distributions between two successive hybrides are distinguishable: a) In hybrid $H_1$, $S$ perfectly emulates the behaviors of the functionality of an SGP and the BE-Contract, and others follow the execution in the real world; b) In hybrid $H_2$, $S$ can perfectly emulate the ‘Init’ phase to initialize the BE-Contract and the ‘commit’ request sent to the SGP. Note that the indistinguishability between $H_2$ and $H_1$ is based on the security definition of the functionality of the SGP; c) In hybrid $H_3$, $S$ uses the randomness which is sampled by the ideal contract in the SGP, instead of the randomness sampled by himself in $H_2$; d) In hybrid $H_4$, $S$ replaces $AEnc_{pk_B}(k_m)$ with $AEnc_{pk_B}(0)$ sent to the BE-Contract. Note that the indistinguishability between $H_4$ and $H_1$ is based on the semantic security of $AEnc$.

## 7 PERFORMANCE ANALYSIS

We proceed to present the theoretic performance analysis of each entity in our design which involves the benchmarking and monetization stages. Concretely, we analyse the performance costs in terms of space, computational and communication complexity.

### 7.1 Benchmarking Stage

Now we theoretically analyse the performance costs of the BM-Contract and a seller participating in this stage. We summarize the costs in TABLE 3. Note that the symbol $|a|$ means the size of element $a$.

In terms of the BM-Contract, the space complexity is $4 \times 256\text{bits} + |\text{prog}| + |\text{outp}|$, since the contract needs to store $Addr_m, ID_m, Com_m, Hash(samples)$ (the total sizes of the four elements are $4 \times 256\text{bits}$), pro and outp. The computational complexity mainly comes from one hash operation. Last, the communication complexity is $|\text{prog}| + 2 \times 256\text{bits} + 2 \times 70\text{bytes} + 3 \times 70\text{bytes} + |\text{outp}|$. Herein, $2 \times 256$ bits describe the sizes of $Com_m$ and $Hash(samples)$ in total; $2 \times 70\text{bytes}$ are the sizes of $\sigma_f$ and $\sigma_{att}$; another $2 \times 70\text{bytes}$ are the total sizes of $tx_{e}^c$ and $tx_{o}^e$.

In terms of a participating seller, the space complexity is $256\text{bits} + |\text{samples}| + |\text{model}| + |\text{prog}| + |\text{outp}|$, $256\text{bits}$ mean the size of $Com_m$. The computational complexity contains the operations of installing program, computing commitment, verifying attestation and evaluating program. Next, the communication complexity is $|\text{prog}| + 2 \times 256\text{bits} + 2 \times 70\text{bytes} + 70\text{bytes} + |\text{model}| + |\text{samples}| + |\text{outp}|$. To be specific, $2 \times 256$ describe the sizes of $Com_m$ and $Hash(samples)$; $2 \times 70\text{bytes}$ are the total sizes of $tx_{e}^c$; another $70\text{bytes}$ represent the size of $\sigma_{att}$.

### 7.2 Monetization Stage

We now proceed to introduce the performance costs during the monetization stage in TABLE 4, where we assign a price to a selling, a buyer, and the BE-Contract.

| Performance | BM-Contract | Seller |
|-------------|-------------|--------|
| Space complexity | $4 \times 256\text{bits} + |\text{samples}|$ | $256\text{bits} + |\text{samples}|$ |
| Computational complexity | one hash operation | program installation, commitment computation, attestation verification and program evaluation |
| Communication complexity | $|\text{prog}| + 2 \times 256\text{bits} + 70\text{bytes}$ | $|\text{prog}| + 2 \times 256\text{bits} + 70\text{bytes}$ |

As for the seller, the space complexity is $2 \times 256\text{bits} + 64\text{bytes} + [AEnc_{pk_g}(k_m)] + 70\text{bytes}$. Here, $2 \times 256\text{bits}$ are the sizes of $Com_k$ and $k_m$; $64\text{bytes}$ represent the size of $pk_B$; another $70\text{bytes}$ refer to the size of $\sigma_o$. The computational complexity comes from the operations of computing commitment $Com_k$ and generating ciphertext of $k_m$. Lastly, the communication complexity is $64\text{bytes} + 2 \times 256\text{bits} + 70\text{bytes} + |AEnc_{pk_g}(k_m)|$. Concretely, the seller fetches $pk_B$ with $64\text{bytes}$ and $Com_k$ with $256\text{bits}$ from the BE-Contract; from its enclave, the seller receives $\sigma_{pk_g}$ and $AEnc_{pk_g}(k_m)$ which are $70\text{bytes} + 64\text{bytes} + |AEnc_{pk_g}(k_m)|$.

In terms of the buyer, we mainly discuss the computational and communication costs. From the aspect of computational complexity, the buyer executes two decryption operations for decrypting $AEnc_{pk_B}(k_m)$ with his private key and
successively decrypting the encrypted model with $k_m$. From the aspect of communication complexity, the buyer needs to submit $Com_{km}, ID_m, pk_{kB}$ and $p_k$, which correspondingly are 256 bits, 256 bits, 64 bytes and 70 bytes.

In terms of the BE-Contract, the space complexity is $2 \times 256 \text{bits} + 64 \text{bytes} + |AEnc_{pk_k}(k_m)| + 2 \times 70 \text{bytes}$, since the contract stores $Com_{km}, ID_m$ which are $2 \times 256 \text{bits}$, $pk_{kB}$ which is 64 bytes, as well as $p_k$ and $\sigma_o$ which are 2 $\times$ 70 bytes. As for the computational complexity, it refers to the operation of verifying attestation $\sigma_o$. The last one, communication complexity comes from $Com_{km}, ID_m, pk_{kB}$ and $p_k$ (sent by the buyer) which are 64 bytes + $2 \times 256$ bits + 70 bytes, and $\sigma_o, pk_{kB}$ and $AEnc_{pk_k}(k_m)$ which are 70 bytes + (64 bytes + $|AEnc_{pk_k}(k_m)|$) (sent by the seller).

8 EXPERIMENTS

In this section, we introduce a prototype implementation and a series of experiments with the standard benchmark datasets.

8.1 Implementation

Model Benchmarking with TEEs. We use the Intel’s SGX as the TEE, since it is widely used. We also employ a memory-safe and lightweight library operating system (LibOS) for SGX, called as Occlum to deploy models in the enclave, through which hundreds of lines of SGX-aware codes need not be written. This way still supports attesting the codes run inside the enclave only if we put an Service Provider ID (SPID) and the associated certificate in the appointed file path, which enables Occlum to access Intel Attestation Service (IAS).

We utilize popular pre-trained models on TensorFlow Lite such as Mobilenet_V1_1.0_224 (MobilenetV1 for short), Mobilenet_V2_1.0_224 (MobilenetV2), NASNet mobile, ResNet_V2_101 (ResNet101) and Inception_V3. Their information are shown in TABLE 5, in which top-1 errors of each model are estimated on ImageNet classification. We consistently convert the format of ImageNet-C images and ImageNet-P sequence frames into the format of bmp, before inputting them into a model.

| Model               | Size     | Top-1 Error Rate |
|---------------------|----------|------------------|
| MobileNetV1         | 16.9 MB  | 29.0%            |
| MobileNetV2         | 14.0 MB  | 28.2%            |
| NASNet mobile       | 21.4 MB  | 26.1%            |
| Inception_V3        | 95.3 MB  | 22.1%            |
| ResNet101           | 178.3 MB | 23.2%            |

Smart Contract. We implement the BM-Contract and the BE-Contract with the Solidity programming language of Ethereum. We deploy the smart contracts to the Ethereum Test Network provided by MetaMask.

8.2 Setup and Evaluation

Benchmark Datasets Setup. We download ImageNet-C, ImageNet-P and ImageNet validation dataset following the instruction of work [18] and construct three benchmark samples. Concretely, ImageNet-C and ImageNet-P are constructed from the ImageNet validation dataset which consists of 50,000 299x299 images with 1000 classes, added by corruptions and perturbations, respectively. The corruptions and perturbations mainly include four categories, such as digital, noise, weather and blur. ImageNet-C has 15 kinds of corruptions and each corruption contains 5 severity levels. They are all applied on the ImageNet validation dataset. Similarly, ImageNet-P has 10 types of perturbation sequences and each sequence contains 31 frames. Each sequence begins with a clean image (i.e. the first frame) being ingested perturbation slightly and an intermediate frame is a perturbed frame of the previous one. The format of sequences is MP4 not JPEG. We consistently convert the format of ImageNet-C images and ImageNet-P sequence frames into the format of bmp, before inputting them into a model.

Three benchmark samples, $Set_1$, $Set_2$ and $Set_3$ then are randomly chosen from ImageNet-C, ImageNet-P and ImageNet validation dataset, respectively. $Set_1$ totally includes $15 \times 5 \times 100$ images, which is constructed by randomly choosing an image with respective to each severity level per corruption among multiple classes. $Set_2$ includes $10 \times 31 \times 100$ frames which are randomly chosen with respect to each perturbation sequence covering multiple classes. Last, $Set_3$ consists of 100 images which are randomly chosen per class.

In addition, we conduct the model evaluation experiment inside SGX on a Ubuntu 18.04 server with a 4-core Intel i5-7500 CPU 3.40 GHz processor and 32 GB RAM.

Model Performance Metrics. We show two robustness metrics and the clean error of pre-trained models in TABLE 5. They are evaluated on benchmark samples $Set_1$, $Set_2$ and $Set_3$, respectively. Like work [18], we select AlexNet to be a baseline, and the robustness metrics of AlexNet are used to standardize the respective metrics of the benchmarked models. Robustness metrics including $mCE$ and $mFP$ as well as clean error $ce$ are calculated with the following formulas:

$$mCE^f = \frac{\sum_{c=1}^{15} CE^f_c}{15}, \quad ce = \frac{\sum_{s=1}^{5} E^f_{s,c}}{\sum_{s=1}^{5} E^f_{s,c}}$$

where $E^f_{s,c}$ is the top-1 error rate of model $f$ on samples with corruption $c$ in severity level $s$, and

$$mFP^f = \frac{\sum_{p=1}^{10} FP^f_p}{10}, \quad FP^f_p = \frac{1}{k \times (r - 1)} \times fp^f_p,$$

where $fp^f_p$ is the flip count on samples with perturbation $p$ given by model $f$, meaning the number of the frames whose classified labels are inconsistent to that of the first frame (clean image) in a sequence. Herein, $k$ is the quantity of sequences and $r$ is the number of frames. Last, $ce^f$ is the clean error rate of model $f$ on $Set_3$.
Fig. 10 shows that Inception V3 owns the stronger corruption and perturbation robustness than others as it has the lowest mCE and mFP. From TABLE 6 we can see that each of models have the higher mCE and mFP than the corresponding ce. That means that these models can perform poorly when meeting corrupted data and perturbed data. Particularly, MobilenetV2 degrades most obviously among all presented models on corrupted data, since it should have a comparably lower clean error 28.0% but shows the highest mCE 87.6%, which indicates it has the worst corruption robustness.

![Fig. 10: mCE and mFP.](image)

![Fig. 11: Relative mCE.](image)

**TABLE 6: Performance metrics of pre-trained models.**

| Model         | ce  | mCE   | mFP  |
|---------------|-----|-------|------|
| AlexNet       | 43.5%| 100.0%| 100.0%|
| MobilenetV1   | 35.0%| 84.8% | 94.6% |
| MobilenetV2   | 28.0%| 87.6% | 93.2% |
| NASNet mobile | 36.0%| 71.8% | 82.4% |
| Inception V3  | 22.0%| 62.8% | 62.2% |
| ResNet101     | 29.0%| 68.5% | 59.6% |

To further describe this observation, we compute another metric, i.e., the relative mCE. It measures the gap between the mCE and the ce, describing a model’s accuracy degradation on the corrupted data. The above observation can be further verified by Fig. 11. Concretely, MobilenetV2 has the top relative mCE 118.9% among all models while Inception V3 has the lowest one 56.0%. In this case, a buyer who wants to obtain a model with corruption robustness can purchase Inception V3 among those benchmarked models. On the other hand, although there not exists a relative metric for mFP, a buyer can choose models with the higher perturbation robustness according to a lower mFP, e.g., ResNet101.

![Fig. 12: mCE on corruption](image)

![Fig. 13: mFP on perturbation](image)

**TABLE 6: Performance metrics of pre-trained models.**

First of all, a seller on one hand needs to upload his model information to the blockchain via transactions, which causes gas costs Gas. Concretely, the most costs of sending transactions come from uploading proofs $p_k$, $p_{ck}$, $p_{rm}$ and commitments $Com_k$, $Com_{rm}$ as described in Section 5.1.3. Proofs can be the attestations generated by the trusted hardware with the Elliptic Curve Digital Signature Algorithm, which are totally 210 bytes as each one is 70 bytes. Commitments can be implemented by using Pedersen commitment algorithm. For reducing the sizes of commitments, we further use a hash function, i.e., SHA-256, to generate the hash values of each commitment, in which each hash value is 256 bits. Thus, the seller expends about $Gas_s$, 57, 174 units (about 0.000057 ETH) to upload the entire model information. On the other hand, the seller has computation cost $Comp_s$ of benchmarking his model.

Now, we explain $Comp_s$ in terms of time complexity with respect to different-size models as shown in TABLE 7. For the column of total time, each row is the total consuming times for benchmarking on samples $Set_1$, $Set_2$ and $Set_3$ (the total size is 38, 600). Also, the separate time costs for evaluating each metric are presented in FIG. 14. In detail, a large-size model, e.g., Inception V3 and ResNet101 could take the sellers more time, but this may deserve, since the large-size model performs a comparably lower classification error, and buyers may prefer to purchase them. But the average time for each query image is also crucial for an online MLaaS system, we would explore this concern in our future work.

**TABLE 7: Time complexity of benchmarking models.**

| Model         | Size     | Total Time (min) | Avg. Time (s) |
|---------------|----------|------------------|---------------|
| MobilenetV1   | 16.9 Mb  | 130.27           | 0.20          |
| MobilenetV2   | 14.0 Mb  | 129.95           | 0.20          |
| NASNet mobile | 21.4 Mb  | 190.36           | 0.30          |
| Inception V3  | 95.3 Mb  | 541.96           | 0.84          |
| ResNet101     | 178.3 Mb | 931.30           | 1.45          |

Secondly, a buyer needs to initiate and deploy BE-Contract interacting with the seller and thus spends gas costs $Gas_b$ for it. Recall that BE-Contract defines three entry points: $Init$, $Request$ and $Publish$. After deploying this contract with a deposit, the buyer would execute the defined logics accordingly every time each entry point is invoked. During a simulated interaction, $Gas_b$ needs 1, 206, 886 units gas, about 0.001207 ETH, in which 981, 901 units for $Init$, 27, 873 units for $Request$ and 197, 112 units for $Publish$. 

Computational Costs and Complexity. We estimate the computational costs of a seller and a buyer accordingly, considering the expends for a seller entering the market and a buyer using our market.


9 DISCUSSION

Beyond object recognition tasks: Currently, there are three leading groups of MLaaS applications, including object recognition, speech recognition and text recognition. One thing needs to do which is replacing the benchmark dataset used in this work with other standard datasets specialized for speech recognition or text recognition. Available benchmark datasets, such as speech commands dataset [79] for speech recognition and SQuAD [80] for text recognition can be used. On the other hand, crafting adversarial examples for these two groups are undergoing investigation [81], [82], which is comparatively less studied than that for object recognition. We envision that the future standardized benchmark datasets help reintegrate the component of benchmarking models in this work.

Cut-edge techniques for mitigating the limitations of Intel’s SGX: (a) Enabling distributed and frequent attestation. Recall that in our design, attestations built by an enclave are regarded as transactions on the blockchain, and they will be verified by the nodes on the blockchain according to the transaction verification protocol. It means that the distributed nodes on the blockchain will frequently request IAS for verifying attestations. Such distributed and frequent requests will lead to a high overhead on IAS, causing a threat of single-point-of-fail. An open remote frequent requests will lead to a high overhead on IAS, requesting IAS for verifying attestations. Such distributed and they will be verified by the nodes on the blockchain.

that paging is inefficient. In our future work, we will explore the off-the-shelf optimization technologies like application-managed paging [85], [86] to reduce the high overhead of paging.

10 CONCLUSION

We present a secure and decentralized model marketplace for MLaaS in this paper. We realize the fair model monetization procedure based on the blockchain, which enables an MLaaS provider to fairly purchase models, eliminating the potential dispute. Treating the blockchain-based procedure as a starting point, we benchmark selling models to obtain their robustness performances used to monetize the models. We guarantee the correctness of the model benchmarking, by leveraging trusted hardware-based proofs and smart contracts. Besides, we envision that our model marketplace can facilitate the sharing of well-trained models and promote the development of MLaaS. We implement a prototype on Ethereum blockchain, and conduct the extensive experiments with the standard benchmark datasets, which demonstrates the affordable performance of our marketplace.

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