

# GOTCHA: A Challenge-Response System for Real-Time Deepfake Detection

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## Abstract

The integrity of online video interactions is threatened by the widespread rise of AI-enabled high-quality deepfakes that are now deployable in real-time. This paper presents GOTCHA, a real-time deepfake detection system for live video interactions. The core principle underlying GOTCHA is the presentation of a specially chosen *cascade* of both active and passive challenges to video conference participants. Active challenges include inducing changes in face occlusion, face expression, view angle, and ambiance; passive challenges include digital manipulation of the webcam feed. The challenges are designed to target vulnerabilities in the structure of modern deepfake generators and create perceptible artifacts for the human eye while inducing robust signals for ML-based automatic deepfake detectors. We present a comprehensive taxonomy of a large set of challenge tasks, which reveals a natural hierarchy among different challenges. Our system leverages this hierarchy by cascading progressively more demanding challenges to a suspected deepfake. We evaluate our system on a novel dataset of live users emulating deepfakes and show that our system provides consistent, measurable degradation of deepfake quality, showcasing its promise for robust real-time deepfake detection when deployed in the wild.

## 1 Introduction

**Overview.** Modern life has made live, online video interactions indispensable. Estimates show that 36.7 million Americans (at least partially) will work from home with video conferencing tools, an uptick of 87% from pre-pandemic levels [4]. This dramatic increase in video interactions creates fertile grounds for novel social-engineering attacks and online fraud. Specifically, high-quality *deepfakes* are now available that faithfully

reproduce a target’s facial appearance and that easily bypass commercial APIs for liveness detection and ID verification [2]. While earlier deepfakes mainly targeted well-known public figures, modern deepfake generators have made it feasible to impersonate any individual (even with limited training images) in the real-time setting [27]. These systems, that we call Real-Time Deep Fakes (RTDFs), pose an urgent, burgeoning threat to the integrity of human interactions across the globe.

Previous research has conventionally studied deepfakes in the offline, non-interactive setting. These techniques rely on detecting unnatural artifacts in the image frequency domain [20], or eye features [14], or inner & outer face features [10], or expressions [21], or biological signals [6]. However, such techniques make no specific assumptions about the computational resources available to the adversary; moreover, they assume that the detector possesses no agency and cannot induce specific actions by the adversary.

**Our contributions.** We depart from this convention and instead consider a different threat model where the detector can interactively pose non-trivial tasks, or *challenges*, to the impersonator based on what they have seen so far. In this model, the onus of consistently maintaining high-quality deepfakes, in real-time, under challenging situations, is now squarely on the adversary. We leverage this asymmetric advantage for the detector to design and validate a systematic *challenge-response* system to identify RTDFs. We call our system GOTCHA, echoing the ubiquitous CAPTCHA test used in online password-based user identification.

At a high level, GOTCHA presents a sequence of interventions, or challenges, to a suspected RTDF. These could either be active (physical) actions required to be performed by the suspect, or be passive (digital) operations such as face flips or noise addition performed on the video feed; see Sec 3 for a comprehensive discussion. Once these interventions are introduced, the induced changes in the video output become immediately

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available for human or machine-level scrutiny.

The key conceptual problem is to develop a catalog of practical challenges (i.e., the “real user” experience is not affected very much) yet maximally informative (i.e., “fake user” video outputs are statistically and visually abnormal). GOTCHA proposes challenges that exploit specific vulnerabilities of each component of the RTDF generation pipeline, including inference speed and high sample complexity (Sec. 2.2). We present a suite of active and passive challenges, which we further categorize into a taxonomy (Sec 3.2).

However, we find that owing to the high quality of current state-of-the-art deepfakes, no single challenge is sufficient to induce artifacts in the video feed that are robust and consistent across participants. Therefore, to boost the likelihood of detection, GOTCHA presents a *cascade* of challenges chosen from our proposed suite. The ordering of which challenges to present to the suspect can be defined via a (scalar) utility function that can be tuned by contextual parameters (participant, appropriateness, security requirements). See Sec 4.1.

A key feature of GOTCHA is that our challenges have been chosen to induce human-perceptible artifacts in the output video frames, while also giving robust signals which can be fed into downstream machine learning (ML) modules for automatic RTDF detection. The interpretability of the artifacts paves the way for added advantages of GOTCHA in real-world deployments, such as audibility and explainability.

We validate GOTCHA on a novel video dataset of 47 participants, each of whom performed 13 challenges, for a total of  $\approx 50$ GB of data consisting of 2.5M video frames. We show that our implementation of GOTCHA provides consistent and measurable degradation of deepfake quality across users, highlighting its promise for RTDF detection in real-world settings. We intend to publicly release this dataset pending peer review.

## 2 Background

We first start with a glossary, and then describe the overall architecture of modern real-time deepfake systems.

### 2.1 Glossary

- **Source:** The impersonated individual.
- **Impersonator:** An individual doing impersonation.
- **Real-Time Deepfake (RTDF):** A live impersonation of a source over video involving a head-shot reenactment or a face-swap.
- **Challenge:** A task, or intervention, defined by our proposed RTDF detection system.
- **Active challenge:** A challenge which requires a non-trivial participant action.

- **Passive challenge:** A challenge that does not require any special action by the participant.

### 2.2 The Real-time Deepfake Generation Pipeline

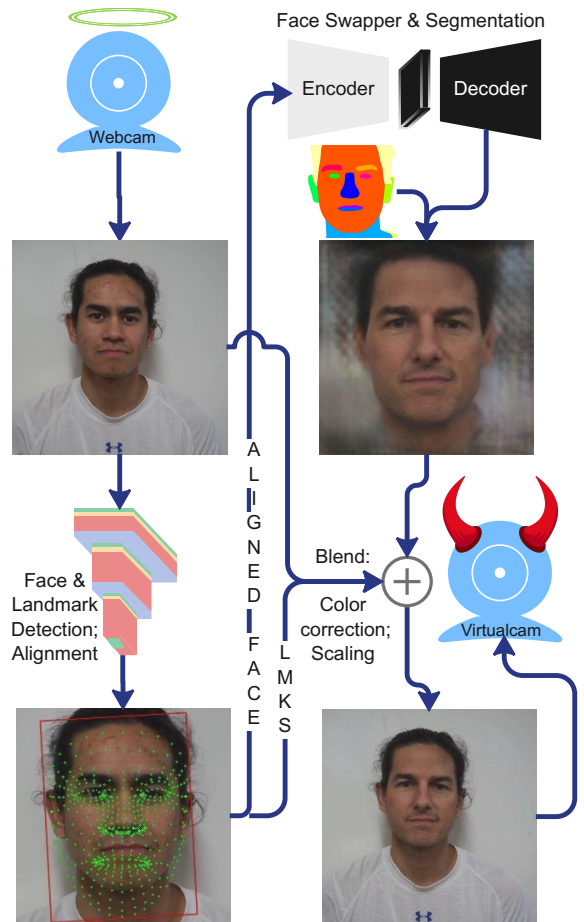


Figure 1: A generic face-swapping RTDF pipeline containing a physical webcam, face and landmark detector, face-swapper (auto-encoder), blending operator and a virtual webcam. The virtual webcam could be piped into a video conferencing software (not shown). Arrows indicate relevant data flows.

Across the literature, several approaches have been proposed to generate deepfakes. While the details differ, they all share roughly the same components. The following list explains each component in the deepfake generation pipeline (also illustrated in Fig. 1).

- **Face Detector (Face):** This module is a neural network that predicts a bounding box per face in a video frame.
- **Landmark Detection (Lmk):** This module is a neural network that detects facial key-points called land-

marks. Landmarks enable reenactment in face-swaps. They help morph the source’s face to fit the impersonator’s face shape.

- **Face Alignment** (*Align*): This module vertically aligns a given input face, which is vital for a robust prediction by the face-swapper. A reverse alignment is later applied to the prediction to match the impersonator’s head.
- **Segmentation** (*Seg*): This module (a) separates the face region into fragments of interest (lips, eyes, nose), (b) derives the convex hull of the face that is visible in the videos, and (c) determine facial boundaries in the presence of occlusions (e.g., hand).
- **Face-Swapper** (*Swap*): This module typically involves an autoencoder neural network. The autoencoder takes the input from the face detector and predicts how the source’s face would look under a given set of facial landmarks, occlusions, and lighting.
- **Blending** (*Blend*): This module performs a post-processing step that stitches together the inner predicted face with the outer face. This step tends to vary across RTDF generation pipelines, involving some combination of blurring, degrading, scaling, compression, fading, and mask boundary<sup>1</sup>.
- **Color Correction** (*Col*): If the impersonator and source do not share the same skin color, then a color correction module samples the color from the outer face region (around the forehead and neck) and adjusts the inner swapped face accordingly.

Each component in the above pipeline assumes a specific distribution over its inputs for proper functioning; this distribution depends on the type of component, its design, and the bias learned from the data. If the inputs venture outside this distribution, the component’s output gets degraded, and artifacts appear in the overall RTDF system output. Based on this intuition, we propose and develop a suite of challenges to target each component in the pipeline. The following section dives into formulating such challenges and categorizing them to form a taxonomy.

### 3 An Abstract Formulation for Challenges

We first begin with an abstract formulation of our challenge-response framework that reliably defends against deepfake realism. We then instantiate this abstraction with concrete candidate challenges and organize them into a taxonomy (Sec. 3.2).

<sup>1</sup>We note in passing that facial reenactment-based RTDF pipelines do not perform segmentation and blending operations.

## 3.1 Challenge Formulation

We start by defining several building blocks: a deepfake generation pipeline, a quality metric, generation tasks, and challenges.

### 3.1.1 Deepfake Generation Pipeline

An RTDF generation pipeline,  $P$ , consists of a trained face-swapper for mapping the impersonator’s face to a source’s face,  $Swap_{imp \rightarrow src}^P$ ; a frame of impersonator’s video  $I_{imp}$ ; detected face region of impersonator  $F_{imp}$ ; the outputs of face alignment  $Align(F_{imp})$ ; the output of landmark detection  $Lmk(F_{imp})$ ; and segmentation  $Seg(F_{imp})$ . A deepfake video frame  $I_{imp \rightarrow src}^P$  is generated as follows:

$$\begin{aligned} F_{imp} &= Face(I_{imp}), \\ F_{src}^P &= Swap_{imp \rightarrow src}^P(Align(F_{imp})), \\ F_{imp \rightarrow src}^P &= Col(F_{src}^P, Lmk(F_{imp})), \\ I_{imp \rightarrow src}^P &= Blend(F_{imp \rightarrow src}^P, Seg(F_{imp})), \end{aligned}$$

where  $F_{imp \rightarrow src}^P$  is the face of *imp* mapped to the face of *src* using  $P$ . A temporal sequence of fake video frames constitutes a video deepfake, denoted by  $[I_{imp \rightarrow src}^P]$ .

### 3.1.2 Quality Metric

In order to assess degradation, we assume the availability of a *quality metric*, which is a function  $Q : \mathbb{R}^{H \times W \times C} \rightarrow [0, 1]$ , where  $H, W$  and  $C$  are dimensions of a single video frame. Here,  $Q$  could either be an trained ML model or any other image statistic(s) that indicates “realism”; the higher the value assigned by the metric, the higher the realism quality of the frame.

We make the following assumption on  $Q$ . Say that an impersonator *imp* impersonates a source *src* using pipeline  $P$  and performs task  $t$  (e.g., looking side-to-side). Also, the same source *src* does the same task  $t$ . Then we assume that exists a non-negative difference between the source’s video frame  $I_{src,t}$  and the corresponding impersonated one  $I_{imp \rightarrow src,t}^P$ . We will be interested in the performance gap:

$$\Delta(src, imp, t, P) = Q(I_{src,t}) - Q(I_{imp \rightarrow src,t}^P). \quad (1)$$

### 3.1.3 Generation Task

We define a generation task as a triplet  $\tau = (T, D, f)$ . First,  $T$  is a set of tasks related to RTDF generation (e.g., tasks could correspond to active physical actions or passive digital operations such as left-right flips or other image manipulation). Next,  $D$  is a probability distribution over  $T$ ; this could be the uniform distribution or other non-uniform distributions based on the utility of tasks in



Figure 2: Exemplars of Occlusion-based challenges. Image (b) belongs to Human-introduced, (c)-(d) to Subject-introduced, (e)-(g) to Real-objects and (h)-(i) to Synthetic subcategory of Occlusion-based challenges. Example (i) contains a self-deepfake, where the source and impersonator are the same identities to emphasize the artifacts. The top row is the ground truth, and the bottom row is the corresponding predicted source image.

T. Third,  $f: \mathbb{T} \rightarrow [\mathbb{I}_{src,t}]$  is a function that maps tasks to videos and generates realistic samples of a  $src$  that are successfully verified  $\forall t \in \mathbb{T}$ .

Let  $\eta \in (0, 1]$ . We require that at least  $\alpha (> 0)$  fraction of true sources are able to successfully be verified, i.e.,

$$Pr_{t \leftarrow D} [|\Delta(src, \phi, t, \phi) - \Delta(src, \phi, t, f)| < \epsilon] > \eta.$$

### 3.1.4 Challenge

We define a challenge as a generation task  $c \in \mathbb{T}$  which requires that for a given impersonator  $imp$  with pipeline  $P$  and source  $src$ ,

$$\exists \epsilon \in (\beta, 1], \text{s.t.}, \Delta(src, imp, c, P) > \epsilon,$$

where  $\beta \in (0, 1]$  is the minimum required degradation level. Our challenge-response system that we instantiate below will consist of a suite of challenges  $\mathcal{C} \subset \mathbb{T}$  that induce the most amount of degradation.

## 3.2 A Taxonomy of Practical Challenges

The previous section shows that a collection of hard tasks form a suite  $\mathcal{C}$ . This section explores a concrete suite of tasks that are useful in practice. We describe an assortment of categories corresponding subcategories. Table 1 summarizes the taxonomy and features of each category along with examples.

### 3.2.1 Occlusion

This category includes challenges that involve any circumstance where the full frontal face is not visible due to the presence of an occluding object or head movement. This category comprises of the following subcategories:

- Human-introduced: This subcategory involves requesting the subject to occlude their face without external objects. This would include actions like covering

the face with hands, standing up and head movement. In particular, head movement presents a natural challenge as it alters the yaw angle from the default  $0^\circ$  (i.e., the face is looking directly to the front), therefore hiding part of the face.

- Real objects: This challenge subcategory requires performing face occlusion with external tangible object. The objects could be everyday objects such as face masks, sunglasses, and handkerchiefs.
- Synthetic: This subcategory passively introduces occlusions by manipulating the video stream acquired by the camera (prior to RTDF generation). The occlusions include random facial cutouts, augmented reality (AR) filters, and stickers.

Fig. 2 illustrates examples of each occlusion-based challenge subcategory.

### 3.2.2 Facial Expressions

These challenges include facial deformations due to distinctive (but natural) facial expressions. This category includes the following subcategories:

- Human-introduced: This subcategory requires the subject to intentionally demonstrate specific emotional expressions, e.g., frowns or laughter.
- Lip movement: This subcategory requires the subject to perform lip movements, for example by reading text or making conversation.
- Micro-expressions: A micro-expression is a brief, involuntary facial expression humans make when experiencing an emotion. It usually lasts 0.5–4.0 seconds and is hard to fake.

### 3.2.3 Facial Distortion

These challenges introduce unnatural deformations of the face images. They can be either performed actively by the subject or passively via video manipulation.



(a) Sad (b) Nervous (c) Speaking (d) Cheek (e) Tongue (f) Affine (g) Side Flash(h) Col. Filter (i) Multiple same faces

Figure 3: Exemplars of Facial Expressions, Facial Distortions, and Surroundings-based challenges. Image (a) belongs to human-introduced, (b) to micro-expressions, and (c) to lip movement subcategory of Facial Expressions. Images (d) and (e) belong to human-introduced and (f) Piecewise Affine to geometric transforms subcategory of Facial Distortions. Image (g) belongs to human-introduced, Image (h) Color Filter to software-introduced, and Image (i) to the synthetic background subcategory of Surroundings. The top row is the ground truth, and the bottom row is the corresponding image of a source.

Table 1: Taxonomy of Various Challenges with their Benefits and Examples.

Category	Sub-category	Component Targeted								Usability					Depl.		Example(s) / Comments	
		Face Detector	Landmark Detection	Face Alignment	Segmentation	Auto-encoder	Blending	Color Correction	Inference Speed	Easy-to-Comprehend	Appropriate-to-Request	Physically-Effortless	No-Equipment-Needed	Detected-by-Humans	High-Sensitivity-Test	Accessible		Server-Compatible
Occlusion	Human-introduced	●	○	●	○	●			●	●	○	●	○	○	○	●	●	Occl. w/ hands or standing w/ facemask, sunglasses. Automatic cut & paste facial.
	Real objects	○	○	●	○	●	○		●	○	○	●	●	●	●	●		
	Synthetic	○	○	○	●		○		○	●	●	○	●	●	●	●		
Facial Expressions	Human-introduced					●			●	○	●	○	○	●	●	●	Anger, Laugh or Scream Surprise element gives reflex Lip & speech not synced	
	Micro-expressions					●			○	○	○		●	●	○	●		
	Lip movement					●			●	●	○	●	●	○	○	●		
Facial Distortion	Human-introduced		○			○	●		●	○	●	●	●	○	○	●	Poke cheek; Tongue out. Automatic affine transforms	
	Geometric transform	○	○	○		●	●	○	○	●	●	○	○	○	○	●		
Surround -ings	Human-introduced					○	●	●	●	●	○		○	○	○	●	Flashing a light from phone Hue via screen or camera Adversarial background w/ faces	
	Software-introduced					○	●	●	○	○	○	○	○	○	○	●		
Additive Info	Steganography					●			○	●	●	○	●	●			Content-specific pattern Multiple duplications of feed	
	Feed overloading						●	●	○	●	●	○	○	●	●			

● = Fully Offered; ○ = Quasi/Partially Offered ; Empty = Not Offered ; w/ = with; Depl. = Deployment.

- **Human-introduced:** This challenge subcategory considers distortions that are distinct from changing facial expressions. These include challenges like poking the left (or right) cheek with a finger, and sticking out a small portion of the tongue.
- **Geometric transforms:** This subcategory passively distorts the face using one (or more) digital image transformations such as affine, scaling, piece-wise affine, or warping.

### 3.2.4 Surroundings

This category includes challenges that alter the subject’s background and surrounding ambience.

- **Human-introduced:** This subcategory involves partici-

pants actively changing the ambience, such as illuminating their own face with a flashlight.

- **Software-introduced:** This subcategory of passive challenges involves synthetically changing the ambience by applying dynamic color filters to the digital video feed, or by changing scene illumination by projecting structured light patterns onto the subject[11].
- **Synthetic background:** This subcategory requires the subject to deploy a curated background image (static or dynamic) during the live interaction, designed to disrupt the RTDF generation pipeline.

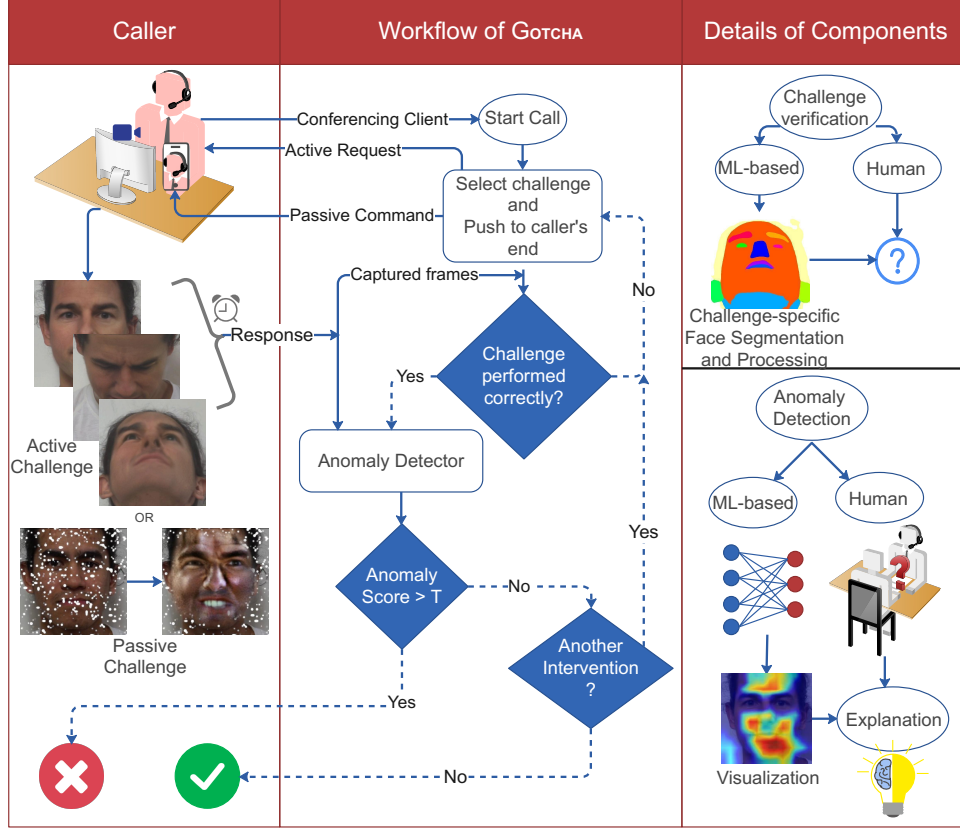


Figure 4: The figure illustrates the interaction of a caller with the GOTCHA pipeline. Bold lines in the middle column are data flows, and dotted lines are decision flows. Here, the active challenge is to look down and look up, while the passive challenge is adding snowflakes via a secure device (e.g., a smartphone).  $T$  is a threshold to limit false positives.

### 3.2.5 Additional Details

These challenges involve appending any extra information to the video feed through the webcam that can be extracted and analyzed automatically.

- **Steganography:** It involves adding a secret key to the video feed, e.g., inducing an imperceptible content-aware hash over the feed [25].
- **Feed overloading:** It overloads the feed with extraneous information, e.g., feed-duplication or noise addition to disrupt the internal components of the RTDF.

Fig. 3 illustrates examples of facial expression, facial distortion, and surroundings-based challenge subcategory.

The above suite of challenges, while non-exhaustive, covers a wide breadth of interventions that, in principle, are deployable within our challenge-response system. At a high level, the suite  $\mathcal{C}$  can be split into two essential categories – **active** and **passive** depending on whether or not the given challenge requires action by the participant. As illustrated across Fig. 2-9, our proposed active challenges are all reasonable tasks and deployable during most live interactions. Passive challenges do not require special actions by the suspect; however, they assume that

the challenge-response system has access to the digital video feed, which can be implemented via a secure camera system. Active challenges require no extra layers of protection; participants could simply be flagged if they refuse to perform the challenge, or perform it incorrectly.

## 4 The GOTCHA System

The previous section introduced an abstract challenge-response framework, a suite of challenges with various categories/subcategories, and a taxonomy of such challenges in terms of usability and deployability. We now concretely instantiate this approach for form our proposed challenge-response system that we call GOTCHA.

We first describe how GOTCHA works. The workflow is illustrated in Fig. 4) and is elaborated as follows:

- Step 1.** When a participant ( $par$ ) connects to a call, infer their context; initialize total score  $\mathcal{E} \leftarrow 0$ ; and select threshold  $T$ .
- Step 2.** Sample a cascade of challenges  $C$  from  $\mathcal{C}_\beta$  and order them into a list using the utility function  $u$ .

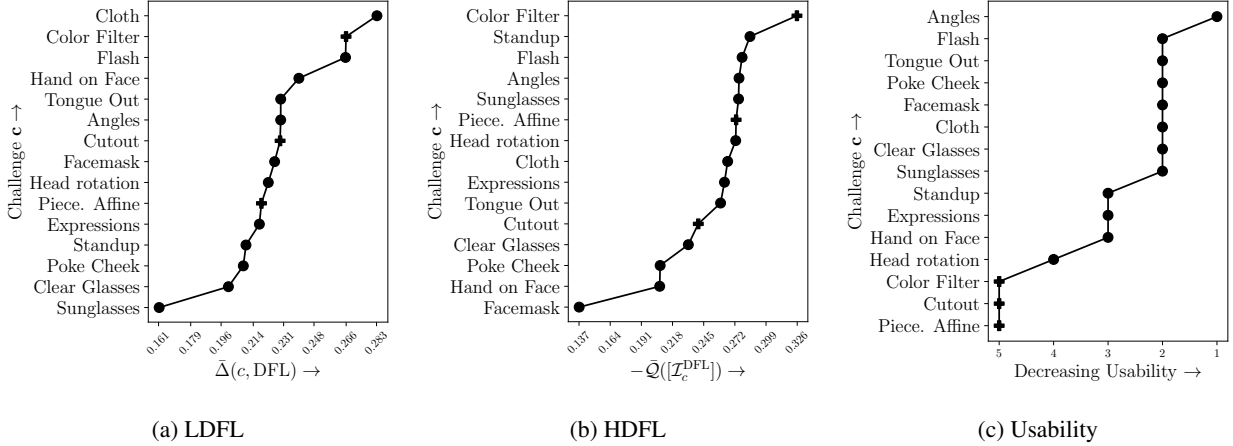


Figure 5: Ordering challenges according to (a) average hardness for a lightly DFL[27] model (LDLFL) trained with restricted data, (b) average hardness for heavily trained DFL[27] (HDFL) model with diverse data, and (c) usability set by an administrator. In (a) the x-axis is the average performance gap, (b) the x-axis is the negative of the average anomaly score, and (c) is the usability rating. + indicates passive challenges and solid circle indicates active challenges.

- Step 3.** Request *par* to perform the next challenge on the list,  $c_i$ ; initialize a timer.
- Step 4.** Capture their video  $[I_{par,c_i}]$  until timeout.
- Step 5.** Verify that *par* performed the challenge. If it fails, go to Step 2.
- Step 6.** Assign score  $[I_{par,c_i}]$  using an anomaly detector  $Q$  with confidence  $p_i$ .
- Step 7.** Increment total score  $\mathcal{E}$  by  $\log p_i * Q([I_{par,c_i}])$ . If  $\mathcal{E} > T$ , set *par* = *imp*. Declare **FAIL**.
- Step 8.** If  $i < |C|$ , go to Step 2.
- Step 9.** If  $\mathcal{E} < T$ , set *par* = *src*. Declare **PASS**.

The following subsections explain the design of each relevant step above: cascading (Step 2), challenge verification (Step 5), anomaly detection (Step 6), decision-making (Steps 7 and 9), and a requirement for utilizing passive challenges.

#### 4.1 Cascading (Step 2)

Given a suite of challenges  $\mathcal{C}_\beta$ , GOTCHA selects a specific number of challenges from the suite and arranges them in a particular order to form a *cascade*  $C$ . Thus,

$$C = \{c_i : c_i \in \mathcal{C}_\beta, u(c_i) \geq u(c_{i-1}), \text{ for } i \in 1, \dots, |C|\}.$$

Here,  $u : \mathcal{C}_\beta \rightarrow \mathbb{R}$  is a non-decreasing utility function and  $|C|$  is the number of required challenges. Both depend on the context  $ctx$  of the participant joining an interaction. The context  $ctx$  comprises of:

- possible actions a participant can do in a live setting,
- actions appropriate to request the participant,
- their environmental settings,
- their ambience, and
- required security level of the interaction.

GOTCHA infers  $ctx$  and functions inside it, since not every challenge applies to every scenario or is required for every participant. Given a sufficiently diverse  $\mathcal{C}$ , it chooses a subset  $C \subseteq \mathcal{C}$ , and using a utility function  $u$ , orders all challenges in  $C$ . To illustrate this step, we consider two example real-world scenarios:

- **Case I: Deploying GOTCHA in a job interview:** Since integrity of the applicant is critical in such scenarios, non-trivial, aggressive active challenges (such as challenging the interviewee to briefly cover their face with a cloth) may be part of the context. The person administering GOTCHA may choose to make sure that the interviewee has access to all physical articles needed to complete the challenges. Fig. 5ab illustrates sample orderings of  $C$ , containing 16 challenges, based on security inferred from an anomaly detector. The challenges become increasingly hard for deepfakes to maintain their quality and are an intermix of passive and active challenges.
- **Case II: Deploying GOTCHA on a video call over a phone with a CEO:** Usability may be key here, so informal or frivolous challenges (such as facial distortions or expressions) may not be appropriate. Challenges using external physical articles may not be desirable. The context here is appropriately modified and GOTCHA adapts its suite of challenges accordingly. Fig. 5c illustrates an example ordering of  $C$ , containing 16 challenges, based on usability (which can be

calibrated up front by the system administrator. The challenges become progressively less usable for participants. Passive challenges are the least intrusive, therefore they appear earlier, followed by user-friendly active challenges.

## 4.2 Challenge Verification (Step 5)

Once a challenge is issued, a human evaluator (or an ML-based module) can verify whether the participant indeed adhered to the challenge by observing the video response. E.g., if the challenge is to look side-to-side, then verification involves asserting a minimum change in yaw angle either by human or automatic methods.

It is important to note that challenge verification is specific to a given challenge, and is independent of anomaly detection, and does not immediately evaluate any particular artifacts.

## 4.3 Anomaly Detection (Step 6)

Each captured challenge video of a participant  $par$ ,  $[I_{par,c}]$ , is presented to a grader with a null hypothesis and a research hypothesis corresponding to whether the video is legitimate or manipulated, respectively:

$$\begin{aligned} H_0 &: \text{Legitimate,} \\ H_1 &: \text{Manipulated,} \\ \Lambda([I_{par,c}]) &= \frac{\mathcal{L}(H_0|[I_{par,c}])}{\mathcal{L}(H_1|[I_{par,c}])}. \end{aligned}$$

Above,  $\mathcal{L}$  is a likelihood function, and  $\Lambda$  is the likelihood ratio.  $H_0$  is rejected if  $\Lambda < s$  and is otherwise failed to reject. [5].

Challenges in GOTCHA are designed to visually degrade RTDFs; therefore, depending on context, both a human volunteer and an ML-based model could score a given video response, and decide whether to reject  $H_0$  or fail to reject  $H_0$  with confidence  $p$ .

## 4.4 Defense Amplification (Step 7)

As a participant  $par$  walks through  $C$ , a grader provides a score for each performed challenge  $c_i$  and a confidence level with which they reject the null hypothesis,

$$p_i = \mathcal{L}(H_1|[I_{par,c_i}]). \quad (2)$$

The cumulative weighted score  $\mathcal{E}$  of the video feed is:

$$\mathcal{E}_k = \sum_{i=1}^k \log p_i * \bar{Q}([I_{par,c_i}]).$$

Here,  $[I_{par,c_i}]$  is the response video, and  $\bar{Q}$  is the average quality metric across all relevant frames in the

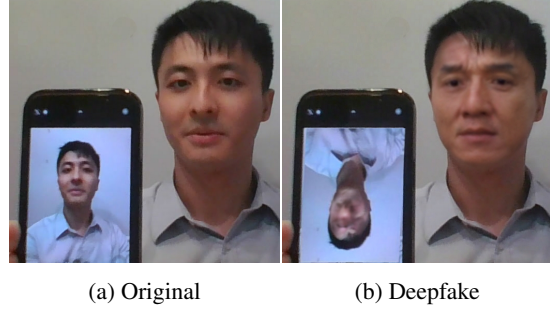


Figure 6: *Demonstration of a trusted device. A participant turns on the back camera in a smartphone and points it towards them, adding live video from the smartphone display to the video feed. Image (a) is a genuine feed and (b) is a smartphone performing a passive challenge (here, flip upside down), resulting in visible artifacts.*

response video. Given a pre-defined threshold  $T$ , if  $\mathcal{E} = \frac{\mathcal{E}_k}{|C|} > T$ , the participant is declared an impersonator ( $par = imp$ ). Otherwise, they are considered genuine ( $par = src$ ).

## 4.5 A Note on Passive Challenges

Passive challenges require no special actions by the user, but are executed by trusted client-side software (or hardware) during the interaction. GOTCHA’s design allows multiple ways to insert trusted components. Two such ways are as follows:

- **Secure webcam:** A trusted webcam (prior to RTDF generation) enables digital manipulation of the raw video feed; however, this assumption requires preparation up front, making it relevant for situations an incentive for the caller to prove their integrity.
- **Smartphone application:** This approach assumes the availability of a smartphone running a secure application (which can be controlled by the GOTCHA system); therefore, it decouples the trusted device from the machine running the RTDF (such as a desktop workstation), providing an additional layer of security. Figure 6 demonstrates an example setting of how this type of setup could be deployed.

## 5 Evaluation

The previous section described the design of GOTCHA and its various components. This section evaluates these components and quantitatively tests a set of challenges against four state-of-the-art real-time deepfake generation pipelines. For thorough evaluation, we also introduce a new dataset of 47 users, each of which performed several challenges.



## 5.1 A New Dataset

We collected a new dataset for evaluating GOTCHA’s performance against current RTDF generation pipelines. The dataset consists of videos of each of the 47 users of various demographics performing 13 active challenges; total video footage per user was about 5-6 minutes. Altogether, the dataset consisted of close to 3M frames of video captured at 60 FPS and 1080p, totaling nearly 50GB of video data. We intend to publicly release this dataset for research use upon completion of peer review.

## 5.2 Anomaly Detection

As discussed above, Step 6 in GOTCHA (anomaly detection) can be performed either via a human scorer or by an ML module. In our validation experiments below, we trained an ML-based anomaly detector for scoring real and deepfake videos. The detector was trained on 600 faces derived from FaceForensics dataset [28]. The inner face region of each image was modified using a composition of benign augmentations, then self-blended with the original head. Two linear neural network heads (for classification and regression) were trained in a self-supervised way using binary cross-entropy and LPIPS [37] as loss functions, respectively.

As the anomaly detector was tested on our dataset (cr. Sec 5.1), there was no identity leakage as there were no shared faces between the training and testing phases. It has the following desirable properties.

- It pinpoints artifacts quickly in a frame. We used EigenCam [23] for visualizing detector’s weights.
- The anomaly score provided by the regression head is higher for deepfake videos than real ones.
- The anomaly score of a deepfake video follows a similar trend as the corresponding real video.

## 5.3 RTDF Generation Pipelines

We evaluate the effectiveness of GOTCHA against four modern RTDF generation pipelines: (i) a lightly trained DeepFaceLab model (LDFL), (ii) a highly trained DeepFaceLab model (HDFL), (iii) Face Swapping Generative Adversarial Network (FSGAN), and (iv) Latent Image Animator (LIA).

In Table 2, we tabulate anomaly scores for each challenge performed against each RTDF pipeline, averaged across all 47 participants as impersonators. For visualization purposes, Figure 8 displays one random frame for each corresponding anomaly score entry in Table 2.

- **Real** corresponds to the original source. The first numerical column in Table 2 and the first column in Figure 8 corresponds to a genuine participant (without any RTDF) responding to the given challenge for each row;

Table 2: Average anomaly scores for each RTDF pipeline variant for each challenge. The top part is active, and the lower are passive challenges.

Chal.	Variant	Real	LDFL	HDFL	FSGAN	LIA
Angles		0.098	0.327	0.276	0.200	0.148
Head rotation		0.135	0.355	0.273	0.234	0.193
Hand on Face		0.076	0.312	0.207	0.192	0.168
Sunglasses		0.123	0.281	0.275	0.197	0.153
Clear Glasses		0.074	0.273	0.232	0.173	0.137
Cloth		0.093	0.370	0.266	0.241	0.187
Facemask		0.071	0.292	0.137	0.193	0.196
Poke Cheek		0.068	0.275	0.207	0.161	0.114
Tongue Out		0.089	0.315	0.260	0.193	0.125
Expression		0.106	0.321	0.263	0.210	0.152
Standup		0.116	0.326	0.285	0.187	0.168
Flash		0.086	0.351	0.278	0.204	0.155
Piece. Affine		0.132	0.350	0.273	0.222	0.191
Cutout		0.068	0.298	0.240	0.203	0.160
Color Filter		0.104	0.372	0.326	0.243	0.143
Average		0.096	0.321	0.253	0.204	0.158

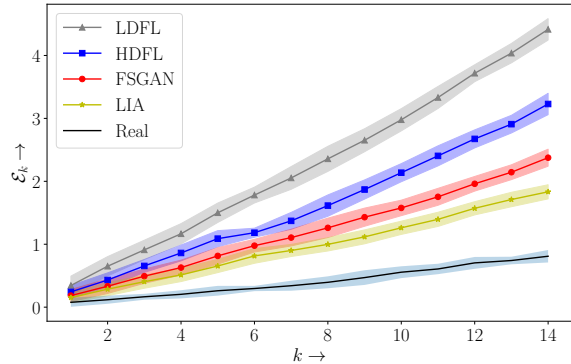


Figure 7: A plot of cumulative weighted score vs. cascade progression ( $k \in [1, \dots, |C|]$ ) for each pipeline. Genuine participants and impersonators walk through a cascade  $C$  consisting of 14 challenges, progressively increasing their cumulative weighted anomaly scores  $\mathcal{E}$ . The manipulated feed results in a higher slope than the genuine one. Thus, challenges provide enough signal for the anomaly detector to classify between feeds and lead to a more robust decision as the cascade progresses.

we observe from the Table that this uniformly gives the lowest anomaly scores.

- **LDFL** corresponds to the output of a lightly trained version of DeepFaceLab [27], trained on participants in our dataset for around 0.5M iterations together with a face-agnostic segmentation module. The dataset contained each participant’s face from multiple angles. As

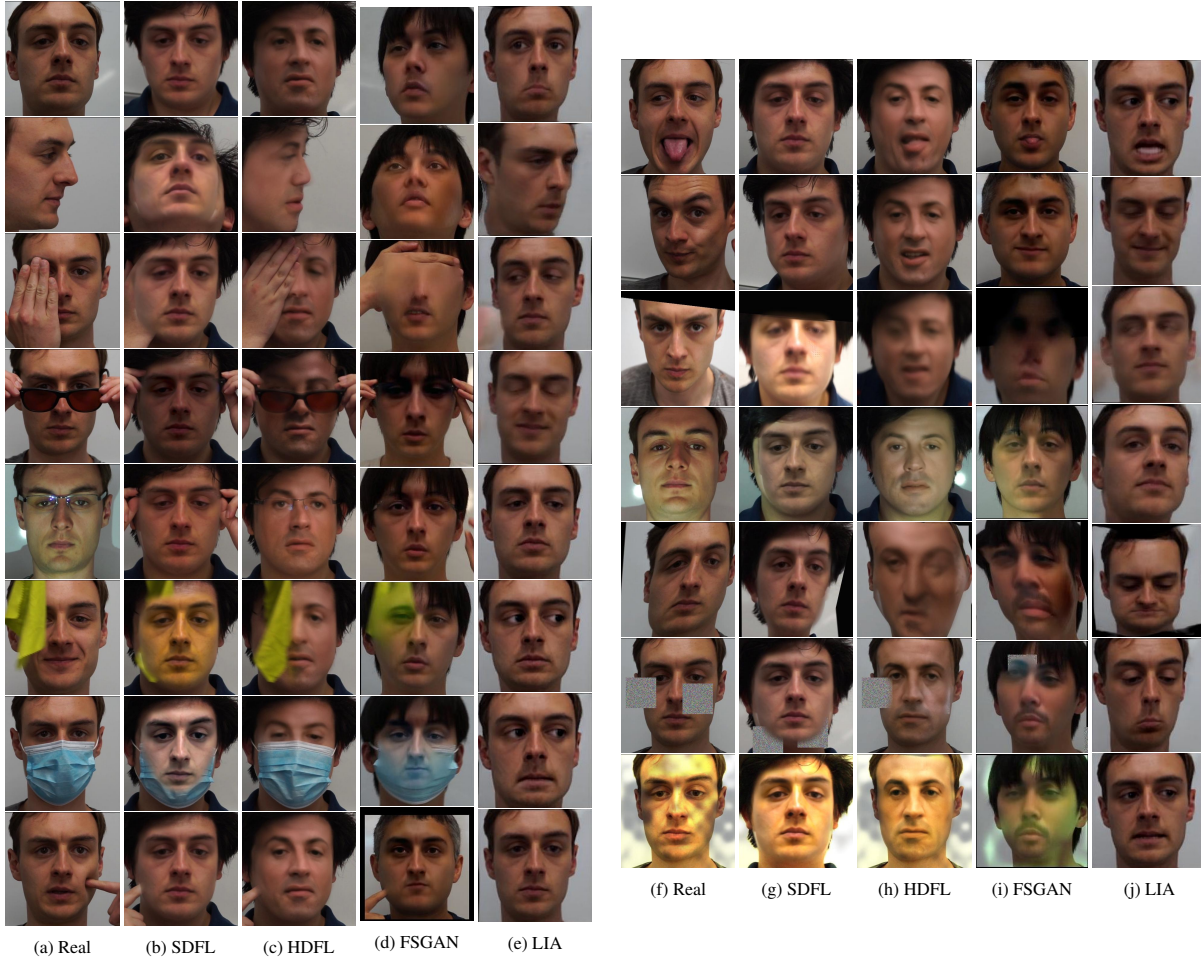


Figure 8: Example frames for each challenge parallel to Table 2. Left five columns are top 8 challenges and second column are remaining 7 challenges. Every frame is a random sample from video of the corresponding challenge.

seen in the second column in Figure 8 and Table 2, the LDFL model generates the most visual artifacts, and also gives the highest anomaly scores. This is due to the fact that the LDFL models for each participant are only trained on very simple data where the source is stationary and only the camera location is spatially varying. We also observed that the corresponding deepfakes were unable to reproduce distinctive mouth movements while speaking or show emotions as needed by the challenge.

- **HDFL** corresponds to the output of a highly trained version of DeepFaceLab [27], trained for around 2M iterations, along with a celebrity-specific segmentation module. As seen in the Table and the Figure, the HDFL model shows the fewest visual artifacts and also gives a correspondingly lower anomaly scores compared to SDFL. In particular, the responses to Occlusion-based challenges are better and show very few artifacts, and cascading multiple challenges for this model appears

to be necessary for reliable detection.

- **FSGAN** corresponds to Version 2 of the Face Swapping Generative Adversarial Network [26]. We find that the scores for FSGAN are somewhere in-between those of LDFL and HDFL.
- **LIA** corresponds to the Latent Image Animator [18], which is a deepfake generation pipeline based on facial reenactment. We find from Table 2 that the anomaly scores are low across different challenges; however, this is not because deepfake quality is high, but rather that the LIA generator is unable to respond to specific challenges and simply reproduces (clean) images of the target. This pipeline likely would fail during the challenge verification step (Step 5).

Fig 7 compares cumulative weighted score of a cascade for each pipeline. It illustrates that as a participant progresses across one of GOTCHA’s cascades, the difference between a fake and genuine feed widens, increasing confidence and trust in its final decision.

## 6 Further Insights on Breaking DeepFakes

As illustrated in Sec 3, GOTCHA presents various challenges that are designed to degrade the performance of an RTDF generation pipeline (Sec. 2.2) and produce human-visible artifacts.

In this section we elaborate upon how a particular component of RTDF pipelines gets targeted by a specific subset of challenges. This provides further insights into the inner workings of each RTDF model, and could pave the way for designing successor challenge-response systems to GOTCHA.

The illustrations in Fig. 9 are based on results derived from the most sophisticated RTDF that we considered in our evaluation, which is a highly-trained DeepFaceLab [27] model (HDFL, see Sec. 5).

### Face detection, landmark detection, face alignment

We found that these three modules were the most robust components of the RTDF pipeline, as they work extremely well even for sideways profiles and distorted faces. We believe that this robustness could be attributed to the availability of massive amounts of face images available as training data, as well as the maturation of deep-learning pipelines as effective deepfake generators.

However, we also found that since these modules are so robust, using these components within specific challenges caused them to output unexpected predictions and this can be used to GOTCHA’s advantage. In Fig. 9b and 9c, they can detect faces and landmarks on smileys drawn on a participant’s hand, a fist, or even on the crease of participants’ shirts (not illustrated). Both subfigures show a garbled deepfake in the detected region. These vulnerabilities could be leveraged within challenge design to induce unanticipated but detectable predictions.

Despite being very robust to head movements, we found that eye occlusions still degrade the performance of all these components; indeed, the eye region forms an essential feature for these detectors (Fig. 2c, Fig. 9d). Also, face landmarks carry limited facial structural information; therefore, facial deformations or depressions induce visible anomalies. For example, with Mediapipe [19] providing 468 landmarks per full frontal face, the RTDF outputs are not able to capture facial depressions; see Fig. 3df).

To summarize, we found facial alignment and landmark detectors are excellent input sanitizers for the rest of the pipeline, but are inherently vulnerable to challenges that produce out-of-distribution data.

### Face-swapper

We found that the face-swapping module stores most of the source-specific knowledge, which makes it the most

vulnerable element of the generation pipeline. Challenges designed to degrade earlier components eventually affect the face-swapper, which is inadequate in handling degraded inputs.

Challenges based on data diversity, or digital feed manipulation (e.g., inserting a mole, or illuminating with structured light), changing emotional expressions and distortions work very well. In Fig. 3gh, lighting changes illuminate a more considerable portion of the face than the initial half and automatically remove an applied color filter, respectively. In Fig. 3f, the model fails to copy the distortions faithfully. In Fig. 3, the generated expressions of the inner face do not match the original expressions of the outer face [21].

Also, in Fig. 8b, we found that LDFL generates the same expression across all challenges as it was trained only on source data containing no expressions. Hence, data diversity is crucial for robust deepfake generation.

### Segmentation

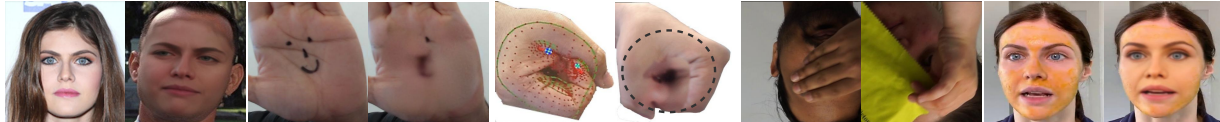
We found that the segmentation module was also very vulnerable. A segmentation mask, provided by this module, becomes crucial for informing the face-swapper of what portion of the face needs to be swapped. Multiple challenge subcategories (especially occlusion-based challenges, Fig. 2 (c)-(i), and facial distortion-based challenges, Fig. 3e)) degrade the quality by targeting the segmentation module.

A pipeline without a segmentation mask makes the deepfake brittle to any occlusions, resulting in highly unnatural artifacts, e.g., the occluding object blending with the face itself (Fig. 2i). Even a generic segmentation mask, which segments out only external objects, could result in artifacts caused by source and impersonator face mismatch. (Fig. 9a).

### Blending and color correction

This step is a composition of post-processing operations that merges the swapped prediction of the source face with the impersonator’s face. We found that any inconsistency between the inner and outer face regarding smoothening, color difference, facial artifacts (e.g., freckles, beards), positioning, and scaling constitutes a blending artifact.

As hyper-parameters controlling post-processing can be tweaked for source and impersonator pair before any interaction, live interaction starts with a well-calibrated merge with minimal blending artifacts. The calibration depends on the match between a source, the impersonator’s face, and environmental conditions (e.g., lighting). Hence, an impersonator doing challenges during the interaction generates blending artifacts due to inconsistent



(a) Seg. mask mismatch (b) Smiley & Deepfake (c) Fist & deepfake on it (d) Misaligned by Occl. (e) Face pack

Figure 9: *Samples showing unexpected behaviors: (a) Segmentation mask mismatch causes source’s (left) hairline to project to impersonator (right), (b)-(c) Face and its landmarks are detected, and the corresponding deepfake (circled); (d) Occlusions result in inverted alignment; (e) Yellow face pack applied on participant’s face changes color across the whole self-deepfake (source = impersonator). Using self-deepfake removes the effect of any skin-color difference on the artifacts.*

hyper-parameters.

The blending step also results in temporal incoherence. Most RTDF generate per-frame outputs, and future predictions do not depend on past ones. We found that randomly placing an object in front of the face causes the face-swap to move around the impersonator’s face, producing human-visible anomalies.

Color correction (CC) is an useful blending step that samples a color from the impersonator’s outer face and distributes it over the predicted source face. Fig. 9e illustrates CC sampling a yellow pixel from an occluding object and incorrectly extrapolating across the deepfake. In Fig. 2g, the imperfection of the segmentation mask makes the green occluding cloth a part of the face, which the CC module samples, producing a visible artifact.

### Inference latency

Online interactions are considered real-time at  $\approx 15$  frames-per-second (FPS) for the human eye. Therefore, an RTDF generation pipeline must have low-enough latency to produce outputs at this speed.

In terms of throughput, we found that the face-swapper module has the highest latency, followed by the blending and landmark detection modules. Generally, in the case of video conferencing, only one human face is present in the input feed, and the SoTA pipelines can deliver results at a reasonable rate. However, if we artificially introduce new “faces” (via, say, hallucinations), the face-swapper intermittently drops frames and eventually overloads the overall feed.

One way to achieve such feed overloading by way of a passive challenge is by feed duplication. This involves progressively replicating more instances of the source’s face in pseudo-random spots into the feed. Due to its robustness property, the face detector will detect multiple faces in the frame, and the face-swapper will slowly increase in latency so as to throttle the feed; clearly, no such lag is present if the participant is genuine and not using an RTDF. In Fig. 10, we quantify this relationship between FPS and the number of faces in the feed.

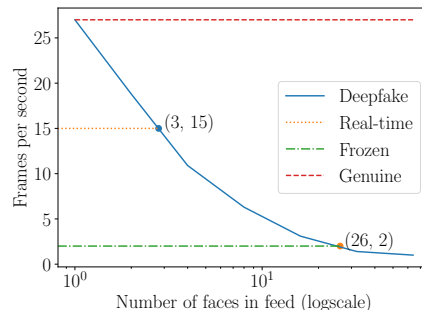


Figure 10: *A plot of frames-per-second vs. number of faces in the video feed. The pipeline can handle any number of faces above the real-time line (here, 3). As the number of faces increases, the FPS rate drops, and with around 26 faces, the video feed gets nearly frozen at 2 FPS (Note: The x-axis is log-scaled).*

## 7 Related Work

Our proposed system builds upon progress from various ideas in the literature including deepfake generation, deepfake & anomaly detection, interpretable ML, anti-spoofing, liveness detection, CAPTCHA systems, and passive challenge examples. Below, we discuss several relevant papers and their relation to our work.

**Deepfake generators.** In this paper we evaluated several state-of-the-art (SoTA) deepfake generators: DeepFaceLab [27], FSGANv2 [26], and Latent Image Animator (LIA) [36]. DeepFaceLab (DFL) is arguably the most sophisticated deepfake generator that is publicly available. It is an any-impersonator-to-one-source method. Both FSGANv2 [8] and LIA [36] are any-impersonator-to-any-source methods which use generic autoencoder networks; these are much more brittle against GOTCHA’s challenges.

**Offline deepfake detection.** There is a large literature on offline deepfake detection approaches; we stress that our work is distinct in that we consider a different (online, interactive) model where the detector can raise

adaptive challenges to the suspect.

Recent work has advocated a learning-based approach for detecting inconsistent features between outer and inner face regions [10]. It uses an identity consistency loss on the extracted features using a transformer network. This approach works well when the target identity is available during inference but fails for non-celebrity targets where ground truth is unavailable.

Sun et al. [31] detect deepfakes with exact geometric measurements; ID-reveal [9] uses behavioural biometrics, while Zhou and Lim [38] utilize audio-video modalities via lip movement and video coherence detection. Groh et al. [13] show that fully automated deepfake detectors do not work well; offline detectors learn spurious, non-interpretable features and as such are not better than purely human evaluators.

Most automated deepfake detectors involve complicated neural network models, and therefore inherit common problems such as vulnerability to adversarial perturbations [24], generalization issues caused by unseen manipulations [12] and inscrutability. These shortcomings ensure that robust, offline deepfake detection continues to be an unsolved problem.

**Liveness detection.** GOTCHA bears resemblance to a parallel line of work studies liveness detection (where the goal is to declare whether a subject is live or not). We discuss some relevant connections below.

In [7], an (offline) face authentication method is proposed that uses two approaches – camera close-ups and head rotations – to detect presentation attacks. It demonstrates good detection accuracy, but suffers against deepfakes on a private dataset. They test their methods on first-order motion models (FOMM) [30] and FaceApp [1]. GOTCHA also can be viewed as a liveness detection method, but under a more stringent threat model; presentation attacks almost always will fail against any active challenge (e.g., requiring that the subject makes a specific facial expression) since it is unlikely that the model has been trained to reproduce such effects.

LiveBugger [17] does an empirical assessment of commercial liveness detection APIs against FOMM-type [30] deepfake spoofing attacks. It consists of an automatic vulnerability detector, a multi-modal face-swap, and an analysis system. It tests image, video, voice, and action-based liveness detection systems, exposing severe security flaws in major APIs. GOTCHA shares concepts like anomaly detection and action-based detection, but its objective is different; the goal is not to expose APIs but evaluating the robustness of SoTA RTDF generation pipelines. See also rtCaptcha [33] which provided a challenge-response system for liveness detection.

**Video Call integrity.** Gerstner and Farid [11] recently introduce a face illumination-based RTDF detection technique; such a challenge can be presumably cas-

caded with other challenges with GOTCHA. The idea is to reflect a specific hue pattern from the participant’s screen onto their face; this verifies the reflection’s integrity, assuming that a trained deepfake cannot generate complex hue illuminations in real-time. The technique has the benefit of not needing any additional hardware. They also show preliminary results on a facial reenactment pipeline.

While preparing this manuscript, we were made aware of a paper under construction describing DF-Captcha [22], which is also a challenge-response system for RTDF detection that employs three categories of challenges: technology-based challenges targeting the generation capability of deepfakes; out-of-distribution-based challenges exploiting the limited training set of the attacker’s model; and audio challenges. Within the taxonomy that we describe above, all such challenges are “active”; our system allows for a much more comprehensive and wider suite of challenges. We also show that since no single challenge can handle all deepfakes, one needs to create a specific cascade consisting of active and passive challenges. Moreover, this manuscript only illustrates limited preliminary results using a facial reenactment pipeline.

**Deepfake disruptors.** Wang et al. [35] introduce a passive challenge for GAN-based deepfake generation. They add imperceptible perceptual perturbations to the  $a$  and  $b$  channels of  $Lab$  color space of source images and test it for deepfakes. They show that the perturbations are robust to benign transformations and reconstruction. FaceSigns [25], similar to neural imaging pipelines [16], is a passive challenge that embeds a content-aware secret-key in images at their time of creation and verifies the images throughout their lifespan.

## 8 Conclusions and Broader Impact

In this paper we propose GOTCHA, a real-time challenge-response system for live video interactions. The core principle underlying GOTCHA is a specially chosen cascade of both active and passive challenges to participants, designed to target vulnerabilities of modern deepfake generation pipelines. We have developed a comprehensive taxonomy of a large set of usable challenges, and use this hierarchy to induce robust, human-interpretable artifacts that degrade deepfake quality and therefore enable deepfake detection in the wild.

Due to the sensitive nature of the impact of deepfakes on society, during the development of our system we considered several risks. Evaluation of our system was a major challenge, since open-source research datasets in this area are scarce. We followed best practices (such as following IRB protocols) to minimize any potential harms and ensure safety of the participants. We did our

best to balance participants across demographic buckets, while acknowledging that our new dataset is too small to capture the full spectrum of human faces; much more work is needed here. Finally, we recognize that effective defense systems (such as GOTCHA) can themselves be leveraged to produce even more powerful deepfakes in the future; regulation may be key to stopping such an “arms race” between attacks and defenses.

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## Appendix

The appendix contains further details of limitations of impersonators, dataset collection, usability and deployability benefits used in taxonomy, implementation details of anomaly detector, the compute environment used, and a note about facial reenactment-based RTDFs.

### A.1 Limitations for Impersonators

An impersonator attempting to construct and launch a successful RTDF attack using a source’s data faces several roadblocks. The following limitations are behind the motivation for designing the challenges endorsed in this paper.

1. **Data Availability:** In order to impersonate a specific source, a diversified and massive amount of facial data (called a face-set) is necessary. An ideal face-set includes the source’s face under various lighting conditions, angles, and maybe occlusions, preferably in the form of high-quality video samples. In reality, individuals sharing their images on social media have a selection bias, as the images tend to be non-occluded frontal faces that the media platform has significantly compressed. Online tutorials advocate against using occluded data for better results, leaving their generated output vulnerable to occlusion. For example, to train a deepfake face mask with DeepFaceLab [27], more than 4,000 diverse images are required.
2. **Facial Similarity:** An impersonator’s face can be mapped to a set of similarly shaped sources’ faces. The excessive dissimilarity between the two faces may cause deterioration and unnaturalistic artifacts, such as stretching or contractions of the deepfake face and blending artifacts.
3. **Computational Resources:** For obtaining a full deepfake face mask, long training times and hardware accelerators (like TPU or GPU) are required. For reference, currently to train a  $320 \times 320$  px face mask model<sup>2</sup> using DeepFaceLab [27] takes around three weeks on an 80 GB NVIDIA A100 using around 5,000 images. For video calls, computational resources could become a bottleneck as impersonators will need to conduct *inference in real-time* ( $\approx 15$  fps), and having access to at least a GPU becomes essential. Recently, Google banned training deepfakes on their Colab platform [3].
4. **Domain Knowledge:** Impersonators must foster expertise with the training protocol since various

<sup>2</sup>For exact specification, refer Appendix

hyperparameters must be chosen to build a successful high-quality deepfake.

5. **Limited Transferability:** For each new target, a new model must be trained from scratch, or an already pretrained model must be retrained on the source’s data for weeks. Although source-agnostic methods exist, like First-order motion model [30] and Latent Image Animator [36], not requiring re-training to perform the face-swap, the results are substantially more brittle due to imperfect disentanglement of identity from other attributes (e.g., pose and expression). Also, these generators use off-the-shelf SoTA face detectors and face landmark detection, carrying forward their shortcomings into their real-time generation process.
6. **Software Skills:** Although various ways to perform a face swap exist, creating one from scratch and integrating it into the present SoTA necessitates significant software development abilities. A new implementation is generally a rip-off of several approaches evaluated in this work or requires a vast number of hit-and-trials.

### A.2 Data collection

After providing consent, the participants were allowed to withdraw their participation at any time. Although the data collected was made available to the research community, a data release form protected each participant’s interests. Unless otherwise stated, all source images used in the paper are samples from the collected dataset.

Each participant will be requested to do one or several examples representing the following categories, with their short form used in the main paper in parenthesis:

1. (Angles) Two minutes of looking directly into the camera (for the NERF).
2. (Head rotation) Rotate head side-to-side. Look up and down. Ask to do 5 seconds per side as far as possible but comfortably. So the video would be around 25 seconds.
3. (Hand on Face) Cover eyes. Cover the left half, right half, and lower half of their face with one of their hands. Each time bring the hand down.
4. (Sunglasses) Wear sunglasses.
5. (Clear Glasses) clear glasses with the shine of the lamp. Get the shine working first, then ask the person to remove the glasses and start recording.
6. (Cloth) Move a small handkerchief or dust cloth in front of the face.

7. (Facemask) Put a facemask and count loudly from 1 to 10. Take off the facemask.
8. (Poke Cheek) Poke one of their cheeks with a finger.
9. (Tongue Out) Take (a small portion of) tongue out.
10. (Expression) Express laughter for 10 seconds and frowning (anger) for 10 seconds.
11. (Standup) Stand up slowly and sit down.
12. (Flash) Dim the room’s light and Flashlight on the face with a torch.

Three passive challenges – Piecewise Affine, Cutout, and Color Filter – were created using the ‘Angles’ video. The dataset also includes recording each participant counting from 1 to 50 with 1 per second.

### A.3 Benefits

GOTCHA considers challenges that encompass three major categories of benefits: targeted deepfake generation pipeline components, usability, and deployability.

#### A.3.1 Usability

This category contains participant-facing benefits, which indicate how practical a challenge is in a video-call setting. Because this category only includes participant-facing benefits, a particular benefit could either awarded an *Offered*, *Not-offered* or *Quasi* (partially offered) status. The following challenges are granted an *Offered* status:

- **Easy-to-Comprehend:** If the challenge requires action (i.e., is active), it is also easily understood, and the task comes naturally to a human participant. *Quasi* is granted if it is difficult to understand, even if done automatically by the camera.
- **Appropriate-to-Request:** If the task must be completed, it can be completed without hesitation or embarrassment. It is still permitted if it is done automatically without the participant’s awareness during the call.
- **Physically-Effortless:** If the participant is not required to do anything except hold a mobile device, say. *Quasi* is granted if performed challenges do not require any more than a simple task to be done, which a participant might even undertake naturally during a video call interaction. All passive challenges are deemed physically effortless.

- **No-Equipment-Needed:** Suppose the participant does not require any extra equipment to complete the task. They would join the video call as usual, with no expectations.
- **Detected-by-Humans:** If the challenge introduces artifacts or inconsistencies that could be perceivable distinctly by humans. *Quasi* is granted if the artifacts could be seen with a keen eye of a human evaluator who might be specifically looking for them. If the challenge would not introduce any particular observable artifacts, *Not-Offered* is granted.
- **High-Sensitivity-Test:** If the artifact is observed or noticed by humans or detected automatically, it could only be generated by a phony video stream with a high probability. If an artifact might be caused due to low video quality or camera angle, then *Quasi* is granted.
- **Accessible:** If the challenge can be accessed by all participants (with or without any disability). If some participants could only do the challenge, then *Quasi* is granted.

#### A.3.2 Deployability

The benefits related to the deployment of the challenge are granted under the following conditions. No *Quasi* is granted for all these challenges, as the challenge either provides it or not.

- **Marginal-Cost:** The cost of doing this challenge does not increase for the participant if they keep on doing it.
- **Server-Compatible:** If an extra plugin or the video conferencing server is not needed. If the server-side needs to be upgraded to handle and evaluate this challenge, then this would be *Not-offered*.
- **Client-Compatible:** If no extra plugin on the video conferencing client is needed. If client-side software needs to be upgraded to handle this challenge and evaluate this, then this would be *Not-offered*.

#### A.3.3 Adversarial to Deepfake Generation Pipeline

Each challenge targets one-or-more components of the deepfake generation pipeline. We grant *Offered* status when a challenge consistently degrades the deepfake due to a component, a *Quasi* status when the challenge does it sometimes, and *Not-offered* status when the challenge does not (or is not expected to) affect that component.

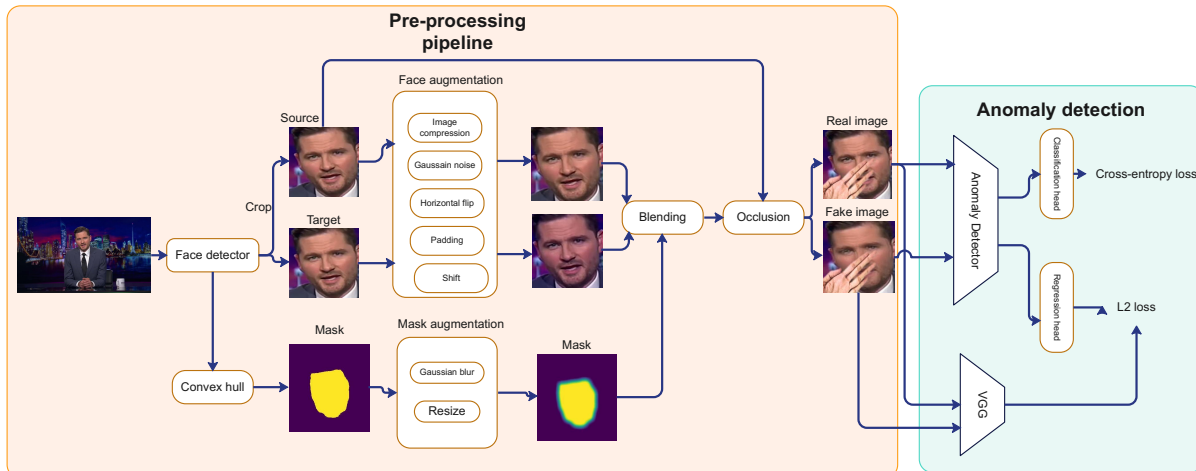


Figure 11: The ML pipeline for training the anomaly detector, which is used as a score function.

## A.4 Anomaly Detector

We train an anomaly detector on the GOTCHA dataset and the fake images generated by DeepFaceLab [27], FS-GANv2 [26], and LIA [36]. As a result, the classifier would learn artifacts specific to these methods, making it less generalizable to other approaches. An ideal detector would focus solely on artifacts, regardless of the identity or background of the impersonators. We observe that the artifacts produced primarily by the deepfake generators are inconsistent between the inner and outer faces, with the colors and high-frequency details of the manipulated regions being out of sync with the rest.

The distinct boundary between the inner and outer faces is an artifact of poor blending, so the inner faces are most likely blurry. These artifacts can be simulated to some extent through modified data augmentation.

Fig. 11 illustrates the anomaly detection pipeline. We simulate artifacts [29] on the FaceForensics dataset [28]. First, we use landmark detection to extract the inner faces. Then, Image compression, Gaussian noise, down-scaling, Gaussian blur, horizontal Flip, resize, PCA, brightness, hue saturation, grayscale, shifting, scaling, and rotation are applied to them. They are then stitched back to the original faces.

Object objects in occlusion-based challenges are unseen by the detector, so they negatively impact its performance. To overcome this, we augment the dataset and its manipulated faces with synthetic objects and hands [34].

According to our quality metric formulation, the score assigned to the fake images should be based on the frame’s realism quality. One candidate is the logits. Unfortunately, this results in a constant score, as no inductive bias is introduced into the model, i.e., the score is independent of the number of artifacts. Cross-entropy loss always causes fake simulated images to be close to

their labels, regardless of how realistic the images are. As a result, we use the regression head to supervise the realism score for each frame. Pseudo-labels are generated by calculating the perceptual loss [15] between the original images and their manipulated pairs.

Next, an EfficientNet-B4 [32] for 400 epochs on the dataset with the learning rate  $1e-3$  SGD optimizer using the cross-entropy loss on the classification head and L2 loss on the regression one.

## A.5 Compute environments

For training DFL [27] models, a 16-core Intel(R) Xeon(R) Platinum 8358 CPU @ 2.60GHz 80 GB of RAM and one NVIDIA A100 with 80 GB VRAM were used. For inference of all pipelines (e.g., during video calls), an octa-core Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz with 32 GB RAM and two NVIDIA RTX 2080 Super GPUs with 8 GB VRAM each were used.

## A.6 Note on Facial Reenactment deepfakes

Facial reenactment involves driving a source image using facial landmarks obtained directly from the puppeteer or simulated via a text-to-speech model. These movements are then mapped onto the latent space of the encoder-decoder to get the desired effect on the source image. Facial reenactment is considered an any-to-any conversion, but it tends to be highly brittle without close face matching and adjusting of hyperparameters for every pair of faces. Hence, in practicality, it is not an any-to-any conversion. Furthermore, it cannot reenact basic human gestures (e.g., looking side-to-side, moving their hand). Thus we claim that the technology for facial reenactment is not ready for practical impersonation. Hence, we do not consider evaluating them rigorously in this work.