

Locally Authenticated Privacy-preserving Voice Input

Ranya Aloufi¹, Andreas Nautsch², Hamed Haddadi¹, David Boyle¹

¹ Imperial College London

² Individual Researcher

ABSTRACT

Increasing use of our biometrics (*e.g.*, fingerprints, faces, or voices) to unlock access to and interact with online services raises concerns about the trade-offs between convenience, privacy, and security. Service providers must authenticate their users, although individuals may wish to maintain privacy and limit the disclosure of sensitive attributes beyond the authentication step, *e.g.*, when interacting with Voice User Interfaces (VUIs). Preserving privacy while performing authentication is challenging, particularly where adversaries can use biometric data to train transformation tools (*e.g.*, ‘deepfaked’ speech) and use the faked output to defeat existing authentication systems. In this paper, we take a step towards understanding security and privacy requirements to establish the threat and defense boundaries. We introduce a secure, flexible privacy-preserving system to capture and store an on-device fingerprint of the users’ raw signals (*i.e.*, voice) for authentication instead of sending/sharing the raw biometric signals. We then analyze this fingerprint using different predictors, each evaluating its legitimacy from a different perspective (*e.g.*, target identity claim, spoofing attempt, and liveness). We fuse multiple predictors’ decisions to make a final decision on whether the user input is legitimate or not. Validating legitimate users yields an accuracy rate of 98.68% after cross-validation using our verification technique. The pipeline runs in tens of milliseconds when tested on a CPU and a single-core ARM processor, without specialized hardware.

CCS CONCEPTS

• Security and privacy → Privacy protections;

KEYWORDS

Authentication, Anonymization, Anti-spoofing, Privacy & Security

1 INTRODUCTION

Online services increasingly use biometric data for authentication. Many recent mobile or IoT devices have at least one built-in mechanism for biometric-based authentication to access various functionalities and apps (*e.g.*, smartphone applications and virtual assistants). These authentication systems use physical characteristics of individuals, such as voices, fingerprints, and faces for identification/verification purposes. ‘Voice ID’ [54] technology, for instance, is a speaker authentication technology that analyzes incoming audio signals and compares them to previously stored ‘voice representations’ and produces a confidence score of how closely the speaker’s voice sample matches the voice representations. Despite biometric authentication/access controls enhancement to many applications, there are also associated privacy and security concerns [14, 15, 18, 95]. There are very few existing ways to provide privacy to users when the risk is that providers of services may be ‘honest-but-curious’ [65] or simply untrustworthy (considering

their business practices and/or usage intent for user data). For instance, Amazon has patented technology to analyze users’ voices to determine emotions and/or mental health conditions [2], and it has been shown that Amazon and third-party services are using smart speaker interaction data for ad targeting [44]. Abundance of such data, data breaches, and unlawful sharing of biometric information with other parties or applications may lead to abusive or harmful uses targeting individuals or groups.

Privacy protection for biometric-based services is increasingly important [45, 46, 71]. Current solutions emphasize either enabling privacy-preserving biometric-based authentication without considering the sharing step afterwards (which may contain sensitive biometric data), or enabling private data sharing by obscuring sensitive attributes, thus preventing authentication. One solution is to encrypting the sensitive data using the encryption schemes [22, 42, 53, 117]. The goal is to show how to process encrypted information by non-trustworthy third parties without disclosing confidential data. Moreover, raw data is still sent as cipher text and may be recoverable by an ‘honest but curious’ service provider. Anonymization, adversarial examples [76, 91], and using synthetic data [10, 37, 80] are other solutions to mitigate privacy concerns, aiming to make the raw input unlinkable by altering a raw signal and/or mapping the identifiable personal characteristics of a given user to another identity [99]. Such techniques can enable fooling (spoofing/faking) of unprotected authentication systems and may present various security implications. Thus, current solutions may neither guarantee either user’s privacy preservation or data integrity.

This paper aims to answer the following question: ‘*Is it possible to authenticate a legitimate user in a privacy-preserving system?*’ We aim to achieve secure and reliable user authentication to prevent adversaries gaining system access by defeating voice biometric checks using ‘faked’ inputs and at the same time achieve privacy preservation by protecting the sensitive attributes of raw biometric voice inputs (*i.e.*, without providing the complete or unaltered raw data to the service provider). We propose a method to enable more secure voice biometric-based local authentication for access to online services that combines configurable privacy-preservation and can run on mobile or constrained devices. Our solution can maintain user anonymity via various contemporary anonymization techniques, while ensuring reliable authentication towards the service provider. We test the effectiveness of the proposed system against a number of leading commercial Voice User Interfaces from Apple, Amazon and Google, and examine performance when connected with custom and leading online voice-based services (*e.g.*, Amazon, Google, IBM, and Mozilla).

Contribution. Our contributions can be summarized as follows:

(i) We present a systematic analysis of online services that verify user identity using biometric data, particularly voice, where this mode is the primary means of communicating/interacting with

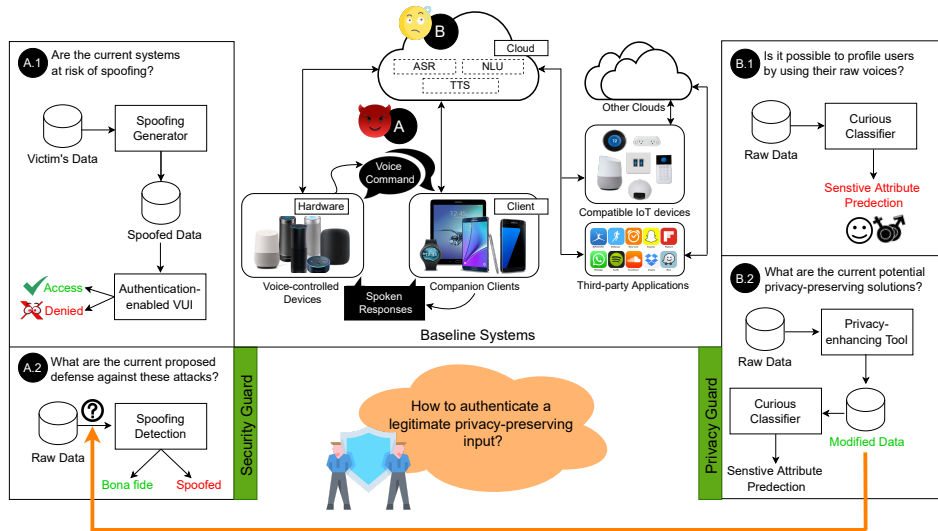


Figure 1: Problem Overview

these services, and considering both security and privacy. For voice-based user interfaces, we show that current services do not achieve sufficient privacy and security simultaneously.

(ii) We propose and develop a secure, configurable privacy-preserving system to address this gap. We present a method that fuses multiple predictors’ decisions to make a final decision about the validity of the user input, and show that our new fusion score for user authentication using multiple modalities achieves 98.68% accuracy in validating a legitimate users without compromising their anonymity.

(iii) We empirically evaluate the proposed approach and systematically analyze its performance on ‘edge’ devices. We demonstrate that the proposed framework can effectively perform low-latency authentication on representative devices in tens of milliseconds.¹

To our knowledge, this work is the first systematic study of spoofing (*i.e.*, for security deceiving) and anonymization (*i.e.*, for privacy protection) within a unified framework. We believe our findings deepen the understanding of the vulnerabilities of biometric-based online services in practical settings and shed light on how to develop more effective, secure *and* private solutions.

2 BIOMETRIC-BASED APPLICATIONS

2.1 Overview

Biometrics are measurements of a person’s unique physical or behavioral characteristics. These measurements, stored in a form of encrypted code, are used as a personal identifier [18]. Biometric-based systems generally compare the existing representatives of biometrics with the provided one, to determine if there is a match or not. These systems might apply different logic and computation mechanics to verify a person, and thus can be divided into two main categories: (1) authentication, which is the process of validating a person’s identity with a ‘one-to-one’ comparison, and (2) identification, which is comparing a person’s identity with all the

¹Code and research artefacts will be open sourced on acceptance for publication.

available enrollment data of the system (all the system users), so this is a ‘one-to-many’ comparison.

2.2 Attacks against Biometric-based Systems

Spoofing attacks. These are direct attacks (Logical Access; LA) that make use of original biometrics to create an artificial version to gain illegitimate access to sensitive or protected resources [36, 107]. For example, Attackers can use advanced techniques such as text-to-speech (TTS) [84] and voice conversion (VC) [101] to fake users’ voices. Attacks then take the form of synthetic speech or converted voice to impersonate a user’s voice for voice assistants like Amazon Alexa or Google Assistant to grant access to sensitive user data such as financial information.

Replay Attacks. In contrast to artificial synthesis, replay attacks (physical access; PA) are well-understood attempts to exploit original biometrics indirectly [107]. An attacker may use a sample collected from a legitimate user to gain access to the target system. For example, the adversary may record users’ voice secretly or from posts on social media. The adversary submits these data to attempt to gain access to the system and resulting data and/or service(s).

Adversarial Attacks. These aim to fool the target model [79]. Evasion attacks, known as adversarial examples, add imperceptible perturbation to the input sample to result in the incorrect prediction of the target models. The attacker may leverage the information of the attacked authentication system to generate spoofed samples and can use such knowledge to generate adversarial samples [4, 6, 21, 25, 26, 62, 82, 96, 103, 114, 120].

2.3 Secure, Privacy-aware Biometric Systems

Encryption-based Methods. In the case of encrypted data, a cryptographic key is securely bound to biometric data, and neither the key nor the biometric can be retrieved from the stored representations [78]. Thus, biometric authentication is done either after decryption or on the encrypted data. Therefore, encrypted

data is protected against the attackers and ‘honest-but-curious’ servers since it is never decrypted. As with our research, in [88], a privacy-preserving cloud-based and multi-party biometric verification system has been proposed, which consists of one deep neural network pretrained to perform feature extraction. By using Paillier Chunkwise, they mask and encrypt extracted features to ensure their safety and privacy. The homomorphic encryption ensured that the biometric data would remain secure outside of the user’s side and kept user privacy intact. In spite of this, Paillier HE does not scale well and cannot provide the functions we require for speech, for example Fourier transforms, noise issues, and principled uncertainty propagation (playing with probabilities extensively) [71, 78].

Adversarial Training-based Methods. GANs have achieved considerable attention from the biometrics research community to further advance matching systems due to their ability in learning robust features, especially in the unseen attack scenario [8]. For example, Mostofa *et al.* in [32] propose a conditional coupled generative adversarial network (CpGAN) architecture for cross-spectral iris recognition by projecting the iris images (acquired in different spectral bands) into a low-dimensional embedding domain to explore the hidden relationship between them. Such methods can be used to filter biometric data and keep only the representations required for authentication purposes. For example, Aloufi *et al.* in [13] propose ‘Emotionless’, a privacy-preserving intermediate layer between users and cloud services to sanitize the voice input, aiming to maintain authentication while preserving user behavioral privacy.

On-device-based Methods. Some works suggest running the systems on the device [35, 97] and designing light encryption systems. Im *et al.* in [43] propose a user-friendly, privacy-preserving face authentication system for smartphones to prevent malicious users from accessing the system. To ensure security, the face feature vector is encrypted and stored on a remote server. This guarantees security against an honest, but the curious server who might try to learn the private feature vector. Using homomorphic encryption, they compute euclidean distance-based matching scores on encrypted feature vectors. The blinding procedure is used for security against malicious clients. However, these systems are still focusing on either user matching or spoofing detection, and may be vulnerable to replay attacks [121].

3 PROBLEM OVERVIEW

3.1 System Model

We consider *always-on* online services (*e.g.*, smart speaker) comprising users and service providers. We assume that these services make use of a biometric authentication system to restrict access to legitimate users. The biometric authentication process consists of two phases: enrollment and recognition. In an enrollment phase, users submit their biometric representations to the service provider who stores the representations along with the user’s ID in a central database. In the test phase, the user requesting access to certain services will submit a new representation to the service provider for authentication. Based on the identity claim, the service provider will retrieve the enrolled representations for comparison. Only if the two representations are close enough under a certain distance metric (a certain threshold θ), the user is successfully authenticated (labelled as a valid/legitimate user). After the authentication

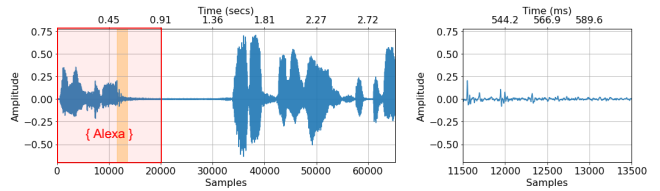


Figure 2: Partially-spoofed signal, saying "Alexa, set an alarm for 10.", where "Alexa," said by spoofing target speaker, and the rest of command by other random speaker.

Table 1: Speaker verification using real and spoofed recordings; the equal error rate (EER) of real-to-real, real-to-fully spoofed, and real-to-partially spoofed (lower EER value means stronger attacks).

Synthesis Type	Raw/Real		Full Spoofing		Partial Spoofing	
	ECAPA	X-vector	ECAPA	X-vector	ECAPA	X-vector
Attack Success (%)	0.06	0.57	0.08	0.16	0.37	0.48

step, these services capture and transmit the raw biometric data to more powerful cloud services for further processing and subsequent actions. Here we require verifiable computation to secure against ‘malicious/spoofed’ clients, and privacy against ‘honest-but-curious’ service provider(s). We use the voice user interface (VUI) as a model for such services, shown in Figure 1. We assume that users interact with online service providers via some smart speaker or smartphone that can collect their biometric data (*i.e.*, voice), and this data is then verified against a server-side biometric database. In this case, the user’s biometric information is used both to activate and to communicate with the service. Consequently, users may expose themselves to the multi-purpose inferences of service providers who, beyond providing legitimate services, may attempt to infer additional sensitive information, *e.g.*, user emotion [2], tone, gender, age, ethnicity, etc.

3.2 Threats to Services Security

A.1 We first ask: ‘Are current biometric-based online services at risk of spoofing/deepfaking?’ Voice spoofing attacks can be used to impersonate a user’s voice and grant access to an attacker. This attack is different to adversarial attacks that add imperceptible perturbations to the input sample to result in the incorrect prediction of the target system [5, 6, 21, 114], which is beyond our analysis’ scope. We use open-source voice modeling tools named ‘FastPitch’ [125] and ‘HiFi-GAN’ [56] to train user voice models (*i.e.*, total 20 models) and generate more realistic spoofing voices and engaging to the listener. To examine the effectiveness of such deepfaking attacks, we experimentally evaluate success rates in Section 5.1. We are also looking at low-source attacks lasting less than two minutes compared to five minutes in their work. In addition, we propose and evaluate an additional spoofing attack setting, *i.e.*, ‘partial spoofing’, against real-world voice interfaces.

3.2.1 Attacking Speaker Verification Models. Speaker verification is integral to many security applications to establish the identity of a user from the characteristics of their voice.

Table 2: Samples of command phrases (out of 70) used in our experiments and the corresponding attack success (%) i.e., activating the service or not using two attacks settings: fully-spoofed (full command by target identity) and partially-spoofed (wake-word by target identity while the rest of command by random speaker).

System	Commands	Attack Success (%) Fully / Partially
Alexa	Alexa, what’s the weather today?	95 / 97.5
	Alexa, set an alarm for 10 pm	85 / 87.5
	Alexa, play song	90 / 92.5
	Alexa, what’s in the news?	80 / 87.5
	Alexa, what’s on my shopping list?	85 / 92.5
Google	Hey Google, what’s the time?	90 / 92.5
	Hey Google, set a timer for 10 minutes.	80 / 87.5
	Hey Google, what does my day look like?	70 / 87.5
	Hey Google, what’s the weather like today?	75 / 87.5
	Hey Google, call my phone.	85 / 90.0
Siri	Hey Siri, find coffee near me.	90 / 92.5
	Hey Siri, where’s my iPhone?	85 / 90.0

Setup. We select two state-of-the-art speaker verification systems: X-vectors [93] and ECAPA-TDNN [28] to evaluate the potential threat of our spoofing attacks on these systems. We use the raw recordings of our dataset (i.e., detailed in Section 5.1) from 20 target speakers as an enrollment set of the verification system. We then use the fake voices as the test set. For the verification test, we compute the speaker embeddings from the enrollment and test sets and choose the threshold that minimizes the equal error rate (EER) for our target speakers, using cosine similarity as the distance metric. The attack is considered successful if the similarity between the attack and enrolled embeddings is above the threshold. For each attack, we repeat the enrollment process 36 times (using different phrases samples) and report the average attack success rate.

Results. We tested a total of 6000 spoofed voices targeting 20 speakers to test the speaker verification systems. The raw/real results in Table 1 represent the matching result between the user’s raw enrolment recordings with the test samples (baseline), then the 3-6 columns represent the matching with fake test samples using different spoofing settings. The results in Table 1 show that the ‘FastPitch’-based attack [125] is highly effective and scored similar EER compared to real recordings results with a slight difference of 2% in a fully-faked settings. Interestingly, the attack’s success outperforms the real recordings on verification systems using X-vector by 41% and 0.09% for fully and partially fake recordings, respectively. Thus, it can deceive the verification system and allow unauthorized access.

Takeaways. The success of these attacks is alarming given that we needed only up to 2 minutes to get the victim’s vocal model, without any further optimization like fine-tuning the generative model or augmenting the training data. An attacker could use speech enhancement tools like VoiceFixer [63] to further improve the quality of the spoofed voices for human listeners².

3.2.2 Attacking Commercial Voice Assistants. Since the commercial models verification systems are effectively a black-box, it is

²DeepFake Audio Samples: <https://github.com/anonymous-ccs22/paper431>

only feasible to assess the physical response on target or malicious activation attempts.

Setup. Our setup evaluates three services: Amazon Alexa, Google Assistant, and Apple’s Siri. The speaker recognition of these systems links to individual accounts, and thus we test the spoofed attack against these systems after setting up them to recognize our 20 participants’ voices. Once a device detects the keyword (i.e., ‘Alexa’, ‘Ok, Google’, and ‘Hey Siri’), it verifies that our participants could successfully use their real voices to log into and access these services. We then use an inexpensive JBL portable speaker located 0.5 m away from the devices to play participants’ spoofed voices, with the process has repeated for each participant separately. We replay each command in Table 2 once and record the responses by a target service. We use the attack success rate to evaluate how effectively spoofed voices can fool these systems. An attacker succeeds if the target commercial service responds to spoofed voices the same way it responds to a real version of the commands.

Results. On average, our spoofed attacks had 70-95% success across all tests on these systems, as reported in Table 2. All 20 participants had at least 1 spoofed/faked command that fooled the tested services (e.g., Amazon Alexa, Google Assistant, and Apple’s Siri). These spoofed/faked commands were able to access private shopping list and check calendar appointments. This shows that an attacker can mimic the victim’s voice and access/use services fraudulently.

Takeaways. Fraudulent ‘deepfaked’ voices are shown to be sufficient to be granted access to and control over these commercial systems. A successful low-resource attack can be trained with approximately 2 minutes of data. Confirming the results in [110], these systems lack the element of verifying the data source validity, thus, there is an urgent need to design solutions that check the integrity of the data before blocking it.

3.2.3 Partial Spoofing. Partially-spoofed utterances contain a mix of both spoofed and real voice segments (see Figure 2).

Setup. Assuming that an attacker wants to create samples that may sound more realistic and convincing, instead of producing a full audio recording where the generative/spoofing model may fail to produce a natural-sounding sample [104], the attacker may replace some words or segments of the real recording. By doing this, the entire meaning of the user’s commands may be changed to the advantage of the attacker. As the focus is gaining access, the phrase we change is the activation words using the target ID. We implemented the same settings as in the previous fully-spoofed experiment, but instead of playing a full deepfaked clip, we combined the spoofed voice (keyword) with a random voice (rest of the command).

Results. We found that a partially-spoofed voice (i.e., the victim’s voice used only for the activation phrase) can give access to systems purportedly protected by voice profiles, see Tables 1 and 2. However, the success of the attack using partial fakes drops to 29% (i.e., using ECAPA verification system). This may be due to that only a small percentage of the recordings have been identified as faked. We use 1 second spoof segment length, and it may be interesting to further investigate how the attacks’ performance might change when the spoof segment length/ratio changes.

Takeaways. The resulting access from partially-spoofed samples

further demonstrates that verification systems are vulnerable, whether independent verification systems or those integrated with commercial devices. This is a future system vulnerability, as such partial spoofed data might be streamed to take advantage of cloud services and there is no guarantee which part of the input will be fraudulent.

3.3 Security Guard

A.2 We next investigate: ‘What are the current proposed defenses against spoofing/deepfaking attacks?’ The detection of faked inputs depends on finding and extracting features from the input that can accurately distinguish between real and spoofed labels. In particular, it aims to detect any artifacts in the input that will match the nature of the deepfake, such as a noisy glitch, phase mismatch, reverberation, or loss of intelligibility [106]. Several features have been proposed to capture these artifacts, including Mel-frequency cepstral coefficients (MFCCs) [111], constant Q cepstral coefficients (CQCCs) [98], and linear frequency cepstral coefficients (LFCCs) [87].

Setup. We use state-of-the-art features LFCC [87], CQCC [98], FastAudio [33], and VOID [9] for liveness and spoofing detection purposes. All of these features were extracted using the ASVspoof 2019 dataset [27] (for baseline performance) and our new dataset. We first calculate the LFCC and CQCC (*i.e.*, cepstral processing) from the recordings. We then compute FastAudio [33], a learnable front-end feature including a short-time fourier transform (STFT) followed by a learnable filterbank layer, and finally, a log compression layer to mimic the non-linearity of human sensitivity to loudness. We also compute VOID features (*i.e.*, 97 features) for a given speech signal [9]. These extracted features are then used as a lightweight feature set for the classification/detection algorithms (*i.e.*, a ‘*bona fide* versus spoofed’ decision). For inputting the raw recording to the classification model, we use AASIST-L [51] and train it directly using our dataset. A high EER indicates the spoofed voice to be a more human-like voice, whereas a lower EER is the better spoofing countermeasure system for detecting spoofing attacks.

Results. Detection performance (EER) of the classification algorithms over two datasets (*i.e.*, ASVspoof and our spoof) is shown in Table 3. We tested the systems on our data for both logical & physical attack types. Note that the current methods may focus on a particular type of attack, either logically or physically, but it is not necessarily the case that if the proposed method achieves success in detecting one type of attacks it should have the same performance for the other. For example, ‘LFCC-LCNN’ reasonably scored 8.90% and 3.50% EERs in detecting logical attacks using ASVspoof and Our spoof, respectively, however its performance significantly degraded in detecting physical attacks by 30-33%. For physical attacks, VOID outperforms the rest by 11.6% and 7.62% using ASVspoof and our spoof, respectively.

Takeaways. Although these systems perform moderately well in detecting spoofing attacks, further advances might be necessary to counter more demanding attacks that might be able to adapt or optimize their performance, such as deepfake and adversarial examples. Our other concern is generalization, since we’ve observed that the performance of these classifiers is decreasing sharply without retraining them on our new data. Research is therefore needed

Table 3: The performance of state-of-the-art detection algorithms on two datasets (ASVspoof and Our spoof) and targeting either direct attacks (Logical Access; LA) [36] or indirect attacks (physical access; PA) [107]. Note: if the system was designed for a specific type of attack, it will unlikely perform well for the other.

Work	Front-end	Dataset		Spoofing Type		EER (%)
		ASVspoof	Our spoof	Logical	Physical	
LFCC-LCNN [106]	LFCC	✓		●		8.90
			✓	●		3.50
		✓			●	42.1
			✓		●	34.9
CQCC-GMM [106]	CQCC	✓		●		15.8
			✓	●		4.76
		✓			●	36.3
			✓		●	21.9
FastAudio [33]	FastAudio	✓		●		1.54
			✓	●		1.06
VOID [9]	VOID	✓			●	11.6
			✓		●	7.62
AASIST-L [51]	Raw	✓		●		0.83
			✓	●		0.64

on features/models that generalize enough and are robust against unseen or partially-spoofed attacks [3, 9, 61, 105, 110].

3.4 Threats to User Privacy

B.1 We ask: ‘Is it possible to profile the users by using their raw biometric data (*i.e.*, voices)?’ We consider an adversary with full access to user data with the aim to correctly infer sensitive attributes (*e.g.*, identity, gender, and accent) about users by exploiting a secondary use of the same data collected for the main task. For example, Aloufi *et al.* in [15] investigate the effectiveness of an attacker (*e.g.*, a ‘curious’ service provider) who may use a deep acoustic models trained for speech recognition or speaker verification to learn further sensitive attributes from user input even if not present in its training data. They found that a relatively weak attacker (*e.g.*, support vector machine classifiers) can achieve high accuracy in inferring sensitive attributes, ranging from 40% to 99.4%, *i.e.*, significantly better than guessing at random. Similarly, Malekzadeh *et al.* in [65] use two face-image datasets and show that deep classifiers can be trained to secretly encode a sensitive attribute of their input data into the classifier’s outputs for the target attribute at inference time.

Setup. We assume that the privacy attack is an ‘honest-but-curious’ service provider’s effort to obtain additional information from the biometric data that has been shared. To test the effectiveness of these attacks, we assume that the sensitive attributes in our dataset are identity, accent, and gender (*i.e.*, available labels). An attacker trains a particular classifier that takes the representation extracted from users’ voices as input and infers these sensitive attributes. We test the success of such attack over binary (*i.e.*, gender) and non-binary (*i.e.*, identity and accent) attributes. We train separate models to classify identity, accent, and gender for the output representation (after extracting these representations from the raw recording) of our dataset. We measure the success of these attacks by the increase in inference accuracy over random guessing.

Results. The success rate for a variety of attacks is presented in Figure 3. We show that inference models have varying performance,

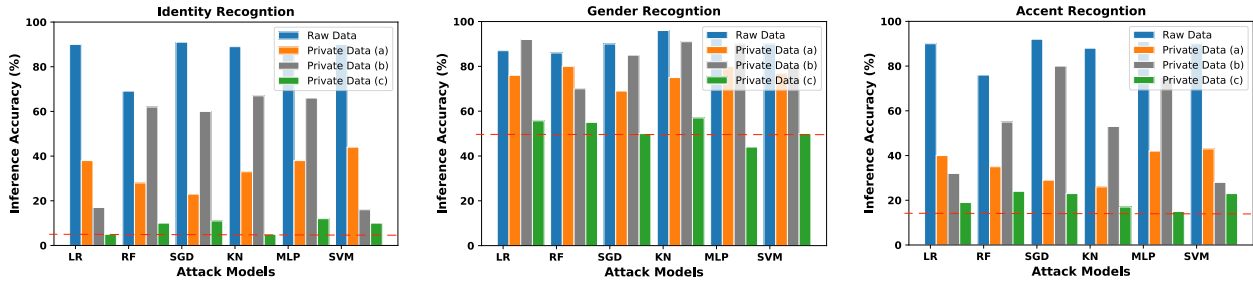


Figure 3: Accuracy in inferring various attributes (e.g., identity, gender, accent) using both raw and private data (i.e., the output of the privacy-preserving tools ((a) signal-based anonymization [52]), (b) voice privacy [99], and (c) disentanglement [15]); the red line represents the random guess per attribute).

ranging from about 40.6% to 80.2% in successfully inferring different attributes from the raw data. The attacker has the opportunity to extract sensitive information with a much higher degree of accuracy than would otherwise be possible by chance. For example, for identity recognition, and assuming that we have 20 different speakers, then the random assumption rate will be ~5% of the time, but when using the ‘MLP’ model the success rate is four times greater than this.

Takeaways. It is very likely that the biometric data obtained in interaction with online services will be utilized to extract a fair amount of personal characteristics, and information about the circumstances and environment of users from their raw data. For example, an overlearning problem might be caused by deep neural networks used for ASR and speaker verification, revealing additional/sensitive information about the users, which threatens to compromise their privacy significantly [16, 92].

3.5 Privacy Guard

B.2 We analyse: ‘What are the current potential privacy-preserving solutions?’. Most of the proposed works focus on protecting/anonymizing speaker identity using voice conversion (VC) mechanisms [11, 81, 94, 99]. Beyond speaker identity, various works propose to protect speaker gender [49] and emotion [13], wherein an edge-based system is proposed to filter affect patterns from a user’s voice before sharing it with cloud services for further analysis. Another direction is protecting users’ privacy by ensuring that sensitive data is not unnecessarily transmitted to service providers [15]. This may be done by optimizing the neural network architecture using quantization/pruning techniques to enable on-device processing.

Setup. Inference attacks (as mentioned in 3.4) may aim to reveal individuals’ sensitive attributes (e.g., their identity, gender, or accent, etc.) that they did not intend or expect to share. To evaluate the performance of the proposed defenses against this type of attack, we used the three best-performing privacy-preserving voice analytic systems (i.e., (a) signal processing-based anonymization [52]), (b) voice privacy baseline (TDNN-based) [99], and (c) disentanglement [15], and trained the attacker’s classifiers on their output. We then measure an attack’s success as the increase in inference accuracy over random guessing [118], and compare this with the inference success of the raw data as our baseline.

Results. Comparing to the inference success from raw data, the

performance of the used privacy protection methods vary from one system to another. Disentanglement (Private Data (c), Figure 3) is shown to offer the best performance. It is approximately in line with guessing at random for all attacker models.

Takeaways. Although the current technologies provide a fair level of privacy protection, new, configurable, privacy-preserving technologies are needed. Different users may have different privacy preferences depending on the devices and services which they are interacting. For instance, when contacting a health service provider, a user may prefer to share raw data without altering it, whereas a user may prefer to filter (i.e., remove) sensitive data when interacting with advertising or other less trusted services.

3.6 Research Gap

Suppose that both Security and Privacy guards (i.e., presented in Sections 3.4 and 3.5) work perfectly to achieve their goals, i.e., the security guard prevents fake entries from entering the system and the privacy guard prevents the leakage of sensitive data in user inputs. Note that we can achieve privacy preservation by the modification of the raw data in two ways, either additive (e.g., adding noise) or extractive (e.g., filtering/removing data). We then ask whether any current or proposed systems offer solutions able to authenticate a legitimate privacy-preserving entry, i.e., can users access these services using a privacy-preserving version of their data?

Setup. We use a subset of our dataset (raw recordings) as a baseline, assuming that such recordings disclose all sensitive information about the user (e.g., identity and accent). For the privacy guard, we apply privacy-enhancing mechanism to hide the sensitive attributes (e.g., disentanglement [15]; the target is to learn discrete units (i.e., speaker-invariant) useful for speech recognition and phoneme classification). We produce a privacy-preserving version of the raw data and test whether it is possible that such input is still valid for accessing online services. A privacy-aware input should maintain the linguistic information while discarding the paralinguistic/speaker-related information like identity, gender, and accent. We first tested the validity of such inputs in the authentication task by measuring the cosine similarity between raw and privacy-protected data using a user verification system. Then, we selected AASIST-L and VOID as two of the best-performing spoofing detection systems to implement the security guard for

both logical and physical spoofing types. We use the spoofing countermeasure decision score (EER) which indicates the similarity of the given privacy-preserving input with genuine one.

Results. For user verification, a high similarity score indicates the protection level is insufficient to safeguard the user’s identity and has less impact on the user verification process. A low similarity score offers better privacy protection but indicates a failure in the verification process (*i.e.*, rejecting a legitimate user). For example, the equal error rate over the raw data is 0.046% (*i.e.*, comparing raw test data with the enrollment one), while the equal error rate of privacy-aware test data is about 0.409%, causing a significant drop about 36% in authentication performance, see Figure 4. A high similarity spoofing score means the privacy-aware inputs are more likely to be classified as human-like.

Takeaways. The current art in biometric voice authentication is still lacking assurances for secure, privacy-preserving identification [7, 86]. Although voice provides a convenient way to communicate with online services, the existing systems could be vulnerable to replay attacks, for example (Section 2.2), and suffer from privacy exposure, which may seriously hinder wider user acceptance and adoption. There is growing interest in biometric data protection using cryptobiometrics techniques [38] such as fuzzy commitment schemes and fuzzy vault schemes. Most of the current secure biometric authentication schemes employ a server-centric model where a service provider maintains a biometric database and is responsible for ensuring the security of the biometric representations. In this case, the users have to fully trust the server in storing, processing, and managing their private data. However, there are still significant challenges associated with these techniques, and they may face various issues related to data distinguishability and data reversibility [7, 22, 42, 43, 48, 60, 86, 88], which might not provide full (or sufficient) privacy.

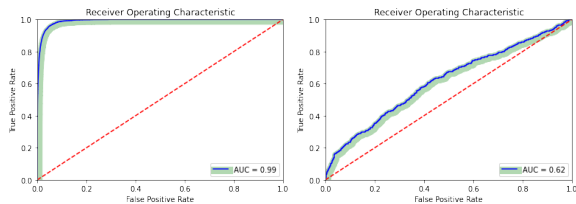


Figure 4: Area under the curve (AUC) of raw data (left) and privacy-preserving data (right).

4 COMPOSABLE AUTHENTICATION FRAMEWORK

We propose a new composable system to enable secure biometric authentication with flexible privacy-preservation for interacting with online services. A key feature of our system is that it can generate verification scores locally on devices (*e.g.*, smartphone or speaker) for authentication purposes instead of sending raw data (*e.g.*, biometric data replete with representations of sensitive attributes). After authentication based on full voice data, users can apply a privacy-enhancing filter over the raw data before sharing it with the cloud-based services to protect certain sensitive

attributes. The system currently offers two options based on user preferences: 1) authentication with filtration and 2) authentication without filtration.

Design Goals. Online services that continuously share users’ biometric data, such as voice interfaces, present a problem of how to design them while simultaneously validating the source of their data (*i.e.*, benign or malicious) and safeguarding their user privacy. Current approaches may verify a user’s identity to activate the system, but then these systems share the raw data without further restrictions about the potential risks to its user privacy. In voice biometric-based systems, for example, we need to (1) build a robust biometric authentication module for these systems to verify their inputs since false rejections and false acceptances may prevent legitimate users from accessing the system, (2) update the enrollment of the users’ voice overtime to capture the changes in their voices (*i.e.*, health issues) to strengthen the performance of these systems, (3) apply privacy-enhancing technologies to protect the users’ sensitive behavioral and biometric characteristics from untrustworthy service providers, and (4) optimize latency and model size as required to effectively run from the ‘edge’. Our framework is designed to satisfy these requirements when sharing our biometric data with online services.

4.1 Stage 1: Front-end Processing

User interaction begins with the front-end, which captures and pre-processes the user’s voice input. The feature extractor then extracts representative features, which can either be used to reflect fraudulent input characteristics or serve as an input for privacy-preserving filters. Voice signal representations are extracted as follows:

(a) Acoustic features. Mel frequency cepstrum coefficients (MFCCs) represent the short-term power spectrum of a sound by linearly cosine transforming a log power spectrum on a nonlinear mel scale of frequency [123]. The MFCC feature extraction technique includes windowing the signal, applying the DFT, taking the log of the magnitude, and then warping the frequencies on a Mel scale, followed by applying the inverse DCT.

(b) Identity features. To extract the unique representations related to the user identity, we use a ‘deep speaker’ model (*i.e.*, using deep residual CNN (ResCNN) architecture) to extract frame-level features from utterances [59]. Then, affine and length normalization layers map the temporally-pooled features to a speaker embedding. The model is trained using triplet loss [89], which minimizes the distance between embedding pairs from the same speaker and maximizes the distance between pairs from different speakers.

(c) Inconsistency features. Artefacts that differentiate spoofs/replays from benign inputs can reside in the spectral or temporal domains. We first compute VOID features (*i.e.*, 97 features) for a given voice signal which includes the following four types of features: (1) low frequencies power features, (2) signal power linearity degree features, (3) higher power frequencies features, and (4) linear prediction cepstrum coefficients (LPCC) [66] features, as its computational complexity is lower than MFCC because it does not require the computation of discrete fourier transforms [9]. Then, we apply AASIST-L [51] which models both spectral and temporal information concurrently using a heterogeneous stacking graph attention layer to accumulate heterogeneous information. It also applies a

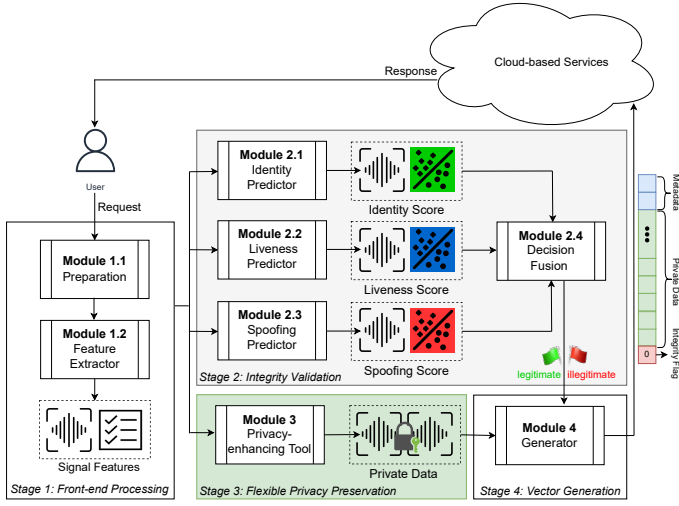


Figure 5: The Proposed Framework

max graph operation that involves a competitive selection of artefacts.

4.2 Stage 2: Integrity Validation

To access and/or activate an online service, a legitimate input, which must be that of a ‘target user’ and must be produced by a ‘live human’ is required; see Algorithm 1 for details. The score predictors use traditional machine learning models to perform the training and testing on the features. Any feature-based classifier (e.g., logistic regression, decision tree, kNN, SVM, and neural network) may potentially be used. The output of the score predictor is the predicted score for each sample.

Module 2.1: Identity Predictor. Verifying user identity involves comparing two inputs, namely the enrollment and testing inputs as $X = (X_{enroll}, X_{test})$, where X_{enroll} denotes a set associated with a known target identity and X_{test} represents a single test sample. The output score (i.e., log-likelihood ratio) is denoted by S_{id} , and the threshold (operating point) is denoted by T_{id} . The final decision is then made upon the comparison of S_{id} to a identity-specific threshold T_{id} : if $S_{id} > T_{id}$ then the target hypothesis is accepted. Otherwise, the non-target hypothesis is accepted.

Module 2.2: Spoofing Predictor. Anti-spoofing works as a verification system by comparing a pair of inputs, namely the enrollment and testing inputs as $X = (X_{enroll}, X_{test})$, where X_{enroll} denotes set of samples corresponding to either genuine or spoofed speech and X_{test} represents a single test sample. The spoofing countermeasure output score is denoted by S_{spoo} and the threshold (operating point) is denoted by T_{spoo} . The spoofing decision is then made upon the comparison of S_{spoo} to a spoofing-specific threshold T_{spoo} : if $S_{spoo} > T_{spoo}$ then the genuine hypothesis is accepted. Otherwise, the spoofed hypothesis is accepted.

Module 2.3: Liveness Predictor. Liveness measurement aims to detect a unique characteristics of the test input X_{test} produced by an actual person and determine whether an input is live-human or

replayed one. Thus, the liveness predictor is to reject all test signals that do not show evidence of liveness regardless of the nature of the spoofing attacks (e.g., speech synthesis or voice conversion). The Liveness measurement output score is denoted by S_{live} and the threshold (operating point) is denoted by T_{live} . The liveness decision is then made upon the comparison of S_{live} to a liveness-specific threshold T_{live} : if $S_{live} > T_{live}$ then the liveness hypothesis is accepted. Otherwise, the replayed hypothesis is accepted.

Module 2.4: Decision fusion Different from multi-biometric fusion methods [30] that used multiple biometrics for authentication, we combine the scores of different prediction tasks using the same modality. We aim at combining the confidence scores of the models constructed from different features, in which each confidence score measures the possibility of classifying a test sample X_{test} into the positive class by one specific model. This is known as fusion at the measurement level or confidence level.

Given a confidence score vector $s = [s_1, s_2, \dots, s_m]$ of a predictor model, where each s_i denotes the score of the i th test sample, and m is the sample number. The only classifiers discussed here are binary ones. All classifiers are assumed to return real values. A normalization step is required to adjust the weighting of each predictor to a common scale such that the combination can be performed. We aggregate the results of applying a number of binary classifiers to input data by leveraging the knowledge captured by each specific binary detector. This allows using independent and possibly specialized classification techniques for each task. The final output score is denoted by $score_{final}$ and the final decision on whether the user input X_{test} is legitimate or not will be made based on this score.

4.3 Stage 3: Flexible Privacy Preservation

We recognise that privacy is subjective, with varying attitudes between users and may even depend on the services (and/or service providers) with whom users interact. We therefore emphasize the importance of enabling different privacy configurations for optimizing the privacy-utility trade-off and advocate promoting transparent privacy management practises. Specifically, the idea is to give the user more control/flexibility over their shared data. Such configurations might vary according to the users’ preferences as to what they want to share with the service provider (i.e., minimum amount of data to enable the primary functionalities). Each configuration might be implemented using a discrete privacy-preserving techniques. For example, anonymization aims to make speech input un-attributable, i.e., to ensure that no utterance can be linked to its original speaker perhaps by altering a raw signal or mapping the identifiable personal characteristics of a given speaker to another identity [58]. In the current design of this module, we strive to protect the privacy of multiple user attributes for various scenarios that depend on biometric input, i.e., sanitizing the raw signal of attributes a user may not wish to share, but without adversely affecting functionality. We set two configurations, where one is removing all the potential sensitive attribute S_{att} (i.e., only enable the main/target functionality F_{att}) and the other (default) shares without preserving privacy. Configuration options may be negotiated between users and service providers, similarly to how location-based services require specific user-granted access in contemporary

Algorithm 1: Integrity Validation using Fused Decision

```
Input :raw data  $x$ 
Output: Integrity label; legitimate or illegitimate
1 initialization and target user enrollment;
2 Function identity Predictor( $x$ ):
   // target and non-target verification
3   1. compute feature embeddings from input  $x$ ;
4   2. retrieve enrolled feature embeddings;
5   3. compute similarity scores between these embeddings;
6   if  $scores > threshold(\theta_{id})$  then
7      $id\_scr \leftarrow$  'accept target';
8   else  $id\_scr \leftarrow$  'reject non-target';
9   return  $id\_scr$ 
10 Function spoofing predictor( $x$ ):
   // benign and spoof detection
11  1. compute feature embeddings from input  $x$ ;
12  2. compute classification scores;
13  if  $scores > threshold(\theta_{spoof})$  then
14     $spf\_scr \leftarrow$  'accept benign';
15    else  $spf\_scr \leftarrow$  'reject spoof';
16  return  $spf\_scr$ 
17 Function liveness predictor( $x$ ):
   // human-live and replayed detection
18  1. compute feature embeddings from input  $x$ ;
19  2. compute classification scores;
20  if  $scores > threshold(\theta_{live})$  then
21     $live\_scr \leftarrow$  'accept live';
22    else  $live\_scr \leftarrow$  'reject replayed';
23  return  $live\_scr$ 
24 while  $interaction.start()$  do
25   repeat
26      $x \leftarrow$  preparing ( $x$ );
27     do in parallel
28        $id\_scr \leftarrow$  identity predictor ( $x$ );
29        $spf\_scr \leftarrow$  spoofing predictor ( $x$ );
30        $live\_scr \leftarrow$  liveness predictor ( $x$ );
31     // train a classifier using these scores confidence
32      $integrity\_label \leftarrow$  fusion ( $id\_scr, spf\_scr, live\_scr$ );
until  $interaction.close()$ ;
```

smartphone app use. We apply a selected privacy configuration to the input X_{raw} to generate an $X_{modified}$ version.

4.4 Stage 4: Streaming Vector Generation

The streaming vector generator combines the integrity flag with the flexible privacy preservation output. We aggregate the results of Stages 2 & 3 before Stage 4, as shown in Figure 5. The generator can add further metadata to add more transparency to privacy protection applications and guide the service provider about the received data (e.g., the type of data modification). We can set different access control settings as 'metadata' for every token entry,

thus defining a set of requirements that must be met for access to be granted (e.g., for multi-users/shared environments) [57]. At the cloud side, a combined input of data and the input validity received, where inauthentic or invalid inputs may be prevented from being sent at the edge device. The extracted input validity will be used to verify the user while the data will be delivered to functional services for further analysis, e.g., Automatic Speech Recognition (ASR) [55, 124], Natural Language Processing (NLP) [29, 40], and/or Speech Synthesis (TTS) [108].

5 EXPERIMENT

5.1 Datasets

New Dataset. We recruited a total of 20 participants to create a new dataset whereby we could ensure full understanding of the ground truth and control of labelling. Using the same recording settings, each participant repeated 36 commands from a prepared list of realistic voice assistant commands. All of the voice samples were recorded at a sampling frequency of 48 kHz. The voice commands were mixed in length (approximately ranging from 2 to 6 seconds) and command types (e.g., setting alarms, asking for news and weather, and calling contacts). 55.14% of the participants were male and 44.86% were female, ensuring that both male and female voice frequency ranges were covered. The participants were in the 18-24 (33.33%), 25-34 (47.62%), and 35-44 (19.05%) age groups. Our participants have different linguistic backgrounds (5 native English speakers (US/UK); 4 native Mandarin speakers; 3 native Middle-eastern speakers; 2 native Marathi speakers; 1 native Italian speaker; 1 native Russian speaker; 1 native Dutch speaker; 1 native Niger-Congo speaker; 1 native German speaker; 1 native Portuguese speaker). We explicitly informed the participants that the purpose of the voice sample collection was to develop and evaluate a secure 'Voice ID' solution, with all institutional policies followed.

Existing Spoofing Dataset. ASVspoof 2019 [27] was collected to facilitate developing voice spoofing detection solutions. It derived from the VCTK dataset which includes speech data captured from 107 speakers (46 males, 61 females) [115]. ASVspoof 2019 includes the following spoofing attack types: (1) spoofing attacks within a logical access (LA) scenario generated with the latest speech synthesis and voice conversion technologies, the application of speech synthesis is referred to as text-to-speech (TTS) and voice conversion (VC) algorithms. (2) replay spoofing attacks within a physical access (PA) scenario generated through 177 replay attack sessions, where each session consists of voice samples recorded under varying replay configurations.

Spoofing Generation. Speech synthesis usually consists of two stages: the first is to extract the synthesized Mel-spectrogram and then use a vocoder to convert it into speech. We consider the low-resource attack scenario, where an attacker may only have access to less than 5 minutes of target user recordings that could be insufficient to train TTS models needing huge training data [108]. We use open-source voice modeling tools 'FastPitch' [125] and 'HiFi-GAN' [56] to train user voice models (i.e., total 20 models). FastPitch is a fully-parallel text-to-speech model based on 'FastSpeech' [84]; a fast, robust, and controllable (generated voice speed and prosody) text-to-speech tool. 'HiFi-GAN' consists of one generator and two discriminators: multi-scale and multi-period discriminators. The

generator and discriminators are trained adversarially along with two additional losses, achieving generality to unseen speakers [56]. We then use the trained models to generate 6000 fully-spoofed voice samples by feeding in target commands as text inputs. After attack generation, we played those attack samples through JBL portable speaker. We also generate 2880 partially-spoofed commands. In particular, we mix the spoofed wake-word utterance using our participants’ voices with a random voice saying the rest of each command. We use ‘Coqui’ TTS framework [75], a library for advanced Text-to-Speech models to generate the random voices.

Ethics. All our study protocols were carefully designed in alignment with institutional regulations designed to protect the privacy and ensure the well-being of our participants. We retain only audio recordings that have been anonymized and stored on secure servers.

5.2 Experimental Settings

We conduct our experiments using a Z8 G4 workstation with Intel (R) Xeon (R) Gold 6148 (2.8 GHz) CPU and 256 GB RAM. The operating system is Ubuntu 18.04. We train and fine-tune all models on an NVIDIA Quadro RTX 5000 GPU. Then, we deploy the system including the trained models on a MacBook Pro with an Quad-Core Intel i7 CPU and a Raspberry Pi 4B with a Broadcom BCM2711 CPU, quad core Cortex-A72 (ARM v8) 64-bit to simulate the specifications of current voice-controlled devices.

Speaker Verification. We select two state-of-the-art speaker verification systems/models: X-vectors [93] and ECAPA-TDNN [28] to evaluate the potential threat of our spoofing attacks on these systems. The models are trained with VoxCeleb1 and VoxCeleb2 data [68] which contain over 100,000 utterances for 7325 celebrities, extracted from videos uploaded to YouTube. The speakers span a wide range of different ethnicities, accents, professions and ages. Both models are reached an Equal Error Rate (EER) of 3.2% and 0.69% respectively. We use the pre-trained models implemented by ‘SpeechBrain’ tool [83].

Commercial Voice Assistants. We choose 3 services: *Amazon Alexa*, *Google Assistant*, and *Apple Siri*. All of these services offer a feature to match the person speaking to a voice sample or ‘Voice ID’ to verify a person’s identity (*i.e.*, similarly to telephone banking, like HSBC [41] and NatWest [70]). A primary account holder would be able then to require a specific Voice ID to access certain commands. For *Amazon Alexa*, it implements a Voice ID to help Alexa recognize the target speaker and provide a personalized experience. To create a Voice Profile, a user repeats a list of Amazon-specified commands, and the profile is then linked to the primary user account. Google Assistant implements ‘Voice Match’ to recognize who’s speaking to it and deliver personalized results. Only one Voice Match profile can be associated with a Google account. To create a Voice Match, a user says a few different phrases and their voice is processed to create a sonic fingerprint. Apple’s Siri can be taught to recognize a user’s voice and then uses it to serve up personalized content. To train Siri for a target user, Siri will ask the user to say “Hey Siri” three different times, then say “Hey Siri, how’s the weather today?” and finally, “Hey Siri, it’s me”. Thus, Siri can recognize the target voice and tailor its responses accordingly.

Table 4: Cross-validation results across models: mean values and standard deviations (in parentheses).

Model	Accuracy	Precision	Recall	F-score
SVM	0.9863 (0.0005)	0.9858 (0.0035)	0.9863 (0.0052)	0.9860 (0.0039)
MLP	0.9862 (0.0004)	0.9850 (0.0129)	0.9862 (0.0233)	0.9858 (0.0087)
kNN	0.8980 (0.0125)	0.9721 (0.0126)	0.8980 (0.0158)	0.9245 (0.0197)
SGD	0.9840 (0.0063)	0.9832 (0.0458)	0.9840 (0.0660)	0.9825 (0.0644)
LR	0.9862 (0.0005)	0.9856 (0.0039)	0.9862 (0.0051)	0.9858 (0.0040)

Evaluation Criteria. We apply the following evaluation criteria to assess the efficacy of our proposed solution:

- (1) *Security.* To authenticate and validate voice input, preventing malicious/faked inputs from activating and using online service features/functions associated with a target user.
- (2) *Privacy.* To evaluate the system’s protection level by measuring how successful is an attacker in inferring sensitive attributes for a given configuration.
- (3) *Utility.* To test the applicability of the system under real-world settings and how effective is the target service/function for which the system is designed.
- (4) *Efficiency.* To evaluate the computational overhead and resources required for the system to operate effectively from the edge, *i.e.*, running on constrained devices.

5.3 Integrity Validation

We start by asking *how accurately can we validate/authenticate system input?*

Setup. Voice input from all sources should be subject to input validation. Our focus is to defend against attacks that input signals ‘sounding’ like a target’s voice to humans and machines alike. We first pre-processed the input (voice) and then extract the acoustic features and embeddings using the proposed framework’s front-end. The features and embeddings extraction might be varied based on the tasks, for example, we used X-vector for speaker embeddings, and AASIST-L and VOID for spoofing and liveness tasks respectively. We used three validation modules: user identity verification, spoofed signal detection (logical), and liveness checking whether the signal is live or recording (physical). Each of these calculates its own decision scores. We extracted these scores for each sample (*i.e.*, speaker similarity score, spoofing score, and liveness score) in our dataset. Each validation module (matchers) can have its own multidimensional feature vector derived from the raw input. We produced approximately 117,000 scores combinations, simulating various input scenarios. After normalizing the scores, we trained a binary classifier to classify the input as legitimate or illegitimate. During the fusion process, match scores outputted by different matchers are consolidated in order to arrive at a final validation decision. The ideal case for an input to be categorized as legitimate is to be validated as the target user, benign/real (*i.e.*, not faked), and a live entry. Otherwise, input is considered illegitimate. Illegitimate inputs may occur if the user is not the target but may be live voice, and the worst case is that it is not of the non-target user, produced by machine and played from a recording.

Evaluation. We apply the 5 classifiers as the final score predictor on our dataset to classify the user’s legitimacy. We follow 5-fold cross-validation. The mean and one standard deviation of the

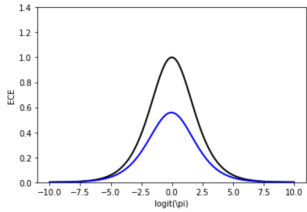


Figure 6: Privacy protection level using lightweight anonymization tool [15]

5-fold test for accuracy, precision, recall, and F score are presented in Table 4. All 5 classifiers achieve over 98% Accuracy, with a Precision rate in excess of 97%. The best model, SVM, achieves 98.63% Accuracy, 98.58% Precision, and 98.63% Recall. The classification results have very small variances. This confirms that the fusion of multiple predictors are indeed useful for the user legitimately classification task. However, there is a possibility that the match scores generated by different predictors may not be homogeneous. For instance, one predictor may provide a distance or dissimilarity measure (a smaller distance indicates a better match), while another may provide a similarity value (a greater similarity shows a better match). Furthermore, the results of the discrete predictors do not have to be of the same numerical range.

5.4 Privacy Protection

Then, we investigate *what privacy configurations can we apply to streaming biometric data and what protection level might a system provide?*

Setup. A flexible privacy module works by applying selected privacy settings over the input data. We used the proposed system in [15] which gave promising results in protecting the sensitive characteristics of the speaker (as reported in Section 3.5). In our case, ‘identity’ is the sensitive property that we want to protect (*i.e.*, part also of user’s authentication). We applied the anonymization method to the raw recordings of our participants to hide their identities and then reproduced the signal. We use the speaker verification system decision score that indicates the similarity of the given utterance with target identity. Then, we use the output scores within the ‘ZEBRA’ framework [72]. ZEBRA measures the average level of privacy protection afforded by a given privacy-preserving solution for a population and the worst-case privacy disclosure for an individual [72]. These metrics can be interpreted using categorical tags, and the odds ratio for recognizing a biometric identity by the lowest l value of a category. Lower odds means less precision for an adversary, and thus more privacy preservation (best is 50: 50 with a category ‘0’).

Evaluation. For privacy protection level, the higher the percentage of dissimilarity between the raw data before modification and after anonymization, the better the identity protection we have. In Figure 6, the black curve corresponds to perfect privacy or zero evidence, where the blue line represents the result (0.309, 1.756, B) in the form of a $(D_{ECE}, \log_{10}(l), \text{tag})$ tuple, where the D_{ECE} (*i.e.*, empirical cross entropy (ECE)) provides an average protection estimation afforded to a population whereas $\log_{10}(l)$ provides additional insights about the protection level afforded in a worst-case

Table 5: The word error rate (WER; lower is better) and real-time factor (RTF; lower RTF is more computationally efficient).

Service	Amazon		Google		IBM		Mozilla		Local Model	
	WER	RTF	WER	RTF	WER	RTF	WER	RTF	WER	RTF
Raw Data	17.26	57.49	18.45	7.35	7.14	2.11	5.95	1.33	5.36	2.20
Private Data	23.21	51.41	85.00	2.87	32.74	1.39	27.38	1.04	11.31	2.06

to an individual. Our results demonstrate that we can achieve a fair level of privacy (*i.e.*, label ‘B’) from the edge using lightweight techniques.

5.5 Utility Evaluation

Assuming that a privacy protection method is implemented, we asked to *what extent privacy-aware data retains utility for the task of interest?*

Setup. Utility is measured by the ability to maintain the main functionality of the online service when using the privacy-preserving inputs. In our example, in voice-controlled interfaces, understanding and responding to voice commands (*i.e.*, automatic speech recognition (ASR)) is the primary task of these services. We use ASR-based metrics to evaluate the quality of the filtered data to demonstrate the proposed framework’s feasibility/compatibility with future/existing transcription systems. We use state-of-the-art ASR systems to transcribe the generated speech back to text and then apply metrics including word error rate (WER) to determine the intelligibility of the resulting speech in terms of higher linguistic content. This reflects that we still have a privacy-preserving version of the raw audio that is sufficiently good for the transcription task. To demonstrate the practical applicability of the proposed framework with current cloud-based models (commercial Speech-to-Text APIs), we use a subset of the Librispeech test dataset (raw recordings) as a baseline, assuming that such recordings disclose all sensitive information about the user. We measure the WER, which is the ratio of edit distance between words in a reference transcript and the words in the output of the speech-to-text engine to the number of words in the reference transcript (*i.e.*, lower WER means the more precise is the model), and the real-time factor (RTF), which is the ratio of CPU (processing) time to the length of the input speech file. A speech-to-text engine with lower RTF is more computationally efficient. We use the ground-truth transcripts within the dataset to calculate the WER of the raw (baseline) and our framework output (privacy-aware generation).

Evaluation. We calculate the word error rate (WER) using the Automatic Speech Recognition (ASR) of current speech-to-text cloud-based services and uses the ground-truth transcripts. Examples include Amazon Transcribe [17], Google Speech [34], IBM Watson [109], Mozilla DeepSpeech [67], and a local transcription model trained on the Librispeech dataset. We can see from the Table 5 that the utility is still maintained with minimal performance penalties of approximately ~6% word error rate (WER) compared to current cloud-based ASR systems. The theoretical privacy vs utility comparison of these approaches is left for future work.

5.6 Real-time Performance

Processing and validating inputs at the source (e.g., at the smartphone or smart speaker) offers a means to counter security and privacy attacks from their onset, and thus we investigate *can we apply input verification and filtration on resource-constrained devices?*

Setup. The idea is to design a fused score that allows us to verify input data integrity at the edge while also selectively protecting privacy against ‘untrusted’ parties. Incorrect input validation can lead to spoofing/injection attacks, memory leakage, and compromised systems.

Evaluation. In our experiment, we deployed both integrity validation and flexible privacy modules on two representative edge platforms: a MacBook Pro and a Raspberry Pi 4B. We report the average inference times, number of features used, and the average memory required by these modules during integrity validation experiments. As shown in Table 6, the results indicate that we can deploy these models on the different edge/cloud devices with promising overall inference time and memory usage in all cases. The results demonstrate the feasibility of applying our system in the real world. It is shown to be efficient for input integrity checking, where the total time required is no more than 0.70 seconds (700 ms) in our experiments. The inference time roughly increases linearly with the length of the tested recording. Memory consumption on the MacBook Pro and Raspberry Pi 4 is 0.006 MB and 0.002 MB, respectively. In addition, more optimization can be applied, including model quantization [47] and knowledge distillation [20, 39], to obtain even faster and smaller models. Such models should be fast enough to run near real-time on an mobile or otherwise constrained device and present minimal performance degradation for the task of interest. We leave for future work additional efforts to explore these optimization approaches for even more constrained devices.

6 FUTURE WORK AND OPEN DIRECTIONS

6.1 Beyond Authentication

The proposed system can be integrated as a plug-in for different application contexts as a way of validating data sources that go beyond giving permissions to the systems.

Synthetic data as privacy-enhancing technology (PET). Our experiments have so far focused on speech processing. As we continue to develop synthesized techniques (like generative models) for a variety of applications including images, videos, etc., these ‘dual-use’ tools [1] have become a difficult challenge. There has been increasing interest in sharing synthetic data instead of real data, which may mitigate privacy risks and preserve data utility [50, 64, 77, 100, 116, 119]. As the primary goal of these technologies is to produce unlinkable data or to improve user anonymity, some might wonder why authentication is necessary. These techniques, however, can also advance the development of deepfake techniques. The question is how to enable verification over sensitive data without violating user privacy, or how to apply verification to privacy-aware or anonymized data. It is therefore important to develop countermeasure techniques that can verify the source/purpose of data. Using our pipeline, we recommend validating the data source at the edge before sharing it, see Figure 1. We plan to integrate new applications [14, 16, 122] with a configurable privacy engine and evaluate the effectiveness of source validation

Table 6: The computational cost by different framework’s modules including: speaker verification (SV), spoofing detection (SD, logical), liveness detection (LD, physical), and privacy-preserving (PP) on two edge representative platforms, namely MacPro (Pro) and Raspberry Pi4 (Pi).

	Measure	Module							
		SV		SD		LA		PP	
		Pro	Pi	Pro	Pi	Pro	Pi	Pro	Pi
Time (sec.)	Extraction	0.34	0.84	0.53	0.67	0.12	0.14	0.04	0.33
	Testing	0.10	0.90	0.01	0.04	0.58	0.59	0.05	0.09
Memory (KB)	Features	192	192	128	128	97	97	100	100
	Memory	2.97	0.73	0.03	0.02	3.50	1.29	0.09	0.03
	Model Size	0.86	0.86	25.3	25.3	2.6	2.6	55	55

in mitigating spoofing attempts while retaining its usefulness in minimizing privacy intrusions.

Distributed Learning and Personalization. The use of distributed machine learning techniques, such as federated learning and split neural networks (or split learning) [102], facilitates machine learning without compromising access to raw data that may contain additional sensitive information. The objective is to design efficient distributed algorithms that operate in the setting where sensitive user data is kept on-device, and a global model running on servers and a personalized one running on personal devices. However, they remain vulnerable to malicious exploitation. First, even without access to raw data, attacks such as data inversion, membership inference, and property inference threaten data privacy [69]. Secondly, distributed learning techniques are inherently vulnerable to backdoor attacks, and the server may not have access to analyze local or source data [113]. A compromised node can affect other nodes, causing a cascade of consequences. We plan to evaluate the proposed system in further distributed settings and measure the effect of blocking participation early before negatively impacting the learning process.

Poisoning Attacks. Poisoning attacks have been studied against sentiment analysis [73], malware clustering [19, 112], worm signature detection [74], DoS attack detection [85], and intrusion detection [24]. In poisoning, the attacker seeks to get their input accepted as training data. It might take weeks for the attacker to achieve their poisoning goal because the training cycle for the model differs [90]. To fix poisoned models, developers need measures that could either stop attacks or detect malicious inputs before subsequent training cycles begin, such as input validity checking, rate limiting, regression testing, manual moderation, and using various statistical techniques to find anomalies [85]. It may be possible to extend our pipeline to add additional restrictions to how many inputs are accepted by individuals in the training data.

6.2 Conclusion and Future Research

Data Size. We have evaluated our system on a limited number of subjects and the system will need to be evaluated with a larger number of participants with a variety of backgrounds in order to better understand performance. A long-term study might consider the possibility of an individual’s characteristics changing over time, such as their voice changing due to illness. In spite of this, we believe periodically updating user enrollment could potentially mitigate such a limitation.

Continuous Authentication. The idea of continuous authentication is to establish the user’s identity not just once at login time but also continuously while the person is using the system [31]. As such, it may detect a change to user identity even after the initial login. In this case, the system needs to account for the fact that a person’s tone response may change during the test time, therefore it is necessary to choose biometric features that are reliable enough against these changes as possible. It would also be helpful to mitigate the false acceptance of fuzzy words by wake-up word detectors [23].

Robustness Measures. In our experiments, we focused on detecting spoofing attacks based on the assumption that every modification to the underlying data must be disclosed. More robustness analyses can be carried out to evaluate the pipeline’s effectiveness against other attacks, such as adversarial spoofing [26] and hidden attacks [5]. In such cases, the system may incorporate additional modules like ensemble for keyword spotting (EKOS) with the authentication to sharpen its robustness and defend against both accidental and adversarial activations [12].

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