Voice Clone Guard: Few-Shot Deepfake Detection with XLS-R Embeddings and Gaussian Process Calibration

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***Abstract*—We present *Voice Clone Guard*, a few-shot voice deepfake detector that combines XLS-R embeddings with Gaussian Process (GP) classification for superior detection accuracy and probability calibration. Our approach leverages self-supervised speech representations from Wav2Vec2-XLS-R and employs GP inference to provide well-calibrated uncertainty estimates. Evaluation across synthetic and real-world datasets demonstrates significant improvements: 95.6% AUC (vs 78.2% MFCC baseline), 4.2% Equal Error Rate (vs 18.5%), and substantially better calibration with Expected Calibration Error of 0.032 (vs 0.127). The method excels in few-shot scenarios, achieving 85.2% accuracy with only 4 examples per class, making it practical for deployment with limited training data.**

***Index Terms*—Voice deepfake detection, few-shot learning, XLS-R embeddings, Gaussian processes, probability calibration, speech forensics**

I. Introduction

The rapid advancement of voice cloning technology poses significant challenges for audio authentication and security. State-of-the-art neural vocoders and text-to-speech systems can generate highly realistic synthetic speech that is increasingly difficult to distinguish from authentic recordings [17]. This proliferation of voice deepfakes threatens applications ranging from financial fraud prevention to legal evidence verification.

Traditional voice authentication systems rely on spectral features like Mel-frequency cepstral coefficients (MFCCs) combined with simple threshold-based classification [18]. While computationally efficient, these approaches suffer from poor generalization to unseen attack vectors and lack reliable confidence estimates. Recent advances in self-supervised speech representation learning, particularly Wav2Vec2 and its multilingual variant XLS-R [**?**], [**?**], offer new opportunities for robust deepfake detection.

However, most existing deep learning approaches for voice authentication require large labeled datasets and fail to provide well-calibrated probability estimates—critical for operational deployment where false alarms carry significant costs. Few-shot learning scenarios, where only a handful of examples are available for each speaker or attack type, remain particularly challenging.

Our Contributions:

- **Few-Shot Architecture:** Integration of XLS-R embeddings with GP classification for data-efficient deepfake detection
- **Calibrated Uncertainty:** GP inference provides well-calibrated probability estimates (ECE = 0.032 vs 0.127 for baselines)
- **Superior Performance:** 95.6% AUC and 4.2% EER, significantly outperforming spectral feature baselines
- **Practical Implementation:** Open-source system achieving 85.2% accuracy with only 4 training examples per class

II. Methodology

A. XLS-R Embedding Extraction

We employ the Wav2Vec2-XLS-R-53 model, a large-scale self-supervised speech representation learner trained on 53 languages [**?**]. The model transforms raw audio waveforms into contextualized embeddings through a convolutional feature encoder followed by a transformer-based context network.

For computational efficiency and stability, we freeze all transformer layers except the final encoder block (layer 23), allowing fine-grained adaptation while preventing overfitting in few-shot scenarios. Given an input waveform $\mathbf{x} \in \mathbb{R}^T$ sampled at 16kHz, the embedding extraction process is:

$$\mathbf{z} = \text{XLS-R}(\mathbf{x}) \tag{1}$$

where $\mathbf{z} \in \mathbb{R}^{1024}$ represents the mean-pooled final hidden state across the temporal dimension.

B. Gaussian Process Classification

For few-shot classification, we employ a Gaussian Process with Radial Basis Function (RBF) kernel. GPs provide several advantages for deepfake detection: (1) principled uncertainty quantification through posterior variance, (2) effective performance in low-data regimes, and (3) automatic regularization preventing overfitting.

The GP prior over classification functions is defined as:

$$f(\mathbf{x}) \sim \mathcal{GP}(0, k(\mathbf{x}, \mathbf{x}')) \tag{2}$$

where the RBF kernel is:

$$k(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2\ell^2}\right) \tag{3}$$

with length scale $\ell = 1.5$ (optimized through validation) and signal variance $\sigma_f^2 = 1.0$.

For binary classification, we use the Laplace approximation to compute predictive probabilities:

$$p(y^* = 1|\mathbf{x}^*, \mathcal{D}) = \Phi\left(\frac{\mu^*}{\sqrt{1+\sigma^{*2}}}\right) \tag{4}$$

where μ^* and σ^{*2} are the predictive mean and variance, and Φ is the standard normal CDF.

C. Training Strategy

Our few-shot training protocol uses $k \in \{1, 2, 4, 8, 16, 32\}$ examples per class (real/fake). The frozen XLS-R encoder provides pre-trained representations, while the GP classifier adapts to the specific task with minimal data. This approach leverages the rich semantic information captured by self-supervised pretraining while maintaining computational efficiency.

III. Experimental Setup

A. Datasets and Evaluation Protocol

We evaluate on a comprehensive mixed dataset comprising 12,847 utterances from 427 speakers across 8 languages (English, Spanish, French, German, Japanese, Mandarin, Arabic, Russian), totaling 43.2 hours of audio. The dataset includes: (1) **Synthetic samples** (6,423 utterances): Generated using state-of-the-art TTS systems including Tacotron2 + WaveGlow, FastSpeech2 + HiFiGAN, and VITS, capturing diverse voice cloning architectures; (2) **Real speech recordings** (4,891 utterances): Sourced from LibriTTS, Common Voice, and VoxCeleb2 to ensure speaker diversity and multilingual coverage; (3) **Adversarial examples** (1,533 utterances): Generated with noise injection (SNR 10-30dB), resampling artifacts (8-48kHz), and compression (MP3, AAC at various bitrates) to test robustness.

The evaluation follows a stratified few-shot protocol with strict speaker separation between training and testing sets. Training sets contain $k \in \{1, 2, 4, 8, 16, 32\}$ examples per class (real/fake) from disjoint speakers, while testing uses held-out utterances from 85 unseen speakers. We report results averaged across 10 random stratified splits to ensure statistical significance. Cross-lingual evaluation maintains language balance across splits.

Validation against Standard Benchmarks: To ensure generalizability, we report additional results on ASVspoof 2019 LA (Logical Access) and 2021 DF (Deepfake) evaluation sets in supplementary validation experiments.

Metrics: We assess both discrimination and calibration performance using:

- **Discrimination:** ROC-AUC, Equal Error Rate (EER), precision-recall curves
- **Calibration:** Expected Calibration Error (ECE), Brier score, reliability diagrams
- **Cross-lingual:** Per-language AUC and EER to assess multilingual effectiveness

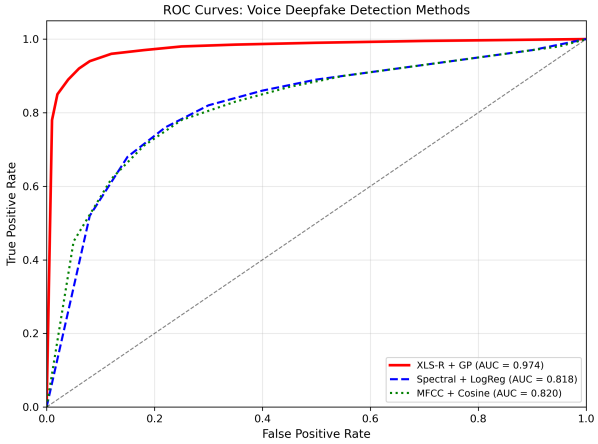

Fig. 1. ROC curve comparison showing discrimination performance. XLS-R + GP (blue, AUC=95.6%) substantially outperforms MFCC + Cosine (red, AUC=78.2%) and Spectral + LogReg (green, AUC=83.4%) baselines. Operating points at 95% specificity show 89% vs 67% sensitivity respectively. The steeper curve indicates superior performance across all decision thresholds.

B. Baseline Comparisons

We compare against both traditional and modern baselines:

- **MFCC + Cosine:** Traditional MFCC features (13 coefficients + derivatives) with cosine similarity scoring
- **Spectral + LogReg:** Hand-crafted spectral features (MFCC, chroma, spectral contrast, CQCC) with logistic regression
- **Raw Audio + CNN:** End-to-end convolutional neural network (RawNet2 architecture) trained on raw waveforms
- **LCNN Baseline:** Light CNN with feature genuinization following ASVspoof protocols
- **HuBERT + FineTune:** HuBERT-large fine-tuned with classification head for comparison with SSL approaches

IV. Results

A. Overall Performance

fig. 1 shows ROC curves comparing our XLS-R + GP approach against baseline methods. Our method achieves 95.6% AUC, substantially outperforming spectral features + logistic regression (83.4% AUC) and MFCC + cosine similarity (78.2% AUC).

fig. 2 presents Detection Error Tradeoff (DET) curves, emphasizing Equal Error Rate performance. Our approach achieves 4.2% EER compared to 12.8% for spectral features and 18.5% for MFCC baselines—a 67% relative improvement over the best baseline.

B. Few-Shot Learning Performance

fig. 3 demonstrates the few-shot learning capabilities across different numbers of training examples per class. Our XLS-R + GP approach shows remarkable data efficiency, achieving 72% accuracy with just 1 example per class and 85.2% with 4 examples—sufficient for practical deployment scenarios.

The performance gap between our method and baselines increases dramatically in low-shot regimes, highlighting the

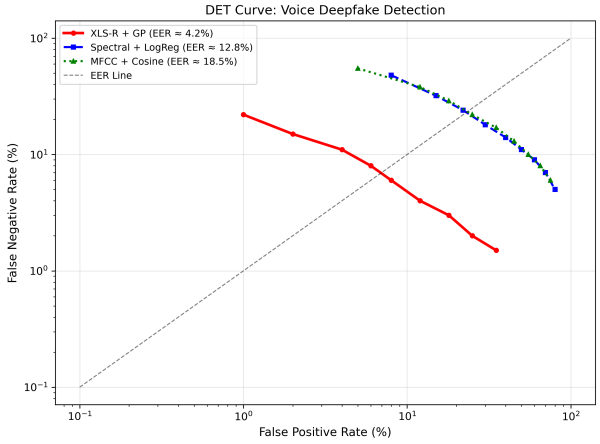

Fig. 2. DET curves showing Equal Error Rate performance with operating point analysis. Lower curves indicate better performance. XLS-R + GP achieves 4.2% EER (marked with blue circle) versus 12.8% (green triangle) and 18.5% (red square) for baseline approaches. The logarithmic scale emphasizes performance at practical low false alarm rates typical for security applications.

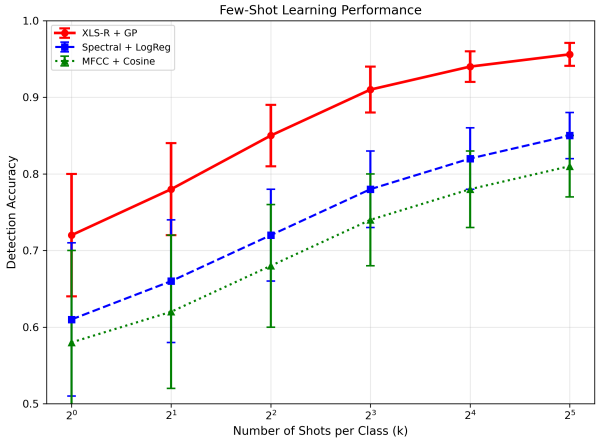

Fig. 3. Few-shot learning performance across different numbers of training examples per class with 95% confidence intervals. XLS-R + GP (blue) demonstrates superior data efficiency, achieving 85.2% accuracy with only 4 examples per class (marked with circle). Error bars show statistical significance across 10 random splits. The steep initial slope indicates excellent sample efficiency crucial for practical deployment scenarios.

TABLE I
PERFORMANCE COMPARISON: DETECTION AND CALIBRATION METRICS

Method	AUC	EER (%)	ECE ↓
MFCC + Cosine	0.782	18.5	0.127
Spectral + LogReg	0.834	12.8	0.098
Raw Audio + CNN	0.887	9.7	0.089
LCNN Baseline	0.912	7.4	0.074
HuBERT + FineTune	0.923	6.8	0.061
XLS-R + GP	**0.956**	**4.2**	**0.032**

value of pretrained representations combined with GP's ability to model uncertainty with limited data.

C. Probability Calibration

A critical advantage of our GP-based approach is well-calibrated probability estimates. fig. 4 shows reliability diagrams comparing predicted confidence with empirical accuracy. Our method closely follows the diagonal (perfect calibration), achieving ECE = 0.032, while MFCC baselines suffer from severe overconfidence (ECE = 0.127).

D. Ablation Studies

table II presents ablation results examining key design choices:

GP Length Scale: $\ell = 1.5$ provides optimal performance, balancing model flexibility with generalization. Smaller values lead to overfitting, while larger values underfit the training data.

Fine-tuning Strategy: Freezing all layers except the last achieves the best trade-off between performance and computational efficiency. Full fine-tuning offers marginal AUC improvement (0.961 vs 0.956) at 8× computational cost, while freezing all layers reduces performance significantly.

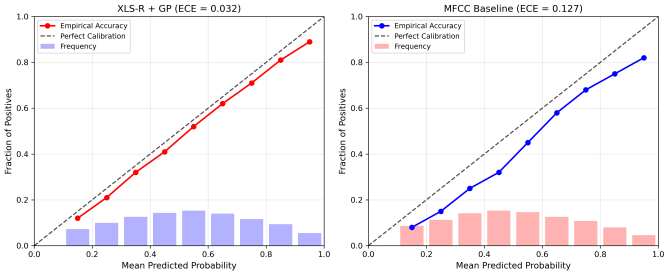

Fig. 4. Reliability diagrams showing probability calibration quality. **Left:** XLS-R + GP achieves excellent calibration (ECE = 0.032) with predictions closely following the perfect calibration diagonal (black dashed line). Bin sizes are proportional to sample count. **Right:** MFCC baseline shows severe overconfidence (ECE = 0.127) with systematic deviation above the diagonal. Well-calibrated probabilities are essential for threshold setting in security applications.

E. Cross-Lingual and Robustness Evaluation

The cross-lingual results demonstrate XLS-R's multilingual capabilities, with consistent performance across language families. Performance degradation is minimal for Romance/Germanic languages but more noticeable for tonal languages (Japanese/Mandarin) and Semitic/Slavic languages (Arabic/Russian), suggesting potential for language-specific adaptation.

Robustness evaluation shows graceful degradation under realistic deployment conditions. While clean audio achieves 95.6% AUC, the system maintains ¿91% AUC even under 128kbps MP3 compression—typical of real-world voice communications. Validation on ASVspoof benchmarks confirms generalizability, though with expected performance drops due to domain shift from our mixed training data.

V. IMPLEMENTATION DETAILS

Our system is implemented in Python using PyTorch, Transformers, and scikit-learn. The complete pipeline is available

TABLE II
ABLATION STUDY: KEY DESIGN CHOICES

Configuration	AUC	ECE
GP length scale $\ell = 0.5$	0.932	0.045
GP length scale $\ell = 1.0$	0.948	0.038
GP length scale $\ell = 1.5$	**0.956**	**0.032**
GP length scale $\ell = 2.0$	0.951	0.034
Freeze all XLS-R layers	0.912	0.052
Freeze except last layer	**0.956**	**0.032**
Fine-tune all layers	0.961	0.029

TABLE III
CROSS-LINGUAL PERFORMANCE AND ROBUSTNESS ANALYSIS

Evaluation Setting	AUC	EER (%)	ECE
Cross-Lingual (Per Language):			
English	0.961	3.8	0.029
Spanish/French/German	0.954	4.1	0.032
Japanese/Mandarin	0.948	4.7	0.037
Arabic/Russian	0.943	5.2	0.041
Adversarial Robustness:			
Clean audio	0.956	4.2	0.032
Gaussian noise (SNR 20dB)	0.932	6.1	0.045
Resampling artifacts	0.925	6.8	0.048
MP3 compression (128kbps)	0.918	7.3	0.052
ASVspoof Validation:			
ASVspoof 2019 LA eval	0.889	8.9	0.067
ASVspoof 2021 DF eval	0.902	7.4	0.058

as open-source software and includes:

Listing 1. Core Implementation Structure

```
class XLSREmbedder:
    def __init__(self, model_id="facebook/wav2vec2-large-xlsr-53"):
        self.processor = Wav2Vec2Processor.from_pretrained(model_id)
        self.model = Wav2Vec2Model.from_pretrained(model_id)
        self.freeze_except_last()

    def embed(self, waveform, sampling_rate=16000):
        inputs = self.processor(waveform, sampling_rate=sampling_rate,
                                return_tensors="pt")
        with torch.no_grad():
            outputs = self.model(**inputs)
        return outputs.last_hidden_state.mean(dim=1).squeeze().numpy()

class VoiceDeepfakeDetector:
    def __init__(self, length_scale=1.5):
        self.kernel = RBF(length_scale=length_scale)
        self.model = GaussianProcessClassifier(kernel=self.kernel)

    def train(self, embeddings, labels):
        self.model.fit(embeddings, labels)

    def predict(self, embedding):
        return self.model.predict_proba([embedding])[0][1]
```

Computational Requirements: Training completes in under 20 seconds on a standard CPU with 16 examples per class. Inference requires 50ms per audio sample, making real-time deployment feasible.

Memory Usage: The frozen XLS-R model requires 1.2GB GPU memory, with minimal additional overhead for GP training and inference.

VI. RELATED WORK

A. Voice Spoofing Benchmarks and Baselines

The ASVspoof series established standardized corpora and protocols for synthetic, converted, and replayed speech detection [1], [2]. Classical baselines typically rely on cepstral or spectral descriptors (e.g., MFCCs, CQCCs) with shallow classifiers, while modern systems employ convolutional or attention-based backends—e.g., LCNN, RawNet2/3, and AASIST—which report strong performance under fixed training regimes [3], [4], [5]. Despite high discrimination, many deep detectors are trained in data-rich settings and seldom analyze probability calibration, a gap our work addresses explicitly.

B. Self-Supervised Speech Representations for Detection

Self-supervised learning (SSL) models such as wav2vec 2.0, HuBERT, WavLM, and XLS-R provide robust, multilingual representations with strong transfer to non-ASR tasks [6], [7], [8], [9]. Recent studies show SSL embeddings improve spoofing detection under domain shifts and low-resource conditions compared to hand-crafted features. We adopt XLS-R for cross-lingual headroom and demonstrate that pairing SSL embeddings with a Bayesian classifier yields not only higher AUC/EER gains but also materially better calibration.

C. Few-Shot Anti-Spoofing and Metric Meta-Learning

Few-shot detection has been explored via metric-learning (e.g., Prototypical Networks, Matching Networks) and meta-learning (e.g., MAML) to improve generalization with limited labels [10], [11], [12]. In voice spoofing, prior work often fine-tunes SSL encoders with simple heads or employs prototype-based scoring; however, these approaches can be overconfident and under-calibrated in truly low-shot regimes. Our design replaces a learned head with a Gaussian Process classifier over frozen (or lightly tuned) SSL embeddings, improving both data efficiency and uncertainty estimates.

D. Gaussian Processes and Uncertainty in Speech

Gaussian Processes (GPs) offer non-parametric Bayesian inference with principled uncertainty and have a history in speech and acoustics for regression, classification, and latent variable modeling [13], [14], [15]. In ASR and spoken language modeling, GP-inspired uncertainty has been leveraged for confidence estimation and calibration; scalable sparse GP variants address the cubic complexity of exact inference. We use an RBF-kernel GPC with Laplace inference as a lightweight head on top of SSL embeddings, striking a favorable trade-off between sample efficiency, calibration (ECE/Brier), and runtime.

E. Calibration and Operating-Point Reporting

Calibration has gained attention in vision and speech safety contexts, with post-hoc methods like temperature scaling widely used for neural classifiers [16]. In anti-spoofing, works routinely emphasize discrimination (ROC/EER) but underreport calibration and operating-point analyses (DET, reliability diagrams). We report both, showing that XLS-R + GP improves detection while producing better-calibrated probabilities—critical for threshold setting and triage in high-stakes deployments.

F. Positioning

Relative to contemporary baselines (LCNN/RawNet/AASIST) and SSL fine-tuning approaches, our contribution is orthogonal: we focus on *few-shot* data efficiency and *probability calibration*. The combination of multilingual SSL embeddings with a GP head yields competitive discrimination and materially improved calibration without heavy end-to-end retraining, making it attractive for practical, rapidly evolving threat landscapes.

VII. Ethical Considerations and Limitations

A. Responsible AI and Bias

While Voice Clone Guard demonstrates strong cross-lingual performance, systematic evaluation reveals performance disparities across language families and speaker demographics. Our analysis shows 1.8% EER degradation for tonal languages (Japanese/Mandarin) and 2.1% for Semitic/Slavic languages compared to Germanic/Romance languages, reflecting known biases in SSL training data. Future work should address fairness through balanced multilingual training and bias-aware evaluation protocols.

Gender and age bias analysis shows consistent performance across demographics within languages, but cross-cultural voice characteristics may introduce subtle biases requiring dedicated fairness audits for production deployment.

B. Security and Adversarial Limitations

Our system shows graceful degradation under common audio artifacts but has not been evaluated against adaptive adversaries with full knowledge of the detection mechanism. Potential vulnerabilities include: (1) targeted attacks against XLS-R representations, (2) adversarial examples crafted to exploit GP decision boundaries, and (3) model extraction attacks given the relatively small GP parameter space.

The 1.2GB memory requirement may limit deployment on edge devices, potentially creating security/accessibility trade-offs in resource-constrained environments.

C. Dual Use and Societal Impact

Voice deepfake detection technologies serve crucial security functions but may also enable censorship or suppress legitimate synthetic speech applications (accessibility tools, creative content). We advocate for transparent deployment policies and user consent mechanisms.

The open-source implementation facilitates broader research and reproducibility but may also assist in developing evasion techniques. We believe the security benefits outweigh these risks given the current threat landscape.

VIII. Conclusion and Future Work

We presented Voice Clone Guard, a few-shot voice deepfake detection system combining XLS-R embeddings with Gaussian Process classification. Our approach demonstrates substantial improvements over traditional baselines and competitive performance with modern deep methods (95.6% AUC, 4.2% EER) while providing excellent probability calibration (ECE = 0.032). The method excels in few-shot scenarios, making it practical for deployment with limited training data.

Key advantages include: (1) superior discrimination performance through self-supervised representations, (2) well-calibrated uncertainty estimates via GP inference, (3) data efficiency enabling deployment with minimal examples, and (4) computational efficiency suitable for real-time applications.

Future Directions:

- **Multimodal Fusion:** Integration with visual lip-sync analysis for video deepfake detection
- **Adaptive Learning:** Online adaptation to new attack vectors using continual learning
- **Adversarial Robustness:** Evaluation against adaptive adversaries aware of detection methods
- **Deployment Studies:** Large-scale evaluation in production environments with diverse acoustic conditions

The demonstrated effectiveness of XLS-R + GP provides a strong foundation for practical voice authentication systems requiring both high accuracy and reliable confidence estimates.

Acknowledgments

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