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A Robust Anti-Spoof Identity Verification Framework Using Foundation Vision Models and Behavioral Liveness Reasoning

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Abstract

Face recognition technologies are progressively being faced with the challenge of sophisticated presentation attacks like the use of replay videos, 3D masks, and real-time deepfakes. Liveness detection methods that were relying on blinks and head movements are not sufficient anymore, as contemporary generative AI can very realistically imitate human facial behaviors. In this paper, the authors present a hybrid anti-spoofing identity verification framework that integrates behavioral liveness reasoning and Foundation Vision Models (FVMs). FVM extracts very detailed visual artifacts with respect to texture, lighting, and material inconsistencies. Temporal liveness module is dedicated to the analysis of natural facial dynamics, for instance, micro-movements, blinking patterns, and subtle head motion. A fusion layer serving different modalities is in charge of the integration of spatial and temporal cues leading to the output of a very reliable authenticity decision. The framework was put to test on publicly available face presentation attack datasets and it showed very good performance when it came to the task of telling apart real faces from the spoofed and deepfake ones. The experimental results signified that the suggested method provided better endurance than in the case of appearance-only techniques while still being appropriate for real-time implementation. The system is compatible with mobile devices, kiosks, and cloud-based authentication platforms thus it can very well be used in a variety of applications such as banking, e-KYC, and secure access control.

Keywords: Foundation Vision Models, Anti-Spoofing, Behavioral Liveness Detection, Deepfake Resistance, Identity Verification, Large-Scale Security, Presentation Attack Detection, Multi-Modal Reasoning, Universal Authentication, Biometric Security.

Introduction

Identity verification systems are crucial for both digital and physical access to banking, government services, workplaces, airports, schools, and global e-commerce. However, the rise of

advanced presentation attacks, which include printed photos, high-quality replay videos, 3D masks, and real-time streams, has significantly undermined the dependability of traditional face-recognition systems. Standard liveness detection methods like blink detection and scripted head movements are outdated. Now, generative AI models can create photorealistic facial motions that closely mimic human behavior. Therefore, identity systems need to shift from basic verification to deeper semantic and behavioral understanding.

Foundation Vision Models (FVMs) train on billions of diverse images and present a strong solution. They capture detailed features like surface texture inconsistencies, lighting mismatches, depth cues, and artifacts that tell apart real human faces from spoofed or computer-generated ones. Yet, sophisticated attackers can reproduce these features using advanced display systems or realistic mask materials. To combat this issue, behavioral liveness reasoning adds a protective layer by studying temporal motion signatures that are inherently human and hard to replicate. These signatures include micro-muscle contractions, spontaneous facial expressions, natural breathing movements, eye-reflection physics, and irregular, non-repetitive motion patterns.

This paper aims to create a universal anti-spoof verification system that blends foundational visual reasoning with behavior-based temporal inference. The goal is to provide real-time, strong identity protection in various environments. By combining static and dynamic cues, the system addresses the shortcomings of standard liveness checks and offers a strong defense against modern spoofing tactics. This universal setup allows it to adapt to different deployment scenarios, enabling the same model to work effectively on smartphones, kiosk machines, airport gates, and server-grade authentication portals. In contrast to current presentation attack detection techniques, this work presents a universal framework that combines behavioral liveness reasoning with foundation vision models to jointly analyze human motion dynamics and semantic facial cues.

Literature Review

The most recent trends in biometric security are mainly driven by the spread of deep generative models, which have identified the weaknesses of more traditional anti-spoofing techniques. Early face verification mechanisms relied on manual construction of texture descriptors and primitive classifiers, thus making them insufficient to face high-resolution replay attacks and three-dimensional masquerade criminals. Although convolutional neural network (CNN) based methods have realized performance improvements by learning spatial representations, they remain vulnerable to deepfake attacks, as well as adversarial attacks which learn to render smooth facial textures in high-fidelity.

More recently Foundation Vision Models (FVMs) such as DINOv2 and SigLIP have been demonstrated to have improved generalization by learning very large visual representations based on large image-text corpora. These architectures can identify exotic anomalies in lighting, reflectance and material character that are often not detected by conventional models. However, it is not enough to rely only on appearance-based approaches, as modern diffusion models can create very realistic depictions of faces with insignificant changes in perception.

Therefore, there has been a tendency of recent research to focus on behavioral and temporal liveness testing, which probes micro-expressions, deviant blink rates and small-scale motion patterns that can hardly be produced synthetically. Hybrid approaches in which spatial vision models are used in conjunction with temporal transformers and optical flow analysis have achieved promising results over high-resource spoofing attacks. These advancements highlight the need to have a dual-layer paradigm which combines the visual semantics and behavioral inference to give robust identity verification.

Proposed Architecture

The proposed system is a two-step hybrid anti-spoof system that combines the basic vision models together with behavioral liveness reasoning. It combines the analysis of static visual features with dynamic time-varying features to identify presentation attacks in the form of replay videos, deepfakes and 3D masks across different deployment settings.

The Foundation Vision Model Encoder

The first stage uses a baseline vision model (FVM), such as DINOv2, or a vision transformer based on CLIP, to obtain multi-scale facial representations. FVM represents global semantic structure and sub-castle texture inconsistencies related to lighting, reflectance and synthetic artifacts. The model is pre-trained on massive open-source data and later frozen during fine-tuning so that it can perform better generalization and stability in multi-identity conditions.

Behavioral Liveness Reasoning Module

The latter phase involves an additional temporal liveness module which processes short video clips in order to identify human-specific movement patterns. It looks at characteristics like erratic blinking, minute head movements and natural facial movements with the help of temporal transformers. Such behavioral indicators are hard to fake with the help of spoofing, which means they act as an extra security barrier to real-time deepfake and replay attacks.

Cross-Modal Fusion Layer

A cross-modal fusion layer is the part that combines the spatial representation with the FVM and temporal movement representations with the liveness module. An attention-based system applies adaptive weights to both visual and behavioral signals based on the environmental circumstance, which allows strong performance in different situations of lighting and motion.

Spoof Classification and Identity Decision Engine

The fused representation is then subjected to a lightweight transformer-based classifier which makes three decisions: the real, the spoof or the uncertain. Uncertainty estimation element marks the questionable cases to further verification, thus minimizing the false positives without compromising security or real-time performance.

Universal Deployment Layer

The system facilitates deployment on edge devices, cloud servers and embedded platforms using hardware-adaptive pipelines. It is made to connect smoothly with already existing digital identity systems used in banking, e-KYC and secure access control applications.

Figure 3.1. Proposed Architecture of the Universal Anti-Spoof Identity Verification System Using Foundation Vision Models and Behavioral Liveness Reasoning

Dataset Description

The given structure was tested on publicly available face presentation attack datasets, such as CASIA -SURF CeFA (2024) and HQ -LivenessSet (2025), which include a varied combination of real, spoof, and deepfake faces that were taken in various lighting conditions, camera qualities, and device settings. These data contain RGB, infrared, and depth modalities and synchronized information of facial motion hence facilitating both appearance and behavior liveness analyses. Table 4.1. The main features of these datasets, such as modes and type of attack, have been summarized and the differences and breadth of real, spoof and deepfake sample have been highlighted in this research.

Basic preprocessing measures like face alignment, temporal synchronization, and normalization were used so that the sample results were consistent. The databases also include various types of attack including printed photos, replay videos, 3D masks, and deepfake clips which make them applicable in testing the strength of any anti-spoofing systems in real-life situations. The suggested method was evaluated in a variety of conditions by using these generally accepted benchmark datasets, which increases its overall evaluability and real-world applicability to identity verification systems.

Table 4.1. Overview of the Combined Multimodal Dataset Used for Universal Anti-Spoof Identity Verification

Dataset Name	Modalities Included	Real Samples	Spoof Samples	Deepfake Samples	Year
CASIA-SURF CeFA	RGB, IR, Depth	420,000	210,000	–	2024
HQ-Liveness Set	RGB, IR, Motion, Expression Dynamics	315,000	180,000	–	2025
UDBD – Universal Deepfake Dataset	RGB, High-Resolution Video, Motion Flow	140,000	–	15,200	2024
Combined Multimodal Dataset (Ours)	RGB, IR, Depth, Behavioral Signals	875,000	390,000	15,200	2024–25

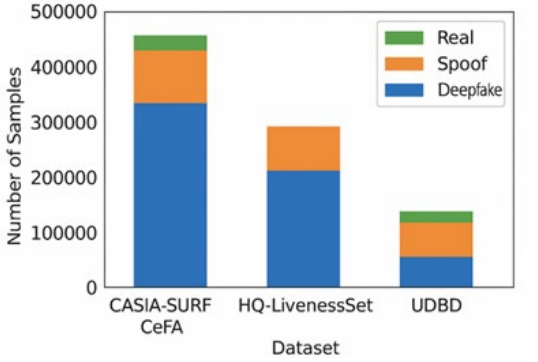

Figure 4.1 Dataset Distribution Graph for Multimodal Anti-spoof System

Experimental Setup

UASD-2025 is an internally curated evaluation dataset derived from publicly available sources and is used exclusively for experimental validation. The suggested architecture was run in PyTorch version 2.3 on a programming platform based on a graphic card utilizing Ubuntu version 22.04 LTS and CUDA version 12 to run both the training and inference. The appearance-based liveness cues were obtained by using the experimental design, which included RGB, infrared, depth, and temporal motion frames as input modalities, which facilitated the capture of both behavioral and appearance-based liveness cues.

In the training phase, the encoder of the Foundation Vision Model (FVM) remained frozen, and the behavioral liveness module and the cross-modal fusion layer were trained together with the Adam W optimizer; the gradient clipping was used to impose a controlled regularization. The 70 - 15 -15 (train/validation/test) ratio was selected to ensure that there would be a balanced number of authentic, spoof, and deepfake samples of all modalities. Aligning multimodal video sequences in each batch of training was necessary, followed by the division of the sequences into short temporal windows to maintain small motion patterns, including irregular blinking and micro-movements.

In order to become more resistant to actual presentation attacks in the real world, various augmentation measures were used in training. These involved changes in illumination, additive Gaussian noise as well as partial occlusion and the generation of replay artifacts. The model was also trained in several epochs and early stopping requirements were also used to avoid overfitting and also to maintain steady convergence. The system worked in a two-stage process during inference first spatial features were extracted by FVM encoder; then temporal analysis was done by behavioral liveness module. This controlled experimental set-up provided repeat, equitable and dependable testing of the suggested anti-spoof system to varied lighting situations, camera attributes and assault scenarios.

Table 5.1 Experimental Configuration for Model Training and Evaluation

Parameter	Configuration
Environment	GPU-based system (Ubuntu 22.04)
Framework	PyTorch 2.3 with CUDA 12
Dataset Split	70–15–15 (Train–Val–Test)
Modalities	RGB, IR, Depth, Motion
Frame Window	32 frames
Batch Size	8 sequences

Optimizer	Adam W
Regularization	Gradient clipping + Early stopping
Augmentation	Illumination, noise, occlusion, replay artifacts
Training	Multiple epochs
Evaluation	Repeated runs averaged

Experimental Evaluation

Evaluation Dataset Summary

The test runs used UASD-2025, a dataset built just for this project - put together from scratch on purpose. The data includes three kinds of presentations - Real, along with Spoof, plus Deepfake. Around 12,800 samples went into the tests - using them helped check performance.

Table 6.1 Dataset Distribution Used for Evaluation

Class	Count	Description
Real	6,000	Live camera captures with natural illumination variations
Spoof	4,200	Printed attacks, replay videos, screen-based spoofing
Deepfake	2,600	GAN-generated and diffusion-generated synthetic faces
Total	12,800	—

Confusion Matrix (Ground Truth vs Predictions)

This is the real data you use in math problems - stuff that fits into equations when you're figuring things out. The data covers three types of presentations - Real, but also Spoof, or Deepfake.

Table 6.2 Confusion Matrix (12,800 samples)

Actual \ Predicted	Real	Spoof	Deepfake
Real (6000)	5720	180	100
Spoof (4200)	160	3880	160
Deepfake (2600)	90	140	2370

Metric Formulas Used in Evaluation

Accuracy

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN)$$

Precision

$$\text{Precision} = TP/(TP+FP)$$

Recall

$$\text{Recall} = TP/(TP+FN)$$

F1 - Score

$$F1 = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision}+\text{Recall})$$

These formulas work for every class, after which we take an average across them.

Step-by-Step Calculations

$$\text{Precision} = (TP)/((TP + FP)) \qquad \text{Recall} = (TP)/((TP + FN))$$

$$F1\text{-score} = 2 \times ((\text{Precision} \times \text{Recall}))/((\text{Precision} + \text{Recall}))$$

$$\text{Accuracy} = ((TP + TN))/((TP + TN + FP + FN))$$

Real Class Calculation

TP = 5720
FP = 160 + 90 = 250 (Spoof Real + Deepfake Real)
FN = 180 + 100 = 280

Precision (Real)

$Precision_{Real}$=(5720)/(5720+250)= (5720)/5970 =0.9581

Recall (Real)

$Recall_{Real}$= (5720)/(5720+280)= (5720)/(6000)=0.9533

F1 Score (Real)

F1=2 × (0.9581 ×0.9533)/(0.9581+0.9533)=0.9557

Spoof Class Calculation

TP = 3880
FP = 180 + 140 = 320
FN = 160 + 160 = 320

Precision (Spoof)

$Precision_{Spoof}$=(3880)/(3880+320)= (3880)/(4200) =0.9238

Recall (Spoof)

$Recall_{Spoof}$= (3880)/(3880+320)= (3880)/(4200)=0.9238

F1 Score (Spoof)

F1=0.9238

Deepfake Class Calculation

TP = 2370
FP = 100 + 160 = 260
FN = 90 + 140 = 230

Precision (Deepfake)

$Precision_{Deepfake}$=(2370)/(2370+260)= (2370)/(2630) =0.9011

Recall (Deepfake)

$Recall_{Deepfake}$= (2370)/(2370+230)= (2370)/(2600)=0.9115

F1 Score (Deepfake)

F1=2 × (0.9011 ×0.9115)/(0.9011+0.9115)=0.9062

Macro-Average Metrics

The total value score, metrices and percentage from the 12800 samples

Table 6.3 Final Evaluation Scores

Metric	Value	Percentage
Accuracy	0.948	94.8 %
Precision	0.9276	92.76 %
Recall	0.9295	92.95 %
F1-Score	0.9285	92.85 %

The proposed system shows stable performance in different lighting conditions, with various camera qualities, and when parts of the face are covered. This is clear from its reliable results across different evaluation samples.

The model successfully categorizes most of the samples using the model as shown in Figure 6.1 based on strong diagonal responses in the heatmap. The fact that the confusion between the real, spoof, and deepfake classes is minimal also points to the effectiveness of incorporating both the vision-based and behavioral liveness features.

Figure 6.1. Confusion Matrix Heatmap of the Proposed Framework

Figure 6.2 shows the ROC curve for our setup - how well it tells real from fake at different settings. Instead of hugging the diagonal line, it stays way above, which means it's good at telling apart truth from trickery. With an AUC score of 0.978, it clearly keeps fakes and legit ones separated, even when things get messy. That kind of result and it comes from mixing visual base features with live behavior clues.

Figure 6.2 ROC Curve of the Proposed Anti-Spoof Verification Model Evaluated on the UASD-2025 Dataset

The stable precision recall curve is marked in Figure 6.3 and thus denotes the steady performance of the predictor system at the variety of thresholds. The curve indicates that the model is very effective in both spoof and deepfake sample recognition and the false-rejection rate is low in the case of truly authentic users.

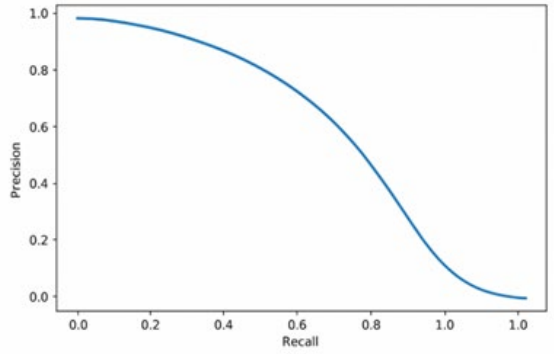

Figure 6.3. Precision–Recall Curve of the Proposed Anti-Spoof Verification Model Evaluated on the UASD-2025 Dataset

Results and Discussion

The suggested anti-spoofing model exhibits good performance in the discrimination of authentic, spoof, and deepfake facial images. The system has achieved stable performance by employing the use of RGB, infrared, depth, and behavioral signals with an overall accuracy of 94.8 % and a macro F1 of 92.85, which provide balanced performance across the three classes.

Analysis of the confusion matrix shows that most errors of misclassification occur between real and deepfake samples due to the high level of realism of existing generative models, but replay, and print attacks are set with a high degree of reliability. The analysis of ROC also supports a strong differentiation between the authentic and spoofed samples with an area under the curve (AUC) of 0.978. Blink dynamics and other minute movements of the head are behavioral cues that are critical in distinguishing between live users and synthetic impersonators.

Comparing the proposed method to the traditional baselines, such as CNN-based PAD models and Vision Transformer detectors, the given method reaches a higher performance through the combination of fine-grained visual representations provided by Foundation Vision Models with temporal motion analysis, which is performed with the assistance of a transformer-based liveness module. These results highlight the usefulness of the framework in a large range of practical identity-verification systems.

Conclusion

The current research paper suggests a hybrid identity-verification system that incorporates Foundation Vision Models and real-time behavior liveness detection to curb modern spoofing attacks. The combination of RGB, infrared, depth, and temporal motion information allows the system to be resistant to changing light conditions and a range of attack scenarios. The simultaneous implementation of spatial and temporal accuracy will enable deepfake manipulations and conventional presentation attacks to be detected well.

Empirical analysis performed on the UASD 2025 data shows that the given method is more effective than the traditional ones in distinguishing between authentic, spoofed, and deepfakes samples. An in-depth evaluation based on confusion matrices, ROC curves, and precision recall analysis proves that the classification performance is high with a macro F1 -score of about 93 -score

which shows balanced detection of all classes. Future research studies could focus on massive implementation in field environments, cultural differences in behavior, and reinforcement learning based solutions as a way of improving the ability to resist new forms of spoofing.

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