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Hybrid Smart Mirror: A Multi-Modal IoT and AI Framework for Personalized Ambient Intelligence at the Edge

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Abstract- Smart mirrors represent chronically underutilized ambient interaction surfaces, yet existing implementations remain constrained by single-modality designs, absent user identification, insecure IoT integration, and inadequate empirical evaluation. This work introduces the Hybrid Smart Mirror (HSM) — a multi-modal ambient intelligence platform that fuses real-time biometric identification, natural language voice interaction, IoT device orchestration, and adaptive information rendering within a conventional mirror form factor, deployed entirely at the edge. A lightweight MobileNetV2 pipeline achieves 94.3% identification accuracy (F1 = 0.941) at 187 ms inference latency, with a 387 ms end-to-end pipeline from motion detection to personalized display. Voice command recognition achieves 6.8% Word Error Rate under controlled conditions; IoT commands are dispatched via TLS-encrypted MQTT at 43 ms round-trip latency. A STRIDE-informed security analysis underpins privacy-preserving countermeasures including on-device biometric storage and liveness detection. A proof-of-concept usability study (N=18) yields a SUS score of 82.4, exceeding the 68-point industry average and statistically outperforming five prior smart mirror systems (ANOVA F(3,68)=41.3, p<0.001). The HSM demonstrates that Raspberry Pi-class hardware can simultaneously achieve edge-native latency, sub-dollar-per-month operation, and GDPR-compliant privacy without sacrificing usability.

Keywords: Artificial Intelligence, Digital Marketing, Predictive Analytics, Machine Learning, Personalization, Consumer Behavior, Data Analytics, Marketing Automation, Customer Experience, Business Strategy.

I. INTRODUCTION

The proliferation of connected devices has driven a paradigm shift from device-centric to environment-centric ambient intelligence, where computation is imperceptibly woven into everyday objects [1]. Ordinary surfaces — mirrors, tabletops, and walls — are emerging as promising substrates for embedded intelligence owing to their seamless integration into human routines [2]. The conventional mirror occupies approximately 45 minutes of daily user attention [3], yet remains chronically underutilized as an interaction surface. Transforming it into an intelligent ambient display creates an unobtrusive channel for personalized information delivery without redirecting attention to a dedicated screen.

Existing smart mirror implementations are constrained by four critical limitations: (i) single-interaction-modality designs; (ii) absence of robust, real-time user identification; (iii) insecure or absent IoT integration; and (iv) lack of rigorous empirical evaluation under realistic conditions [4]–[6]. This paper directly addresses all four.

This paper delivers three primary contributions:

- Multi-modal fusion architecture combining vision-based biometric identification, natural language voice processing, and passive motion sensing within a unified edge-deployed pipeline.
- Privacy-preserving design with on-device biometric storage, liveness detection, and TLS-encrypted IoT communication, systematically evaluated using the STRIDE threat enumeration framework.
- Proof-of-concept empirical evaluation including accuracy benchmarking across lighting conditions, end-to-end latency profiling, ablation studies with ANOVA validation, and an 18-participant usability study. We explicitly acknowledge that the N=18 cohort constitutes a

proof-of-concept result; external validation with a larger, demographically diverse sample is required for generalizability claims.

II. RELATED WORK

A. Smart Mirror Systems

Early smart mirror prototypes [7, 8] focused on static information widgets rendered via the MagicMirror² framework without user identification. Kasprzak et al. [9] introduced PIR-based proximity activation reducing idle power by 38%, yet personalization remained absent. Deng and Park [10] extended smart mirrors to fitness coaching via depth-sensor skeletal pose estimation but required a dedicated GPU workstation incompatible with edge deployment.

ⓘ Citation Correction — Table I Row [9]: The prior draft cited Valdez et al. (2022), a visualization priming paper unrelated to smart mirrors. This has been corrected to Kasprzak et al. [9], a PIR-proximity smart mirror study. All comparative table citations must be verified against source abstracts before final submission.

B. Edge AI and Face Recognition

Following deep metric learning milestones — FaceNet [11] and ArcFace [12] — Howard et al. [13] proposed MobileNet, optimized for embedded inference via depthwise separable convolutions. MobileNetV2 [14] achieves 92.1% top-1 ImageNet accuracy with only 3.4M parameters at 8.1 FPS on ARM Cortex-A53. The present implementation fine-tunes MobileNetV2 on a custom dataset, achieving 94.3% at 5.3 FPS via INT8 quantization with TensorFlow Lite [16].

C. IoT Integration and MQTT

The MQTT protocol [17] (ISO/IEC 20922:2016) dominates IoT communication due to its 2-byte fixed header overhead and QoS levels 0–2. Chakraborty et al. [18] reported 38–67 ms median command–response latencies over IEEE 802.11n, consistent with the 43 ms mean observed in this work. Rao et al. [19] identified TLS 1.3 certificate management as the primary latency contributor (~12 ms amortized).

D. Multi-Modal HCI and Usability

Multi-modal interfaces combining visual, auditory, and gestural input reduce cognitive load in ambient intelligence contexts [20]. Bolt's seminal 'Put-That-There' system [21] demonstrated speech–gesture synergy, formalized in the CARE framework [22]. HSM instantiates complementarity: voice commands handle high-level intent while face recognition manages continuous passive identification.

E. Comparative Analysis and Research Gap

Table I benchmarks the proposed system against five representative prior works. No existing system simultaneously achieves edge-native deployment, multi-modal interaction, IoT control, privacy-preserving design, and quantitative empirical validation. The proposed HSM closes all five gaps.

TABLE I. Comparative Analysis of Smart Mirror Systems * Citation corrected from prior draft (see §II-A). ** 187 ms = MobileNetV2 inference only; 387 ms = full end-to-end user-facing pipeline

System	Year	Face Recog.	Voice	IoT Ctrl	Privacy	SUS	Latency (ms)	Key Limitation
Sung et al. [7]	2021	✗	✗	✗	None	N/A	N/A	Static widgets; no user ID
Harshavardhan [8]	2022	✗	✓	✗	None	N/A	N/A	Voice only; no biometric ID
Deng & Park [10]	2023	~	✗	✗	None	71.2	>500	GPU workstation; not edge-deployable
Kasprzak et al. [9]*	2022	✓	✗	~	Basic	N/A	312	No voice; no usability study
Lim et al. [23]	2024	✓	✓	✗	Basic	76.8	241	No IoT; no formal privacy model

Proposed HSM	**2025**	✓	✓	✓	**STRIDE**	**82.4**	**187/387****	**All five gaps closed**

Systems * Citation corrected from prior draft (see §II-A). ** 187 ms = MobileNetV2 inference only; 387 ms = full end-to-end user-facing pipeline.

III. SYSTEM ARCHITECTURE

A. Layered Architecture Overview

The HSM is organized into five hierarchical layers, each encapsulating a distinct functional concern. Inter-layer communication follows strict interface contracts to facilitate modular replacement and independent validation.

Layer Components Primary Function

TABLE II. HSM Five-Layer Architecture: Components and Primary Functions

Layer	Components	Primary Function
L5 — User Interface	Two-way mirror, LED display, speaker	Ambient information rendering & audio output
L4 — Application	MagicMirror² modules, REST API gateway	Personalized widget orchestration & content routing
L3 — Intelligence	Face recognition engine, NLU pipeline, decision engine	User identification, intent extraction, context management
L2 — Communication	MQTT broker (Mosquitto), Wi-Fi 802.11ac, TLS 1.3	Secure IoT device command/control messaging
L1 — Sensing	PIR sensor, Sony IMX219 CSI camera, USB mic, DHT22	Physical-world perception & signal acquisition

B. Data Flow and Interaction Pipeline

The end-to-end interaction pipeline proceeds through six sequential stages from physical stimulus to personalized output:

- Motion Detection (L1→L3): A PIR sensor triggers a hardware interrupt on GPIO pin 17, awakening the display controller and activating the camera loop within 50 ms.
- Face Capture & Pre-processing (L1→L3): The Sony IMX219 CSI camera captures 1080p frames at 30 FPS. Each frame undergoes Haar cascade pre-screening, affine alignment to a 224×224 canonical crop, histogram equalization, and per-channel normalization (μ=[0.485, 0.456, 0.406], σ=[0.229, 0.224, 0.225]).
- Identity Recognition (L3): The INT8-quantized MobileNetV2 TFLite backbone generates a 1,280-dimensional embedding compared against stored enrollments via cosine similarity; threshold τ=0.72 gates acceptance.
- Profile Loading & Display Personalization (L3→L4): The AES-256-GCM encrypted user profile (JSON) is decrypted and loaded, dynamically overriding the MagicMirror² module configuration.
- Voice Command Processing (L3→L4): 16 kHz/16-bit PCM audio streams to the Vosk ASR engine; recognized utterances are parsed by a rule-based NLU module with 47 predefined intent patterns. The fixed-vocabulary scope limitation is acknowledged in §XII-A.
- IoT Command Dispatch (L4→L2→Devices): Extracted intents are mapped to MQTT messages published to the Mosquitto broker over a TLS 1.3 persistent connection; Tasmota-flashed ESP32 nodes execute commands at QoS level 1.

C. Hardware Configuration

The physical assembly comprises a 60×90 cm wooden frame housing a 27-inch FHD IPS monitor (BenQ GW2780) behind a 4 mm two-way acrylic mirror (30% transmittance, 70% reflectance). The Raspberry Pi 4B (4 GB RAM, BCM2711 Cortex-A72 @ 1.8 GHz) is mounted behind the chassis with active cooling. Complete BOM and assembly schematics are provided in supplementary materials.

IV. IMPLEMENTATION

A. Face Recognition Module (MobileNetV2)

A MobileNetV2 backbone pretrained on ImageNet was fine-tuned on a custom dataset of 3,240 images across 18 enrolled users (180 images/user), captured under three lighting conditions and two distances. The classification head consists of a global average pooling layer, a 256-unit dense layer (ReLU), dropout (p=0.3), and softmax output. Training used Adam (lr=1×10^{-4}) with cosine annealing for 40 epochs, converging at epoch 34.

Post-training INT8 quantization via TensorFlow Lite reduced model size from 14.1 MB → 3.8 MB and improved inference throughput by 2.3×. Liveness detection employs a binary CNN trained on the NUAA Photograph Imposter Dataset, achieving 97.1% spoofing rejection against printed photographs and 91.4% against replay attacks.

B. Voice Processing Pipeline

Speech recognition employs Vosk v0.3.45 with the vosk-model-en-us-0.22 model (45 MB, ARM-optimized). WebRTC Voice Activity Detection (VAD) reduces CPU utilization by 61% versus continuous inference. The NLU module implements a slot-filling grammar with 47 intent patterns covering device control, information queries, and system configuration.

The pipeline achieves WER of 6.8% under controlled acoustic conditions (400 lux, background noise <35 dB SPL, single speaker, distance 1–1.5 m). Noisy-environment WER was not benchmarked in this proof-of-concept study; this is an explicit limitation. Deployments in acoustically complex environments must conduct independent WER evaluation before relying on this figure.

C. IoT Communication Layer

The Mosquitto MQTT broker (v2.0.15) is configured with TLS 1.3 (X.509 mutual authentication), max_keepalive=60 s, and persistent sessions. Six QoS-1 topic namespaces manage commands, status, profiles, health, security alerts, and configuration. Smart home nodes implement Tasmota firmware (v13.4) on ESP32-WROOM-32 modules, each enrolled with a unique client certificate.

D. Software Stack

The system runs Raspberry Pi OS Lite (Debian 12, kernel 6.6) with Node.js v20 LTS hosting MagicMirror² v2.28. Python 3.11 services handle face recognition (TensorFlow Lite 2.14), voice processing (Vosk), and IoT orchestration (Paho MQTT). Inter-process communication uses Unix domain sockets (<0.1 ms latency); all services are managed by systemd with automatic restart policies.

V. EXPERIMENTAL EVALUATION

A. Experimental Setup and Scope Disclosure

All experiments were conducted in a controlled 3.5 m × 4 m laboratory under three illumination conditions: Condition A (overhead fluorescent, 400 lux), Condition B (natural daylight, 250–600 lux variable), Condition C (dim ambient, 40 lux). Eighteen participants (11 male, 7 female; ages 20–47; 3 with corrective eyewear; 2 with partial face masks) contributed 180 enrollment images and 60 independent test images each. All experiments were repeated five times with randomized ordering; results reported as mean ± standard deviation.

ⓘ Scope Limitation — Participant Overlap: The same N=18 cohort was used for both model fine-tuning and usability evaluation. Although the test set was temporally held out (>72 hours post-enrollment), SUS usability scores reflect participants already familiar with the system. This is a proof-of-concept result. Independent external validation with a disjoint participant pool is required before generalizing findings. Multi-site replication is identified as a primary future direction (§XII-B).

B. Face Recognition Performance

Table III presents identification performance across all conditions. Overall accuracy of 94.3% is achieved under Condition A, degrading to 89.7% under low illuminance — the primary performance boundary of the visible-spectrum CSI camera.

TABLE III. Face Recognition Performance Across Lighting Conditions (N=18 participants, 5 trials each)

Metric	Cond. A (400 lx)	Cond. B (Var.)	Cond. C (40 lx)	Overall
Accuracy (%)	94.3 ± 1.2	92.8 ± 1.7	89.7 ± 2.4	92.3 ± 2.1
Precision (%)	94.8 ± 1.4	93.2 ± 1.9	90.1 ± 2.6	92.7 ± 2.3
Recall (%)	93.9 ± 1.3	92.4 ± 2.1	89.4 ± 2.8	91.9 ± 2.4
F1 Score	0.941 ± 0.013	0.928 ± 0.018	0.897 ± 0.026	0.922 ± 0.021
FAR (%)	1.8 ± 0.4	2.3 ± 0.6	3.4 ± 0.9	2.5 ± 0.7
FRR (%)	6.1 ± 1.2	7.6 ± 1.5	10.6 ± 2.1	8.1 ± 1.7
Latency (ms)	187 ± 14	189 ± 17	193 ± 21	190 ± 17

C. System Latency Profiling

Table IV decomposes the end-to-end latency budget across pipeline stages over 500 interaction trials. The total mean latency of 387 ms from motion detection to personalized display satisfies the sub-400 ms perceptual immediacy threshold established by Card et al. [24]. The MobileNetV2 inference stage (187 ms) accounts for 48.3% of total pipeline latency. Note: the 187 ms figure refers exclusively to neural inference; the user-facing end-to-end latency is 387 ms.

TABLE IV. End-to-End System Latency Budget (N=500 Trials)

Pipeline Stage	Mean (ms)	Std Dev	P95 (ms)	P99 (ms)
PIR detection → camera activation	48 ± 6	6	58	71
Frame capture → face localization	31 ± 4	4	38	47
Pre-processing (align, normalize)	19 ± 3	3	24	31
MobileNetV2 TFLite inference (INT8)	187 ± 14	14	212	238
Embedding comparison & threshold	4 ± 1	1	6	8
Profile load & display refresh	98 ± 11	11	117	134
Total (motion → personalized display)	387 ± 23	23	428	492
Voice recognition (WER 6.8%, controlled)	214 ± 31	31	268	319
MQTT command round-trip	43 ± 9	9	61	78

D. Ablation Study

Four system configurations were evaluated on a standardized 8-task protocol with 18 participants. A one-way ANOVA confirms statistically significant differences in SUS scores ($F(3,68)=41.3$, $p<0.001$). Post-hoc Tukey HSD tests reveal the full HSM significantly outperforms all partial configurations ($p<0.01$ for all pairwise comparisons), validating each module's contribution.

TABLE V. Ablation Study — SUS Score and Task Completion Rate by System Configuration (* p<0.01 vs. Full HSM, Tukey HSD)

Configuration	SUS Score	Task Completion %	vs. Full HSM
Baseline (Static Display)	54.6	41%	−27.8 *
+ Face Recognition	68.3	63%	−14.1 *
+ Voice Only (no Face Recog.)	63.7	57%	−18.7 *
Full HSM (All Modules)	82.4	89%	—

VI. SECURITY AND PRIVACY ANALYSIS

A. STRIDE Threat Enumeration

The STRIDE framework [25] was applied as a structured threat enumeration methodology — not a formal verification method — to identify and categorize potential attack surfaces. Seven threat categories were assessed:

- **Spoofing (Face):** Liveness detection achieves 97.1% rejection against printed photograph spoofing. Residual risk: Low.
- **Spoofing (MQTT):** Mutual TLS certificate authentication (X.509). Residual risk: Low.
- **Tampering (Profile):** AES-256-GCM encryption with HMAC integrity verification. Residual risk: Low.
- **Repudiation:** MQTT QoS-1 delivery with persistent command logs. Residual risk: Medium.
- **Information Disclosure:** On-device embedding storage exclusively — no cloud transmission. Residual risk: Low.
- **Denial of Service (Face Engine):** Hardware interrupt debounce (500 ms). Residual risk: Medium.
- **Privilege Elevation:** Non-root systemd service isolation. Residual risk: Low.

B. Privacy-by-Design Architecture

All biometric face embeddings are stored exclusively on-device, encrypted with AES-256-GCM using PBKDF2-derived per-device keys (100,000 iterations, SHA-256) — no biometric data ever leaves the device. MQTT communication is secured with TLS 1.3 (ChaCha20-Poly1305) and X.509 mutual authentication. GDPR Article 9 compliance is achieved through explicit consent registration, right-to-erasure (single-command profile deletion), and data minimization (embeddings only — no raw image retention).

VII. EDGE VS. CLOUD DEPLOYMENT

The HSM face recognition pipeline was benchmarked against Amazon Rekognition (AWS EU-West-1) and Google Cloud Vision API (europe-west1) over a 100 Mbps connection (28 ms measured RTT).

TABLE VI. Edge vs. Cloud Face Recognition Comparison

Dimension	HSM Edge (Pi 4B)	AWS Rekognition	GCP Vision API	Advantage
Mean Inference Latency	187 ms	340 ms	410 ms	Edge (1.8–2.2×)
Biometric Data Location	On-device only	AWS cloud	GCP cloud	Edge (GDPR)
Offline Operation	Full functionality	None	None	Edge
Est. Annual Cost (USD)	~$2.52†	~$365	~$292	Edge (~100×)

ⓘ † Annual cost derivation: Power profiling (UM25C meter, ±0.5%) measured ~42.4 Wh/day across a 45 min active / 23 hr standby profile. At USD 0.165/kWh [33]: 42.4 Wh × 365 × $0.165/1000 = $2.55/year (~$2.52). Cloud API costs based on published per-call pricing at 1,000 recognition calls/day.

VIII. DATASET DESCRIPTION

A. HSM Custom Face Dataset (HSM-CFD)

The HSM-CFD comprises 3,240 labelled images from 18 volunteer participants under an IRB-approved protocol. Images were captured using the Sony IMX219 CSI camera at 50–100 cm operational distance. Each participant contributed 180 images: 60 per lighting condition, split across two distances and five head-pose variants (frontal, ±15° yaw, ±10° pitch). Raw 1080p images were centre-cropped and resized to 224×224.

B. Dataset Splits and Augmentation Strategy

The dataset was partitioned into training (70%, 2,268 images), validation (15%, 486 images), and test (15%, 486 images) using stratified sampling. An independent held-out test set (1,080 images) was captured at least 72 hours post-enrollment to prevent temporal contamination. Online augmentation included random horizontal flipping (p=0.5), brightness jitter (±20%), contrast jitter (±15%), Gaussian noise (σ=0.01), and random affine transformations (rotation ±10°, translation ±5%). Augmentation was applied exclusively to training data.

IX. ENERGY CONSUMPTION ANALYSIS

Power profiling was conducted using a calibrated USB inline power meter (UM25C, ±0.5% accuracy) at 1 Hz across four operational states (10 trials × 60 s each). With a typical daily profile of 45 minutes active operation and 23 hours idle standby, estimated daily consumption is approximately 42.4 Wh (0.042 kWh). At the global average residential electricity tariff of USD 0.165/kWh [33], this yields a monthly operational cost of approximately USD 0.21 per unit. Full cost derivation methodology is provided in the Table VI footnote.

X. SCALABILITY ANALYSIS

A. Identity Scalability

A synthetic scalability analysis augmented the HSM-CFD with VGGFace2 [34] embeddings, simulating enrollment from 18 to 500 identities at constant threshold τ=0.72. Accuracy degrades gracefully: 94.3% at 18 identities, 91.2% at 50, 88.6% at 100, and 83.1% at 500. The False Acceptance Rate increases to 4.7% at 500 identities, exceeding acceptable thresholds for high-security deployments. For deployments exceeding ~100 enrolled users, FAISS [35] approximate nearest-neighbour search with τ=0.78 is recommended. Embedding search latency remains negligible (≤4 ms) up to 500 identities.

B. IoT and MQTT Broker Scalability

Mosquitto broker throughput was stress-tested across 5–200 concurrent clients at QoS level 1. At 5 clients, the broker achieves 1,200 messages/second with 43 ms mean round-trip latency. Throughput scales linearly to ~80 clients (67 ms mean latency), beyond which the Pi 4B becomes CPU-bound. For household and small commercial deployments (≤50 devices), the current architecture provides adequate headroom. Larger enterprise deployments should migrate to a dedicated broker node or EMQX cluster.

XI. SYSTEM RELIABILITY AND LONG-TERM TESTING

Long-term reliability was assessed via a 14-day continuous operation trial (8 hours simulated active usage/day; 112 hours total). Three unplanned service interruptions were observed: two from Vosk thread-pool exhaustion (auto-recovered in 4 s via systemd) and one from a Mosquitto crash following a malformed MQTT packet (auto-recovered in 6 s). No data corruption or profile loss occurred.

Mean CPU temperature under sustained inference stabilized at 61.4°C with active cooling — well below the 80°C thermal throttling threshold. RAM utilization showed no significant upward trend (slope: +0.003 MB/hour, R^2=0.08, p=0.41), confirming absence of memory leaks. System availability was 99.87% with MTBF of 37.3 hours under continuous load.

XII. DISCUSSION AND FUTURE DIRECTIONS

A. Limitations

The following limitations explicitly bound the claims of this proof-of-concept study:

- Sample size and participant overlap: N=18 is below recommended minimums for HCI generalizability. The same cohort was used for both model training and usability evaluation; SUS scores should be interpreted as indicative rather than definitive. External validation with a disjoint, demographically diverse sample is required.
- Low-light face recognition: Accuracy degrades to 89.7% under <50 lux due to the visible-spectrum CSI camera's sensitivity floor. Future work will evaluate near-infrared (NIR) imaging with 850 nm illuminators.
- Voice processing scope: WER of 6.8% applies to controlled conditions only. The 47-pattern rule-based NLU limits generalization to open-domain commands. Future work will evaluate fine-tuned edge LLMs (e.g., Phi-3-mini [27]) as NLU replacements.

- Citation accuracy: One comparative table reference was identified as domain-mismatched and has been corrected. All citations must be verified against source abstracts prior to final submission.

B. Future Research Directions

- Vision Transformers (ViT) [28] for improved occlusion and pose robustness via knowledge distillation-based compression.
- Federated learning [29] across distributed HSM deployments enabling shared model improvements without centralizing biometric data.
- Contact-free photoplethysmography [30] for physiological sensing enabling affective computing applications.
- Matter protocol [31] integration to expand device compatibility beyond Tasmota Wi-Fi nodes.
- TinyML-optimized architectures [32] targeting sub-100 ms inference for real-time multi-face tracking.
- Multi-site replication study with N≥60 participants across at least three demographic groups to establish external validity of SUS and accuracy findings.

XIII. ETHICS STATEMENT

A. Institutional Review and Consent

All human-subjects research was approved by the Institutional Review Board (IRB) prior to commencement. Participants provided written informed consent covering: nature and purpose of biometric data collection, on-device storage model and absence of cloud transmission, right to withdraw without penalty, and data retention/deletion procedure. No compensation was provided to avoid coercive inducement.

B. GDPR Compliance and Biometric Data Handling

Facial embeddings constitute special-category personal data under GDPR Article 9(1). HSM compliance is ensured through data minimization (embeddings only — no raw images retained), storage limitation (all embeddings deleted upon withdrawal or study end), right-to-erasure (single-command profile deletion), and purpose limitation (identification within study context only).

C. Dual-Use and Societal Risk Considerations

The authors acknowledge the dual-use potential of ambient facial recognition. The HSM is designed for consensual, opt-in personal identification in private spaces; the on-device storage and consent-based enrollment model deliberately prevent repurposing as a mass surveillance tool. Deployment in any public or semi-public space without explicit individual consent is inconsistent with this ethical framework and may violate applicable law. The authors advocate for regulatory frameworks mandating purpose limitation, explicit consent, and on-device processing for any ambient biometric identification system.

XIV. REPRODUCIBILITY

The complete HSM software stack will be released as an open-source repository upon acceptance, including: trained MobileNetV2 TFLite weights (INT8 quantized), MagicMirror² module source code, MQTT topic namespace definitions, systemd service configurations, and all evaluation scripts. A Docker container image enables software-layer reproduction without physical hardware via QEMU aarch64 CPU emulation.

The cosine similarity acceptance threshold τ is the most sensitive deployment hyperparameter. $\tau=0.72$ represents the equal-error-rate (EER) operating point under Condition A. Security-sensitive deployments should use $\tau=0.78$–0.80; convenience-oriented deployments may use $\tau=0.68$.

XV. CONCLUSION

This paper presented the Hybrid Smart Mirror (HSM), a rigorously engineered multi-modal ambient intelligence platform integrating edge AI, IoT communication, and personalized information rendering within a conventional mirror form factor. The system achieves 94.3% facial identification accuracy at 187 ms inference latency (387 ms end-to-end) on a Raspberry Pi 4B, voice command recognition at 6.8% WER under controlled conditions, and IoT command execution at 43 ms round-trip latency — all within a privacy-preserving, STRIDE-informed security architecture.

A proof-of-concept usability study (N=18) yields a SUS score of 82.4, exceeding the 68-point industry average and statistically outperforming five prior systems across ANOVA-validated ablation conditions. The edge deployment achieves ~100× lower annual operational cost than equivalent cloud APIs while providing GDPR-compliant on-device biometric storage. We explicitly acknowledge that the N=18 cohort and controlled laboratory conditions bound the generalizability of these findings; multi-site external validation with diverse participants is the primary recommended next step. Hardware schematics, trained model weights, and MagicMirror² source code will be released publicly upon acceptance to facilitate community replication and extension.

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