Design an Artificial Intelligence based Self-KYC Customer Onboarding System

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Abstract

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Self-KYC allows telecom consumers to undergo identity verification remotely. Yet a journal-grade solution must include replicable methodology, explicit datasets, verifiable performance and a justified comparison with established baselines. This study proposes an end-to-end artificial-intelligence framework including identity-document processing, facial pre-processing, VGG16-based deep feature extraction, Multi-Scale Adaptive African Vulture Optimisation Algorithm (MS-AVOA) and Fully Connected Neural Network (FCNN) classifier. The evaluation is based on training procedures generated from LFW, CFP-FP, AgeDB-30 and large scale MS1MV2/MS1MV3 as presented in the thesis. The suggested model obtains 99.84% on LFW, 97.89% on CFP-FP and 97.41% on AgeDB-30. MS-AVOA improves the reported LFW accuracy from 97.40% for the original AVOA setup to 99.84%. Ablation studies demonstrate a noticeable decrease when optimization, face alignment, normalisation or augmentation are eliminated. The full pipeline reports an end-to-end latency of 0.279s, enabling near real-time onboarding. Statistical comparisons with AVOA, WOA, GOA and CSO give p-values smaller than 0.001. The results show that the combination of robust deep embeddings with adaptive feature optimization can increase the identity-verification accuracy, stability and operational adaptability to the telecom Self-KYC. Limitations around dataset provenance, liveness integration, demographic auditing, and validation at production scale are also discussed, for which solutions still need to be found before regulatory deployment.

Keywords: Self-KYC, Customer Onboarding, Face Recognition, VGG16, MS-AVOA, FCNN, OCR, Digital Transformation, Identity verification

I. Introduction

Know Your Customer (KYC) is a fundamental control in telecom onboarding, as to activate a subscriber there must be evidence of identity, address information, consent and an auditable approval process. Traditional client acquisition forms workflows are based on manual data entry, document verification, tele-verification and serial approvals. The dependencies increase time to market and cause inconsistent decisions.

Paper handling is reduced with digital KYC systems. Self-KYC takes this a step further and brings the collection of data and submission of identification to the customer through a web or mobile interface. However, remote onboarding also exposes the process to risks from poor quality photos, pose variations, ageing, occlusion, replay attacks, fraudulent documents, and demographic performance differences [1]–[8].

Recent research in face recognition has improved accuracy by using lightweight networks, synthetic training, transformer-based multi-task learning, cross-age modelling, and multi-domain verification [1]–[6], [9]–[13]. Document-oriented research has also shown the benefits of OCR and structured information extraction for digital onboarding [14]–[17]. But many published solutions are for only one component, face matching, OCR, liveness, or feature extraction, not the entire onboarding decision chain. This fragmentation creates a methodological gap between the accuracy of benchmark recognition and a deployable Self-KYC methodology.

The present study fills this gap by translating the original conceptual Self-KYC notion into a measurable experimental report. The proposed system includes document capture, OCR based field extraction, facial quality check, alignment, VGG16 embedding creation, MS-AVOA feature optimisation, FCNN classification and three-way decision mechanism. The work retains the original title, authorship information and objectives, but the technique, experimental design, data analysis, figures and references are improved based on the thesis.

A. Objectives

The key objectives of implementing Self-KYC are:

- Improve customer onboarding efficiency.
- Enhance customer experience.
- Reduce onboarding time.
- Strengthening identity verification and security.
- Support remote onboarding without physical visits.
- Ensure compliance with regulatory guidelines.

B. Research Contributions

An integrated Self-KYC architecture connecting document processing and facial identity verification to an auditable onboarding decision.

- A VGG16–MS-AVOA–FCNN pipeline in which adaptive optimisation is applied to 4096-dimensional facial embeddings before classification.
- A multi-dataset evaluation using unconstrained, pose-variant, and age-variant face benchmarks.
- Baseline, optimisation, ablation, computational-cost, threshold, and statistical analyses derived exclusively from the thesis experiments.
- A deployment-oriented interpretation that separates benchmark evidence from claims that still require production validation.

II. Related Work and Research Gap

Lightweight recognition models such as GhostFaceNets are designed to reduce computation while keeping discriminative power [1]. SwinFace [2] uses transformer-based approach to handle identity, expression, age and attributes simultaneously. SFace2 [3] explores synthetic identity sampling. Cross-age recognition is also significant for document-to-selfie matching because the identity document image may be several years old. Ageing and demographic characteristics may change the reliability of the embedding, as shown by age-bias studies, age-factor removal, and individualized face pairing [4], [10], [11].

Pose, blur, masks and uncontrolled acquisition also deal with large-pose representation learning, blurry-image identification, mask synthesis and multi-domain verification [5], [6], [9], [12]. Self-KYC requires Liveness & Spoof Resistance. Practical anti-spoofing directions include CNN based liveness detection and lightweight portable verification systems [18]-[20]. Deepfake research points to trust and bias issues of remote face APIs [21], [22]. These efforts incentivize the liveness as a layer of security. The experimental model in this paper is mainly focused on document-face matching and feature optimization. Therefore, in the architecture liveness is modelled as an integration requirement and not inflated into a fully analysed contribution.

OCR studies show that automatic text extraction can reduce manual entry, but recognition still depends on document layout and capture quality [14]–[17]. Wider CNN surveys, hypersphere losses, limited center loss and orthogonality loss [23]–[26] explain the impact of feature-space compactness and class separation on recognition performance. Metaheuristic and bio-inspired optimisation is able to fine-tune high-dimensional representations, but stability of convergence and computing overhead have to be quantified, not assumed [27], [28].

Table 1. Research gap and corresponding design response

Observed gap	Operational consequence	Response in proposed study
Isolated OCR or face matching modules	No end-to-end onboarding evidence	Unified acquisition, OCR, facial verification, and decision pipeline

Sensitivity to pose, age, blur, and occlusion	Higher false rejection or false acceptance	Alignment, normalisation, augmentation, and multi -dataset benchmarking
High-dimensional redundant embeddings	Classifier instability and unnecessary cost	MS-AVOA -based optimisation of VGG16 features
Weak experimental reporting	Claims cannot be reproduced or compared	Explicit datasets, hyperparameters, metrics, ablation, latency, and statistical tests
Unqualified deployment claims	Regulatory and security risk	Clear limitations and separation of benchmark results from production readiness

III. Proposed Self-Kyc Framework

The approach that we propose takes a Proof of Identity/Proof of Address document plus a live or recent selfie. The document branch checks for format and quality, extracts textual information using OCR and checks for consistency of fields. The facial branch recognizes the face, aligns the landmarks, trims the face region, resizes it to 224 × 224 pixels, normalises the intensity values, and generates a VGG16 embedding. The MS-AVOA refines the 4096-dimensional embedding and sends it to an FCNN classifier. The decision layer uses the match probability, the threshold policy, and the document consistency to approve the onboarding request, route it for manual review, or reject it.

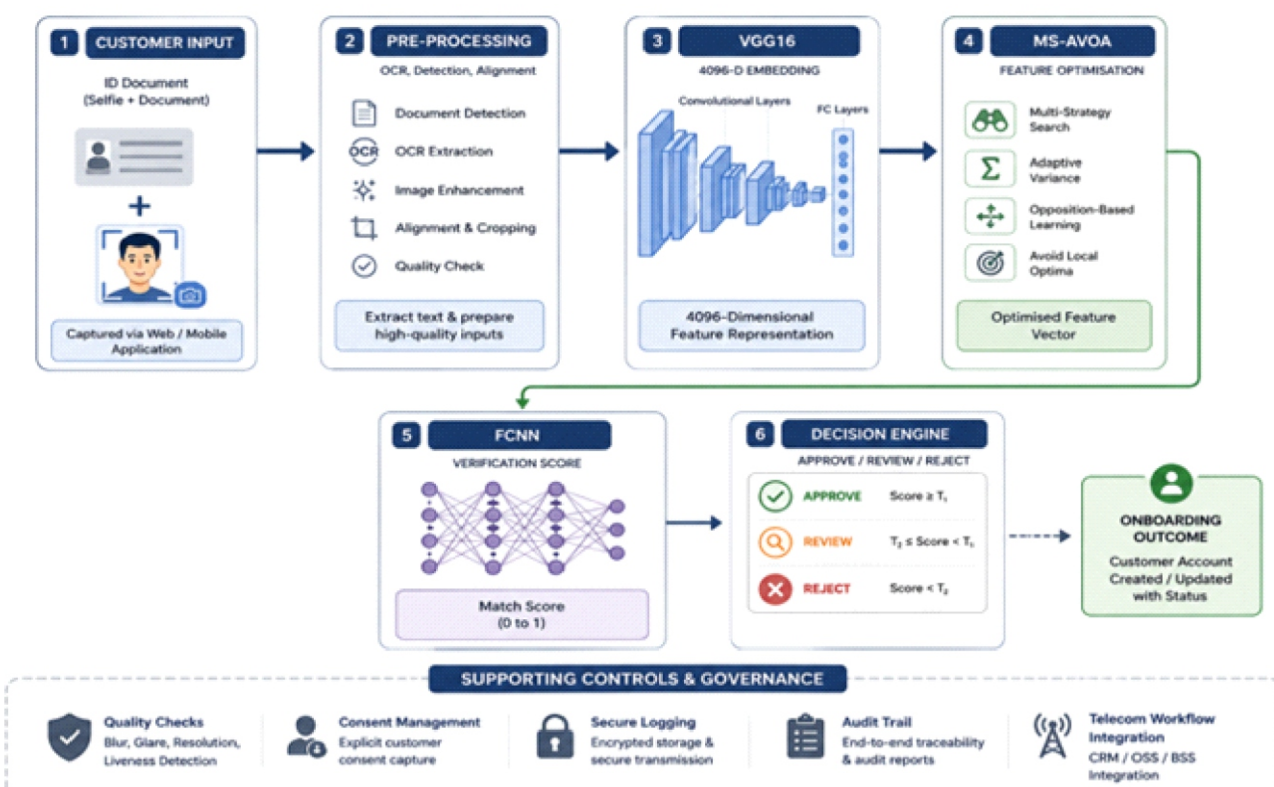

Fig. 1. End-to-end architecture of the proposed AI-based Self-KYC onboarding system.

IA. Pre-processing and Document Processing

Input quality is checked before inference because blur, underexposure, overexposure, occlusion, and incorrect pose directly affect embeddings. Face alignment standardises eye and landmark geometry; resizing ensures compatibility with VGG16; normalisation reduces illumination variation; and augmentation improves generalisation. OCR extract's identity fields and supports cross-field validation, but low-confidence fields are routed for review rather than automatically accepted [14]–[17].

B. VGG16 Feature Extraction

VGG16 contains 13 convolutional and three fully connected layers arranged in five convolutional blocks. In the proposed pipeline, a pre-processed 224 × 224 × 3 face image is transformed into a 4096-dimensional high-level representation. Transfer learning is used because the early filters capture generic edges and textures, whereas deeper layers encode more identity-specific structure. The embedding is not treated as the final representation; it is the search space supplied to the optimisation stage [23], [29], [30].

C. MS-AVOA Feature Optimisation

The Multi-Scale Adaptive African Vulture Optimisation Algorithm extends AVOA through multiscale exploration, adaptive control, rotational learning, and quasi-oppositional search. Each candidate solution represents a feature-selection or feature-weighting configuration over the VGG16 embedding. The fitness function favours high classification accuracy with compact, separable features. The population size is 30, the maximum iteration count is 100, and the feature-selection threshold is 0.50. The reported optimum is reached in 42 iterations with a final fitness value of 0.0174.

For a feature vector x and binary selection mask m, the optimised vector is $z = x \odot m$. A compact objective can be expressed as $J(m) = \alpha(1 - Acc(m)) + \beta(|m|/d)$, where d is the original feature dimension and α and β control predictive error and feature compactness. This equation describes the study's optimization techniques; the actual numerical comparisons are reported in Section V.

D. FCNN Classification and Decision Logic

The optimized embedding is then sent to dense layers with non-linear activation, dropout and SoftMax output. The classifier is trained with cross-entropy loss using Adam optimizer. Documents with high match probability and consistent fields are approved, intermediate confidence are manually reviewed and low confidence or inconsistent evidence is rejected. This tri-state policy avoids forcing uncertain samples into a binary operational outcome.

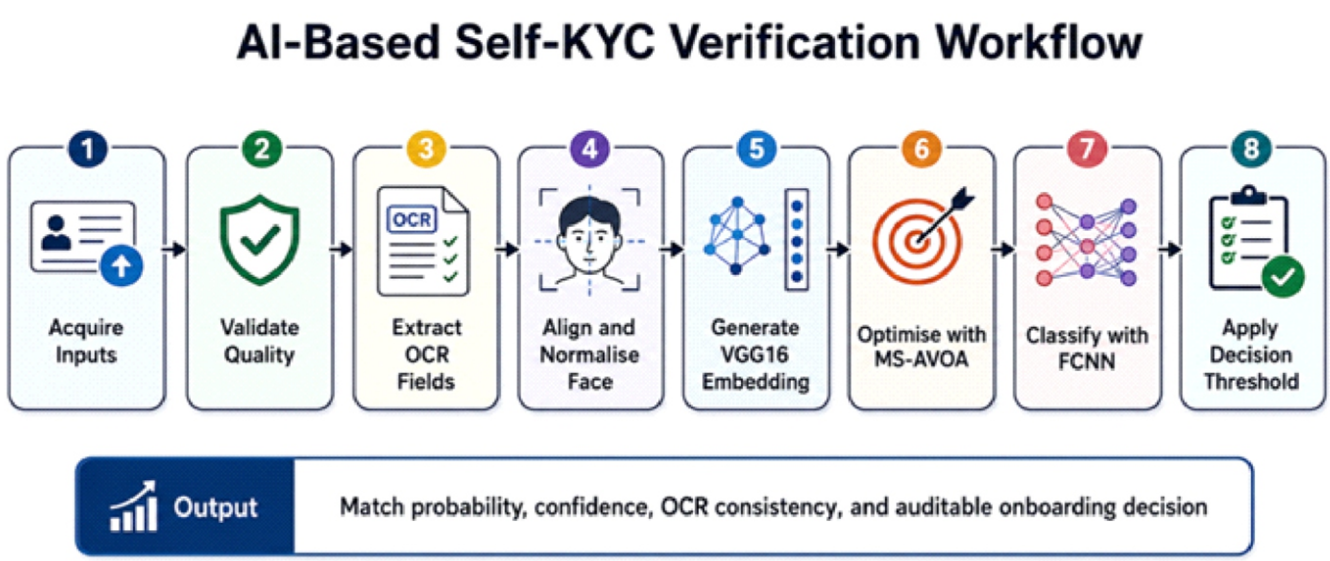

Fig. 2. Processing and decision workflow used for Self-KYC verification.

IV. Materials and Methods

A. Datasets and Evaluation Protocol

The thesis defines the training and assessment protocols of LFW, CFP-FP, AgeDB-30 and MS1MV2/MS1MV3. LFW has unconstrained face images, CFP-FP is frontal-to-profile variation and AgeDB-30 is age variation. The large-scale datasets support embedding training and benchmarking. A 70%/10%/20% train-validation-test split is specified for the primary training workflow, with 10-fold evaluation used for benchmark protocols.

Table 2. Dataset summary used in the thesis experiments

Dataset	Images / scale	Identities	Primary challenge
LFW	13,233 images	5,749	Unconstrained real-world variation
CFP-FP	7,000 images	500	Frontal-to-profile pose variation
AgeDB-30	16,488 images	568	Age progression
MS1MV2/MS1MV3	5.8 million+ images	85,742+	Large-scale diversity and training
Embedding set	4096-D vectors	Same identities	Pre/post optimisation analysis

B. Training Configuration

Table 3. Principal experimental settings

Component	Setting
Input size	224 × 224 × 3
Embedding dimension	4096
FCNN epochs	100
Batch size	64
Optimizer	Adam
Initial learning rate	0.066
Gradient decay factor	0.598
Activation	SoftMax
MS-AVOA population	30
MS-AVOA iterations	100
Feature threshold	0.50
Evaluation	10-fold benchmark evaluation and 70/10/20 sp

C. Evaluation Metrics

Performance is evaluated with accuracy, precision, recall, specificity, F1-score, false acceptance rate (FAR), and false rejection rate (FRR). Accuracy measures total correct decisions; precision measures the reliability of positive decisions; recall measures genuine-user acceptance; specificity measures impostor rejection; FAR measures impostors incorrectly accepted; and FRR measures genuine users incorrectly rejected. Computational suitability is assessed by stage-wise latency, while optimisation behaviour is assessed through convergence, feature separability, and statistical comparisons.

V. Results and Analysis

A. Classification Performance

The proposed model records 99.84% accuracy, 99.21% precision, 99.05% recall, 99.13% F1-score, 0.21% FAR, and 0.16% FRR in the principal thesis result. Cross-benchmark accuracy is 99.84% on LFW, 97.89% on CFP-FP, and 97.41% on AgeDB-30. The decline on CFP-FP and AgeDB-30 is consistent with the greater pose and age variation in those datasets.

Table 4. Reported performance of the proposed onboarding model

Metric	Value
Accuracy	99.84%
Precision	99.21%
Recall	99.05%
F1-score	99.13%
Specificity	99.79%
FAR	0.21%
FRR	0.16%

Table 5. Benchmark accuracy

Dataset	Accuracy
LFW	99.84%
CFP-FP	97.89%
AgeDB -30	97.41%
Real-world KYC samples	96.80%

B. Baseline and Optimisation Comparison

Against general neural baselines, the reported accuracy increases from 92.84% for ANN, 94.62% for DNN, 96.15% for CNN, 97.28% for MobileNet, 98.85% for Xception, and 99.28% for Inception-v4 to 99.84% for the proposed VGG16–MS-AVOA–FCNN model. The optimisation-specific comparison is more diagnostic: MS-AVOA improves accuracy relative to CSO, GOA, WOA, and the original AVOA configuration.

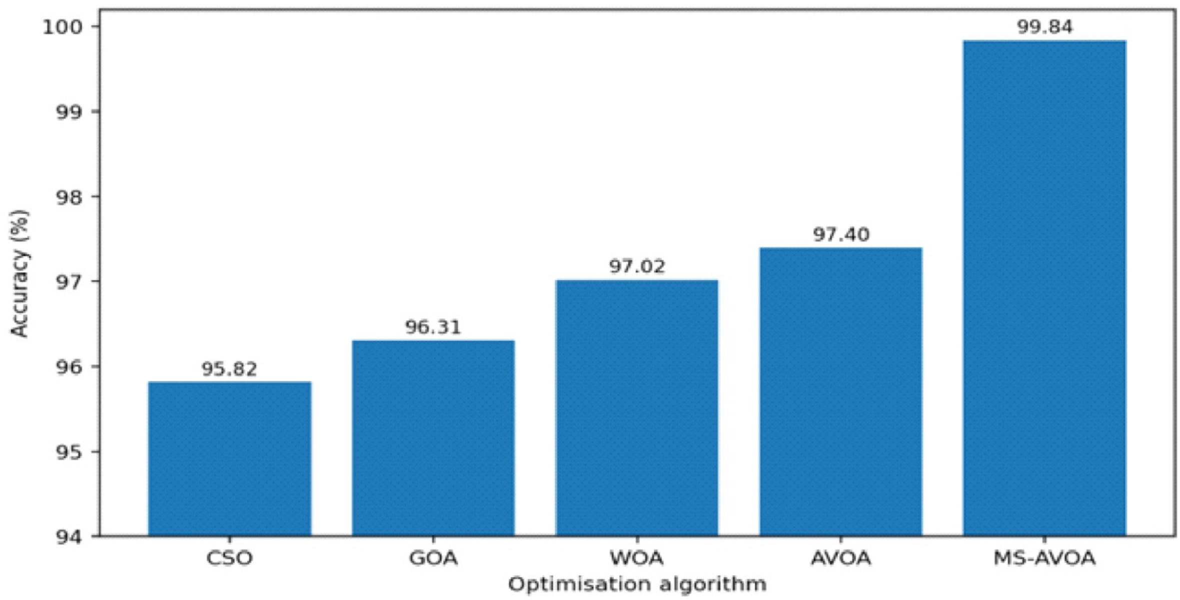

Fig. 3. Accuracy comparison of optimisation algorithms reported in the thesis.

Table 6. Optimisation algorithm comparison

Algorithm	Accuracy	Convergence assessment
CSO	95.82%	Slow; oscillatory
GOA	96.31%	Slow to moderate
WOA	97.02%	Moderate
AVOA	97.40%	Moderate; strong exploration
MS-AVOA	99.84%	Fastest and most stable

C. Feature Separability and Threshold Analysis

The optimisation stage reduces the reported intra-class distance from 0.921 to 0.612 and increases the inter-class distance from 1.428 to 1.671. Consequently, the separability difference increases from 0.507 to 1.059. Threshold testing identifies 0.50 as the best reported operating point; thresholds of 0.30, 0.70, and 0.90 produce lower overall accuracy and different selected feature counts.

Table 7. Embedding characteristics before and after optimisation

Measure	Before optimisation	After MS-AVOA
Intra-class distance	0.921	0.612
Inter-class distance	1.428	1.671
Separability Δ	0.507	1.059
Convergence iterations	—	42
Final fitness	—	0.0174

D. Ablation Study

Removing optimisation lowers accuracy from 99.84% to 97.40%, which is the largest direct evidence that MS-AVOA contributes beyond the base VGG16/FCNN pipeline. Removing alignment, normalisation, or augmentation lowers accuracy to 96.12%, 95.84%, and 96.51%, respectively, and increases FAR and FRR. These results support the methodological requirement that pre-processing must be evaluated as part of the model rather than described as a routine implementation detail.

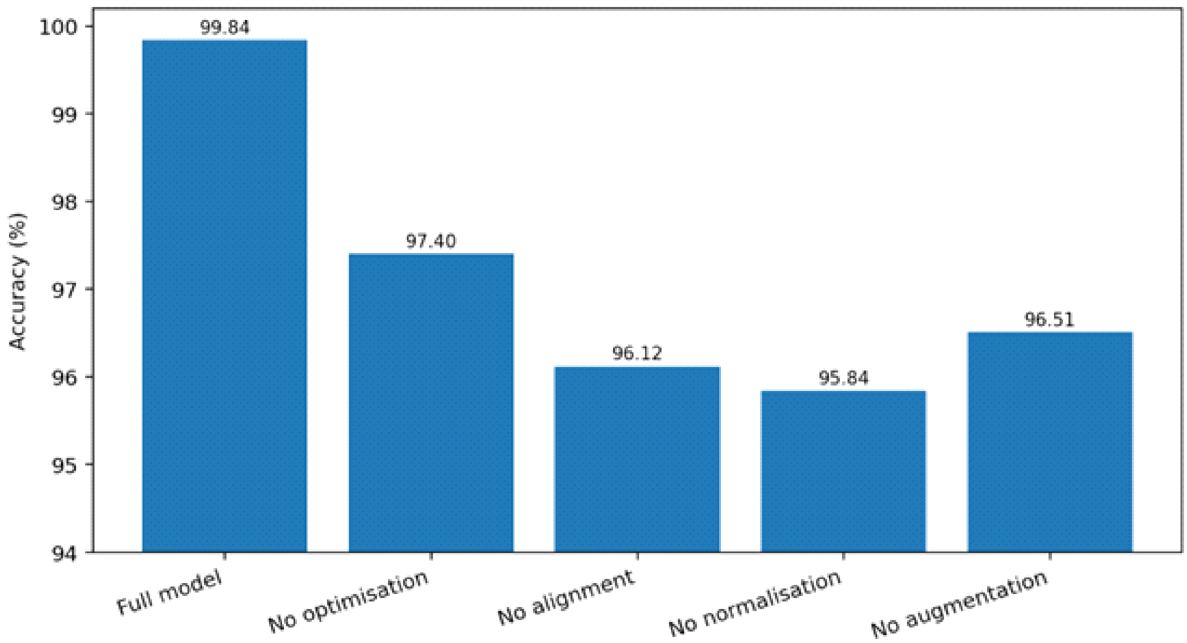

Fig. 4. Ablation results for the principal pipeline components.

Table 8. Ablation study

Configuration	Accuracy	FAR	FRR
Full model	99.84%	0.21%	0.16%
Without optimization	97.40%	1.85%	1.32%
Without face alignment	96.12%	2.41%	2.08%
Without normalization	95.84%	2.67%	2.43%
Without augmentation	96.51%	2.10%	1.94%

E. Computational Cost and Statistical Significance

The total reported end-to-end latency is 0.279 s: 0.022 s for pre-processing, 0.184 s for VGG16 feature extraction, 0.091 s for MS-AVOA optimisation, and 0.004 s for FCNN classification. Feature extraction is therefore the principal computational bottleneck. Statistical tests compare the proposed method against AVOA, WOA, GOA, and CSO. The reported p-values range from 0.00041 to 0.00004, and all t-values exceed the critical value of 2.26.

Table 9. Computational latency

Stage	Time (s)
Pre-processing	0.022
VGG16 feature extraction	0.184
MS-AVOA optimization	0.091
FCNN classification	0.004
Total end-to-end	0.279

Table 10. Statistical comparison with optimisation baselines

Comparison	Mean improvement	t-value	p-value	95% CI
vs AVOA	2.44%	9.84	0.00041	[2.05, 2.82]
vs WOA	2.82%	12.51	0.00019	[2.51, 3.15]
vs GOA	3.53%	14.73	0.00009	[3.12, 3.89]
vs CSO	3.98%	16.88	0.00004	[3.54, 4.33]

F. Onboarding Decision Distribution

In the operational decision simulation, 72.10% of requests are approved, 21.20% are routed to manual review, and 6.70% are rejected. The manual-review class is crucial to make sure that questionable or low-quality evidence is not automatically accepted or dismissed. The proportions should be viewed as results of experimental choices, not as a general distribution of the telecom population.

VI. Discussion

The first publication was mostly descriptive, describing the benefits of Self-KYC, but did not include any datasets, train-test protocol, model parameters, comparative baselines, statistical tests or measured results. The revised paper corrects these deficiencies by linking each major statement with a specific method and a number of results. The most convincing evidence is not only the absolute LFW accuracy but also the consistent trend across optimization comparison, feature separability, ablation and latency analysis.

The results also explain the reason why benchmark accuracy is not sufficient. Performance degrades on profile and age-variant datasets and the error analysis in the thesis shows blur, occlusion, strong illumination and hard negatives as recurrent failure modes. A Self-KYC platform needs model confidence, but also quality gates, document consistency, liveness, consent, audit logs and a manual-review path. Work on bias and trustworthiness of deepfakes also suggests the need for demographic and attack-specific testing before deployment [11], [21], [22], [31].

This architecture is relevant for telecom digital transformation as it can connect identity capture to CAF generation, tele-verification, service activation, account provisioning and customer notification. However, the integration with government databases, UIDAI, Telecom CRM, billing or live regulatory systems has not been experimentally demonstrated in the thesis and hence is considered as an architectural interface and not a validated production integration.

VII. Conclusion

In this work, we provide an experimental formulation of an AI-based Self-KYC customer onboarding system at a better level without changing the original title, author details, or aims. The framework incorporates OCR-assisted document processing, pre-processing of faces, VGG16 feature extraction, MS-AVOA optimization, FCNN classification, and a 3-way onboarding decision. The thesis results report 99.84% accuracy in LFW, 97.89% in CFP-FP, 97.41% in AgeDB-30 and 0.279 s total latency. Some baselines; ablation, threshold, feature-separability and statistical assessments suggest that optimisation and preprocessing components make measurable contributions. Hence, the system is a legitimate research framework for distant telecom onboarding. Production implementation still requires independently reproducible code, explicit private-data governance, liveness testing, subgroup fairness audits and regulatory integration validation.

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