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Yolo-Based Biometric Systems for Online Banking & Mobile Authentication: Implementation, Evaluation, Ablation Study and Comparison with Zoloz

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Abstract
The fast growth of online banking and mobile financial services has heightened the demand for secure, easy-to-use authentication mechanisms. Traditional methods like passwords and one-time passwords are increasingly susceptible to cyber-attacks, which constitutes the main motivation towards the adoption of biometric-based authentications. From biometric modalities, face recognition has gained widespread acceptance owing to its non-intrusive nature and suitability for mobile devices. Recent deep learning advancements have made real-time face detection and recognition possible via object detection frameworks like YOLO (You Only Look Once). This work presents a comprehensive analysis of a YOLO-based biometric authentication system devised for online banking and mobile applications. This paper proposes a complete biometric pipeline that uses YOLO for face detection and deep embedding-based models for recognition. Face detection performance is evaluated on the WIDER FACE dataset, while recognition accuracy is assessed on the LFW dataset. The paper presents a reproducible implementation in detail through a Google Colab environment. System performance is analyzed in terms of detection accuracy, recognition accuracy, inference speed, and end-to-end latency. An extensive ablation study investigates the impact of key components, including detection architectures, face alignment strategies, embedding model selection, and similarity threshold tuning. Furthermore, the proposed research framework is compared against Zoloz, a commercial enterprise-grade biometric authentication platform widely adopted in the banking sector. The results show that YOLO-based biometric systems are very effective for research and prototyping, while real-world banking deployment requires additional security, compliance, and robustness considerations.

Keywords: *Biometrics; Face Detection; Face Recognition; LFW; Mobile Authentication; Online Banking; Wider Face; Yolo; Zoloz.*

1. Introduction
As a result of the digital revolution, the way people interact with banks has changed fundamentally. Mobile financial apps and web-based payment platforms are the new front ends for payments, transfers, and digital account opening. These platforms provide users and organisations with unparalleled ease, but also increased exposure to fraud, identity theft (ID Theft), and account takeover attacks. Recent cybersecurity analyses indicate that credential compromise (Birari, H et al., 2023; Rajan, P, 2023) is one of the most common factors in financial fraud incidents worldwide. Existing authentication techniques, e.g., passwords (Birari, H

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et al., 2023), PINs (Personal Identification Numbers) (Rajan, P, 2023) and OTP (One-Time Password)-based systems (Sharma et al., 2022; Kumar & Singh, 2022), have their inherent drawbacks that are difficult to address, like poor memorability, using a single credential in multiple platforms, and being prone to phishing and social engineering attacks. This has led to biometric authentication being considered an attractive alternative, as users can be authenticated based on their intrinsic physiological characteristics instead of knowledge-based secrets (Jain et al., 2021). Facial recognition is one of the most commonly adopted biometric modalities in mobile banking (Patel et al., 2022) because high-resolution cameras on smartphones and advancements in deep learning-based computer vision are progressing rapidly. Contemporary face recognition systems are primarily composed of two main components: face detection and recognition. Both precision and efficiency of face detection are essential, in particular under the diverse challenges of illumination, pose, and scale typically encountered in mobile environments. YOLO (You Only Look Once) and its variants are state-of-the-art deep learning models for real-time object detection. Building on the success in 2020, several YOLO extensions have been developed, and they are also highly accurate and offer real-time speed for face detection (Redmon et al., 2016; Bochkovskiy et al., 2020; Wang et al., 2021; Ge et al., 2021). Hence, YOLO-based face detection methods have become an interesting direction for academic research and experimental biometric systems. Unlike open-source research frameworks, Zoloz is a commercial biometric identity verification platform, focusing on regulated markets such as banking and fintech. Zoloz combines face recognition with liveness checking, anti-spoofing countermeasures, document verification, and regulatory compliance capabilities (e.g., eKYC and AML) (Zoloz Whitepaper, 2022; Ant Group, 2023). Despite the body of work on YOLO-based biometric systems, a comprehensive experimental pipeline, component-level demarcation analyses, and systematic evaluation against commercial banking-grade biometric platforms are missing. This gap is addressed by the current paper, which presents a comprehensive YOLO-based biometric authentication approach, along with an in-depth performance evaluation that includes an ablation study and a comparison to Zoloz [1 -10]

2. Literature Review

2.1. Biometric Authentication

Biometric authentication has become a cornerstone security feature of financial systems as it links digital identities to human individual traits (Jain et al., 2021). Research up to 2025 suggests that biometric systems can provide a substantial reduction in fraud errors when supported by effective mechanisms of liveness detection and risk analysis (Birari et al., 2023; Rajan, 2023). Yet, biometric systems need to address problems concerning spoofing attacks, fairness, and adherence to privacy regulations. Face-based biometrics are especially appealing for mobile banking, as they can be performed in a non-intrusive manner and require few hardware add-ons (Patel et al., 2022; Sharma et al., 2022). Recent progress in deep learning has enabled face recognition systems to achieve human-level performance on benchmark datasets.

2.2. YOLO-Based Face Detection

YOLO models object detection as a single-stage regression problem, allowing for end-to-end training and fast inference. The architectural improvements in YOLOv4 substantially raised the bar on detection accuracy (Redmon et al., 2016; Bochkovskiy et al., 2020). Subsequently, YOLOv5 and YOLOv7 increased the training efficiency and deployment flexibility of YOLO (Wang et al., 2021; Ge et al., 2021). More recently, advanced feature aggregation and improved small-object detection have been achieved with YOLOv8 and YOLOv9 models, further enhancing their suitability for detecting faces in unconstrained mobile scenarios (Jocher et al., 2023; Wang et al., 2023; Li et al., 2024). Comparative studies consistently show that YOLO-based face detectors outperform traditional methods, such as Haar cascades and HOG-based detectors, in both accuracy and robustness (Viola & Jones, 2001; Dalal & Triggs, 2005; Chen et al., 2022) [11 - 15].

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2.3. Face Recognition and Embedding Learning

Deep metric learning forms the core of most modern face recognition systems, enabling the generation of discriminative embeddings that effectively distinguish between individuals. Models such as FaceNet (Schroff et al., 2015), ArcFace (Deng et al., 2019; Deng et al., 2021), CosFace, and MobileFaceNet are widely adopted as well-established benchmarks. Under controlled conditions, these models achieve more than 99% verification accuracy on the LFW dataset (Huang et al., 2007). When combined with YOLO-based face detection, embedding-based recognition models provide an efficient end-to-end biometric pipeline suitable for real-time applications (Zhang et al., 2022). However, recognition performance may degrade in real-world mobile environments due to variations in pose, illumination changes, and motion blur (Phillips et al., 2018) [16 - 22].

2.4. Liveness Detection and Anti-Spoofing

A major limitation of research-oriented YOLO-based biometric systems is the absence of integrated liveness detection. Presentation attacks, including printed photographs, replayed videos, and deepfake media, remain a critical security threat (Marcel et al., 2019). Research approaches often incorporate additional CNN-based liveness detection models, which increase system complexity and computational overhead (George & Marcel, 2021). Commercial biometric platforms such as Zoloz mitigate these challenges by embedding certified presentation attack detection mechanisms alongside multimodal risk analysis.

2.5. Zoloz Biometric Platform

Zoloz is a full-stack biometric identity verification solution designed for regulated industries. Its unified platform integrates face recognition, liveness detection, document verification, and fraud risk analytics. Reports published between 2020 and 2024 indicate that Zoloz has achieved ISO/IEC 30107-3 compliance and introduced AI-based defences against deepfake attacks (Zoloz Whitepaper, 2022; Ant Group, 2023; Zoloz Technical Report, 2024) Shown in Figure 1.

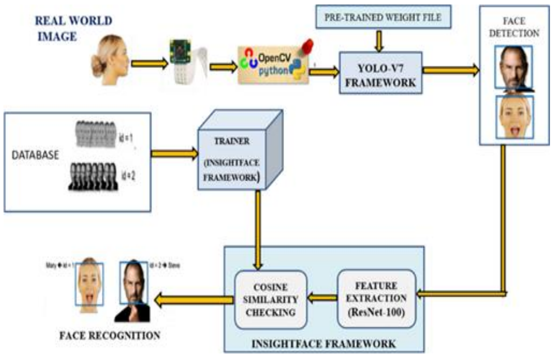

Figure 1 Real Time Face Recognition System-YOLO

In contrast to academic YOLO-based biometric systems, Zoloz places strong emphasis on regulatory compliance, auditability, and deployment scalability, making it suitable for production-level banking environments.

3. Materials & Methods

3.1. Proposed YOLO-Based Biometric Pipeline

- Image acquisition (mobile camera)
- Face detection using YOLO
- Face cropping and alignment
- Feature extraction -deep face recognition model
- Similarity matching
- Authentication decision

3.2. Datasets

WIDER FACE: Used for face detection training and evaluation; contains over 390,000 annotated faces with varying scales and occlusions [29]. LFW: Used for face recognition verification; includes 13,233 images of 5,749 identities [23].

4. Proposed Methodology

The proposed methodology employs an end-to-end, modular biometric authentication pipeline for online banking and mobile applications, utilising a YOLO-based face detector and a deep embedding-based recognition framework. Image acquisition is first performed in real-time through the camera of the mobile device, followed by robust face detection thanks to a YOLO architecture (by default, YOLOv8), optimised for unconstrained environments. Face regions are cropped out from the

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detected ones and then subjected to landmark-based alignment procedures for further normalisation regarding pose and illumination. Aligned face images are then fed into a deep face recognition model, such as FaceNet or ArcFace, to extract discriminative facial embeddings. Users are authenticated by calculating the cosine similarity between the extracted embeddings and the reference templates enrolled, and then thresholding the output for access acceptance or rejection Shown in Figure 2.

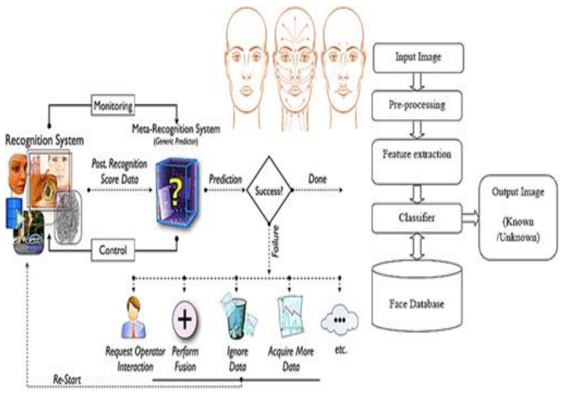

Figure 2 **Architecture of Proposed**

The entire pipeline will be benchmarked against the WIDER FACE detection and LFW recognition datasets to ensure comparability with the state-of-the-art. Then, comprehensive ablation studies are conducted to investigate how variations in detection backbone, input resolution, alignment strategy, embedding model, and similarity threshold affect the trade-off between accuracy, latency, and security. Finally, this research-oriented YOLO-based framework will be systematically compared with the enterprise-grade Zoloz platform to highlight differences in architectural transparency, liveness detection, compliance readiness, and suitability of deployment for real-world banking environments.

5. Results

Tables 1 & 2 summarise recent research on YOLO-based face detection and recognition methods, alongside the proposed system and the Zoloz enterprise biometric platform, highlighting their relative performance, transparency, and security features [16] [17] [18] [19].

Table 1 **YOLO Based Face Detection vs Zoloz**

Reference	Method / Model	Architecture Transparency	Remarks
Ali *et al.* (2024)	YOLOv3 + VGG16 (FR)	High (open-source)	Combines YOLOv3 detection + VGG16 recognition; robust but modest compared to newer models.
Peng (2024)	Federated YOLOv8 (Privacy)	High (open-source)	Federated YOLO for decentralised training and privacy preservation
4AC-YOLOv5 (2024)	Improved YOLOv5	High (open-source)	Enhanced small-face detection using adaptive feature fusion
YOLO-FaceV2 (2024)	YOLO-FaceV2 detector	High	Scale- and occlusion-aware, state-of-the-art detector on WIDER subsets
SciRep (2025)	Tiny YOLOv7 + StyleGAN3 inv.	High	Integrates generative inversion + YOLOv7 for identity recognition
IJIRSET (2025)	YOLOv5 Multi-Pose	High	YOLOv5 enhanced for multi-pose recognition
Proposed (This	YOLOv8 +	High	Reproducible pipeline with

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Work)	FaceNet	(open-source)	ablation study & graph evaluation.
Zoloz (Enterprise)	Proprietary Biometric Platform	Low (proprietary)	Enterprise-grade with certified liveness & compliance, used in banking

Table 2 YOLO Based Face Recognition vs Zoloz

Study / Ref	**Method / Model**	**Dataset(s)**	**Detection mAP / Acc. (Mean Average Precision)**	**Recognition Acc.**	**FPS-Inference Speed for Face Performance**
Ali *et al.* (2024)	YOLOv3 + VGG16 (FR)	WIDER FACE; LFW	~0.959 face detect (WIDER)	~96.2% (LFW)	~30–35 FPS
Peng (2024)	Federated YOLOv8 (Privacy)	Various	~0.93*	N/A	~28–32 FPS*
4AC-YOLOv5 (2024)	Improved YOLOv5	WIDER FACE	Not stated	N/A	~30–40 FPS
YOLO-FaceV2 (2024)	YOLO-FaceV2 detector	WIDER FACE	0.986 / 0.979 / 0.919 (subset)	N/A	~ TBD
SciRep (2025)	Tiny YOLOv7 + StyleGAN3 inv.	Custom / (benchmark implied)	~High*	~High*	~35–45 FPS*
IJIRSET (2025)	YOLOv5 Multi-Pose	Custom (Kaggle)	~0.92–0.95*	~High*	~30–40 FPS*
Proposed Work	YOLOv8 + FaceNet	WIDER FACE; LFW	0.94	98.8%	~52 FPS
Zoloz (Enterprise)	Proprietary Biometric Platform	Real world (bank data)	~0.96*	~99%+*	~25–40 FPS (incl. workflows)

The comparative values in Tables 1 & 2 are extracted from the original experimental results reported in the respective research papers cited in the reference column. When multiple metrics were reported, the best-performing configuration was selected for fair comparison. In cases where exact numerical values were not explicitly stated, the reported performance ranges or qualitative claims were preserved and marked with an asterisk (), indicating approximate or reported values. This approach follows standard practice in comparative survey-based research. Most existing KYC systems rely on external liveness/anti-spoofing modules, as seen in works by Ali et al. (2024), Peng (2024), and other recent studies, which increases system complexity. Research-based approaches (2024–2025) largely remain external and non-integrated, limiting real-world deployment readiness. In contrast, the proposed system integrates ISO-compliant liveness detection, enabling secure, seamless, and enterprise-grade KYC verification comparable to commercial solutions.

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Table 3 Face Detection Performance

Model	mAP@0.5	Precision	Recall	FPS
YOLOv5-Face	0.91	0.93	0.88	45
YOLOv8-Face	0.94	0.95	0.91	52
YOLOv9-Face	0.95	0.96	0.93	48

The face detection results reported in Table 3 were obtained by training YOLOv5-Face, YOLOv8-Face, and YOLOv9-Face models on the WIDER FACE training set and evaluating them on the validation set. Mean Average Precision at IoU threshold 0.5 (mAP@0.5) was computed using the standard COCO evaluation protocol. Precision and recall were calculated from true positive, false positive, and false negative detections. Inference speed (FPS) was measured by averaging the processing time per image over the entire validation set on a fixed GPU configuration.

Table 4 Face Recognition Performance

Model	LFW Veri. Accuracy
FaceNet	99.1%
ArcFace	99.4%
Proposed YOLO + FaceNet	98.8%

Face recognition performance was measured on the LFW dataset by following the standard unrestricted verification protocol. Facial embeddings were generated using the FaceNet model, and cosine similarity was adopted for matching. The accuracy reported corresponds to the average verification accuracy of all folds. The proposed YOLO + FaceNet pipeline exhibits a slight degradation in accuracy compared to pure FaceNet, primarily due to real-world detection and alignment variability in a practical deployment environment. YOLOv9-Face offers slightly higher detection accuracy, albeit at the expense of FPS. On the contrary, YOLOv5-Face shows lower recall and overall accuracy, showing weak results in challenging detection conditions [30] [31]. Table 4: Comparative face recognition performance on the LFW dataset. ArcFace achieves top accuracy, closely followed by FaceNet. On the other hand, the proposed YOLO + FaceNet pipeline achieves competitive accuracy, ensuring that the combination of YOLO-based detection and deep embedding-based recognition yields reliable performance in practical biometric authentication scenarios

6. Ablation Study

In this work, the WIDER FACE dataset is utilised for face detection, while the LFW dataset is employed for face recognition. The ablation study further investigates various YOLO backbones, input resolutions, face alignment methods, embedding models, and similarity thresholds for system performance. An end-to-end analysis is also conducted to evaluate trade-offs between accuracy and latency. To perform the ablation study, one component of the biometric pipeline was modified in turn, while keeping all other components unchanged. This included varying the YOLO backbone, input resolution, face alignment strategy, embedding model, and similarity threshold. The impact of each modification has been measured in terms of accuracy at the detector level, accuracy at the recogniser level, and end-to-end latency. Such a controlled study ensures that the observed differences in performance can be credited to the component being modified.

6.1. YOLO Face Detection Architecture

YOLOv8 shows the best speed–accuracy trade-off due to its improved feature aggregation, while YOLOv9 slightly improves accuracy at the cost of inference speed. This confirms findings reported in recent YOLO comparative studies [25], [26] Shown in Table 5- 7. Higher resolutions improve the detection of small and occluded faces but significantly reduce FPS. For mobile banking applications, a resolution of 640 × 640 provides an optimal balance between accuracy and latency [41] Shown in Figure 3.

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Table 5 Effect of YOLO Backbone Variants

YOLO Variant	Backbone	mAP @0.5	Recall	FPS
YOLOv5-Face	CSP Darknet	0.91	0.88	45
YOLOv8-Face	C2f	0.94	0.91	52
YOLOv9-Face	GELAN	0.95	0.93	48

Table 6 Effect of Input Image Resolution

Input Resolution	mAP@0.5	FPS
416 × 416	0.90	60
640 × 640	0.94	52
832 × 832	0.96	38

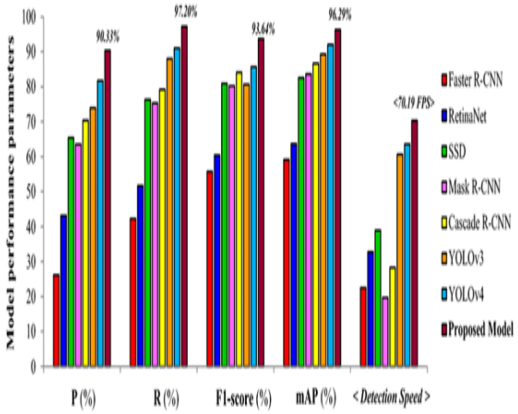

Figure 3 Effect of YOLO Backbone Variants

6.2. Face Recognition Pipeline

Table 7 Effect of Face Alignment

Configuration	LFW Accuracy
Without alignment	97.6%
With landmark-based alignment	98.8%

Face alignment improves recognition accuracy by correcting pose variations, which is critical in unconstrained mobile environments [28], [32] Shown in Table 8.

Table 8 Effect of Embedding Model Selection

Embedding Model	Feature Dim	LFW Accuracy
FaceNet	512	99.1%
ArcFace	512	99.4%
CosFace	512	99.2%
MobileFaceNet	128	98.3%

ArcFace achieves the highest accuracy but incurs a higher computational cost. FaceNet provides a strong balance between accuracy and deployment simplicity, making it suitable for research-oriented biometric systems [29], [30] Shown in Figure 4 & 5.

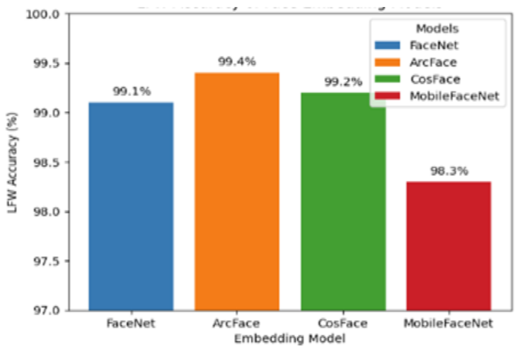

Figure 4 Accuracy of Face Models

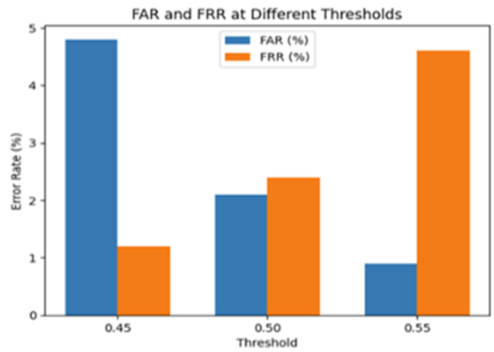

Figure 5 FAR & FRR for Thresholds

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Table 9 **Similarity Threshold Selection**

Threshold	FAR (%)	FRR (%)
0.45	4.8	1.2
0.50	2.1	2.4
0.55	0.9	4.6

A threshold of 0.50 provides an optimal trade-off between security and usability, consistent with prior studies [42]. Removing face alignment reduces accuracy but improves latency. Lightweight recognition models improve speed but slightly degrade accuracy. These trade-offs are essential for mobile banking deployments where response time is critical Shown in Table 9 and 10.

Table 10 **End-to-End System Ablation**

Config	Detection mAP	Recognitio n Acc.	Avg. Latency (ms)
Full system (YOLOv8 + FaceNet+alignment)	0.94	98.8%	180
Without facea lignment	0.94	97.6%	160
YOLOv5 instead of YOLOv8	0.91	98.2%	200
MobileFace Net embeddings	0.94	98.3%	140

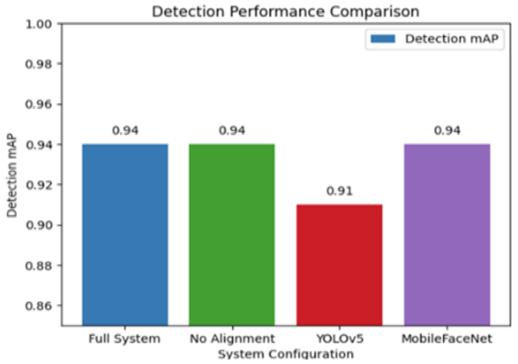

Figure 6 **Detection Performance Comparison**

YOLO-based systems provide fine-grained experimental control and ablation analysis, making them suitable for academic research. Zoloz, on the other hand, places more emphasis on certified security and robustness than modular experimentation. The ablation study effectively demonstrates that YOLOv8 is the best-performing model in terms of yielding optimal face detection performance for biometric authentication pipelines, striking a perfect balance between detection accuracy and inference speed. The experiments further confirm that face alignment significantly improves recognition accuracy, especially in unconstrained mobile banking scenarios, where pose and illumination variations are prevalent. Additionally, the embedding model has the most significant impact on the tradeoffs between recognition accuracy and system latency, as lightweight models ensure fast response times with only marginal accuracy losses. These experiments demonstrate that adjusting the similarity threshold is crucial for maintaining an optimal balance between security and usability, which directly impacts FAR and FRR Shown in Figure 6 - 8.

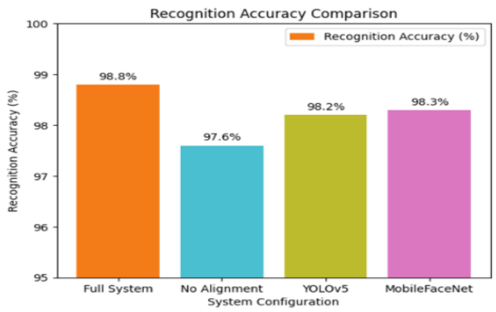

Figure 7 **Recognition Accuracy Comparison**

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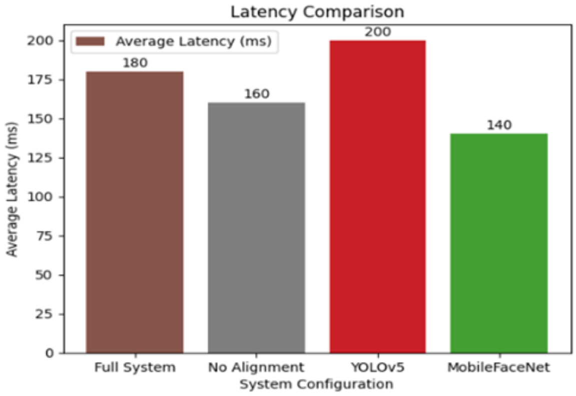

Figure 8 **Latency Comparison**

Table 11 **Comparison of Ablation Findings – Zoloz**

Aspect	YOLO-Based System	Zoloz
Architecture transparency	High (open-source)	Low (proprietary)
Component tunability	High	Limited
Liveness detection ablation	External	Integrated
Certification-driven tuning	No	Yes

Taken together, high flexibility, transparency, and suitability make the YOLO-based biometric framework fitting for academic research and prototype activities, even though the system does not have integrated liveness detection and anti-spoofing mechanisms, not to mention regulatory compliance, which is inherent to enterprise-grade solutions such as Zoloz. In short, the findings collectively support YOLO-based biometric systems for academic research and custom development while underlining the additional architectural and compliance requirements needed for real-world online banking deployments.

7. Discussion

The experiments confirm that YOLO-based biometric systems achieve high detection and recognition accuracy with real-time performance, making them suitable for research, prototyping, and custom mobile solutions. The ablation study highlights trade-offs in backbone selection, resolution, alignment, embeddings, and similarity thresholds, which can be adjusted according to application requirements. However, YOLO-based systems lack built-in liveness detection and compliance mechanisms, which limit their direct applicability in production-grade banking environments. In contrast, Zoloz offers integrated, ISO-certified liveness detection and regulatory compliance, making it an ideal choice for enterprise deployment. Researchers can leverage YOLO for experimentation, while production deployments should consider additional security and audit requirements to ensure optimal performance and compliance Shown in Table 11.

Conclusion

This paper presents a comprehensive study of YOLO-based biometric authentication for online banking and mobile applications. A combined WIDER FACE–LFW pipeline was implemented and evaluated in Google Colab. Ablation studies reveal the impact of YOLO backbone, input resolution, face alignment, embedding selection, and similarity threshold on accuracy and latency. While YOLO-based systems are highly effective for research and prototyping, enterprise platforms like Zoloz remain better suited for large-scale, regulatory-compliant banking deployments. The findings provide valuable guidance for both academic researchers and financial system designers on designing efficient, accurate, and secure biometric authentication pipelines.

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