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Real-Time Student Attendance Recognition Using a Centroid Based MTCNN–ArcFace Framework

Suci Putri Widyani [1], Suroso [1,*], Ahmad Taqwa [1]

[1] Politeknik Negeri Sriwijaya, Indonesia
[*] Corresponding author: Suroso, Politeknik Negeri Sriwijaya, Indonesia
suroso@polsri.ac.id

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Abstract
Student attendance remains susceptible to proxy attendance and operational inefficiencies, while many face recognition systems are evaluated only on benchmark datasets and rarely investigate identity representation strategies under real-world educational conditions. This study evaluates a hybrid MTCNN–ArcFace framework incorporating centroid-based identity representation, application-specific threshold calibration, and real-time validation for automated student attendance. A quantitative experimental design was conducted using a locally collected dataset from a secondary school. MTCNN was employed for face detection and alignment, whereas ArcFace with a ResNet-50 backbone generated facial embeddings that were aggregated into centroid templates for identity matching. The framework was assessed through offline performance evaluation and operational deployment. The proposed approach achieved 92.86% accuracy, 97.22% precision, 92.86% recall, and a 93.49% F1-score, with a 4.76% false acceptance rate and 2.38% false rejection rate. In addition, centroid representation reduced template storage requirements and supported efficient real-time recognition using limited enrollment samples. These findings demonstrate that centroid-based identity representation enhances the practicality of deep face recognition for educational attendance systems by improving computational efficiency while maintaining reliable recognition performance in authentic school environments.

Keywords: arcface; automated student attendance; centroid template; educational biometrics; face recognition

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INTRODUCTION

Educational institutions are increasingly integrating artificial intelligence (AI) into learning and institutional management to improve the efficiency and quality of educational services (Parameswara et al., 2026). Beyond learning and academic analytics, AI is increasingly applied to administrative processes requiring reliable identity verification. Student attendance remains one such process, yet many institutions continue to rely on manual or card-based authentication despite its inefficiency and vulnerability to proxy attendance (Ali et al., 2024). Conventional biometric technologies, including RFID cards and fingerprint scanners, also face limitations related to identity sharing, environmental conditions, hygiene, and user convenience (Salazar-Jurado et al., 2023; Sunaryono et al., 2021; Susanto et al., 2024). Consequently, contactless facial biometrics have emerged as a practical solution for automated identity verification in educational attendance systems (Faruque et al., 2022; Guo et al., 2022).

Deep face recognition has become the dominant paradigm for biometric identification because it learns compact and discriminative facial embeddings, enabling robust open-set recognition under variations in pose, illumination, and facial expression (Musto et al., 2023; Shu et al., 2025; Singhal et al., 2025). Recent advances have further extended deep face recognition through Vision Transformer-based architectures and foundation models, improving feature representation and deployment efficiency across biometric applications (Shahreza & Marcel, 2025). Among existing approaches, the integration of MTCNN for face detection and alignment with ArcFace based on a pre-trained ResNet-50 backbone consistently provides robust recognition by combining accurate facial alignment with highly discriminative embeddings (Shuang et al., 2024; Singhal et al., 2025; Zhalgas et al., 2025). Consequently, this framework has become a widely adopted solution for educational biometric applications.

Most previous studies have demonstrated the effectiveness of deep face recognition for automated attendance systems. However, existing research has primarily emphasized algorithmic comparisons while giving less attention to methodological factors affecting practical deployment. Although ArcFace consistently outperforms earlier models such as FaceNet and SFace, recognition performance remains sensitive to pose variation, facial occlusion, and unconstrained illumination, emphasizing the importance of robust face alignment and identity representation (Singhal et al., 2025; Zhalgas et al., 2025). Many studies also rely on benchmark datasets such as LFW and VGGFace2, which provide standardized evaluation but do not fully represent the variability of operational educational environments (Nagrath et al., 2021; Shi & Tang, 2022). Conventional closed-set evaluation protocols may also overestimate deployment performance compared with operational gallery probe scenarios (Shu et al., 2025). Consequently, recognition reliability remains affected by illumination, occlusion, natural movement, and computational constraints, highlighting the need for robust identity representation and comprehensive real-world validation (Deng et al., 2023; Nguyen-Tat et al., 2024).

Biometric representation has become a fundamental aspect of deep face recognition because recognition performance depends not only on discriminative facial embeddings but also on how multiple enrollment samples are represented during identity matching. Representation learning transforms biometric data into compact feature embeddings that preserve identity information for similarity-based recognition, making effective template construction essential (Musto et al., 2023). Accordingly, various template representation strategies have been proposed, including multiple-template matching and representative templates. Compared with multiple-template matching, representative templates simplify similarity computation while preserving essential identity information, making them suitable for biometric systems with limited enrollment data and computational resources (Andriyanov & Dementiev, 2024). Among these approaches, centroid-based identity representation represents each identity using a single embedding derived from multiple enrollment samples. However, its effects on embedding stability, recognition reliability, and computational efficiency remain insufficiently investigated in real-world educational biometric systems.

Significant progress has been achieved in deep face recognition; however, key scientific challenges persist in educational biometric applications (Shu et al., 2025; Singhal et al., 2025). It remains unclear how centroid-based identity representation affects embedding stability under limited enrollment conditions compared with multiple-template matching (Andriyanov & Dementiev, 2024; Chen et al., 2024). Likewise, although threshold calibration determines the trade-off between false acceptance and false rejection, it is often regarded as an implementation parameter rather than a systematically evaluated component of biometric system design (Melzi et al., 2024; Micheletto & Marcialis, 2024). Moreover, the computational implications of centroid-based identity representation remain underexplored, particularly in educational deployments where recognition reliability must be balanced with operational efficiency

(Andriyanov & Dementiev, 2024; Chen et al., 2024). Addressing these questions is essential to developing educational biometric systems that balance recognition accuracy, computational efficiency, and reliable decision calibration.

Accordingly, this study introduces an integrated educational biometric framework combining MTCNN-based face detection, ArcFace feature extraction, centroid-based identity representation, application-specific threshold calibration, and real-time operational validation. The proposed framework contributes by jointly evaluating identity representation, threshold calibration, and operational performance under limited enrollment conditions. It further provides an empirical evaluation of centroid-based identity representation and validates the framework in a real Indonesian secondary school, extending the literature on educational biometric face recognition.

METHOD

This study employed a quantitative experimental design to evaluate the proposed hybrid MTCNN–ArcFace framework for student attendance. The overall research workflow, illustrated in Figure 1, consists of dataset collection, face detection and alignment, feature extraction, centroid construction, threshold evaluation, and both offline and real-time validation. The dataset comprised approximately 160 facial images of 28 students (13 males and 15 females) aged 16–17 years, captured under natural outdoor lighting using a 12 MP smartphone camera at an approximate distance of 1.5 m with moderate pose variations. Following MTCNN preprocessing, the dataset was divided into 70% enrollment and 30% testing sets using stratified sampling to preserve identity distribution while ensuring sufficient samples for centroid construction and unbiased performance evaluation.

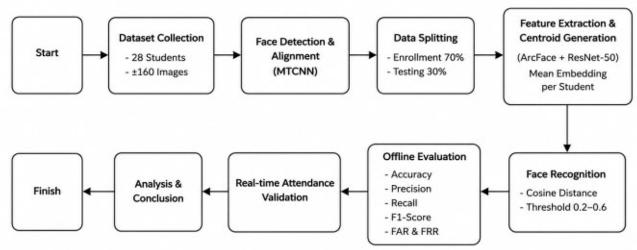

Figure 1. Research workflow of the proposed mtcnn–arcface attendance system

Face detection, alignment, and feature extraction were performed using the proposed MTCNN–ArcFace framework, as shown in Figure 2. MTCNN detected and aligned facial images to 112 × 112 pixels using five facial landmarks, after which a pre-trained ArcFace model with a ResNet-50 backbone generated 512-dimensional L2-normalized embeddings. During enrollment, embeddings from the same individual were averaged into a centroid template to reduce intra-class variation. During inference, probe embeddings were matched against the stored centroids using cosine distance, and the nearest centroid determined the predicted identity.

Cosine distance thresholds ranging from 0.20 to 0.60 at 0.05 intervals were evaluated to identify the optimal verification threshold. Performance at each threshold was assessed using accuracy, weighted precision, recall, F1-score, FAR, and FRR. The final threshold was determined through a weighted multi-criteria scoring scheme that prioritized accuracy (70%) and F1-score (20%), with smaller weights assigned to precision, recall (4% each), FAR, and FRR (1% each). Processing time was measured separately and was not included in the threshold selection process.

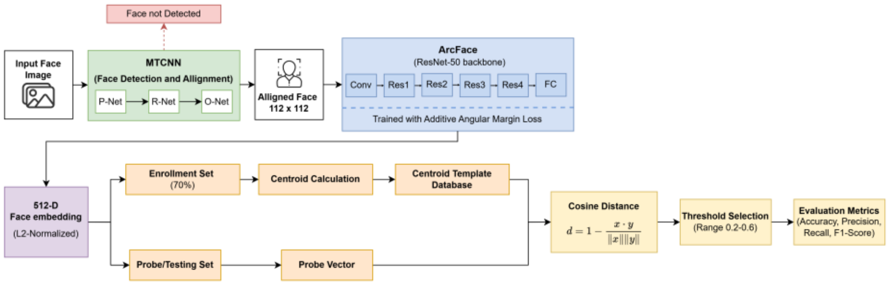

Figure 2. Block diagram of the proposed mtcnn–arcface face recognition pipeline

System performance was assessed at two tiers via offline and real-time trials. The offline assessment gauged the face detection rate, recognition precision, weighted recall, F1-score, FAR, FRR, threshold efficiency, confusion matrix, and average processing duration. Real-time verification integrated the centroid database into a Python attendance application utilizing OpenCV for facial recognition. The validation included a recognition trial for each of the 28 enrolled students with a 12 MP smartphone camera in natural outdoor light from about 1.5 m away, while attendance logs noted the recognized identity, timestamp, recognition outcome, and cosine distance score. Every experiment was conducted in Python utilizing the DeepFace, OpenCV, Scikit-learn, and Matplotlib libraries, and run on a workstation with an Intel Core i7-12700H CPU, 16 GB DDR5 RAM, and an NVIDIA GeForce RTX 3050 graphics card.

RESULTS AND DISCUSSION

Results

This section presents the experimental evaluation of the proposed centroid-based MTCNN–ArcFace framework using both offline and real-time experiments. The evaluation includes face detection, threshold optimization, recognition performance, robustness analysis, and real-time attendance validation. Additional analyses, including multiple-template comparison, ROC analysis, and repeated experiments, provide a comprehensive assessment of recognition performance and computational efficiency in educational biometric systems.

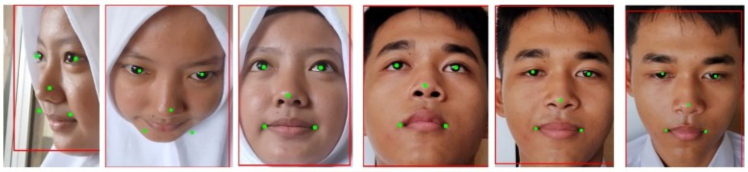

Figure 3. Examples of face detection and landmark

Table 1. MTCNN face detection results

Total Images	Detected	Not Detected	Detection Rate	Landmark Success Rate
± 160	± 160	0	100%	97.5%

Figure 3 presents representative examples of face detection and facial landmark localization using MTCNN, while the quantitative performance is summarized in Table 1. All testing images were successfully detected, resulting in a 100% detection rate and a 97.5% landmark success rate. MTCNN consistently localized facial regions and five facial landmarks across frontal, side, and tilted poses, enabling reliable facial alignment before feature extraction. Because no detection failures were observed, subsequent recognition errors were associated primarily with embedding representation and similarity matching rather than face detection, providing a reliable foundation for the subsequent recognition experiments.

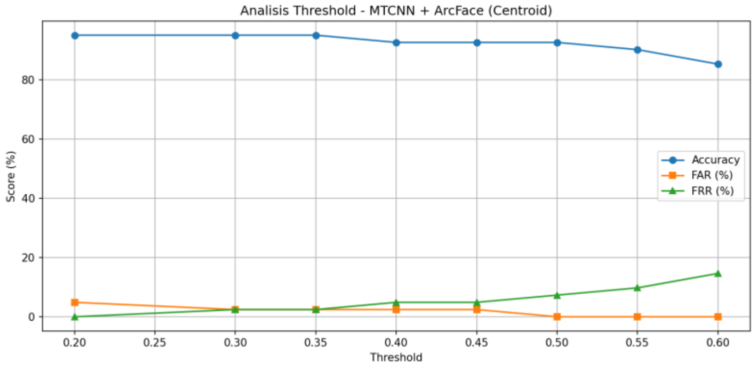

Figure 4. Threshold analysis accuracy, far, and frr

Table 2. Evaluation metrics per threshold value

Threshold	Accuracy (%)	FAR (%)	FRR (%)	Score
0.20	95.24	4.76	0.00	0.9338
0.30	92.86	4.76	2.38	0.9130
0.35	95.86	4.76	2.38	0.9130
0.40	90.48	2.38	7.14	0.8948
0.45	88.10	2.38	9.52	0.8740
0.50	88.10	0.00	11.90	0.8760
0.55	85.71	0.00	14.29	0.8502
0.60	83.33	0.00	16.67	0.8294

Table 3. Recognition performance at optimal threshold (0.30)

Accuracy	Precision	Recall	F1-Score	FAR	FRR
92.86%	97.22%	92.86%	93.49%	4.76%	2.38%

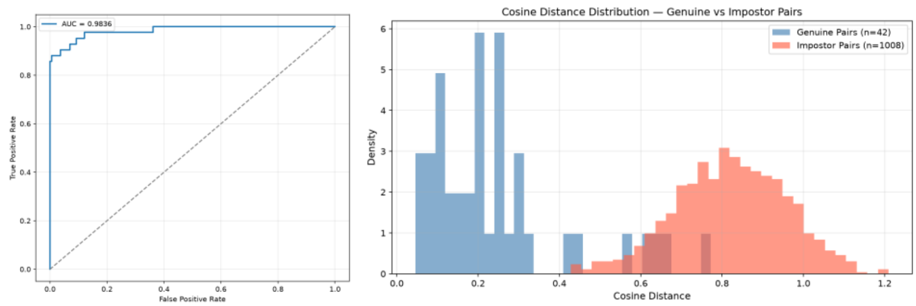

Figure 5. Roc and cosine distribution

Figure 4 illustrates the effect of varying the cosine distance threshold on recognition performance, while Tables 2 and 3 summarize the corresponding quantitative evaluation. As the threshold increased, the operating point progressively shifted from lower FRR toward lower FAR, illustrating the expected trade-off between recognition security and usability. Recognition accuracy remained relatively stable between thresholds of 0.20 and 0.35 but gradually declined as the decision boundary became more restrictive. Although the highest accuracy was achieved at lower threshold values, threshold selection was based on a multi-criteria strategy that considered both recognition accuracy and the balance between FAR and FRR. Based on this criterion, a threshold of 0.30 was selected because it provided the most balanced verification performance while maintaining high recognition accuracy, making it suitable for subsequent real-time evaluation.

The ROC curve and the distribution of cosine distances for genuine and impostor pairs are shown in Figure 5. The proposed centroid-based MTCNN–ArcFace framework achieved an AUC of 0.9836, demonstrating excellent capability to distinguish between matching and non-matching identities over a range of verification thresholds. Genuine pairs were predominantly clustered at lower cosine distance values, whereas impostor pairs were concentrated at considerably higher distances. Although a slight overlap occurred around the decision threshold, the separation between the two distributions remained sufficiently distinct to support accurate and reliable threshold-based identity verification.

Table 4. Centroid vs multiple-template comparison

Method	Templates	Accuracy	FAR	FRR	Inference Time
Multiple Template	98	88.10%	11.90%	0.00%	0.1061
Centroid	25	92.86%	4.76%	2.38%	0.0445

A comparison between the proposed centroid-based identity representation and conventional multiple-template matching is provided in Table 4. By representing each enrolled individual with a single centroid, the proposed approach reduced template storage requirements by 74.5% and accelerated inference by approximately 2.38×. At the same time, it achieved higher recognition accuracy and a lower FAR than the conventional multiple-template strategy. These findings demonstrate that the centroid representation effectively captures the essential characteristics of each identity while substantially decreasing the computational cost associated with template matching.

Table 5. Repeated experiments (mean ± sd)

Metric	Mean ± SD	95% CI
Accuracy (%)	93.81 ± 3.23	90.98–96.64
Precision (%)	96.67 ± 1.95	94.95–98.38
Recall (%)	93.81 ± 3.23	90.98–96.64
F1-Score (%)	94.19 ± 2.76	91.77–96.61
FAR (%)	3.81 ± 2.43	1.68–5.94
FRR (%)	2.38 ± 2.13	0.51–4.25

The robustness of the proposed framework was further assessed through five independent experimental runs using different random seeds while preserving the same evaluation protocol. The results, reported in Table 5, show that recognition performance remained highly consistent across all trials, as reflected by the low standard deviations and narrow 95% confidence intervals for each evaluation metric. This consistency indicates that the centroid-based framework delivers stable and reproducible performance under repeated experimental conditions.

The confusion matrix and recognition results across different facial pose categories are presented in Figure 6. Of the 42 testing samples, the proposed framework correctly identified 41, while a single side-view image was rejected as Unknown because its cosine distance exceeded the predefined verification threshold. Recognition remained consistently reliable for frontal and moderately tilted faces, whereas side-view images exhibited a noticeable decline in performance, reflected by lower recognition accuracy and increased FAR and FRR values. These findings suggest that facial pose was the dominant factor affecting recognition under the evaluated conditions. In contrast, moderate variations in illumination and facial expression had only a marginal effect on system performance, provided that facial landmarks were detected accurately.

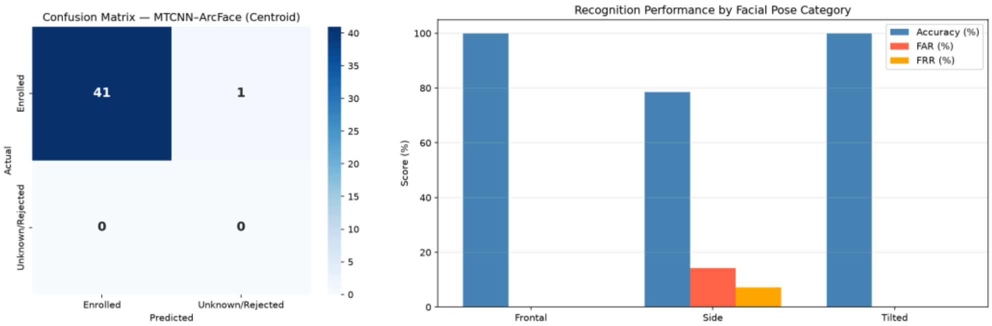

Figure 6. Confusion matrix and pose analysis

Figure 7. Real time face recognition and attendance logging

Table 6. Quantitative results of real-time attendance validation

Recognition Attemps	Successful Recognitions	Success Rate	False Acceptances	False Rejections
28	26	92.86%	0	2

Figure 7 illustrates the proposed attendance system during real-time operation, covering face detection, feature extraction, centroid-based identity verification, geofencing validation, and automatic attendance logging. The examples include both successful recognitions (green bounding boxes) and correctly rejected unknown faces (red bounding boxes). As reported in Table 6, the framework achieved a real-time recognition accuracy of 92.86%, closely matching the offline evaluation. Rejected faces produced cosine distance values above the predefined verification threshold, preventing incorrect identity assignment.

Discussion

The findings demonstrate that centroid-based identity representation provides an effective approach for educational face recognition under limited enrollment conditions. This finding suggests that reliable recognition performance depends not only on discriminative facial embeddings but also on how multiple enrollment samples are represented during identity matching. Consequently, the present study provides empirical evidence supporting the application of centroid-based identity representation in educational biometric systems with limited enrollment data, thereby extending current research on prototype-based face recognition in real-world educational environments.

The improved recognition performance can be explained by the way centroid-based identity representation summarizes multiple enrollment embeddings into a single representative template rather than treating each enrollment image independently. From the perspective of embedding representation learning, averaging multiple embeddings reduces the influence of sample-specific variations caused by pose, illumination, and facial expression while preserving identity-consistent characteristics across enrollment samples (Musto et al., 2023). This interpretation is consistent with prototype-based face recognition, where representative templates provide more stable identity references while reducing the number of similarity comparisons required during recognition (Andriyanov & Dementiev, 2024). This helps explain why centroid representation reduced the number of stored templates by 74.5%, achieved approximately 2.38× faster inference, and simultaneously improved recognition accuracy compared with multiple-template matching. These findings suggest that centroid-based identity representation provides an effective balance between computational efficiency and recognition reliability, making it particularly suitable for educational biometric systems operating with limited enrollment data and computational resources.

This finding further suggests that recognition performance in educational face recognition depends not only on the choice of feature extraction algorithms but also on how facial identities are represented and decision thresholds are calibrated. A possible explanation is that centroid-based identity representation reduces the influence of enrollment variability while application-specific threshold calibration enables a more balanced separation between genuine and impostor embeddings. This may explain why the proposed framework maintained high recognition performance using only five to six enrollment images per student while simultaneously reducing template storage and inference time. Unlike many previous attendance studies that primarily compare recognition algorithms (Susanto et al., 2024; Zhalgas et al., 2025), the present findings highlight identity representation and threshold calibration as equally important components for practical biometric deployment. Nevertheless, these observations were obtained under relatively controlled acquisition conditions and a homogeneous student population; therefore, further validation is required to determine whether similar advantages can be maintained across larger and more diverse educational environments.

The balanced operating point observed at the threshold of 0.30 suggests that the proposed decision boundary achieved an appropriate compromise between false acceptance and false rejection for the evaluated dataset. This finding can be explained by the separation between genuine and impostor embedding distributions, where the selected threshold effectively minimized overlap between the two classes under the evaluated conditions. In biometric systems, threshold selection determines the balance between security (FAR) and usability (FRR), making threshold calibration an application-specific process rather than a universally applicable parameter (Melzi et al., 2024). This explains why identical FAR and FRR values were obtained at the selected threshold, indicating a well-calibrated operating point for the target population (Micheletto & Marcialis, 2024). Nevertheless, variations in population diversity, image quality, acquisition conditions, and the number of enrolled identities may alter the embedding distribution and consequently shift the optimal decision boundary. These findings therefore highlight the importance of application-specific threshold calibration and suggest that future educational biometric systems may benefit from adaptive thresholding strategies capable of dynamically adjusting decision boundaries across different operational environments (Micheletto & Marcialis, 2024).

These findings should be interpreted with caution because the proposed framework was evaluated using a relatively small dataset collected from a single Indonesian high school with students of similar age and demographic characteristics. Although this setting reflects the intended application, the limited demographic variability may simplify embedding separability and restrict the external validity of the findings when applied to larger and more heterogeneous populations. A possible implication is that increasing the number of enrolled identities may introduce greater intra-class and inter-class variability, potentially affecting centroid stability and requiring recalibration of both identity representation and decision thresholds. Furthermore, the only observed misclassification occurred under partial facial occlusion, suggesting that recognition performance remains dependent on reliable facial landmark localization and sufficiently visible facial features, particularly under more challenging acquisition conditions (Zhalgas et al., 2025). Consequently, further validation using larger educational datasets, expanded biometric databases, and large-scale operational deployment is required to determine the generalizability and scalability of the proposed framework.

This study demonstrates that centroid-based identity representation offers an effective and computationally efficient solution for deep face recognition under limited enrollment conditions. By combining centroid representation with application-specific threshold calibration and real-time validation, the proposed framework improves both recognition reliability and operational efficiency. Beyond student attendance, the approach has potential applications in smart classrooms, examination authentication, campus access control, and educational identity management. Further evaluation using larger and more diverse datasets is needed to assess its scalability and broader applicability.

CONCLUSION

This study demonstrated the feasibility of a hybrid MTCNN–ArcFace framework with centroid-based identity representation for face recognition-based student attendance in a real school environment. The findings show that centroid-based representation provides an efficient and reliable solution for educational biometric systems with limited enrollment data, while emphasizing the importance of application-specific threshold calibration and real-time validation. Although the proposed framework contributes to the practical deployment of deep face recognition in educational biometrics, the results should be interpreted in light of the relatively small dataset, controlled acquisition conditions, and limited demographic diversity. Future research should investigate adaptive thresholding, long-term centroid stability, and validation across larger, more diverse multi-site educational environments.

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