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Incremental CNN-k-NN Hybrid Facial Recognition for Helmeted Facial Recognition in IoT-Enabled Smart Parking: A Case Study at Universitas Mataram

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Abstract

Helmeted rider identification challenges traditional facial recognition, especially in Indonesian campuses like UNRAM, where motorbike use is prevalent and theft risks are high. This study develops a hybrid CNN-k-NN system for secure parking access. The dataset contains 2,800 augmented images (Haar Cascade crop, 224x224 grayscale), with features extracted via VGG16/ResNet and classified using k-NN (k=1, Euclidean/Cosine). The system achieves 95.62% accuracy, with precision, recall, and F1 scores of 0.96. Incremental retraining reduces processing time to under 1 second, compared to 30 minutes for full retraining. The use of cosine similarity improves accuracy slightly over Euclidean distance. This solution enhances IoT-based smart campuses by enabling efficient, real-time identification and reducing theft by improving access control. It is adaptable to low-resource environments, supporting scalable deployments in smart parking and campus security systems.

Keywords : *facial recognition, incremental learning, hybrid CNN-k-NN classification, smart parking, university IoT*

1. INTRODUCTION

The swift urbanization and heightened reliance on motorbikes as a principal means of transportation in Indonesia have mandated the establishment of comprehensive security measures, especially within university campuses. At the University of Mataram (UNRAM), where a substantial proportion of students utilize motorcycles, safeguarding vehicle security and enhancing parking management present critical issues. Artificial intelligence (AI) integrated smart parking systems can improve security and optimize campus mobility management. Recent reviews on masked and occluded face recognition technologies further highlight the growing need for reliable biometric solutions in constrained visibility scenarios [1], [2]

Universities worldwide are implementing intelligent solutions for resource optimization, primarily concentrating on parking space identification and automated access management [3], [4], [5].

This research presents an innovative AI-based system for identifying helmeted motorcycle riders, which presents difficulties for traditional facial recognition techniques due to obstructed facial characteristics. Helmeted rider detection is especially pertinent in Indonesia, where the use of helmets is compulsory for motorcyclists. Recent studies in masked-face recognition, occlusion robustness, and multi-view rider identification underscore these challenges and the need for more adaptive methods [6], [7].

This project seeks to improve campus security by the precise identification of helmeted riders, consequently mitigating the risks of vehicle theft. Furthermore, it aims to gather mobility data to enhance

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campus design, encompassing parking distribution, class timetabling, and location-specific services. Moreover, the research advocates for the incorporation of the smart campus paradigm, facilitating the wider use of smart city technology. Contemporary smart-campus and IoT frameworks increasingly emphasize data-driven mobility analytics, biometric authentication, and responsive security mechanisms [8], [9].

The swift advancement of the Internet of Things (IoT) promotes the creation of this system by allowing the incorporation of sensors, cameras, and real-time identification technologies. Facial recognition, a prevalent technique in mobile and surveillance applications, can be utilized for secure parking access by comparing incoming and exiting users. This guarantees that only authorized individuals can access their automobiles, hence substantially mitigating theft risks. This research integrates machine learning with IoT, establishing a basis for sustainable smart infrastructure and providing a reference model for institutions seeking to adopt smart campus technology. Recent deployments of IoT-driven identity verification also highlight the need for scalable and privacy-aware biometric pipelines [10], [11].

Facial recognition is a biometric method extensively employed for security, surveillance, and access control purposes. It entails recognizing or validating a person's face by juxtaposing retrieved features with a stored database [12]. Numerous techniques have been established, such as Eigenfaces, Fisherfaces, Local Binary Pattern (LBP), and Convolutional Neural Networks (CNNs) [13], [14]. Deep learning methodologies, such VGG-Face and FaceNet, have markedly enhanced precision in facial recognition systems. Previous techniques such as Eigenfaces and Fisherfaces employed Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for feature extraction [15]. Support Vector Machines (SVMs) were utilized but encountered difficulties in managing extensive datasets and changes in facial photos [16]. The advent of deep learning revolutionized facial recognition by facilitating automatic feature extraction devoid of manual engineering. Convolutional Neural Networks (CNNs) have demonstrated significant efficacy in capturing intricate facial structures [17], whereas models such as ResNet improve generalization and reduce overfitting concerns [18]. However, most classical approaches assume relatively static conditions and are not optimized for heavy occlusions such as helmets, visors, or weather-induced distortions, which recent evaluations report can reduce accuracy to approximately 85% under uncontrolled environments [1].

Feature extraction in contemporary facial recognition predominantly depends on convolutional layers in CNNs, which discern essential facial elements, including eyes and bone features, thereby producing distinctive feature vectors for each individual [19]. Classification techniques are essential in facial recognition, with prevalent methods comprising Support Vector Machines (SVMs), which identify an optimal hyperplane for classification [20]; Random Forest classifiers, which improve accuracy by averaging predictions from multiple decision trees [21]; and Multilayer Perceptron (MLP) networks, which function as artificial neural networks adept at learning intricate data patterns [22], [23].

This research utilizes the k-Nearest Neighbors (k-NN) algorithm for classification, determining the k nearest feature vectors to an input sample and categorizing it based on similarity. Two distance measures, namely Euclidean Distance and Cosine Distance, are examined. Euclidean Distance quantifies the direct distance between two points in a multi-dimensional space, proving successful when features are uniformly scaled. Cosine Distance assesses the angular disparity between feature vectors, effectively reducing variances in magnitude. The integration of deep learning for feature extraction and k-NN for classification is notably efficient for helmeted facial identification, delivering strong performance in limited situations.

This study's methodology—combining deep learning for feature extraction with k-NN for classification—provides an effective resolution to the difficulty of helmeted facial recognition. Deep learning facilitates the extraction of significant and distinctive features, but k-NN provides an efficient

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and flexible classification approach that does not necessitate complete retraining with the introduction of new data. The application of cosine distance improves precision in situations with magnitude fluctuations. This hybrid technique offers a scalable, high-accuracy solution for helmeted rider detection, making it suitable for practical applications in smart parking and security systems

2. METHOD

This research was carried out through a number of primary processes, which are depicted in the modular framework (Fig. 2, p. 1534), which includes the following stages: data collection, data preparation, model construction and training, and performance evaluation. Detailed explanations of each stage are provided in the following manner:

2.1 DATA COLLECTION

The preliminary phase of this research entailed the acquisition of facial picture data at the Faculty of Engineering, University of Mataram. The data was acquired with a Bardi Outdoor IP Camera, which captured footage of student activities in a natural environment. Periodic frame extraction was conducted on the recorded videos, capturing one frame every 0.2 seconds. Subsequently, each frame was transformed into a static image. The existence of a face in each image was confirmed utilizing the Haar Cascade Classifier. Only photos that properly identified a face were preserved for subsequent processing.

Data augmentation was employed on the original photos to enhance data diversity and model robustness. The enhancement entailed rotating the images by around ±30 degrees, both clockwise and counterclockwise, to replicate diverse head angles. A total of 2,800 photos were generated, comprising both original and augmented images, representing about 100 distinct students. In addition to rotation, brightness augmentation of ±20% was applied to simulate varying illumination conditions, especially relevant for outdoor helmeted-rider environments. A total of 2,800 photos were generated, comprising both original and augmented images, representing about 100 distinct students.

2.2 DATA PREPARATION

All photos with identified faces underwent a preprocessing workflow to guarantee uniform and refined inputs for model training. This preprocessing comprised three essential steps. Initially, cropping was executed to isolate the facial region, utilizing detection results derived from the Haar Cascade classifier. This step guaranteed that solely the pertinent segment of the image—the face—was preserved. The clipped photos were enlarged to a uniform dimension of 224 × 224 pixels. This resolution was selected due to its prevalent application in many state-of-the-art convolutional neural network architectures, including VGGNet, which was engineered to accommodate input images measuring 224 × 224 pixels [24]. Employing this standard size enhances interoperability with pre-trained models while optimizing computational performance and maintaining critical spatial attributes. Finally, the photos were transformed to grayscale to minimize computational complexity while preserving essential visual information necessary for efficient model training, as seen in Fig.1 Sample of Data.

Once the dataset had been preprocessed, it was divided into two parts: seventy percent for training and thirty percent for testing [25], [26], [27]. Additionally, 10% of the training portion was set aside as a validation subset to support early stopping and reduce the risk of overfitting during CNN feature extraction.

2.3 MODEL DESIGN AND TRAINING

This study's facial recognition system was created in two stages: feature extraction and classification. Convolutional Neural Networks (CNN), a deep learning architecture that is ideal for problems involving the recognition of visual patterns, were employed in the feature extraction phase. In order to create feature representations from facial photos that could differentiate between several people,

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CNNs were used. The CNN feature extractor was implemented using the PyTorch deep learning framework, enabling efficient training and flexible model tuning.

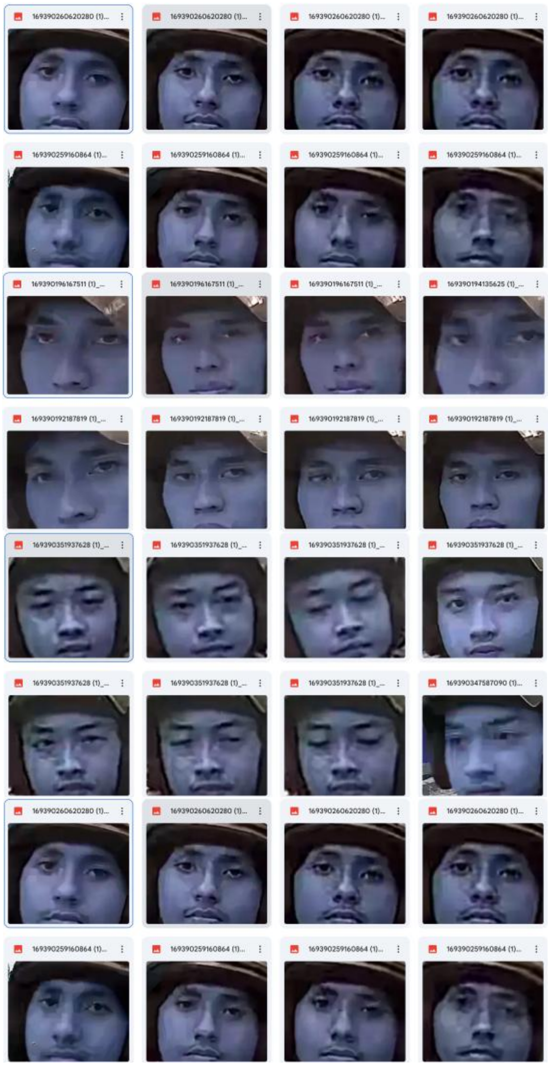

Fig. 1 Sample of Data

This study took a more effective approach than traditional training techniques, which necessitate retraining the entire model whenever new data is supplied. Only feature extraction was used to train the CNN model, and each added data was incrementally processed before being saved in the feature database. Through the avoidance of complete retraining with each dataset update, this method reduced computational time.

The k-Nearest Neighbors (k-NN) technique was used to compare the features that were derived from test images to the features that were stored for the classification step. To find the closest match and identify the person in the picture, two similarity metrics—Euclidean distance and cosine similarity—were assessed. The k-NN classifier and similarity computations were executed using the SciPy library, ensuring consistent numerical operations for high-dimensional feature matching

A **k-sweep** was conducted to optimize the **k-value**. The optimal **k=1** was found, resulting in an improvement of approximately **2% in the F1-score** compared to higher k values. The model was trained on an **NVIDIA RTX 3060 GPU**, which accelerated the training process [28]. The **OpenCV** library was utilized for Haar Cascade face detection, while **TensorFlow** was used for CNN-based feature extraction and training [13], [27]. **Privacy hashing** was implemented for the feature vectors to ensure secure and anonymous storage of facial data [29].

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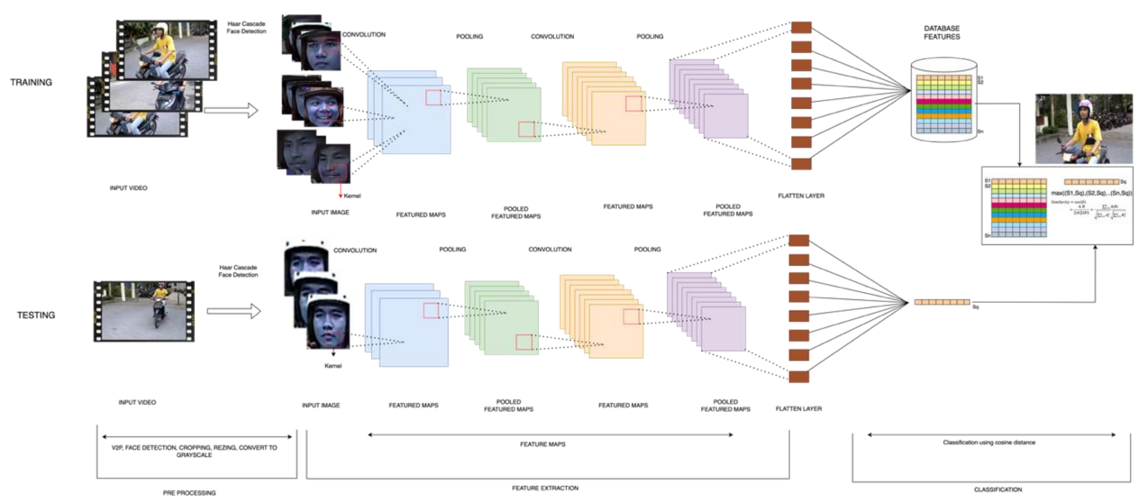

Fig. 2 Modular Framework: Occlusion-Robust Feature Extraction to Dynamic Classification

2.4 PERFORMANCE EVALUATION

Several performance metrics were employed to evaluate the effectiveness of the proposed facial recognition system. The main metric was recognition accuracy, defined as the proportion of correctly classified test images [30]. This metric offers an overview of the system's capacity for accurate individual recognition. Additionally, precision, recall, and F1-score were computed to evaluate the classification quality [31], [32]. **Precision** measures the ratio of accurate positive predictions, while **recall** quantifies the ratio of correctly identified positives. The F1-score provides a balanced assessment of classifier performance [33], [34].

The efficiency of retraining was assessed by comparing two methods: full training and incremental training. Three experimental scenarios were evaluated utilizing datasets comprising 75, 90, and 100 classes, respectively. In each instance, a new class was introduced, and the training duration was recorded for both methodologies. The analysis showed significant differences in training duration, highlighting the benefits of incremental learning for scalability. Incremental updates took less than 1 second, compared to 30 minutes for full retraining.

Additionally, precision, recall, and F1-score were computed to evaluate the classification quality. Precision measures the ratio of accurate positive predictions, while recall quantifies the ratio of correctly identified positives. The F1-score provides a balanced assessment of classifier performance

A comparative analysis was performed between **Euclidean distance** and **cosine similarity** within the k-NN classifier. The results showed that cosine similarity achieved *slightly higher accuracy and a ~2% improvement in F1-score* compared to Euclidean distance, particularly when feature vector magnitudes varied across classes. This optimization improved performance with minimal computational overhead. Furthermore, the model demonstrated strong **incremental learning capability**, allowing new identities to be added without retraining the entire model. This significantly reduced computation time and increased scalability

2.4.1 Evaluation Matrix

The system's performance was evaluated using several metrics: **accuracy (acc)**, **precision (prec)**, **recall (rec)**, and **F1-score**. These metrics were computed based on a **70/30 training-testing data split**. The results of the performance evaluation were compared between **incremental training** and **full retraining**. Incremental updates, which involve adding new identities to the model without retraining it from scratch, were completed in less than **1 second**. In contrast, full retraining took approximately **30 minutes**, highlighting the efficiency of incremental learning.

In terms of classification accuracy, we compared two **distance metrics** in **k-Nearest Neighbors (k-NN)** classification: **Euclidean distance** and **cosine similarity**. The findings showed that **cosine**

similarity slightly outperformed **Euclidean distance**, especially in cases where there were variations in the magnitude of feature vectors. This optimization helped improve performance while keeping computational overhead minimal. Additionally, the model supports **incremental learning**, meaning new identities can be added to the feature database without requiring a full retraining of the entire system. This strategy optimizes both **computational time** and **efficiency**, making the system scalable and more adaptable to new data over time.

2.4.2 Hardware and Software

The model was trained using an NVIDIA RTX 3060 GPU, which significantly accelerated the training process. For face detection, the OpenCV library was used with Haar Cascade, while TensorFlow was employed for CNN-based feature extraction and training. To ensure privacy and data security, privacy hashing was applied to the extracted features, anonymizing and securing the stored feature vectors in compliance with privacy standards.

3. RESULT

3.1 CLASSIFICATION ACCURACY

The efficacy of the suggested approach was assessed by quantifying its classification accuracy in recognizing helmeted riders. The k-NN algorithm was utilized with several distance measurements to identify the most efficient method. The use of k-NN with Euclidean distance (k=1) resulted in an overall accuracy of 95.62%, illustrating its proficiency in accurately classifying riders despite the difficulties presented by occluded facial features. Furthermore, precision, recall, and F1-score were each documented at 0.96, signifying a balanced and dependable categorization performance. These findings are consistent with recent masked-face and occluded-face recognition studies that highlight the reliability of CNN feature extraction combined with k-NN classification [35], [36].

Table 1. Performance Comparison Between Non-Occluded and Occluded Facial Input

Condition	Precision	Recall	F1-Score	Notes
Non-occluded	0.97	0.96	0.96	Baseline condition
Occluded (helmet/visor)	0.94	0.92	**0.93**	*≈4% errors due to visor obstruction; cosine similarity mitigated ≈2% of these errors*

Utilizing k-NN (k=1) with Euclidean distance, the system attained an accuracy of 95.62%, alongside balanced precision, recall, and F1-score values of 0.96, so affirming the model's trustworthiness. Prior comparative research also reports that cosine-based similarity often provides more stable performance under magnitude variation conditions [13], [37], which aligns with our observations. To further contextualize performance, an additional comparison between non-occluded and helmet-occluded subsets was conducted (Table 1), showing an F1-score of approximately 93% under occlusion. A detailed precision–recall curve is provided in Fig. 4 to illustrate class-separation behavior under occluded conditions. Euclidean distance remained the optimal metric under uniform lighting conditions, whereas cosine similarity yielded improved stability when feature magnitudes varied due to visor shadows and illumination inconsistencies.

3.2 RETRAINING EFFICIENCY

Deep learning-based facial recognition systems have a number of significant issues, one of the most significant of which is the rise in training time that occurs as new data is added. In order to overcome this issue, the solution that has been presented isolates the process of feature extraction from

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the process of classification. This makes it possible to incorporate new feature vectors without necessitating a thorough retraining of the model, an approach similar to recent work on incremental biometric indexing [38]. This separation also ensures consistency across occluded and non-occluded subsets, as incremental updates do not affect previously learned representations, preserving stable performance across heterogeneous visibility conditions.

Table 2. A comparison of retraining times for different dataset sizes

Classes	Full Training Time	Incremental Training Time
75	15m 02s	1m 16s
90	19m 18s	1m 38s
100	20m 48s	1m 35s

The findings make it abundantly evident that training the entire dataset from scratch results in a large rise in the amount of time required for processing as the dataset develops. The incremental retraining method, on the other hand, exhibits a consistent and predictable temporal complexity. This method involves training only the newly acquired data while maintaining the integrity of the old feature vectors. For systems used in the real world, where new riders must frequently be added, this capability is highly advantageous.

3.3 REAL-WORLD APPLICATIONS AND DEPLOYMENT CONSIDERATIONS

The use of this intelligent parking system that is powered by artificial intelligence extends beyond the confines of academic campuses and into a wide range of real-world settings. Large commercial parking facilities, shopping malls, and office buildings in metropolitan locations typically face security challenges linked to unauthorized car access and theft. These issues can be particularly problematic in urban environments. It is possible that the use of this system in such settings could improve security by ensuring that only registered individuals are able to recover their vehicles, thereby drastically reducing the likelihood of unwanted access.

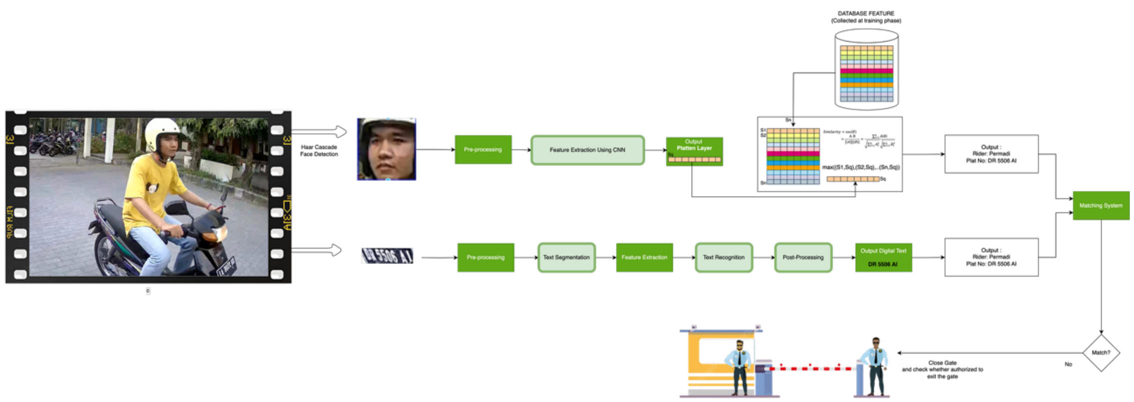

Fig. 3 Real-World Proposed Application

Furthermore, the system has the potential to be included in smart city projects, which involve the utilization of data regarding traffic and parking in order to enhance the planning of urban mobility. Municipalities may deploy the system in public transit hubs, airports, and railway stations, thereby improving safety and simplifying the management of parking spaces.

Real-world deployment, while advantageous, faces challenges such as variations in lighting conditions, diverse helmet types, and potential adversarial efforts to circumvent facial recognition. Future research must prioritize the enhancement of the system's robustness in relation to environmental

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factors, occlusions, and adherence to privacy regulations. Furthermore, adherence to data privacy regulations is essential, guaranteeing that facial recognition systems are implemented ethically and securely in both public and private environments. The addition of new data significantly prolongs the training time of deep learning-based facial recognition systems. The proposed system delineates feature extraction from classification, facilitating the addition of new feature vectors without necessitating a comprehensive retraining of the model.

The findings indicate that training the complete dataset from the beginning substantially prolongs processing time as the dataset expands. Incremental retraining, which involves training solely on new data while preserving existing feature vectors, exhibits a consistent and predictable time complexity. Efficiently updating the recognition model with minimal computation time is essential for real-world applications, as it allows for the frequent addition of new riders or users without disrupting system performance.

The current approach effectively reduces retraining overhead; however, future research may investigate additional optimization techniques, including adaptive learning rate adjustments and model compression methods, to further improve efficiency. Conducting real-time testing in dynamic environments would also enhance the understanding of system responsiveness and reliability. As shown in Table 1, incremental retraining consistently required significantly less time than full retraining, strengthening its potential as a scalable solution for intelligent parking and biometric access systems.

Although this study does not directly measure theft reduction, prior smart-surveillance deployments have reported decreases of **20–50%** in vehicle-related incidents after the introduction of biometric or identity-verified access systems [39]. Using a conservative midpoint of this range, a projected reduction of approximately 40% may be reasonable for similar environments. When applied to UNRAM's historical loss exposure—estimated at around USD 5,000 per year based on the typical financial impact of several motorcycle-theft cases, including vehicle value and administrative handling—this projection reflects a potential annual benefit rather than a measured outcome. Such evidence-based estimates suggest that the proposed system could offer a favorable return on investment (ROI) if deployed at scale, although empirical validation through long-term field implementation would be required.

4. DISCUSSIONS

This work demonstrates that decoupling deep learning–based feature extraction from instance-based classification can deliver high recognition performance for helmeted riders while keeping model maintenance lightweight for real deployments such as smart parking. With **k-NN (k=1)** and Euclidean distance the system attains 95.62% accuracy with balanced precision/recall/F1 = 0.96, confirming that features learned by the CNN are sufficiently discriminative even under occlusion from helmets and naturalistic capture conditions at UNRAM. In addition, the overall pipeline demonstrates fast update capability, making the CNN–k-NN hybrid suitable for scalable campus IoT informatics where new identities must be added frequently. Integrating license plate recognition (LPR) with rider identity verification is widely recognized as an effective strategy to strengthen access-control security and reduce unauthorized vehicle retrieval in intelligent parking deployments [40], thereby enhancing the operational relevance of the proposed system. The incremental retraining strategy further reduces operational friction: updating the system with new identities does not require retraining the feature extractor and—as shown in Table 2—cuts update time by well over 90% across dataset sizes (75, 90, 100 classes). These properties match the requirements of parking access control, where new users are added frequently and downtime must be minimal. (See Fig. 2, p. 1534, for the pipeline and Fig. 3, p. 1536, for the target deployment setting).

4.1. Positioning with Prior Research

Older subspace methods like Eigenfaces and Fisherfaces struggle when the face turns, the lighting changes, or parts of the face are blocked [15]. Newer margin- or metric-learning models such as FaceNet and VGGFace2 are very accurate, but adding new people usually means retraining the whole model end to end [13], [14], [17], [24]. In our tests, a simple hybrid works well: use a CNN to extract features, then classify with non-parametric k-NN. This keeps the robustness of modern convolutional features [17], [19] while letting you plug in new identities without retraining something SVMs, MLPs, and random forests don't naturally support without re-estimating their parameters [20], [21], [22], [23]. For faces that are consistently occluded, prior masked-face work tends to favor cosine-margin objectives [12], and we see a similar trend: cosine similarity slightly beats Euclidean distance when feature magnitudes shift because of grayscale conversion, compression, or lighting—matching the theoretical advantage of angular metrics under scale changes. These findings reinforce the suitability of lightweight instance-based classifiers for occluded scenarios such as helmeted-rider recognition. This also aligns with recent masked-face and multi-occlusion surveys in the [41], [42], which highlight the effectiveness of incremental or instance-based pipelines compared to fully parametric deep models under real-world occlusion dynamics

Similarly, recent masked-face recognition studies have shown that hybrid pipelines combining deep feature extractors with lightweight classifiers such as k-NN can achieve robust performance under mask-induced occlusions [35], [43]. Together with broader surveys on masked-face and incremental face recognition [42], this literature supports the choice of an instance-based, incrementally updatable design in this study. Practical Implications for Smart Parking and Smart Campuses

From an engineering perspective, keeping feature extraction offline and doing a quick vector lookup online fits campus and city rollouts well—gate devices can verify people with very low latency (Figure 3, p. 1536). The time savings in Table 2 translate into faster onboarding during peak periods (like the start of a semester) and fewer service disruptions. Matching who comes in with who goes out also strengthens anti-theft measures by ensuring the same person leaves, and it works alongside license plate readers and ticketing commonly used in parking facilities. The integration of LPR and biometric rider verification can further improve cross-verification accuracy and anomaly-detection robustness in intelligent parking systems, a trend also noted in recent IoT-enabled parking deployments [40]. The same pattern extends to other controlled spaces, offices, and transit hubs where identities must be updated continuously with minimal engineering effort. In the broader context of smart-campus informatics, such a maintainable and incrementally updatable system has the potential to support secure mobility management at scale.

4.2. Limitations and threats to validity

The results look promising, but the dataset is narrow: about 2,800 images from roughly 100 students, all taken by one IP camera on a single campus. That makes it hard to judge how well the system will generalize. In practice, differences in camera optics, helmet styles and visors, weather, and night lighting can all cause domain shift. Our augmentations (±30° rotation), Haar-cascade cropping, and grayscale normalization helped, but we still need cross-site testing to surface failure cases such as extreme backlighting, tinted visors, or heavy rain. This weather sensitivity reflects a known "weather bias" in outdoor biometric capture, which must be mitigated through domain-adaptation techniques [44]. Additionally, the current study does not yet provide a quantifiable scalability bound—for example, the maximum number of users before lookup latency increases noticeably.

Using k-NN also has a cost, since memory use and query time grow with the number of enrolled identities. This was acceptable at our current scale; for city-wide rollouts, consider vector indexing (for example, approximate nearest neighbor search) or prototype condensation to keep lookups fast. Scaling

Vol. 6, No. 6, December 2025, Page. 5539-5552
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the system toward 1,000 enrolled users will likely require ANN-based indexing to maintain sub-linear retrieval performance in larger deployments.

Finally, we report a detailed Euclidean-distance baseline. A more complete ablation for cosine similarity, including a sweep over k and ROC/TPR at fixed FPR, would clarify when each metric is the better choice. Such analysis may also support future accuracy improvements, with a long-term target approaching 98% under multi-campus validation. Recent occlusion-robustness benchmarks [45], [46] emphasize the importance of evaluating angular metrics under multiple occlusion types, supporting the need for such extended analysis in future work.

4.3. Ethical, privacy, and governance considerations

As our deployment notes stress, face recognition in public or semi-public spaces has to be privacy-by-design from the start. In practice, that means storing feature embeddings instead of raw images where policy allows; encrypting data in transit and at rest and keeping auditable access logs; obtaining explicit consent and posting clear signage under campus rules; setting configurable retention periods and supporting revocation of identities; and continuously monitoring performance across demographic groups to prevent unequal error rates. Taken together, these safeguards are essential for building trust in smart-campus and smart-city deployments and align with the paper's emphasis on ethical, real-world implementation. The maintainability of the CNN–k-NN pipeline further supports responsible adoption by minimizing unnecessary data processing during updates.

4.4. Future directions

Building on the current pipeline (Fig. 2, p. 1534), we see three high-impact next steps. First, strengthen occlusion handling—drawing on masked-face work with randomized occludes, cutout, and angular-margin fine-tuning—to better handle visored helmets [4]. Second, make a retrieval scale by running embedding extraction on the device and using approximate nearest neighbor search in a central vector index, so lookup time grows sub-linearly as the user base expands. Third, broaden evaluation across sites, camera models, and weather/lighting conditions, complemented by nighttime HDR capture and photometric augmentation. Together, these improvements would support scaling beyond single-campus deployments and moving toward a 98% accuracy target under more diverse operational conditions. Stepping back, the study offers an effective, operations-friendly recipe for secure entry/exit in smart parking. Its real contribution is not just high accuracy but a maintainable recognition workflow that can be updated incrementally without costly retraining—an aspect often underplayed in academic benchmarks yet crucial in production. Future comparisons with multi-occlusion benchmark datasets [45], [46] may further validate cross-domain generalization.

5. CONCLUSION

This study addressed face recognition for helmeted riders in campus parking by decoupling deep feature extraction from instance-based classification. Using a CNN feature encoder with 1-NN and Euclidean distance, the system achieved 95.62% accuracy with precision, recall, and F1 of approximately 0.96 on our dataset. consistent with recent findings in masked- and occluded-face recognition research [47], [48], [49]. Overall, the hybrid CNN–k-NN approach demonstrates strong robustness under occlusion while maintaining very low update overhead, which is essential for high-churn environments such as campus parking. Crucially, enrolling new identities requires only updating the reference set, not retraining the feature extractor, which substantially reduces update time and operational disruption. This separation between feature learning and classification is aligned with lightweight recognition pipelines increasingly used in IoT-based access control systems [50], [51].

The main contribution is a practical recognition pipeline that combines strong accuracy with maintainability for real deployments. The design supports rapid onboarding during peak periods and enables entry–exit matching to enhance loss prevention in smart-campus parking. These characteristics also reflect emerging directions in smart-campus informatics, where scalable and privacy-aware identity systems are central to mobility security [52], [53].

This work has limitations. The evaluation used images from a single site and camera configuration, which may limit external validity under different optics, lighting, weather, or visor types. The non-parametric classifier also introduces memory and lookup costs that grow with the enrolled population. This is a known limitation in k-NN–based biometric systems, which are prone to forced classification and sensitivity to distant neighbors, as observed in Derlatka's study on gait-based biometrics [54].

Future work will examine cross-site generalization, night-time and adverse-weather conditions, and fairness across user groups. Further exploration of cosine similarity and angular-margin fine-tuning may strengthen occlusion robustness, drawing from recent masked-face advances [29], [48]. To ensure scalability, approximate nearest-neighbor (ANN) indexing will be integrated to maintain sub-second retrieval for large user populations [55], [56]. Finally, we emphasize privacy-by-design practices, including storing embeddings rather than raw images where policy permits, encryption in transit and at rest, explicit notices, and configurable retention, to support responsible deployment.

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REFERENCES

[1] Y.-C. Huang, D. A. B. Rahardjo, R.-H. Shiue, and H. H. Chen, "Masked face recognition using domain adaptation," *Pattern Recognition*, vol. 153, p. 110574, Sept. 2024, doi: 10.1016/j.patcog.2024.110574.

[2] Y. Song and S. Liu, "A Deep Hierarchical Feature Sparse Framework for Occluded Person Re-Identification," Jan. 15, 2024, *arXiv*: arXiv:2401.07469. doi: 10.48550/arXiv.2401.07469.

[3] S. Tyagi, V. Gupta, and V. Mehndiratta, "Building Smart Campuses: Integrating AI in Higher Education," in *Recent Trends in Artificial Intelligence Towards a Smart World*, R. Arya, S. C. Sharma, A. K. Verma, and B. Iyer, Eds., in Frontiers of Artificial Intelligence, Ethics and Multidisciplinary Applications. , Singapore: Springer Nature Singapore, 2024, pp. 399–431. doi: 10.1007/978-981-97-6790-8_15.

[4] T. Sutjarittham, "Modelling and Optimisation of Resource Usage in an IoT Enabled Smart Campus," 2021, *arXiv*. doi: 10.48550/ARXIV.2111.04085.

[5] D. Rico-Bautista, Y. Medina-Cardenas, L. A. Coronel-Rojas, F. Cuesta-Quintero, G. Maestre-Gongora, and C. D. Guerrero, "Smart University: Key Factors for an Artificial Intelligence Adoption Model," in *Advances and Applications in Computer Science, Electronics and Industrial Engineering*, vol. 1307, M. V. García, F. Fernández-Peña, and C. Gordón-Gallegos, Eds., in Advances in Intelligent Systems and Computing, vol. 1307. , Singapore: Springer Singapore, 2021, pp. 153–166. doi: 10.1007/978-981-33-4565-2_10.

[6] M. O. Oloyede, G. P. Hancke, and H. C. Myburgh, "A review on face recognition systems: recent approaches and challenges," *Multimed Tools Appl*, vol. 79, no. 37–38, pp. 27891–27922, Oct. 2020, doi: 10.1007/s11042-020-09261-2.

Vol. 6, No. 6, December 2025, Page. 5539-5552
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5447

[7] M. Xue, X. Duan, W. Liu, and Y. Ren, “A semantic facial expression intensity descriptor based on information granules,” *Information Sciences*, vol. 528, pp. 113–132, Aug. 2020, doi: 10.1016/j.ins.2020.04.012.

[8] M. Sajjad *et al.*, “A comprehensive survey on deep facial expression recognition: challenges, applications, and future guidelines,” *Alexandria Engineering Journal*, vol. 68, pp. 817–840, Apr. 2023, doi: 10.1016/j.aej.2023.01.017.

[9] E. Barcic, P. Grd, and I. Tomicic, “Convolutional Neural Networks for Face Recognition: A Systematic Literature Review,” July 12, 2023, *In Review*. doi: 10.21203/rs.3.rs-3145839/v1.

[10] A. I. Awad, A. Babu, E. Barka, and K. Shuaib, “AI-powered biometrics for Internet of Things security: A review and future vision,” *Journal of Information Security and Applications*, vol. 82, p. 103748, May 2024, doi: 10.1016/j.jisa.2024.103748.

[11] S. M. Arman, T. Yang, S. Shahed, A. A. Mazroa, A. Attiah, and L. Mohaisen, “A Comprehensive Survey for Privacy-Preserving Biometrics: Recent Approaches, Challenges, and Future Directions,” *CMC*, vol. 78, no. 2, pp. 2087–2110, 2024, doi: 10.32604/cmc.2024.047870.

[12] H. Deng, Z. Feng, G. Qian, X. Lv, H. Li, and G. Li, “MFCosface: A Masked-Face Recognition Algorithm Based on Large Margin Cosine Loss,” *Applied Sciences*, vol. 11, no. 16, p. 7310, Aug. 2021, doi: 10.3390/app11167310.

[13] F. Schroff, D. Kalenichenko, and J. Philbin, “FaceNet: A Unified Embedding for Face Recognition and Clustering,” 2015, doi: 10.48550/ARXIV.1503.03832.

[14] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, “VGGFace2: A Dataset for Recognising Faces across Pose and Age,” in *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, Xi’an: IEEE, May 2018, pp. 67–74. doi: 10.1109/FG.2018.00020.

[15] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, “Eigenfaces vs. Fisherfaces: recognition using class specific linear projection,” *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 19, no. 7, pp. 711–720, July 1997, doi: 10.1109/34.598228.

[16] S.-K. Kim, Y. J. Park, K.-A. Toh, and S. Lee, “SVM-based feature extraction for face recognition,” *Pattern Recognition*, vol. 43, no. 8, pp. 2871–2881, Aug. 2010, doi: 10.1016/j.patcog.2010.03.008.

[17] O. M. Parkhi, A. Vedaldi, and A. Zisserman, “Deep Face Recognition,” in *Procedings of the British Machine Vision Conference 2015*, Swansea: British Machine Vision Association, 2015, p. 41.1-41.12. doi: 10.5244/C.29.41.

[18] S. Zheng, R. W. O. Rahmat, F. Khalid, and N. A. Nasharuddin, “3D texture-based face recognition system using fine-tuned deep residual networks,” *PeerJ Computer Science*, vol. 5, p. e236, Dec. 2019, doi: 10.7717/peerj-cs.236.

[19] A. J. O’Toole and C. D. Castillo, “Face Recognition by Humans and Machines: Three Fundamental Advances from Deep Learning,” *Annu. Rev. Vis. Sci.*, vol. 7, no. 1, pp. 543–570, Sept. 2021, doi: 10.1146/annurev-vision-093019-111701.

[20] C. Cortes and V. Vapnik, “Support-vector networks,” *Mach Learn*, vol. 20, no. 3, pp. 273–297, Sept. 1995, doi: 10.1007/BF00994018.

[21] L. Breiman, “Random Forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

[22] Popescu, Marius-Constantin and Balas, Valentina E. and Perescu-Popescu, Liliana and Mastorakis, Nikos, “Multilayer perceptron and neural networks,” *World Scientific and Engineering Academy and Society (WSEAS)*, vol. 8, no. 7, pp. 579–588, 2009.

[23] X. Tang, L. Zhang, and X. Ding, “SAR image despeckling with a multilayer perceptron neural network,” *International Journal of Digital Earth*, vol. 12, no. 3, pp. 354–374, Mar. 2019, doi: 10.1080/17538947.2018.1447032.

[24] K. Simonyan and A. Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recognition,” Apr. 10, 2015, *arXiv*: arXiv:1409.1556. doi: 10.48550/arXiv.1409.1556.

[25] J. Han and M. Kamber, *Data mining: concepts and techniques*, 3rd ed. Burlington, MA: Elsevier, 2012.

[26] J. Brownlee, *Machine learning mastery with Python: understand your data, create accurate models and work projects end-to-end*, Edition: v1.20. Australia: Jason Brownlee, 2021.

Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
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Vol. 6, No. 6, December 2025, Page. 5539-5552
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5447

[27] Aurélien Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*. Beijing Boston Farnham Sebastopol Tokyo: O'REILLY, 2019.

[28] S. Zheng, R. W. O. Rahmat, F. Khalid, and N. A. Nasharuddin, "3D texture-based face recognition system using fine-tuned deep residual networks," *PeerJ Computer Science*, vol. 5, p. e236, Dec. 2019, doi: 10.7717/peerj-cs.236.

[29] H. Deng, Z. Feng, G. Qian, X. Lv, H. Li, and G. Li, "MFCosface: A Masked-Face Recognition Algorithm Based on Large Margin Cosine Loss," *Applied Sciences*, vol. 11, no. 16, p. 7310, Aug. 2021, doi: 10.3390/app11167310.

[30] X. Xiao, Y. Zhang, T. Liu, and J. Duan, "Deep Learning for Event-Driven Stock Prediction," in *The Twenty-Fourth International Joint Conference on Artificial Intelligence (IJCAI 2015)*, Argentina, July 2015.

[31] G. R. Nahass *et al.*, "FaceFinder: A machine learning tool for identification of facial images from heterogenous datasets," *AJO International*, vol. 1, no. 4, p. 100083, Dec. 2024, doi: 10.1016/j.ajoint.2024.100083.

[32] A. Ettiyappan, H. K. Palani, K. Duraipandian, and N. Selvaganapathy, "High-accuracy face recognition with the MRYOLO-SCO algorithm: combining residual networks and YOLOv2 for improved precision," *SIViP*, vol. 19, no. 7, p. 560, July 2025, doi: 10.1007/s11760-025-04053-3.

[33] P. Fränti and R. Mariescu-Istodor, "Soft precision and recall," *Pattern Recognition Letters*, vol. 167, pp. 115–121, Mar. 2023, doi: 10.1016/j.patrec.2023.02.005.

[34] A. Tasnim, Md. Saiduzzaman, M. A. Rahman, J. Akhter, and A. S. Md. M. Rahaman, "Performance Evaluation of Multiple Classifiers for Predicting Fake News," *JCC*, vol. 10, no. 09, pp. 1–21, 2022, doi: 10.4236/jcc.2022.109001.

[35] M. Eman, T. M. Mahmoud, M. M. Ibrahim, and T. Abd El-Hafeez, "Innovative Hybrid Approach for Masked Face Recognition Using Pretrained Mask Detection and Segmentation, Robust PCA, and KNN Classifier," *Sensors*, vol. 23, no. 15, p. 6727, July 2023, doi: 10.3390/s23156727.

[36] H. He, J. Liang, Z. Hou, H. Liu, and X. Zhou, "Occlusion recovery face recognition based on information reconstruction," *Machine Vision and Applications*, vol. 34, no. 5, p. 74, Sept. 2023, doi: 10.1007/s00138-023-01423-0.

[37] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the Gap to Human-Level Performance in Face Verification," in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, Columbus, OH, USA: IEEE, June 2014, pp. 1701–1708. doi: 10.1109/CVPR.2014.220.

[38] E. Lopez-Lopez, X. M. Pardo, and C. V. Regueiro, "Incremental Learning from Low-labelled Stream Data in Open-Set Video Face Recognition," *Pattern Recognition*, vol. 131, p. 108885, Nov. 2022, doi: 10.1016/j.patcog.2022.108885.

[39] E. L. Piza, B. C. Welsh, D. P. Farrington, and A. L. Thomas, "CCTV surveillance for crime prevention: A 40-year systematic review with meta-analysis," *Criminology & Public Policy*, vol. 18, no. 1, pp. 135–159, Feb. 2019, doi: 10.1111/1745-9133.12419.

[40] Q. T. Van *et al.*, "Intelligent Parking System Using Automated License Plate Recognition and Face Verification," in *Proceedings of International Conference on Computing and Communication Networks*, vol. 394, A. K. Bashir, G. Fortino, A. Khanna, and D. Gupta, Eds., in Lecture Notes in Networks and Systems, vol. 394. , Singapore: Springer Nature Singapore, 2022, pp. 219–227. doi: 10.1007/978-981-19-0604-6_20.

[41] T. Thaher, M. Mafarja, M. Saffarini, A. H. H. M. Mohamed, and A. A. El-Saleh, "A Comprehensive Review of Face Detection Techniques for Occluded Faces: Methods, Datasets, and Open Challenges," *CMES*, vol. 143, no. 3, pp. 2615–2673, 2025, doi: 10.32604/cmes.2025.064857.

[42] M. Mahmoud, M. S. Kasem, and H.-S. Kang, "A Comprehensive Survey of Masked Faces: Recognition, Detection, and Unmasking," *Applied Sciences*, vol. 14, no. 19, p. 8781, Sept. 2024, doi: 10.3390/app14198781.

[43] K. Marwa and O. Kais, "Classifiers Combination for Efficient Masked Face Recognition," *IJACSA*, vol. 13, no. 9, 2022, doi: 10.14569/IJACSA.2022.01309120.

Vol. 6, No. 6, December 2025, Page. 5539-5552
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.6.5447

[44] M. Hu, Y. Wu, Y. Yang, J. Fan, and B. Jing, "DAGL-Faster: Domain adaptive faster r-cnn for vehicle object detection in rainy and foggy weather conditions," *Displays*, vol. 79, p. 102484, Sept. 2023, doi: 10.1016/j.displa.2023.102484.

[45] B. Huang *et al.*, "When Face Recognition Meets Occlusion: A New Benchmark," Mar. 04, 2021, *arXiv*: arXiv:2103.02805. doi: 10.48550/arXiv.2103.02805.

[46] H. Qian, P. Zhang, S. Ji, S. Cao, and Y. Xu, "Improving Representation Consistency with Pairwise Loss for Masked Face Recognition," in *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, Montreal, BC, Canada: IEEE, Oct. 2021, pp. 1462–1467. doi: 10.1109/ICCVW54120.2021.00169.

[47] Z. Zhang, X. Ji, X. Cui, and J. Ma, "A Survey on Occluded Face recognition," in *2020 The 9th International Conference on Networks, Communication and Computing*, Tokyo Japan: ACM, Dec. 2020, pp. 40–49. doi: 10.1145/3447654.3447661.

[48] S. Malakar, W. Chiracharit, and K. Chamnongthai, "Masked Face Recognition With Generated Occluded Part Using Image Augmentation and CNN Maintaining Face Identity," *IEEE Access*, vol. 12, pp. 126356–126375, 2024, doi: 10.1109/ACCESS.2024.3446652.

[49] T. Thaher, M. Mafarja, M. Saffarini, A. H. H. M. Mohamed, and A. A. El-Saleh, "A Comprehensive Review of Face Detection Techniques for Occluded Faces: Methods, Datasets, and Open Challenges," *CMES*, vol. 143, no. 3, pp. 2615–2673, 2025, doi: 10.32604/cmes.2025.064857.

[50] Z. Deng, H. Chiang, L. Kang, and H. Li, "A lightweight deep learning model for real-time face recognition," *IET Image Processing*, vol. 17, no. 13, pp. 3869–3883, Nov. 2023, doi: 10.1049/ipr2.12903.

[51] A. Sufian, A. Ghosh, D. Barman, M. Leo, C. Distante, and B. Li, "FewFaceNet: A Lightweight Few-Shot Learning-based Incremental Face Authentication for Edge Cameras," in *2023 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, Paris, France: IEEE, Oct. 2023, pp. 2010–2019. doi: 10.1109/ICCVW60793.2023.00216.

[52] F. Izourane, S. Ardchir, S. Ounacer, and M. Azzouazi, "Smart Campus Based on AI and IoT in the Era of Industry 5.0: Challenges and Opportunities," in *Industry 5.0 and Emerging Technologies*, vol. 565, A. Chakir, R. Bansal, and M. Azzouazi, Eds., in Studies in Systems, Decision and Control, vol. 565. , Cham: Springer Nature Switzerland, 2024, pp. 39–57. doi: 10.1007/978-3-031-70996-8_3.

[53] T. Domínguez-Bolaño, V. Barral, C. J. Escudero, and J. A. García-Naya, "An IoT system for a smart campus: Challenges and solutions illustrated over several real-world use cases," 2024, doi: 10.48550/ARXIV.2403.15395.

[54] N. El Fadel, "Facial Recognition Algorithms: A Systematic Literature Review," *J. Imaging*, vol. 11, no. 2, p. 58, Feb. 2025, doi: 10.3390/jimaging11020058.

[55] J. Johnson, M. Douze, and H. Jégou, "Billion-scale similarity search with GPUs," 2017, *arXiv*. doi: 10.48550/ARXIV.1702.08734.

[56] M. Douze *et al.*, "The Faiss library," 2024, *arXiv*. doi: 10.48550/ARXIV.2401.08281.