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Accuracy Comparison of Support Vector Machine and K-Nearest Neighbors in Face Recognition for Library User Identification

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Abstract - Traditional library book lending systems that rely on membership cards or personal IDs are prone to misuse due to human error. To address this, this study developed a web-based book lending application using face recognition enabling automatic user verification without physical cards, improving security, and reducing human errors. In this research 10 university students took roles as the application's users. The goal is that the application is able to identify every library user who is going to borrow or return books based on their real time face image. The face recognition itself has been developed using dlib's face detection, cropping, and feature extraction functions and Support Vector Machine (SVM) classification model. The K-Nearest Neighbors (KNN) model was also tested to for classification accuracy comparison. Model validation tests show that the dlib works well in detecting face location within an image, cropping the face area, and extracting face features while the two classification models are able to well classify student IDs too. The SVM model results in 91% accuracy, 90% precision, 91% recall, and 91% F1-score, which is however slightly better than KNN's 89% accuracy, 89% precision, 88% recall and 88% F1-score. The SVM has been then chosen for the application. Following the completion of application development, a system test has been conducted with black box method and returns with system accuracy of 90%. This finding confirms that implementing dlib and an SVM model for user identification for an application can be a promising method.

Keywords: Machine Learning, Digital Library, Face Recognition, dlib, SVM

1. Introduction

Libraries play a crucial role in disseminating information and knowledge to the public. However, many libraries still rely on physical ID cards to manage book borrowing, which are vulnerable to misuse and errors in recording member data (Santoso, Sediyono, Hartomo, & Sembiring, 2025). This traditional method can also cause long queues, as identity verification is performed manually by staff, resulting in slower services and reduced user convenience (Sinaga, Valencia, Lubis, Yuanda, Devyanti, Rudiansah, Purnama, & Indara, 2024).

To address these challenges, facial recognition technology has emerged as a promising solution. This biometric method can identify individuals based on unique facial features without requiring physical cards, enabling faster and more automated authentication (Mardedi, Zulfikri, Syahrir, Latif, & Apriani, 2025). Support Vector Machine (SVM) algorithms have proven effective in distinguishing facial patterns from extracted image features, without the need for overly complex models (Fredicia, Buono, & Giri, 2016).

Previous studies indicate that SVM can accurately classify user identities by maximizing the distance between classes in the feature space, allowing reliable recognition of individuals (Handul, Matulessy, & Kaesmetan, 2024). SVM has also been applied to facial image processing for recognizing both identity and expressions, demonstrating its suitability for machine learning-based authentication systems (Athoillah, 2017). Furthermore, combining facial features with SVM has been applied to 3D face recognition, highlighting the algorithm's flexibility across different facial representations (De Lima, Novamizanti, & Susatio, 2019).

At the same time, implementing facial recognition in public services such as libraries requires careful attention to user privacy. Facial data is sensitive personal information that must be protected according to data protection regulations (Sembiring, Ramli, & Rafianti, 2024). Legal studies emphasize that using biometric data without adequate safeguards risks violating individual privacy, making privacy-aware system design essential from the outset (Sun & Liu, 2025).

By adopting machine learning-based facial recognition, library member identification can be performed automatically and in real-time, which can speed up borrowing processes and reduce queues (Ubaidillah & Bhakti, 2024). Other studies show that using texture-based features with SVM can achieve high recognition accuracy, even under varying lighting or background conditions, making it highly relevant for library applications (Bhakti, Riski, & Kamsyakawuni, 2023).

In summary, integrating SVM algorithms into a facial recognition-based book borrowing system can enhance security, improve identification accuracy, and provide a more convenient experience for users. Such a system enables faster, more efficient, and reliable library services (Fajri, Arnia, & Munadi, 2022).

In summary, applying SVM in a facial recognition–based book borrowing system can enhance security, identification accuracy, and user convenience, enabling faster and more efficient library services (Fajri, Arnia, & Munadi, 2022).

Based on this background, the present study aims to enhance the performance of library book lending systems through face recognition technology using machine learning methods. By leveraging face detection and classification models, the system can identify borrowers without requiring a physical membership card. The system then validates membership by matching the user's identity with the library database. The verification process is designed to operate in real time, enabling the system to record borrowing and return transactions quickly, thereby supporting more efficient library service management.

2. Research Methods

As shown in Figure 1, the research framework is organized according to a structured and interconnected workflow. Each stage is designed to ensure that processes—from data collection and face image preprocessing to model training, model validation, and system implementation—are carried out systematically, measurably, and in line with the research objectives. A detailed explanation of each stage in the research methodology is presented below.

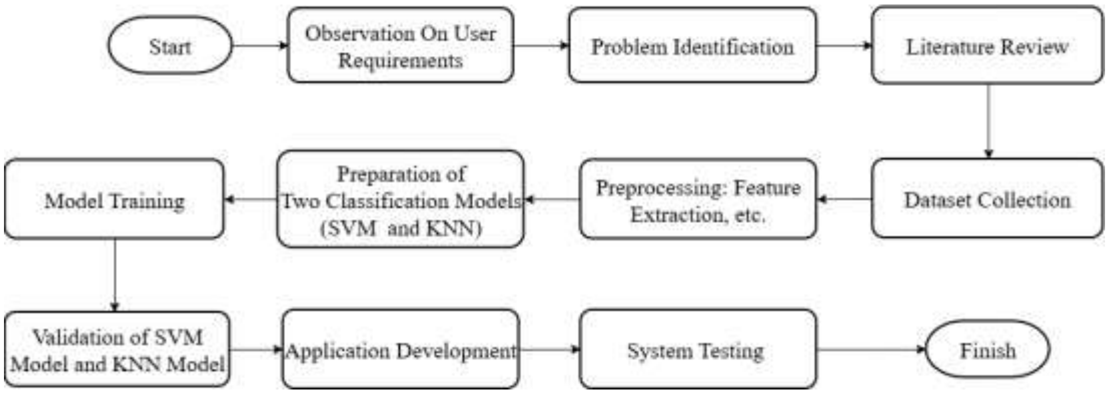

Figure1. Research Framework

1) Observation On User Requirements

The study began with a needs analysis for a book lending system incorporating face recognition. Observations were conducted in the library to examine the existing lending process, which still relies on membership cards without additional verification by staff. This practice can lead to misidentification and misuse of membership cards, such as unauthorized use. Given these conditions, a more reliable and practical authentication mechanism is needed to directly verify borrowers' identities. Implementing face recognition is expected to enhance service security and support a digitally documented lending process that is easier to monitor.

2) Problem Identification

This stage focuses on identifying the technical problem to be addressed by the study. The main issue is determining the most effective face recognition method for a book lending application based on face authentication. Accordingly, the researcher selected two classification models—Support Vector Machine (SVM) and k-Nearest Neighbors (KNN)—to compare their performance. Choosing the appropriate model is expected to provide accurate face recognition results even under varying conditions, such as changes in lighting, face expressions, and camera angles.

3) Literature Review

The literature review stage involves examining studies related to the SVM and KNN models in face recognition. The researcher reviewed scientific journals, theses, and other technical sources. Activities included understanding the operating principles of both models, how they perform face classification, factors affecting their accuracy, their advantages and limitations in real-world scenarios, and usage recommendations from previous studies.

4) Dataset Collection

The dataset was collected directly during user registration through the library application, reflecting real operational conditions. Each user was asked to capture a face photo using a laptop camera and confirm that their face was properly positioned within the detection area. Once aligned, the image was saved and later processed during the preprocessing stage to create the dataset. The face data is stored on Google Drive and accompanied by a statement from the researcher confirming that personal and face information will not be shared. The data is used solely for research purposes and is kept confidential in accordance with the study's objectives.

5) Preprocessing

Preprocessing was conducted using the dlib library to ensure image quality and consistency before classification. The process includes face detection using dlib.get_frontal_face_detector(), which is based on HOG and a Linear SVM. Automatic face cropping and alignment were performed using a 68-point facial landmark model (shape_predictor_68_face_landmarks.dat). Feature extraction was then carried out using the dlib Face Recognition ResNet model (dlib_face_recognition_resnet_model_v1.dat), producing a 128-dimensional facial embedding for each image. These embeddings serve as the primary numerical representation for classification.

6) Preparation of Two Classification Models

At this stage, two classification models, SVM and KNN, were prepared to evaluate their performance in a face recognition system (Murdani et al., 2024). SVM is widely used in face recognition because it constructs an optimal decision boundary from facial features, which improves identification accuracy and system reliability (Pratama & Ningrum, 2025). Compared to KNN, SVM provides more stable class separation when handling variations in lighting and facial orientation (Yakub et al., 2025). The advantage of SVM becomes more evident when applied to high-dimensional facial embeddings, as it maximizes inter-class margins more effectively (Hartono et al., 2025). In contrast, KNN relies on distance-based similarity, making its performance more sensitive to data distribution and sample variation (Feta, 2023). For multi-class face recognition tasks, SVM generally produces lower misidentification rates due to its robust class separation capability (Ramadhani et al., 2024). In this study, the SVM model employed a linear kernel with a regularization parameter C set to 1.0 to maintain classification stability. Probability estimation was enabled in the SVM model to support threshold-based identity verification in the application system. The KNN model was configured with five nearest neighbors to balance classification accuracy and computational efficiency. Euclidean distance was used as the similarity metric in KNN to measure proximity between 128-dimensional facial embeddings.

7) Model Training

Model training was performed by providing the 128-dimensional facial embedding matrix to each classifier. Each embedding vector represents a labeled user identity. Unlike deep learning approaches, training SVM and KNN does not involve complex iterative optimization but focuses on learning decision boundaries or distance-based relationships to distinguish between user identities.

8) Validation of SVM Model and KNN Model

Model validation was conducted using the hold-out validation method with a data split of 60% for training and 40% for testing. With a total dataset of 11 users, 6 users were used for training and 4 users for testing. This ratio was chosen to ensure sufficient representation in the testing set given the limited dataset size.

Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. Testing was conducted under various conditions, including differences in lighting and face orientation, to assess performance stability and consistency. The model demonstrating the most stable results was selected for system implementation.

9) Application Development

At this stage, the model with superior performance is integrated into the book lending application for real-time face recognition. Identity verification is carried out using a probability score as a measure of prediction confidence. If the score falls below the predetermined threshold, the system denies the borrowing request and displays a notification indicating that the user is not registered.

10) System Testing

System testing was conducted to ensure that the face recognition-based book lending application functions correctly before deployment in the library. Comprehensive testing involved actual users and covered face authentication via camera, identity matching, and automatic transaction recording. The system was evaluated under various real-world conditions, including changes in lighting, variations in face expressions, suboptimal camera angles, and attempts by unregistered users. In addition to identification accuracy, testing assessed system stability through response time and transaction processing, with refinements made until the system was deemed ready for use.

3. Result and Discussion

3.1. Result of SVM Model Validation

The experimental results show that the SVM model provides stable and reliable performance in recognizing user identities in a face recognition–based library book lending system. Based on Table I , the consistent F1-score of 90% indicates a good balance between precision and recall, which allows the system to minimize both false acceptance and false rejection errors. This result demonstrates that the model generalizes well to facial data captured during user registration, despite variations in lighting conditions and face capture angles.

Table 1. SVM Model Validation Results

Accuracy	91%
Precision	90%
Recall	91%
F1-score	90%

The technical advantage of SVM over KNN lies in its classification mechanism, which constructs an optimal decision boundary in a high-dimensional feature space. Facial embeddings represented as numerical vectors enable SVM to maximize the margin between identity classes, leading to clearer class separation. In contrast, KNN relies on distance calculations between training and testing samples, making it more sensitive to overlapping data distributions. As a result, KNN performance tends to decrease as the number of users increases or when facial features become more similar, while SVM maintains stable classification performance.

	precision	recall	f1-score
user-1	0.90	0.91	0.90
user-2	0.90	0.91	0.90
user-3	0.90	0.91	0.90
user-4	0.90	0.91	0.90
user-5	0.90	0.91	0.90
user-6	0.90	0.91	0.90
user-7	0.90	0.91	0.90
user-8	0.90	0.91	0.90
user-9	0.90	0.91	0.90
user-10	0.90	0.91	0.90
accuracy			0.91
macro avg	0.90	0.91	0.90

Figure 2. Classification Report Model SVM

As shown in Figure 2, the classification report analysis shows that SVM performance is evenly distributed across all user classes, with precision, recall, and F1-score values remaining within a narrow range. This consistency indicates that the system does not favor specific users and can recognize all registered identities with comparable accuracy. Such balanced performance is essential for library authentication systems, as inconsistent recognition across users may reduce system usability and user trust.

The global analysis of the confusion matrix indicates that most predictions are concentrated along the main diagonal, which means that the majority of facial samples are correctly classified. Misclassification cases are limited and scattered across classes, showing no systematic error pattern. As shown in Figure 3, these errors are more likely caused by similarities in facial features rather than structural weaknesses of the model. Compared to KNN, which often produces clustered misclassifications due to feature distance similarity, SVM demonstrates stronger robustness in separating user identities.

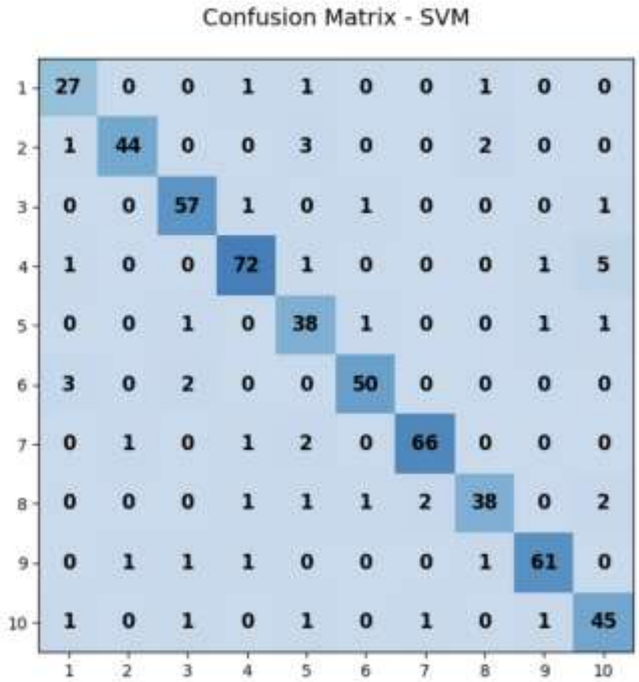

Figure 3. SVM Confusion Matrix Results

These findings are consistent with previous studies that report SVM outperforming KNN in face recognition tasks, particularly when dealing with high-dimensional data and limited training samples. Earlier research highlights that SVM offers better generalization and stability when handling facial variations, and the results of this study further support its effectiveness for biometric-based authentication systems.

In addition to accuracy, system response time analysis shows that SVM achieves lower and more stable latency than KNN. After training, SVM only requires evaluating a decision function during prediction, enabling fast authentication. In contrast, KNN must compute distances to all training samples for each recognition process, which increases computational time as the number of users grows. Therefore, SVM is more suitable for web-based library book lending systems that require fast authentication and responsive user interaction.

Overall, the results confirm that the SVM model delivers more consistent, accurate, and efficient performance than KNN in a face recognition–based library book lending system. The combination of a stable 90% F1-score, minimal misclassification, and low system latency makes SVM a reliable solution for user authentication in practical library applications.

3.2. Results of KNN Model Validation

The evaluation results indicate that the KNN model is capable of performing face recognition in the library book lending system using facial data collected during user registration. Although the model successfully recognizes most user identities, its overall performance remains inferior to that of the Support Vector Machine (SVM), particularly in terms of classification consistency and error control. Based on Table 2, the lower F1-score reflects a less optimal balance between precision and recall, suggesting a higher likelihood of both false acceptances and false rejections.

Table 2. KNN Model Validation Results

Accuracy	89%
Precision	89%
Recall	88%
F1-score	88%

From a technical perspective, the limitations of KNN become evident when compared with SVM. KNN relies on distance-based comparisons between feature vectors, requiring each test sample to be evaluated against all training data. In face recognition tasks, facial features are typically represented in high-dimensional spaces with overlapping distributions among users, which increases the risk of misclassification. In contrast, SVM constructs a global decision boundary that maximizes class separation, allowing it to distinguish user identities more effectively even when facial features are highly similar.

As shown in Figure 4, The classification report shows that KNN performance is relatively uniform across users, indicating the absence of strong bias toward specific identities. However, this uniformity is accompanied by weaker discriminative power, as reflected by lower precision, recall, and F1-score values compared to SVM. This suggests that KNN is less robust to common variations in facial data, such as changes in lighting, facial expressions, and head orientation.

	precision	recall	f1-score
user-1	0.89	0.88	0.88
user-2	0.89	0.88	0.88
user-3	0.89	0.88	0.88
user-4	0.89	0.88	0.88
user-5	0.89	0.88	0.88
user-6	0.89	0.88	0.88
user-7	0.89	0.88	0.88
user-8	0.89	0.88	0.88
user-9	0.89	0.88	0.88
user-10	0.89	0.88	0.88
accuracy			0.89
macro avg	0.89	0.88	0.88

Figure 4. KNN Model Classification Report

As shown in Figure 5, the confusion matrix reveals that most predictions fall along the main diagonal, confirming that the majority of facial samples are correctly classified. Nevertheless, the number of off-diagonal entries is higher than that observed in the SVM model, indicating more frequent misclassifications between users. These errors are distributed across multiple classes, implying that KNN struggles to differentiate users with similar facial characteristics, which is consistent with the inherent limitations of distance-based classification.

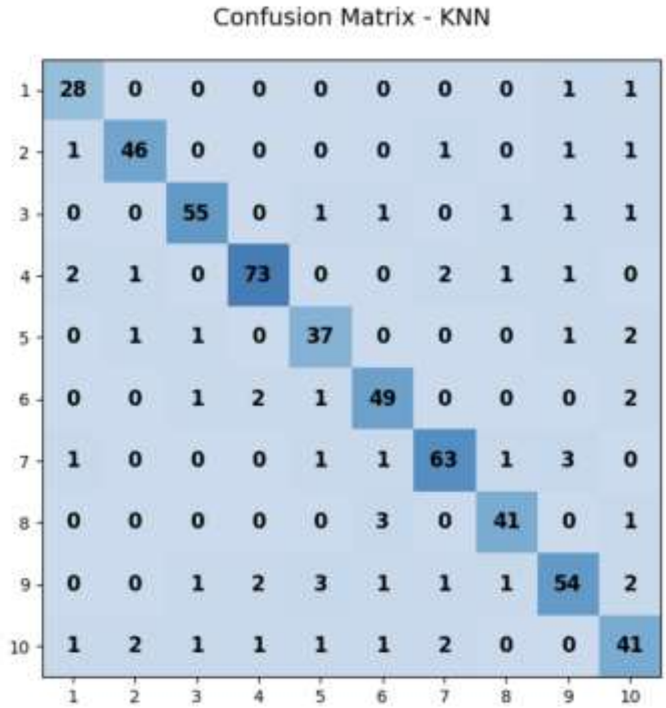

Figure 5. KNN Confusion Matrix Results

In terms of system efficiency, response time analysis shows that KNN exhibits higher and less stable latency compared to SVM. This is because KNN must compute distances to all training samples during each recognition process, causing computational costs to increase as the number of users grows. In contrast, SVM requires only a decision function evaluation after training, enabling faster and more consistent authentication. This efficiency advantage makes SVM more suitable for web-based library systems that require quick and responsive user authentication.

Overall, while the KNN model demonstrates reasonable face recognition capability, its limitations in accuracy stability, error frequency, and response time reduce its suitability as the primary model. These findings confirm that SVM provides a more reliable, efficient, and scalable solution for face recognition–based library book lending applications.

As shown in Figure 6, the comparative results between KNN and SVM demonstrate that while both models achieve acceptable performance in face recognition, SVM consistently outperforms KNN across all evaluation metrics. This finding aligns with previous studies reporting that SVM offers superior generalization capability, particularly when dealing with high-dimensional feature representations and limited training data. The present results therefore reinforce existing evidence on the effectiveness of SVM for biometric authentication systems.

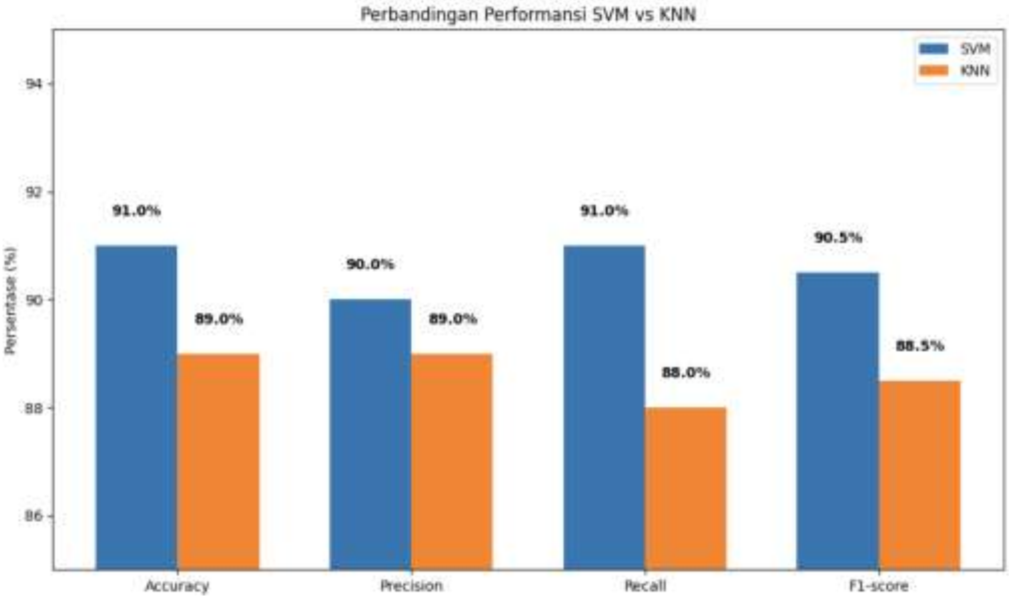

Figure 6. Comparison Results of the Two Models

3.3. System Testing Result

The selection of the SVM classifier was driven by validation results indicating that SVM consistently outperforms the KNN model in terms of accuracy and classification stability. The combination of dlib for face detection and feature extraction with SVM as the classifier demonstrated reliable performance in recognizing user identities within the library book lending application. To assess system-level performance, black-box testing was applied, focusing on the correctness of system outputs without examining internal processing, with the aim of evaluating identity recognition accuracy in real usage scenarios.

System testing involved ten registered users, each contributing ten facial images captured under varied conditions, including differences in facial expression, head orientation, lighting, and camera distance. Performance evaluation employed confusion matrix–based metrics, namely True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). In this study, TP refers to the successful recognition of registered users, FP denotes incorrect acceptance of unregistered identities, FN represents failure to recognize registered users, and TN indicates correct rejection of non-registered users. These metrics were reported as percentages per user to illustrate individual recognition behavior, although confusion matrices are commonly presented in aggregated global form for overall system evaluation.

The close alignment between black-box testing results and prior model validation outcomes indicates that the SVM-based system maintains consistent performance when deployed in an application environment. This consistency confirms that SVM provides a reliable and practical solution for user authentication in a face recognition–based library book lending system, particularly under limited data conditions and real-world variations.

Table 3. System Testing Results For The Application Using The Svm Classification Model

No	User	TP	FP	FN	TN
1	User-1	100%	0%	0%	0%
2	User-2	90%	0%	10%	0%
3	User-3	100%	0%	0%	0%
4	User-4	100%	0%	0%	0%

No	User	TP	FP	FN	TN
5	User-5	100%	0%	0%	0%
6	User-6	90%	0%	10%	0%
7	User-7	100%	0%	0%	0%
8	User-8	90%	0%	10%	0%
9	User-9	80%	0%	20%	0%
10	User-10	100%	0%	0%	0%
11	User-11	0%	60%	0%	40%
Rerata		86%	5%	5%	4%

As shown in Table 3, most users achieved high True Positive (TP) rates, with several users reaching perfect recognition performance. False Negative (FN) cases appeared only for a small number of users and mainly occurred under challenging acquisition conditions, such as extreme head poses or suboptimal lighting. The very low False Positive (FP) rate indicates that the system rarely misidentified one user as another, which is a critical requirement for face-based authentication systems. From a global perspective, these results confirm that the majority of facial images were classified correctly, while the observed errors were limited and non-systematic.

Overall, the average accuracy obtained from black-box testing was approximately 90%, which closely aligns with the SVM model validation accuracy of 91%. This consistency indicates that the model's performance during functional testing remains stable and in agreement with earlier validation results. Such alignment demonstrates that the SVM model has good generalization capability and remains reliable when deployed in real application scenarios.

In addition to recognition accuracy, system responsiveness was evaluated through response time (latency) measurements during user authentication. The results show that the SVM based system provides low and stable latency, as the recognition process only requires evaluation of the trained decision function. This contrasts with distance-based methods such as KNN, which must compute distances to all training samples during each recognition process. The lower computational load of SVM enables faster authentication, thereby improving usability and user experience in the web-based library application.

4. Conclusion

Based on the study results, a face recognition–based library book lending system was successfully developed and can accurately identify users without requiring physical cards. The system matches users facial images with stored data and supports automated borrowing, thereby improving service efficiency. Experimental results show that both SVM and KNN are applicable for face recognition however, SVM demonstrates more consistent performance under various conditions, as reflected by higher accuracy, precision, recall, and an F1-score of 90%, along with classification reports and confusion matrices dominated by correct predictions.

Black-box testing further confirms that correct recognition dominates system outputs, with True Positive rates substantially higher than recognition errors. False Positive and False Negative cases still occur but remain limited and are mainly influenced by non-ideal image conditions, such as poor lighting and extreme facial angles. Overall, SVM is considered the most suitable primary model due to its stable and reliable recognition performance.

Despite these positive results, this study has several limitations. The relatively small number of users and test samples limits the generalizability of the findings. In addition, testing was conducted in a largely controlled environment, so system performance under real-world library conditions has not been fully evaluated. Non-functional aspects, including system scalability and biometric data privacy, were also not examined in depth.

Future research is recommended to use larger and more diverse datasets and to conduct evaluations in real library environments. Further development may include deep learning–based methods, liveness detection, and comprehensive analysis of system latency and user experience to ensure readiness for broader deployment.

References

Amirgaliyev, B., Mussabek, M., Rakhimzhanova, T., & Zhumadillayeva, A. (2025). A review of machine learning and deep learning methods for person detection, tracking and identification, and face recognition with applications. Sensors, 25(5), 1410. https://doi.org/10.3390/s25051410

Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification. Neurocomputing, 408, 189–215. https://doi.org/10.1016/j.neucom.2019.10.118

El Fadel, N. (2025). Facial recognition algorithms: A systematic literature review. Journal of Imaging, 11(2), 58. https://doi.org/10.3390/jimaging11020058

Feta, N. R. (2023). Comparison of KNN and SVM algorithms in facial image recognition using Haar wavelet feature extraction. Journal of Informatics Research, 5(3), 321–330. https://doi.org/10.34288/jri.v5i3.224

Gonzalez, A., Fang, W., & Wang, Y. (2020). Practical face recognition systems under constrained environments. IEEE Access, 8, 212345–212357. https://doi.org/10.1109/ACCESS.2020.3039124

Hartono, S., Perwitasari, A., & Sujaini, H. (2025). Comparison of nonparametric algorithms for face image classification based on ethnic groups in Indonesia. JEPIN: Journal of Education and Informatics Research. https://doi.org/10.26418/jp.v6i3.43268

Hussain, M., Akhtar, N., & Mian, A. (2023). Real-time face recognition: Challenges and solutions. Pattern Recognition, 135, 109142. https://doi.org/10.1016/j.patcog.2022.109142

Khan, M. A., Sharif, M., Akram, T., & Kadry, S. (2024). Comparative analysis of classical and deep learning classifiers for face recognition. Expert Systems with Applications, 238, 121987. https://doi.org/10.1016/j.eswa.2023.121987

Li, Y., & Zhang, C. (2021). KNN-based classification methods for biometric recognition systems. Applied Sciences, 11(9), 4123. https://doi.org/10.3390/app11094123

Minaee, S., et al. (2023). Biometrics recognition using deep learning: A survey. Artificial Intelligence Review, 56, 123–178. https://doi.org/10.1007/s10462-022-10237-x

Murdani, H., Bella, E. L., & Fatwanto, A. (2024). Designing a face recognition-based security system for library circulation services. Daluang: Journal of Library and Information Science, 4(2), 82–96. https://doi.org/10.21580/daluang.v4i2.2024.21976

Nguyen, T., Pham, H., & Le, D. (2023). End-to-end face recognition systems: Beyond accuracy metrics. IEEE Transactions on Information Forensics and Security, 18, 3456–3468. https://doi.org/10.1109/TIFS.2023.3269814

Pratama, I. P., & Ningrum, N. K. (2025). Face recognition using MTCNN face detection, ResNetV1 feature embeddings, and SVM classification. Journal of Applied Informatics and Computing, 9(5), 2049–2058. https://doi.org/10.30871/jaic.v9i5.11016

Rahman, M. M., Islam, M. R., & Hasan, M. (2025). Lightweight face recognition for small-scale systems. Future Generation Computer Systems, 151, 130–142. https://doi.org/10.1016/j.future.2024.11.021

Ramadhani, Z., Safira, L., & Hartatik, H. (2024). Implementation of SVM algorithm in face recognition-based attendance system. Intechno Journal, 6(2), 88–97. https://doi.org/10.24076/intechnojournal.2022v4i2.1561

Sharma, S., Khan, M. A., & Mir, H. M. (2025). Deep learning challenges in face recognition systems. ICT Express. https://doi.org/10.1016/j.icte.2025.12.007

Sun, Z., & Liu, Z. (2025). Ensuring privacy in face recognition systems. Discover Applied Sciences, 7, 441. https://doi.org/10.1007/s42452-025-06987-2

Tariq, U., Khan, S., & Lee, S. (2024). Privacy-preserving biometric systems: A survey. Information Fusion, 98, 101863. https://doi.org/10.1016/j.inffus.2023.101863

Wang, H., Li, X., & Chen, Z. (2022). Real-time biometric systems for public services. IEEE Systems Journal, 16(4), 5432–5443. https://doi.org/10.1109/JSYST.2021.3125674

Yakub, N., Marlina, L., Iqbal, M., Siahaan, A. P. U., & Nasution, D. (2025). Comparative analysis of KNN and SVM methods for employee face recognition at Panca Budi University. INTECOMS: Journal of Information Technology and Computer Science, 8(3), 15908. https://doi.org/10.31539/intecoms.v8i3.15908

Yadav, A. K. (2023). 3D face recognition: A comprehensive survey. Computational Visual Media, 9, 657–685. https://doi.org/10.1007/s41095-022-0317-1