Journal of Information System and Technology Management
EISSN: 0128-1666
JISTM
Volume 11 Issue 42 (March 2026) PP. 409-422

JOURNAL OF INFORMATION SYSTEM AND TECHNOLOGY MANAGEMENT (JISTM)
www.gaexcellence.com/jistm

ADVANCEMENT IN CRIMINAL IDENTIFICATION FOR ENHANCED PUBLIC SAFETY: SVM-BASED FACE RECOGNITION WITH VGG ARCHITECTURE

Zainab Othman[1], Nurbaity Sabri[2], Nurrul Azleen Roslan[3], Wan Azra Sofea Batrisyia Jasman[4], Nurazian Mior Dahalan[5], Hajar Izzati Mohd Ghazalli[6*], Khyrina Airin Fariza Abu Samah[7], Nurul Hidayah Mat Zain[8]

[1] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
zainab_othman@uitm.edu.my https://orcid.org/0000-0002-1272-620X
[2] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
nurbaity_sabri@uitm.edu.my https://orcid.org/0000-0002-7823-9279
[3] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
2022771599@student.uitm.edu.my https://orcid.org/0009-0008-2027-4697
[4] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
2023600718@student.uitm.edu.my https://orcid.org/0009-0008-3204-2404
[5] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
nurazian@uitm.edu.my https://orcid.org/0009-0003-5846-1379
[6] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
hajarizzati@uitm.edu.my https://orcid.org/0009-0000-4437-3667
[7] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
khyrina783@uitm.edu.my https://orcid.org/0000-0002-0632-6330
[8] Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia
nurul417@uitm.edu.my https://orcid.org/0000-0002-5772-569X
*Corresponding Author

Article Info:

Article history:
Received date: 20.01.2026
Revised date: 12.02.2026
Accepted date: 22.03.2026
Published date: 31.03.2026

Abstract:

Face recognition technology helps Malaysia's Royal Military Police (RMP) identify criminals faster. Manual identification at roadblocks makes errors and wastes time. Criminal activities are getting worse, but current identification systems do not work well enough. Better criminal identification systems have become necessary for police work. This research presents a Criminal Face Recognition System that identifies

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

To cite this document:

Othman, Z., Sabri, N., Roslan, N. A., Jasman, W. A. S. B., Dahalan, N. M., Ghazali, H. I. M., Abu Samah, K. A. F., & Mat Zain, N. H. (2026). Advancement In Criminal Identification for Enhanced Public Safety: SVM-Based Face Recognition with VGG Architecture. *Journal of Information System and Technology Management, 11* (42), 409-422.

DOI: 10.35631/JISTM.1142024

criminal faces using accurate image matching. The study improves public safety and supports RMP operations. Deep learning methods power the system, combining Support Vector Machine (SVM) with Visual Geometry Group (VGG) architecture. Test results show 93.50% accuracy, proving the system works well for recognizing known criminals and its strength when processing new faces. These technological advancement puts the RMP ahead in using new technology, showing their commitment to public safety and security. Installing such systems fixes current identification problems while giving police reliable tools for catching criminals. Police need modern solutions that work against changing criminal methods and this system provides those tools.

Keyword:

Criminal Identification, Facial Recognition, Royal Military Police (RMP), Support Vector Machine (SVM), Visual Geometry Group (VGG)

© The authors (2026). This is an Open Access article distributed under the terms of the Creative Commons Attribution (CC BY NC) (http://creativecommons.org/licenses/by-nc/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact jistm@gaexcllence.com.

Introduction

Malaysia's Royal Military Police (RMP) oversee keeping the people safe, stopping crime, and making sure the safety of its citizens. The RMP's task has made it even more important to have good ways to find crimes and investigate them as crime rates keep increasing (Kumar et al., 2022). For instance, the RMP faced significant difficulties in tracking a perpetrator involved in a serious case of child sexual assault in Section 19 (Kawi, 2021).

These technological advancement puts the RMP ahead in using new technology, showing their commitment to public safety and security. Installing such systems fixes current identification problems while giving police reliable tools for catching criminals. Police need modern solutions that work against changing criminal methods, and this system provides those tools (Kumar et al., 2022). Conventional techniques, such as fingerprint analysis, possess inherent limitations, especially when offenders intentionally refrain from leaving fingerprints at crime scenes (Muley et al., 2022). To tackle these problems, the RMP use different strategies like CCTV monitoring and witness sketches (Kuan, 2022). Roadblocks and partnerships with other police agencies are key parts of catching suspects (Alzubaidi et al., 2021; Joseph, 2018). Malaysia's big and varied geography make finding suspects harder, which often causes identification problems and mistakes (Dang & Sharma, 2017). Media report (Mutlag et al., 2020) shows police are still trying to fight rising crime through roadblocks and other methods. But relying on manual identification still creates big problems since these methods do not have

Journal of Information System and Technology Management
EISSN: 0128-1666
JISTM
Volume 11 Issue 42 (March 2026) PP. 409-422
the tech needed for good face recognition. The Gombak Toll Plaza robbery shows how old approaches can hurt innocent people and slow down investigations (Abdullah et al., 2017).

The former Inspector General of Police, Tan Sri Acryl Sani Abdullah emphasized how important roadblocks are for public safety, but missing advanced face recognition tech during operations hurt their effectiveness (Kuan, 2022). Criminal identification needs to be accurate for public safety and justice since mistakes cause wrongful arrests and damage police work.

Literature Review

Deep Learning

Deep Learning (DL) represents a sophisticated machine learning subset that uses artificial intelligence for analyzing complex datasets through interconnected node layers, which mirror human brain neural networks. DL techniques include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs demonstrates effectiveness in extracting features from images which highly suitable for image recognition tasks. RNNs excellent in sequential data analysis. Generative Adversarial Networks (GANs) gets employed for generating new data samples that resembles input data, which enhance DL model robustness (Alzubaidi et al., 2021). The ability of DL to process unstructured data and derive valuable insights have led to breakthroughs across image recognition, natural language processing, and various fields. This positions it as an innovation driving force and advancement across multiple industries.

Image Processing

Image processing covers techniques that manipulate and analyze digital images by improving image quality, extracting information, making analysis easier (Joseph, 2018). The field employs methods like restoration, enhancement, compression, segmentation, registration and recognition for specific goals. Analog and digital are two broad categories. Analog image processing manipulates physical images through analog circuits and devices, which proves effective in real-time applications like video processing. Digital image processing relies on computer algorithms handling digital images. Key advantages of digital approaches include greater flexibility, managing complex operations on large datasets, compatibility with various digital formats. Medicine, criminal investigations, video surveillance are areas where this approach finds wide application and demonstrates its versatility and importance.

Face Detection

Face detection is critical computer vision technique focused on identifying and locating human faces in digital images and videos. The process involves algorithms using methods like edge detection and pattern recognition for identifying potential facial regions. Once areas are found, further evaluation determine whether they correspond to actual faces. Face detection is subset of object detection, involving identifying and locating objects within images or videos. This technique proves vital for applications in security, image analysis, many other fields (Dang & Sharma, 2017). Figure 1 shows a four-stage process for recognizing people in video or images.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

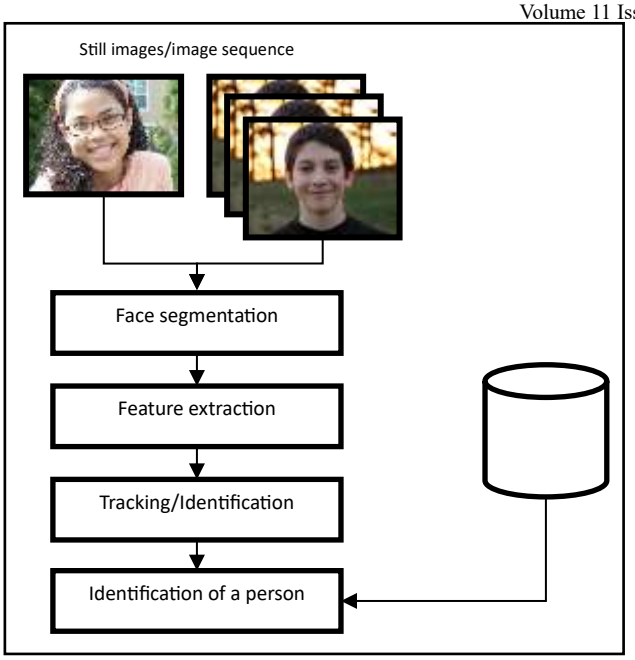

Figure 1: The General Process of Face Detection

Input starts with either still pictures or a series of frames. At first, this visual data goes through face segmentation, which is important because it locates and separates the face area itself from all the background clutter. The isolated face then moves to feature extraction. This part applies algorithms to get distinct, measurable biometric templates from the face, for instance, eye distances or facial outlines. Next, those extracted features become utilize in the tracking/identification stage. For positive identification, the features compared against a pre-existing database of facial data. That leads to the last part which confirms or denies who the individual is. This entire process moves sequential from grabbing raw video or images to figuring out identity, forming the main flow for most modern systems in facial recognition.

Haar Cascades is a widely adopted machine-learning method for object detection, specifically tailored for face detection in images and videos. This technique utilizes Haar-like features to identify key facial attributes such as the eyes, nose, and mouth. The classifier is trained with both positive and negative image sets to distinguish between target objects and non-targets, enabling real-time detection of multiple instances. However, Haar Cascades is limited by its reliance on frontal face detection and rectangular box scans, which reduces its effectiveness for recognizing faces from non-frontal angles.

Feature Extraction

Feature extraction is a fundamental process in image analysis, aiming to extract meaningful information from images for classification purposes (Mutlag et al., 2020). Techniques such as Visual Geometry Group 16-layer (VGG-16), MobileNet and Residual Network (ResNet) are commonly used to address the challenges of high-dimensional data.

MobileNet

MobileNet is a family of convolutional neural network (CNN) architectures designed for efficient inference on mobile and edge devices. It provides with goals of low latency, small model size, and reasonable accuracy.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

ResNet

ResNet is a family of deep convolutional neural network architectures that introduce residual (or skip) connections to allow very deep networks to be trained effectively. ResNet made it practical to train networks with tens or hundreds of layers, pushing performance on large-scale image recognition tasks (e.g., ImageNet) and downstream tasks (detection, segmentation).

VGG-16

The VGG-16 model, developed by Visual Geometry Group at University of Oxford, is convolutional neural network known for its straightforward and deep architecture. It features 13 convolutional layers and 3 fully connected layers, uses small convolutional filters and max-pooling layers for effective hierarchical feature extraction. VGG-16 excels in image classification and are widely used for transfer learning due to its ability learning diverse and complex features (Ichsan et al., 2024). Figure 2 shows the architecture of VGG-16.

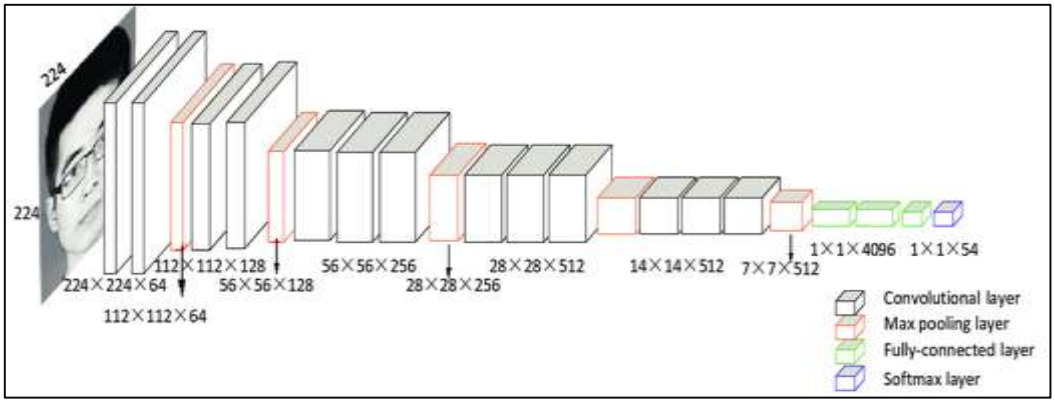

Figure 2: The Architecture of the VGG-16 Model

Source: (Pei et al., 2019)

Comparison

Table 1 summarizes the comparison between VGG-16, ResNet and MobileNet in terms of their strength and weakness.

Table 1: Feature Extraction Model Comparison

Model	Strengths	Weaknesses
VGG-16	Simple, easy to use for transfer learning and feature-map inspection (Pardede et al., 2021)	Very large model size and FLOPs which leads to slow inference and high memory (Hsia et al., 2021)
ResNet	Residual connections enable much deeper nets with stable training (He et al., 2016)	Heavier than mobile nets, higher latency (Zhang et al., 2021)
MobileNet	MobileNet delivers very good performance given efficiency constraints (Qin et al., 2025)	The lighter architecture may struggle more on very challenging tasks (Qin et al., 2025)

Journal of Information System and Technology Management
EISSN: 0128-1666
JISTM
Volume 11 Issue 42 (March 2026) PP. 409-422

Deeper models like ResNet can offer higher performance, they need more resources and are harder to manage MobileNet is lightweight and fast but may lose some accuracy. The VGG-SVM approach was chosen for its balance of accuracy and simplicity. VGG-16, combined with SVM, gives strong feature extraction and reliable classification, making it a practical choice.

Face Recognition

Facial recognition technologies leverage various classifiers to enhance identification accuracy. The primary classifiers include Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and K-Nearest Neighbors (KNN). Each classifier has its strengths:

SVM

Effective in binary classification and known for robust performance with complex data, SVM offers interpretable models and memory efficiency. However, it is sensitive to noisy data and may struggle with scalability to large datasets (Krebs et al., 2024).

CNN

Convolutional Neural Networks are highly accurate and efficient in facial recognition, benefiting from hierarchical feature representation and automatic feature extraction. CNNs, however, can be computationally intensive and challenging to interpret (Abdulrazzaq & Radhi, 2025).

KNN

K-Nearest Neighbors is simple and intuitive, offering robustness to noisy data. Its main drawbacks include computational complexity and sensitivity to feature scaling (Halder et al., 2024). Table 2 shows the differences between SVM, KNN and CNN.

Table 2: Face Recognition Classifier Comparison

Method	Advantages	Disadvantages
SVM	Effective classification, interpretable models, memory efficiency, flexibility with complex data	Sensitivity to noisy data, parameter sensitivity, scalability to large datasets
KNN	No training phase, Robust to noisy data, Simple and intuitive.	Computational complexity, sensitivity to feature scaling, memory-intensive
CNN	Highly accurate, efficient facial recognition, Hierarchical representation, and automatic feature extraction.	Computational complexity and datasets can be time-consuming, and interpretability challenges.

The proposed approach implements Haar Cascade for face detection, integrates a pre-trained VGG Face model for feature extraction, PCA for dimensionality reduction, and SVM for classification. This comprehensive framework aims to deliver high-performance face recognition tailored for criminal identification.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

Methodology

In a criminal identification system, face detection is first used to locate and isolate the face in an image, followed by face extraction, where features such as the facial structure and key points are extracted. Finally, face recognition compares these extracted features against a database of known individuals using an SVM classifier, producing a result that identifies whether the individual in the image is a criminal or an innocent person.

In this section, the face recognition process is carried out with five stages: user input/data collection, face detection, feature extraction, classification and face recognition result. The system provides feedback indicating whether the individual is classified as "criminal" or "innocent" as shown in Figure 3.

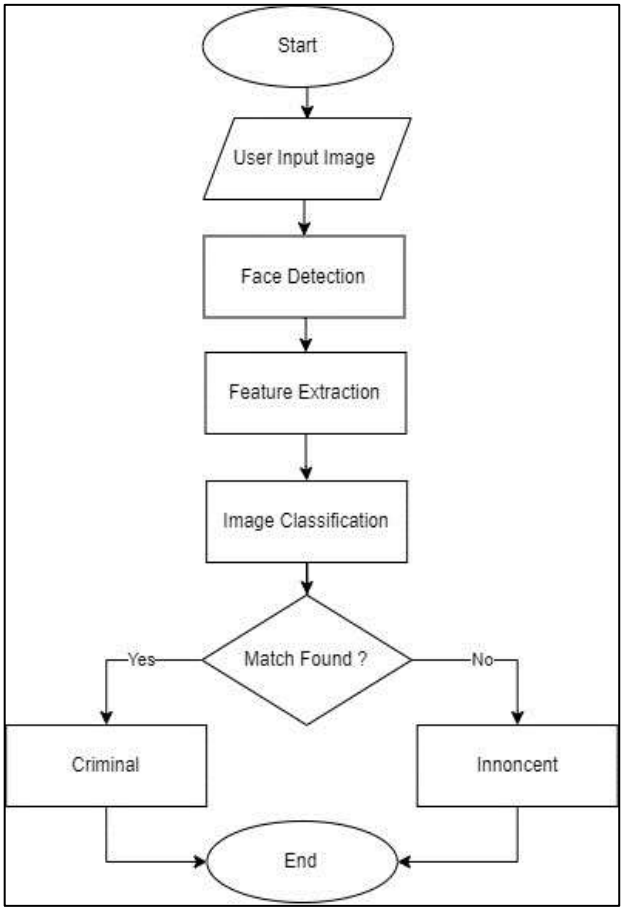

Figure 3: Facial Recognition System

The system process initiates by accepting a user input for analysis. The image subsequently proceeds into the Face Detection module, whose primary role is locating and isolating any human faces present within the visual data. Once a face is successfully detected, the extracted facial region is fed into the Feature Extraction component. This signature then becomes the input for Image Classification. During classification, the system attempts to determine if a match exists between the input signature and profiles within a repository of known identities.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

Data Collection

Dataset including 1200 images from UiTM Jasin students were employed, encompassing six different classes. This approach allows the system to be tested and evaluated without infringing upon the privacy of real criminals.

Pre-Processing

In this study, each facial image was first pre-processed before being used for recognition. The VGG-Face model was modified to extract features from its second-last layer, producing numerical face descriptors instead of classification outputs. The dataset of face images was loaded from a saved file, and each image was normalized by dividing pixel values by 255 to scale them between 0 and 1. All images were then resized to 224×224 pixels to match the input requirement of the VGG architecture. Using the modified model, each image was passed through the network to generate a 2622-dimensional embedding vector that represents the unique facial features. These feature vectors were later used as inputs to the SVM classifier for criminal identification.

Face Detection

The goal of face detection is to locate and identify the presence of faces within an image or video. This step involves finding the coordinates or bounding boxes around faces. The Haar Cascade algorithm scans the entire image to find regions that contain faces. By installing TensorFlow and Keras, access to optimized methods and efficient implementations is obtained, enabling effective and rapid data training. The output is usually a rectangular box (bounding box) around the detected face(s) as shown in Figure 4.

Figure 4: Detection Flow

Face Extraction

Face extraction sometimes referred to as face cropping or face alignment involves isolating and preparing the detected face(s) for further processing, such as recognition, analysis, or feature extraction. After face detection, the face region is cropped out of the image, removing unnecessary background. Face extraction often also involves converting the face into a feature vector.

Classification

After reducing the feature vectors with PCA, SVM trained on these reduced feature vectors to classify images into different categories, like identifying different individuals in facial recognition. During the classification process, the data is divided into 90% training data and

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

10% test data. Classification performance will be evaluated using confusion matrix. It evaluates how well the model classifies instances into different categories (e.g., "criminal" vs. "innocent"). The hyperparameters used are regularization parameter, C which is set to 5.0 and the kernel coefficient, γ set to 0.001.

Cross-Validation

The training dataset consists of 1200 images, with 200 images per individual captured from various angles. Our evaluation is grounded in a comparative analysis of expected and actual outcomes, bolstered by visual aids. The unequivocal success of this test highlights the model's proficiency in recognizing familiar faces, especially those of identified criminals.

Testing

A confusion matrix is a table that assesses the performance of an SVM model by offering a detailed comparison between its predictions and the actual labels. It displays the counts of true positives, true negatives, false positives, and false negatives. The confusion matrix evaluates how well SVM model distinguishes between classes, allowing the calculation of metrics like sensitivity and specificity. High sensitivity means the SVM accurately identifies positive cases, while high specificity indicates it correctly identifies negative cases. The F-Score (F-Measure), combining precision and sensitivity, provides an overall measure of classification effectiveness.

Results and Discussions

A dataset comprising 1,200 images was utilized for training and testing purposes. The training set consisted of 1,067 images, which accounts for 90% of the total dataset, while the testing set comprised 133 images, making up the remaining 10%. The choice of a 90-10 split for training and testing was driven by the constraint of limited dataset availability.

Table 3 displays the results of testing a criminal identification system using a confusion matrix. Each row represents a different test case (Test 1 to Test 6), and each column represents a different criminal type (C1 to C6). The values in each cell indicate the number of correct (diagonal values) and incorrect (off-diagonal values) classifications for each criminal type across 22 test instances.

Table 3: Testing of Confusion Matrix

Test	C1	C2	C3	C4	C5	C6
1	21				1	
2		22				
3	1		21			
4	1			20		1
5	1				21	
6			3			19

Table 4 provides a summary of the performance of a criminal identification system based on the confusion matrix data. It shows the number of True Positives (TP) and False Negatives (FN) for each criminal type. For each criminal type, the TP value represents the number of

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

correct identifications made by the system, while the FN value indicates the number of times the system failed to correctly identify that criminal type. For example, for Criminal 1, the system correctly identified the criminal 21 times but missed it once. Similarly, Criminal 2 was accurately identified in all 22 cases with no missed instances. The table highlights the system's overall accuracy and areas where it may need improvement, with a range of TP values from 19 to 22 and FN values from 0 to 3 across different criminal types.

Table 4: Result of Confusion Matrix

Criminal	TP	FN
1	21	1
2	22	0
3	21	1
4	20	2
5	21	1
6	19	3

Accuracy for each criminal is calculated by dividing the number of correct identifications (True Positives) by the total number of tests for that criminal and then multiplying by 100 to express it as a percentage as formula:

$$Accuracy = (\frac{Number\ of\ correct\ Tests}{Total\ Number\ of\ Tests}) \quad 1$$

Table 5 displays the accuracy for each criminal type.

Table 5: Accuracy

Criminal	Accuracy (%)
1	95
2	100
3	95
4	90
5	95
6	86

To determine the overall accuracy of the system, the individual accuracy percentages are summed and then divided by the number of criminal types. This calculation is shown as follows:

∑ Individual Accuracy=95+100+95+90+9+86

=561%

The calculation for overall accuracy by using the following formula:

$$Accuracy = \frac{\sum Individual\ Accuracy\ Percentages}{Number\ of\ Individual} \quad 2$$

Overall Accuracy = 561% / 6 = 93.5%

Journal of Information System and Technology Management
EISSN: 0128-1666
JISTM
Volume 11 Issue 42 (March 2026) PP. 409-422

Although only the VGG-16 + SVM configuration was implemented in this study, the model's 93.5% accuracy is consistent with findings in related works using other classifiers. For example, CNN-based systems often achieve 94 – 96% accuracy but require higher training time and GPU resources (Abdulrazzaq & Radhi, 2025), while MobileNet-based systems typically achieve around 88 – 90% due to their lightweight design (Alzubaidi et al., 2021). The present work therefore demonstrates that VGG-SVM offers a practical compromise. High accuracy with moderate computational complexity which is suitable for deployment in real-time or resource-limited criminal identification systems.

This overall accuracy indicates that the system performs quite well, achieving an average accuracy rate of 93.5% across different criminal categories. However, Criminal 6 has the lowest accuracy at 86%, suggesting an area that may need further improvement. Figure 6 and 7 show the samples interface of the system developed.

Figure 5: Main Page

Figure 6: Result of Criminal

Conclusion

In conclusion, the criminal identification system employing VGG-16 for feature extraction and SVM for classification shows impressive performance with overall accuracy of 93.5%. This high accuracy reflects the system's effectiveness in correctly identifying and classifying criminals across various categories. The system achieves notable accuracy rates for most criminal types, with Criminal 2 achieving perfect 100%. However, slightly lower accuracy at 86% of Criminal 6 shows that further refinement may be needed for enhancing performance in this category. Overall, integration of VGG-16 and SVM has proven robust approach for criminal identification, achieving impressive results and highlighting areas for potential improvement.

Despite high accuracy achieved by proposed face recognition system, several limitations and ethical considerations must be acknowledged. The system's performance can be significantly affected by variations in lighting, facial angles, image resolution, and occlusions such as glasses or masks, which may lead to false positives or negatives. The system works best when the subject is looking directly at the camera (frontal view). As the angle of the face rotates away from the camera, the recognition rate may drop. Common items like sunglasses, medical masks, scarves, hats, beards, and even hands covering the face hide the key feature points used for biometric measurement.

Future work will extend this study by empirically comparing the proposed model with other deep learning architectures such as ResNet and MobileNet, and with different classifiers including CNN and KNN. Such comparative testing will provide deeper insights into the trade-offs between accuracy, speed, and computational requirements for criminal face recognition.
To enhance the performance of the Criminal Face Recognition System, cameras with high resolution is recommended for better image capture, regularly update the criminal image database, and fine-tune the system for various environmental conditions. Implementing a confidence threshold can reduce false positives, and proper user training will maximize the system's utility. Also, in the future, using larger datasets may increase the accuracy. Lastly, conducting real-world tests may help find areas for further refinement before full scale deployment.

Acknowledgements: The authors would like to express their gratitude to the Faculty of Computer and Mathematical Sciences (FSKM) for providing the necessary facilities and support for this research. We also acknowledge the International Conference on Mathematical Sciences and Statistics (MIC3ST 2025) for the platform to present and refine the preliminary findings of this work.

Funding Statement: No Funding.

Conflict of Interest Statement: The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission to the International Journal of Information System and Technology Management (JISTM).

Ethics Statement: This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.

Author Contribution Statement: All authors contributed significantly to the development of this manuscript. Zainab Othman, Nurbaity Sabri, Nurrul Azleen Roslan and Wan Azra Sofea Batrisyia Jasman were responsible for the conceptualization, methodology, and overall supervision of the study. They also handled data collection, analysis, and interpretation of results. Nurazian Mior Dahalan, Hajar Izzati Mohd Ghazalli, Khyrina Airin Fariza Abu Samah and Nurul Hidayah Mat Zain contributed to the literature review, drafting, and critical revision of the manuscript. All authors read and approved the final version of the manuscript prior to submission.

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 42 (March 2026) PP. 409-422

References

Abdullah, N. A., Saidi, M. J., Rahman, N. H. A., Wen, C. C., & Hamid, I. R. A. (2017). Face recognition for criminal identification: An implementation of principal component analysis for face recognition. AIP Conference Proceedings, 1891(1). https://doi.org/10.1063/1.5005335/886787

Abdulrazzaq, N. A., & Radhi, A. M. (2025). Face Recognition Using Convolutional Neural Networks: A Review. Journal of Al-Farabi For Engineering Sciences, 4(1).

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data 2021 8:1, 8(1), 1–74. https://doi.org/10.1186/S40537-021-00444-8

Dang, K., & Sharma, S. (2017). Review and comparison of face detection algorithms. Proceedings of the 7th International Conference Confluence 2017 on Cloud Computing, Data Science and Engineering, 629–633. https://doi.org/10.1109/CONFLUENCE.2017.7943228

Halder, R. K., Uddin, M. N., Uddin, M. A., Aryal, S., & Khraisat, A. (2024). Enhancing K-nearest neighbor algorithm: a comprehensive review and performance analysis of modifications. Journal of Big Data, 11(1), 1–55. https://doi.org/10.1186/S40537-024-00973-Y/FIGURES/5

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition (pp. 770–778). http://image-net.org/challenges/LSVRC/2015/

Hsia, S. C., Wang, S. H., & Chang, C. Y. (2021). Convolution neural network with low operation FLOPS and high accuracy for image recognition. Journal of Real-Time Image Processing, 18(4), 1309–1319. https://doi.org/10.1007/S11554-021-01140-9/FIGURES/6

Ichsan, A., Riyadi, S., & Pardede, D. (2024). Analysis of Logistic Regression Regularization in Wild Elephant Classification with VGG-16 Feature Extraction. Journal of Computer Networks, Architecture and High-Performance Computing, 6(2), 783–793. https://doi.org/10.47709/CNAHPC.V6I2.3789

Joseph, S. (2018). Image processing techniques and its applications: an overview. Int. J. Adv. Res. Innov. Ideas Educ. (IJARIIE), 4, 2168–2174.

Kawi, M. R. (2021, January 7). Kes remaja dirogol tahanan lokap: 2 anggota polis digantung kerja serta-merta. https://www.bharian.com.my/berita/nasional/2021/01/776980/kes-remaja-dirogol-tahanan-lokap-2-anggota-polis-digantung-kerja

Krebs, R., Bagui, S. S., Mink, D., & Bagui, S. C. (2024). Applying Multi-CLASS Support Vector Machines: One-vs.-One vs. One-vs.-All on the UWF-ZeekDataFall22 Dataset. Electronics 2024, Vol. 13, Page 3916, 13(19), 3916. https://doi.org/10.3390/ELECTRONICS13193916

Kuan, S. (2022, November 23). Nationwide roadblocks part of police's omnipresence strategy. https://www.nst.com.my/news/nation/2022/11/854053/nationwide-roadblocks-part-polices-omnipresence-strategy#google_vignette

Kumar, A., Baalamurugan, K. M., & Balamurugan, B. (2022). Real-Time Facial Components Detection Using Haar Classifiers. Proceedings - International Conference on Applied Artificial Intelligence and Computing, ICAAIC 2022, 949–956. https://doi.org/10.1109/ICAAIC53929.2022.9793034

Muley, A., Darade, R., Pathan, A., Muley, A., Darade, R., & Pathan, A. (2022). Criminal Identification Using 2D Face Recognition System. JETIR, 9(6), b753–b769. https://www.jetir.org/view?paper=JETIR2206199

Mutlag, W. K., Ali, S. K., Aydam, Z. M., & Taher, B. H. (2020). Feature Extraction Methods: A Review. Journal of Physics: Conference Series, 1591(1), 012028. https://doi.org/10.1088/1742-6596/1591/1/012028

Pardede, J., Sitohang, B., Akbar, S., & Khodra, M. L. (2021). Implementation of Transfer Learning Using VGG16 on Fruit Ripeness Detection. International Journal of Intelligent Systems and Applications, 13(2), 52–61. https://doi.org/10.5815/ijisa.2021.02.04

Pei, Z., Xu, H., Zhang, Y., Guo, M., & Yee-Hong, Y. (2019). Face recognition via deep learning using data augmentation based on orthogonal experiments. Electronics (Switzerland), 8(10). https://doi.org/10.3390/electronics8101088

Qin, D., Leichner, C., Delakis, M., Fornoni, M., Luo, S., Yang, F., Wang, W., Banbury, C., Ye, C., Akin, B., Aggarwal, V., Zhu, T., Moro, D., & Howard, A. (2025). MobileNetV4: Universal Models for the Mobile Ecosystem. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) , 15098 LNCS, 78–96. https://doi.org/10.1007/978-3-031-73661-2_5

Zhang, C., Benz, P., Argaw, D. M., Lee, S., Kim, J., Rameau, F., Bazin, J.-C., & Kweon, I. S. (2021). ResNet or DenseNet? Introducing Dense Shortcuts to ResNet (pp. 3550–3559)