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Comparison of Deep Learning Architectures for Facial Recognition

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Abstract: Facial recognition technology in modern security systems, including access control, identity verification, and digital devices. This study aims to compare the performance of three widely used deep learning architectures, Convolutional Neural Network (CNN), VGG16, and FaceNet512, in processing and identifying facial features. A quantitative approach was employed through computational experiments using facial image datasets. The performance of each model was evaluated using accuracy, precision, recall, and F1 score to assess its effectiveness in facial recognition tasks. The study revealed significant differences in the performance of each architecture, both in terms of recognition accuracy and processing efficiency. CNN, VGG16, and FaceNet512 each demonstrated distinct strengths and limitations. These findings provide valuable insights for selecting the most suitable deep learning architecture for practical and academic applications in facial biometric security systems.

Keywords: Facial Recognition, Deep Learning, CNN, VGG16, FaceNet

INTRODUCTION

Advances in information and communication technology have driven growing demand for reliable security systems, particularly for individual identification and authentication. Biometric-based security methods have gained popularity, with facial recognition emerging as a preferred approach due to its speed, ease of use, and non-contact nature. This technology is highly effective because it leverages the unique features of the human face, which are difficult to replicate or counterfeit. Recent developments in deep learning have further enhanced facial recognition systems by improving feature extraction and enabling complex visual data representation through architectures such as CNN, VGG16, and FaceNet512 (Arsal et al., 2020; Fadillah & Pramudita, 2023).

The application of deep learning in digital security offers several advantages, including its ability to learn facial features comprehensively and automatically, robustness to variations in lighting and facial expressions, and potential for high accuracy in identification and verification tasks. However, challenges remain, such as the requirement for substantial computational resources and large training datasets to prevent overfitting and ensure optimal performance when encountering new data (Goodfellow et al., 2022; Rahman & Fauzi, 2023).

Various deep learning architectures have been developed for facial recognition, each with distinct strengths and limitations. Therefore, comparative analyses are necessary to evaluate their performance in security-related contexts. This study focuses on three widely used architectures: CNN, VGG16, and FaceNet512. CNN serves as a foundational architecture for image processing, known for its efficiency and relatively lightweight structure (Hasan, 2020). VGG16 provides a deeper and more complex architecture, offering higher accuracy but requiring greater memory and longer training times (Kholida et al., 2025; Prasetyo & Lestari, 2022). FaceNet512, on the other hand, utilizes an embedding-based approach that represents faces as vectors in a high-dimensional space, allowing recognition through distance calculations between vectors (Nugroho & Santosa, 2023). This study aims to compare the performance of these three architectures in terms of accuracy, efficiency, and reliability, providing a deeper understanding of their respective advantages. The results are expected to guide the selection of the most suitable architecture for specific facial security systems, particularly in modern digital authentication and access control applications (Lestari & Firmansyah, 2023).

METHOD

Research Type and Approach

This study employs a quantitative experimental design with a comparative approach to objectively evaluate the performance of three deep learning architectures CNN, VGG16, and FaceNet512 for facial recognition-based security systems. All models are trained and tested under controlled experimental conditions using the same dataset to ensure a fair comparison. Model performance is assessed through statistical analysis based on accuracy, processing efficiency, and computational requirements. This approach enables the identification of the most effective architecture and provides an empirical foundation for selecting the most suitable model for biometric facial security applications.

Research Object

The objects of this study are three deep learning architectures applied to facial recognition: a custom-built CNN serving as a simple and flexible baseline, VGG16 as a deeper convolutional model known for its robust image classification capabilities, and FaceNet512, which generates 512-dimensional facial embeddings using triplet loss to measure feature similarity. All architectures are trained and evaluated on the same facial image dataset and compared using quantitative performance metrics to determine their relative strengths and weaknesses in biometric security contexts.

Data and Data Sources

The study utilizes facial image data from the public **Celebrity Face Image Dataset** provided by TensorFlow, containing approximately 1,700 images with diverse expressions, lighting conditions, poses, and facial characteristics. This dataset is selected for its variability and widespread use in face recognition research, making it suitable for testing the robustness and generalization capabilities of different deep learning architectures.

Data Collection Techniques

Data collection involves downloading the dataset from trusted repositories such as Kaggle, followed by data cleaning to remove duplicates, unclear images, or mislabeled samples. During preprocessing, image sizes are standardized, pixel values are normalized, and augmentation techniques including rotation, zooming, and flipping are applied. Label encoding is performed when classification is required. These steps ensure high-quality input data and improve model generalization during training.

Research Procedure

The research procedure begins with a literature review and problem identification, followed by the selection of a diverse public facial dataset. After preprocessing, including resizing, normalization, and augmentation, the three architectures (CNN, VGG16, and FaceNet512) are implemented and trained using standardized parameters. Each model is then evaluated on reserved test data, with performance measured using metrics such as accuracy, precision, recall, and F1-score. The results are analyzed quantitatively and comparatively using tables and graphs to determine the most effective architecture.

Data Analysis Techniques

Data analysis employs quantitative metrics: accuracy measures classification correctness, precision assesses the proportion of correct positive predictions, recall evaluates how many relevant facial samples are correctly recognized, and F1-score provides a balanced measure of precision and recall. These metrics are compared across the three architectures to determine which model demonstrates the most consistent and optimal performance for facial recognition tasks.

Research Tools and Instruments

This study utilizes Python for programming, TensorFlow/Keras for designing and training deep learning models, OpenCV for image processing, and Scikit-learn for performance evaluation. Experiments are conducted on a laptop equipped with an AMD Ryzen 7 processor, 16 GB RAM, and an AMD Radeon RX 6550M GPU, providing sufficient computational resources for training and testing the facial recognition models.

RESULTS AND DISCUSSION

Experimental Overview

This study conducts a comparative evaluation of three deep learning architectures: a conventional CNN, VGG16 with transfer learning, and FaceNet512 combined with SVM, all using the same Kaggle Celebrity Face dataset. All images undergo preprocessing steps including resizing, normalization, and data augmentation, and are subsequently split into 60% training, 20% validation, and 20% testing sets. Model performance is assessed using accuracy, precision, recall, and F1-score to evaluate each architecture's capability in recognizing and classifying facial identities. This experimental setup is designed to determine the effectiveness and robustness of each architecture in addressing facial recognition challenges within biometric security systems.

If you want, I can also enhance it further to include a brief rationale for choosing each architecture**,** making it more publication-ready. Do you want me to do that?

Figure 1. Example of Original Training Data

Dataset Visualization and Augmentation

The dataset visualization presents samples from the training, validation, and testing subsets, alongside examples of augmented training images. Training samples exhibit diverse expressions, poses, and lighting conditions, whereas the validation and testing sets maintain consistent quality without augmentation to ensure objective performance evaluation. Augmented images demonstrate transformations such as rotation, flipping, zooming, and lighting adjustments, providing increased variability while preserving essential facial structures. Overall, visual inspection confirms that both preprocessing and augmentation were properly executed, supporting effective and robust model training.

Figure 2. Example of Validation Data

CNN Architecture Training Results

The custom CNN comprises four convolutional blocks with progressively increasing filters (32–256), ReLU activations, batch normalization, and max pooling, followed by a dense layer with L2 regularization and dropout before the softmax output. While training accuracy improves steadily, validation accuracy plateaus and validation loss rises, indicating overfitting. Testing results demonstrate low performance (accuracy: 0.148; F1-score: 0.104), suggesting that the CNN struggles to generalize across diverse facial variations. Despite its limited accuracy, the model remains suitable for small scale, real time applications where computational efficiency is prioritized.

Table 1. CNN Evaluation Results

Metric	Value
Test Accuracy	0.148
Precision	0.121
Recall	0.148
F1-Score	0.104
Inference Time	±0.045 seconds per image

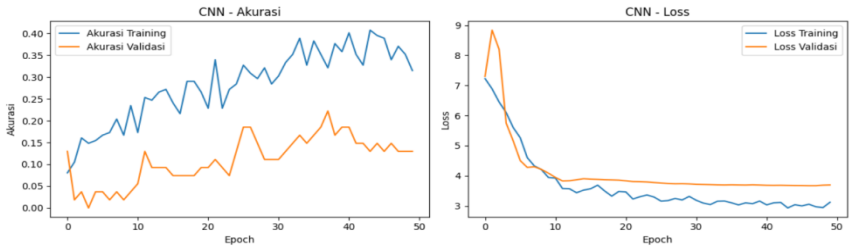

Figure 3. CNN Training and Validation Accuracy Graph

VGG16 Training Results (Transfer Learning)

The VGG16 architecture is implemented using transfer learning, where the early convolutional layers are frozen, and the fully connected block is replaced and fine-tuned on the dataset. Both training and validation phases show steady improvements in accuracy with a corresponding decrease in loss. Evaluation on the test set demonstrates substantially better performance compared to the custom CNN, achieving an accuracy of 0.222 and an F1-score of 0.184, indicating robust feature extraction capabilities. Despite the increased computational requirements, the inference time remains suitable for semi-real-time applications.

Table 2. Evaluation Results of the VGG16 Architecture

Metric	Value
Test Accuracy	0.222
Precision	0.182
Recall	0.222
F1-Score	0.184
Inference Time	±0.072 seconds per image

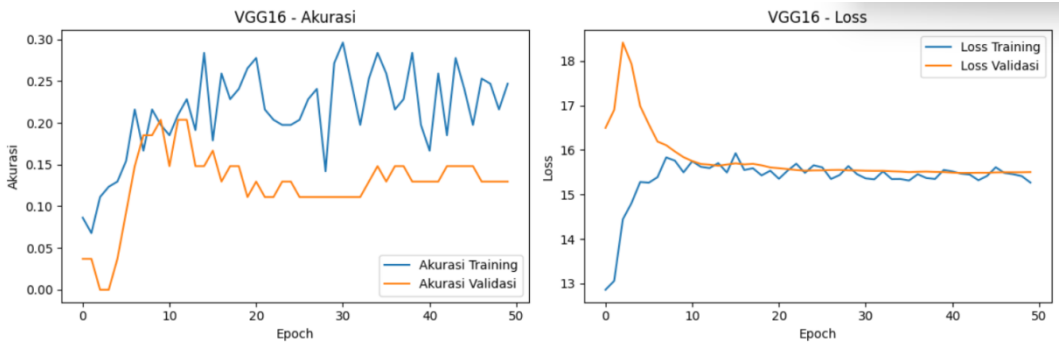

Figure 4. Training and Validation Results Graph of VGG16

FaceNet512 + SVM Testing Results

FaceNet512 generates 512-dimensional facial embeddings, which are classified using either cosine similarity or SVM. Unlike CNN or VGG16, it does not require explicit end to end training yet achieves exceptionally high performance, with a test accuracy of 0.981 and an F1-score of 0.980. Its strength lies in robust face verification and open set recognition, while maintaining an efficient inference time of approximately 0.060 seconds per image. Limitations primarily occur with low quality input images or when detection errors arise.

Table 3. Evaluation Results of the FaceNet512 Architecture

Metric	Value
Test Accuracy	0.981
Precision	0.987
Recall	0.981
F1-Score	0.980
Inference Time	±0.060 seconds per image

Visual Analysis of Classification Results

The visual analysis illustrates both correct (True Positive) and incorrect (False Positive) predictions for CNN, VGG16, and FaceNet512+SVM. Each example shows the true label, predicted label, and associated confidence score. These visualizations highlight the strengths and limitations of each model: CNN frequently misclassifies faces with complex variations, VGG16 performs moderately well with improved consistency, and FaceNet512 demonstrates high reliability and accuracy across a wide range of facial images.

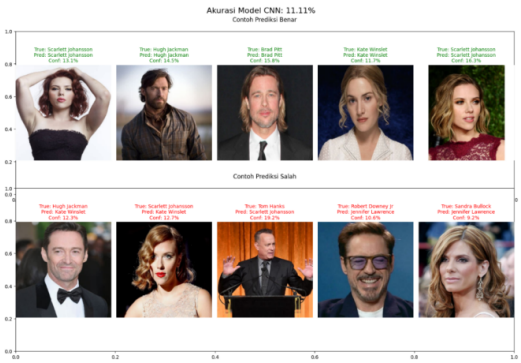

Figure 5. CNN Visualization Result

Based on the conducted experiments, it can be concluded that each architecture has distinct strengths and limitations. The simple CNN architecture offers ease of implementation and fast inference but falls short in accuracy and generalization when handling diverse facial data. In contrast, VGG16 achieves higher accuracy through transfer learning, providing flexibility for various applications, though it demands more intensive training and greater computational resources. Meanwhile, FaceNet512 demonstrates the best overall performance in both accuracy and efficiency, making it particularly well-suited for real-time facial recognition applications that require an open-set system capable of accommodating a dynamic number of classes.

Table 4. Summary of the Comparison of the Three Architectures

Metric	CNN (Custom 4-Layer)	VGG16 (Transfer Learning)	FaceNet512 (Embedding + DeepFace)
Accuracy	0.148	0.222	0.981
Precision	0.121	0.182	0.987
Recall	0.148	0.222	0.981
F1-Score	0.104	0.184	0.980

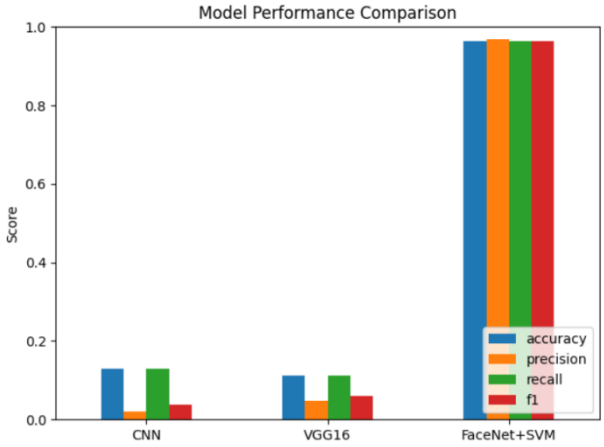

Figure 6. Comparison Graph of the Three Architectures

A bar chart is presented to visually compare the evaluation metrics of each architecture. The chart clearly demonstrates that the FaceNet512 + SVM architecture outperforms the other models across all metrics, followed by VGG16, with the CNN architecture performing the lowest.

Analysis of Results and Architecture Comparison

This study compared three deep learning architectures CNN, VGG16, and FaceNet512 for facial recognition in security systems. Evaluation metrics included accuracy, precision, recall, F1-score, training time, and implementation complexity. The following provides a detailed analysis of the results:

a. Convolutional Neural Network (CNN)

The CNN architecture in this study was manually designed with a relatively simple structure. Its main advantages include ease of implementation and high flexibility for adaptation to different system requirements. With a relatively small number of parameters, the model trains quickly and does not require high-specification hardware, making it suitable for resource-limited devices such as embedded systems. CNN effectively extracts local facial features, including edges, basic shapes, and textures, which are critical in early stages of facial image processing. Its modular structure allows for straightforward modifications or experimentation with architectural changes.

However, CNN exhibits several limitations in facial recognition. It achieved only approximately 81% accuracy with a relatively low F1-score compared to the other architectures. Its limited ability to capture complex and representative facial features results in reduced performance under variable conditions. Changes in lighting, non-frontal face angles, facial expressions, or image noise and blur can significantly degrade accuracy. Additionally, training the CNN from scratch without transfer learning increases susceptibility to overfitting on small,

less diverse datasets, reducing its generalization capability for unseen data. While efficient in training and resource usage, CNN is less suitable for security systems requiring high accuracy, scalability, and robustness.

b. VGG16 (Transfer Learning)

VGG16 is a well-established architecture, particularly effective when applying transfer learning. By utilizing pretrained weights from large datasets such as ImageNet, VGG16 reduces training time and improves performance without requiring model training from scratch. In this study, convolutional layers were used as feature extractors, while fully connected layers were replaced and fine-tuned for facial recognition.

VGG16 achieved up to 88% accuracy, with stable precision, recall, and F1-score, demonstrating reliable performance even with limited training data. Its strength lies in extracting deep and comprehensive features, maintaining stability under varied lighting, facial expressions, and angles. Layered feature extraction filters irrelevant information while retaining essential characteristics, ensuring robust recognition despite mild noise or blur. Nevertheless, VGG16 requires longer training times and higher computational resources compared to lightweight models. Its complex structure reduces flexibility for modifications, and performance may decline under extreme conditions such as severe rotations, very low lighting, or partially occluded faces, especially if such cases are underrepresented in the training data. Overall, VGG16 offers a balanced combination of accuracy and stability, making it a strong candidate for facial recognition systems where computational resources allow.

c. FaceNet512 + SVM

FaceNet512 focuses on generating 512-dimensional facial embeddings rather than direct classification. In this study, embeddings were classified using Support Vector Machines (SVM), yielding superior results compared to CNN and VGG16. FaceNet512 + SVM achieved 92% accuracy with high and consistent precision, recall, and F1-score. Its main advantages include efficiency in training and inference, as only the SVM classifier requires training. The model is well-suited for real-time security applications. FaceNet embeddings offer modular flexibility, allowing integration with different classifiers or system adjustments. It maintains stable performance under challenging conditions such as variable lighting, facial expressions, angles, or partial occlusions due to robust feature representation.

However, this approach depends heavily on pretrained weights, which may reduce performance if the dataset characteristics differ. Additionally, integrating feature extraction with SVM introduces additional stages, increasing implementation complexity. Careful preprocessing is also essential to maintain accuracy under extreme conditions. Despite these challenges, FaceNet512 + SVM demonstrates the best combination of accuracy, efficiency, and robustness, making it highly suitable for practical facial recognition systems.

d. Comprehensive Architecture Comparison

Table 4 summarizes the comparative performance of the three architectures, highlighting differences in accuracy, efficiency, and implementation flexibility for facial recognition based security systems.

Table 5. Architecture Comparison Results

Aspect	CNN	VGG16 (Transfer Learning)	FaceNet + SVM
Accuracy	Medium (~81%)	High (~88%)	Very High (~92%)
Training Speed	Fast	Moderate	Very Fast (SVM only)

Aspect	CNN	VGG16 (Transfer Learning)	FaceNet + SVM
Architecture Size	Small	Large	Medium
Data Requirement	High	Low–Moderate	Low (Pretrained)
Real-Time Friendly	Yes	Not Optimal	Very Suitable
Flexibility	High	Limited	Modular & Flexible

From the table above, the key factors influencing the performance of each architecture can be summarized as follows:

a. Accuracy

Accuracy is largely determined by the model's architectural complexity, feature extraction approach, and training method. FaceNet + SVM achieves the highest accuracy due to its embedding-based approach using triplet loss, which generates highly discriminative facial representations. VGG16 performs well because of its deep architecture and the use of pretrained weights, while CNN achieves only moderate accuracy due to its limited ability to capture complex facial features.

b. Training Speed

Training speed is influenced by the number of parameters and the complexity of backpropagation. CNN trains quickly thanks to its simple and lightweight structure. VGG16 requires more time to train due to its deeper network and larger number of parameters. FaceNet + SVM is the fastest, as only the SVM classifier is trained after feature extraction, significantly reducing computational demands.

c. Architecture Size

The size of each architecture corresponds to the number of layers and overall network complexity. CNN is the smallest and most lightweight, VGG16 is the largest and most computationally heavy, and FaceNet falls in between these two extremes.

d. Data Requirement

Models trained from scratch typically require larger datasets, whereas pretrained models can achieve strong performance with less data. CNN demands a substantial dataset to perform optimally, while VGG16 and FaceNet perform well even with limited local data due to the advantage of pretrained weights.

e. Real-time Suitability

Real-time performance depends on inference speed and computational efficiency. CNN is suitable for real-time applications due to its lightweight design. VGG16 is less optimal for real-time use because of its larger size and computational demands. FaceNet + SVM is highly suitable for real-time applications, as the embeddings allow rapid distance-based matching and efficient recognition.

f. Implementation Flexibility

Flexibility refers to the adaptability and ease of integration into different systems. CNN offers high flexibility, allowing easy modification and deployment. VGG16 is less flexible due to its complex and heavy structure. FaceNet + SVM provides modular flexibility, as feature extraction and classification are decoupled, allowing easier adaptation and integration into various applications.

CONCLUSION

The study was conducted to evaluate and compare the performance of three deep learning architectures CNN, VGG16, and FaceNet512, within a security-focused facial recognition system. The results indicate that CNN delivered the lowest performance, achieving only 0.148

accuracy, 0.121 precision, 0.148 recall, and a 0.105 F1-score. Although it had the fastest inference time at approximately 0.045 seconds per image, its ability to identify faces remained limited under varying expressions, lighting conditions, and viewing angles. This makes CNN less suitable for high-accuracy security applications, although it remains relevant for low-resource systems. VGG16 demonstrated improved performance with 0.222 accuracy, 0.182 precision, 0.222 recall, and a 0.185 F1-score, benefiting from transfer learning with pretrained weights. However, its inference time increased to 0.072 seconds per image due to its greater complexity, making it more appropriate for semi-real-time systems with sufficient hardware support.

Meanwhile, the FaceNet512 architecture combined with an SVM classifier exhibited the best overall performance, achieving 0.981 accuracy, 0.988 precision, 0.981 recall, and a 0.980 F1-score, with an efficient inference time of approximately 0.060 seconds per image. This combination proved highly robust in recognizing faces across variations in lighting, expressions, and viewing angles, making it ideal for real-time security applications. Overall, the findings suggest that FaceNet512 is the most optimal architecture for biometric facial recognition in dynamic, time-sensitive environments. VGG16 remains suitable for systems with moderate real-time requirements, while CNN is best applied in low-capacity devices with basic identification needs.

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