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Comparative Analysis of Fingerprint Patterns Whorl, Loop, and Arch Using K-Nearest Neighbor and Recurrent Neural Network

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Abstract

Fingerprints are among the most reliable biometric identifiers due to their unique and permanent nature. In forensic identification, fingerprints are grouped into three basic patterns: Whorl, Loop, and Arch. This study compared the performance of K-Nearest Neighbor (KNN) and Long Short-Term Memory (LSTM)-based Recurrent Neural Network (RNN) in classifying these three patterns. A dataset of 600 fingerprint images (200 per class) was preprocessed through grayscale conversion, resizing to 224×224 pixels, Gaussian filtering, and CLAHE contrast enhancement. Features were extracted using a combination of Gabor Filter (64 features) and Histogram of Oriented Gradients (8,100 features), producing an 8,164-dimensional feature vector. The dataset was split into 70% training, 15% validation, and 15% testing data. KNN was tested with K = 3, 5, 7, 9 using Euclidean distance, while RNN-LSTM was implemented with 64, 128, and 256 units using the Adam optimizer and early stopping. KNN with K = 7 achieved the highest accuracy of 97.78%, with a training time of only 0.205 seconds, while RNN-LSTM with 128 units reached 93.33% accuracy in 31.461 seconds. KNN proved roughly 153 times faster to train and more accurate, making it the more efficient method for this classification task.

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1. Introduction

Fingerprints are among the most reliable forms of biometric identification because they are unique and permanent for each individual. Consequently, they are widely used in security systems, forensic investigations, and attendance monitoring (Jannah et al., 2024). In forensic science, fingerprints are classified into three basic patterns: Whorl, Loop, and Arch. This classification was introduced by Sir Edward Henry in 1900 and remains a standard for identification today (Reo Rizki Ananda et al., 2025).

The need for fast and accurate automated identification systems has encouraged the adoption of machine learning and deep learning techniques for fingerprint pattern recognition (Reo Rizki Ananda et al., 2025). Two widely used methods are K-Nearest Neighbor (KNN), a simple supervised learning algorithm that classifies data based on feature similar=ity, and Recurrent Neural Network (RNN), a deep learning architecture capable of capturing sequential patterns in data (Asmaraloka et al., 2025). In

fingerprint classification systems, errors frequently arise from poor-quality images, such as those that are contaminated, partially cropped, or captured at an oblique angle. These issues are generally caused by human error during image acquisition (Manoppo, 2025).

The applications of KNN and RNN algorithms have been extensively investigated across various domains, including handwritten pattern recognition (Asmaraloka et al., 2025), rainfall prediction (Al-Hadid et al., 2026), agricultural yield prediction (Adhany et al., 2025), economic and financial forecasting (Alkahfi et al., 2024), decision support systems for student placement (Alyasis & Octaviano, 2025), and personality detection based on fingerprints (Gunawan et al., 2025). In biometric image processing, feature extraction methods such as Histogram of Oriented Gradients (HOG) and Gabor Wavelet have also demonstrated effectiveness in applications such as brain tumor classification (Adilah & Azizah, 2022), iris recognition (Ahmad & Sari, 2025), fingerprint-based personality type detection (Aliffiyah & Pratiwi, 2025), and biometric attendance systems (Anggriani & Bandawati, 2025). Studies examining fingerprint pattern distributions within specific populations (Aulia et al., 2024), along with comprehensive reviews of the KNN algorithm (Halder et al., 2024), further support the premise that the combination of appropriate feature extraction techniques and classification algorithms significantly influences biometric system accuracy. Nevertheless, research specifically comparing the performance of KNN and RNN based on Long Short-Term Memory (LSTM) for classifying the three basic fingerprint patterns using a combination of Gabor Filter and HOG features remains limited (Wijaya & Widasari, 2024).

Based on this background, this study aims to analyze and compare the performance of KNN and RNN-LSTM algorithms in classifying Whorl, Loop, and Arch fingerprint patterns using accuracy, precision, recall, F1-score, and computational time as evaluation metrics. The findings are expected to provide a reference for determining the most optimal method for developing fingerprint-based biometric systems.

2. Research Methodolgy

This study employed a quantitative experimental approach using a supervised learning scheme, in which the models were trained on fingerprint images labeled with one of three classes (Whorl, Loop, or Arch) and subsequently evaluated based on their ability to classify new data (Hisyam, 2025). The overall research process consisted of dataset collection, image preprocessing, feature extraction, training and testing data partitioning, KNN and RNN-LSTM model training, performance evaluation, and comparative analysis of the results (Listiana & Anam, 2025; Wibowo, 2025), as illustrated in Figure 1.



Figure 1. Research Stages

The dataset used in this study consisted of 600 fingerprint images obtained from the Kaggle platform, evenly distributed across three classes (Whorl, Loop, and Arch), with 200 images per class (Miranda et al., 2020; Nasir et al., 2024). The detailed dataset specifications are presented in Table 1.

Table 1. Dataset Specifications

Characteristic	Description
Total Number of Images	600 images
Number of Classes	3 classes (Whorl, Loop, Arch)
Distribution per Class	200 images per class
Image Size	224 × 224 pixels (after resizing)
Image Format	Grayscale (8-bit)

Training Data	420 images (70%)
Validation Data	90 images (15%)
Testing Data	90 images (15%)

The preprocessing stage involved converting images to grayscale, resizing them to 224 × 224 pixels, reducing noise using a Gaussian filter, and enhancing contrast using Contrast Limited Adaptive Histogram Equalization (CLAHE) to make fingerprint ridge patterns more distinct and easier to recognize (Sintiani, 2024; Muchtar et al., 2024). Feature extraction was performed using a combination of the Gabor Filter, which generated 64 local texture and orientation features, and the Histogram of Oriented Gradients (HOG), which generated 8,100 gradient and global structural features. Consequently, a combined feature vector with 8,164 dimensions was obtained for each image.

The dataset was then partitioned into training, validation, and testing sets using a ratio of 70%, 15%, and 15%, respectively. The KNN algorithm was implemented with different values of K (3, 5, 7, and 9) using Euclidean distance. Meanwhile, the RNN-LSTM model was implemented with different numbers of units (64, 128, and 256) in a two-layer LSTM architecture, using the Adam optimizer and an early stopping mechanism to prevent overfitting. The performance of both models was evaluated using accuracy, precision, recall, F1-score, training time, and inference time. The results were then comprehensively compared at both the overall level and the individual fingerprint pattern class level.

3. Results And Discussions

The best configurations were obtained using the KNN algorithm with K = 7 and the RNN-LSTM model with 128 units. A performance comparison of the two models on the same 90 test images is presented in Table 2.

Table 2. Performance Comparison of KNN (K = 7) and RNN-LSTM (128 Units)

Evaluation Metric	KNN (K = 7)	RNN-LSTM (128 Units)
Accuracy	97.78%	93.33%
Precision (macro average)	97.78%	93.68%
Recall (macro average)	97.78%	93.33%
F1-score (macro average)	97.78%	93.38%
Training Time (seconds)	0.205	31.461
Inference Time per Image (seconds)	0.00646	0.01266

As shown in Table 2, the KNN algorithm achieved an accuracy of 97.78%, substantially outperforming RNN-LSTM, which achieved only 93.33%. The precision, recall, and F1-score of KNN were also consistently 97.78%, indicating that the model performed reliably in recognizing all three fingerprint patterns. The most significant difference was observed in training time: KNN required only 0.205 seconds, whereas RNN-LSTM required 31.461 seconds, approximately 153 times longer. This difference is expected because RNN-LSTM has a substantially more complex network architecture with numerous parameters that must be optimized during training. Nevertheless, the difference in inference time for a single new image was relatively small, at 0.00646 seconds for KNN and 0.01266 seconds for RNN-LSTM.

The performance comparison at the individual class level is presented in Figure 2.

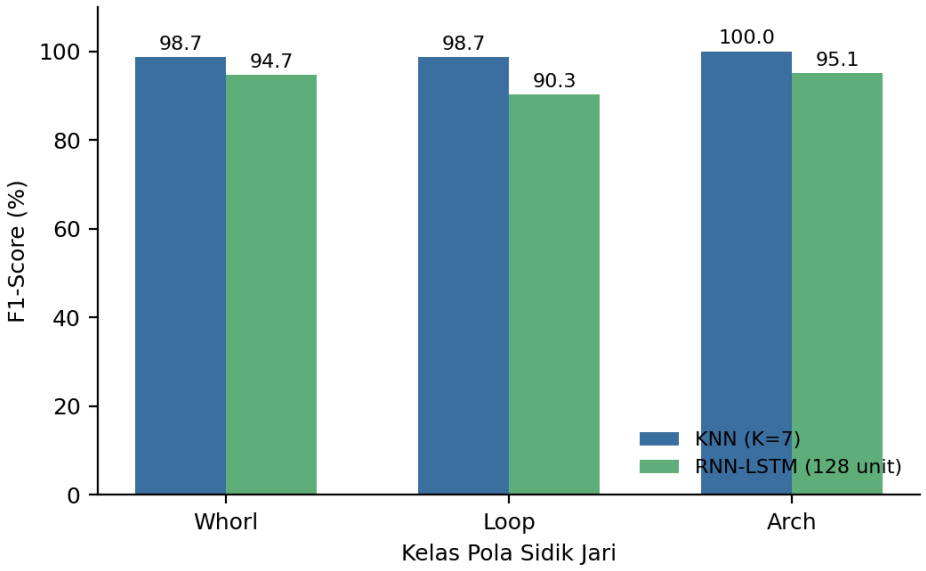


Figure 2. Comparison of F1-Scores Across Fingerprint Pattern Classes

Figure 2 shows that KNN consistently outperformed RNN-LSTM across all three classes. For the Whorl pattern, KNN achieved an F1-score of 98.7%, compared with 94.7% for RNN-LSTM. For the Loop pattern, KNN obtained 98.7%, whereas RNN-LSTM achieved only 90.3%, representing its lowest performance in this study. For the Arch pattern, KNN achieved a perfect F1-score of 100%, while RNN-LSTM obtained 95.1%. RNN-LSTM experienced the greatest difficulty in recognizing the Loop pattern, possibly because of the greater morphological variation within this class, which may have made the learned feature representations insufficiently discriminative for accurate classification.

Overall, the combination of Gabor Filter and HOG features proved effective as a hybrid feature extraction strategy. Gabor Filter captures local texture and orientation information from fingerprint ridges, whereas HOG captures gradient information and global structural characteristics more comprehensively. The synergy between these methods therefore produces a rich image representation. The superior performance of KNN in this study indicates that, for a medium-sized dataset containing 600 images with sufficiently discriminative extracted features, a simpler algorithm can outperform a substantially more complex deep learning model in both classification accuracy and computational efficiency. Nevertheless, RNN-LSTM still has potential for further improvement through the addition of training data, enhanced regularization, or a more optimized architecture.

4. Conclusion

Based on the experimental results, feature extraction from Whorl, Loop, and Arch fingerprint images was successfully performed using a combination of Gabor Filter (64 features) and Histogram of Oriented Gradients (HOG) (8,100 features), resulting in a combined feature vector with 8,164 dimensions per image. The KNN algorithm was implemented with K values of 3, 5, 7, and 9, while the RNN-LSTM model was evaluated using 64, 128, and 256 units. The experimental results demonstrated that KNN with K = 7 achieved superior classification performance, with an accuracy of 97.78%, compared with 93.33% for RNN-LSTM with 128 units. KNN was also substantially more computationally efficient, requiring only 0.205 seconds for training, compared with 31.461 seconds for RNN-LSTM, making it approximately 153 times faster. Furthermore, KNN achieved higher precision, recall, and F1-score, reaching 97.78% for all three metrics, whereas RNN-LSTM obtained 93.68%, 93.33%, and 93.38%, respectively. These findings indicate that, under the experimental conditions of this study, KNN outperformed RNN-LSTM in both classification accuracy and computational efficiency for three-class fingerprint pattern recognition. Future research should extend fingerprint classification to more detailed pattern subcategories and investigate additional feature extraction techniques, such as Local

Binary Pattern (LBP) and Convolutional Neural Networks (CNNs). Further studies could also evaluate alternative distance metrics for KNN and explore advanced recurrent architectures, such as Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU). In addition, K-fold cross-validation should be applied to larger and more diverse datasets to provide a more robust assessment of model generalization and the reliability of the comparative results.

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