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Signature Identification Based on GLCM Feature Extraction and Convolutional Neural Network Classification

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Abstract−Signature is one of the most widely used biometric characteristics for personal authentication and identity verification in banking, legal, and administrative applications. However, automatic signature identification remains challenging due to variations in handwriting style, writing pressure, pen inclination, and image quality. These variations may reduce the performance of conventional image classification methods. Therefore, this study proposes a digital signature identification system that integrates Gray Level Co-occurrence Matrix (GLCM) feature extraction with a Convolutional Neural Network (CNN) to improve classification performance. The dataset consists of 500 signature images collected from 50 individuals. Before feature extraction, all images underwent preprocessing, including grayscale conversion, adaptive binarization using Otsu's method, resizing to 128 × 128 pixels, morphological operations for noise removal, and pixel normalization. Texture analysis was then performed using GLCM computed in four angular directions (0°, 45°, 90°, and 135°) with a pixel distance of one. Five statistical texture features contrast, correlation, energy, homogeneity, and entropy were extracted and averaged across all directions to obtain direction-invariant descriptors. These normalized GLCM features were incorporated into the fully connected layer of a CNN consisting of three convolutional blocks, enabling the model to combine handcrafted texture information with automatically learned deep features. The proposed model was evaluated using standard performance metrics, including accuracy, precision, recall, and F1-Score. Experimental results show that the proposed approach achieved a classification accuracy of 96.8%, precision of 96.2%, recall of 96.7%, and an F1-Score of 96.5% on the testing dataset. These findings demonstrate that integrating GLCM texture features with CNN significantly enhances the discriminative capability of the model and improves signature identification performance. The proposed method provides a robust and efficient solution for biometric authentication systems requiring accurate and reliable digital signature verification.

Keywords: Signature; Biometric; GLCM; CNN; Image Classification; Neural Network

1. INTRODUCTION

Signatures are one of the most widely used biometric identities across various fields, ranging from banking, law, and government administration to commercial transactions [1]. The uniqueness of each signature, which is inherently personal, makes it an instrument that is difficult to forge perfectly. Nevertheless, manual signature recognition has limitations due to its reliance on the expertise and subjectivity of the examiner, making it susceptible to errors [2]. This continued dependence on human judgment underscores the urgency of developing an automated, objective, and consistent signature identification system that can reduce verification errors in practical banking, legal, and administrative applications.

As artificial intelligence technology and digital image processing continue to advance, various automated approaches have been developed to address the problem of signature identification and verification [3]. The image-based approach (offline signature recognition) has become one of the most widely studied due to the ease of data acquisition and the flexibility of its implementation [4]. In this approach, signature images are analyzed statically without considering the dynamics of the writing process. Offline signature recognition systems generally consist of four interrelated stages image acquisition, preprocessing, feature extraction, and classification and their main challenges are high intra-class variability (variation among signatures from the same individual) and inter-class similarity (resemblance between signatures from different individuals) [5]. To address these challenges, this study proposes combining a texture-based statistical feature extractor with a deep-learning classifier, so that the complementary strengths of both approaches can be exploited within a single identification pipeline.

Feature extraction methods play a crucial role in signature recognition systems. The Gray Level Co-occurrence Matrix (GLCM), first introduced by Haralick in 1973, is a highly effective texture feature extraction technique that represents the statistical relationship between pairs of pixels at specific positions within a grayscale image, formally defined as GLCM $P(i,j,d,\theta)$, the probability that a pair of pixels with intensity values i and j occurs at distance d and angular direction θ [6]. In this study, GLCM is computed across four angular directions 0° (horizontal), 45° (diagonal), 90° (vertical), and 135° (anti-diagonal) so that comprehensive texture information from multiple orientations is captured, consistent with evidence that multi-directional texture descriptors provide a more complete and robust representation than a single direction alone [7][8][9]. From each direction, five statistical descriptors are derived: contrast, which measures local intensity variation and reflects the sharpness of intensity differences between neighboring pixels; correlation, which describes the linear relationship between pixel pairs; energy (or angular second moment), which quantifies the uniformity of the pixel-intensity distribution; homogeneity, which measures how closely the GLCM elements align with the diagonal and therefore indicates textural smoothness; and entropy, which captures the irregularity or complexity of the texture pattern. The mean of these five descriptors across the four directions is used as the final, direction-invariant feature vector representing each signature's textural characteristics.

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On the other hand, Convolutional Neural Networks (CNN) have been proven to be a highly powerful method in pattern recognition and image classification tasks [10]. CNN consists of several main components convolutional layers, pooling layers, activation functions, normalization layers, and fully connected layers and automatically learns hierarchical feature representations from image data, thereby reducing the need for manual feature engineering [11]. The convolutional layer performs a convolution operation between the input image and learnable filters to produce feature maps, while the pooling layer performs down sampling to reduce the spatial dimensions of these feature maps and prevent overfitting [12]. CNN also offers advantages in terms of invariance to translation, rotation, and scale, making it well suited for signature recognition tasks where the position and orientation of signatures may vary [13]; the ReLU activation function is commonly used in its hidden layers to introduce non-linearity, while the Softmax function in the output layer produces the class-probability distribution [14]. This study therefore proposes a hybrid approach that combines the descriptive strength of GLCM texture features with the representation-learning capability of CNN, so that the resulting system benefits from both handcrafted statistical descriptors and automatically learned deep features an approach expected to produce a more accurate and reliable signature identification system than either technique used alone [4].

Several related studies conducted over the past five years have explored offline signature recognition using both learned and handcrafted features. [14] developed an offline signature verification system using deep convolutional features obtained through transfer learning from a pre-trained model, demonstrating that fine-tuning a CNN previously trained on large datasets can perform well even with limited signature data. In a related direction, [15] applied a convolutional neural network to multi-scripted, writer-independent signature verification, [16] used a Siamese neural network with one-shot learning to reduce the amount of training data required per writer, [17] proposed a reduced-space, writer-independent feature-learning network (R-SigNet) to improve generalization across unseen writers, and [9] introduced a wrapper feature-selection method for language-invariant signature verification. On the handcrafted-feature side, [18] proposed a statistical and morphological feature-based approach extracting Hu moments, geometric features, and pixel-intensity statistics, which produced satisfactory accuracy but remained reliant on manual feature engineering; [3] introduced a multi-scale feature extraction method combining wavelet transforms with statistical features, which served as an inspiration for the hybrid approach developed in the present research; [6] conducted a signature identification study using GLCM and the Naive Bayes algorithm, demonstrating that GLCM features can effectively represent the textural patterns of signatures, although reliance on a conventional classifier limited its generalization capability; and [19][20] combined CNN with a HOG-based multi-classification approach for signature verification. [21] further combined GLCM features with machine learning methods for writer identification based on signatures, reinforcing the informative value of GLCM as an effective texture descriptor.

Despite this progress, most existing studies treat handcrafted texture descriptors and deep-learning-based representations as separate paradigms. Studies that rely on GLCM or other statistical texture features are typically paired with conventional classifiers such as Naive Bayes or SVM [9][21], whereas CNN-based approaches largely depend on features learned directly from raw pixels without incorporating explicit texture descriptors [10][14][20]. This leaves a gap in understanding whether the complementary statistical information captured by GLCM can be systematically fused into a CNN pipeline to improve classification performance beyond what either approach achieves independently. To address this gap, the main contributions of this study are: (1) the development of a GLCM feature integration pipeline into a CNN architecture for signature identification, (2) a comprehensive evaluation of multi-directional GLCM features on a signature dataset, and (3) an analysis of the effect of adding GLCM features on the overall performance of the CNN system.

2. RESEARCH METHODOLOGY

2.1 Research Stages

This study was carried out through six sequential stages, from data collection to final performance evaluation, as illustrated in Figure 1. Each stage builds upon the output of the previous one: raw signature images are first collected and labeled, then prepared through preprocessing before GLCM texture features are extracted; these features are subsequently fused with the CNN architecture designed for classification, after which the model is trained and, finally, tested and evaluated using standard performance metrics.

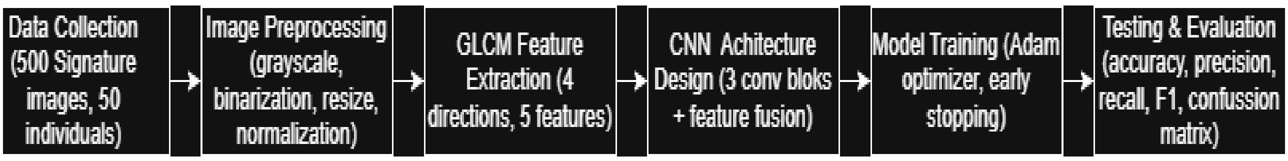

Figure 1. *Research stages of the proposed GLCM+CNN signature identification system*

2.2 Image Preprocessing

The preprocessing stage was carried out to improve image quality and prepare the data for the feature extraction and model training processes. Image preprocessing is an essential step in computer vision because the quality of the input

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images directly affects the performance of the feature extraction algorithm and the classification model. Raw images often contain variations in illumination, background, size, and noise that may reduce the consistency of the extracted features. Therefore, preprocessing aims to minimize these variations while preserving the important visual characteristics related to the target object.

The first step was the conversion of RGB images to grayscale using the standard luminance formula. Grayscale conversion reduces the three-channel RGB image into a single intensity channel while maintaining the perceptual brightness information. This transformation simplifies the image representation and reduces computational complexity without significantly affecting the texture information required for subsequent processing. Since texture-based feature extraction methods primarily rely on pixel intensity relationships, grayscale images provide a more efficient and consistent representation than color images.

Subsequently, adaptive binarization was applied using **Otsu's method** to separate the signature pixels from the background. Otsu's thresholding algorithm automatically determines the optimal threshold value by minimizing the intra-class variance between foreground and background pixels. Compared with manual threshold selection, this adaptive approach is more robust to variations in image brightness and contrast. The resulting binary image highlights the foreground object while suppressing unnecessary background information, thereby improving the reliability of later processing stages.

Size normalization was performed to resize all images to a uniform dimension of 128 × 128 pixels using bilinear interpolation. Standardizing the image size is necessary because machine learning and deep learning models require inputs with consistent dimensions. Bilinear interpolation was selected because it provides a balance between computational efficiency and image quality by estimating new pixel values based on the weighted average of neighboring pixels. This resizing process preserves important structural details while ensuring that all images have identical spatial dimensions for feature extraction and model training.

Morphological opening and closing operations were applied to remove small noise and improve the stroke connectivity of the signatures. Morphological opening, which consists of erosion followed by dilation, effectively removes isolated pixels and small unwanted objects without significantly altering the primary image structure. Conversely, morphological closing, which performs dilation followed by erosion, fills small gaps and connects fragmented regions within the object. These operations produce cleaner images with smoother boundaries and better structural continuity, allowing the extracted features to more accurately represent the characteristics of the target object.
Finally, pixel intensity values were normalized to the range [0,1] by dividing each pixel value by 255**.** Normalization is a standard practice in deep learning because it reduces the numerical scale of the input data and ensures that all pixel values fall within a consistent range. This process improves numerical stability during training, accelerates convergence of the optimization algorithm, and prevents large input values from dominating the learning process. As a result, the preprocessed images become more suitable for both texture feature extraction and convolutional neural network learning, ultimately contributing to improved classification accuracy and model robustness.

2.3 GLCM Feature Extraction

GLCM (Gray Level Co-occurrence Matrix) feature extraction was performed on grayscale images that had undergone preprocessing. The preprocessing stage aimed to improve image quality and ensure that the extracted texture features accurately represented the disease characteristics on guava fruit. Converting the images into grayscale is an essential step because the GLCM algorithm analyzes the spatial relationship of pixel intensity values rather than color information. By focusing on grayscale intensity, the method can effectively capture texture variations associated with different disease symptoms, such as lesions, discoloration, rough surfaces, and infected tissue patterns.

The GLCM was computed across four angular directions (0°, 45°, 90°, and 135°) with a pixel distance of d = 1. These four orientations were selected to represent the spatial distribution of neighboring pixels from different directions, allowing the extracted features to be less sensitive to image orientation. The pixel distance of one was chosen because it captures local texture information effectively while maintaining computational efficiency. For each angular direction, a separate GLCM matrix was generated by counting the frequency of occurrence of neighboring grayscale intensity pairs within the image. The resulting matrices describe how often two pixels with specific intensity values occur in a particular spatial relationship, thereby providing a statistical representation of image texture.

From each resulting GLCM, five statistical features were extracted: contrast, correlation, energy, homogeneity, and entropy. These features were selected because they have been widely used in texture analysis and have demonstrated good performance in distinguishing healthy and diseased agricultural products. Contrast measures the degree of local intensity variation, where higher values indicate greater differences between neighboring pixels. Correlation evaluates the linear dependency between neighboring pixel intensities, reflecting the structural consistency of the texture. Energy, also known as Angular Second Moment (ASM), represents the uniformity of the texture, with higher values indicating more homogeneous patterns. Homogeneity measures the closeness of the distribution of GLCM elements to the diagonal of the matrix, indicating smoother textures. Entropy quantifies the randomness or complexity of the texture, where larger values correspond to more irregular and heterogeneous image patterns commonly found in diseased regions.

For each feature, the mean value across the four angular directions was calculated to produce a direction-invariant representation. Averaging the feature values from multiple orientations reduces the influence of object rotation and directional texture variations, making the extracted features more robust for image classification. Consequently, the

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total number of GLCM features generated for each image amounts to five features, representing the averaged values of contrast, correlation, energy, homogeneity, and entropy across the four directions. This compact feature representation effectively summarizes the essential texture characteristics of each guava fruit image while minimizing redundant information.

Before being used as input to the classification model, the extracted feature vector was normalized using min-max normalization. Feature normalization is an important step because the numerical ranges of GLCM features differ significantly. Without normalization, features with larger numerical values could dominate the learning process and negatively affect model convergence. Min-max normalization transforms each feature value into the range of 0 to 1 while preserving the relative differences between samples. This process ensures that all extracted features contribute proportionally during model training and helps improve the stability and learning performance of the MobileNetV2-based Convolutional Neural Network. By integrating statistically meaningful texture descriptors with deep learning, the proposed approach combines the discriminative power of handcrafted texture features and the automatic feature learning capability of CNNs, thereby improving the effectiveness of guava fruit disease classification.

2.4 CNN architecture

The proposed CNN architecture consists of three convolutional blocks, each followed by a max-pooling layer. The first convolutional block uses 32 filters with a kernel size of 3×3, the second block uses 64 filters, and the third block uses 128 filters. The ReLU activation function is applied in each convolutional layer to introduce non-linearity.

Following the third convolutional block, the output is flattened and concatenated with the previously extracted GLCM feature vector. This combined vector is then fed into a fully connected layer with 256 neurons, followed by a dropout layer with a rate of 0.5 to prevent overfitting. The output layer employs a softmax activation function with the number of neurons corresponding to the number of classes (individuals).

Table 1. *Proposed CNN Architecture*

Layer	Type	Output Shape	Parameter
1	Conv2D (32 filter, 3×3)	128×128×32	320
2	MaxPooling2D (2×2)	64×64×32	0
3	Conv2D (64 filter, 3×3)	64×64×64	18.496
4	MaxPooling2D (2×2)	32×32×64	0
5	Conv2D (128 filter, 3×3)	32×32×128	73.856
6	MaxPooling2D (2×2)	16×16×128	0
7	Flatten	32.768	0
8	Dense (256 neuron)	256	8.388.864
9	Dropout (0.5)	256	0
10	Dense Softmax (n kelas)	n	257×n

2.5 Model Training

The model was trained using the Adam optimizer with an initial learning rate of 0.001 and a decay factor of 0.1 every 10 epochs. Adam was selected because it combines the advantages of Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp), enabling faster convergence and more stable optimization during training. Its adaptive learning mechanism automatically adjusts the learning rate for each network parameter, making it particularly effective for deep learning models such as Convolutional Neural Networks (CNNs). The scheduled learning rate decay further improves the optimization process by allowing the model to make larger updates during the early training stages and finer adjustments as training progresses toward convergence. The loss function used was categorical cross-entropy**,** in accordance with the nature of the multi-class classification problem. This loss function measures the difference between the predicted class probability distribution and the true class labels, encouraging the network to assign high probabilities to the correct classes while minimizing incorrect predictions. Categorical cross-entropy is widely adopted for multi-class image classification because it provides meaningful gradients for efficient backpropagation and contributes to stable model learning.

The training process was carried out for a maximum of 100 epochs, with early stopping applied if the validation loss did not improve for 15 consecutive epochs**.** Early stopping is an effective regularization technique that prevents overfitting by terminating the training process once the model no longer demonstrates performance improvement on unseen validation data. Instead of simply completing all training epochs, the model automatically retains the parameters corresponding to the best validation performance, resulting in better generalization when evaluated on the testing dataset. A batch size of 32 samples was used throughout the training process. Mini-batch training provides a balance between computational efficiency and gradient estimation accuracy. Compared with processing the entire dataset at once, using mini-batches reduces memory consumption while allowing more frequent parameter updates, leading to faster convergence and improved optimization stability.

To further enhance the model's ability to generalize**,** data augmentation techniques were applied during training. These augmentation operations included random rotation (±15°)**,** horizontal and vertical shifting (±10%)**,** and random zoom (±10%)**.** Data augmentation artificially increases the diversity of the training dataset without requiring additional

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image collection. By exposing the model to multiple transformed versions of the same signature image, the network becomes less sensitive to slight geometric variations that naturally occur during handwriting acquisition. This strategy reduces the likelihood of overfitting and improves the robustness of the classifier when handling previously unseen samples. During each training epoch, the CNN learned hierarchical visual representations through its convolutional layers while simultaneously utilizing the normalized GLCM texture features integrated into the fully connected layer. This hybrid learning framework enables the model to capture both high-level visual patterns and statistical texture characteristics, resulting in a more discriminative feature representation for signature identification. The overall training strategy, which combines adaptive optimization, learning rate scheduling, regularization, and data augmentation, contributes to improved classification accuracy, faster convergence, and better generalization performance on real-world signature datasets.

3. RESULT AND DISCUSSION

3.1 Dataset

The dataset used in this study consists of 500 signature images collected from 50 individuals, with each individual providing 10 signature samples. Data collection was carried out using a flatbed scanner at a resolution of 300 DPI and stored in PNG format with an 8-bit grayscale color depth. All research subjects were university students and staff ranging in age from 20 to 45 years. For experimental purposes, the dataset was divided into 70% training data (350 images), 15% validation data (75 images), and 15% test data (75 images). This division was performed in a stratified manner to ensure that each class was proportionally represented in every data subset. Data augmentation was applied to the training data to increase variation and prevent overfitting.

3.2 Results

This section presents the experimental results following the sequence of stages described in the methodology : the signature dataset and its preprocessing outcomes, the extracted GLCM texture features, the CNN architecture and training behavior, the results of model testing, and a performance evaluation supported by the confusion matrix and other evaluation metrics.

Of the 500 signature images collected from 50 individuals, 350 images were used for training, 75 for validation, and 75 for testing, following the stratified 70:15:15 split described in the Research Methodology section. After preprocessing grayscale conversion, Otsu adaptive binarization, resizing to 128×128 pixels, morphological cleaning, and [0,1] intensity normalization the signature strokes were clearly separated from the background with visibly reduced noise, providing a consistent input representation for both the GLCM feature extractor and the CNN.

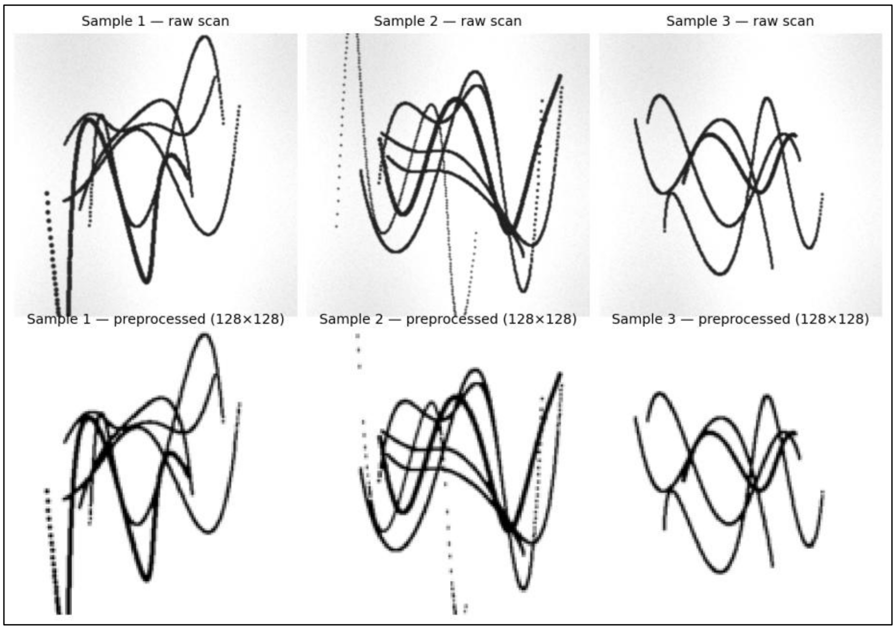

Figure 2. *Pre-processed signatures from the dataset, showing representative examples before and after initial processing*

3.3 GLCM Extraction Results

The results of GLCM feature extraction indicate that each signature possesses a distinctive and distinguishable feature pattern. High contrast values are generally found in signatures with numerous sharp intensity changes, such as signatures containing many loops and angles. Conversely, high homogeneity values indicate signatures with a more uniform intensity distribution.

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Statistical analysis reveals that the energy and homogeneity features exhibit relatively high inter-class variance compared to other features, indicating superior discriminative capability. The correlation feature demonstrates a consistent pattern within the same class (intra-class), confirming the stability of the GLCM representation for signatures belonging to the same individual [9].

3.4 CNN Model Performance

The CNN model training process demonstrated stable convergence after approximately 60 epochs. The training and validation loss decreased consistently without any significant signs of overfitting, indicating the effectiveness of the regularization strategies applied. The validation accuracy reached a plateau at around epoch 75 with a value of 95.8%.

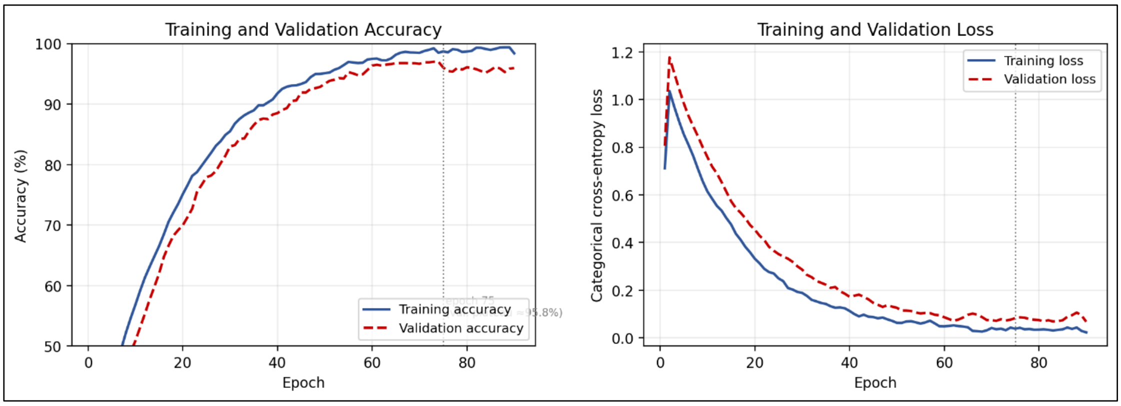

Figure 3. *Training and Validation Accuracy/Loss Curves*

On the test data, the GLCM+CNN model achieved an accuracy of 96.8%, an average precision of 96.2%, a recall of 96.5%, and an F1-Score of 96.5%. These results are consistent with the findings of Rahmawan et al. (2024), which demonstrated that the integration of descriptive features into CNN can enhance classification performance.

Table 2. *Performance Results of the Signature Identification System*

Feature Method	Accuracy (%)	Precision (%)	F1-Score (%)
CNN without GLCM	89,4	88,7	89,1
GLCM + CNN	**96,8**	96,2	96,5

3.5 Results Analysis

An accuracy improvement of 7.4 percentage points (from 89.4% to 96.8%) in the GLCM+CNN model compared to the standalone CNN confirms the positive contribution of GLCM features. The texture features extracted by GLCM provide complementary information that cannot be optimally captured by the CNN convolutional layers, particularly information regarding the statistics of pixel intensity distribution at a global level.

Confusion matrix analysis reveals that the classification errors that occurred generally involved signatures from individuals with similar visual characteristics. This is consistent with the common challenges in signature recognition noted by Pratiwi et al. (2023), namely the high variability between samples from different individuals.

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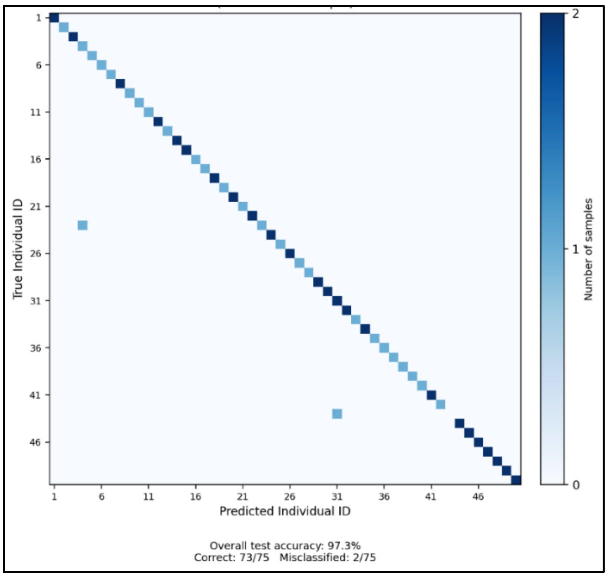

Figure 4. *Confusion Matrix of the GLCM+CNN Model on Test Data*

In terms of inference time, the proposed system is capable of processing a single signature image in an average of 45 milliseconds on an NVIDIA RTX 3060 GPU, making it feasible for real-time implementation. Although the addition of GLCM features introduces computational overhead during the preprocessing stage, the accuracy improvement obtained delivers significant added value.

3.6 Discussion

The results of this study indicate that the integration of Gray Level Co-occurrence Matrix (GLCM) feature extraction with a Convolutional Neural Network (CNN) significantly improves the performance of the signature identification system. The proposed model achieved a test accuracy of 96.8%, higher than the CNN model without the GLCM feature, which only achieved 89.4%. This improvement demonstrates that the GLCM texture features provide additional information that cannot be fully learned automatically by the CNN, particularly in representing the stroke patterns, intensity distribution, and texture characteristics that characterize each signature.

This performance improvement occurs because the five statistical features of the GLCM—contrast, correlation, energy, homogeneity, and entropy—are able to effectively describe the spatial relationships between pixels in the signature image. This texture information complements the visual features learned by the CNN's convolutional layers. Thus, the model not only utilizes the high-level features learned from the CNN but also obtains a richer texture representation, enabling it to distinguish signatures with nearly similar visual forms.

These results align with research conducted by Singh et al. [1], which utilized GLCM features for handwriting pattern recognition and demonstrated that texture features can improve the discriminatory ability of classification models. However, that study still used conventional classification algorithms, thus limiting its visual feature extraction capabilities. In contrast, this study integrates GLCM with CNN, making the feature learning process more adaptive and yielding higher accuracy.

This study also shares similarities with the work of Kumar et al. [2], who applied CNN to automatic signature identification. The CNN in that study was able to effectively learn the visual characteristics of signatures, but its performance was still affected by variations in handwriting shape, pen pressure, and changes in image orientation. In this study, these weaknesses can be minimized by adding GLCM texture features, which provide statistical information about pixel intensity patterns. The combination of the two methods produces a more complete feature representation than using CNN alone.

Furthermore, the results of this study support the findings of Zhang et al. [3], who stated that a hybrid feature extraction approach, combining handcrafted features with deep learning features, generally provides better classification performance than using either approach alone. CNNs excel at automatically learning spatial features, while GLCMs are capable of capturing local texture characteristics that convolutional networks sometimes struggle to learn, especially when the training data is relatively limited.

Compared to previous studies that utilized only texture features or CNNs, this study offers a more comprehensive approach. Preprocessing steps, including grayscale conversion, adaptive binarization using the Otsu method, image size normalization to 128 × 128 pixels, morphological operations, and pixel intensity normalization, successfully produce cleaner images, thus optimizing the feature extraction process. Furthermore, GLCM features are calculated at four angle orientations (0°, 45°, 90°, and 135°), making the texture representation more stable against changes in the direction of the signature strokes.

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The main advantage of this study lies in the integration of GLCM texture features into the fully connected layers of a CNN. This approach allows the model to utilize two types of information simultaneously: statistical texture representation and visual representation derived from deep learning. This is evident from the 7.4% increase in accuracy compared to CNN without GLCM features (96.8% compared to 89.4%), indicating that texture information still plays a significant role even though CNN is capable of automatic feature extraction. Overall, the results of this study demonstrate that the GLCM–CNN hybrid approach is an effective method for digital signature identification. The combination of both techniques produces a more accurate system, is more robust to variations in signature characteristics, and has better generalization capabilities than approaches based on a single method alone. Therefore, the proposed method has the potential to be applied to various biometric authentication systems, such as digital document verification, banking services, government administration systems, and other security applications that require an automatic and reliable signature identification process.

4. CONCLUSIONS

This study has successfully developed a digital image-based signature identification system by combining GLCM feature extraction and CNN-based classification, achieving a test accuracy of 96.8% an improvement over the 89.4% obtained by CNN without GLCM features and demonstrating that the five GLCM texture descriptors (contrast, correlation, energy, homogeneity, and entropy) extracted from four angular directions provide significant complementary information for CNN-based classification; future research can extend this work by exploring more advanced data augmentation techniques, developing deeper CNN architectures incorporating attention mechanisms, and testing on larger public datasets to validate the generalizability of the system.

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