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A Survey of Signature Recognition Systems: Comparative Analysis of Methods and Techniques

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Abstract: This literature survey explores advancements in machine learning methodologies, specifically focusing on Artificial Neural Networks (ANN), Back Propagation Neural Networks (BPNN), and Hidden Markov Models (HMM), and their application in offline signature recognition. Highlighting key techniques, the survey reviews the use of Histogram of Oriented Gradients (HOG) and Fuzzy Min-Max Classification (FMMC), which achieve a 96% recognition rate through a diverse signature database. Additionally, it examines the Efficient Fuzzy Kohonen Clustering Network (EFKCN) algorithm, demonstrating improved accuracy in signature pattern recognition up to 70%. Emphasizing preprocessing stages, feature extraction, and robust classification frameworks, the study offers a comparative analysis of these methodologies, elucidating their theoretical foundations, practical implementations, and performance metrics.

Index Terms: Artificial Neural Networks (ANN), Back Propagation Neural Networks (BPNN), and Hidden Markov Models (HMM), Histogram of Oriented Gradients (HOG) and Fuzzy Min-Max Classification (FMMC), Efficient Fuzzy Kohonen Clustering Network (EFKCN) algorithm

I. INTRODUCTION

This literature survey examines recent advancements in offline signature recognition, integrating neural networks and image processing techniques.

Signature recognition is crucial in biometric verification, providing secure solutions across various applications. This paper examines the effectiveness of three prominent machine learning models: Artificial Neural Networks (ANN), Back Propagation Neural Networks (BPNN), and Hidden Markov Models (HMM). ANN's layered architecture and learning capabilities, along with BPNN's iterative error correction mechanism, have advanced pattern recognition.

HMM contributes robust solutions for sequence prediction, crucial for analyzing temporal patterns in signatures. The survey highlights cutting-edge techniques such as Histogram of Oriented Gradients (HOG) and Fuzzy Min-Max Classification (FMMC), which have achieved impressive recognition rates.

Additionally, the Efficient Fuzzy Kohonen Clustering Network (EFKCN) algorithm has shown substantial improvements in accuracy. By emphasizing preprocessing, feature extraction, and sophisticated classification frameworks, this paper aims to provide a thorough analysis of these methodologies, comparing their performance and offering insights into the current advancements in offline signature recognition systems.

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II. BASIC CONCEPTS

A. DATA ACQUISITION

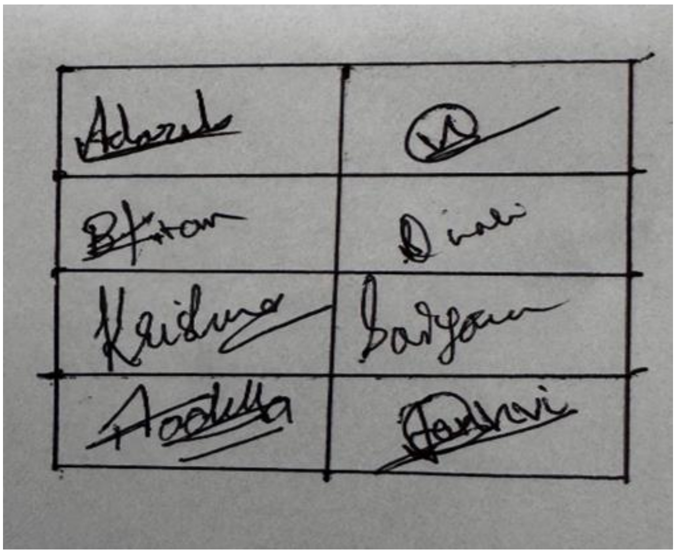

Fig. A1. sample signatures

Handwritten signatures are collected and some unique features are extracted to create knowledge base for each and every individual. A standard database of signatures for every individual is needed for evaluating performance of the signature verification system and also for comparing the result obtained using other techniques on the same database [3].

For training and testing of the signature recognition and verification system 675 signatures are used. The signatures were taken from 56 persons [2].

For training and testing the recognition system, we use our signature database, because with this type of data, no international database is offered in this context due to the privacy problems.

In this paper, a database of about 240 signatures is used. The signatures were taken from 12 persons (20 signatures from each). For training the system, a subset of 120 signatures is used, and the remaining signatures are used for testing [5].

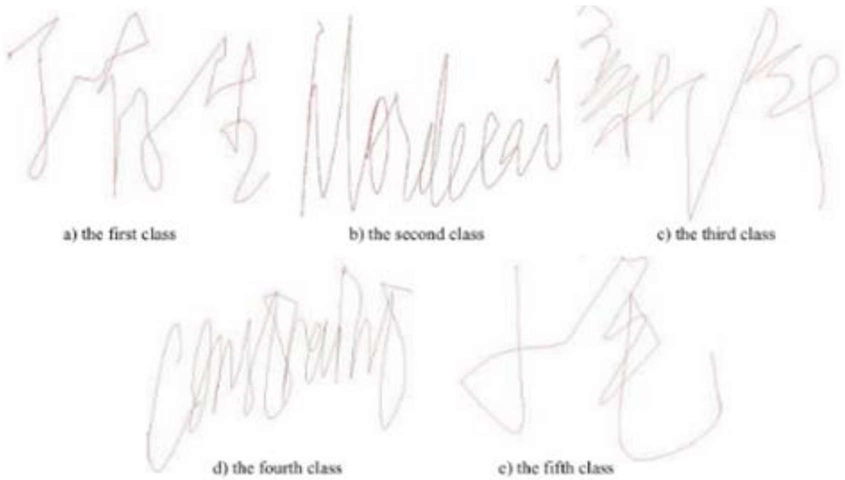

Fig. A2. classes of signatures

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B. PRE-PROCESSING

B.1. Color to Grayscale Conversion

Color images are converted to grayscale to simplify the processing pipeline. Grayscale images have only one channel, which reduces computational complexity and focuses on intensity information relevant for signature analysis, as color information is not critical for distinguishing signatures [2].

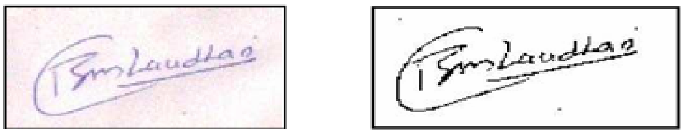


Fig. B1. converting into grayscale

B.2. Noise Reduction (Median Filtering)

Median filtering is used to remove noise such as salt-and-pepper interference while preserving the edges of the signature. This step smoothens the image and improves the quality by eliminating random noise that could affect the accuracy of subsequent steps like thresholding and feature extraction [2].

B.3. Resizing

Resizing ensures that all images are brought to a standard resolution, typically 512x512 pixels. This standardization helps in maintaining uniformity in processing and analysis, ensuring that the system performs optimally regardless of the original size of the signature images [3].

Fig. B2. Resizing

B.4. Background Elimination and Thresholding

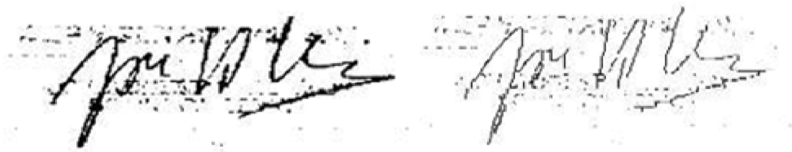
By applying thresholding, the image is converted to a binary format where the signature is separated from the background. This step ensures that the signature is distinctly identified as an object (with a pixel value of 1) against a uniform background (with a pixel value of 0), simplifying further processing like normalization and feature extraction [1].

B.5. Width Normalization

Normalizing the width and height of the signature images to a standard size ensures consistency across different samples. This step adjusts for variations in signature dimensions caused by differences in scanning or signing practices, making it easier to compare and analyze signatures by maintaining a uniform reference size [1].

B.6. Thinning

Thinning reduces the signature to a one-pixel-wide representation. This step removes variations in stroke thickness, ensuring that the focus is on the shape and structure of the signature rather than its physical dimensions.
It helps in creating a consistent representation of the signature's essential features [1].



Original noisy signature corresponding skeleton

Fig. B3 skeletonised image

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C. TRAINING THE MODEL

C.1. Feature Extraction and Skeleton Analysis

Pixel Labeling: Each pixel in the signature is labeled based on one of four orientations (0º, 45º, 90º, 135º). This step involves initializing the orientation labels for pixels in the signature.

Pixel Tracking: After labeling, the algorithm tracks the pixels to extract strokes of the signature. This tracking is performed independently for each orientation to ensure comprehensive stroke extraction.

Stroke Normalization: The extracted strokes are normalized to standardize their representation, making them ready for the recognition stage [1].

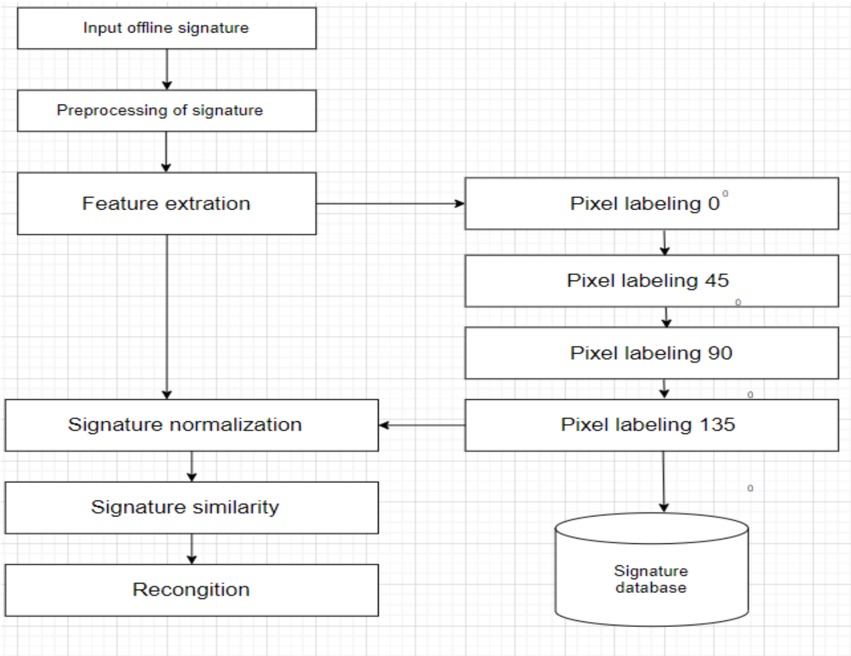

Fig. C1. CNN model

C.2. Feature Extraction for Classification

Invariant Central Moments: Central moments are calculated to capture translation invariance. These moments are normalized to achieve both translation and scale invariance. This feature set helps in minimizing within-class variations and increasing inter-class differences.

Zernike Moments: These moments are used for rotation normalization. The Zernike polynomials project the image function onto orthogonal basis functions, allowing for rotation invariance and easy image reconstruction [2].

C.3. Convolutional Neural Networks (CNNs)

Preprocessing: The preprocessed grayscale images are loaded into the CNN model.

Model Training: Using the Keras library with TensorFlow backend, the CNN model is trained on these images to learn features and patterns for signature recognition. The model is evaluated based on its performance in recognizing and classifying signatures [3].

C.4. Signature Processing and Training:

Image Conversion: Signature images are converted from RGB to grayscale, then to binary, and further to an inverted binary format to unify the signature pattern.

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Normalization: The images are normalized using Hu's moment invariants to ensure invariance to scale, rotation, and transformation changes.

Training Data: Signatures are trained under various conditions, and the model identifies the owner based on the Euclidean distance between the test signature and cluster centers derived from training signatures [2].

C.5. Fuzzy Min-Max Classification (FMMC) and K Nearest Neighbours (KNN)

Model Architecture: The FMMC model comprises input, hidden, and output layers. Training involves adjusting the hyperboxes in the hidden layer to match input images, guided by parameters such as vigilance and sensitivity.

Learning Process: For each training input, the system expands, overlaps, and contracts hyperboxes to accurately classify the image.

Distance Calculation: The KNN model calculates the Manhattan distance between the test image and training images.

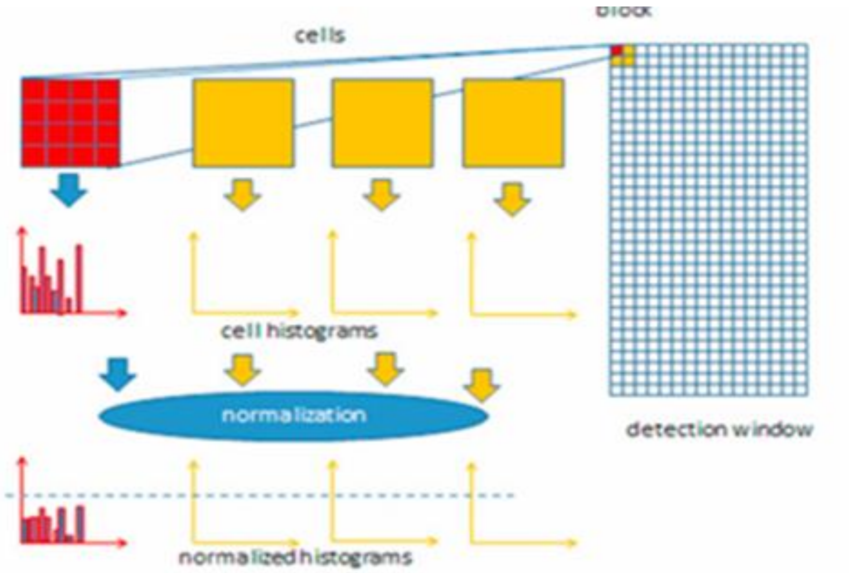

Fig. C2. HOG model

Classification: The test image is classified based on the nearest neighbours' classes, ensuring that only the closest objects influence the classification result [5].

C.6. 2D-Hidden Markov Models (HMMs)

Feature Extraction: Each 2D signature image is converted into a 1D feature vector by extracting 16 DCT coefficients from segmented blocks.

HMM Training: The HMM is trained using five signature images per user. The Baum-Welch algorithm optimizes the model parameters to maximize the likelihood of observation data.

Parameter Estimation: Initial estimates for the HMM parameters are obtained using k-means clustering, and iterative updates refine these estimates based on the observed data [6].

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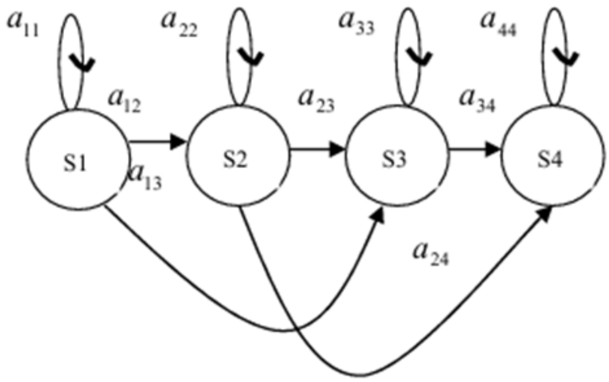

Fig. C3. HMM model

D. RECOGNITION

D.1. Signature Recognition System Testing

The signature recognition system involves both training and testing phases to verify and validate the model's effectiveness in distinguishing between genuine and forged signatures.

Signature recognition compares a given signature against a database to identify the signer. Testing in this phase ensures the system can accurately identify signatures from a pre-defined database. The approach used a back-propagation neural network (ANN) with a high recognition rate of 100% for the 56 signatures in the database. Testing with additional random signatures resulted in some false positives, which were addressed by a subsequent verification step to ensure robustness against both false positives and negatives [1][7][8].

D.2. Convolutional Neural Network (CNN)

Model Architecture: A CNN was implemented using Keras with TensorFlow backend. The architecture included several convolutional and max-pooling layers, followed by fully connected layers. The model was evaluated with different dataset split ratios (e.g., 60:40, 70:30, 80:20).

Performance Metrics: Accuracy and loss metrics were plotted to gauge model performance. The highest accuracy achieved was 99.7% with an 80:20 data split. The model showed very low overfitting or underfitting, providing reliable performance metrics for validation sets [3].

D.3. FMMC, HOG, KNN

Dataset: The testing involved a dataset of 300 signature images (150 genuine and 150 forged). The system's performance was evaluated based on its ability to correctly identify genuine and forged signatures.

Feature Extraction and Classification: Various feature extraction methods (e.g., HOG, Profile Projection, Loci) were compared using classifiers like kNN and FMMC. HOG descriptors outperformed other methods, achieving a recognition rate of 96% with FMMC. The FMMC method demonstrated superior performance compared to kNN in terms of recognition accuracy [4][5].

D.4. Hidden Markov Model (HMM)

Feature Extraction: The HMM-based system used Discrete Cosine Transform (DCT) features to segment signature images into HMM states. The Viterbi algorithm computed the likelihood of observed vectors, and the system achieved a recognition performance of 99.2%, with only four out of 500 signatures not recognized [6].

D.5. Performance Metrics

False Acceptance Ratio (FAR) and False Rejection Ratio (FRR): Testing also involved measuring the FAR and FRR, which are crucial for evaluating the precision of the signature verification system. With a threshold variance of 90%, the system achieved a FAR of 1.6% and an FRR of 3%, reflecting effective balance between acceptance and rejection rates [7].

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Ref. no.	Research Paper	Authors	Methodology	Remarks
[1]	SIGNATURE RECOGNITION SYSTEM USING ARTIFICIAL NEURAL NETWORK	Yirga Yayeh Munaye and Getaneh Berie Tarekegn	ANN, SVM, MATLAB	Restricted to image quality and less feature extraction
[2]	Signature Recognition & Verification System Using Back Propagation Neural Network	Nilesh Y. Choudhary, GF'S GCOE, Jalgaon, India Mrs. Rupal Patil, GF'S GCOE, Jalgaon, India Dr. Umesh. Bhadade, Prof. Bhupendra M Chaudhari	Back Propagation ANN	It gives the poor performance for signature that is not in the training phase
[3]	Handwritten Signature Verification using Deep Learning	Eman Alajrami, Belal A. M. Ashqar, Bassem S. Abu-Nasser, Ahmed J. Khalil, Musleh M. Musleh, Alaa M. Barhoom, Samy S. Abu-Naser	CNN	This implementation may be considered extreme. Shows 99.7% accuracy
[4]	Offline Signature Recognition and Verification System using Efficient Fuzzy Kohonen Clustering Network (EFKCN) Algorithm	Dewi Suryani, Edy Irwansyah, Ricki Chindra	Fuzzy C-Mean (FCM) algorithm and KCN's all vector update	Shows relatively better results with 70% accuracy
[5]	An Efficient Signature Recognition System Based on Gradient Features and Neural Network Classifier	Ouadae El Melhaoui, Soukaina Benchaou	Histogram of Oriented Gradients (HOG), Fuzzy Min-Max classification (FMMC) and K Nearest Neighbours (KNN)	The proposed system has achieved good results; a 96 % accuracy was obtained
[6]	Offline Signature Recognition using Hidden Markov Model (HMM)	Dr. S. Adebayo Daramola, Prof. T. Samuel Ibiyemi	DCT Feature Extraction, 2D-Signatures Model	Contributed greatly to the generation of robust signature model
[7]	Offline signature recognition using neural networks approach	Ali Karounia, Bassam Dayab, Samia Bahlak,	ANN	The system is robust and can detect random, simple and semi-skilled forgeries
[8]	Designing an Offline Method for Signature Recognition	Mehdi Radmehr, Seyed Mahmoud, Mohsen Nikpour, Abbas Yaser	Radon Transform, SVM and Fractal Dimension	Challenges for future (i) extract more effective features (ii) combine SVM-based classifier with other signature recognition methods

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[9]	Online handwritten signature verification system based on DWT features extraction and neural network classification	Maged M. M. Fahmy	DWT and Neural Network Classification.	The combination of DWT and neural network classification provides a robust approach for signature verification, enhancing accuracy and detection capabilities
[10]	Handwritten signature forgery detection using convolutional neural networks	S. Jerome Gideon, et al	CNN	This study effectively demonstrates the application of Convolutional Neural Networks (CNNs) for detecting signature forgeries, showcasing high accuracy in identifying complex forgery patterns
[11]	Handwritten Signature Recognition: A Convolutional Neural Network Approach	Krishnaditya Kancharla, Varun Kamble, Mohit Kapoor	CNN	This paper highlights the use of Convolutional Neural Networks (CNNs) for handwritten signature recognition, achieving promising results in identifying signatures accurately
[12]	Handwritten signature recognition using deep learning	B. Mustafa, R. Taha, O. M. Fahmy, S. M. Afifi	Deep learning	The study demonstrates the efficacy of deep learning for signature recognition, offering automation and high accuracy
[13]	An Evolving Signature Recognition System	B. Jayasekara, A. Jayasiri, L. Udawatta	Adaptive Learning	The paper presents a novel approach with adaptive learning to handle evolving signature patterns, improving long-term accuracy
[14]	Dynamic Signature Verification System Based on One Real Signature	M. Diaz, A. Fischer, M. A. Ferrer, R. Plamondon	Sigma-Lognormal Modeling	The system innovatively minimizes enrollment data to just one signature while achieving robust verification
[15]	Machine learning-based offline signature verification systems	M. Muzaffar Hameed, Rodina Ahmad, Miss Laiha Mat Kiah, Ghulam Murtaza	Systematic Review	This review provides a comprehensive understanding of machine learning advancements in offline signature verification

III. CONCLUSION

This survey paper comprehensively reviewed various methods for signature recognition, highlighting their strengths and limitations. Signature recognition, a crucial aspect of security and personal identification, benefits significantly from advanced computational techniques. We explored several approaches, including traditional Back Propagation Neural Networks (BPNNs), Convolutional Neural Networks (CNNs), and Hidden Markov Models (HMMs), each offering unique advantages.

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CNNs emerged as a highly effective model for signature recognition, achieving remarkable accuracy rates up to 99.7% when tested with different dataset splits. The CNN's ability to automatically learn and extract features from image data makes it superior in handling the intricate patterns of signatures. On the other hand, HMMs, coupled with Discrete Cosine Transform (DCT), demonstrated robust performance with a 99.2% recognition rate, excelling in temporal sequence modeling and dynamic pattern recognition.

Among the methods discussed, CNNs stand out as the best approach due to their high accuracy, efficiency in feature extraction, and adaptability to various input variations. Combining CNNs with other techniques like HMMs or feature extraction methods could further enhance performance by leveraging the strengths of each method.

In conclusion, while CNNs provide the most effective standalone solution for signature recognition, integrating them with additional methods offers a promising avenue for future research, potentially improving accuracy and reliability even further.

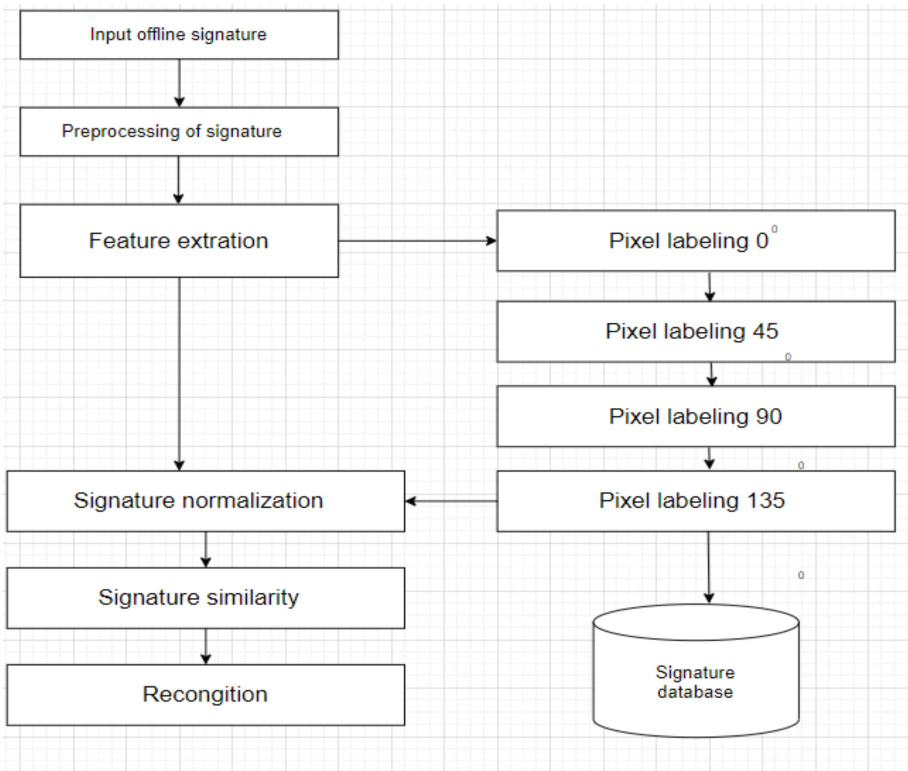

Fig. 3.1 CNN model

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