IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SURVEY ON DETECTION OF FORGERY IN HANDWRITTEN SIGNATURES

[1] Mytee Abhisha Dunna, [2] Avula Pavani, [3] Mortala Nikhitha, [4] Swapna C

[1] Lead Author, [2] Lead Author, [3] Lead Author, [4] Assistant Professor

Department of Artificial Intelligence and Data Science,

Stanley College of Engineering and Technology for Women

Telangana, India

Abstract: In contemporary operations, the reliance on signatures for personal identification and transaction authorization introduces a significant fraud vulnerability. Instances of forged signatures have surged, causing substantial financial losses. To address this, we propose a Signature Verification System using Convolutional Neural Network (CNN) technology. Leveraging TensorFlow, Matplotlib, Pandas, and Keras, the system uses geometric measures to analyze signatures and generate a reference for verifications. The goal is to surpass existing methods in reliability, efficiency, and accuracy. Decisions on signature authenticity employ a threshold approach. Parameters in the feature space are meticulously analyzed, and if the absolute difference between the original and verification signature surpasses a predefined threshold, the signature is flagged as potentially forged. This nuanced decision-making process ensures accurate verification outcomes. In conclusion, our Signature Verification System provides a robust, efficient, and accurate solution for detecting forged signatures in various transactions. The incorporation of CNN technology makes it a valuable asset in the ongoing battle against signature-related fraud.

Index Terms – Signature, CNN, Forgery, Original, Deep Learning.

I. INTRODUCTION

Detection of forgery in handwritten signatures is a critical endeavor in document verification, aimed at distinguishing between authentic signatures and fraudulent imitations. Handwritten signatures are widely utilized as a primary method of personal identification in legal, financial, and administrative contexts. However, the advent of digital technology has facilitated the replication of signatures, enabling forgers to produce counterfeit signatures with remarkable precision. This poses significant challenges to document security and authentication processes.

Various techniques have been employed for the detection of forged signatures, with advances in machine learning playing a prominent role in recent years. Convolutional Neural Networks (CNNs), in particular, have demonstrated promising capabilities in analyzing and classifying handwritten signatures based on distinct features and patterns. By leveraging large datasets of annotated signatures, CNNs can learn to automatically identify irregularities indicative of falsified signatures, thereby enhancing forgery detection accuracy and efficiency.

The detection of forged signatures holds significant implications for legal compliance, financial integrity, and personal security. Instances of signature forgery can lead to disputes, legal complications, and financial losses, undermining trust and credibility in various sectors. Addressing this challenge requires a multifaceted approach, combining technological innovation with regulatory measures and awareness initiatives to safeguard against unauthorized alterations and fraudulent transactions. Continued research and development efforts are essential for advancing the state-of-the-art in forgery detection and ensuring the reliability and effectiveness of signature authentication processes in an increasingly digitized world.

II. Literature Survey

Umair Tariq, Zonghai Hu, Rokham Tariq, Muhammad Shahid Iqbal, and Muhammad Sadiq [1],(2023) In their work, the authors proposed an innovative embedded system tailored for offline Urdu handwritten signature verification, addressing the scarcity of Urdu datasets in the existing literature. The system involves five fundamental steps: data acquisition, pre-processing, feature extraction, signature registration, and signature verification. Feature extraction leverages an enhanced sinusoidal signal multiplied by a Gaussian function as a 2D Gabor filter, analyzing various signature attributes. The framework integrates a majority voting (MV) algorithm to enhance accuracy, resulting in promising results with an overall accuracy of 95.13% on a private dataset and 97.46% on a public English handwritten signature dataset.

Daniel Raj, Venu Gopal, and Padmapriya Nammalwar [2],(2022) The authors proposed an automatic offline signature identification system using graph theory approaches. Scanned signatures from the Kaggle dataset are collected for offline signature data. The method involves pre-processing, vertex point extraction using the midpoint traverse method, and feature extraction utilizing edge, average edge, and average edge D-distance. Support Vector Machine (SVM) is employed for classification, and the system's accuracy is assessed using False Acceptance Ratio (FAR) and False Rejection Ratio (FRR). The proposed method is also compared with existing deep-learning techniques in the literature.

Victoria Ruiz-Parrado, Ismael Linares, Angel SanchezJosẽ F. Vẽlez [3], (2020) This group of researchers proposed the use of Siamese Neural Networks for performing forgery detection in an offline signature verification process with a writer-independent context. They utilized three types of data, including the GAVAB dataset, a proposal of compositional synthetic signature generation, and the GPDS Synthetic dataset. Siamese Neural Networks were trained initially using the GAVAB dataset, and the integration of original and synthetic signatures led to improved training results. The system demonstrated generalization capabilities, achieving an impressive overall accuracy of 97.46%.

Bilal Hadjadji, Youcef Chibani, and Hassiba Nemmour [4], (2017) The authors introduced an Open Handwritten Signature Identification System (OHSIS) for offline handwritten signature identification. The system utilized the Curvelet Transform (CT) and the One-Class classifier based on Principal Component Analysis (OCPCA). Binarization of signatures was performed as a pre-processing method, and CT was explored for feature generation due to its efficiency in characterizing curves within the signature image. The authors proposed a new combination approach based on the Choquet fuzzy integral to improve the robustness of the OHSIS. The evaluation was based on the Identification rate, reflecting the percentage of instances correctly identified.

Shih Yin Ooi, Andrew Beng Jin Teoh, Ying Han Pang, and Bee Yan Hiew [5], (2016) The authors proposed a method to compensate for the lack of dynamic information from static signature images. The approach involved using the discrete Radon transform (DRT), principal component analysis (PCA), and probabilistic neural network (PNN). Pre-processing steps included a median filter and grey scaling of images to remove noise and minimize database storage. The authors used a Probabilistic neural network (PNN) instead of a similarity-matching concept, achieving promising results with a dataset containing genuine signatures and forgeries collected from multiple writers and forgers. Future work was suggested to include a larger database of signatures with forgeries and a more powerful specification of PC support for a more reliable system.

Mustafa Berkay Yılmaz and Berrin Yanıkoğlu [6], (2016) The authors introduced a system employing a score-level fusion of complementary classifiers utilizing different local features such as histogram of oriented gradients, local binary patterns, and scale-invariant feature transform descriptors. Each classifier incorporates a feature-level fusion representing local features at coarse-to-fine levels. Two classifier approaches were explored: global and user-dependent. User-dependent classifiers were trained separately for each user to differentiate genuine signatures, while a single global classifier was trained with vectors from query and reference signatures of all users, learning the importance of different dissimilarities.

Saied Fazli and Shima Pouyan [7], (2015) Fazli and Pouyan focused on offline signature recognition and verification systems utilizing neural networks. The proposed system includes preprocessing, feature extraction, and classification steps. It allows users to verify whether a signature is original or fake, achieving a recognition ratio of 93.5% for 700 signatures and a verification ratio of 97% for distinguishing original signatures from fake ones.

Yasmine Guerbai, Youcef Chibani, and Bilal Hadjadji [8], (2015) The authors proposed the use of a One-Class Support Vector Machine (OC-SVM) based on writer-independent parameters for handwritten signature verification. The OC-SVM considers only genuine signatures and adjusts the optimal threshold in the decision function to reduce misclassification. This modification is particularly useful when available handwritten signature samples are limited.

Raul Sanchez-Reillo, Oscar Miguel-Hurtado, and R. Blanco-Gonzalo [9], (2014) The study observed the increasing use of biometric verification with the rise of mobile devices, focusing on handwritten signatures as a common method. The authors conducted experiments with 43 users signing 60 times across three sessions and eight devices, including six mobile devices. The study utilized a Dynamic Time Warping (DTW)-based algorithm, obtaining results based on interoperability, feedback, and modality tests, aiming to contribute to more accurate models for signature verification.

Shalini Bhatia, Pratik Bhatia, Dheeraj Nagpal, and Sandhya Nayak [10], (2013) This group proposed a signature verification system using the Error Back Propagation Training Algorithm in the Neural Network Toolbox of MATLAB. The system is characterized by low cost, low intrusion, good performance, and the use of a natural biometric, the signature. The two-step method involves signature identification followed by individual verification, both carried out by Neural Networks trained using the Error Back-Propagation Training Algorithm.

Samaneh Ghandali, Mohsen Ebrahimi Moghaddam, and Mohammad Javad Khosravi[11], (2012) The authors emphasized the importance of biometric features in authentication systems, particularly focusing on offline signature identification and verification. They proposed a two-phase system where the identification phase is based on Triangular Spatial Relationship (TSR), and the verification phase combines Discrete Wavelet Transform (DWT), Gabor filter, and image fusion methods. Experimental results confirmed the robustness and precision of the method against translation, scaling, and rotation.

J. Vargas-Bonilla, M. A. Ferrer-Ballester, C. Travieso-González, and J. B. Alonso [12], (2011) The proposed method for offline handwritten signature verification works at the global image level and employs statistical texture features, including the co-occurrence matrix and local binary pattern. The method includes background removal and histogram processing to reduce the influence of different writing ink pens. The SVM model is trained using genuine samples and random forgeries, and reasonable results are achieved on the MCYT-75 and GPDS-100 Corpuses.

Sigari, Mohamad-Hoseyn, Pourshahabi, Muhammad Pourreza, and Hamid [13], (2011) The authors introduced a method for offline handwritten signature identification and verification based on Gabor wavelet transform. The method aims to offer a simple and robust feature extraction method with reduced dependency on the nationality of the signer. The system was tested on four signature datasets with different nationalities, including Iranian, Turkish, South African, and Spanish signatures.

D. Bertolini, Luiz Oliveira, E. Justino, and R. Jabourin [14], (2010) The authors addressed two important issues in offline signature verification. They proposed a novel graphometric feature set capturing the curvature of essential segments within signatures using Bezier curves. Additionally, they advocated for an ensemble of classifiers based on the extracted graphometric features using a genetic algorithm, demonstrating efficacy in reducing false acceptances.

Luana Batista, Eric Granger &Robert Sabourin [15], (2010) The authors proposed an approach based on the combination of discrete hidden Markov Models (HMMs) in the ROC space to improve the performance of off-line signature verification systems. By training an ensemble of user-specific HMMs with different configurations and combining them in the ROC space, the composite ROC curve provides a more accurate estimation of system performance, reducing average error rates and HMM states.

Jing Wen, Bin Fang, Y.Y. Tang, Tai Ping Zhang [16], (2009) The authors proposed two models utilizing rotation-invariant structure features for offline signature verification. Elaborately extracted ring-peripheral features describe internal and external structure changes periodically. The proposed methods effectively improve verification accuracy and address the side effects of outlier training samples through a selection strategy.

Loris Nanni and Alessandra Lumini [17], (2008) The authors presented an online signature verification system based on local information and a one-class classifier, the Linear Programming Descriptor classifier (LPD). Information is extracted as time functions of dynamic properties of signatures, and the LPD classifier is trained using the DCT coefficients. Results from the SUBCORPUS-100 MCYT Bimodal Biometric Database show performance improvement with both random and skilled forgeries.

Guler, Inan, Meghdadi, and Majid [18], (2008) The authors proposed a method for automatic handwritten signature verification relying on global features summarizing different aspects of signature shape and dynamics. The algorithm focuses on detecting the signature without attention to its thickness and size, achieving acceptable correctness in detecting the signature through preprocessing, analysis, and dynamic time-warping classification.

Stephane Armand, Michael Myer Blumenstein, and Vallipuram Muthukkumarasamy [19], (2007) The authors introduced an enhanced version of the MDF feature extractor for signature verification. Six-fold cross-validation was performed to investigate new feature values of MDF, leading to encouraging results in terms of verification rate. The merging of MDF technology with new features showed promising results in enhancing the efficiency of the signature verification system.

Gady Agam and Suneel Suresh [20],(2007) The authors proposed a curvewarping approach for reducing variability in matching signatures, not limited by 1-D parameterization. The novel approach uses particle dynamics and minimizes a cost function through an iterative solution of a system of first-order ordinary differential equations. The proposed approach handles complex curves and is evaluated using real-world signed documents.

D. Muramatsu, M. Kondo, M. Sasaki, S. Tachibana, and T. Matsumoto [21], (2006) The authors proposed a Monte Carlo-based Bayesian scheme for digital signature verification. The algorithm has two phases: the learning phase, where semi-parametric models are trained using the Markov Chain Monte Carlo (MCMC) technique, and the testing phase, where signatures are tested against test data. The algorithm achieved an Equal Error Rate (EER) of 1.2% against the MCYT signature corpus using random forgeries for learning and skilled forgeries for evaluation.

Madasu Hanmandlu, Mohd Hafizuddin Mohd Yusof, and Vamsi Krishna Madasu [22], (2005) The authors introduced a new system for handwritten signature verification using the quadtree structure of the histogram template. The methodology includes an artificial immune Recognition System (AIRS) that uses an SVM classifier for robust classification. Experiments on datasets like MYCT75, GPDS 300, and GPDS-4000 showed that AIRSVM outperformed AIRS or SVM classifiers.

Hairong Lv, Wenyuan Wang, Chong Wang, and Qing Zhuo [23], (2005) The authors proposed an off-line Chinese signature verification method based on support vector machines. The method incorporates both static features (moment features, 16-direction distribution) and dynamic features (gray distribution, stroke width distribution). A support vector machine is used for signature classification, and experiments on real datasets demonstrated an average error rate of 5%.

Miguel A. Ferrer, Jesús B. Alonso, and Carlos M. Travieso [24], (2005) The authors presented geometric signature features for offline automatic signature verification based on the signature envelope and interior stroke distribution in polar and Cartesian coordinates. The features, calculated using 16-bit fixed-point arithmetic, were tested with different classifiers, such as hidden Markov models, support vector machines, and Euclidean distance classifiers, showing promising results in discriminating between random and simple forgeries.

Hanmandlu M, Murali Mohan K, R. Chakraborty, Sourav Goyal, Sumeer Choudhury, and D. Roy [25], (2003) The authors introduced the "box method" for feature extraction in handwritten character identification. The method divides the input binary image into subimages or "boxes" and calculates vector distance normalized by the number of pixels in each box. Both neural networks and fuzzy logic were used, yielding promising results of around 97% using neural networks and 98% using fuzzy logic, independent of various parameters like fonts and size.

Hiok Chai Quek and Ruo wei Zhou [26], (2002) The authors proposed a system based on a fuzzy neural network called POPFNN-TVR, designed to identify forged images effectively. POPFNN-TVR's strengths include learning ability, generalization ability, and advanced computational ability. Experimental results demonstrated the efficiency of POPFNN-TVR in an anti-forgery system.

Mohamed A. Ismail and Samia G. Omar [27], (2000) The authors presented a two-phase system for signature recognition and verification. The recognition technique uses a multistage classifier and a combination of global and local features, while the verification technique is based on fuzzy concepts. Experimental results showed favorable performance for each proposed technique in various aspects.

Drouhard, Jean Pierre and Sabourin, Robert, and Godbout, Mario [28], (1996) The authors proposed a neural network approach as the first stage of an Automatic Handwritten Signature Verification System. The directional Probability Density Function was used as a global shape factor, and its discriminating power was enhanced through filtering. The backpropagation network (BPN) classifier demonstrated superiority compared to the threshold classifier and performed favorably against the k-nearest-neighbor classifier.

Hong Yan [29], (1994) The author proposed a novel method for digit recognition using the nearest neighbor classifier. The strategy involved obtaining prototypes from training samples and creating a nearest-neighbor classifier, which was then mapped to a multi-layer perceptron. The neural network was mapped back to the closest neighbor classifier with improved prototypes after training, achieving high recognition accuracy.

C. L. Walker, M. Brown, and Temple H. Fay [30], (1988) The authors discussed a recognition system for unconstrained hand printed symbols, focusing on OCR techniques for accuracy. Smart thinning algorithms produced centerline-thinned stick-figure images, and recognition logic with feature extraction algorithms identified characters or rejected them. Results from a numeric character database exhibited an efficiency rate of 97%, with substitution and rejection error rates of 0.3% and 2.7%, respectively. Preliminary results for recognizing alphabetic characters were also outlined.

III. METHODOLOGY

3.1 Data Collection

Data collection for forgery or real signature detection involves gathering a dataset comprising a variety of genuine signatures along with their corresponding forged counterparts from different possible resources such as Publicly available datasets, Document repositories, or Collecting from individuals.

3.2 Data Preprocessing

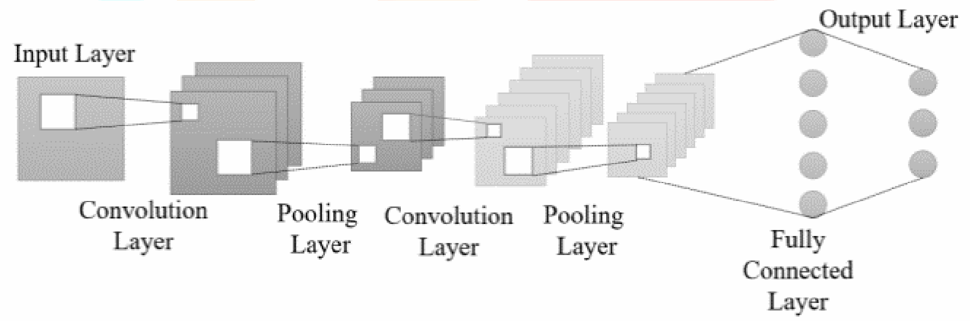
In the inaugural phase, meticulous attention is directed toward the Image acquisition, purification, and structuring of data to detect whether a signature is forged or real. This procedural step encompasses Image Cleaning, removing any unwanted artifacts or background noise from the images using techniques such as Gaussian blur or median blur or Thresholding to convert images to binary format, Normalization, and Normalizing the size and orientation of the signature images to ensure consistency. This may involve Resizing the images to a standard size, such as 128x128 pixels or 256x256 pixels while preserving the aspect ratio. Augment the dataset to increase its size and diversity, using techniques like rotation, flipping, scaling, cropping, and adding noise. This helps improve the model's generalization ability. Rotate the images to align them horizontally or vertically if necessary.

3.3 Model Architecture Design

Designing the architecture of a Convolutional Neural Network (CNN) architecture for a handwritten signatures image dataset involves crafting a network that can effectively extract features from the input images and classify them as genuine or forged signatures. Input layer, to accept grayscale or color images of fixed dimensions representing handwritten signatures. The input size can be determined based on the dimensions of the dataset images (e.g., 128x128 pixels). Convolutional Layers, stacking multiple convolutional layers to extract features from the input images. Each convolutional layer includes Convolutional filters (kernels) to perform feature detection, ReLU (Rectified Linear Unit) activation functions to introduce non-linearity, Optional batch normalization layers to stabilize and accelerate training and Max pooling layers to downsample the feature maps and reduce computational complexity. Feature Extraction, Continue stacking convolutional layers to increase the depth and complexity of the features captured. Flatten the output of the convolutional layers into a one-dimensional vector to prepare it for input to the fully connected layers. Fully Connected Layers, Add one or more fully connected (dense) layers to perform classification based on the extracted features. Output layer, with a single neuron and an activation function for classification.

3.4 Model Compilation

We first import necessary modules from TensorFlow's Keras API. We initialize a sequential model, allowing us to build the model layer by layer sequentially. We add convolutional layers for feature extraction using the Conv2D and MaxPooling2D layers. We flatten the feature maps into a one-dimensional vector using the Flatten layer. We add fully connected layers for classification using the Dense layer. A dropout layer is added for regularization to prevent overfitting. Finally, we compile the model using the Adam optimizer, binary cross-entropy loss function (suitable for binary classification tasks), and accuracy as the evaluation metric.



Compile the CNN model with an appropriate loss function, optimizer, and evaluation metrics. For classification tasks, common loss functions include categorical cross-entropy or binary cross-entropy. Popular optimizers include Adam, RMSprop, and SGD. Check the performance using evaluation metrics such as accuracy, precision, recall, F1-score, etc., depending on the nature of the problem.

3.5 Model Training

Training a CNN model for a handwritten signatures image dataset involves feeding the training data to the model and updating its parameters through backpropagation to minimize the loss function. We specify the number of epochs (complete passes through the entire dataset) and batch size (number of samples per gradient update). We use the fit method to train the model on the training data (X_train, y_train) for the specified number of epochs. We also provide validation data (X_val, y_val) to monitor the model's performance on unseen data during training. After training, we evaluate the model's performance on the test set (X_test, y_test) using the evaluate method, which returns the test loss and accuracy. Finally, we visualize the training history using Matplotlib to observe the training and validation loss/accuracy trends over epochs.

IV. Conclusion

Handwritten signatures hold paramount significance in both social and legal realms, serving as vital tools for verification and authentication. The acceptance of a signature relies on its certainty of origin, requiring assurance that it indeed emanates from the intended person. Despite the low probability of two signatures crafted by the same individual being identical, the variability in signature properties even within a single person's output poses a formidable challenge in detecting forgeries.

In the era of pervasive digitization, the demand for efficient user verification methods has surged across various facets of daily life, accompanied by new challenges in professional environments. As technology unfolds new possibilities, there emerges a pressing need for advanced methods and algorithms to address evolving authentication requirements.

To meet this demand, a novel method has been proposed, offering an effective system for signature verification. Leveraging Python and its libraries in conjunction with a Convolutional Neural Network (CNN), this method excels in offline signature verification, marking notable enhancements in both efficiency and accuracy. Particularly adept at identifying skilled forgeries, the approach underscores the intersection of cutting-edge technology and signature authentication, paving the way for robust verification in the digital age.

V. Acknowledgment

WE WOULD LIKE TO EXPRESS OUR SINCERE GRATITUDE TO OUR GUIDE MRS. SWAPNA C, ASSISTANT PROFESSOR, ADCE DEPARTMENT AND OUR HEAD OF THE DEPARTMENT, DR. K. VAIDEHI FOR THEIR VALUABLE SUGGESTIONS AND SUPPORT DURING THE RESEARCH AND IN WRITING THIS PAPER.

References

[1] Umair Tariq, Zonghai Hu, Rokham Tariq, Muhammad Shahid Iqbal, and Muhammad Sadiq (2023). Identification of Proper and Improper Signatures Using Graph Theory Techniques

[2] Umair Tariq, Zonghai Hu, Rokham Tariq, Muhammad Shahid Iqbal, and Muhammad Sadiq (2022). High-Performance Embedded System for Offline Signature Verification Problem Using Machine Learning

[3] Ruiz, V., Linares, I., Sanchez, A., and Velez, J. F. (2020). Off-line Handwritten Signature Verification Using Compositional Synthetic Generation Of Signatures And SiameseNeuralNetworks.Neurocomputing.

[4] Hadjadji, Bilal Chibani, Youcef Nemmour and Hassiba (2017). An Efficient Open System for Offline Handwritten Signature Identification Based on Curvelet Transform and One-Class, Principal Component Analysis. Neurocomputing.

[5] Shih Yin Ooi, Andrew Beng JinTeoh, Ying HanPang, and Bee Yan Hiew (2016). Image-Based Handwritten Signature Verification Using Hybrid Methods of Discrete Radon Transform, Principal Component Analysis, and Probabilistic Neural Network. Applied Soft Computing.

[6] Mustafa Berkay Yilmaz and Berrin Yanikoglu (2016). Score Level Fusion of Classifiers in Off-line Signature Verification. Information Fusion.

[7] Saeid Fazli & Shima Pouyan,(2015). High-Performance Offline Signature Verification and Recognition Method using neural network.International Journal of Advanced Studies in Computer Science and Engineering..

[8] Guerbai, Yasmine Chibani, Youcef Hadjadji and Bilal (2015). The effective use of the one-class SVM classifier for handwritten signature verification based on writer-independent parameters. Pattern Recognition.

[9] Blanco-Gonzalo R., Sanchez-Reillo R., Liu-Jimenez,J. and Miguel-Hurtado O. (2014). Performance Evaluation Of Handwritten Signature Recognition In Mobile Environments. IET Biometrics.

[10] Bhatia, Shalini Bhatia, Pratik Bhatia, Pratik Nagpal, Dheeraj Nayak and Sandhya (2013).Online Signature Forgery Prevention. International Journal of Computer Applications.

[11] Ghandali, S., M. Moghaddam and M. Khosravi (2012). A new system for offline signature identification and verification. International Journal of Signal and Imaging Systems Engineering.

[12] Sigari, Mohamad-Hoseyn, Pourshahabi, Muhammad Pourreza and Hamid (2011). Offline Handwritten Signature Identification and Verification Using Multi-Resolution Gabor Wavelet. International Journal of Biometrics and Bioinformatics.

[13] Vargas-Bonilla, J.Ferrer-Ballester, Miguel Travieso, Carlos Alonso and Jesús (2011). Off-line signature verification based on gray-level information using texture features. Pattern Recognition.

[14] Diego Bertolini, Luiz Soares de Oliveira, Edson Justino, and Robert Sabourin (2010). Reducing forgeries in writer-independent off-line signature verification through an ensemble of classifiers. Pattern Recognition.

[15] Batista, L., Granger, E. & Sabourin, R. (2010). Improving the performance of HMM-based off-line signature verification systems through a multi-hypothesis approach. International Journal on Document Analysis and Recognition.

[16] Wen, Jing Fang, Bin Tang, Yuan Zhang, and Tai Ping (2009). Model-based signature verification with rotation invariant features. Pattern Recognition.

[17] Nanni, Loris Lumini and Alessandra (2008). A Novel Local Online Signature Verification System. Pattern Recognition Letters.

[18] Guler, Inan, Meghdadi and Majid (2008). A different approach to offline handwritten signature verification using the optimal dynamic time warping algorithm. Digital Signal Processing.
[19] Hanmandlu, M., Yusof, M. H. M., & Madasu, V. K. (2005). Off-line Signature Verification And Forgery Detection Using Fuzzy Modeling. Pattern Recognition.
[20] Hairong Lv, Wenyuan Wang, Chong Wang, and Qing Zhuo (2005). Off-line Chinese Signature Verification Based on Support Vector Machines. Pattern Recognition Letter.
[21] Armand, S., Blumenstein, M. and Muthukkumarasamy,V. (2007). Off-line Signature Verification Using an Enhanced Modified Direction Feature with Single and Multi-classifier Approaches. IEEE Computational Intelligence Magazine.
[22] D. Muramatsu, M. Kondo, M. Sasaki, S. Tachibana and T. Matsumoto (2006). A Markov Chain Monte Carlo Algorithm for Bayesian Dynamic Signature Verification. IEEE Trans. on Information Security.
[23] Hairong Lv, Wenyuan Wang, Chong Wang, and Qing Zhuo (2005). Off-line Chinese Signature Verification Based on Support Vector Machines. Pattern Recognition Letter.
[24] Madasu Hanmandlu, K.R. Murali Mohan, Sourav Chakraborty and Sumeer Goyal (2003). Unconstrained handwritten character recognition based on fuzzy logic. Pattern Recognition.
[25] Chai Quek & R.W. Zhou (2002). Antiforgery: A novel pseudo-outer product based fuzzy neural network driven signature verification system. Pattern Recognition Letters.
[26] Mohamed Ismail, Samia Omar, and Gad, S (2000). Off line Arabic Signature Recognition and Verification. Pattern Recognition.
[27] Ferrer-Ballester, M. A., J. Alonso and C. Travieso González (2005). Offline geometric parameters for automatic signature verification using fixed-point arithmetic. IEEE Transactions on Pattern Analysis and Machine Intelligence.
[28] Drouhard, J.P Sabourin, Robert Godbout and Mario (1996). A neural network approach to off-line signature verification using directional PDF. Pattern Recognition.
[29] Hong Yan (1994). Handwritten digit recognition using an optimized nearest neighbor classifier. Pattern Recognition Letters.
[30]C. L. Walker, M. Brown and Temple H. Fay (1988). Handprinted symbol recognition system. Pattern Recognition.