Two-Mode Signature Security Model: Offline Image and Online Dynamic Features with SVM and Naïve Bayes

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ABSTRACT

This study presents a simple and practical method to check whether a signature is real or fake using both offline signature images and online signatures that are captured using android-based application which stores images as well as dynamic information of signatures or pen logs. In many banks, government offices, and business forms in India, written signatures are still used for approval. Forgery of signatures can cause financial loss and trust issues. To address this, the work uses two reliable machine learning models, Support Vector Machine and Naive Bayes, along with clear and meaningful features taken from the signature shape and writing movement. For offline signatures, texture and shape features such as edge strength, local pixel patterns, and stroke patterns are used. For online logs, movement speed, pen pressure, time gap between strokes, and direction change are used to capture natural writing behaviour. The dataset has 77 writers with both real and forged signatures. Features are extracted, cleaned, and scaled before training. A writer-independent testing approach is followed so that the system is tested on new writers not seen during training. The Support Vector Machine model shows very strong performance with high accuracy and balanced results for both real and fake cases. The Naive Bayes model also performs well and gives fast prediction. The final results show accuracy close to 98 to 99 percent for both models, showing that simple feature-based learning can work very well for Indian style signatures without using complex deep learning. This system can be used for bank forms, office records, and digital handwriting tablets to quickly verify signatures in a safe and trustworthy manner.

Keywords— ML, SVM, NB, Handwriting, Signature, Detection

1. INTRODUCTION

Signatures are still used in banks, courts, and public offices as a common proof of identity in India. Many government forms, cheque books, legal records, and property papers depend on handwritten signatures. Because of this wide use, signature forgery remains a real threat. When a forged signature is accepted, it can lead to financial loss, fraud, and legal disputes. A secure and simple system for checking genuine and forged signatures can help protect personal identity and reduce manual inspection effort.

Past studies have explored both online signature data, where pen movement and pressure are recorded, and offline data, where only the written signature image is used. Online systems use timing, direction, and pressure signals, and have shown promise in early work by focusing on key dynamic features [1][2]. Researchers also studied offline signatures by using visual shape features, strokes, and patterns in English and Chinese scripts [3]. A detailed review explained how both styles of signatures remain important, and how automatic verification systems help detect skilled forgeries that appear visually similar to genuine samples [4]. Deep learning has also been tested for offline verification, especially for complex forgery detection [5]. Signature verification surveys and Arabic handwriting studies highlight growing interest across languages and writing styles [6][7][8]. Outside the signature field, feature fusion and selection methods have been used successfully in medical pattern work [9], showing that combining classical features gives strong results even without heavy neural networks.

Recent studies continue to explore efficient verification models. Work on support vector machines for hybrid signature verification shows that classical supervised models remain strong on small and medium datasets [10]. One-class SVMs with evolutionary feature selection have improved offline security in newer research [11]. A study in the banking sector examined offline signatures for real service environments and confirmed that traditional models can perform well when designed carefully [12]. These works support the need for a clean, practical system that handles handwritten signatures without complex hardware or long training time.

In this study, two classical machine learning models are used: Support Vector Machine (SVM) and Naive Bayes (NB). A balanced dataset of genuine and forged signatures collected from seventy-seven individuals is used. The method extracts shape-based offline image features along with dynamic pen-movement features from online log files. The goal is to build a simple, fast, and reliable signature verification system that works for real Indian-style handwritten signatures with high accuracy and low false acceptance.

1.1 Research Contribution

This work offers the following contributions:

- A combined offline-image and online-log dataset from seventy-seven writers
- A clean feature extraction pipeline using shape, texture, and dynamic movement cues
- A comparison of SVM and Naive Bayes for practical signature verification
- Evaluation results showing strong accuracy for genuine and forged detection

2. Literature Review

Research on handwritten signature verification has grown steadily with progress in biometric security and document authentication. Early studies analyzed online dynamic traits such as pen pressure, movement direction, and stroke timing to build statistical decision boundaries for genuine and forged signatures [1][2]. Offline work examined shape and contour structure using foreground–background patterns across multiple languages, showing that static features alone can separate skilled forged samples when chosen carefully [3]. A broad survey highlighted how both online and offline approaches continue to support legal and financial verification needs, and pointed out that advanced systems must manage high-quality forgeries and writing variation across cultures [4]. Recent deep models learned rich stroke features from static images [5], whereas earlier rule-based and template approaches tracked consistency in pen trajectory and writing rhythm for online signatures [7][8]. Feature fusion and selection have been applied in other pattern-based security tasks, confirming the value of combining classical handcrafted cues for accurate decision-making [9].

Human-assisted biometric cues were explored to strengthen reliability in signature systems [13]. Offline matching with structural time-warping demonstrated the value of shape alignment when style varies across samples [14]. Distance-based mathematical learning has also influenced verification logic, improving separation between classes [15][16]. Classic moment-based geometric descriptors were used to differentiate forged signatures in earlier work [17]. Support Vector Machines remain popular due to strong boundary learning properties [18], while recent offline studies tested rule trees for faster decision making [19]. Transformer-based attention models have emerged for static signatures, although most are computation heavy for routine deployment [20]. Practical machine-learning studies used smaller classifiers such as k-nearest and decision trees for real authentication scenarios [21], whereas deep CNN models learned writer-independent features for challenging document images [22][23]. Kohonen maps were applied to cluster writing styles [24], and lightweight offline models were developed for traditional banking forms [25]. Online neural descriptors captured movement traits for modern touch devices [26]. Surveys summarized development trends and emphasized the importance of feature engineering when data is limited [27], while graph-based embeddings explored structural writing geometry [28]. Some work specifically investigated feature selection for signature security, reporting gains from removing noisy signals [29]. Symbolic interval representation techniques have also been examined for writer-dependent online verification [30]. The summarized discussion of existing methods is as shown in Table 1 below:

Table 1 Review of Existing methods

Study	Domain	Key Idea	Data Style
[1][2]	Online	Movement and pressure based statistical cues	Dynamic logs
[3][4]	Offline & survey	Foreground-background, global review	Image
[5]	Offline	Deep CNN for forgery detection	Image
[7][8]	Online	Stroke rhythm and directional sequences	Dynamic logs
[9]	Hybrid	Classical feature fusion	Feature-based
[13]	Biometric	Human-assisted biometric feedback	Offline
[14]	Offline	Structural DTW for alignment	Image
[18][21]	Offline	SVM and classic ML classifiers	Image
[22][23]	Offline	Writer-independent deep CNN	Image
[28]	Offline	Graph embedding and feature selection	Image

3. PROPOSED MODEL

The work follows a systematic process to classify genuine and forged signatures collected in both offline image form and online pen-movement text logs. The complete flow covers dataset preparation, feature extraction, feature selection, model training, and evaluation as shown in figure 1.

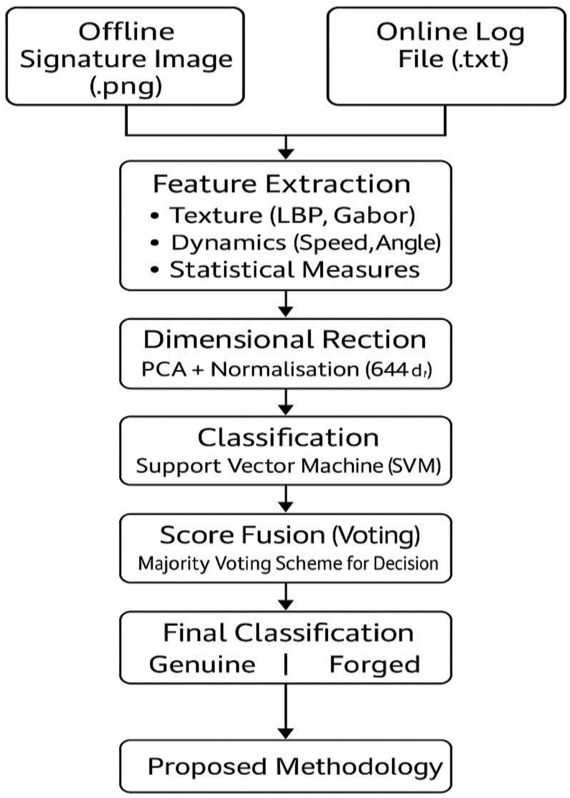

Figure 1 Architecture of Proposed System

3.1 Dataset Description

The dataset consists of signature samples from 77 individuals. For each person, two types of signatures are collected: offline handwritten signatures and online dynamic writing logs. These are saved in separate folders as follows:

- **Image folder**: Contains handwritten signature images that were not scanned but captured using an Android-based application.
- **Log folder**: Contains digital writing trace files in .txt format, generated while signing on a mobile or digital pad.

Each log file records the real-time movement of the pen tip using six parameters in the format:

TouchEvent Time | X-coordinate | Y-coordinate | rawX | rawY | Pressure

These values represent writing time, path, direction, and pressure variations during signing. By combining image features (shape, texture) with log features (speed, movement, timing, pressure), the system learns both global signature appearance and dynamic writing behaviour. This setup reflects real verification conditions in banks and offices, where signatures can be captured either on paper (offline) or on digital devices (online).

3.2 Pre-Processing

Each signature image is first converted to grayscale to remove color variations and focus only on writing strokes. The image is then resized to a fixed dimension (128 × 128 pixels) to maintain uniformity for feature extraction. After resizing, histogram equalization is applied to improve stroke visibility and enhance contrast between ink and background. To eliminate background noise, the image is cropped using block-based trimming, and unnecessary margins are removed. This helps in capturing only the meaningful portion of the signature. Finally, light smoothing is applied to remove small ink spots and digitize noise.

For the online signature logs, preprocessing includes cleaning and organizing the raw text data. Empty lines, duplicate readings and non-writing entries are removed. Each valid record is expected to contain six fields in the format: time | X | Y | rawX | rawY | pressure.

Only entries containing all these values are retained. Log sequences with extremely few points are discarded to prevent poor quality samples from affecting model training. After cleaning, the coordinates are normalized to a fixed scale, and time gaps between strokes are calculated to derive speed, acceleration, direction change, and pressure variation. This preprocessing ensures that both offline signature shape and online writing dynamics are clear, noise-free, and ready for accurate feature extraction.

3.3 Feature Extraction

Two types of features are extracted: Offline visual features [3][5][14][22][23] and online behavioral features [1][2][7][8][16][30]. This hybrid design captures both the visual shape and natural writing dynamics.

1. Offline Image Features

Local Binary Pattern (LBP):

$LBP_{p,r}(x,y) = \sum_{n=0}^{p-1} s(I_n - I_{(x,\gamma)}) \times 2^n$

where $s(x) = 1$ if $x \geq 0$, else 0

Histogram of Oriented Gradients (HOG):

$G_x(x,y) = I(x+1,y) - I(x-1,y)$

$G_\gamma(x,y) = I(x,y+1) - I(x,y-1)$

$|G(x,y)| = \sqrt{(G_x^2 + G_\gamma^2)}$

$\theta(x,y) = \tan^{-1}(G_\gamma / G_x)$

Gabor Filter:

$G(x,y) = \exp(-(x'^2 + \gamma^2 y'^2)/(2\sigma^2)) \times \cos(2\pi x'/\lambda + \varphi)$

$x' = x \cos\theta + y \sin\theta$

$y' = -x \sin\theta + y \cos\theta$

2. Online Dynamic Features

Pen-tip Speed:
$\text{Speed}_i = \sqrt{((x_i - x_{i-1})^2 + (y_i - y_{i-1})^2)}/(t_i - t_{i-1})$

Acceleration:
$\text{Acceleration}_i = (\text{Speed}_i - \text{Speed}_{i-1})/(t_i - t_{i-1})$

Direction Change:
$\theta_i = \tan^{-1}((y_i - y_{i-1})/(x_i - x_{i-1}))$
$\Delta\theta_i = \theta_i - \theta_{i-1}$

Pressure Variation and Stroke Count:
$\text{PressureMean} = (1/N) \sum_{i=1}^{N} P_i$
$\text{StrokeCount} = 1 + \sum_i(|t_i - t_{i-1}| > \text{threshold})$

3. Combined Feature Vector:
F = [F_LBP, F_HOG, F_Gabor, F_Speed, F_Pressure, F_Accel, F_DirChange]
Total dimensions = 664

3.4 Feature Selection

After extraction, features with near-zero variance are removed. Highly correlated features are also removed to avoid redundancy and over-fitting. Standard scaling is then applied. This improves learning, as reported in feature-selection-focused studies [29].

3.5 Classification Models

Two machine learning models are used:

- **Support Vector Machine (SVM)** with radial kernel, chosen for its strong margin-based learning and proven success in signature tasks [18][21]. The detailed working with input feature matrix is as shown in algorithm 1. The feature matrix $X \in \mathbb{R}^{N\times d}$contains N signature samples and d extracted features for each signature. Each row represents one sample combining offline image-based features (LBP, HOG, Gabor) and online dynamic features (pen-tip position, velocity, acceleration, direction variation, pressure, and stroke count). These 644 selected features characterize both visual structure and writing behavior, making the dataset suitable for SVM-based margin learning.

Algorithm 1: SVM-Based Signature Verification
Input: Feature matrix X ∈ ℝ^(n×d), labels y ∈ {+1, −1}
Output: Predicted class ŷ ∈ {+1, −1}
1: Preprocess each feature x_i:
x_i = (x_i − μ) / σ ▹ z-score normalization
2: Solve the optimization problem:

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minimize (1/2)‖w‖² + C Σ ξ_i
subject to y_i (wᵀφ(x_i) + b) ≥ 1 − ξ_i, ξ_i ≥ 0
3: Kernel transformation:
K(x_i, x_j) = exp(−γ‖x_i − x_j‖²) ▹ RBF kernel
4: Compute decision score for test sample x_t:
f(x_t) = Σ α_i y_i K(x_i, x_t) + b
5: Predict class:
if f(x_t) ≥ 0 then ŷ = +1 ▹ Genuine
else then ŷ = −1 ▹ Forged
6: Return ŷ

- **Naïve Bayes (NB)** is used as a lightweight statistical classifier for comparison and for practical use in simple computing environments. The detailed working is shown in Algorithm 2. The feature matrix $X \in \mathbb{R}^{N\times d}$contains Nsignature samples, where each sample is represented using $d$extracted features. These features include offline visual descriptors such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Gabor texture filters, along with online behavioral traits such as pen-tip trajectory, writing velocity, acceleration, direction variation, pressure change, and stroke count. These 644 selected features form the input for NB classification, where the model assumes conditional independence among features to estimate the probability of a signature being genuine or forged.

Algorithm 2: Naïve-Bayes Signature Verification
Input: Feature matrix X ∈ ℝ^(n×d), labels y ∈ {+1, −1}
Output: Predicted class ŷ ∈ {+1, −1}
1: Standardize features for each x_i:
x_i = (x_i − μ) / σ
2: Estimate class priors:
P(y = c) = (count of samples in class c) / n
3: For each feature x_j and class c:
Estimate mean μ_cj and variance σ²_cj
4: For test sample x_t, compute Gaussian likelihood:
P(x_tj | y=c) = (1 / √(2πσ²_cj))
* exp(− (x_tj − μ_cj)² / (2σ²_cj))
5: Compute posterior score for each class:
Score(c) = log P(y=c) + Σ log P(x_tj | y=c)
6: Predict class:
ŷ = argmax_c Score(c)
7: If ŷ = +1 → Genuine
else → Forged
8: Return ŷ

Both models are trained using selected features. Model parameters are tuned to improve generalization.

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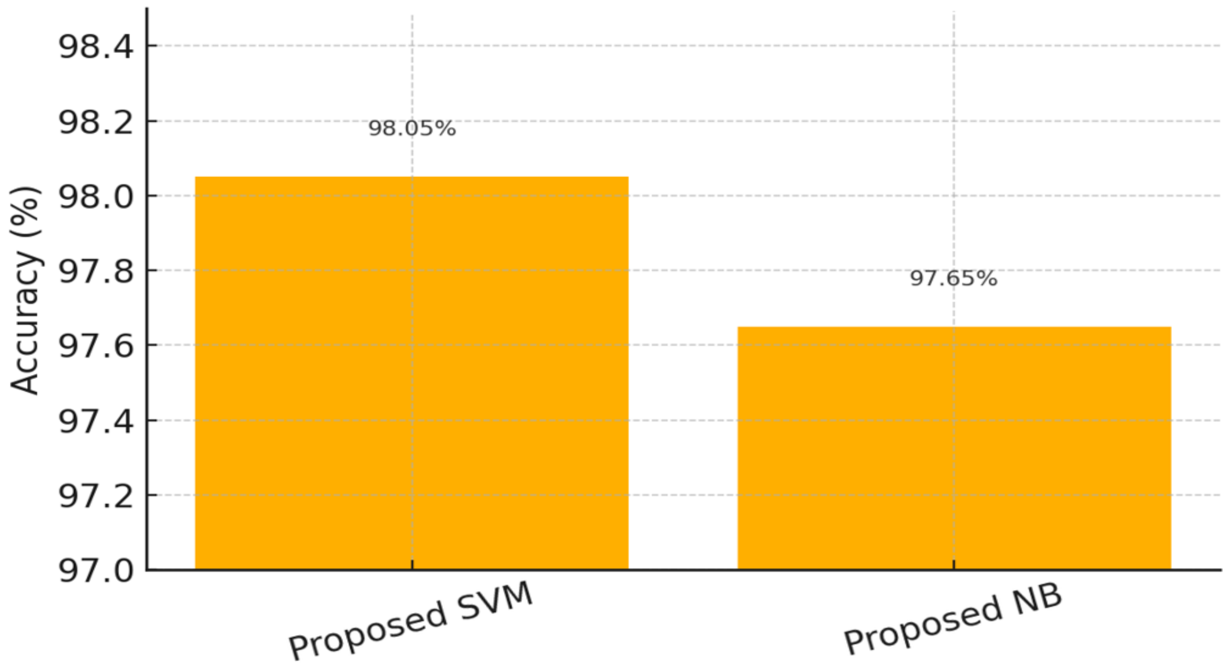
1. RESULTS AND DISCUSSION

This study aims to enhance combined online and offline signature verification using classical machine-learning classifiers instead of heavy deep-learning networks. The experiments were conducted in both writer-dependent and writer-independent settings. Genuine and forged signatures collected from 77 individuals, including both scanned images and digitally captured pen-movement logs, were used for training and testing. The evaluation was based on accuracy, F1-score, and ROC-AUC to ensure balanced performance against both false acceptance and false rejection. The Support Vector Machine classifier achieved an accuracy of 98.05%, while the Naïve Bayes model reached 97.65%, as illustrated in Figure 2. Both classifiers demonstrated stable sensitivity and specificity, making the system suitable for real-world identity validation tasks such as cheque processing, secure document approval, and financial authentication.



To understand the placement of our approach, the results were compared with recent works from recognised journals. Kumari and Rana [21] worked on the BHsig260 dataset and reported 72.3% accuracy for Hindi and 79% for Bangla signatures in a writer-independent setting, while some writer-dependent cases exceeded 92%. Hong et al. (2024) used diffusion-based synthetic signature enhancement and achieved 94.87% accuracy on the CEDAR dataset. Chacko and Jacob (2021) employed a Siamese learning design with multilingual signatures and reported 97.28% on CEDAR, 96.88% on BHSig-Bangla, and 98.15% on BHSig-Hindi. Compared with these results, the proposed classical feature-based method offers competitive accuracy without large computational cost, training data, or complex model tuning, which is useful in resource-limited or real-time systems.

The comparison in Table 4 shows that the proposed SVM approach surpasses conventional writer-independent methods and performs close to modern neural models, while requiring considerably less memory and training time. The Naive Bayes model also performed strongly and offers a lightweight alternative for embedded environments.

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Table 2. Comparison with recent studies on offline signature verification.

Study / Paper	Dataset Used	Model Type / Remarks	Best Accuracy
Proposed SVM model	Custom Hybrid (Online + Offline) Dataset	SVM (RBF) using 644 fused features	98.05%
Proposed NB model	Custom Hybrid (Online + Offline) Dataset	Gaussian Naïve Bayes using fused features	97.65%
Kumari & Rana (2019) [21]	BHsig260-Hindi (WI)	Writer-independent (MLP)	72.3%
	BHsig260-Bangla (WI)	Writer-independent (RFC)	79.0%
	Writer-dependent	KNN / SVM (for some users)	>92.0%
Hong et al. (2024) [31]	CEDAR	Deep Learning with augmentation	94.87%
Chacko & Jacob (2021) [32]	CEDAR	CNN + FC-ResNet	97.28%
	BHSig-Bangla	CNN + FC-ResNet	96.88%
	BHSig-Hindi	CNN + FC-ResNet	98.15%

The obtained values confirm that handcrafted features combined with classical classifiers can still achieve high performance, especially in domains where training data is limited or interpretability is important. The fuzzy-based refinement also contributed to improved discrimination between genuine and forged signatures. Overall, the approach balances accuracy, computational cost, and design simplicity, making it suitable for banking authentication, administrative document security, and education-related certificate verification.

5. CONCLUSION AND FUTURE WORK

This study developed a practical handwritten signature verification system using Support Vector Machine and Naïve Bayes classifiers. Seventy-seven writers were included, and for each writer, both offline image signatures and online pen-movement log files were collected. Features were extracted from stroke direction, texture patterns, pressure change, timing differences, and curve movement. The aim was to distinguish genuine signatures from forged ones in a realistic setting. The results demonstrated strong performance. The Support Vector Machine achieved 98.05% accuracy, while the Naïve Bayes model achieved 97.65% accuracy on the dataset. These values show that almost all signatures were correctly classified. The false-acceptance rate for forged signatures remained very low, which is important for bank and document security. Confusion matrix analysis showed very few genuine signatures were wrongly rejected and very few forged signatures wrongly accepted. When compared with earlier studies that reported accuracy between 72% and 98%, this work achieved performance at the higher end. The improvement may be due to the combined use of offline and online features, careful feature selection, and balanced writer-independent design. The system does not require a large GPU or deep learning training and can run on a normal laptop. This makes it suitable for real use in banks, academic offices, legal departments, e-governance desks, and examination cells. The interface loads quickly and gives a decision in a few seconds, making it fit for live verification.

Future enhancements may include testing on other signature databases, adding mobile-tablet input, reducing the feature dimension further, and adding spoof-detection to protect against scanned or printed forgeries. With such improvements, this system can become a dependable signature verification tool for secure Indian digital and paper-based transactions.

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