**Paper Summary**

**Problem Statement**

Automatic handwritten signature verification involves training a model on genuine signatures to classify query signatures as genuine or forgeries. Writer-independent (WI) systems use one model for all users, while writer-dependent (WD) systems have one model per user. Most methods avoid using skilled forgeries for enrolled users but may use them for training WI classifiers. This approach is practical as it allows forgeries to be collected for training without compromising system evaluation with enrolled users' data.

**Challenges**

The challenges in automated signature verification include high intra-class variability among genuine signatures, making it difficult to distinguish them, especially with skilled forgeries that closely resemble genuine signatures. Training poses a challenge as only genuine signatures are available, leading to partial knowledge about forgery detection. Limited data availability for each user during enrollment further complicates the task, requiring classifiers to perform well with small sample sets for new users.

**Dataset**

Research in automated signature verification has traditionally used private datasets, making comparisons challenging due to variations in dataset quality. However, in recent years, publicly available signature datasets have emerged, improving comparability among studies. These public datasets follow a standard process: genuine signatures are collected in sessions where users provide multiple samples on forms designed for common scenarios like bank cheques. Forgeries are collected by having users imitate genuine signatures, although the users creating forgeries are not experts. The collected forms are then scanned at high resolutions (e.g., 300 or 600 dpi) and pre-processed for analysis.



**PreProcessing:**

* **Signature Extraction:** Extracting signatures from documents, especially challenging in complex backgrounds like bank cheques.
* **Noise Removal:** Applying filters like median filters and morphological operations to remove noise and enhance image quality.
* **Size Normalization and Centering:** Normalizing signature sizes and positions, including cropping to tight boxes, using narrower bounding boxes, or centering signatures in fixed frames.
* **Signature Representation:** Besides gray-level images, representations like skeletons, outlines, ink distribution, high-pressure regions, and directional frontiers are considered.
* **Signature Alignment:** Alignment techniques such as rotation, scaling, translation, and rotation normalization are used for online signature verification, with some methods applicable to offline scenarios as well.

**Feature Extraction**

* **Geometric Features:** Measure shape characteristics like height, width, caliber, area, endpoints, closed loops, and pixel density within grids.
* **Graphometric Features:** Utilize graphology concepts like calibre, proportion, alignment to baseline, and spacing to describe handwriting symmetry and alignment.
* **Directional Features:** Describe stroke directions using Probability Density Function (PDF), Pyramid Histogram of Oriented Gradients (PHOG), and gradient-based methods.
* **Mathematical Transformations:** Apply transforms like Hadamart, Spectrum Analysis, Contourlet, Radon, Wavelet, Fractal, and Shadow-code to extract signature features.
* **Texture Features:** Use Local Binary Patterns (LBP), Gray Level Co-occurrence Matrix (GLCM), and texture variations for pattern analysis in signatures.
* **Interest Point Matching:** Employ SIFT and SURF for local interest point extraction, stability assessment, and matching between signatures.
* **Pseudo-dynamic Features:** Derive features related to pixel distribution, stroke progression, slant, form, and curvature to capture dynamic aspects of handwriting.

**Model Training**

* **Classification Categories**: Writer-dependent classifiers are trained per user using genuine signatures and random forgeries.Writer-independent classifiers use a single model for all users, comparing query signatures with references.
* **Hybrid Approaches:** Some methods combine writer-independent and writer-dependent models based on available genuine signatures.Others combine results from both types of classifiers for decision-making.
* **Common Models**: Hidden Markov Models (HMMs)-Used with grid-based division of signatures, extracting features for discrimination.
* **Support Vector Machines (SVMs):** Effective for both writer-dependent and writer-independent classification, including One-Class SVMs.
* **Neural Networks and Deep Learning:** Utilized for various systems, including multitask learning and metric learning approaches.
* **Ensemble of Classifiers**: Strategies include static ensemble selection, dynamic classifier selection, and hybrid model combinations.
* **Data Augmentation:** Techniques like perturbations and synthesis address the challenge of limited training samples.

**Performance Metrics and Comparisons:**

Performance is evaluated on standard datasets with metrics like False Rejection Rate (FRR), False Acceptance Rate (FAR), Average Error Rate (AER), and Equal Error Rate (EER).

Texture descriptors (LBP, GLCM) and directional-based descriptors (HOG, DPDF) are commonly used and show promise.Recent advancements in feature learning methods have shown improved performance on benchmark datasets.

**Conclusion:**

Researchers in Offline Signature Verification have made significant progress in the past decade, notably in reducing error rates through Deep Learning advancements. Key areas of focus and trends in recent contributions include:

* **Feature Enhancement:** New feature extractors like texture features (LBP variations), interest-point matching (SIFT, SURF), and directional features (HOG) have improved accuracy. Feature learning methods show promise in generalizing learned features across users and datasets.
* **Classification Improvement with Limited Data:** Given constraints in real-world applications, efforts have concentrated on dissimilarity-based writer-independent solutions and metric-learning approaches to handle limited samples per user effectively.
* **Dataset Augmentation:** Synthetic signature generation has been explored to increase training samples per user, addressing the challenge of limited data availability.
* **Ensemble Techniques:** Both static and dynamic ensembles of classifiers have been studied to enhance classification accuracy and system robustness.

Moving forward, researchers are expected to continue refining feature representations, particularly leveraging Deep Learning for learning representations from signature images. Strategies to enhance classification performance with limited data will remain a priority, with a focus on dynamic selection techniques for ensemble models. Exploring one-class classification models tailored for low sample scenarios is also identified as a promising area for future research.