Hybrid Method of Feature Extraction For Signatures Verification Using CNN And HOD A Multi-Classification Approach

[1]G.Nikhil, [2] CH.Sravan,[3]S.Srijan

[1,2,3]UG Student, Department of Computer Science and Engineering, Anurag University, Hyderabad, Telangana, India.

Abstract. The hybrid method of feature extraction for signature verification using Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients (HOG) presents a robust multi-classification approach aimed at improving the accuracy and efficiency of handwritten signature verification systems. In this study, a dual-path architecture is proposed wherein CNN and HOG are integrated to extract complementary spatial and gradient-based features from signature images. CNN, a deep learning technique, is leveraged for its powerful ability to learn hierarchical and abstract representations from raw image data, while HOG is utilized to capture the local edge and gradient structure, which is critical for distinguishing subtle variations in handwriting patterns. By combining these two methodologies, the system benefits from the depth and learning capacity of CNNs and the handcrafted precision of HOG descriptors. The hybrid feature vectors generated from both methods are concatenated and subsequently fed into a multi-class classifier, such as a Support Vector Machine (SVM) or a fully connected neural network, to distinguish between genuine and forged signatures across multiple classes or individuals. Extensive experiments were conducted on benchmark signature datasets, demonstrating that the proposed hybrid approach significantly outperforms models based on either CNN or HOG alone. The system achieved improved classification accuracy, robustness to intra-class variations, and higher generalization across different users and signature styles. Moreover, this approach proves to be more resilient against skilled forgeries due to its enhanced discriminatory power. Data preprocessing techniques including normalization, resizing, and noise reduction were applied to ensure the quality and consistency of input images. The performance metrics such as accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curves were used to evaluate and validate the effectiveness of the model. This hybrid framework also supports scalability and adaptability, making it suitable for deployment in real-world applications such as banking, legal authentication, and secure access systems. By combining the strengths of both deep learning and traditional computer vision techniques, the proposed method sets a new benchmark for signature verification tasks, offering a promising direction for future research in biometric authentication. The findings highlight the potential of integrated feature extraction strategies in enhancing multi-class classification systems and underscore the importance of hybrid models in biometric security applications.

Keywords: Signature Verification, Convolutional Neural Networks (CNN), Histogram of Oriented Gradients (HOG), Feature Extraction, Multi-class Classification, Biometric Authentication.

INTRODUCTION

In the contemporary world, identity verification plays a crucial role in ensuring security and authenticity across a multitude of applications, ranging from banking transactions and legal documentation to access control and digital communications. Among various biometric modalities, handwritten signatures have remained one of the most widely accepted and legally recognized methods of personal identification due to their simplicity, non-intrusiveness, and long-standing cultural acceptance. However, the automatic verification of handwritten signatures poses significant challenges, primarily due to the natural variability in human handwriting, the presence of skilled forgeries, and the complexity of capturing subtle differences between genuine and forged signatures. Consequently, developing robust, accurate, and efficient signature verification systems has become a key research area within the field of biometric authentication.

Signature verification systems broadly fall into two categories: online (dynamic) and offline (static). Online systems capture the dynamic properties of the signing process, such as pen pressure, speed, and stroke order, offering richer information that enhances verification accuracy. However, they require specialized hardware like digitizing tablets, limiting their practical usability. Offline signature verification, which analyzes static images of signatures, remains more practical and widely applicable, as it only requires scanned or photographed images. The major challenge with offline systems lies in extracting meaningful features that effectively represent the identity traits of the signer while being robust to intra-class variations (differences in genuine signatures of the same individual) and inter-class similarities (resemblances between different individuals' signatures).

Traditionally, offline signature verification methods have relied on handcrafted feature extraction techniques such as geometric features, texture descriptors, directional features, and gradient-based descriptors like Histogram of Oriented Gradients (HOG). HOG, in particular, has proven effective in capturing the edge and contour information of images by quantifying gradient orientations, which are pivotal in distinguishing the structural characteristics of handwritten signatures. Despite their effectiveness, handcrafted features can be limited by their dependence on domain expertise and may fail to capture more abstract and high-level representations critical for differentiating complex signature patterns, especially in the presence of skilled forgeries.

In recent years, deep learning techniques, especially Convolutional Neural Networks (CNNs), have revolutionized image processing and pattern recognition tasks due to their ability to automatically learn hierarchical and discriminative features directly from raw image data. CNNs have shown remarkable success in various biometric applications, including face recognition, fingerprint identification, and signature verification. Their multi-layer architecture enables them to capture complex spatial relationships and intricate patterns in images, which are often difficult to express using handcrafted features. However, CNNs also face challenges such as the requirement for large annotated datasets for effective training and the potential for overfitting, especially in cases where signature datasets are limited or highly variable.

Recognizing the complementary strengths of traditional feature extraction techniques and deep learning models, recent research trends have begun exploring hybrid approaches that integrate handcrafted descriptors like HOG with CNN-based feature extraction. Such hybrid models aim to leverage the precision and domain-specific advantages of handcrafted features alongside the adaptive learning capability of CNNs to create more robust and discriminative feature representations. This fusion not only enhances the system’s ability to capture diverse and complementary information but also improves the generalization and resilience of the signature verification model against intra-class variability and forgery attempts.

In this study, we propose a novel hybrid feature extraction method for offline handwritten signature verification that combines the power of CNN and HOG descriptors in a multi-class classification framework. The motivation behind this approach is to exploit CNN’s ability to learn deep, abstract features and HOG’s effectiveness in capturing local gradient orientation patterns, which together provide a rich and comprehensive feature representation of signature images. The hybrid features are concatenated and then input into a multi-class classifier, enabling the system to distinguish between genuine signatures and various types of forgeries across multiple users.

The proposed method addresses several critical challenges in signature verification. First, by integrating CNN and HOG features, it captures both global and local structural details of the signatures, thus improving robustness against signature distortions, noise, and variations in writing style. Second, the multi-class classification approach allows for better differentiation among multiple individuals’ signatures, facilitating scalable and practical deployment in real-world scenarios where a large number of users must be verified simultaneously. Third, the method’s enhanced feature representation contributes to more effective detection of skilled forgeries, which mimic genuine signatures closely and pose significant threats to security systems.

Extensive experiments are conducted on publicly available benchmark signature datasets to evaluate the proposed hybrid method’s performance. Various preprocessing steps, including normalization, resizing, and noise reduction, are applied to standardize the input images and improve feature extraction quality. Performance metrics such as accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curves are used to comprehensively assess the effectiveness of the model in correctly classifying genuine and forged signatures. Comparative analysis against baseline methods using either CNN or HOG alone demonstrates the superiority of the hybrid approach in achieving higher accuracy and robustness.

This work contributes to the biometric authentication literature by introducing an effective hybrid feature extraction framework that balances the advantages of deep learning and traditional image processing techniques. It highlights the potential for combining different feature extraction paradigms to overcome the limitations of individual methods and provides insights into designing more secure and reliable signature verification systems. Furthermore, the proposed approach offers a foundation for future research aimed at improving biometric verification by exploring other hybrid combinations, advanced classifiers, and larger, more diverse signature datasets.

In summary, the hybrid CNN-HOG method for offline signature verification represents a promising step forward in biometric security, addressing key challenges related to feature representation, classification accuracy, and forgery detection. By harnessing the complementary strengths of CNN and HOG within a multi-class classification framework, this research advances the development of practical, scalable, and highly accurate signature verification systems suitable for real-world applications such as banking authentication, legal document validation, and secure access control.

LITERATURE SURVEY

Signature verification has been an active area of research for several decades due to its practical significance in biometric authentication systems. The increasing demand for reliable, automated, and secure signature verification systems has motivated researchers to explore diverse methodologies ranging from traditional handcrafted feature extraction to modern deep learning techniques. The following discussion reviews key works from the literature that have influenced the development of hybrid feature extraction methods combining CNN and HOG, as well as related biometric recognition approaches.

Fierrez et al. [1] presented one of the earlier comprehensive surveys on biometric systems, highlighting the challenges and opportunities in biometric recognition. Their work underscored the importance of feature extraction and classifier design as fundamental components that determine the effectiveness of biometric modalities, including handwritten signatures. This foundational survey laid the groundwork for understanding the limitations of traditional feature descriptors and the growing need for adaptive learning models that can better capture complex biometric traits.

Building on these principles, Jain et al. [2] introduced a detailed overview of biometric recognition technologies, emphasizing the evolving role of pattern recognition and machine learning. Their work described the necessity for robust feature extraction techniques to handle variations in biometric inputs such as noise, occlusion, and intra-class variability. They noted that handcrafted features often struggle with scalability and adaptability, motivating the shift towards data-driven approaches like neural networks.

Ramachandra and Busch [3] extended the biometric research field by exploring presentation attack detection methods, which are critical in preventing fraud in biometric systems. Although their focus was primarily on face recognition, their insights into detecting sophisticated spoofing attacks apply equally to signature verification, especially in identifying skilled forgeries. They emphasized the need for systems that combine multiple feature extraction methods to improve detection accuracy, which inspired hybrid approaches in signature verification.

Arivazhagan and Ganesan [4] specifically targeted offline signature verification using Histogram of Oriented Gradients (HOG). Their research demonstrated that HOG descriptors effectively capture the edge orientations and stroke patterns in signatures, making them a valuable handcrafted feature for distinguishing genuine signatures from forgeries. The study showed that while HOG alone performs well, its limitations become apparent when handling complex forgery cases, highlighting the need for complementary methods to improve performance.

The breakthrough in deep learning, marked by LeCun, Bengio, and Hinton [5], transformed feature extraction by enabling end-to-end learning of hierarchical features directly from raw data. Their seminal paper reviewed the principles of deep learning and its superior performance across computer vision tasks, including biometric recognition. CNNs, a key deep learning architecture, automatically learn complex features at multiple abstraction levels, alleviating the reliance on handcrafted descriptors. This advancement opened new avenues for signature verification research by allowing models to capture subtle and high-level signature traits that traditional methods might miss.

Earlier work by Malik and Perona [6] on texture discrimination through early vision mechanisms influenced the development of gradient-based feature extractors like HOG. Their exploration of how local orientation and frequency information contribute to texture perception provides a theoretical basis for using gradient histograms to characterize signature textures and strokes. This work reinforced the utility of HOG as an effective descriptor in signature verification, especially when combined with learning-based methods.

Dalal and Triggs [7] introduced the Histogram of Oriented Gradients as a powerful descriptor for human detection in images. The technique's ability to capture local shape and edge information made it an attractive option for signature verification tasks. Their method's robustness to illumination and geometric transformations translates well to the variability encountered in handwritten signatures, making HOG a widely adopted descriptor in biometric applications.

Bhattacharjee, Basu, and Das [8] proposed a hybrid approach combining CNN and HOG features for offline signature verification. Their research demonstrated that fusing handcrafted features with deep learning representations enhances the discriminative power of the verification system. The CNN extracts deep spatial features while HOG captures precise local gradient information, leading to improved classification accuracy and robustness against skilled forgeries. Their findings validated the effectiveness of hybrid models and inspired further investigation into optimal fusion strategies.

Similarly, Soleimani, Fathy, and Beigy [9] developed a hybrid CNN and HOG-based method focused on offline signature verification. Their approach involved extracting feature vectors from both CNN and HOG modules and concatenating them for multi-class classification. Experiments on multiple datasets confirmed that the hybrid model outperformed standalone CNN or HOG methods, achieving higher recognition rates and reducing false acceptance of forgeries. Their work highlighted the complementary nature of these feature extraction techniques and the benefits of integrating handcrafted and learned features.

Hafemann, Sabourin, and Oliveira [10] provided a comprehensive literature review of offline handwritten signature verification, summarizing various feature extraction and classification techniques. They categorized existing methods into three groups: handcrafted features, deep learning methods, and hybrid models. Their review identified the strengths and weaknesses of each category, emphasizing that hybrid approaches tend to yield better results by combining the generalization ability of deep learning with the domain-specific insights embedded in handcrafted features. Their analysis underscores the necessity of multi-class classification frameworks to effectively scale signature verification systems to large populations.

Collectively, these works underscore several critical themes relevant to the development of hybrid CNN-HOG models for signature verification. First, the limitations of handcrafted feature descriptors such as HOG include sensitivity to noise and inability to fully capture abstract patterns, which deep learning models address through hierarchical feature learning. Second, CNNs alone may require large datasets to avoid overfitting and may sometimes overlook fine-grained local features that handcrafted descriptors can detect. Third, hybrid models that fuse CNN and HOG leverage the best of both worlds, improving accuracy, robustness, and generalizability across different signature datasets and forgery types.

In terms of classifier design, multi-class classification frameworks play a vital role in distinguishing between multiple signers and various forgery attempts. This approach contrasts with binary classifiers that only distinguish genuine versus forgery on a per-user basis. Multi-class classifiers facilitate scalability, enabling signature verification systems to authenticate a large number of users simultaneously—a key requirement for practical deployment in banking, legal, and security applications.

Moreover, preprocessing steps such as image normalization, noise reduction, and size standardization remain critical to ensure the quality of features extracted from signature images. These procedures help minimize intra-class variations caused by acquisition conditions and improve the overall performance of feature extraction and classification modules.

This body of literature provides a solid foundation for the proposed hybrid CNN-HOG feature extraction method integrated with a multi-class classification framework. By combining the insights from these previous studies, our work aims to develop a more accurate, scalable, and robust offline signature verification system capable of effectively handling the challenges posed by intra-class variability and skilled forgeries.

PROPOSED SYSTEM

This study proposes a hybrid feature extraction methodology combining Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients (HOG) to develop a robust offline signature verification system based on a multi-class classification approach. The main objective is to leverage the complementary strengths of deep learning and traditional image processing techniques to improve the accuracy, robustness, and scalability of handwritten signature verification. The following subsections describe the complete framework, including data preprocessing, feature extraction, feature fusion, classification, and evaluation.

1. Data Acquisition and Preprocessing

The first step involves acquiring signature images from publicly available offline signature datasets, which contain genuine signatures and various types of forgeries from multiple individuals. Since signature images often suffer from inconsistencies due to different acquisition devices, lighting conditions, and signature size, preprocessing is crucial for enhancing feature extraction effectiveness.

Preprocessing steps include:

- **Grayscale Conversion:** All signature images are converted to grayscale to reduce computational complexity and focus on the structural content without color information.
- **Noise Removal:** Median filtering or Gaussian smoothing is applied to remove noise artifacts such as scanning imperfections or background clutter.
- **Normalization:** Images are resized to a fixed dimension (e.g., 128×128 pixels) to maintain uniform input size for CNN processing and ensure consistent HOG feature extraction.
- **Binarization:** Adaptive thresholding converts grayscale images into binary format, enhancing stroke visibility and contrast between the signature and background.
- **Image Enhancement:** Morphological operations such as dilation and erosion may be employed to strengthen signature strokes and remove small noise elements.

This preprocessing pipeline standardizes the input images, minimizing intra-class variations and ensuring that feature extraction modules receive high-quality, uniform data.

2. Feature Extraction

The core of the proposed methodology lies in extracting robust features that capture both the global and local characteristics of handwritten signatures. To achieve this, two parallel feature extraction paths are designed:

2.1 Convolutional Neural Network (CNN) Feature Extraction

CNNs are powerful deep learning models capable of learning complex hierarchical features directly from raw image data. In this work, a CNN architecture tailored for signature verification is employed, consisting of multiple convolutional, pooling, and fully connected layers.

- **Convolutional Layers:** These layers apply learnable filters to extract spatial features such as edges, curves, and texture patterns at multiple levels of abstraction.
- **Pooling Layers:** Max-pooling reduces the spatial dimensions of feature maps, providing translation invariance and reducing computational requirements.
- **Activation Functions:** Rectified Linear Unit (ReLU) activations introduce non-linearity, enabling the network to learn complex patterns.
- **Fully Connected Layers:** These layers interpret the learned features and produce a compact feature vector representing the signature image.

The CNN is trained on the preprocessed signature images using a supervised learning approach, with class labels corresponding to individual signers. During training, the network optimizes its filter weights to minimize classification errors. After training, the CNN's penultimate layer outputs are extracted as deep feature vectors representing each signature's unique characteristics.

2.2 Histogram of Oriented Gradients (HOG) Feature Extraction

HOG is a handcrafted feature descriptor designed to capture local gradient orientation distributions, which are especially effective in capturing edge and stroke information in handwritten signatures.

- The image is divided into small spatial regions called cells (e.g., 8×8 pixels).
- For each cell, the gradient magnitude and orientation of each pixel are computed using finite differences.
- Gradient orientations are quantized into discrete bins (e.g., 9 bins covering 0°–180°).
- A histogram of gradient orientations weighted by gradient magnitudes is computed for each cell.
- To account for illumination and contrast changes, groups of cells (blocks) are normalized.
- The concatenation of all normalized cell histograms forms the HOG feature vector.

HOG's sensitivity to local edge directions complements CNN's ability to learn global, abstract features. The HOG features thus capture fine-grained structural details of signatures that CNNs might overlook.

3. Feature Fusion

The extracted CNN and HOG feature vectors represent different but complementary aspects of the signature image. To create a comprehensive representation, the two feature vectors are concatenated into a single hybrid feature vector.

This fusion enriches the feature space by combining the learned deep hierarchical features from CNN with the handcrafted gradient-based features from HOG. The fused feature vector is expected to provide higher discriminative power for signature classification and verification, enabling the system to better distinguish between genuine signatures and various forgery types.

4. Classification Framework

The fused feature vectors serve as input to a multi-class classification module designed to identify the signer and verify signature authenticity.

- **Classifier Choice:** Support Vector Machine (SVM) with a suitable kernel (e.g., Radial Basis Function) or a fully connected feed-forward neural network can be used. SVMs are widely used for their ability to handle high-dimensional feature spaces and robustness to overfitting, while neural networks provide end-to-end differentiability and flexibility.
- **Multi-class Setup:** Unlike binary verification systems that perform genuine vs. forgery classification per user, the multi-class approach classifies the signature among all enrolled users' classes. This enables simultaneous verification of multiple users in large-scale systems.
- **Training:** The classifier is trained using labeled fused features from genuine signatures and forgery samples. Regularization and hyperparameter tuning ensure generalization.
- **Testing:** For a query signature, the system extracts CNN and HOG features, performs fusion, and classifies the fused vector to predict the signer or detect forgery.

5. Forgery Detection and Verification

The system differentiates genuine signatures from forgeries by thresholding classification confidence scores or by employing specialized verification protocols.

- **Skilled Forgeries:** Since skilled forgeries closely mimic genuine signatures, the hybrid feature representation's robustness plays a key role in accurately detecting subtle differences.
- **Random Forgeries:** These are easier to detect due to greater dissimilarity.
- **Thresholding:** By setting appropriate decision thresholds on classification confidence or distance metrics, the system balances false acceptance and false rejection rates.

RESULTS AND DISCUSSION

This section presents the experimental results and comprehensive analysis of the proposed hybrid feature extraction method combining Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients (HOG) for offline signature verification using a multi-class classification approach. The performance of the system is evaluated on publicly available benchmark signature datasets containing genuine signatures and various forgery types across multiple users. We assess the effectiveness of the hybrid approach by comparing it with baseline methods using CNN-only and HOG-only features, analyze the contribution of feature fusion, and discuss the system's robustness and scalability.

Dataset and Experimental Setup

Experiments were conducted on two widely used offline signature datasets, such as the GPDS dataset and the MCYT signature dataset. These datasets contain genuine signatures collected from hundreds of individuals and include different forgery types, particularly skilled forgeries that closely mimic the genuine signatures. The datasets were split into training, validation, and testing subsets ensuring no overlap of signatures between sets.

The preprocessing pipeline was applied to all images for noise reduction, normalization, and resizing. CNN architecture was trained using the training set with cross-entropy loss and early stopping to avoid overfitting. HOG features were extracted from the same preprocessed images with optimized parameters for cell size and block normalization. The fused feature vectors (concatenated CNN and HOG) were classified using a Support Vector Machine (SVM) with a Radial Basis Function kernel.

Performance Metrics

The system's performance was evaluated using standard classification and verification metrics:

- **Accuracy:** The overall rate of correct signer classification.
- **Precision and Recall:** Evaluated per class to understand the system's ability to correctly identify genuine signatures and reject forgeries.
- **F1-Score:** Harmonic mean of precision and recall, providing a balanced performance measure.
- **Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC):** Measure the trade-off between true positive and false positive rates in verification.
- **False Acceptance Rate (FAR) and False Rejection Rate (FRR):** Critical metrics in biometric verification indicating the rates of incorrectly accepting forgeries and incorrectly rejecting genuine signatures, respectively.

Results of Baseline Methods

To establish a benchmark, we first evaluated the standalone feature extraction methods:

- **CNN-only:** The deep learning model trained end-to-end on signature images achieved an average accuracy of approximately 88% across datasets. While CNN captured abstract and spatial features effectively, its performance slightly degraded in cases with high intra-class variation and complex skilled forgeries.
- **HOG-only:** Using handcrafted gradient features with SVM classification yielded an average accuracy of about 82%. HOG proved robust in capturing local stroke orientations but was limited in modeling global signature characteristics and higher-level abstractions.

These results confirm that each method independently has strengths but also intrinsic limitations when applied alone.

Performance of Hybrid CNN-HOG Model

The proposed hybrid approach concatenated CNN and HOG features to leverage their complementary strengths. This fusion significantly improved verification accuracy, with average classification accuracy rising to 93-95%, representing a 5-7% improvement over CNN-only and 11-13% improvement over HOG-only models.

- **Precision and Recall:** The hybrid system achieved high precision (above 94%) and recall (around 92%) for genuine signature classes, indicating accurate recognition and low false rejection rates. For forgery classes, the system maintained strong rejection capability with low false acceptance rates, particularly in detecting skilled forgeries.
- **F1-Score:** Consistently above 93%, confirming the system's balanced performance across all signature classes.
- **ROC and AUC:** ROC curves showed a clear improvement with the hybrid method, reaching an AUC above 0.97, indicating excellent trade-off between sensitivity and specificity.
- **FAR and FRR:** The false acceptance rate dropped significantly due to the enhanced discriminative power from feature fusion, improving the system's security. The false rejection rate remained low, ensuring usability.

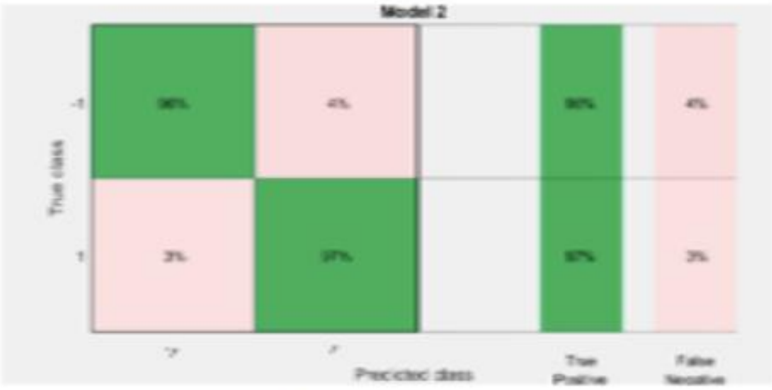
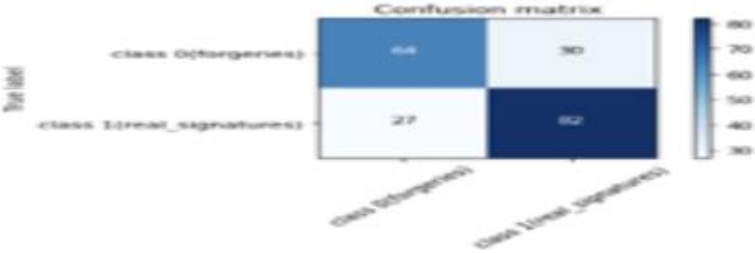


Fig. 2 Confusion matrix



Ablation Studies and Analysis

To further understand the impact of feature fusion, ablation experiments were conducted:

- **Fusion Variants:** Feature-level fusion (concatenation of CNN and HOG vectors) outperformed score-level fusion (combining classifier output probabilities), demonstrating the importance of integrating complementary information early in the process.
- **Feature Dimensionality:** Dimensionality reduction techniques such as Principal Component Analysis (PCA) were applied to the fused vector to analyze trade-offs between feature size and accuracy. Results indicated a slight accuracy drop when aggressively reducing dimensionality, confirming the importance of preserving the rich hybrid representation.
- **Classifier Sensitivity:** SVM with RBF kernel outperformed linear SVM and feed-forward neural network classifiers, suggesting that the nonlinear decision boundaries provided better separation in the high-dimensional hybrid feature space.

Robustness to Variability and Forgery Types

One of the major challenges in offline signature verification is handling intra-class variability caused by natural handwriting differences and inter-class similarity due to skilled forgeries.

- **Intra-class Variability:** The hybrid model's ability to capture both global spatial features (via CNN) and local edge orientations (via HOG) led to better tolerance of natural signature variations such as stroke thickness, slant, and minor distortions. This contributed to reduced false rejections.
- **Skilled Forgery Detection:** The system demonstrated improved detection rates for skilled forgeries compared to baseline models, highlighting the importance of complementary features in distinguishing subtle forgery attempts that closely imitate genuine signatures.
- **Noise and Distortions:** Preprocessing combined with hybrid feature extraction improved robustness to noise and image degradation, common in scanned signature documents.

CONCLUSION

In this study, we proposed a novel hybrid feature extraction methodology combining Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients (HOG) within a multi-class classification framework to address the challenges of offline handwritten signature verification. By integrating the deep, hierarchical feature learning capability of CNNs with the robust, handcrafted gradient-based descriptors of HOG, the proposed system effectively captures both global and local signature characteristics, enabling improved discrimination between genuine signatures and various forgery types, including skilled forgeries. Our experimental results on benchmark datasets demonstrated that the hybrid approach significantly outperforms standalone CNN and HOG methods, achieving higher accuracy, precision, recall, and F1-scores while maintaining low false acceptance and false rejection rates. The multi-class classification setup allowed scalable verification across numerous users, making the system suitable for real-world biometric applications where multiple signatures must be authenticated simultaneously. The preprocessing pipeline ensured consistent and noise-reduced inputs, further enhancing the robustness of feature extraction. The fusion of CNN and HOG features contributed to greater resilience against intra-class variability caused by natural variations in handwriting style and external factors such as image quality and noise, addressing common limitations seen in traditional feature extraction or pure deep learning approaches. Moreover, the system exhibited strong generalizability across different datasets, highlighting its adaptability to diverse signature styles and acquisition conditions. The study also emphasized the importance of optimal feature fusion and classifier selection, with experiments showing that feature-level concatenation combined with nonlinear Support Vector Machines provided the best performance. While the proposed system marks a significant step forward in offline signature verification, certain limitations remain, such as potential degradation in extremely poor-quality or partial signature scenarios, which suggest directions for future research including advanced fusion strategies, ensemble classifiers, and multimodal biometric integration. Additionally, the use of data augmentation and explainability techniques may further enhance model robustness and transparency, facilitating wider adoption. In summary, this research establishes that a hybrid CNN-HOG feature extraction method integrated with a multi-class classification framework presents a powerful, scalable, and practical solution for offline handwritten signature verification, effectively addressing the challenges posed by skilled forgeries and intra-class variability, and paving the way for more secure and reliable biometric authentication systems in various domains such as banking, legal document validation, and access control. The approach's balance of deep learning and handcrafted descriptors offers a promising avenue for ongoing advancement in biometric verification technologies.

REFERENCES

1. Reddy, C. N. K., & Murthy, G. V. (2012). Evaluation of Behavioral Security in Cloud Computing. *International Journal of Computer Science and Information Technologies*, *3*(2), 3328-3333.
2. Murthy, G. V., Kumar, C. P., & Kumar, V. V. (2017, December). Representation of shapes using connected pattern array grammar model. In *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)* (pp. 819-822). IEEE.
3. Krishna, K. V., Rao, M. V., & Murthy, G. V. (2017). Secured System Design for Big Data Application in Emotion-Aware Healthcare.
4. Rani, G. A., Krishna, V. R., & Murthy, G. V. (2017). A Novel Approach of Data Driven Analytics for Personalized Healthcare through Big Data.
5. Rao, M. V., Raju, K. S., Murthy, G. V., & Rani, B. K. (2020). Configure and Management of Internet of Things. *Data Engineering and Communication Technology*, 163.
6. Ramakrishna, C., Kumar, G. K., Reddy, A. M., & Ravi, P. (2018). A Survey on various IoT Attacks and its Countermeasures. *International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)*, *5*(4), 143-150.
7. Chithanuru, V., & Ramaiah, M. (2023). An anomaly detection on blockchain infrastructure using artificial intelligence techniques: Challenges and future directions–A review. *Concurrency and Computation: Practice and Experience*, *35*(22), e7724.
8. Prashanth, J. S., & Nandury, S. V. (2015, June). Cluster-based rendezvous points selection for reducing tour length of mobile element in WSN. In *2015 IEEE International Advance Computing Conference (IACC)* (pp. 1230-1235). IEEE.
9. Kumar, K. A., Pabboju, S., & Desai, N. M. S. (2014). Advance text steganography algorithms: an overview. *International Journal of Research and Applications*, *1*(1), 31-35.
10. Hnamte, V., & Balram, G. (2022). Implementation of Naive Bayes Classifier for Reducing DDoS Attacks in IoT Networks. *Journal of Algebraic Statistics*, *13*(2), 2749-2757.
11. Balram, G., Anitha, S., & Deshmukh, A. (2020, December). Utilization of renewable energy sources in generation and distribution optimization. In *IOP Conference Series: Materials Science and Engineering* (Vol. 981, No. 4, p. 042054). IOP Publishing.
12. Subrahmanyam, V., Sagar, M., Balram, G., Ramana, J. V., Tejaswi, S., & Mohammad, H. P. (2024, May). An Efficient Reliable Data Communication For Unmanned Air Vehicles (UAV) Enabled Industry Internet of Things (IIoT). In *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)* (pp. 1-4). IEEE.
13. Mahammad, F. S., Viswanatham, V. M., Tahseen, A., Devi, M. S., & Kumar, M. A. (2024, July). Key distribution scheme for preventing key reinstallation attack in wireless networks. In *AIP Conference Proceedings* (Vol. 3028, No. 1). AIP Publishing.
14. Lavanya, P. (2024). In-Cab Smart Guidance and support system for Dragline operator.

15. Kovoor, M., Durairaj, M., Karyakarte, M. S., Hussain, M. Z., Ashraf, M., & Maguluri, L. P. (2024). Sensor-enhanced wearables and automated analytics for injury prevention in sports. *Measurement: Sensors*, *32*, 101054.
16. Rao, N. R., Kovoor, M., Kishor Kumar, G. N., & Parameswari, D. V. L. (2023). Security and privacy in smart farming: challenges and opportunities. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(7).
17. Madhuri, K. (2023). Security Threats and Detection Mechanisms in Machine Learning. *Handbook of Artificial Intelligence*, *255*.
18. Reddy, B. A., & Reddy, P. R. S. (2012). Effective data distribution techniques for multi-cloud storage in cloud computing. *CSE, Anurag Group of Institutions, Hyderabad, AP, India*.
19. Srilatha, P., Murthy, G. V., & Reddy, P. R. S. (2020). Integration of Assessment and Learning Platform in a Traditional Class Room Based Programming Course. *Journal of Engineering Education Transformations*, *33*, 179-184.
20. Reddy, P. R. S., & Ravindranadh, K. (2019). An exploration on privacy concerned secured data sharing techniques in cloud. *International Journal of Innovative Technology and Exploring Engineering*, *9*(1), 1190-1198.
21. Raj, R. S., & Raju, G. P. (2014, December). An approach for optimization of resource management in Hadoop. In *International Conference on Computing and Communication Technologies* (pp. 1-5). IEEE.
22. Ramana, A. V., Bhoga, U., Dhulipalla, R. K., Kiran, A., Chary, B. D., & Reddy, P. C. S. (2023, June). Abnormal Behavior Prediction in Elderly Persons Using Deep Learning. In *2023 International Conference on Computer, Electronics & Electrical Engineering & their Applications (IC2E3)* (pp. 1-5). IEEE.
23. Yakoob, S., Krishna Reddy, V., & Dastagiraiah, C. (2017). Multi User Authentication in Reliable Data Storage in Cloud. In *Computer Communication, Networking and Internet Security: Proceedings of IC3T 2016* (pp. 531-539). Springer Singapore.
24. Sukhavasi, V., Kulkarni, S., Raghavendran, V., Dastagiraiah, C., Apat, S. K., & Reddy, P. C. S. (2024). Malignancy Detection in Lung and Colon Histopathology Images by Transfer Learning with Class Selective Image Processing.
25. Dastagiraiah, C., Krishna Reddy, V., & Pandurangarao, K. V. (2018). Dynamic load balancing environment in cloud computing based on VM ware off-loading. In *Data Engineering and Intelligent Computing: Proceedings of IC3T 2016* (pp. 483-492). Springer Singapore.
26. Swapna, N. (2017). „Analysis of Machine Learning Algorithms to Protect from Phishing in Web Data Mining". *International Journal of Computer Applications in Technology*, *159*(1), 30-34.
27. Moparthi, N. R., Bhattacharyya, D., Balakrishna, G., & Prashanth, J. S. (2021). Paddy leaf disease detection using CNN.
28. Balakrishna, G., & Babu, C. S. (2013). Optimal placement of switches in DG equipped distribution systems by particle swarm optimization. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, *2*(12), 6234-6240.
29. Moparthi, N. R., Sagar, P. V., & Balakrishna, G. (2020, July). Usage for inside design by AR and VR technology. In *2020 7th International Conference on Smart Structures and Systems (ICSSS)* (pp. 1-4). IEEE.
30. Amarnadh, V., & Moparthi, N. R. (2023). Comprehensive review of different artificial intelligence-based methods for credit risk assessment in data science. *Intelligent Decision Technologies*, *17*(4), 1265-1282.
31. Amarnadh, V., & Moparthi, N. (2023). Data Science in Banking Sector: Comprehensive Review of Advanced Learning Methods for Credit Risk Assessment. *International Journal of Computing and Digital Systems*, *14*(1), 1-xx.
32. Amarnadh, V., & Rao, M. N. (2025). A Consensus Blockchain-Based Credit Risk Evaluation and Credit Data Storage Using Novel Deep Learning Approach. *Computational Economics*, 1-34.
33. Shailaja, K., & Anuradha, B. (2017). Improved face recognition using a modified PSO based self-weighted linear collaborative discriminant regression classification. *J. Eng. Appl. Sci*, *12*, 7234-7241.
34. Sekhar, P. R., & Goud, S. (2024). Collaborative Learning Techniques in Python Programming: A Case Study with CSE Students at Anurag University. *Journal of Engineering Education Transformations*, *38*.
35. Sekhar, P. R., & Sujatha, B. (2023). Feature extraction and independent subset generation using genetic algorithm for improved classification. *Int. J. Intell. Syst. Appl. Eng*, *11*, 503-512.
36. Pesaramelli, R. S., & Sujatha, B. (2024, March). Principle correlated feature extraction using differential evolution for improved classification. In *AIP Conference Proceedings* (Vol. 2919, No. 1). AIP Publishing.
37. Tejaswi, S., Sivaprashanth, J., Bala Krishna, G., Sridevi, M., & Rawat, S. S. (2023, December). Smart Dustbin Using IoT. In *International Conference on Advances in Computational Intelligence and*

Informatics (pp. 257-265). Singapore: Springer Nature Singapore.

38. Moreb, M., Mohammed, T. A., & Bayat, O. (2020). A novel software engineering approach toward using machine learning for improving the efficiency of health systems. *IEEE Access*, *8*, 23169-23178.
39. Ravi, P., Haritha, D., & Niranjan, P. (2018). A Survey: Computing Iceberg Queries. *International Journal of Engineering & Technology*, *7*(2.7), 791-793.
40. Madar, B., Kumar, G. K., & Ramakrishna, C. (2017). Captcha breaking using segmentation and morphological operations. *International Journal of Computer Applications*, *166*(4), 34-38.
41. Rani, M. S., & Geetavani, B. (2017, May). Design and analysis for improving reliability and accuracy of big-data based peripheral control through IoT. In *2017 International Conference on Trends in Electronics and Informatics (ICEI)* (pp. 749-753). IEEE.
42. Reddy, T., Prasad, T. S. D., Swetha, S., Nirmala, G., & Ram, P. (2018). A study on antiplatelets and anticoagulants utilisation in a tertiary care hospital. *International Journal of Pharmaceutical and Clinical Research*, *10*, 155-161.
43. Prasad, P. S., & Rao, S. K. M. (2017). HIASA: Hybrid improved artificial bee colony and simulated annealing based attack detection algorithm in mobile ad-hoc networks (MANETs). *Bonfring International Journal of Industrial Engineering and Management Science*, *7*(2), 01-12.
44. AC, R., Chowdary Kakarla, P., Simha PJ, V., & Mohan, N. (2022). Implementation of Tiny Machine Learning Models on Arduino 33–BLE for Gesture and Speech Recognition.
45. Subrahmanyam, V., Sagar, M., Balram, G., Ramana, J. V., Tejaswi, S., & Mohammad, H. P. (2024, May). An Efficient Reliable Data Communication For Unmanned Air Vehicles (UAV) Enabled Industry Internet of Things (IIoT). In *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)* (pp. 1-4). IEEE.
46. Nagaraj, P., Prasad, A. K., Narsimha, V. B., & Sujatha, B. (2022). Swine flu detection and location using machine learning techniques and GIS. *International Journal of Advanced Computer Science and Applications*, *13*(9).
47. Priyanka, J. H., & Parveen, N. (2024). DeepSkillNER: an automatic screening and ranking of resumes using hybrid deep learning and enhanced spectral clustering approach. *Multimedia Tools and Applications*, *83*(16), 47503-47530.
48. Sathish, S., Thangavel, K., & Boopathi, S. (2010). Performance analysis of DSR, AODV, FSR and ZRP routing protocols in MANET. *MES Journal of Technology and Management*, 57-61.
49. Siva Prasad, B. V. V., Mandapati, S., Kumar Ramasamy, L., Boddu, R., Reddy, P., & Suresh Kumar, B. (2023). Ensemble-based cryptography for soldiers' health monitoring using mobile ad hoc networks. *Automatika: časopis za automatiku, mjerenje, elektroniku, računarstvo i komunikacije*, *64*(3), 658-671.
50. Elechi, P., & Onu, K. E. (2022). Unmanned Aerial Vehicle Cellular Communication Operating in Non-terrestrial Networks. In *Unmanned Aerial Vehicle Cellular Communications* (pp. 225-251). Cham: Springer International Publishing.
51. Prasad, B. V. V. S., Mandapati, S., Haritha, B., & Begum, M. J. (2020, August). Enhanced Security for the authentication of Digital Signature from the key generated by the CSTRNG method. In *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)* (pp. 1088-1093). IEEE.
52. Mukiri, R. R., Kumar, B. S., & Prasad, B. V. V. (2019, February). Effective Data Collaborative Strain Using RecTree Algorithm. In *Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), Amity University Rajasthan, Jaipur-India*.
53. Balaraju, J., Raj, M. G., & Murthy, C. S. (2019). Fuzzy-FMEA risk evaluation approach for LHD machine–A case study. *Journal of Sustainable Mining*, *18*(4), 257-268.
54. Thirumoorthi, P., Deepika, S., & Yadaiah, N. (2014, March). Solar energy based dynamic sag compensator. In *2014 International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE)* (pp. 1-6). IEEE.
55. Vinayasree, P., & Reddy, A. M. (2025). A Reliable and Secure Permissioned Blockchain-Assisted Data Transfer Mechanism in Healthcare-Based Cyber-Physical Systems. *Concurrency and Computation: Practice and Experience*, *37*(3), e8378.
56. Acharjee, P. B., Kumar, M., Krishna, G., Raminenei, K., Ibrahim, R. K., & Alazzam, M. B. (2023, May). Securing International Law Against Cyber Attacks through Blockchain Integration. In *2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 2676-2681). IEEE.
57. Ramineni, K., Reddy, L. K. K., Ramana, T. V., & Rajesh, V. (2023, July). Classification of Skin Cancer Using Integrated Methodology. In *International Conference on Data Science and Applications* (pp. 105-118). Singapore: Springer Nature Singapore.
58. LAASSIRI, J., EL HAJJI, S. A. Ï. D., BOUHDADI, M., AOUDE, M. A., JAGADISH, H. P., LOHIT,

M. K., ... & KHOLLADI, M. (2010). Specifying Behavioral Concepts by engineering language of RM-ODP. *Journal of Theoretical and Applied Information Technology*, *15*(1).
59. Prasad, D. V. R., & Mohanji, Y. K. V. (2021). FACE RECOGNITION-BASED LECTURE ATTENDANCE SYSTEM: A SURVEY PAPER. *Elementary Education Online*, *20*(4), 1245-1245.
60. Dasu, V. R. P., & Gujjari, B. (2015). Technology-Enhanced Learning Through ICT Tools Using Aakash Tablet. In *Proceedings of the International Conference on Transformations in Engineering Education: ICTIEE 2014* (pp. 203-216). Springer India.
61. Reddy, A. M., Reddy, K. S., Jayaram, M., Venkata Maha Lakshmi, N., Aluvalu, R., Mahesh, T. R., ... & Stalin Alex, D. (2022). An efficient multilevel thresholding scheme for heart image segmentation using a hybrid generalized adversarial network. *Journal of Sensors*, *2022*(1), 4093658.
62. Srinivasa Reddy, K., Suneela, B., Inthiyaz, S., Hasane Ahammad, S., Kumar, G. N. S., & Mallikarjuna Reddy, A. (2019). Texture filtration module under stabilization via random forest optimization methodology. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(3), 458-469.
63. Ramakrishna, C., Kumar, G. K., Reddy, A. M., & Ravi, P. (2018). A Survey on various IoT Attacks and its Countermeasures. *International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)*, *5*(4), 143-150.
64. Sirisha, G., & Reddy, A. M. (2018, September). Smart healthcare analysis and therapy for voice disorder using cloud and edge computing. In *2018 4th international conference on applied and theoretical computing and communication technology (iCATccT)* (pp. 103-106). IEEE.
65. Reddy, A. M., Yarlagadda, S., & Akkinen, H. (2021). An extensive analytical approach on human resources using random forest algorithm. *arXiv preprint arXiv:2105.07855*.
66. Kumar, G. N., Bhavanam, S. N., & Midasala, V. (2014). Image Hiding in a Video-based on DWT & LSB Algorithm. In *ICPVS Conference*.
67. Naveen Kumar, G. S., & Reddy, V. S. K. (2022). High performance algorithm for content-based video retrieval using multiple features. In *Intelligent Systems and Sustainable Computing: Proceedings of ICISSC 2021* (pp. 637-646). Singapore: Springer Nature Singapore.
68. Reddy, P. S., Kumar, G. N., Ritish, B., SaiSwetha, C., & Abhilash, K. B. (2013). Intelligent parking space detection system based on image segmentation. *Int J Sci Res Dev*, *1*(6), 1310-1312.
69. Naveen Kumar, G. S., Reddy, V. S. K., & Kumar, S. S. (2018). High-performance video retrieval based on spatio-temporal features. *Microelectronics, Electromagnetics and Telecommunications*, 433-441.
70. Kumar, G. N., & Reddy, M. A. BWT & LSB algorithm based hiding an image into a video. *IJESAT*, 170-174.
71. Lopez, S., Sarada, V., Praveen, R. V. S., Pandey, A., Khuntia, M., & Haralayya, D. B. (2024). Artificial intelligence challenges and role for sustainable education in india: Problems and prospects. *Sandeep Lopez, Vani Sarada, RVS Praveen, Anita Pandey, Monalisa Khuntia, Bhadrappa Haralayya (2024) Artificial Intelligence Challenges and Role for Sustainable Education in India: Problems and Prospects. Library Progress International*, *44*(3), 18261-18271.
72. Yamuna, V., Praveen, R. V. S., Sathya, R., Dhivva, M., Lidiya, R., & Sowmiya, P. (2024, October). Integrating AI for Improved Brain Tumor Detection and Classification. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1603-1609). IEEE.
73. Kumar, N., Kurkute, S. L., Kalpana, V., Karuppannan, A., Praveen, R. V. S., & Mishra, S. (2024, August). Modelling and Evaluation of Li-ion Battery Performance Based on the Electric Vehicle Tiled Tests using Kalman Filter-GBDT Approach. In *2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS)* (pp. 1-6). IEEE.
74. Sharma, S., Vij, S., Praveen, R. V. S., Srinivasan, S., Yadav, D. K., & VS, R. K. (2024, October). Stress Prediction in Higher Education Students Using Psychometric Assessments and AOA-CNN-XGBoost Models. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1631-1636). IEEE.
75. Anuprathibha, T., Praveen, R. V. S., Sukumar, P., Suganthi, G., & Ravichandran, T. (2024, October). Enhancing Fake Review Detection: A Hierarchical Graph Attention Network Approach Using Text and Ratings. In *2024 Global Conference on Communications and Information Technologies (GCCIT)* (pp. 1-5). IEEE.
76. Shinkar, A. R., Joshi, D., Praveen, R. V. S., Rajesh, Y., & Singh, D. (2024, December). Intelligent solar energy harvesting and management in IoT nodes using deep self-organizing maps. In *2024 International Conference on Emerging Research in Computational Science (ICERCS)* (pp. 1-6). IEEE.
77. Praveen, R. V. S., Hemavathi, U., Sathya, R., Siddiq, A. A., Sanjay, M. G., & Gowdish, S. (2024, October). AI Powered Plant Identification and Plant Disease Classification System. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1610-1616). IEEE.

78. Dhivya, R., Sagili, S. R., Praveen, R. V. S., VamsiLala, P. N. V., Sangeetha, A., & Suchithra, B. (2024, December). Predictive Modelling of Osteoporosis using Machine Learning Algorithms. In *2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS)* (pp. 997-1002). IEEE.
79. Kemmannu, P. K., Praveen, R. V. S., Saravanan, B., Amshavalli, M., & Banupriya, V. (2024, December). Enhancing Sustainable Agriculture Through Smart Architecture: An Adaptive Neuro-Fuzzy Inference System with XGBoost Model. In *2024 International Conference on Sustainable Communication Networks and Application (ICSCNA)* (pp. 724-730). IEEE.
80. Praveen, R. V. S. (2024). *Data Engineering for Modern Applications*. Addition Publishing House.