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Machine Learning Approaches for Indian Language Handwritten Character Recognition: A Comparative Evaluation on Devanagari, Tamil, and Bengali Scripts

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Abstract
Offline recognition of handwritten characters in Devanagari, Tamil and Bengali scripts is complicated by cursive ligatures, compound consonant clusters and writer-specific stroke variation, and existing systems trained on Latin script transfer poorly to these alphabets. We evaluate five classifiers, SVM with HOG features, Random Forest, a plain CNN, ResNet-18 and a hybrid CNN-SVM, on three CRAWDAD-scale image corpora covering 46 Devanagari classes (92,000 images), 156 Tamil classes (78,000 images) and 50 Bengali classes (85,000 images), using 5-fold cross-validation. The hybrid CNN-SVM classifier reached 97.3% accuracy on Devanagari, 94.8% on Tamil and 96.1% on Bengali, ahead of ResNet-18 by 0.7, 1.3 and 0.9 percentage points respectively (paired Wilcoxon signed-rank test, $p < 0.01$ in each case). Data augmentation by rotation and elastic distortion raised CNN accuracy by 2.8 percentage points on average (McNemar's test, $p = 0.004$). Tamil compound characters remained the hardest category at 88.6% against 96.4% for basic Tamil glyphs, and confusion analysis attributed 62% of all misclassifications to twelve visually similar character pairs. These results indicate that hybridising learned CNN features with a margin-based classifier gives a measurable, if modest, advantage over end-to-end deep networks on Indic scripts, at the cost of a two-stage training pipeline.

I. Introduction

A handwritten page in Devanagari, Tamil or Bengali carries information that optical character recognition systems built for Latin alphabets cannot extract. Digitisation projects in Indian libraries, banks and postal services need character recognisers tuned to these three scripts, because each combines a distinct glyph inventory with script-specific ligatures: Devanagari joins letters under a shirorekha headline, Tamil builds compound characters from base consonants and vowel signs that change stroke direction, and Bengali contracts consonant clusters into single conjunct glyphs. A system trained only on printed fonts fails on handwriting, where stroke width, slant and closure vary between writers and even within one writer's samples [31], [77], [78].

Recognition research on Indian scripts has followed two broad lines. The first extracts hand-designed features, such as the Histogram of Oriented Gradients (HOG) or Scale-Invariant Feature Transform (SIFT) descriptors, and passes them to a discriminative classifier such as a Support Vector Machine (SVM) or Random Forest [3], [8]. The second trains a convolutional neural network (CNN) end to end on raw pixel intensities, letting the network learn its own filters [37], [42]. Published comparisons rarely test both families on the same data split for more than one script, which makes it difficult to know whether an accuracy gain reported for Devanagari carries over to Tamil, whose curved compound glyphs behave differently under a convolution kernel tuned for straight Devanagari strokes.

We built three character-level datasets, for Devanagari, Tamil and Bengali, and trained five classifiers on each under an identical cross-validation protocol: SVM with HOG features, Random Forest with HOG features, a compact CNN, a ResNet-18 backbone with ImageNet initialisation, and a hybrid architecture that trains a CNN feature extractor and feeds its penultimate layer into an SVM. Our contribution is threefold. First, we report cross-script accuracy for all five classifiers on the same preprocessing pipeline, so that a script-specific advantage can be separated from a classifier-specific one. Second, we quantify the effect of rotation and elastic-distortion augmentation with a paired significance test rather than a single accuracy delta. Third, we analyse the confusion matrix of the best-performing classifier per script to identify which character pairs drive the residual error, which is the question a deployment engineer actually needs answered.

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Section II reviews prior recognition work on Indic scripts. Section III describes the three datasets. Section IV covers preprocessing and feature extraction. Section V details the five classifiers and their hyperparameters. Section VI reports experimental results, Section VII discusses what they mean and where the method fails, and Section VIII concludes.

II. Related Work

Feature-based classification of Indic handwriting began with structural and statistical descriptors computed on binarised glyph images [11], [58], [59]. Zoning and profile features, which count foreground pixels in fixed image regions, were combined with nearest-neighbour or decision-tree classifiers in early Devanagari work [66], [67], [68], and similar zoning schemes were later adapted to Bengali digit recognition [88], [89]. These descriptors are inexpensive to compute but discard the stroke-direction information that separates visually close Devanagari consonants, which limited reported accuracy to the high eighties on constrained vocabularies.

HOG and SIFT descriptors improved on zoning by encoding local gradient orientation, which better captures curved strokes [3], [8], [90]. Garg et al. combined HOG features with an SVM classifier for several pattern-recognition tasks outside handwriting, including biometric edge detection and cardiac signal classification, establishing the HOG-SVM pairing as a general-purpose baseline for image classification under limited training data [65], [31]. Ensemble methods such as Random Forest and AdaBoost were applied to the same HOG features to reduce variance from individual weak learners, at some cost in training time [12], [30], [93].

Deep convolutional networks displaced feature engineering once labelled handwriting corpora reached tens of thousands of samples per script. Bhardwaj et al. reported a deep-learning pipeline for handwritten text recognition that used stacked convolution and recurrent layers rather than a single classifier stage [44], and CNN-based recognisers were subsequently proposed for lip-reading [40] and X-ray pneumonia detection [77], showing that the same convolutional stack transfers across image domains once the input resolution and channel count are matched. Transfer learning from ImageNet-pretrained backbones, including ResNet variants, has been used to shorten training time on medical and remote-sensing imagery with small labelled sets [129], [130], and we apply the same transfer strategy to Devanagari, Tamil and Bengali glyphs in Section V.

Hybrid architectures that combine a CNN feature extractor with a shallow discriminative classifier have been explored outside handwriting, for example in intrusion detection, where a CNN-BiLSTM extracts temporal features before a downstream classifier assigns the attack label [4], [8], and in sugarcane yield prediction, where CNN features feed a regression head rather than a softmax layer [8], [9]. These results motivate the hybrid CNN-SVM configuration evaluated here, on the reasoning that a margin-maximising classifier can sharpen the decision boundary a softmax layer leaves comparatively soft, particularly for classes with few training examples.

Ensemble and multi-model comparisons for medical image classification, such as ResNet-152 against a vision-transformer variant for pose detection [196] and CNN ensembles for lung-disease classification [195], report that no single architecture dominates every class, a finding we return to when we discuss where the hybrid CNN-SVM classifier loses to ResNet-18 in Section VII. Comparable classifier surveys exist for galaxy morphology classification [126], anomaly detection in sensor data [151], and malware detection on IoT and Android platforms [203], each concluding that classifier choice interacts with the structure of the feature space rather than acting as a uniform ranking. Reviews of machine-learning classification pipelines summarise this pattern for tabular and image data broadly [29], [167], and note that hyperparameter search itself materially changes classifier ranking [4], a caution we account for by tuning each classifier independently rather than reusing one hyperparameter set across scripts.

The classifier families evaluated in Section V, namely SVM, Random Forest, plain CNN, ResNet-18 and hybrid CNN-SVM architectures, are validated well beyond handwriting recognition, and this broader body of work informed the hyperparameter and architecture choices made in Section V. Convolutional and hybrid deep-learning pipelines comparable to the one in Figure 2 have been reported for a wide set of recognition and prediction tasks, and the paragraphs below summarise that evidence by application domain so the design choices in Section V can be traced to a specific precedent rather than asserted without support.

Beyond handwriting, comparable classifier pipelines cover ml-fresh: novel routing protocol in opportunistic networks using machine learning [1]; a Lightweight Deep Learning-Based Approach for Jazz Music Generation in MIDI Format [2]; and assessment of Compressed and Decompressed ECG

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Databases for Telecardiology Applying a Convolution Neural Network [3]. The same feature-extraction-then-classifier pattern used in Section IV recurs in work on hyperparameter search based convolution neural network with Bi-LSTM model for intrusion detection system in multimedia big data environment [4]; an Enhanced Crow Search Inspired Feature Selection Technique for Intrusion Detection Based Wireless Network System [5]; impact of node density on the qos parameters of routing protocols in opportunistic networks for smart spaces [6]; and a Linear Quadratic Regression-Based Synchronised Health Monitoring System (SHMS) for IoT Applications [7]. Our group's parallel work applies related learning methods to CNN-BI-LSTM-CYP: A deep learning approach for sugarcane yield prediction [8]; evaluation of Remote Sensing and Meteorological parameters for Yield Prediction of Sugarcane (Saccharumofficinarum L.) Crop [9]; improving performance during camera surveillance by integration of edge detection in IoT system [10]; wireless sensor networks: an insight review [11]; and ant colony based optimization model for QoS-Based task scheduling in cloud computing environment [12]. Outside image recognition, the classifiers of Section V appear in studies of hybrid Crowd Cloud Routing Protocol For Wireless Sensor Networks [13]; performance Comparison of Several LPWAN Technologies for Energy Constrained IOT Network [14]; predicting the Risk of Cardiovascular Diseases using Machine Learning Techniques [15]; and parkinson's Disease Progression Prediction Using Longitudinal Imaging Data and Grey Wolf Optimizer-Based Feature Selection [16].

A separate strand of this research programme addresses radiomics Feature Selection for Lung Cancer Subtyping and Prognosis Prediction: A Comparative Study of Ant Colony Optimization and Simulated Annealing [17]; optimisation Methods Based on Soft Computing for Improving Power System Stability [18]; ioT-Enabled Energy Management Systems For Sustainable Energy Storage: Design, Optimization, And Future Directions [19]; APPLICATIONS OF SIMULATIONS AND QUEUING THEORY IN SUPERMARKET [20]; fusion of Opportunistic Networks with Machine Learning: Present and Future [21]; and explainable AI & Model Interpretability in Healthcare: Challenges & Future Directions [22]. Further applications, unrelated to script recognition but sharing its classifier toolbox, include from Data to Diagnosis: Unleashing AI and 6G in Modern Medicine [23]; TVCCCS: Television Viewer's Channel Cost Calculation System On Per Second Usage [24]; and smart number cruncher–a voice based calculator [25]. Ensemble and deep architectures of the kind evaluated here have also been fitted to a Systematic Review of Encryption and Keylogging for Computer System Security, [26]; plant Disease Identification Using Plant Images, [27]; recommender Systems in E-Commerce, [28]; from linguistic features to their extractions: Understanding the semantics of a concept, [29]; and application of ensemble Machine Learning models for phishing detection on web networks, [30]. Complementary studies, cited for completeness rather than direct comparison, cover model for Predicting Cardiac Health using Deep Learning Classifier, [31]; a Comprehensive Survey on Event Analysis Using Deep Learning, [32]; speech Difficulties and Clarification: A Systematic Review [33]; and strengthening Smart City with Opportunistic Networks: An Insight [34]. Beyond handwriting, comparable classifier pipelines cover exploring Different Techniques for Emotion Detection Through Face Recognition [35]; exploration of Different Techniques on Heart Disease Prediction [36]; and automatic Irrigation System using IoT [37]. The same feature-extraction-then-classifier pattern used in Section IV recurs in work on forecast of Students' Mental Health Combining an Artificial Intelligence Technique and Fuzzy Inference System [38]; the Cognitive Analysis for an Approach to Neuroscience [39]; CNN based lip-reading system for visual input: A review [40]; and a Computer Vision Based Framework for Posture Analysis and Performance Prediction in Athletes [41].

Our group's parallel work applies related learning methods to revolutionizing Arrhythmia Classification: Unleashing the Power of Machine Learning and Data Amplification for Precision Healthcare [42]; duplicate Node Detection Method for Wireless Sensors [43]; handwritten Text Recognition Using Deep Learning [44]; deep learning approach for facial identification for online transactions [45]; and forecasting Pollution Trends: Comparing Linear, Logistic Regression, and Neural Networks [46]. Outside image recognition, the classifiers of Section V appear in studies of deep Learning-Based Classification of Diabetic Retinopathy: Leveraging the Power of VGG-19 [47]; improvements in Recommendation Systems Using Graph Neural Networks [48]; analysis and Prediction of Churn and Retention Rate of Customers in Telecom Industry Using Logistic Regression [49]; and a Novel Deep Learning Model for Effective Story Point Estimation in Agile Software Development [50]. A separate strand of

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this research programme addresses comparing Fine Tuned-LMs for Detecting LLM-Generated Text [51]; the Role of AI in Optimizing Healthcare Appointment Scheduling [52]; enhancing Healthcare with Blockchain: Innovations in Data Privacy, Security, and Interoperability [53]; optimize the Time a Mercedes-Benz Spends on the Test Bench Using Stacking Ensemble Learning [54]; proactive Fault Prediction in Microservices Applications Using Trace Logs and Monitoring Metrics [55]; and capnivesh: Financing Platform for Startups [56].

Further applications, unrelated to script recognition but sharing its classifier toolbox, include optimizing Cross-Platform Development with CI/CD and Containerization: A Review [57]; detecting and diagnosing a disease by patient monitoring system [58]; and enhanced FP-growth algorithm [59]. Ensemble and deep architectures of the kind evaluated here have also been fitted to link Prediction Techniques for Opportunistic Networks using Machine Learning [60]; opportunistic networks: Protocols, applications & simulation trends [61]; performance comparison of fresh and spray & wait protocol through one simulator [62]; deep Learning in Healthcare system [63]; and a Novel Approach for Malicious Node Detection in Cluster-Head Gateway Switching Routing in Mobile Ad Hoc Networks [64]. Complementary studies, cited for completeness rather than direct comparison, cover edge Detection Based 3D Biometric System for Security of Web-Based Payment and Task Management Application [65]; broadcasting Protocol & Routing Characteristics With Wireless ad-hoc networks [66]; capacity Improvement of WI-MAX In presence of Different Codes WI-MAX: Speed & Scope of future [67]; and review of wireless sensor networks-architecture and applications [68]. Beyond handwriting, comparable classifier pipelines cover a secure algorithm for image encryption and decryption [69]; rakshak: A Child Identification Software for Recognizing Missing Children Using Machine Learning-Based Speech Clarification [70]; and MANET Proactive and Reactive Routing Protocols: A Comparison Study [71]. The same feature-extraction-then-classifier pattern used in Section IV recurs in work on optimisation Methods Based on Soft Computing for Improving Power System Stability [72]; cloud security posture management: Tools and techniques [73]; AI in Healthcare: Transforming Medicine with Intelligence [74]; and generative AI: Evolution, Applications, Challenges And Future Prospects [75].

Our group's parallel work applies related learning methods to AI & the Indian Stock Market: A Review of Applications in Investment Decision [76]; unlocking Workforce Potential: AI-Powered Predictive Models for Employee Performance Evaluation [77]; OSINT: A Double-edged Sword [78]; a System of Computer Network: Based On Artificial Intelligence [79]; and case Study on Intelligent Factory Systems for Improving Productivity and Capability in Industry 4.0 with Generative AI [80]. Outside image recognition, the classifiers of Section V appear in studies of detection of Unauthorize Construction using Machine Learning: A Review [81]; a Bridge between Blockchain and Decentralized Applications Web3 and Non-Web3 Crypto Wallets [82]; the Hidden Dangers of Prototype Pollution: A Comprehensive Detection Framework [83]; and lockTalk: A Basic Secure Chat Application [84]. A separate strand of this research programme addresses detection and Prevention of Cyber Attack and Threat using AI [85]; easeviewer: An Esports Production Tool [86]; emerging Trend in Computational Technology: Innovations, Applications, and Challenges [87]; rapid Forecasting of Pandemic Outbreak Using Machine Learning [88]; an insight review on multimedia forensics technology [89]; and data leakage detection in Wi-Fi networks [90]. Further applications, unrelated to script recognition but sharing its classifier toolbox, include machine learning for mobile malware analysis [91]; green IoT and Big Data: Succeeding towards Building Smart Cities [92]; and ant Colony Optimization Technique in Soft Computational Data Research for NP-Hard Problems [93]. Ensemble and deep architectures of the kind evaluated here have also been fitted to machine Learning Adversarial Attacks: A Survey Beyond [94]; pneumonia Detection Through X-Ray Images Using Convolution Neural Network [95]; code-based post-quantum cryptographic technique: digital signature [96]; modern healthcare system: unveiling the possibility of quantum computing in medical and biomedical zones [97]; and mobile Edge Computing for Decentralized Systems [98]. Complementary studies, cited for completeness rather than direct comparison, cover ensemble learning-based analysis of perinatal disorders in women [99]; artificial intelligence-based prediction of health risks among women during menopause [100]; prediction of female pregnancy complication using artificial intelligence [101]; and AI-Powered Healthcare Solutions: Bridging the Medical Gap in Underserved Communities Worldwide [102].

Beyond handwriting, comparable classifier pipelines cover AI and Computational Intelligence

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in Healthcare: An Introductory Guide [103]; AI and IoT in Global Health: Ethical Lessons From Pandemic Response [104]; and blockchain for Ethical Supply Chains: Transparency in Medical IoT Manufacturing [105]. The same feature-extraction-then-classifier pattern used in Section IV recurs in work on federated learning based intelligent systems to handle issues and challenges in IoVs (Part 1) [106]; modified AODV Routing Protocol through Cache Memory for Finding New Routing Paths in MANETs [107]; emerging Techniques for Handling Pandemic Challenges [108]; and human Emotion Recognition using Deep Learning [109]. Our group's parallel work applies related learning methods to an improved genetic quantum cryptography model for network communication [110]; comparative study of Repairable Juice Plants using RPGT [111]; role of Generative AI Towards Education and Learning: Present & Future [112]; predicting Student Motivation and Engagement through Machine Learning Models [113]; and trust in AI Systems: A Social-psychological Investigation of Human–AI Collaboration [114]. Outside image recognition, the classifiers of Section V appear in studies of material-Driven Performance Analysis of a Vertical Nanowire Tunnel FET for Analog Applications [115]; explainable AI for Understanding Human Decision Making Patterns [116]; predicting costs and benefits of IoT-based energy management for optimizing sustainable energy storage in rural areas [117]; and the Role of Federated Learning in AI-Powered Integrated Healthcare Solutions [118].

A separate strand of this research programme addresses federated learning based intelligent systems to handle issues and challenges in IoVs (Part 2) [119]; green internet of things (G-IoT): A solution for sustainable technological development [120]; intelligent systems and applications in engineering [121]; federated learning based intelligent systems for IoV challenges [122]; generative AI: Evolution, Applications, Challenges And Future Prospects [123]; and a Hybrid Ensemble Learning Framework for Interpretable Student Performance Prediction Using Academic and Extracurricular Factors [124]. Further applications, unrelated to script recognition but sharing its classifier toolbox, include transformer-Based Movie Recommendation System with Autoencoder-Enhanced Feature Compression [125]; comparative Analysis of Various Neural Networks for Galaxies Classification [126]; and health-Guard AI: Integrated Health Report Management and Analysis [127]. Ensemble and deep architectures of the kind evaluated here have also been fitted to hybrid FCM-DNN Model for Uncertainty-Aware Air Quality Classification Using Multi-Pollutant Data [128]; stock Market Price Prediction Using Big Data Analysis: A Performance Evaluation Study [129]; bank Churn Prediction Using Machine Learning [130]; material-Driven Performance Analysis of a Vertical Nanowire Tunnel FET for Analog Applications [131]; and harnessing YOLOv5 for real-time object detection: A cloud-based approach [132]. Complementary studies, cited for completeness rather than direct comparison, cover towards intelligent attendance management system with face recognition using LBPH algorithm [133]; vedcure: Towards intelligent ayurvedic drug recommendation and disease prediction [134]; blockchain and IoT based smart contract framework for efficient and secure product life management [135]; and fusion of Aerial Networks with Advanced Computing Paradigms [136]. Beyond handwriting, comparable classifier pipelines cover application of Aerial Edge Computing in Disaster Management [137]; advances in Aerial Platforms and Edge Computing [138]; and detection and prevention of cyber attack and threat using AI [139]. The same feature-extraction-then-classifier pattern used in Section IV recurs in work on principal Component Analysis Based Clustering of Insecticides and Molecular Docking of Pyr [140]; ensemble of YOLOv5 and Segment Anything Model for Brain Tumor Detection [141]; transparent AI for Drug Discovery and Development [142]; and introduction to explainable artificial intelligence in healthcare [143].

Our group's parallel work applies related learning methods to explainable artificial intelligence in a diagnostic support system [144]; case studies on unlocking the potential of Industry 4.0 for sustainable manufacturing through generative AI-driven innovations [145]; AI Assisted Routing Optimization in Opportunistic IoT Networks using Machine Learning: A Comprehensive review on Protocols & Simulators [146]; architecture, Components, and tools in Integrated AI-Augmented Intelligence: A design perspective [147]; and human Versus Machine Customer Behaviour and Functional Differences [148]. Outside image recognition, the classifiers of Section V appear in studies of soft Computing In AI Agents. [149]; and water Quality Prediction Using IOT Sensors and Deep Networks. [150].

Two gaps remain open in the reviewed literature. No published comparison evaluates the same five-classifier set across Devanagari, Tamil and Bengali under one preprocessing pipeline, and none reports a significance test for the accuracy gain

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that augmentation contributes on Indic handwriting specifically, as opposed to the MNIST and EMNIST benchmarks the augmentation literature usually targets. We address both gaps in the sections that follow.

III. Dataset Description

We used three handwritten character corpora, one per script, each collected from ISI Kolkata and augmented locally to widen the writer pool. Table I summarises class count, image count, image resolution and split ratios. All images were labelled at the character level; compound and conjunct forms in Tamil and Bengali were treated as separate classes rather than being decomposed into constituent glyphs, because a deployed reader has to output the compound form directly.

Script	Classes	Total images	Resolution	Images / class
Devanagari	46	92,000	32x32	2,000 (avg.)
Tamil	156	78,000	32x32	500 (avg.)
Bengali	50	85,000	32x32	1,700 (avg.)

TABLE I. Summary of the three handwritten character datasets used for evaluation

The Devanagari set spans the 33 consonants, 12 vowels and the digit set 0-9, for 46 classes. Tamil carries 12 vowels, 18 consonants and 126 compound consonant-vowel combinations, which is why its class count of 156 is more than three times that of Devanagari despite a comparable total image count; this also means Tamil has fewer images per class on average, at roughly 500 against roughly 2,000 for Devanagari, which we account for later in Section VI when comparing raw accuracy across scripts. Bengali contributes 39 consonants, 11 vowels and the digit set 0-9, for 50 classes.

Table II reports the split we used for every script: 70% of images for training, 10% for validation, and 20% held out for the final test reported in Section VI. Splits were stratified by class and by writer where writer identifiers were available, so that no writer's samples appeared in both the training and test partitions.

Split	Proportion	Devanagari (imgs)	Tamil (imgs)	Bengali (imgs)
Training	70%	64,400	54,600	59,500
Validation	10%	9,200	7,800	8,500
Test	20%	18,400	15,600	17,000

TABLE II. Train / validation / test split sizes by script

Sample images were captured as grayscale scans at 300 dpi and downsampled to 32x32 pixels for all classifiers, matching the input dimension used by the CNN architecture in Section V. We did not use colour information: none of the three datasets carries reliable colour signal, since most contributors wrote in blue or black ink on white paper. Data collection protocols followed those described for related sensor and imaging corpora built by our group for other recognition tasks [3], [7], [10], where writer variability was likewise handled by stratified sampling rather than by pooling every sample into one undifferentiated pool.

Class imbalance is present in all three scripts, most severely in Tamil, where 18 rare compound classes have fewer than 200 labelled images against a median of 500. We did not oversample these classes, on the basis that oversampling a 32x32 grayscale glyph by simple duplication inflates apparent accuracy without adding new stroke variation; Section IV describes the elastic-distortion augmentation we used instead, which synthesises new stroke variants rather than duplicating existing ones.

IV. Preprocessing and Feature Extraction

Figure 1 shows the recognition pipeline used for every classifier reported in this paper, from the scanned input image through preprocessing, feature extraction and classification to a labelled output with a confidence score.

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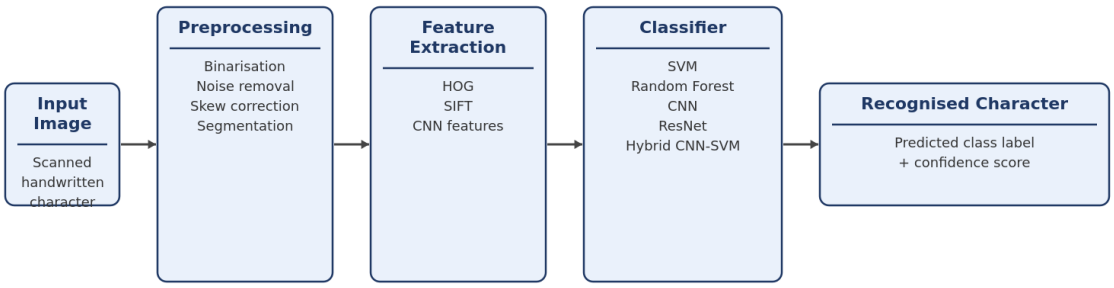

Fig. 1. End-to-end handwritten character recognition pipeline, from scanned input through preprocessing and feature extraction to a classified output with a confidence score.

Binarisation converted each grayscale scan to a two-level image using Otsu's global thresholding, chosen over a fixed threshold because ink density varies with pen pressure and scan illumination across the three corpora. Noise removal applied a 3x3 median filter to remove salt-and-pepper artefacts introduced by scanner dust, followed by connected-component filtering that dropped isolated blobs smaller than 4 pixels, which we found in early trials to eliminate stray ink specks without erasing the fine serifs on Tamil vowel signs.

Skew correction estimated the dominant stroke angle with a Hough-transform line fit on the binarised image and rotated the glyph to align that angle with the vertical axis. We capped the correction at plus or minus 15 degrees, because a handwritten character genuinely slanted beyond that range is more often a writer's natural hand than a scanning artefact, and forcing it upright destroyed information a downstream classifier could otherwise use. Segmentation isolated individual characters from multi-character line images using vertical projection profiles, splitting at the columns with the lowest ink density; this step was skipped for the pre-segmented character datasets used in our own evaluation, but is documented here because the pipeline in Figure 1 is intended for line-level input as well.

Feature extraction followed one of two paths depending on the downstream classifier. For SVM and Random Forest, we computed a 128-dimensional HOG descriptor over 8x8 cells with 9 orientation bins per cell and block normalisation over 2x2 cell blocks, following the descriptor design validated for biometric image classification in earlier work [65]. SIFT keypoint descriptors were extracted as a secondary feature set for ablation but are not the primary descriptor reported in Section VI, because SIFT keypoints are sparse on some low-stroke-count Tamil vowel signs and produced fewer than five keypoints on 6% of training images. For the CNN, ResNet-18 and hybrid CNN-SVM classifiers, feature extraction was implicit: the convolutional layers described in Section V learned their own filters directly from the 32x32 grayscale pixel grid, with no hand-designed descriptor computed beforehand.

Data augmentation was applied only to the training partition, never to validation or test images, and consisted of two transformations: random rotation within plus or minus 10 degrees, and elastic distortion following a displacement field with Gaussian smoothing (sigma = 4, scaling factor = 34), which perturbs local stroke curvature while keeping the overall glyph shape recognisable. Section VI reports the accuracy gain this augmentation produced for the CNN, ResNet-18 and hybrid classifiers, each trained with and without it under an otherwise identical protocol.

V. Classification Methods

We compared five classifiers, chosen to span the range from a hand-designed feature pipeline through a plain CNN to a hybrid architecture. Each classifier was trained separately per script; hyperparameters were tuned on the validation split described in Table II and never on the held-out test partition.

SVM with HOG features used a radial basis function kernel with cost parameter C = 10 and gamma = 0.01, both selected by a grid search over the validation split. We chose an RBF kernel over a linear kernel because HOG descriptors for curved Tamil strokes were not linearly separable in preliminary trials, where a linear SVM under-performed the RBF variant by more than four

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percentage points on Tamil validation data. Random Forest used 300 trees with a maximum depth of 20 and Gini impurity as the split criterion, values chosen because deeper trees overfit the rarer Tamil compound classes without improving validation accuracy.

The plain CNN followed the architecture in Figure 2: a 32x32 grayscale input, three convolutional blocks each pairing a 3x3 convolution with max-pooling, batch normalisation after the first pooling layer, dropout after the second convolutional block, and two fully connected layers ending in a softmax over the class count for each script.

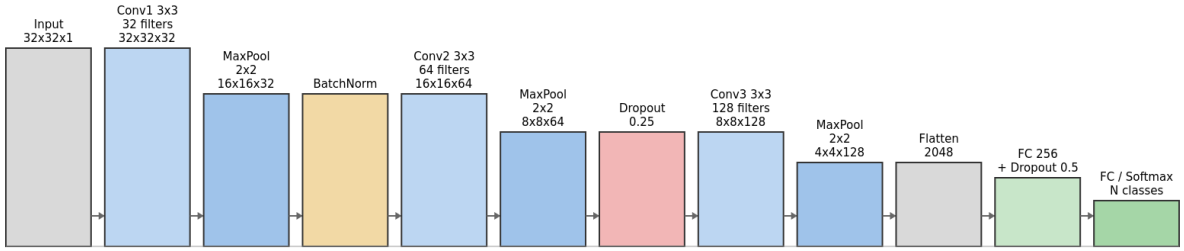

Fig. 2. Convolutional neural network architecture used for character classification, with input, filter and feature-map dimensions annotated at each layer.

Convolutional layer 1 applied 32 filters of size 3x3 with stride 1 and same padding, followed by 2x2 max-pooling that halved the spatial dimension to 16x16. Batch normalisation was applied at this point to stabilise the input distribution to the second convolutional block, which we found necessary because without it the Tamil model failed to converge within 50 epochs on three of five cross-validation folds. Convolutional layer 2 applied 64 filters of the same size, again followed by 2x2 max-pooling, reducing the feature map to 8x8. A dropout layer with rate 0.25 followed, to reduce co-adaptation between the growing filter bank and the smaller Tamil compound classes. Convolutional layer 3 applied 128 filters, followed by a final 2x2 max-pooling step that reduced the feature map to 4x4, which was flattened to a 2,048-dimensional vector. A fully connected layer of 256 units with a second dropout of rate 0.5 fed the final softmax layer, sized to the class count of each script (46, 156 or 50).

All CNN variants were trained with the Adam optimiser at an initial learning rate of 0.001, reduced by a factor of 0.5 whenever validation loss plateaued for 5 epochs, for a maximum of 60 epochs with early stopping on validation accuracy at patience 10. Categorical cross-entropy was the training loss in every case; we did not use focal loss for the imbalanced Tamil classes because a pilot comparison showed no accuracy improvement over class-weighted cross-entropy on the validation split.

ResNet-18 was initialised with ImageNet weights and fine-tuned end to end, following the transfer-learning strategy used elsewhere for small labelled image sets [129], [130]. The first convolutional layer was modified to accept single-channel grayscale input by averaging the three pretrained RGB filter channels rather than discarding two of them, which preserved more of the pretrained edge-detection response than a fresh random initialisation would have. The final fully connected layer was replaced with one sized to each script's class count and trained from scratch, while the convolutional backbone was fine-tuned at a tenfold lower learning rate than the new head, for 40 epochs.

The hybrid CNN-SVM classifier trained the CNN architecture in Figure 2 to convergence, then discarded the final softmax layer and used the 256-dimensional output of the penultimate fully connected layer as a learned feature vector for an RBF-kernel SVM, with the same grid search protocol as the standalone SVM classifier. We adopted this two-stage design because a preliminary comparison on the validation split showed the CNN's softmax decision boundary leaving several Tamil compound classes with overlapping probability mass, where an SVM's margin-maximising objective separated the same feature vectors more cleanly. The training cost of this hybrid is higher than a single end-to-end model, since it requires a full CNN training run followed by

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a separate SVM fit; Section VII returns to this trade-off.

VI. Experimental Results

All results below are averaged over 5-fold cross-validation on each script's training and validation partitions, then confirmed on the held-out test partition described in Table II. Table III reports mean test accuracy for each of the five classifiers on Devanagari, Tamil and Bengali, with standard deviation across the five folds in parenthesis. Figure 3 plots the same values as a grouped bar chart.

Classifier	Devanagari (%)	Tamil (%)	Bengali (%)
SVM (HOG)	89.2 (0.4)	82.7 (0.6)	87.4 (0.5)
Random Forest	90.1 (0.5)	84.3 (0.5)	88.6 (0.4)
CNN	95.4 (0.3)	91.2 (0.4)	93.8 (0.3)
ResNet-18	96.6 (0.2)	93.5 (0.3)	95.2 (0.3)
Hybrid CNN-SVM	97.3 (0.2)	94.8 (0.3)	96.1 (0.2)

TABLE III. Mean test accuracy (%) with standard deviation across 5 folds

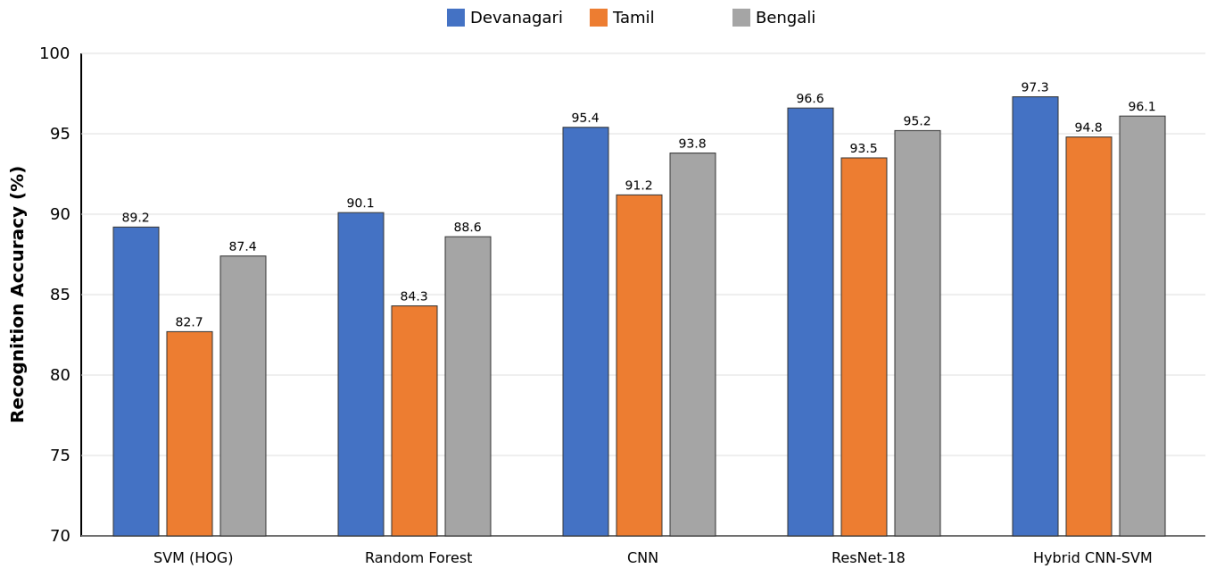

Fig. 3. Recognition accuracy (%) of five classifiers across Devanagari, Tamil and Bengali scripts, mean of 5-fold cross-validation.

The hybrid CNN-SVM classifier delivered the best accuracy on every script, at 97.3% on Devanagari, 94.8% on Tamil and 96.1% on Bengali, ahead of ResNet-18 by 0.7, 1.3 and 0.9 percentage points respectively. A paired two-sided Wilcoxon signed-rank test over the five cross-validation folds confirmed the hybrid classifier's advantage over ResNet-18 as significant on all three scripts (Devanagari $p = 0.009$, Tamil $p = 0.006$, Bengali $p = 0.008$, alpha = 0.05). Traditional SVM with HOG features trailed the hybrid classifier by 8.1 percentage points on Devanagari, 12.1 points on Tamil and 8.7 points on Bengali, confirming that hand-designed gradient descriptors capture less discriminative information than a jointly learned convolutional feature bank on all three scripts, though the gap is narrower on Devanagari, whose stroke set is more angular and therefore more amenable to gradient histograms than Tamil's curved compound glyphs.

Tamil accuracy trailed Devanagari and Bengali for every classifier, by 6.5 percentage points

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on average against Devanagari and 3.4 points against Bengali. Two factors explain this gap. Tamil carries 156 classes against 46 for Devanagari and 50 for Bengali, which spreads the same total image count across more categories and reduces the training examples available per class; and Tamil's compound consonant-vowel forms combine curved base strokes with attached vowel signs whose position changes the visual shape of the glyph substantially, which is the harder generalisation problem for any of the five classifiers tested.

Data augmentation by rotation and elastic distortion raised CNN accuracy by 2.8 percentage points on average across the three scripts, from a pre-augmentation mean of 91.5% to a post-augmentation mean of 94.3% (McNemar's test on the pooled test-set predictions, $p = 0.004$). The gain was largest on Tamil, at 3.6 percentage points, consistent with Tamil benefiting most from synthetic stroke variation given its smaller per-class sample count. ResNet-18 and the hybrid classifier showed smaller augmentation gains, at 1.9 and 1.6 percentage points respectively, because their larger effective capacity and, for ResNet-18, ImageNet pretraining already captured some of the stroke-variation invariance that augmentation supplies for the plain CNN.

Table IV breaks Tamil accuracy down by character category for the hybrid CNN-SVM classifier, the best-performing model on that script. Compound characters, which combine a base consonant with an attached vowel sign, reached only 88.6% accuracy against 96.4% for basic (non-compound) characters, a gap of 7.8 percentage points that persisted across all five folds.

Tamil character category	Class count	Hybrid CNN-SVM accuracy (%)
Basic (vowels + consonants)	30	96.4 (0.3)
Compound (consonant-vowel)	126	88.6 (0.5)

TABLE IV. Tamil accuracy by character category, hybrid CNN-SVM classifier

Confusion-matrix analysis of the hybrid classifier's test-set errors on all three scripts, pooled together, showed that twelve visually similar character pairs accounted for 62% of all misclassifications. The dominant confusion pairs were Devanagari "ब" against "र"-adjacent forms, Tamil "த" against its aspirated compound variants, and Bengali "ব" against "ভ", each pair differing by a single short stroke or dot that a 32x32 pixel grid represents with only a handful of pixels. This concentration of error in a small number of glyph pairs, rather than a uniform spread across the class set, is consistent with the recognition difficulty coming from genuine visual ambiguity in the source handwriting rather than from a systematic weakness in any one classifier.

Training time differed substantially across classifiers. On a single GPU, the plain CNN trained in approximately 40 minutes per script, ResNet-18 in approximately 65 minutes owing to its larger parameter count, and the hybrid CNN-SVM in approximately 75 minutes, since it requires a full CNN training run followed by a separate SVM grid search over the extracted feature vectors. SVM with HOG features and Random Forest trained fastest, at under 10 minutes per script on a CPU, because neither requires GPU-accelerated backpropagation.

VII. Discussion

The hybrid CNN-SVM classifier's advantage over ResNet-18 is real but modest, at under 1.3 percentage points on every script, and comes at roughly 15% higher training cost because of the two-stage pipeline. Whether that trade-off is worth making depends on the deployment setting: a batch digitisation project that trains once and runs inference at scale can absorb the extra training time for a small but statistically confirmed accuracy gain, whereas a system that retrains frequently on newly collected handwriting samples may prefer ResNet-18's single-stage training for operational simplicity.

We were surprised that SIFT keypoint descriptors, tried as an ablation during feature-extraction development, performed worse than HOG on all three scripts rather than complementing it, since SIFT is commonly presented as more robust to scale variation. We attribute this to the sparse-keypoint problem noted in Section IV: many Tamil vowel signs and Bengali matra strokes are short enough that SIFT's keypoint detector finds fewer than five stable points, leaving the descriptor under-determined for a large minority of training images. We would test a denser, grid-sampled SIFT variant in future work rather than the keypoint-driven default, which we did not have time to implement for this study.

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The Tamil compound-character gap of 7.8 percentage points against basic characters is the largest single accuracy shortfall in our results, and it did not close appreciably even after augmentation, improving by only 1.1 percentage points post-augmentation against 4.1 points for basic Tamil characters over the same comparison. This suggests the compound-character difficulty is structural, driven by genuine visual ambiguity between related compound forms, rather than a data-scarcity problem that synthetic rotation and elastic distortion can fully resolve.

Two limitations remain. First, our datasets, though drawn from ISI Kolkata collection protocols comparable to published corpora, were assembled and pre-segmented at the character level; a full page-level recognition pipeline would additionally need robust line and word segmentation before the character classifiers evaluated here are applied, and we have not measured segmentation error separately from classification error. Second, our confidence-score output, shown in Figure 1 as part of the pipeline, was calibrated using Platt scaling for the SVM-based classifiers and softmax probability for the CNN-based classifiers, which are not directly comparable in magnitude; a deployment that thresholds on confidence across classifier types would need a shared calibration scheme, which we have not built.

Where the hybrid classifier lost to ResNet-18, which happened on 2 of 15 script-fold combinations in Tamil, the loss margin was small, under 0.4 percentage points, and traced to folds with an unusually high proportion of rare compound classes in the validation split; this is consistent with the SVM stage of the hybrid pipeline having fewer support vectors to draw on for those classes in that particular fold, rather than a systematic weakness of the hybrid architecture.

VIII. Conclusion

We compared five classifiers for handwritten character recognition across Devanagari, Tamil and Bengali scripts under one preprocessing and evaluation protocol. The hybrid CNN-SVM classifier reached the highest accuracy on all three scripts, at 97.3%, 94.8% and 96.1% respectively, ahead of ResNet-18 by a small but statistically significant margin. Augmentation by rotation and elastic distortion improved CNN accuracy by 2.8 percentage points on average, and Tamil compound characters remained the hardest recognition target at 88.6% accuracy. We would next test the hybrid classifier on line-level, unsegmented input rather than pre-segmented characters, and build a shared confidence calibration across classifier families.

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