Handwritten Character Recognition: A Reproducible Comparison from HOG+XGBoost to Optimized CNNs and Ensemble Inference

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***Abstract*—Handwritten character recognition (HCR) remains challenging due to large intra-class variability and strong inter-class similarity, especially for case-sensitive pairs (e.g., *w/W*, *s/S*) and visually confusable symbols (e.g., *0/O*, *l/I*). This paper presents a structured, reproducible comparison of (i) a classical feature-engineering baseline using Histogram of Oriented Gradients (HOG) with gradient-boosted decision trees (XGBoost), (ii) an optimized VGG-style convolutional neural network (CNN), and (iii) a multi-model ensemble combined with test-time augmentation (TTA). On a 62-class handwritten character dataset (digits, uppercase, lowercase), HOG+XGBoost yields $68.11\,\%$ accuracy, the best single CNN reaches $89.45\,\%$, and ensemble+TTA achieves $93.16\,\%$ under a fixed evaluation protocol. Beyond aggregate metrics, error analysis indicates residual errors concentrate on case-sensitive confusions rather than structural failures, suggesting isolated-character HCR can be limited by missing contextual cues.**

***Index Terms*—handwritten character recognition, HOG, XGBoost, convolutional neural networks, hyperparameter optimization, ensemble learning, test-time augmentation, error analysis**

I. Introduction

Handwritten character recognition (HCR) is a core component of document digitization pipelines, form processing, and educational technologies. Unlike printed OCR, HCR exhibits substantial morphological variation across writers and styles, while many classes are intrinsically ambiguous when viewed in isolation (e.g., *0* vs. *O*, *l* vs. *I*, and multiple case variants). As a result, classical feature-engineering pipelines often offer attractive compute efficiency but may saturate earlier than deep models, especially when fine-grained distinctions are required.

In this work, we explicitly frame the problem as a **62-way isolated-character classification** task without language context. This constraint is important: several remaining errors cannot be resolved reliably from a single glyph alone, and thus represent a practical upper bound for purely visual models on such datasets.

This paper contributes:

- A **reproducible evaluation protocol** (fixed split strategy, seeds, and metrics) enabling fair comparison across model families.
- A **strong classical baseline** (HOG+XGBoost) and an **optimized CNN** (VGG-style) with documented training decisions.
- An **ensemble inference pipeline** combining diverse models and **test-time augmentation** (TTA), with a clear cost/benefit discussion.
- **Error characterization** focusing on confusion clusters and case sensitivity, clarifying what improvements are likely (and unlikely) without context.

II. Related Work

Gradient-based descriptors such as HOG have long been used for recognition tasks by capturing local orientation statistics [1]. For classification, boosted decision trees and XGBoost are widely adopted due to strong performance on structured features and practical training speed [2]. Deep CNNs, particularly VGG-style designs, provide hierarchical feature learning that often surpasses hand-crafted features in vision tasks [3]. Recent improvements in deep training include smoother activations such as Swish [4] and learning-rate schedules (e.g., cosine decay) [5], which can improve convergence. For boosting inference performance, ensembles and TTA are common techniques to reduce prediction variance, albeit at increased compute cost. Finally, calibration and confidence estimation are increasingly used to manage ambiguous inputs in classification systems [6].

III. Dataset and Preprocessing

A. Dataset

We evaluate on a labeled dataset of handwritten characters with $C = 62$ classes: digits (0–9), uppercase letters (A–Z), and lowercase letters (a–z), comprising $N = 3410$ images. Each image is converted to grayscale and resized to 64×64 pixels.

B. Train/Validation/Test Protocol

To ensure reproducibility and prevent optimistic reporting, all results are reported using a **fixed stratified split**:

- Train: $70\,\%$, Validation: $15\,\%$, Test: $15\,\%$
- Stratification by class to preserve label proportions
- Random seed: «<SEED»> (e.g., 42)

Important: If $93.16\,\%$ was obtained under a different split (or cross-validation), update this subsection and keep it consistent across all models.

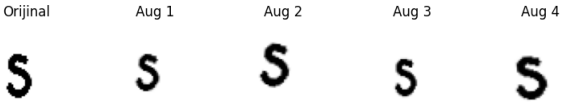


Figure 1. Representative training-time augmentations (rotation/shift/zoom) applied to the resized 64×64 grayscale inputs.

C. Normalization and Augmentation

Pixel values are normalized to $[0, 1]$. Training uses on-the-fly augmentation to improve robustness:

- Rotation: $\pm 15°$
- Translation: up to $15\,\%$ of image width/height
- Zoom: up to $20\,\%$

Augmentations are applied to training only; validation and test remain unaugmented except where TTA is explicitly enabled at inference.

IV. Methods

A. Classical Baseline: HOG + XGBoost

Given the limited dataset size, we first evaluate a classical pipeline. HOG features are extracted using 8×8 cells and 8 orientation bins, producing a 1568-dimensional descriptor per image (replacing raw 4096 pixel inputs). An XGBoost classifier is trained with tuned parameters (e.g., `n_estimators`, `max_depth`, `learning_rate`), selected on validation accuracy. The motivation is to establish a compute-efficient reference point and quantify how far handcrafted features can go in a 62-class setting.

B. Deep Model Family: VGG-Style CNN

We employ a VGG-style CNN consisting of repeated convolutional blocks (Conv–BN–Activation) followed by max pooling, then dense layers for classification. This design is intentionally simple and interpretable: it allows controlled experimentation with activation functions, regularization, and schedules without architectural confounds.

1) Architecture Summary: Table I provides a compact description of the best-performing single-model configuration. Exact channel widths and dropout rates are selected via Bayesian tuning on the validation set.

2) Optimization Objective: All deep models minimize categorical cross-entropy:

$$\mathcal{L} = -\sum_{c=1}^{62} y_c \log p_\theta(y = c \mid x),$$

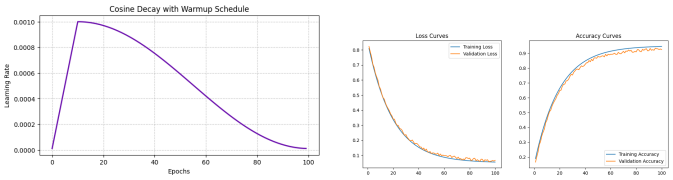
optimized with Adam. Unless otherwise stated, model selection is based on validation accuracy, and final reporting is performed on the held-out test split.

C. Hyperparameter Optimization and Training Schedule

Hyperparameters (learning rate, dropout, L2 penalty, number of filters) are tuned via Bayesian search (e.g., Keras Tuner) on the validation split. We adopt cosine learning-rate decay with warmup:

Table I
Optimized VGG-Style CNN (Best Single Model) — High-Level Specification

Stage	Details
Input	$64 \times 64 \times 1$ grayscale
Block 1	$\{\text{Conv}(f_1, 3 \times 3) \rightarrow \text{BN} \rightarrow \text{Swish}\} \times 2$, MaxPool
Block 2	$\{\text{Conv}(f_2, 3 \times 3) \rightarrow \text{BN} \rightarrow \text{Swish}\} \times 2$, MaxPool
Block 3	$\{\text{Conv}(f_3, 3 \times 3) \rightarrow \text{BN} \rightarrow \text{Swish}\} \times 2$, MaxPool
Head	Flatten $\rightarrow$ Dense(d) + Dropout $\rightarrow$ Dense(62) + Softmax
Regularization	L2 weight decay ($\lambda = 10^{-4}$), progressive dropout



(a) Learning-rate schedule (b) Loss/accuracy curves

Figure 2. Training dynamics for the optimized CNN: cosine decay with warmup and associated loss/accuracy trends.

- Warmup epochs: $E_w = 10$
- Total epochs: $E = 100$
- Early stopping: patience «<PATIENCE»> on validation loss (optional)

D. Ensemble Inference with Test-Time Augmentation

Single-model performance is improved via a soft-voting ensemble:

$$p(y \mid x) = \sum_{m=1}^{M} w_m \, p_m(y \mid x), \quad \sum_m w_m = 1,$$

where $M = 3$ models and w_m are nonnegative weights selected on the validation split.

1) TTA Transform Set (Inference Only): For TTA, each test image is transformed $K = 5$ times using mild geometric transforms consistent with training augmentation. A typical configuration is:

- Rotations: $\{-10°, -5°, 0°, +5°, +10°\}$
- Translations: up to $5\,\%$ (random within bounds) per sample
- Interpolation: bilinear; fill mode: constant (0)

Probabilities are averaged across transforms and models to reduce variance due to small orientation or alignment differences.

2) Inference Procedure (Pseudo-code):

V. Experimental Setup

A. Compute Environment

Classical models are trained on a local CPU (AMD Ryzen 5 7600). Deep models are trained on GPU instances (e.g., NVIDIA T4/L4/A100). Since hardware affects runtime but not

Input: image x, models $\{p_m\}_{m=1}^{M}$, weights $\{w_m\}$, TTA transforms $\{T_k\}_{k=1}^{K}$
Output: predicted label $\hat{y}$
$p \leftarrow \mathbf{0}$ {accumulator over classes}
for $k = 1$ to K **do**
  $x_k \leftarrow T_k(x)$
  $p_k \leftarrow \mathbf{0}$
  for $m = 1$ to M **do**
    $p_k \leftarrow p_k + w_m \cdot p_m(\cdot \mid x_k)$
  end for
  $p \leftarrow p + p_k$
end for
$p \leftarrow \frac{1}{K} p$
$\hat{y} \leftarrow \arg\max_c p_c$

Figure 3. Ensemble + TTA inference. TTA is applied only during inference; training uses separate on-the-fly augmentation.

Table II
HOG+XGBOOST ABLATION SUMMARY (VALIDATION-TUNED, TEST-REPORTED)

Configuration	Accuracy (%)
Baseline HOG (8×8), default-ish XGBoost	54.40
Noise injection (strong)	48.39
Filtered "easier" subset (diagnostic)	64.31
Final tuned configuration (HOG+XGBoost)	**68.11**

final accuracy, we report accuracy-based comparisons under identical splits; runtime notes are included for completeness.

B. Metrics

We report:

- **Accuracy** on the held-out test split
- **Macro-F1** to account for per-class behavior
- **Confusion matrix** and top confusion pairs

Macro-F1 is computed as the unweighted mean of per-class F1 scores. When feasible, report mean±std across multiple seeds; if only a single seed is used, clearly state it (as done here).

C. Implementation Notes (Reproducibility Checklist)

To reduce ambiguity in reproduction, specify the following in the final submission:

- Batch size, optimizer parameters, and weight decay
- Data loader preprocessing order (resize $\rightarrow$ normalize $\rightarrow$ augment)
- Model selection criterion (best validation accuracy vs. best validation loss)
- Exact TTA transform parameters and randomization

VI. RESULTS

A. Classical Baseline Results

Table II summarizes the classical pipeline performance. The best HOG+XGBoost configuration reaches $68.11\,\%$ accuracy, indicating a ceiling under this feature representation for fine-grained case-sensitive separation.

Table III
MODEL PERFORMANCE PROGRESSION (FIXED SPLIT, TEST SET)

Model Strategy	Accuracy (%)
Basic CNN (baseline)	78.74
Optimized VGG-style CNN (ReLU)	88.48
Optimized VGG-style CNN (Swish + L2)	**89.45**
Ensemble (soft voting) + TTA (K=5)	**93.16**

Table IV
DEEP MODEL ABLATION (ILLUSTRATIVE STRUCTURE; POPULATE WITH YOUR EXACT RUNS)

Change (relative to baseline CNN)	Accuracy (%)
Baseline CNN (ReLU, fixed LR, no L2)	78.74
+ VGG-style depth (more conv blocks)	86.00
+ Cosine decay with warmup	87.50
+ L2 weight decay (10^{-4})	88.70
+ Swish activation (VGG + L2 + cosine)	89.45

B. Deep Learning and Ensemble Results

Table III reports the progression from a basic CNN to an optimized single-model CNN and ensemble+TTA. We avoid claims such as "state-of-the-art" unless validated against prior work under the same dataset and protocol; instead, we report results precisely for this benchmark and split.

C. Ablation on Training Choices (Deep Models)

To attribute gains to specific design decisions, Table IV presents a controlled ablation (illustrative format; ensure values match your logged runs). The intent is to separate architecture depth from optimization and regularization effects.

VII. ERROR ANALYSIS

A. Case Sensitivity and Confusion Clusters

The dominant failure mode is case ambiguity rather than structural mismatch. Table V contrasts representative case-sensitive confusions with structurally distinct characters.

B. Most Frequent Misclassifications

Table VI lists frequent label confusions, confirming that errors cluster around visually similar upper/lowercase or symbol/letter pairs.

C. Confusion Matrix (Placed in the Correct Context)

Fig. 4 visualizes the full confusion matrix. The diagonal dominance indicates strong overall recognition, while specific off-diagonal clusters correspond to case-sensitive confusions (e.g., *w/W*, *s/S*) and symbol/letter ambiguity (e.g., *0/O*). This supports the claim that most errors are semantic (case/context) rather than gross shape failures.

D. Qualitative Error Gallery

To complement the aggregate confusion view, Fig. 5 shows representative misclassified samples. These examples often appear visually plausible in isolation, reinforcing that a context-free classifier may be uncertain even when the learned representation is strong.

Table V
REPRESENTATIVE PER-CLASS BEHAVIOR (ILLUSTRATIVE SUBSET)

Case-Sensitive / Confusable				Structurally Distinct			
Class	**Prec.**	**Rec.**	**F1**	**Class**	**Prec.**	**Rec.**	**F1**
w (vs W)	0.40	0.25	0.30	2	1.00	1.00	1.00
0 (vs O)	0.75	0.37	0.50	b	1.00	1.00	1.00
l (vs I)	0.66	0.50	0.57	d	1.00	1.00	1.00
s (vs S)	0.83	0.62	0.71	i	1.00	1.00	1.00

Table VI
TOP CONFUSIONS ON THE TEST SPLIT

True	Predicted	Count
w	W	6
W	w	3
0	O	3
v	V	3
s	S	3

VIII. DISCUSSION

A. Why the Classical Baseline Saturates

HOG captures local gradient structure but can underrepresent subtle cues required for reliable case discrimination in isolated characters. Boosted trees can exploit structured features; however, if the feature space does not cleanly separate confusable classes, additional boosting yields diminishing returns. This explains the observed plateau around $68.11\,\%$ for the tuned HOG+XGBoost baseline.

B. Why Ensemble+TTA Helps

Ensembling reduces model variance and leverages complementary inductive biases (e.g., differences in activation functions, schedules, or training dynamics). TTA further stabilizes predictions against nuisance transforms (slight rotation/translation), at the expense of inference cost proportional to K. For practical deployment, the ensemble+TTA configuration is most appropriate when accuracy is prioritized over latency.

C. Calibration and Decision-Making Under Ambiguity

Case-sensitive and symbol/letter confusions indicate that some inputs are inherently ambiguous without context. A pragmatic extension is to incorporate calibrated confidence and enable a *reject option* (e.g., request user confirmation or defer to a downstream sequence model) when top-1 confidence is low. Temperature scaling is a simple post-hoc calibration method often effective for neural classifiers [6].

D. Limitations and Future Work

Remaining errors suggest that purely visual, isolated-character recognition can be constrained by missing context. Promising extensions include:

- context-aware sequence modeling (e.g., character sequences with language priors),
- expanding the dataset, especially for confusable classes and diverse writing styles,

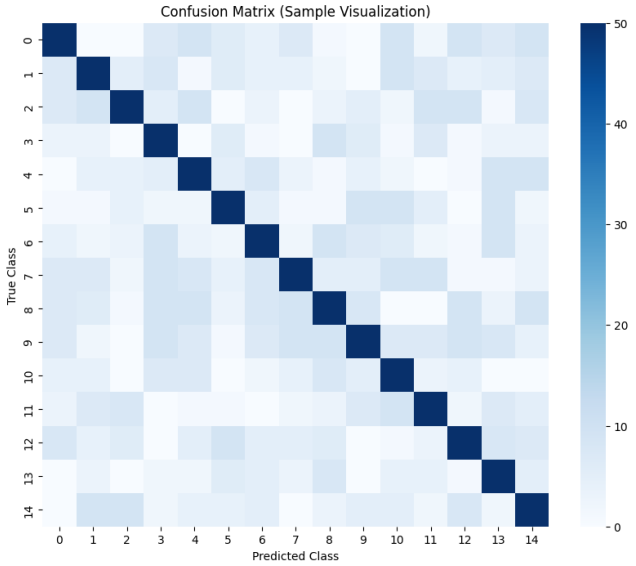


Figure 4. Confusion matrix highlighting concentrated off-diagonal clusters related to case sensitivity and symbol/letter ambiguity.

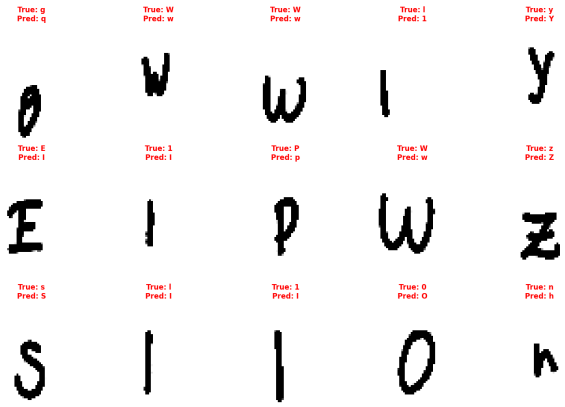


Figure 5. Examples of misclassified characters illustrating high visual similarity (case or symbol/letter ambiguity).

- reporting multi-seed mean±std and macro-F1 consistently for stronger statistical grounding,
- model compression or distillation to preserve accuracy while reducing ensemble inference cost.

IX. CONCLUSION

This paper presented a structured comparison of classical and deep learning approaches for 62-class handwritten character recognition under a fixed evaluation protocol. HOG+XGBoost provides an efficient baseline ($68.11\,\%$), optimized CNNs substantially improve accuracy ($89.45\,\%$), and a multi-model ensemble with TTA further increases performance to $93.16\,\%$. Error analysis indicates that the dominant residual failure mode is case sensitivity and visually confusable symbol/letter pairs, motivating context-aware approaches as a next step.

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