Classical Face Recognition Under Real-World Variations

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Motivation

- Face recognition predates deep learning: explicit features + linear modeling.
- Classical methods remain relevant for:
  - interpretability and analyzable failure modes,
  - low compute / embedded settings,
  - limited training data regimes.
- Goal: compare global vs local representations under real-world degradations.

Problem Definition

Dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$, $x_i \in \mathbb{R}^{H \times W}$, $y_i \in \{1, \ldots, C\}$.

Learn a classifier $f : \mathbb{R}^{H \times W} \to \{1, \ldots, C\}$.

Robustness via degradations $\delta_\alpha(\cdot)$ (illumination, noise, blur, rotation, crop, occlusion).

Accuracy:

$$\text{Acc} = \frac{1}{|\mathcal{D}_{test}|} \sum_{(x_j, y_j) \in \mathcal{D}_{test}} \mathbb{I}\big(f(\delta_\alpha(x_j)) = y_j\big).$$

Methods Overview

Global subspace methods

- **Eigenfaces (PCA)**: project faces into top-variance linear subspace; 1-NN in PCA space.
- **Fisherfaces (PCA+LDA)**: discriminative projection maximizing between-class / within-class scatter.

Local texture method

- **LBPH**: Local Binary Patterns + regional histograms; nearest-neighbor with χ^2 distance.

Baseline

- **TinyCNN** trained from scratch (no augmentation/pretraining).

Eigenfaces (PCA)

1. **Center data**

$$\boldsymbol{\mu} = \frac{1}{N}\sum_i \mathbf{x}_i, \quad X = [\mathbf{x}_1 - \boldsymbol{\mu}, \dots, \mathbf{x}_N - \boldsymbol{\mu}]$$

2. **Compute PCA**

$$C = \frac{1}{N} X X^\top \quad \to \quad U_K \text{ (top eigenvectors = eigenfaces)}$$

3. **Project and classify**

$$\mathbf{z} = U_K^\top (\mathbf{x} - \boldsymbol{\mu})$$

1-NN in PCA space (Euclidean distance).

Fisherfaces (PCA + LDA)

Within/Between scatter:

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^\top, \quad S_W = \sum_{i=1}^{c} \sum_{\mathbf{x} \in X_i} (\mathbf{x} - \mu_i)(\mathbf{x} - \mu_i)^\top.$$

Solve $S_B\mathbf{w} = \lambda S_W\mathbf{w}$ (max $c - 1$ directions).

Small sample size: S_W singular in pixel space $\Rightarrow$ PCA to $k_{\text{pca}} \leq N - c$, then LDA to $k_{\text{lda}} \leq c - 1$.

Key practical point: stability strongly depends on controlling/capping k_{pca}.

LBPH: Local Binary Pattern Histograms

LBP code at (x, y) (basic 3×3):

$$\mathrm{LBP}(x, y) = \sum_{p=0}^{7} s(g_p - g_c)2^p, \quad s(t) = \begin{cases} 1 & t \geq 0 \\ 0 & t < 0 \end{cases}$$

LBPH: split image into regions $\{R_j\}$, compute LBP histograms per region, concatenate.

Matching via χ^2 distance:

$$\chi^2(S, M) = \sum_{i,j} \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}}.$$

Hyperparameters: sampling points P, radius R, number of regions.

Datasets

ORL (AT&T)

- 40 subjects, 10 images/subject, grayscale.
- Moderate variation: expression, slight pose, glasses.
- Good for low-data sensitivity analysis.

Yale

- Frontal faces with systematic illumination variations.
- Challenging for global appearance models; classic benchmark for illumination robustness.

Evaluation Protocol

- Accuracy vs # training images per subject (fixed test identities, repeated random draws).
- Robustness sweeps with controlled degradations:
  - blur, noise, photometric jitter,
  - rotation, flips,
  - cropping / partial occlusion.
- Report mean and uncertainty (std / CI depending on experiment).

Global Comparison (Low-Data)

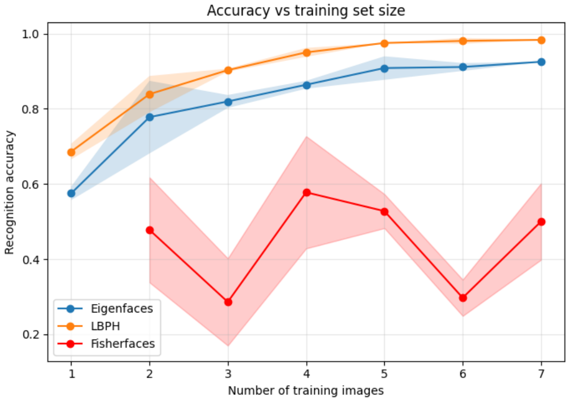
ORL

- Eigenfaces: strong dependence on train size; saturates ∼92–93%.
- LBPH: consistently higher; saturates early ≥97%.
- Fisherfaces: config-sensitive; capping k_{pca} stabilizes performance.

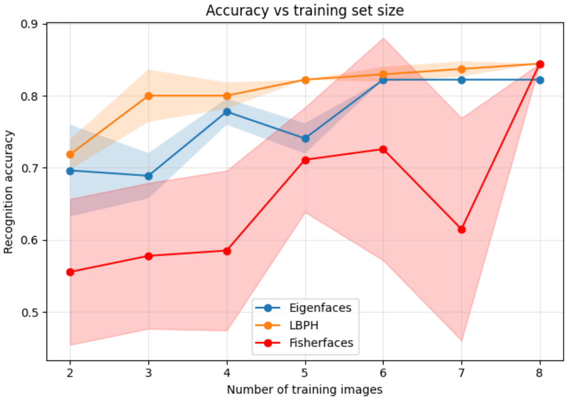
Yale

- Overall lower due to illumination.
- Eigenfaces saturates ∼82%.
- LBPH ∼84–85% with better robustness.
- Fisherfaces: benefits from more data; still sensitive to geometry shifts.

Global Comparison Figures



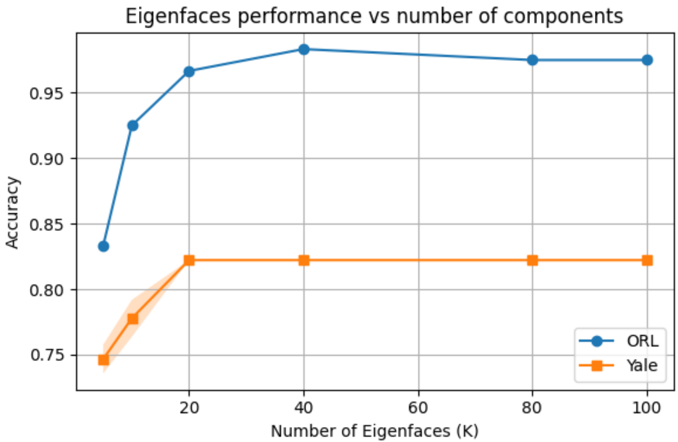
ORL: Eigenfaces vs LBPH



Yale: Eigenfaces vs LBPH

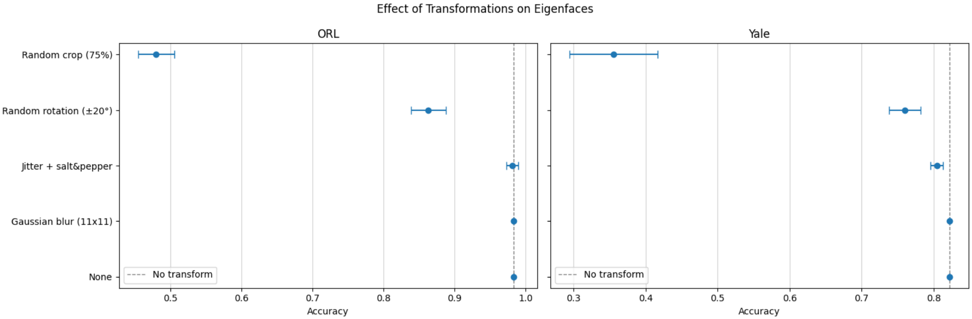
Eigenfaces: Hyperparameter Dependence

- **Hyperparameter K:** accuracy improves quickly then saturates beyond $K \approx 50$.

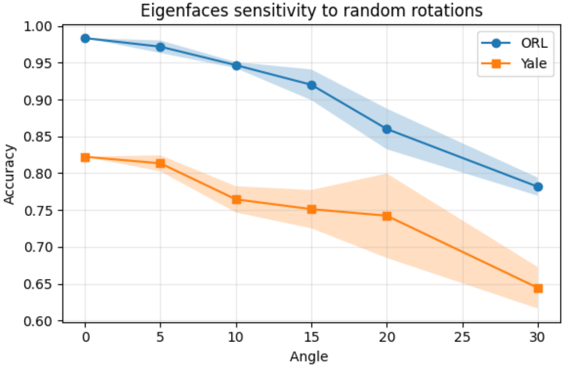


Eigenfaces: Global Transformations

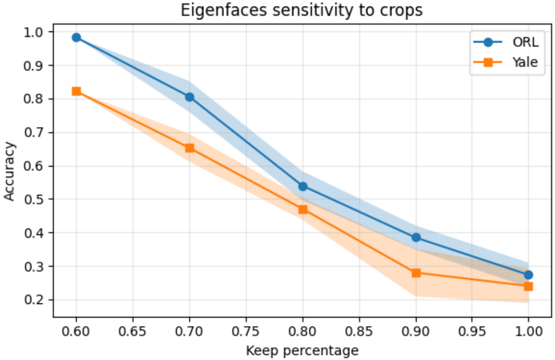
- **Most destructive:** geometric misalignment (rotation, crop).
- **Moderate effect:** photometric jitter + salt-and-pepper noise (global corruption impacts projection).



Eigenfaces: Geometric Robustness



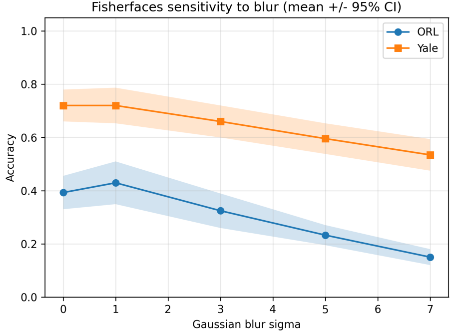
Rotation

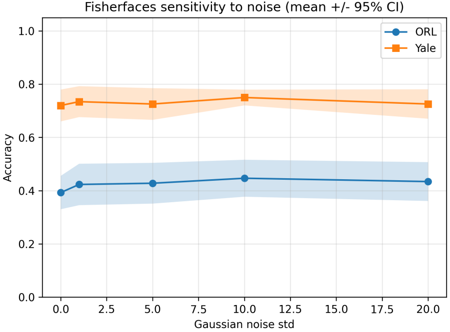


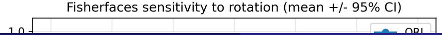
Cropping

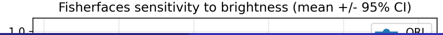
Fisherfaces: Key Results

- Dominant design choice: k_{pca}.
  - Paper-aligned $k_{\text{pca}} = N - c$ can induce peaking/non-monotonicity (esp. ORL).
  - Fixed/capped k_{pca} improves stability and accuracy.
- Test-only degradations: blur, Gaussian noise, rotation, brightness scaling, flips.
- Major bottleneck: **geometry** (rotation/flip) $\gg$ small additive noise.



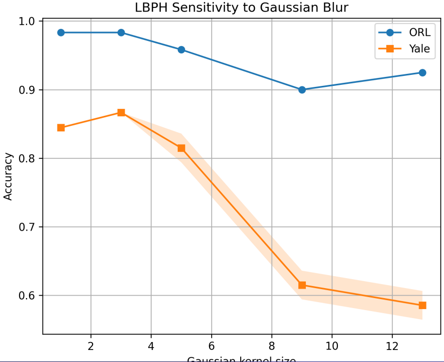


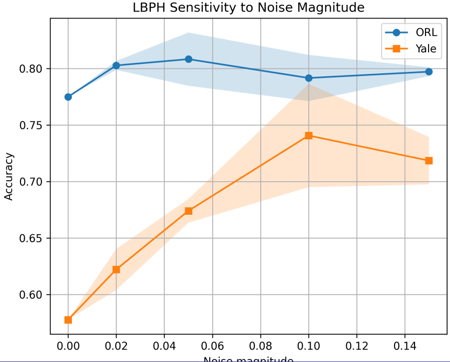




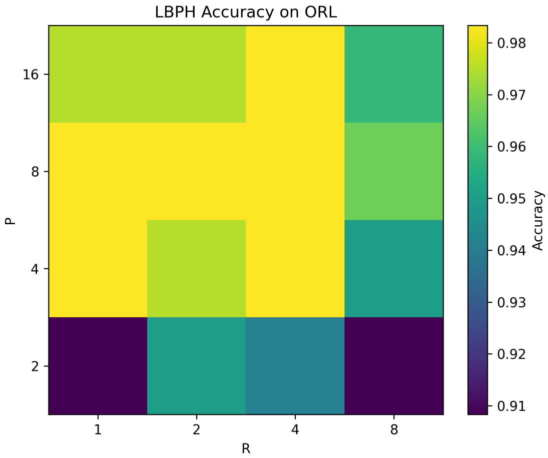
LBPH: Key Results

- Hyperparameters P, R: relatively insensitive; good region around $P \in [4, 8]$, $R \in [2, 4]$.
- Robust to photometric jitter and salt-and-pepper noise (local encoding).
- Rotation tolerance up to moderate angles; degrades beyond $\sim 15^\circ$.
- Main failure mode: **cropping** (removes critical facial regions / breaks spatial layout).
- Also sensitive to heavy blur (esp. Yale).

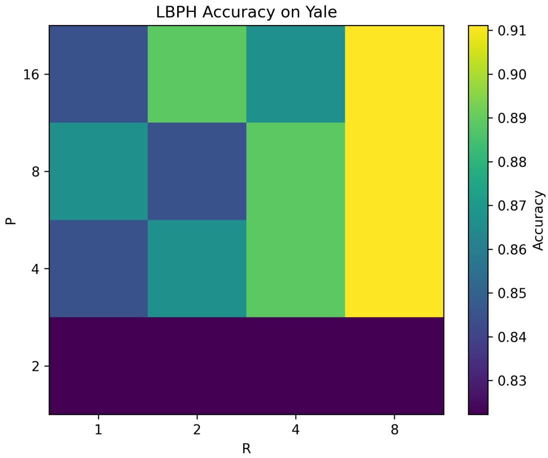




LBPH: Hyperparameter Sensitivity



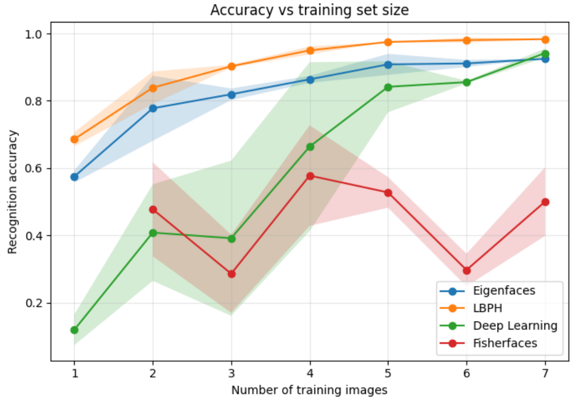
ORL: P, R sweep



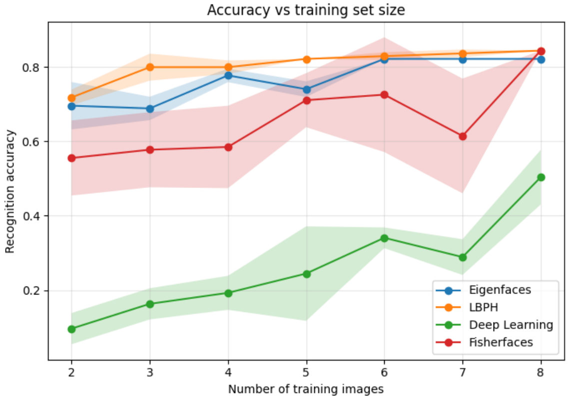
Yale: P, R sweep

Deep Learning Baseline (TinyCNN)

- Trained from scratch (grayscale, CE loss, Adam), no augmentation/pretraining.
- ORL: improves with train size, but weak in low-data; likely overfits.
- Yale: consistently low + high variance $\Rightarrow$ data scarcity hurts generalization.



ORL



Yale

Conclusions / Takeaways

- Clear hierarchy in your regime:
  - **Eigenfaces**: fragile under misalignment and illumination shifts.
  - **Fisherfaces**: better discrimination/illumination handling, but stability hinges on k_{pca}.
  - **LBPH**: most reliable overall in low-data and illumination variability; fails under heavy crop/blur.
- Deep learning (from scratch) underperforms without enough data or stronger regularization.
- Practical message: classical methods remain useful baselines with interpretable failure modes.

Code: `https://github.com/fotisk07/VIC-Project`

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