

Classical Face Recognition Under Real-World Variations

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

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

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

Accuracy:

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

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): Core Idea

Vectorize image $\mathbf{x} \in \mathbb{R}^D$. Mean $\boldsymbol{\mu} = \frac{1}{N} \sum_i \mathbf{x}_i$. Centered matrix $X = [\mathbf{x}_1 - \boldsymbol{\mu}, \dots, \mathbf{x}_N - \boldsymbol{\mu}] \in \mathbb{R}^{D \times N}$.

PCA subspace $U_K \in \mathbb{R}^{D \times K}$ from covariance $C = \frac{1}{N} X X^\top$.

Projection:

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

Classification: 1-NN (Euclidean) in \mathbf{z} -space.

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):

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

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.

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.

- 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

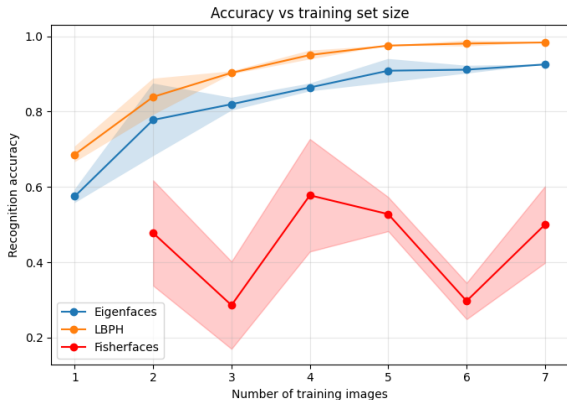
- Eigenfaces: strong dependence on train size; saturates $\sim 92\text{--}93\%$.
- LBPH: consistently higher; saturates early $\geq 97\%$.
- Fisherfaces: config-sensitive; capping k_{pca} stabilizes performance.

(Insert your figures on the next slide.)

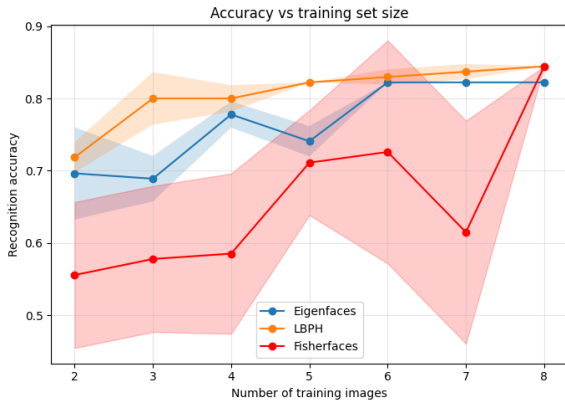
Yale

- Overall lower due to illumination.
- Eigenfaces saturates $\sim 82\%$.
- LBPH $\sim 84\text{--}85\%$ with better robustness.
- Fisherfaces: benefits from more data; still sensitive to geometry shifts.

Global Comparison Figures



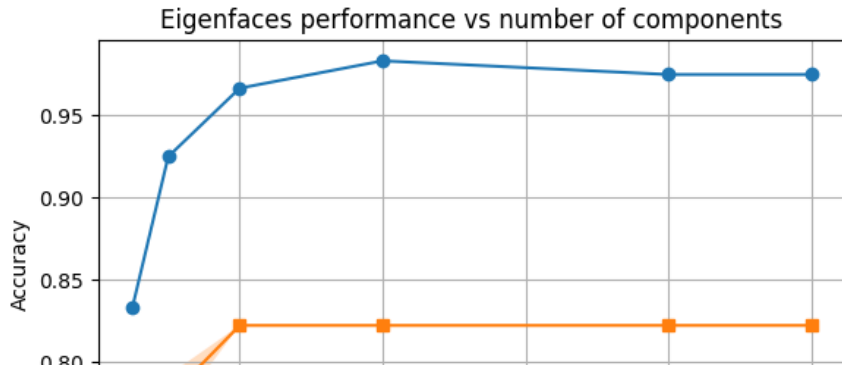
ORL: Eigenfaces vs LBPH



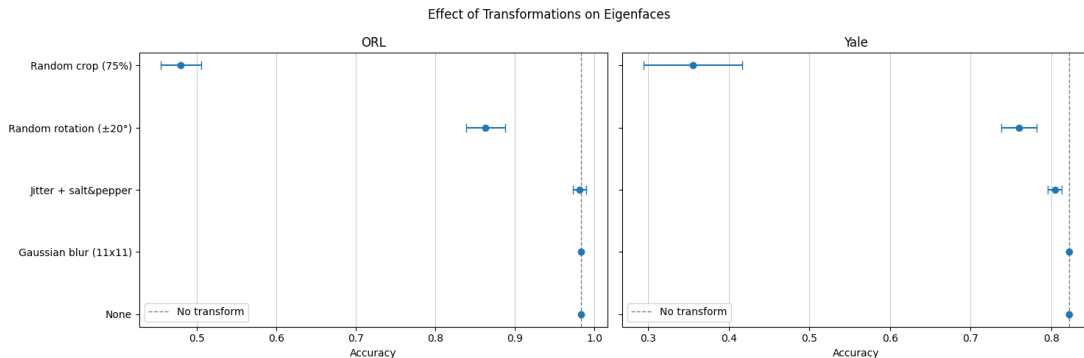
Yale: Eigenfaces vs LBPH

Eigenfaces: Robustness Findings

- **Hyperparameter K :** accuracy improves quickly then saturates beyond $K \approx 50$.
- **Most destructive:** geometric misalignment (rotation, crop).
- **Moderate effect:** photometric jitter + salt-and-pepper noise (global corruption impacts projection).
- **Less effect:** blur (in your experiments: relatively mild degradation).

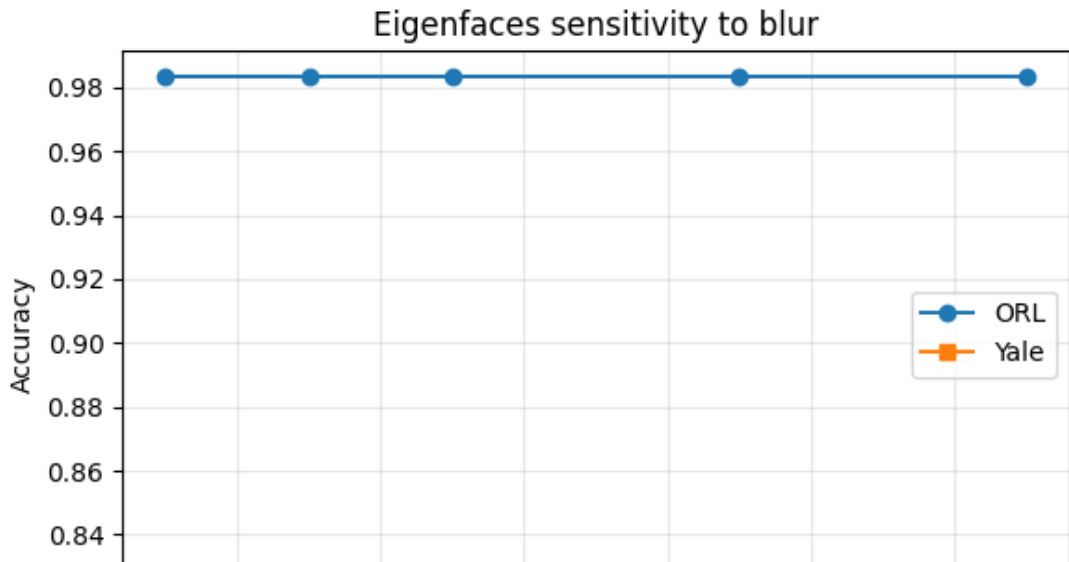


Eigenfaces: Robustness Curves



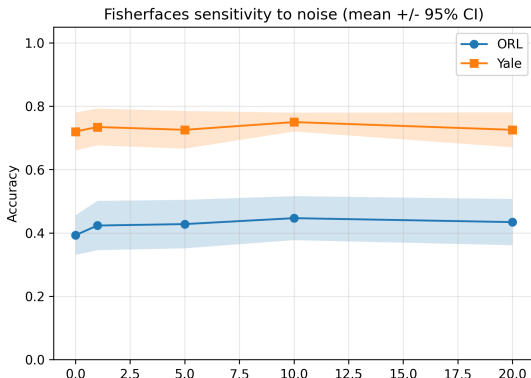
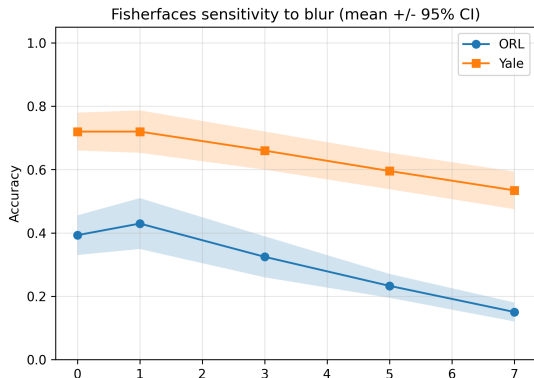
(Optional detailed breakdown slide below.)

Eigenfaces: Breakdown by Transformation



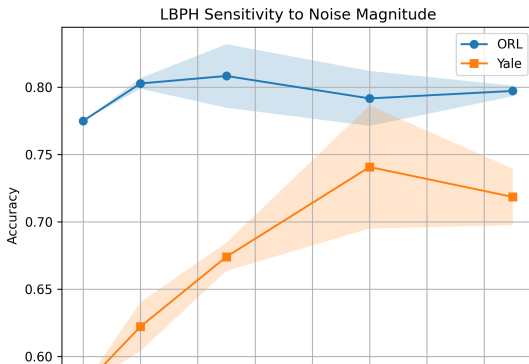
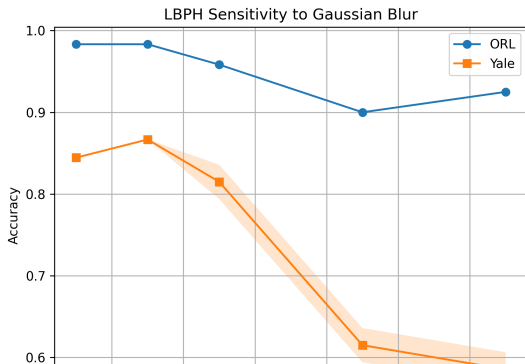
Fisherfaces: Key Results

- Dominant design choice: k_{pca} .
 - Paper-aligned $k_{pca} = N - c$ 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.

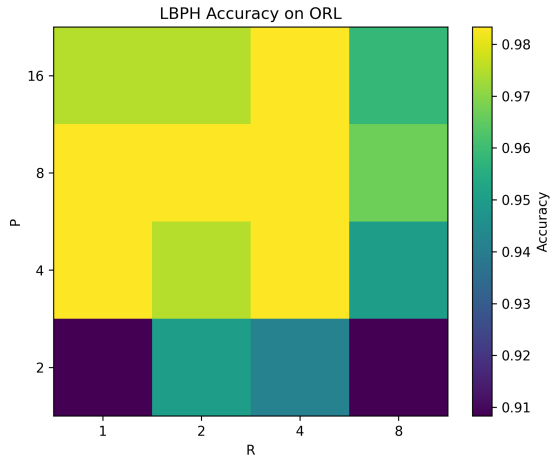


LBPH: Key Results

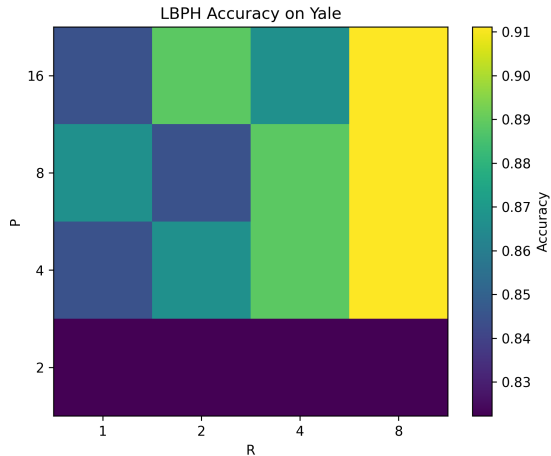
- Hyperparameters P, R : relatively insensitive; good region around $P \in [4, 8]$, $R \in [2, 4]$.
- Robust to photometric jitter and salt-and-pepper noise (local encoding).
- Rotation tolerance up to moderate angles; degrades beyond $\sim 15^\circ$.
- Main failure mode: **cropping** (removes critical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



LBPH: Hyperparameter Sensitivity



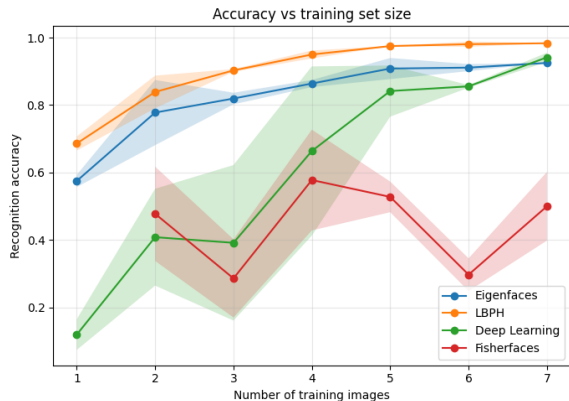
ORL: P, R sweep



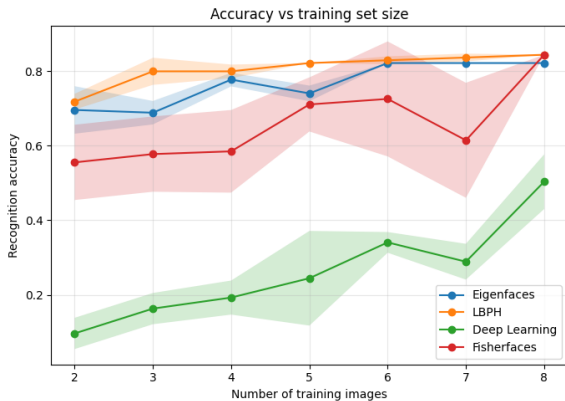
Yale: P, R sweep

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

- 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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