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An Experimental Analysis of Illumination, Pose, and Background Variations on Classical Face Detection and Recognition Performance

Sumit Kumar Srivastava[1]
Research Scholar
Department of Computer Science and Engineering,
Bhagwant University, Ajmer, Rajasthan

Prof. (Dr.) V.K. Sharma[2]
Supervisor & Guide
Bhagwant University, Ajmer, Rajasthan

Abstract

Due to their ease of use and computational effectiveness, traditional face recognition methods like Local Binary Patterns (LBP) and Principal Component Analysis (PCA) have been thoroughly researched conventional face recognition techniques such as Local Binary Patterns (LBP) and Principal Component Analysis (PCA) are widely used because they are simple to implement and computationally efficient. However, their performance in real-world situations is still limited. This paper presents an experimental study to examine how elements like changes in circumstances of lighting, variations in face pose, complex backgrounds influence the performance of conventional face recognition methods. Recognition accuracy is assessed using benchmark datasets representing controlled, semi-controlled, and unconstrained environments. The experimental results show that classical methods perform well in controlled conditions but their accuracy decreases significantly when illumination varies or when backgrounds become complex. These findings highlight the limitations of manually designed feature-based approaches and indicate the need for more advanced representation learning methods for reliable biometric recognition.

Keywords: Face Recognition, Illumination Variation, Pose Variation, Background Complexity, PCA, LBP, Classical Biometrics

1. Introduction

Face recognition has emerged as a well-known biometric technique due to its non-intrusive nature and ease of acquisition. Early research in face recognition primarily relied on classical machine learning techniques, including holistic methods such as Principal Component Analysis (PCA) and texture-based descriptors like Local Binary Patterns (LBP). These approaches offered computational simplicity and achieved promising results under laboratory-controlled conditions.

Despite their early success, classical face recognition systems encounter substantial challenges when deployed in unconstrained environments. Real-world facial images are affected by variations in illumination, pose, facial expressions, occlusion, and background clutter. Among these factors, illumination variation, pose changes, and background complexity play a dominant role in degrading recognition accuracy.

This study focuses on experimentally quantifying the impact of these three factors on classical face recognition performance. By evaluating PCA- and LBP-based recognition across datasets exhibiting increasing environmental complexity, this work provides empirical evidence of the limitations inherent in handcrafted feature representations.

2. Literature Review:

1. Rai proposed a real-time face detection system designed for mobile devices. The system is developed using **OpenCV**, a widely used toolkit for computer vision applications. It consists of two main layers: **image pre-processing** and **face detection**.
In the pre-processing layer, images are converted to **greyscale** to simplify processing. **Gaussian smoothing** is applied to reduce noise, while **binarization** and **contrast enhancement** are used to highlight key features in the smoothed images. The face detection layer utilizes **Haar-like features**, which are commonly employed in OpenCV-based face detection algorithms. This approach allows the system to efficiently detect faces in real-time on mobile platforms. [1]

2. Ranjani R, Priya C discussed that Face recognition techniques can generally be classified into three categories: **neural network-based techniques**, **statistical methods**, and the earlier **geometrical feature-based and pattern matching approaches**. [2]

3. Turk and Pentland advocated **Principal Component Analysis (PCA)**, which employs a linear transformation, is widely recognized as an effective method for reducing data dimensionality.[3]

3. Classical Face Recognition Framework

The experimental framework utilizes two classical face recognition techniques: Local Binary Patterns (LBP) and Principal Component Analysis (PCA).

PCA represents facial images as linear combinations of eigenvectors derived from the training dataset, enabling effective dimensionality reduction while capturing global facial appearance. However, PCA is sensitive to variations in illumination and face alignment, which can impact recognition accuracy.

LBP extracts local texture features by encoding the connections between a pixel and its neighbouring pixels into binary patterns & constructing corresponding histograms. Although LBP demonstrates improved robustness to local illumination changes, it lacks the ability to model global facial structure and semantic information.

In the proposed pipeline, detected faces are adjusted in size to a fixed resolution and grey scale conversion. PCA and multi-scale LBP features are extracted independently, and the resulting feature vectors are evaluated using cosine similarity and k-nearest neighbour (k-NN) classification.

4. Face detection

Face detection is a critical pre-processing stage in face recognition systems, tasked with accurately localizing face region while excluding irrelevant background content. It has been widely studied in computer vision due to its importance in numerous applications, including biometrics, security, and human–machine interaction. Modern face detection techniques range from classical approaches such as Viola–Jones and Haar cascades to more recent deep learning–based models, each with distinct performance trade-offs under varying conditions like illumination, pose, and background complexity. Research has shown that image quality factors—including noise, resolution, blur, and lighting—significantly influence both detection and recognition performance, with degraded inputs leading to poorer outcomes across traditional algorithms and deep models alike.
Moreover, errors in face localization can propagate through the recognition pipeline, exacerbating misclassification and reducing overall system reliability. This sensitivity highlights the necessity of selecting appropriate detection techniques calibrated to input quality if robust recognition results are to be achieved, especially in unconstrained real-world imaging scenarios. Extracting the facial region can be challenging under certain conditions, such as when the skin tone closely matches the background, when parts of the face are in shadow, or when the subject is not directly facing the camera.

5. Face recognition

The three primary classes of face recognition techniques are statistical methods, neural network-based methods, and geometrical feature-based and pattern matching methods.
The first methods for face identification relied on the face's geometric characteristics. The fundamental idea behind these techniques is to determine the relative locations and sizes of important facial features including the mouth, nose, eyebrows, and eyes [26]. In addition to these local features, global information such as the overall face contour is often incorporated to improve classification and recognition performance.

Fig 2. Learning and classification process.

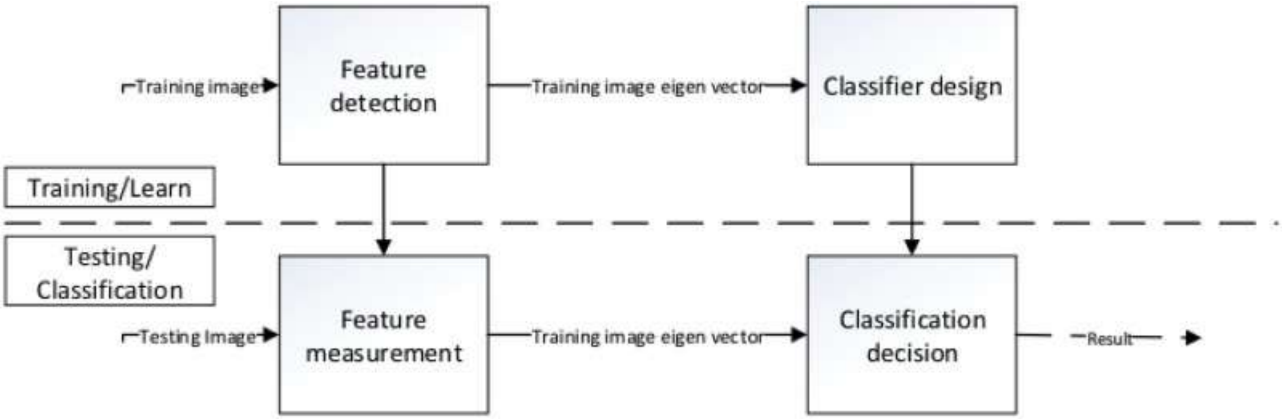
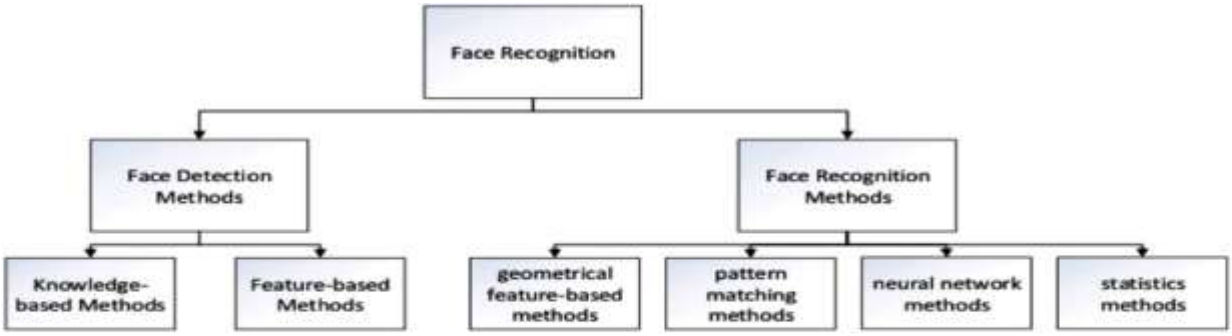


Fig 2. Varying Pose Conditions in Face Recognition

Pattern matching methods constitute one of the simplest strategies within the pattern recognition domain. In this approach, facial images stored in a dataset are treated as reference patterns. When a new image is presented for recognition, a similarity or correlation measure is computed between the stored patterns and the incoming picture in order to identify the individual. While conceptually straightforward, these Techniques are sensitive to alterations Pose in lighting, expressions on the face, which can limit their effectiveness in unconstrained environments.

Fig 3. Face recognition system.



6. Principal component analysis

Data is frequently expressed as vectors and matrices in computer science, especially when it comes to Big Data. When it comes to photos, a higher resolution translates into a larger matrix. Efficiency must still be taken into account, even though modern computers are capable of processing enormous volumes of data in comparatively little time.

Principal component analysis has been widely recognized as an efficient data dimensionality reduction method using a linear transformation [30]. While reducing the data dimensionality, retaining significant information is the basic requirement.

In statistics, mean value, standard deviation, and variance are always used to analyze the distribution and variation of a set of data. These three values can be calculated with Eqs (1), (2) and (3).

$$\overline{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

$$s = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n-1}} \tag{2}$$

$$s^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n-1} \tag{3}$$

However, mean value, standard deviation, and variance functions only work for one-dimensional data. In computer science, the data is always multi-dimensional. So, a new measurement which conveys a relationship among data of different dimension needs to be included, which is covariance. Normally, covariance is able to describe the relationship between two random variables, as shown in Eq (4). (4)

$$cov\,(X,Y) = \frac{\sum_{i=1}^{n} X_i - X\,(Y_i - Y)}{n-1} \tag{4}$$

Therefore, as the dimension increases, multiple covariances need to be calculated, e.g. the number of covariance needed when dealing with n-dimensional data is shown in Eq (5).

$$\frac{n!}{(n-2)! \times 2} \tag{5}$$

Fortunately, a matrix approach offers a perfect solution for this calculation. The Eq (6) shows the definition of a covariance matrix.

$$C_{n\times n} = (c_{i,j}, c_{i,j} = cov\,(Dim_i, Dim_j)) \tag{6}$$

Eq (7) shows the covariance matrix of a dataset with three dimensions $\{x, y, z\}$.

$$C = \begin{pmatrix} cov\,(x,x) & cov\,(x,y) & cov\,(x,z) \\ cov\,(y,x) & cov\,(y,y) & cov\,(y,z) \\ cov\,(z,x) & cov\,(z,y) & cov\,(z,z) \end{pmatrix} \tag{7}$$

Therefore, as the dimension increases, multiple covariance's need to be calculated, e.g. the number of covariance needed when dealing with n-dimensional data is shown in Eq (5).

$n!(n-2)!\times 2$ (5)

Fortunately, a matrix approach offers a perfect solution for this calculation. The Eq (6) shows the definition of a covariance matrix.

It can be found that covariance matrix is a symmetric matrix, whose diagonal shows the variance of each dimensions.

After generating the covariance matrix, we are able to calculate its eigenvalues and eigenvectors through Eq (8).

$A\times\alpha=\lambda\times\alpha$ (8)

Where A stands for the original matrix, λ stands for an eigenvalue of A, and α represents the eigenvector according to eigenvalue λ. Usually eigenvalues are sorted in descending order, which corresponds to the importance of the eigenvector. We can choose how much information to retain. In this case, selecting a good threshold with which useful information is retained, whereas less significant information is removed, becomes important.

7. Framework Design model

In this section, we offer a face recognition system that uses Principal Component Analysis (PCA), a common method for picking important features and reducing data size. The proposed framework delineates the entire face recognition pipeline, from initial pre-processing to final identification, while offering alternative strategies at each stage to accommodate varying application requirements. This modular design provides flexibility for software developers to adapt the system to different use cases and computational environments.

The framework is specifically designed to handle challenging and unconstrained scenarios, such as non-uniform illumination, extreme facial expressions, variations in image acquisition devices or formats, and diverse camera angles. For instance, pre-processing steps may be adjusted to normalize lighting conditions, while feature extraction and matching algorithms can be selected based on dataset characteristics and performance requirements. In addition to the built-in alternatives provided in the framework, we also discuss supplementary methods that can further enhance recognition accuracy and robustness under adverse conditions.

The proposed framework is designed to organize the face recognition process in a modular and flexible manner, which not only supports the systematic evaluation of PCA-based methods but also serves as a practical guideline for implementing and customizing real-world face recognition applications. By structuring the pipeline into distinct, well-defined stages, the framework allows each phase—ranging from image acquisition and pre-processing to feature extraction, dimensionality reduction, and classification—to be independently configured or replaced, depending on the specific specifications for the application.

Moreover, this framework provides clear guidance on how alternative methods and adjustments can be incorporated at each stage, enabling developers and researchers to experiment with different pre-processing techniques, feature extraction algorithms, and matching strategies while maintaining a coherent overall structure. By promoting both flexibility and systematic evaluation, the framework ensures that PCA-based face recognition systems can be rigorously assessed and reliably adapted to varied scenarios. A detailed illustration of the framework, showing the workflow and optional adaptation paths, is presented in the following section.

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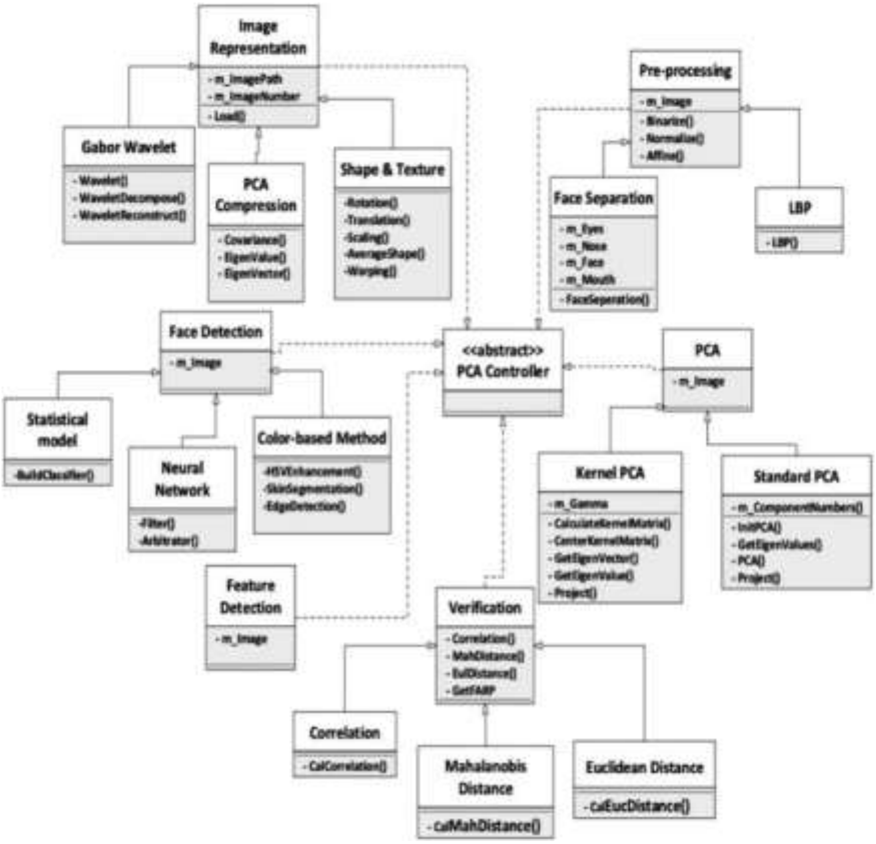
Fig 4. Framework design model.



Face recognition is a critical task in computer vision and biometrics, involving multiple sequential stages to achieve accurate and robust identification. The process typically includes **pre-processing**, **face detection**, **feature representation**, and **dimensionality reduction**. Each stage plays a vital part in guaranteeing the system's dependability and effectiveness.

1. Pre-Processing

Pre-processing enhances image quality and standardizes facial data, which is essential for improving recognition performance. It reduces noise, compensates for illumination variations, and ensures that features extracted in subsequent stages are meaningful.

1.1 Face Segmentation

Face segmentation, also referred to as face separation, isolates the facial region from the background to minimize irrelevant information. Common approaches include:

- **Region-of-interest (ROI) cropping** based on detected facial landmarks such as the eyes, nose, and mouth.
- **Masking techniques** to focus exclusively on the facial area.

Segmentation improves computational efficiency and reduces the influence of background noise, enhancing overall system accuracy.

1.2 Local Binary Pattern (LBP)

Local Binary Pattern is a widely used Descriptor of texture for facial recognition. It encodes local spatial patterns by contrasting every pixel with its neighbours.

- Each neighbouring pixel is assigned a binary value depending on whether its intensity is higher than or equivalent to the canter pixel.
- These binary codes are aggregated into a histogram representing the texture of the face.

2. Face Detection

Finding and detecting faces in an image is known as face detection. Accurate detection is critical as it directly impacts the effectiveness of subsequent recognition stages. Common techniques include:

2.1 Statistical Models

Statistical methods, such as **Eigen faces** and **Fisher faces**, model the probability distribution of facial features using techniques like Local Binary Patterns (LBP) and Principal Component Analysis (PCA).

- **Advantages:** Computationally efficient for standardized and well-aligned images.
- **Limitations:** Sensitive to changes in posture, lighting, and occlusion.

2.2 Neural Networks

Neural networks, particularly **Convolutional Neural Networks (CNNs)**, learn hierarchical features directly from raw image data.

- **Advantages:** High accuracy and robustness to variations in pose, expression, and illumination.
- **Limitations:** Require large datasets and significant computational resources.

2.3 Color-Based Methods

Color-based approaches exploit skin tone distributions in different Color spaces (RGB, HSV, YCbCr) to detect faces.

- **Advantages:** Simple and computationally light.
- **Limitations:** Sensitive to lighting conditions, ethnicity variations, and complex backgrounds.

A feature diagram can be used to display the framework (Figure 4), where each step uses a specific method. At each stage of the face recognition process, different feature choices create several versions, each with its own benefits and suitable situations. By combining these variations, the framework can support at least 108 possible applications: two options for pre-processing and PCA, and three options for face recognition, face detection, and verification. However, because some variants can be combined, skipped, or used alongside other simple mathematical methods, the actual number of applications our framework can handle is much higher than 108. In fact, our system can cover over 150 cases, even with a conservative estimate. This makes it very useful for software developers, even though these examples don't include every possible face recognition scenario.

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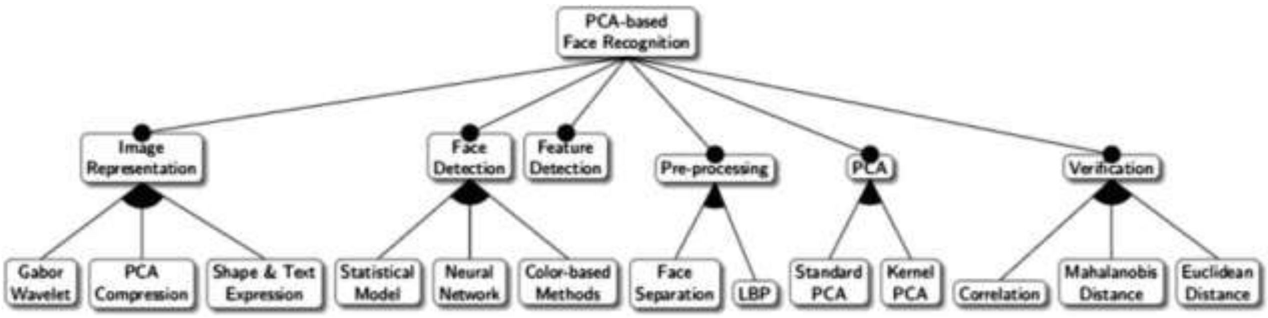
Fig 5. Framework as a feature diagram.



8. Experimental Setup

Three representative datasets were used in the trials to analyse the effects on the environment:

● **ORL Face Dataset**: Controlled acquisition with uniform background and frontal pose.

Table 1: Experimental setup details for face recognition using the ORL Face Dataset

Parameter	**Specification**
Dataset Used	ORL (AT&T) Face Dataset
Number of Subjects	40 individuals
Total Images	400 facial images
Images per Subject	10 images per person
Image Resolution	92 × 112 pixels
Image Type	Grey scale frontal face images
Variations Present	Expression, lighting conditions, facial details (with/without glasses), slight pose variation
Pre processing	Face alignment, cropping, normalization, and resizing where required
Training–Testing Split	5 images per subject for training and 5 for testing (standard protocol)
Feature Extraction Method	Principal Component Analysis (PCA) / LDA / Deep feature extraction (as applied)
Classification Technique	k-NN / SVM / Neural Network classifier
Evaluation Metric	Recognition accuracy (%)
Validation Method	Hold-out validation / k-fold cross-validation
Implementation Environment	Python (OpenCV, Scikit-learn, TensorFlow/PyTorch) or MATLAB
Hardware Configuration	Standard CPU system; GPU used if deep learning methods are applied

● **Extended Yale B Dataset**: Strong illumination variations with consistent pose.

Table 2: Experimental setup details using the Extended Yale B Face Dataset

Parameter	**Specification**
Dataset Used	Extended Yale B Face Dataset
Number of Subjects	38 individuals
Total Images	2,414 frontal face images
Images per Subject	Approximately 64 images per person
Image Resolution	192 × 168 pixels
Image Type	Grey scale frontal face images

Variations Present	Large illumination variations under controlled pose
Pre processing	Face cropping, illumination normalization, resizing, and intensity normalization
Training–Testing Split	Commonly 50% images for training and 50% for testing or protocol-based split
Feature Extraction Method	PCA / LDA / Sparse Representation / Deep Learning features
Classification Technique	k-NN, SVM, Sparse Representation Classifier, or Neural Networks
Evaluation Metric	Recognition accuracy (%)
Validation Method	Hold-out validation or k-fold cross-validation
Implementation Environment	Python (OpenCV, Scikit-learn, TensorFlow/PyTorch) or MATLAB
Hardware Configuration	CPU-based system; GPU used for deep learning experiments

● **Labeled faces in the Wild (LFW)**: Unconstrained images with diverse pose, lighting, and background conditions.

Table 3: Experimental Setup Using Labelled Faces in the Wild (LFW) Dataset

Parameter	**Specification**
Dataset Used	Labeled Faces in the Wild (LFW) Dataset
Number of Subjects	5,749 individuals
Total Images	13,233 face images
Images per Subject	Varies (many subjects have only one image; some have multiple images)
Image Resolution	Typically 250 × 250 pixels (aligned versions available)
Image Type	Color images collected in unconstrained environments
Variations Present	Pose, illumination, expression, background, occlusion, and image quality variations
Pre processing	Face detection, alignment, cropping, resizing, and normalization
Training–Testing Protocol	Standard LFW pair protocol (6,000 face pairs: 3,000 matched and 3,000 mismatched)
Task Type	Face verification or recognition
Feature Extraction Method	Deep CNN features / PCA / LBP / other descriptors
Classification Technique	Similarity measurement, SVM, or deep learning classifiers
Evaluation Metric	Verification accuracy (%) and ROC metrics
Validation Method	10-fold cross-validation (standard LFW protocol)
Implementation Environment	Python (OpenCV, TensorFlow, PyTorch, Scikit-learn) or MATLAB
Hardware Configuration	CPU system; GPU recommended for deep learning models

Faces were pre-processed using standard normalization techniques and evaluated under identical classification protocols. Recognition accuracy was used as the primary evaluation metric.

9. Impact of Illumination Variation

Significant intra-class variations in facial appearance are caused by changes in illumination, which often exceed the differences between different individuals. Because Principal Component Analysis (PCA) depends on global pixel intensity distributions, its performance deteriorates substantially under extreme lighting conditions. Findings from tests using the Extended Yale B dataset confirm that PCA accuracy drops dramatically when faces are subjected to severe illumination variations.

LBP demonstrates comparatively improved resilience by encoding local texture information; however, under severe shadowing and directional lighting, even LBP fails to maintain consistent recognition performance. The observed LBP-based accuracy of approximately 45% on Extended Yale B confirms that local descriptors alone are insufficient to compensate for drastic illumination changes.

These results imply that classical approaches primarily rely on stable acquisition contexts and lack illumination-invariant representations.

10. Impact of Pose Variation

By changing the spatial relationships between important features, pose variation has an impact on facial geometry. Feature misalignment is introduced by variations from the near-frontal alignment assumed by classical approaches.

Labelled Faces in the Wild (LFW) dataset experiments indicate that both PCA and LBP struggle to handle non-frontal facial views, even though datasets such as ORL and Extended Yale B exhibit minimal pose variations. When faces are captured at oblique angles, critical regions, including the eyes and mouth, are partially occluded, which significantly reduces the consistency and discriminative power of the extracted features.

Fig 6. LBP result.

On LFW, recognition accuracy drops to approximately 7–10%, indicating that pose variation combined with uncontrolled acquisition severely limits classical recognition capability.

11. Impact of Background Complexity

Background complexity, particularly in cases of inaccurate detection and alignment, introduces extraneous visual information into the facial region. Since classical feature extractors operate directly on local textures or pixel intensities, they are highly susceptible to interference from the background. In unstructured datasets, faces often occupy only a small portion of the image and are surrounded by cluttered scenes. Misaligned detections result in the inclusion of non-facial pixels, corrupted feature representations, and an increased rate of false matches. Experimental results confirm that background clutter, especially when combined with variations in illumination and pose, is a significant factor contributing to the degradation of recognition performance.

12. Discussion

The findings reveal a clear performance hierarchy: traditional methods perform adequately in controlled environments but fail to generalize to real-world scenarios. While Local Binary Patterns (LBP) demonstrates greater robustness compared to PCA, both approaches suffer from inherent limitations due to their manually designed feature representations. The combined effects of illumination, pose, and background complexity highlight the inability of traditional methods to learn invariant and discriminative features. These limitations have motivated the adoption of deep learning-based embedding models, which offer superior generalization capabilities and can representations directly from data.

13. Result/Conclusion

An experimental investigation of the effects of illumination variations, pose changes, and background complexity on traditional face recognition systems. The results demonstrate significant performance degradation under real-world conditions, confirming that conventional methods are inadequate for reliable biometric verification in unconstrained environments.

These findings offer empirical support for the shift to hybrid approaches and deep learning-based recognition frameworks. The research creates a fundamental standard for later incorporation of sophisticated representation learning methods into biometric identification systems.

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