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# Enhancing Facial Recognition Accuracy through KNN Classification with Principal Component Analysis and Local Binary Pattern

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**ABSTRACT-** Recent developments in deep learning techniques have led to remarkable progress in facial recognition. As a component of biometric verification, human face recognition has become widely used in a variety of applications, including surveillance systems, home entry access, mobile face unlocking, and network security. Conventional facial recognition techniques are especially useful when dealing with low-resolution photos or difficult lighting situations. The K-nearest neighbor (KNN) classifier has been used in this paper. KNN is a non-parametric, instance-based learning algorithm that is commonly used for classification tasks. Principal Component Analysis (PCA) and local binary pattern (LBP) are used in this study to develop face identification. Both contrast stretching and grayscale were used to ensure ease of computation. The study was conducted on two separate and through multiple tests with different values for k, the highest accuracy obtained was at k=1 for both datasets. The smaller user dataset achieved 91% accuracy and CASIA-WebFace obtained 87% model accuracy.

**Keywords:** Face Recognition, Haar Cascade, Principal Component Analysis, Local Binary Pattern, K-Nearest Neighbor.

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## 1. INTRODUCTION

Face recognition technology has emerged as a versatile and transformative tool across various domains, offering innovative solutions for identity verification and management. In contrast to traditional personal verification methods, which range from manual options like taking attendance on paper to automatic methods such as using RFID cards [1], and with extensive image processing method with LBP algorithm [2], Face recognition with PCA [3].

Facial recognition has gained widespread adoption in diverse applications, including social media, mobile devices, security systems, and law enforcement. When compared to other biometric devices, facial recognition offers unique advantages [4]. Techniques like K-Nearest Neighbors (K-NN) and Principal Component Analysis (PCA) continue to play pivotal roles in face recognition algorithms [5]. There are many models available that utilize the PCA method for its efficient and accurate results when dealing with facial recognition [6]. Similarly, in [4], the authors used PCA on a relatively large dataset of 3000 individuals and demonstrated high accuracy through a view-based approach.

Other methods, like the discrete wavelet transform and the discrete cosine transform (DCT), are two well-liked suggested models. It is employed for image compression and efficient data representation, transforming spatially correlated pixel data into frequency domain coefficients. This facilitates effective compression of image data while preserving essential information [7]. The transform can also be employed within a face recognition system for feature extraction and representation of facial images. It aids in compressing the image data while concentrating important facial features in lower-frequency components, which is beneficial for achieving accurate recognition [8,9]. KNN is a classification algorithm that operates by identifying the K training samples closest to a given sample in the specified space and classifying them based on the majority of their neighbors [10]. This method, though conceptually simple, remains highly effective for face identification. The KNN algorithm is a non- parametric lazy learning algorithm that can be used for classification and regression problems [5]. The combination of PCA and KNN strikes a balance between recognition accuracy and speed [11-12].

PCA serves as a dimensionality reduction technique useful and functions by projecting the original high- dimensional facial images onto a lower-dimensional subspace that encapsulates the most crucial data features [13].

The novelty of our approach lies in handling variations in facial expressions and slight pose changes by integrating Local Binary Patterns (LBP) with Principal Component Analysis (PCA).

While PCA reduces dimensionality by capturing significant global features, it may miss critical local variations essential for distinguishing facial expressions. LBP, focusing on local texture features, effectively manages these variations by analyzing pixel relationships. Combining LBP with PCA addresses the limitations of PCA-only models, significantly improving accuracy to 91%, compared to 85% for LBP with KNN.

[26] and 81% for PCA with KNN [14]. Additionally, using Haar cascades from OpenCV for frontal face detection enhances the model's robustness. Haar cascades detect faces under varied lighting and pose conditions through multi-stage feature evaluation, starting from simple to complex features. This method ensures quick and accurate identification of facial regions, making our model precise and adaptable. Thus, it is well-suited for real-world applications like user authentication and attendance monitoring, where facial expressions and slight pose variations are common.

In this research, we undertake a three-phase process to achieve facial identification: initial facial localization, feature extraction, and final classification. The initial phase, facial localization, involves the initial detection of facial regions within the input image, often depicted as bounding boxes encompassing facial positions. Subsequent to this, the feature extraction phase is tasked with extracting inherent facial attributes, which are then subjected to classification and recognition processes. Moreover, classification represents the pivotal step of matching input data with corresponding entries in a database.

However, when dealing with facial images, the collection of a substantial quantity of samples from a single individual presents a formidable challenge. The intrinsic complexity arises from the fact that the number of pixels within the data significantly surpasses the number of available samples. This intricacy renders neural networks ill-suited for this particular problem. As a pragmatic solution, we employ the K-nearest neighbor (K-NN) rule to do a good job of recognition.

Facial data is readily obtainable manually via webcam, making it one of the most accessible biometrics. The research seeks to advance the field of facial identification by integrating the K-Nearest Neighbor classification method with Principal Component Analysis (PCA) for feature extraction [14]. KNN is chosen for classification, a method renowned for its simplicity and effectiveness in the context of face identification. In this study, we utilize an image dataset of 138 participants to evaluate the proposed method.

To further ensure robustness and generalization capabilities, we also validated our approach using the larger and more diverse frontal face dataset, CASIA- WebFace.

This document is organized into various sections. *Section 2* presents previous studies related to facial recognition and other similar fields. It is followed by *section 3*, which entails the different methodologies used in the proposed study of this paper. Section 4 contains the results of the experiment and their analysis. Comparison between the proposed system and other established models is shown in *section 5*. Finally, the paper concludes with *section 6*.

## 2. LITERATURE SURVEY

This section dives into a broad spectrum of technologies that serve as the foundation for the proposed system. The application of facial recognition using LBP (local binary pattern) and KNN for classification has been done before and serves as a foundation for improvement in the field. The paper includes an in-depth review of the KNN classifier, local binary pattern, Eigenface and principal component analysis.

One of the studies conducted [15] utilized scalable sub-windows for face image analysis, extracting Local Binary Pattern (LBP) histograms to capture intricate facial details. Transforming the multi-class problem into binary classification streamlined complexity, aided by the Chi- square distance metric. The chi-square distance metric is used due to its effectiveness in quantifying dissimilarity between corresponding Local Binary Pattern (LBP) histograms of face images.

Ada Boost machine learning enhances similarity learning between image pairs. By iteratively adjusting the weights of misclassified samples, it improves the performance of the classification model. Comparing the two-reconstruction method, Local Binary Pattern and Haar Cascade [16] obtained greater accuracy. [17] suggest utilizing the neural network principle or create a PCA based facial recognition system by using three stage preprocessing, PCA and face recognition.

The feature extraction procedure takes place in two stages: during the training and testing phases of the methodology. This separation lays the groundwork for the principal component analysis, also known as the Eigenface method, to be applied during the processing stage. PCA is a statistical method aimed at reducing data storage while maintaining effective data representation. It transforms the 2-D face picture into a compact main- element space, known as the projection of self-space [18]. Similarly, the studies of [19,20] also use the LBP technique. In [19], it is proposed to enhance facial recognition algorithm and improve the rotation invariability of LBP and analysis the result for week light and expression change image based on LBP. Further in [20], the study delves into the intricate realm of face recognition performance by investigating the effectiveness of Local Binary Pattern (LBP) features on various facial expressions like anger, disgust, fear, happiness, sadness, and surprise. Highlighting the popular open CV uses and classifiers [21] for image processing, face identification, object detection and face recognition among other uses. An open CV based face recognition approach with LBBH algorithm is proposed by [22] and making the attendance system adequately by averting proxies.

In the seminal work by [23], the pivotal discussion revolves around Eigenface, Fisher face, and LBPH. It emphasizes the importance of similarity between test and training images for optimal performance across methods.

Fisherface demonstrates superior handling of lighting variations, closely followed by linear subspace. Removing principal components enhances Eigenface under lighting variation, but other methods perform better. Increasing principal components in Eigenface improves correlation performance, with a point of diminishing returns observed. Fisherface proves adept at handling lighting and expression variations. The study emphasizes the need for robust face detection methods and the exploration of shadow modeling techniques to address performance degradation under extreme lighting conditions. [24] proposed a rapid visual object detection method with high accuracy. It employs the "Integral Image" representation for fast feature computation, an AdaBoost-based learning algorithm for efficient feature selection, and a cascade method for quick background region elimination. In face detection, it matches leading systems' performance, operating at 15 frames per second in real-time. The approach significantly accelerates face detection, showing potential for broader applications.

The model in [25] utilizes Haar Cascade for face detection due to its effectiveness in rapidly identifying faces in images or video frames based on specific features like edges and lines without extensive computational resources. Haar Cascade is used to efficiently locate multiple faces in a single detection process, making it suitable for real-time applications. Another effective and widely applicable approach is proposed in [14], which uses K-nearest neighbor (KNN) for classification and principal component analysis (PCA) for identification. Preprocessing methods like contrast stretching and grayscale conversion enhance image quality. The model underscores the crucial insight that the accuracy of the system is contingent upon the chosen value of k, where higher values of k are associated with diminished accuracy. Experiments on different k values reveals varying accuracy levels, with the best result obtained at 81% for k = 1.

The study in [26] presented facial recognition's importance in security, addressing challenges posed by facial variations. It combines LBP for feature extraction with K-NN for classification. It shows effectiveness in handling diverse facial characteristics.

High accuracy rates are obtained through experiments conducted on the CMU PIE and LFW datasets. In particular, K = 4 produces the highest accuracy on the CMU PIE database, and the LBP features and K-NN classifier demonstrate their effectiveness in unrestricted environments on the LFW dataset.

# 3. PROPOSED TECHNIQUES

There are two main phases in facial recognition using the K-Nearest Neighbor Method: training and testing phases, respectively. The proposed model uses an initial dataset of 690 images divided into 138 distinct classes. Two images are allocated for testing, while three images are assigned for training in each class. During the training phase, the model analyzes the input images to discern the unique characteristics of each distinct class. These features serve as significant benchmarks for subsequent recognition tasks. *Figure 2* illustrates the training phase in detail. In contrast, the testing phase entails supplying the model with unseen test data and assessing the model's overall performance in terms of accuracy and its ability to correctly identify or classify the images based on the features it has learned during the training phase. *Figure 3* provides a detailed depiction of the testing phase.

## 3.1 Dataset Used

The image dataset utilized is sourced from manual shoots and captured via webcam. It comprises 690 images from 138 subjects, taken from various angles. The images captured by the program are extracted from real-time video frames. The dataset has not undergone segmentation, retaining a sizable background surrounding the face object. Sample input images are shown in *figure1*. For broader validation of the system, we used the CASIA-WebFace dataset, which contains 11000 images, focused on frontal faces.

**Figure 1.** Example input images

## 3.2 Image Optimization

Image optimization plays an important role in improving the quality and clarity of images, making them more suitable for analysis and display. In the face identification system using the K-Nearest Neighbor method, image optimization involves a lot of stages. First, the Region of Interest (ROI) is identified within the image. Then, the image is converted to grayscale for simplification. Finally, contrast stretching is applied to enhance the contrast levels in the image. This helps in improving the visibility of details and features. This technique stretches the intensity values of the image to cover the desired range, thereby enhancing information while preserving other details.

## 3.3 Feature Analysis

Feature analysis helps in discerning the distinctive attributes of an input image, facilitating the classifier's ability to make precise decisions during classification. In addition to the well-established Principal Component Analysis (PCA) method, which is popular for its ability to reduce data dimensions while retaining crucial information, another prominent technique employed in this study is Local Binary Pattern (LBP). LBP is widely recognized and utilized across various domains, including biometrics, image processing, and data compression, owing to its effectiveness in capturing texture information.

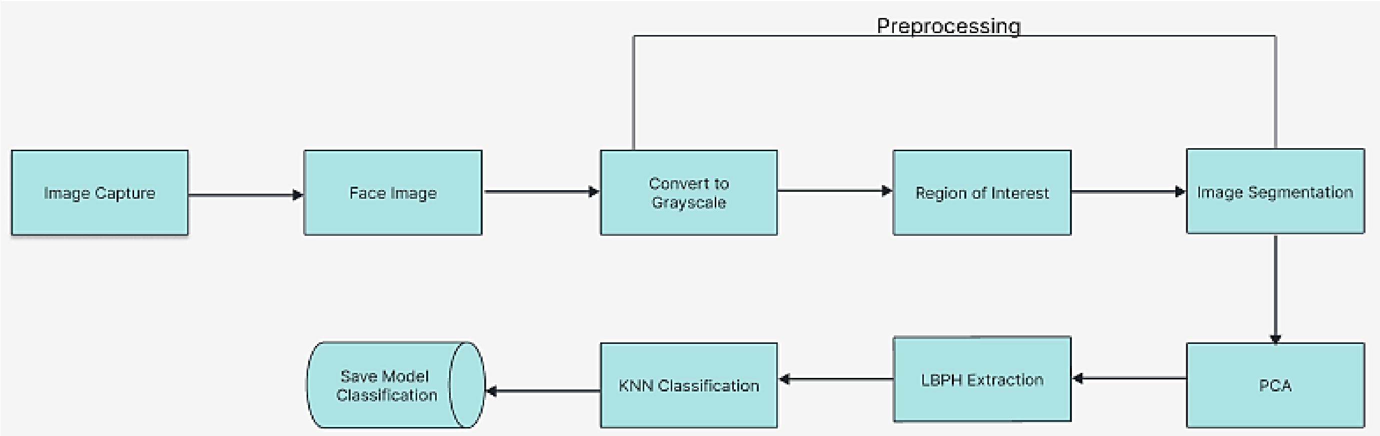


**Figure 2.** Training phase of face recognition

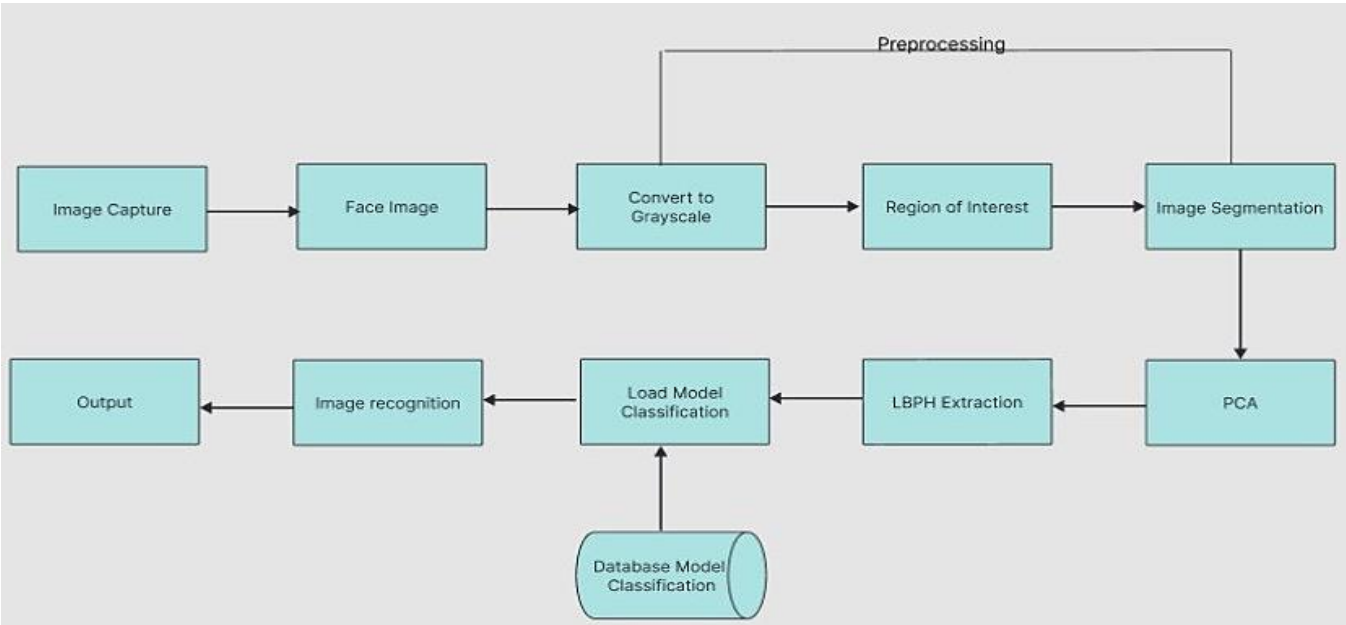


**Figure 3.** Testing phase of face recognition

PCA generates Eigenfaces by describing faces as linear combinations of eigenvector weights derived from a covariance matrix.

LBP evaluates each pixel in relation to its neighboring pixels, encoding texture patterns within the image. These binary patterns are then aggregated into histograms, forming a concise representation of the image's texture characteristics.

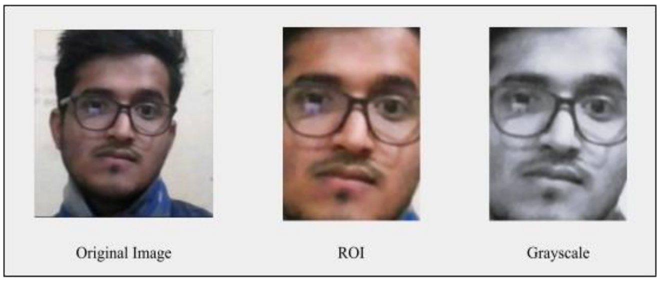


**Figure 4**. Image optimization

The following *figure 4* displays the results of image enhancement in facial recognition research employing the KNN method. In face recognition, LBP efficiently captures subtle texture nuances, essential for accurate identification. The integration of PCA and LBP in the face identification system ensures a comprehensive representation of facial features,

leveraging both the global structural information captured by Eigenfaces and the local texture details captured by LBP.

### 3.4 KNN Classification

In the face identification process, classification is a crucial step where training data taken from face datasets is compared with testing data. Among various classification algorithms, the K-Nearest Neighbor (KNN) method is particularly useful due to its simple yet effective working.

KNN operates by comparing testing samples with training samples, assigning each testing sample to the nearest neighbor class based on a specified value of k. However, determining the optimal *k* value poses a significant challenge as it directly impacts the performance of the KNN algorithm.

In face identification systems, the classification stage leverages the KNN method, using eigen-images obtained from the feature extraction process as input.

### 3.5 Proposed Algorithm

1. Initialize necessary variables and parameters.
2. Set '*k*' for KNN (Number of neighbors).
3. Collect facial data for training and testing.
4. Preprocess the collected data.
5. Apply Principal Component Analysis (PCA) to extract Eigenfaces features.
6. Extract features using Local Binary Patterns (LBP).
7. Train the K-Nearest Neighbors (KNN) model with PCA features
8. Detect faces using Haar-Cascade with OpenCV.
9. Test the face recognition system using the trained KNN model.
10. For each detected face:
    • Extract LBP features.
    • Find k-nearest neighbors using the Euclidean distance matrix.
11. Assess the performance of the facial recognition system.
12. Output the final results, including recognized faces and performance metrics.
13. Conclude the process.

## 4. RESULTS AND ANALYSIS

The experiments utilized manually gathered image datasets. The subsequent section presents a test of the face identification system using the K-Nearest Neighbor method with varying values of the parameter k, which denotes the number of neighboring points considered in each class.

In *table 1*, a testing procedure was conducted employing the KNN method with value of parameter k = 1, utilizing facial training data spanning 15 distinct classes, each comprising 3 training data points and 2 testing data points. The obtained accuracy, or F1-score, was an impressive 91%.

**Table 1. Performance metrics when k = 1**

| Name | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Jay Sati | 1.00 | 0.50 | 0.67 | 2 |
| Himanshu | 1.00 | 1.00 | 1.00 | 2 |
| Rahul Pandey | 1.00 | 1.00 | 1.00 | 2 |
| Ankur Joshi | 0.67 | 1.00 | 0.80 | 2 |
| Raj Aryan | 1.00 | 1.00 | 1.00 | 2 |
| Devansh Sati | 1.00 | 1.00 | 1.00 | 2 |
| Aryan | 1.00 | 1.00 | 1.00 | 2 |
| Swastik | 1.00 | 1.00 | 1.00 | 2 |
| Amritesh Bisht | 0.67 | 1.00 | 0.80 | 2 |
| Ayush | 1.00 | 1.00 | 1.00 | 2 |
| Nitin Rawat | 1.00 | 1.00 | 1.00 | 2 |
| Rajesh Joshi | 0.67 | 1.00 | 0.80 | 2 |
| Shubham Singh | 1.00 | 0.50 | 0.67 | 2 |
| Milind Pandey | 1.00 | 1.00 | 1.00 | 2 |
| Deepak Sinha | 1.00 | 1.00 | 1.00 | 2 |
| **Avg / total** | **0.93** | **0.93** | **0.91** | **30** |

While the majority of individuals could be identified successfuly, there were instances where certain testing data points remained unidentified. This discrepancy might be attributed to several factors, including the clarity of facial positions in the testing data.

Additionally, variations in webcam quality, lighting conditions, and facial expressions could also have contributed to the challenge of identifying some data points.

In *table 2*, the same testing protocol was executed to assess the system with parameter k=2, leveraging facial training data spanning across 15 distinct classes. The results yielded an F1-score of 70%. However, an interesting observation was made, revealing a decrease in accuracy when compared with the F1-score of 91% at k = 1.

This occurrence is attributed to both precision and recall scoring less, suggesting a lack of proximate neighbors suitable for identification recommendations. Thus, this underscores the intricacies and challenges inherent in facial recognition systems, particularly when faced with sparse or heterogeneous data distributions.

**Table 2. Performance metrics when k = 2**

| Name | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Jay Sati | 0.50 | 0.50 | 0.50 | 2 |
| Himanshu | 1.00 | 1.00 | 1.00 | 2 |
| Rahul Pandey | 0.67 | 1.00 | 0.80 | 2 |
| Ankur Joshi | 0.50 | 1.00 | 0.67 | 2 |
| Raj Aryan | 1.00 | 1.00 | 1.00 | 2 |
| Devansh Sati | 0.33 | 0.50 | 0.40 | 2 |
| Aryan | 1.00 | 1.00 | 1.00 | 2 |
| Swastik | 0.67 | 1.00 | 0.80 | 2 |
| Amritesh Bisht | 0.50 | 0.50 | 0.50 | 2 |
| Ayush | 0.33 | 0.50 | 0.40 | 2 |
| Nitin Rawat | 1.00 | 1.00 | 1.00 | 2 |
| Rajesh Joshi | 0.50 | 0.50 | 0.50 | 2 |
| Shubham Singh | 1.00 | 1.00 | 1.00 | 2 |
| Milind Pandey | 0.33 | 0.50 | 0.40 | 2 |
| Deepak Sinha | 0.50 | 1.00 | 0.67 | 2 |
| **Avg / total** | **0.65** | **0.76** | **0.70** | **30** |

*Table 3* illustrates the testing procedure employed for the K-Nearest Neighbor (KNN) method with a parameter k = 3, utilizing facial training data comprising 15 distinct classes, resulting in an F1 score of 66%. The research outcomes of the facial identification system utilizing K- Nearest Neighbor (KNN) or eigenface are divided into two phases: training and testing processes.

The model demonstrates outstanding performance metrics, achieving the highest accuracy at k = 1 with 91%, followed by 70% at k = 2, and 66% at k = 3. These findings highlight the impact of the parameter k on accuracy, revealing a trend where higher k values correspond to lower accuracy in face identification using KNN.

**Table 3. Performance metrics when k = 3**

| Name | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Jay Sati | 0.50 | 1.00 | 0.67 | 2 |
| Himanshu | 1.00 | 0.50 | 0.67 | 2 |
| Rahul Pandey | 0.50 | 1.00 | 0.67 | 2 |
| Ankur Joshi | 0.50 | 0.50 | 0.50 | 2 |
| Raj Aryan | 0.33 | 0.50 | 0.40 | 2 |
| Devansh Sati | 0.67 | 1 | 0.80 | 2 |
| Aryan | 0.33 | 0.50 | 0.40 | 2 |
| Swastik | 1.00 | 0.50 | 0.67 | 2 |
| Amritesh Bisht | 1.00 | 1.00 | 1.00 | 2 |
| Ayush | 1.00 | 1.00 | 1.00 | 2 |
| Nitin Rawat | 0.33 | 0.50 | 0.40 | 2 |
| Rajesh Joshi | 1.00 | 1.00 | 1.00 | 2 |
| Shubham Singh | 0.25 | 0.50 | 0.33 | 2 |
| Milind Pandey | 0.67 | 1.00 | 0.80 | 2 |
| Deepak Sinha | 1.00 | 0.5 | 0.67 | 2 |
| **Avg / total** | **0.67** | **0.73** | **0.66** | **30** |

### 4.1 Evaluation on the CASIA-WebFace Dataset

To further validate our facial recognition method, we extended our evaluation to the CASIA-WebFace dataset, which is a large and diverse collection of frontal face images. The utilized dataset consists of 11000 images from 2200 individuals, offering a robust testbed for assessing the generalization capabilities of our approach. Our experiments yielded highest accuracy for k=1 which was 87.5%, this indicates that the nearest neighbor approach is highly effective in correctly classifying new face images. The recognition accuracy for the proposed model as observed is shown in *table 4*.

**Table 4. Accuracy comparison between used datasets**

| | Accuracy | | |
|---|---|---|---|
| Dataset Used | *k = 1* | *k = 2* | *k = 3* |
| Smaller dataset | 0.913 | 0.701 | 0.664 |
| CASIA-WebFace Dataset | 0.875 | 0.860 | 0.852 |

Changing the value of *k* to 2 and 3 respectively, there is a slight decrease in accuracy, which is typical for KNN classifiers as they begin to consider more neighbors, potentially introducing more variability and ambiguity in classification decisions. The consistent performance across different *k* values confirms that our method can generalize well to large and varied datasets. Our analysis indicated that the number of PCA components had a notable effect on the system performance. Selecting 120 components achieved the best balance, as increasing the number of components beyond this point led to diminishing returns, while decreasing them resulted in a loss of critical information, thereby reducing recognition accuracy. Similarly, the LBP parameters, specifically a radius of 2 and 16 points were found essential for capturing local texture features. This configuration outperformed other tested values, showing resilience against variations in facial expressions and enabling the model to maintain high accuracy by effectively encoding local texture patterns crucial for accurate face recognition.

In addition to these traditional accuracy metrics, we evaluated our facial recognition system based on computational efficiency by measuring the average processing time per image on a standard desktop computer with an AMD Ryzen 9 processor and 16GB of RAM. The processing times were averaged across all images, for our initial dataset of 690 images, the training time was approximately 7 minutes, and the testing time was 0.15 seconds per image.

For the CASIA-WebFace dataset of 11,000 images, the training time was 101 minutes, and the testing time was 0.24 seconds per image. These results indicate a well- optimized system capable of handling large-scale data efficiently. These results indicate the system's viability for real-time applications, particularly in scenarios where slight delays are acceptable.

Robustness to environmental conditions was evaluated by testing the system under varying lighting conditions, background clutter, and different facial expressions. The accuracy of the system was measured across these conditions to assess its adaptability and reliability in real- time operations.

## 5. COMPARATIVE ANALYSIS

In the comprehensive overview presented in *table 5*, diverse techniques and their effectiveness are highlighted. [14] introduced a facial recognition model using PCA for dimensionality reduction along with KNN as the classifier, achieving an accuracy of 81% on a dataset of 790 images. The model developed by [20] uses the LBP method on the BU-3DFE dataset, achieving an accuracy of 82.33% with a dataset of 2,500 images, though it wasn't considered for real-world scenarios. [26] combined the KNN classifier with the LBP descriptor, achieving an 85.71% accuracy on 6,000 images sourced from the LFW dataset, but similar to the previous method, it was not deployed in real-world conditions. The Naive Bayes and Eigenface method proposed by [28] showed a higher accuracy of 89.5% on a relatively small dataset of 200 images but did not account for the efficient use of computational resources. Another model put forward by [29] introduced a face recognition model based on the Eigenface method, achieving an accuracy of 81.8% on the ORL dataset, although the number of images was not specified. In the paper proposed by [10], different face recognition methods were used in conjunction to find the optimal combination. The LDA method used without any dimensional reduction had a lower accuracy of 78% on a 500-image user dataset and showed possibilities for real-world deployment. Similarly, the SVM technique by [30] achieved an accuracy of 78% on the FERET dataset of 400 images but without any substantial possibility for real-world applications.

**Table 5. Comparison Analysis with different technologies of established models**

| Method | Technique | Dataset | No. of image in dataset | Real-world deployment | Accuracy |
|---|---|---|---|---|---|
| [10] | LDA only reduction | User Dataset | 500 | Yes | 0.78 |
| [14] | PCA + KNN | User Dataset | 790 | No | 0.81 |
| [20] | LBP | BU - 3DFE | 2500 | No | 0.8233 |
| [26] | LBP + KNN | LFW | 6000 | No | 0.8571 |
| [28] | Naive Bayes + Eigenface | User Dataset | 200 | No | 0.895 |
| [29] | Eigenface | ORL | Not specified | No | 0.818 |
| [30] | SVM | FERET | 400 | No | 0.78 |
| Proposed | PCA + LBP + KNN | User Dataset | 690 | Yes | 0.9137 |

The proposed method of this study integrates PCA, LBP, and KNN, achieving a higher accuracy of 91.37% on a user dataset of 690 images and being suitable for real- world deployment. This approach demonstrates superior performance over other techniques, especially in practical applications like user authentication on personal devices, access control in secure areas, and integration with attendance monitoring systems. It excels not only in accuracy but also in effectively handling variations in facial expressions and slight pose changes. By leveraging the global feature extraction capabilities of PCA and the local texture analysis provided by LBP, our model overcomes the limitations of models that rely solely on PCA. This strategy captures subtle texture variations crucial for distinguishing between different facial expressions. Additionally, incorporating Haar cascades from OpenCV for efficient frontal face detection enhances the model's robustness, enabling it to perform well under diverse lighting conditions and pose variations. This ensures the model's precision and adaptability, making it capable of handling real-world scenarios effectively. The combination of PCA, LBP, and KNN thus contributes to enhanced accuracy and adaptability, showcasing competitive performance compared to state-of-the-art techniques. *Figure 5* highlights graphical representation of diverse techniques used in various other established models.

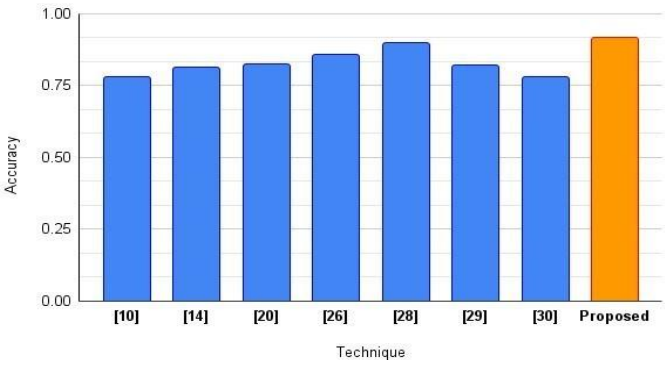


**Figure 5**. Accuracy of different Facial Recognition Models

## 6. CONCLUSION

In this paper, we presented a face identification system using the KNN classifier, integrating Haar Cascade from OpenCV for rapid and accurate face detection. This approach ensures robust detection, allowing recognition up to 15 degrees off-center, making it suitable for real- time applications. Our model combines LBP for robust texture descriptors and PCA for dimensionality reduction, optimizing performance and enhancing accuracy. Experiments were conducted on two datasets: a user dataset of 690 images and the CASIA-WebFace dataset of 11,000 images. Varying the parameter k demonstrated its sensitivity to system accuracy, with the highest accuracy achieved at 91.3% for k = 1 on the user dataset and 87.5% on the CASIA-WebFace dataset. An inverse relationship was observed between the parameter k value and accuracy; higher k values resulted in lower accuracy for face identification using KNN. For our initial dataset of 690 images, the training time was approximately 7 minutes, and the testing time was 0.15 seconds per image. For the CASIA-WebFace dataset of 11,000 images, the training time was 101 minutes, and the testing time was 0.24 seconds per image. These results indicate a well- optimized system capable of handling large-scale data efficiently and demonstrate the system's viability, particularly in scenarios where slight delays are acceptable. The system's efficient processing times and robustness ensure consistent performance across varying conditions. However, further improvements in handling extreme lighting conditions could enhance overall accuracy. Exploring other deep learning methods and advanced feature extraction techniques could further improve results.

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*Conflict of Interest:* To the best of my knowledge, this work has no conflicts of interest, and no significant money has been provided for it that may have impacted the findings. As the corresponding author, I certify that the identified author has reviewed and approved this work for submission.

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