Face Identification

Dev Pandya Akshat Jain Ujjwal Jain Lavangi Parihar
Chaital V Ghan Devansh Panchal Ketan Suthar

IIT JODHPUR

Abstract

This project investigates the effectiveness of three face identification methods: Local Binary Patterns (LBP), Histogram of Oriented Gradients (HoG), and Convolutional Neural Networks (CNN). By extracting features using these techniques, the study compares their performance in classifying face images into predefined categories. Evaluating factors such as accuracy, computational efficiency, and robustness to variations, the research offers insights into the strengths and limitations of each approach, informing their practical applications in fields like security and human-computer interaction.
Keywords: Face identification, Comparative analysis, LBP, HoG, CNN, Computational efficiency.

Contents

1 Introduction

Facial recognition technology is widely used in security, authentication, and personalized services. This project compares three techniques—Local Binary Patterns (LBP), Histogram of Oriented Gradients (HoG), and Convolutional Neural Networks (CNN)—for classifying facial images into predefined categories. We aim to evaluate the effectiveness of these techniques in terms of accuracy and computational efficiency.

The report outlines the methodology, including dataset description, feature extraction techniques, and classification models. It presents experimental results, performance evaluation, and comparative analysis, contributing to understanding machine learning concepts in facial recognition tasks.

1.1 Dataset

Labeled Faces in the Wild (LFW) is a renowned database of face photographs designed for studying unconstrained face recognition. Developed by researchers at the University of Massachusetts, Amherst, it consists of 13,233 images of 5,749 individuals, sourced from the web and processed using the Viola Jones face detector.

With 1,560 individuals having multiple distinct photos, the dataset offers ample variation for robust evaluation. Notably, deep-funneled images within the dataset have shown superior performance across various face verification algorithms.

In this project, we utilize the deep-funneled version of the LFW dataset to explore facial image classification techniques. Our aim is to evaluate different methods' effectiveness in addressing the challenges of unconstrained face recognition, contributing to advancements in the field.

1.2 Figures

Keep all the figures in Figs.

Figure 1: Example dataset image from LFW

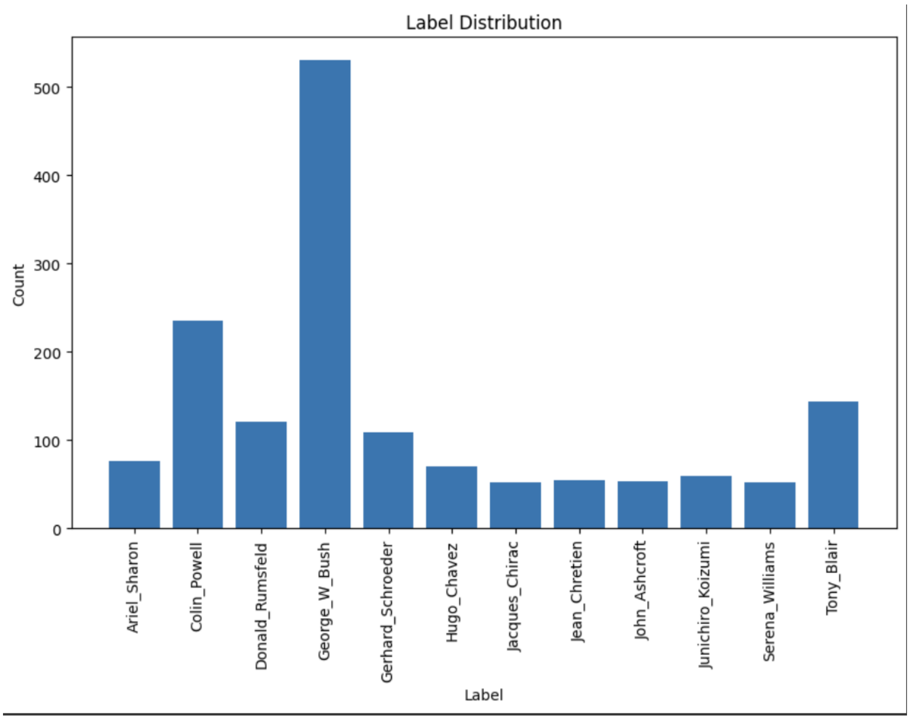

Figure 2: Visualising Label Distribution

2 2 Approaches Tried

For the face identification task, we have explored three distinct feature extraction techniques—Local Binary Patterns (LBP), Histogram of Oriented Gradients (HoG), and Convolutional Neural Network (CNN) features. Here's a brief overview of each method and their role in face identification:

2.1 Local Binary Patterns (LBP)

- **Description:** LBP is a texture descriptor that is used to describe local spatial patterns and the texture of an image. The basic idea of LBP is to summarize the local structure in an image by comparing each pixel with its surrounding neighborhood.
- **Application in Face Recognition:** LBP is particularly useful for face recognition due to its robustness against monotonic grayscale changes caused by illumination variations. It's computationally efficient and can be used to capture fine details of the face which are essential for identifying individuals.

2.2 Histogram of Oriented Gradients (HoG)

- **Description:** HoG involves counting occurrences of gradient orientation in localized portions of an image. This method captures edge or gradient structure that is very informative about the shape of a face.
- **Application in Face Recognition:** HoG features are useful for capturing the outline and contours of facial features such as the jawline, nose, eyes, and mouth. These features are less sensitive to lighting variations and can provide a robust basis for identifying faces across different lighting conditions.

2.3 Convolutional Neural Networks (CNN)

- **Description:** CNNs are deep learning models known for their ability to capture hierarchical patterns in data. In the context of image processing, CNNs can automatically learn and generalize features from raw images.

3 Experimental Setup and Results

3.1 Local Binary Patterns (LBP)

Our experiments with LBP involved testing different configurations, including:

1. k **Values:**
   - Best Accuracy: 39.32% (When 10 components are taken with $k = 50$)

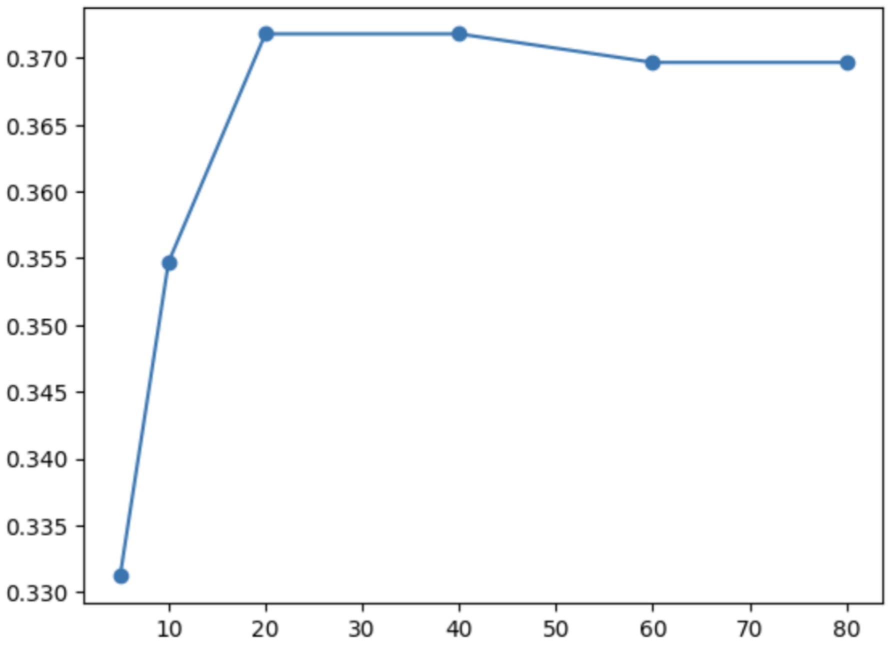

Figure 3:

Kernel Types:

- Best on RBF Kernel: Best Accuracy: 39.10%

Random Forest:

- Best Accuracy: 40.17%

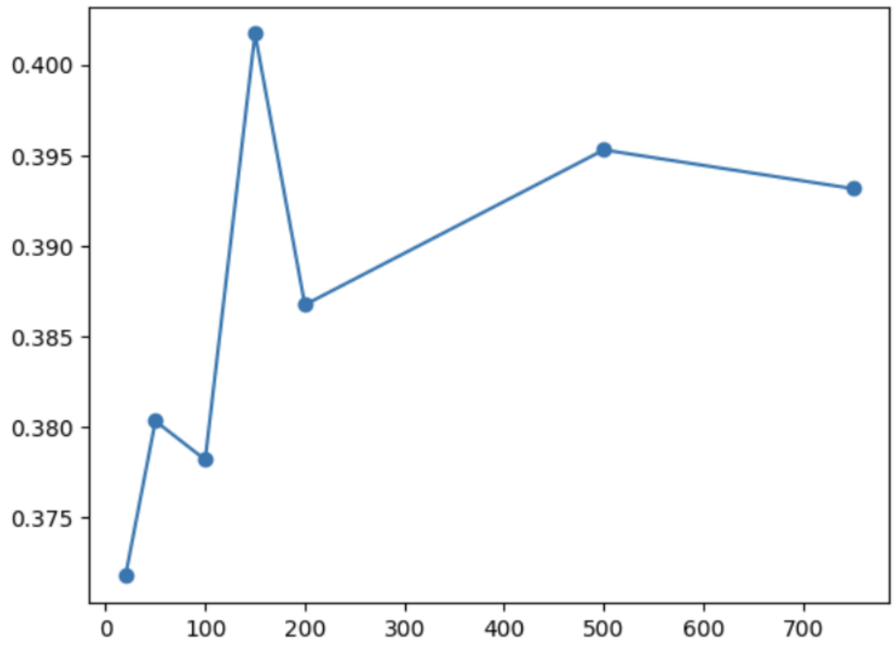

Figure 4: Random Forest fit on LBP features

ANN (Artificial Neural Network):

- Best Accuracy: 42%

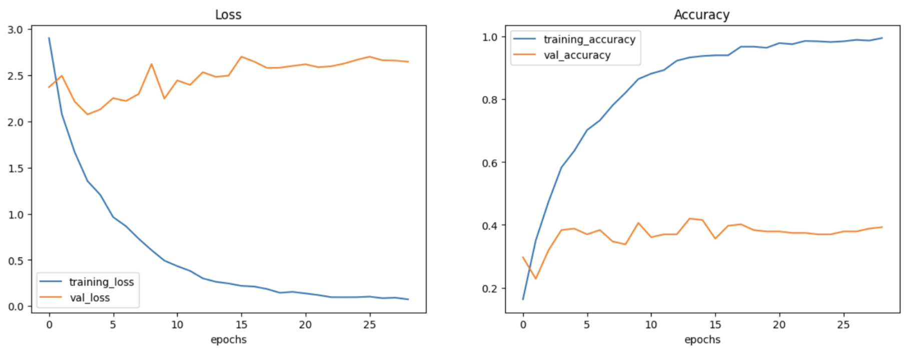

Figure 5: ANN model on LBP features

3.2 Histogram of Oriented Gradients (HoG)

For HoG features, we explored different configurations such as:

1. k **Values:**
   - Best Accuracy: 78.53% (When 10 components are taken with $k = 10$)
2. **Kernel Types:**
   - Best on RBF Kernel: Best Accuracy: 55.77%
3. **LDA followed by SVM**
   - Best accuracy is obtained for linear kernel and 10 components for LDA with accuracy 84.29%
4. **ANN (Artificial Neural Network):**
   - Best Accuracy: 88.46%

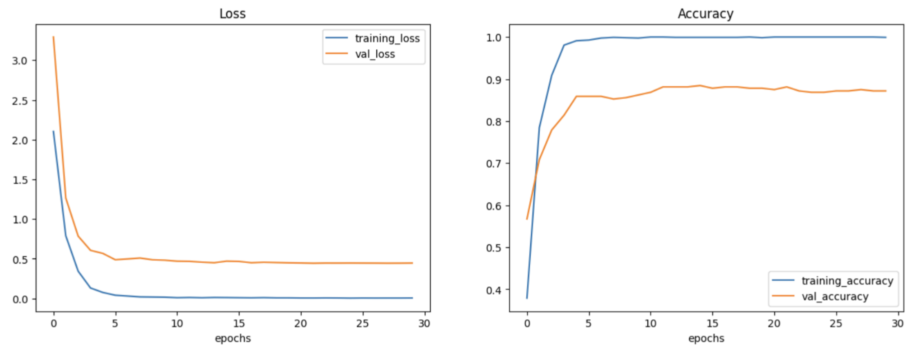

Figure 6: ANN model on HoG features

3.3 Convolutional Neural Network (CNN)

With CNN, we experimented with:

1. k **values:**

    - Best Accuracy: 53.21% (when $k = 10$)
    - **LDA followed by knn:**
        - Best Accuracy: 72.12% (When 10 components are taken with $k = 10$)
    - **LDA followed by SVM**
        - Best accuracy is obtained for RBF kernel and 10 components with accuracy: 74.44%
    - **ANN (Artificial Neural Network):**
        - Best Accuracy: 79.17%

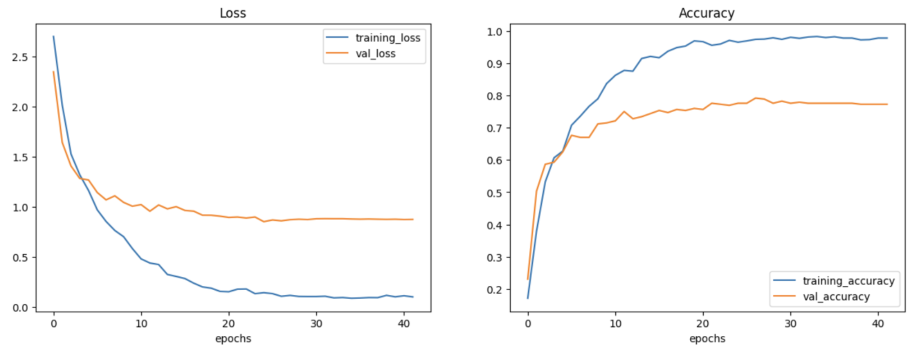

Figure 7: ANN model on CNN features

3.4 Conclusion

After testing and implementing different models on LBP, HoG, and CNN features, we conclude that the best accuracy is obtained for the ANN model on HoG features.

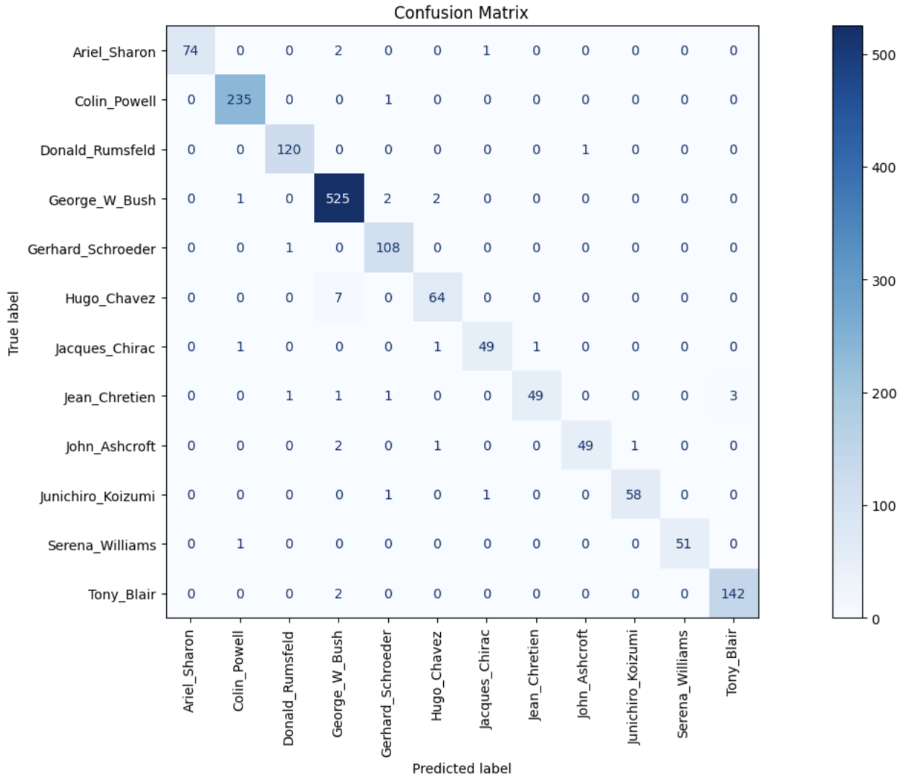

Figure 8: Confusion Matrix display of ANN on HoG

3.5 Test Results of Our Selected Model

Utilizing the Artificial Neural Network (ANN) model with Histogram of Oriented Gradients (HoG) features, we conducted predictions on ten randomly selected images from our dataset.

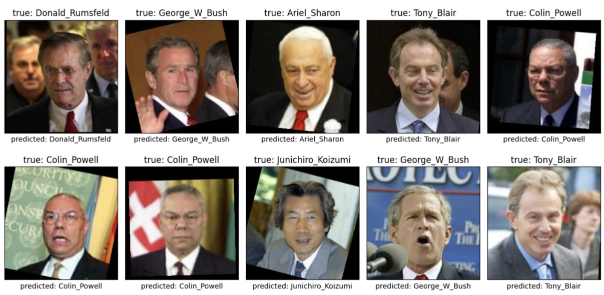

Figure 9: Visualizing predictions on our best model for 10 random images from the dataset

4 Summary

Our project aimed to explore and compare three distinct feature extraction techniques—Local Binary Patterns (LBP), Histogram of Oriented Gradients (HoG), and Convolutional Neural Network (CNN) features—for facial image classification tasks. We utilized the Labeled Faces in the Wild (LFW) dataset, a comprehensive collection of face photographs designed for unconstrained face recognition studies.

First, we provided an introduction to the LFW dataset, detailing its origins, size, and significance in the field of face recognition research. Next, we outlined the experimental setup, including the methodologies employed for each feature extraction technique.

For LBP, we investigated various configurations such as different k values and kernel types, noting their corresponding accuracies. Similarly, in the case of HoG, we explored different parameters like the number of components and kernel types, analyzing their impact on classification performance. With

CNN, we experimented with adjusting the number of components and neighbors, assessing their effectiveness in facial image classification.

After conducting comprehensive experiments, we presented our findings, highlighting the best accuracy achieved for each feature extraction technique. We observed that the ANN model on HoG features yielded the highest accuracy among all techniques tested.

In conclusion, our project contributes to the understanding of feature extraction techniques in facial image classification tasks. We demonstrated the effectiveness of HoG features, particularly with an ANN model, for accurate and robust facial recognition. Our findings provide valuable insights for researchers and practitioners in the field of computer vision, guiding future developments in facial recognition technology.

A Contribution of each member

1. Akshat Jain(B22CS007): Worked on CNN model, studied and compared the results for all the three extracted features.
2. Dev Pandya(B22AI016): Worked on LBP model, studied and compared the results for all the three extracted features
3. Devansh Panchal(B22CS021): Worked on CNN model, and handled data preprocessing.
4. Ketan Suthar(B22EE041): Worked on LBP model, prepared the project page.
5. Lavangi Parihar(B22EE044): Worked on HOG model, prepared the project report.
6. Chaital Ghan(B22CS020): Worked on HOG model, and prepared the project report.
7. Ujjwal Jain(B22CS057): Worked on CNN model, and prepared the project page.