Facial Recognition with Advanced Machine Learning Techniques

Using the Labeled Faces in the Wild Dataset

Anuj Rajan Lalla, Sarth Sanjay Joshi, Abhinav Swami, Satyam Sharma, Sanjeet Athawale

Indian Institute of Technology, Jodhpur
CSL2050: Pattern Recognition and Machine Learning
Group - 14

April 21, 2024

Abstract

This research investigates the application of advanced machine learning techniques for facial recognition using the Labeled Faces in the Wild (LFW) dataset, addressing challenges such as high dimensionality and class imbalance through innovative feature extraction methods and dimensionality reduction techniques. Our findings reveal significant insights into the performance trade-offs associated with different feature-classifier combinations.

Table of Contents

Introduction to Facial Recognition

- Facial recognition technology has transformed security and identity verification across various sectors.
- Despite its widespread use, the technology faces significant challenges such as variability in lighting, pose, and expressions.
- Accurate and robust facial recognition is crucial for applications ranging from mobile security to border control.

The Labeled Faces in the Wild (LFW) Dataset

- The LFW dataset is a benchmark for studying unconstrained facial recognition.
- Consists of over 13,000 images of faces collected from the web.
- Each image is labeled with the name of the person in the photo, encompassing 5,749 different individuals.
- The dataset poses challenges due to high variability in terms of pose, lighting, and background.

Figure 1: Workflow of Facial Recognition System

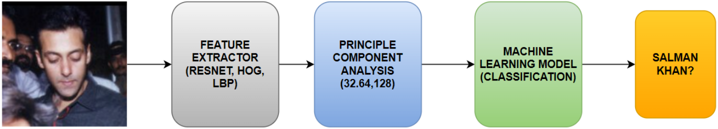

Figure: Generalized working diagram of our facial recognition system.

Figure 2: Challenge of Class Imbalance

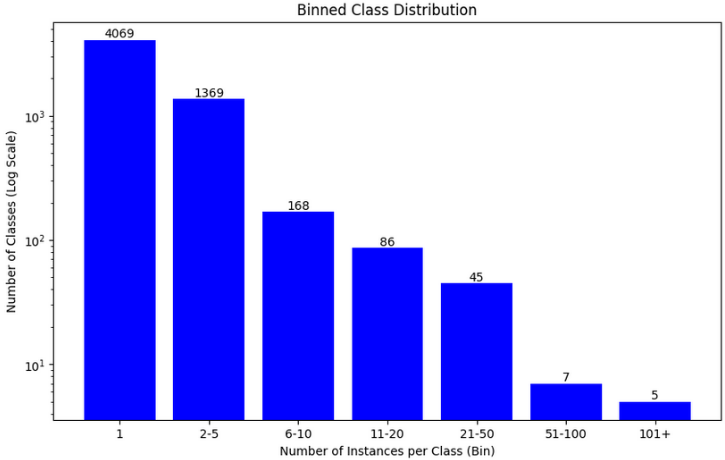

Figure: Illustration of the challenge of class imbalance within the LFW dataset.

Objectives of This Study

- To apply advanced machine learning techniques to improve the accuracy and efficiency of facial recognition.
- Address the challenges of high dimensionality and class imbalance in the LFW dataset.
- Evaluate the effectiveness of various feature extraction methods and classifiers.

Methodology Overview

- Our methodology involves a series of steps to enhance facial recognition performance using the LFW dataset.
- Key components include:
  1. Feature extraction from face images using various techniques.
  2. Dimensionality reduction to manage high-dimensional data.
  3. Classification using several machine learning models to identify individuals.
- This combination of methods is tested for its effectiveness in improving accuracy and computational efficiency.

Feature Extraction Techniques

- **Pre-trained ResNet:** Utilizes a deep convolutional network pre-trained on a large dataset. It extracts high-level abstract features from face images, capturing complex patterns that are crucial for recognition.
- **Histogram of Oriented Gradients (HOG):** Focuses on the structure of shapes within the face by capturing the direction and intensity of edges. It is very effective in recognizing facial contours and expressions.
- **Local Binary Patterns (LBP):** An efficient texture descriptor that analyzes local textural patterns in an image. LBP is robust against changes in lighting and can detect fine-grained textural differences in facial images.

Dimensionality Reduction with PCA

- High-dimensional features pose challenges in model training and performance due to the curse of dimensionality.
- **Principal Component Analysis (PCA):** A statistical technique used to reduce the dimensions of the feature sets while retaining most of the variance.
- PCA transforms the high-dimensional data into a lower-dimensional subspace, improving computational efficiency and reducing noise.
- We apply PCA differently for each feature extraction method to optimize performance.

Classification Models

- **K-Nearest Neighbors (KNN):** A non-parametric model that classifies new cases based on a majority vote of the nearest neighbors.
- **Logistic Regression:** Provides probabilistic outputs for binary classification and is extended to multiclass classification via techniques like one-vs-rest (OVR).
- **Support Vector Machine (SVM):** Effective in high-dimensional spaces, SVM works well for clear margin of separation and is robust against overfitting.
- **Random Forest:** An ensemble of decision trees that improves classification accuracy and controls overfitting through averaging.
- **XGBoost:** An advanced implementation of gradient boosted decision trees known for its performance and speed in classification challenges.

Feature Extraction and Dimensionality Reduction

- **Feature Extraction Methods:**
  - Pre-trained ResNet: Extracts a 2048-dimensional feature vector per image.
  - Histogram of Oriented Gradients (HOG): Produces a 70,308-dimensional vector.
  - Local Binary Patterns (LBP): Provides a 256-dimensional feature vector.
- **Dimensionality Reduction with PCA:**
  - Applied to manage the high dimensionality of the extracted features.
  - PCA dimensions explored: 32, 64, and 128.

Model Training and Evaluation

- **Classification Models Tested:**
  - K-Nearest Neighbors (KNN), Logistic Regression, SVM, Random Forest, and XGBoost.
  - Each model tested with PCA-reduced features from the three extraction methods.
- **Performance Metrics:**
  - Accuracy metrics including Top-1 and Top-5 accuracies were primarily used to evaluate model performance.
- **Experimental Findings:**
  - Detailed results are presented for each model and feature extraction method, focusing on how dimensionality reduction impacts performance.

ResNet Based Feature Extraction Results

PCA Dimension	Model	Top-1 Accuracy	Top-5 Accuracy
32	KNN	0.29	1.00
	Logistic Regression	0.52	0.78
	SVM	0.67	0.82
	Random Forest	0.63	0.76
	XGBoost	0.21	0.25
64	KNN	0.31	1.00
	Logistic Regression	0.70	0.89
	SVM	0.87	0.94
	Random Forest	0.55	0.68
	XGBoost	0.22	0.26
128	KNN	0.32	1.00
	Logistic Regression	0.73	0.91
	SVM	0.91	0.96
	Random Forest	0.36	0.51
	XGBoost	0.14	0.25

Table: Performance of Classification Models on PCA-Reduced Features using ResNet

HOG Feature Extraction Results

PCA Dimension	Model	Top-1 Accuracy	Top-5 Accuracy
32	KNN	0.24	1.00
	Logistic Regression	0.57	0.76
	SVM	0.58	0.71
	Random Forest	0.42	0.53
	XGBoost	0.16	0.20
64	KNN	0.26	1.00
	Logistic Regression	0.83	0.93
	SVM	0.82	0.91
	Random Forest	0.39	0.49
	XGBoost	0.22	0.25
128	KNN	0.27	1.00
	Logistic Regression	0.97	0.99
	SVM	0.97	0.98
	Random Forest	0.37	0.46
	XGBoost	0.23	0.27

Table: Performance of Classification Models on PCA-Reduced Features using HOG

LBP Feature Extraction Results

PCA Dimension	Model	Top-1 Accuracy	Top-5 Accuracy
32	KNN	0.22	1.00
	Logistic Regression	0.03	0.09
	SVM	0.00	0.00
	Random Forest	0.39	0.51
	XGBoost	0.04	0.09
64	KNN	0.22	1.00
	Logistic Regression	0.03	0.09
	SVM	0.00	0.00
	Random Forest	0.33	0.43
	XGBoost	0.04	0.10
128	KNN	0.22	1.00
	Logistic Regression	0.03	0.09
	SVM	0.00	0.00
	Random Forest	0.15	0.24
	XGBoost	0.04	0.10

Table: Performance of Classification Models on PCA-Reduced Features using LBP

Precision, Recall, and F1-Score for SVM

Feature Method	Precision	Recall	F1-Score
ResNet	0.96	0.98	0.97
HOG	0.99	1.00	1.00

Table: Performance Metrics for SVM using ResNet and HOG Features

Key Insights and Challenges

- **Effective Feature-Classifier Combinations:**
  - ResNet with SVM and Logistic Regression shows high effectiveness, especially at higher PCA dimensions.
  - HOG features perform well with SVM and Logistic Regression, utilizing edge and gradient information effectively.
  - LBP features underperform with almost all models, highlighting the non discriminative nature of the features.
- **Class Imbalance Impact:**
  - Significant class imbalance affects sensitive models for all models.
  - SVM benefits from its ability to focus on challenging examples near the decision boundary, performing better in imbalanced settings.
  - Balanced versions of Logistic Regression and SVM were initially tried to robustly deal with the class imbalance, but were later dropped due to computational constraints.
- **Computational Efficiency and PCA:**
  - PCA crucially reduces feature dimensionality from ResNet and HOG, balancing computational efficiency with data integrity.
  - Fine-tuning PCA dimensions helps optimize the trade-off between representativeness and computational demands.

Future Research Directions (1/2)

- **Exploring Advanced Feature Extraction Methods:**
  - Investigate newer deep learning architectures that may offer more robust feature extraction capabilities than current models like ResNet.
  - Explore hybrid feature extraction techniques combining the strengths of methods such as HOG and LBP with deep learning approaches to enhance detail capture in facial features.
- **Optimizing Classifier-Feature Combinations:**
  - Systematic testing of different combinations of features and classifiers to identify the most effective pairings for challenges posed by datasets like LFW.
  - Implement automated machine learning (AutoML) frameworks to efficiently explore numerous algorithms and parameter settings, aiming to discover optimal configurations without extensive manual tuning.

Future Research Directions (2/2)

- **Developing More Robust Algorithms for Class Imbalance:**
  - Research into algorithms specifically designed to handle significant class imbalances, such as cost-sensitive learning and minority oversampling techniques.
  - Evaluate ensemble methods that improve model performance by leveraging multiple learning algorithms to obtain better predictive performance.
- **Application-Specific Model Tuning:**
  - Tailor models to specific application needs such as real-time processing, mobile platforms, or high-security environments, where performance requirements might vary significantly.
  - Develop custom solutions that integrate seamlessly with existing technology stacks in various industries, enhancing usability and adoption.

Conclusion

- **Key Findings:**
  - Our study demonstrated the effectiveness of various feature extraction methods and classifiers on the LFW dataset, highlighting the superior performance of ResNet features with SVM and Logistic Regression.
  - PCA played a crucial role in managing high-dimensional data, enabling efficient computation without significant loss of information.
- **Implications:**
  - These findings can inform the development of more accurate and efficient facial recognition systems, particularly in scenarios involving large and imbalanced datasets.
  - Future research can build on these results to explore new feature extraction techniques and classifier combinations to further enhance performance.

Contributions

- **Anuj Rajan Lalla:** Implemented models and maintained GitHub repo structure. Prepared Report, Github Code and Spotlight video
- **Sarth Sanjay Joshi:** Midreport preparation , contribution in GitHub code. Web deployment of best model and web demo
- **Abhinav Swami:** Preparation of Accuracies code. Preparation of project page using HTML and CSS .
- **Satyam Sharma:** Midreport preparation and code . Feature Extraction and references for report
- **Sanjeet Athawale:** Midreport preparation and code , Feature extraction code and accuracies code