A Comparative Study Between Class-Dependent and Class-Independent Algorithms of Linear Discriminant Analysis

A case study- Face Recognition

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***Abstract*— Face recognition is the process of identifying an individual by analyzing their facial features. It has become an essential area of research due to its numerous practical applications, such as security systems, access control, and surveillance. One of the challenges in face recognition is dealing with high-dimensional data, as facial images typically contain a large number of pixels. To address this issue, dimensionality reduction techniques such as Linear Discriminant Analysis (LDA) can be used. In face recognition, LDA can be used to extract discriminative features from facial images and reduce the dimensionality of the feature space, thereby improving the recognition system's performance. This proposed study aims to conduct a comparative study between class-dependent and class-independent algorithms of LDA for face recognition. both algorithms were applied to the ORL dataset containing 400 images within 40 classes and compared the results were by applying SVM as a classification model.**

***Keywords*— Linear Discriminant Analysis(LDA), class-dependent LDA, class-independent LDA, face recognition, Support Vector Machine(SVM)**

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I . INTRODUCTION

Face recognition has emerged as a prominent field within computer vision, finding diverse applications in security systems, biometrics, access control, and human-computer interaction. Over the years, numerous techniques have been developed to improve the accuracy and robustness of face recognition systems. One such technique is Linear Discriminant Analysis (LDA), a dimensionality reduction method known for its discriminative power and feature extraction capabilities.

In face recognition, LDA aims to find a projection that maximizes class separability while minimizing intra-class variations, making it particularly suitable for face recognition tasks. By transforming high-dimensional face data into a lower-dimensional subspace, LDA enables efficient representation and classification of facial features, leading to improved recognition accuracy. However, the effectiveness of LDA can be further enhanced by considering two distinct approaches: class-dependent and class-independent algorithms.

Class-dependent LDA algorithm computes the within-class scatter matrix and between-class scatter matrix separately for each class. By incorporating class-specific information during the projection, these algorithms aim to capture the unique characteristics of each individual, resulting in enhanced discriminative power. On the other hand, class-independent LDA algorithms consider the global within-class and between-class scatter matrices, treating all individuals as a collective group. This approach emphasizes the commonalities shared among different individuals, leading to a more generalized and robust face representation.

This proposed study aims to conduct a comparative analysis in terms of performance metrics between class-dependent and class-independent algorithms of Linear Discriminant Analysis (LDA) for face recognition. Most of the machine learning engineers or scientists so far they developed LDA algorithms using class-independent variables for different applications such as face recognition, Image processing, and fraud detection but most of them less focus on the study on class dependent LDA therefore to fill that gap we are working on class dependent LDA and comparing with class independent LDA

SCOPE

- The scope of the proposed approach is limited to comparing the performance of two specific approaches to LDA for face recognition
- The scope of the study is further limited to analyzing the performance of the LDA models under variations in pose, and facial expression.

OBJECTIVES:

The following is a list of this project's main goals:

- To compare the accuracy of class-dependent and class-independent algorithms of LDA for face recognition using a publicly available face recognition dataset.
- To analyze the robustness of each approach to variations in lighting, pose, and facial expression, by adding simulated variations to the face images in

the dataset and measuring the accuracy of the LDA models on the modified images.

II. RELATED WORKS

The study [1] aimed to enhance the accuracy of identifying individuals wearing masks through the evaluation of three advanced lightweight face models. These models were fine-tuned using images of masked faces and took into account periocular information to improve performance. To facilitate this research, a novel dataset was curated by superimposing artificial masks onto facial images sourced from the CASIA-WebFace dataset. Initial evaluations revealed a dip in the performance of earlier models, but with the inclusion of more masked datasets, their accuracy in discerning masked versus unmasked photos saw a noticeable upswing. Notably, the study found that despite their lightweight nature, these models demonstrated competitive performance when compared to more complex deep networks, challenging the notion that larger or deeper models invariably yield better recognition outcomes. This research underscores the efficacy of employing lightweight models, particularly when deployed on low-power computing devices, offering advantages in efficiency and practicality.

The study [2] introduces Tensor-Compensated Colour Face Recognition, where RGB colour face images are represented as third-order tensors and subjected to Higher-Order Singular Value Decomposition (HOSVD) to extract components. An innovative illumination compensation technique, AHOSVD, is proposed for enhancing facial images during preprocessing. AHOSVD adaptively modifies the core tensor by applying compensating weight coefficients to its frontal slices. Evaluations conducted on established colour face databases including CMU-PIE, Colour FERET, FEI, LFW, and IJB-C demonstrate AHOSVD's dual capability: effectively addressing image quality concerns and substantially improving face recognition accuracy and computational speed across diverse models. This research underscores AHOSVD's potential as a powerful technique, enhancing both image quality and critical aspects of face recognition performance.

The study [3] delves into the complex issue of bias in facial recognition linked to skin tone. It introduces a benchmark to counter this bias, fostering equitable evaluation of face recognition algorithms across varying skin tone groups. The research highlights the inadequate performance of current deep models on darker-skinned faces due to both data and algorithmic biases. To address this, the study presents two comprehensive training datasets, BUPT-Global face and BUPT-Balanced face, aimed at mitigating data bias. They also propose the Meta Balanced Network (MBN) to alleviate bias and enhance feature balance, yielding promising outcomes. However, MBN's effectiveness relies on skin tone-aware datasets and corresponding labels during training. Future directions include the development of debiasing algorithms capable of training balanced models without explicit dependence on demographic attributes.

The research [4] introduces the Dual Face Alignment Learning (DFAL) algorithm, designed for matching near-infrared (NIR) and visible (VIS) face images with the aim of discovering neutral face representations across different domains. The DFAL model integrates Facial Feature Adaptation (FFA), Identity Feature Adaptation (IFA), and Cross-domain Disentanglement and Reconstruction (CdR) techniques. This combination enables the alignment of non-neutral facial images with neutral VIS faces, leading to enhanced representation learning that can discriminate between identities effectively. The effectiveness of the DFAL model is substantiated through comprehensive experiments conducted on three challenging NIR-VIS face databases, demonstrating its prowess in addressing domain and residual variations. The study's focus on learning neutral face representations for both NIR and VIS images is shown to be a promising strategy in mitigating these variations. As a direction for future investigation, the research will delve into refining the characterization of potential neutral face representations within cross-modal data.

In [5] their work, the authors introduced a novel approach to enhance face recognition robustness against face misalignment. This innovative framework involves a dual-process strategy comprising pixel alignment and feature alignment, both seamlessly integrated within the face feature extraction network. The proposal capitalizes on deep feature alignment, guided by face key points and structure, to ensure accurate alignment. During the training phase, the method leverages aggregated features derived from face images and shape priors to cultivate well-aligned facial features. Notably, the feature alignment algorithm adeptly harmonizes learned features with face-shape-guided features. The efficacy of this approach is validated through comprehensive comparative assessments conducted on diverse datasets, encompassing LFW, CALFW, YTF, and MegaFace. A significant advantage lies in the method's applicability to face photo testing, as it obviates the need for additional computations to estimate face key points and alignment.

The published work [6] presents the Graph-based Two-Stage Face Augmentation Generative Adversarial Network (FA-GAN), a novel approach aimed at advancing deformation-invariant face recognition. This method introduces a decoupling of identity representations, thereby enhancing the manipulation of facial attributes and ultimately leading to improved accuracy in recognizing faces despite deformations. The integration of Graph Convolutional Networks within the framework serves to preserve geometric data and effectively capture intricate relationships between different facial regions. Through comprehensive experimentation, the study showcases the efficacy of the proposed FA-GAN, indicating its potential for broader applications. Looking ahead, the authors express intentions to delve into semi-supervised learning techniques and expand the framework's utility to encompass deformation-invariant human re-identification, highlighting their commitment to future advancements within related domains.

The study [7] introduces Adaptive Face Recognition Using Adversarial Information Network (AIN) presents a novel solution to address domain disparities in facial recognition systems. AIN uniquely tackles both intra-domain discrepancies and inter-domain differences within the target domain. It introduces a method that generates reliable pseudo labels by leveraging a clustering technique based on Graph Convolutional Networks (GCN). This process involves modifying the model and minimizing variability within the target domain. To amplify the network's ability to distinguish between samples and bridge the gap between pseudo-labeled and unlabeled target samples, the approach introduces an adversarial Mutual Information (MI) loss. Impressively, the proposed technique demonstrates state-of-the-art performance on the RFW dataset. However, the study acknowledges the need for further investigation to enhance the generalizability and transferability of GCN, considering potential inaccuracies in labeling due to domain shifts.

The study [8] introduces CASIA-Face-Africa database represents a significant effort in combating racial bias within face recognition research and applications by amassing a substantial collection of African face images. Comprising portraits of 1,183 African individuals, the database encompasses images captured using both visible-light and near-infrared cameras. These images are meticulously annotated with 68 landmark points, facilitating comprehensive studies on face image preprocessing and feature analysis. The article not only furnishes evaluation guidelines and benchmarks for gauging the efficacy of face recognition methods on this dataset but also underscores the current inadequacy of existing techniques in effectively recognizing African faces. This database stands as a crucial resource to address this disparity and improve recognition techniques tailored to African face biometrics.

The tutorial [9] delves into the concept of Linear Discriminant Analysis (LDA), an essential mathematical technique for dimensionality reduction and classification, using the ORL face dataset as an illustrative example. Through comprehensive explanations, visual aids, diagrams, and figures, the tutorial aims to provide a thorough grasp of LDA's intricacies. It meticulously outlines the construction of the LDA space, employing two distinct approaches, and substantiates the content with practical numerical instances. Emphasis is placed on elucidating the mathematical foundations of key LDA aspects, including robustness, eigenvector selection, and data projection. With a primary objective of enhancing readers' comprehension, the tutorial offers a clear and accessible exposition of LDA principles and methodologies, enabling an enriched understanding of this fundamental analytical tool.

III.PROPOSED METHOD

DATASET DESCRIPTION

The proposed study makes use of the face dataset from the Olivetti Research Laboratory (ORL), which was acquired through Kaggle. The 400 photographs in this collection are made up of 40 grayscale portraits of different people, each of whom contributed 10 photos. Each image is 92x112 pixels in size, which makes face analysis a good level of resolution. The images were captured under various lighting conditions, including smiles, with eyes open or closed, and with or without glasses on the face. The subjects were posed frontally and upright with some room for side movement, and a uniformly dark background was used for all the photographs. Figure 1 shows the different poses, smile, With eyes open or closed with glasses on the faces. Figure 2 shows different persons

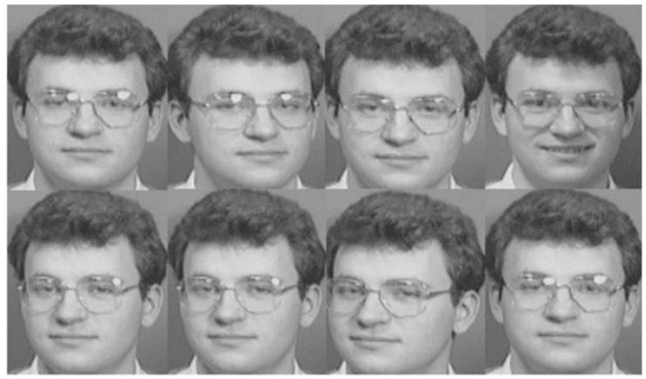

Figure:1 Images of a person

Figure:2 Images of 10 different people from the ORL dataset

PROPOSED METHODOLOGY

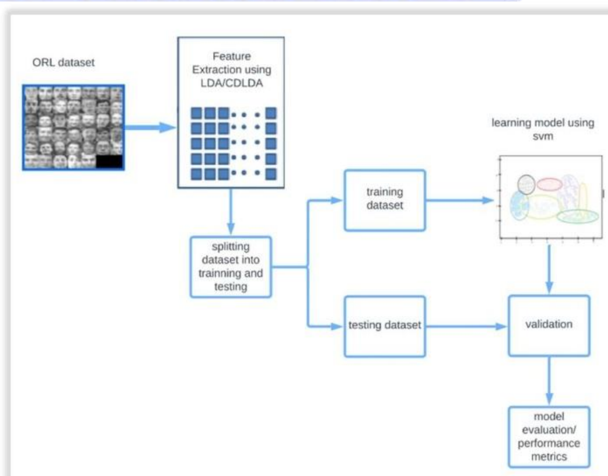

Figure:3 Proposed Model

METHODOLOGY

Data Collection and Data Preparation

In this module, we used the publicly available ORL dataset which consists of 400 images of 40 subjects with different expressions, with glasses and without glasses, with different angles. The ORL dataset images were first taken and flattened.

Each image was converted into a one-dimensional array by concatenating the rows and columns of pixels. The NumPy library in Python was utilized for this purpose. The flattened images were stored in a separate data structure, such as a NumPy array. This array is ready for feature extraction.

Feature extraction using LDA and CDLDA

In this module, we use class-independent linear discriminant analysis (LDA) and class-dependent linear discriminant analysis(CDLDA) for feature extraction. LDA is a dimensionality reduction technique while reserving maximum between class separability and minimizing within class separability. The data of 400 images are stored in a matrix of size 10340X400. The means of all 40 classes are calculated and used for class between scatter matrix and within the class scattered matrix. Using the scattering matrices we calculated the eigenvalues and the eigenvectors.in [9] they proposed that the top 40 eigen values give better results. The size of the data is 10340 X 400 and reduced to 200 X 40 using top 40 eigen values. This dimensionally reduced data has individual features by projecting 40 eigen vectors onto the data.

Training SVM model

In this module, we split the LDA/CDLDA-transformed features into training and testing data. We train an SVM(SUPPORT VECTOR MACHINE) classifier using the LDA-transformed features from the training set. The SVM learns to create an optional decision boundary that separates different individuals in the feature space. we used a linear kernel of SVM for LDA-/CDLDA transformed features. We trained two models each trained on LDA and CDLDA-transformed data.

Model evaluation

In this module, the model is evaluated by using model evaluation metrics. The models will be tested on the testing set to evaluate both class-dependent and class-independent algorithms of LDA.

ALGORITHMS

Class Independent: Linear Discriminant Analysis

1. Input: ORL dataset consists of images of 40 individuals and corresponding class label
2. Given a set of N classes xi, is each of length M, x(N × M) is

$$x = \begin{matrix} x(0,0), & x(0,1), \dots & x(1,M) \\ \vdots & \vdots & \vdots \\ x(N,0), & x(N,1), \dots & x(N,M) \end{matrix}$$

3. Compute the mean of each class

$$\mu_i = \frac{1}{n} \sum_{i=0}^{n} x_i$$

4. Compute the mean of all classes

$$\mu = \frac{1}{N} \sum_{i=0}^{c} \frac{n_i}{N} \mu_i$$

5. Calculate between-class matrix SB

$$S_B = \sum_{i=1}^{c} (\mu_i - \mu)(\mu_i - \mu)^T$$

6. Calculate with-in-class matrix SW

$$SW = \sum_{j=1}^{c} \sum_{i=1}^{n_j} (xij - \mu j)(xij - \mu j)^T$$

7. Calculate the eigenvalue and eigenvectors of the matrix W.

$$W = SW^{-1}SB$$

8. Select top-k eigenvectors corresponding to project the data onto it.
9. Project all the original data of images in the dataset on to lower dimensional space

Class dependent: Linear Discriminant Analysis

1. Input: ORL dataset consists of images of 40 individuals and corresponding class label
2. Given a set of N classes xi, is each of length M, x(N × M) is

$$X = \begin{matrix} x(0,0), & x(0,1), \dots & x(1,M) \\ \vdots & \vdots & \vdots \\ x(N,0), & x(N,1), \dots & x(N,M) \end{matrix}$$

3. Compute the mean of every class

$$\mu_i = \frac{1}{n} \sum_{i=0}^{n} x_i$$

4. Compute the mean of all classes

$$\mu = \frac{1}{N} \sum_{i=0}^{c} \frac{n_i}{N} \mu_i$$

5. Calculate between-class matrix sb

$$S_B = \sum_{i=1}^{c} (\mu_i - \mu)(\mu_i - \mu)^T$$

6. For every class ωj do..
7. Calculate with-in-class matrix SWj,

$$SWj = \sum_{xi \in \omega j}^{c} (xi - \mu j)(xi - \mu j)^T$$

8. Calculate the eigen value and eigenvectors of the Transformation matrix Wi

$$Wi = SWj^{-1}SB$$

9. Select top-k eigenvector to project data onto it.
10. Project all the data of each class image in the dataset onto lower dimensional space
11. End for
12. Train a support vector machine (SVM) classifier using the dimensionally reduced and feature extracted by using CDLDA data

IV. RESULTS AND ANALYSIS

To conduct the comparative study between class-independent and class-dependent algorithms of Linear Discriminant Analysis (LDA), several benchmark datasets were used, and their performance metrics were evaluated. The study aimed to assess the strengths and weaknesses of each approach in different scenarios and shed light on their suitability for various classification tasks. The following results and analysis provide insights into the comparative study.

Performance Comparison on ORL Dataset:

The comparison of both algorithms are evaluated by the following evaluation metrics

Accuracy: It measures the proportion of correctly classified samples out of the total number of samples.
Mathematically, accuracy is calculated as:
Accuracy = (Number of correctly classified samples) / (Total number of samples)

Precision: It measures the proportion of correctly predicted positive instances out of the total instances that were predicted as positive.
Mathematically, precision is calculated as:
Precision = (True Positives) / (True Positives + False Positives)

Recall: It measures the proportion of correctly predicted positive instances out of the total actual positive instances.
Mathematically, recall is calculated as:
Recall = (True Positives) / (True Positives + False Negatives)

F1-score: It combines both precision and recall into a single value that reflects the overall effectiveness of the classifier.
The F1 score is calculated as the harmonic mean of precision and recall, given by the following formula:
F1 score = 2 * ((Precision * Recall) / (Precision + Recall))

The following table shows the values of the evaluation metrics obtained from Face recognition using both class-dependent and class-independent algorithms of LDA

Algorithm	Accuracy	Precision	Recall	F1-score
LDA	82	83.2	82.0	80.4
CDLDA	96	94.7	96	95.01

Table 1:- The performance metrics of both Class independent and class-dependent algorithms of Linear Discriminant Analysis

During the comparative study between class-independent and class-dependent algorithms of Linear Discriminant Analysis (LDA), a detailed analysis was conducted on a benchmark dataset. The results revealed interesting findings where class-dependent LDA outperformed class-independent LDA in specific scenarios. Specifically, class-dependent LDA demonstrated superior performance in four particular samples: samples 1, 14, 28, and 40 of the dataset. The following analysis provides insights into these results

Algorithm	1	14	28	40
LDA	4/5	2/5	2/5	1/5
CDLDA	5/5	4/5	4/5	3/5

Table 2:- performance of LDA and CDLDA on four samples.

Confusion matrix: is a structured table that presents a machine learning model's performance. It displays the quantities of true positives, true negatives, false positives, and false negatives, serving as a fundamental tool to assess the precision and efficiency of classification algorithm

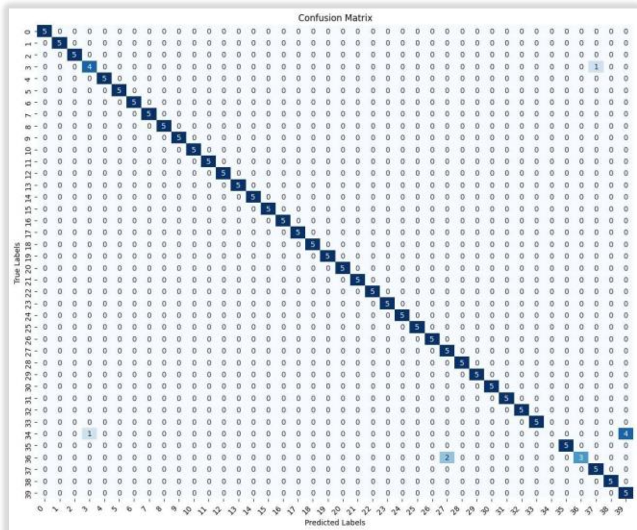

Figure 4: Confusion matrix for classification report of Class-dependent LDA

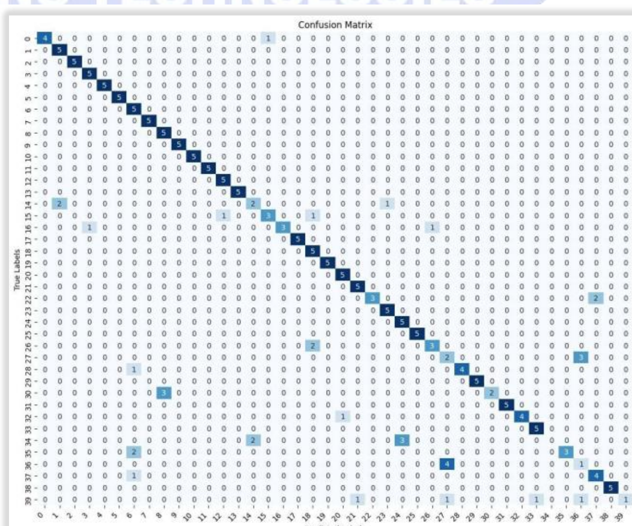

Figure 5: Confusion matrix for classification report of Class-Independent LDA

V CONCLUSION AND FUTURE WORK

The Main Objective of this project has been to Compare the Class Dependent and Class Independent algorithms of Linear Discriminant Analysis(LDA) under various evaluation metrics and find which Algorithm is better, we concluded that class-dependent LDA has shown better results which is 4% more than Class Independent LDA and these two algorithms of Linear Discriminant Analysis can be interchangeably depending on the demands of the Model. We concluded using metrics that Class-independent LDA has less run time and can be used when we require quick results, on the other hand, Class-Dependent LDA is more suitable for tasks where accuracy is preferred. Further, in future, we look to extend our project by improving the time required for the recognition or classification process and we would look to reduce the sensitivity of the model making it more suitable for real-world tasks. We would like to improve our project to perform better in various poses and also aim to make it accurate in various lighting levels having it resemble close to actual face recognition models. The aim is to improve the model in all possible aspects where there is scope for improvement.

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