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Face Recognition Using Incremental Learning

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ABSTRACT

Face Recognition has grown to become a most useful technology in a variety of applications in recent years with the advancement of technologies and digitalization. It plays a huge and significant role in safety and security services as well as reducing manual and unnecessary human labor. Machine Learning, a subset of Artificial Intelligence, has grown exponentially since the access and advancement of high-end computers increased. Previous methods for Face Recognition like PCA (Principal Component Analysis)rely upon the Static Datasetsbut the issue with the static datasets is that all the images of the faces may not be available before the training of the model. This problem is addressed by the concept of Dynamic Training Dataset which is implemented in the Incremental Learning Methodswhere the model continuously learns on the new data (images) added to the original dataset. Another advantage of dynamic training over batch-mode training is the option of addition and deletion of samples from the model and the time efficiency. The Real-Word Applications require a constantly evolving model with time which is provided by the Incremental Learning Methods. This paper aims to provide a comparative study of the performance of various types of incremental methods, be it Supervised, Unsupervised, Semi-Supervised, or Hybrid on different Face Datasets.

Keywords: Incremental Learning, Face Recognition, Machine Learning, Artificial Intelligence, Supervised, Unsupervised, Semi-Supervised, Hybrid

INTRODUCTION

Since the dawn of time, human identity has been defined by their faces. Face Recognition, which is an implementation of Machine Learning algorithms to make the machine extract and learn the facial features from the historical face data, is an active area of research in the Machine Learning community due to its important applications in fields like Safety, Security, Gaming, and Law Enforcement, Banking, etc.Face recognition is a one-to-many method that compares an input test image to all face templates used in training, with the result being the input test image's identity. The most challenging part of Face Recognition is Illumination, Pose Orientation, Face Rotation, Background, Occlusion, etc. One way to tackle these complex temporal and spatial variations is to have a large dataset that covers all these variations. Incremental Learning also helps with these challenges as the dynamic dataset is tend to increase with time.

Computer Vision

Computer Vision is a subset of Artificial Intelligence that deals with images and videos as input data. Computer Vision allows the computer to derive insights out of the data which are in the form of Images, Video, etc. Computer Vision is like the eye-brain functionality of Artificial Intelligence. It breaks down the image input data (labeled) into arrays of pixels and then performs various operations on it according to the implemented algorithm.

Image Processing

It is the core component of Computer Vision. It treats all the images as 2D signals and applies different types of signal processing to it like Visualization, Recognition, Sharpening, restoration, etc. An image can be identified as arrays of pixels where each pixel ranges from (0 to 255) and represents the intensity of a color (RGB – Red, Green, Blue) or (A – Opacity), its dimensions can be represented as Width x Height, for e.g., an image with dimension 800 x 600 has 240000 pixels.

FACE RECOGNITION USING INCREMENTAL METHODS

Incremental Learning solves the issues and challenges offered by the Face Recognition process especiallythe Data Availability issue prior to the training of the model. Incremental Learning addresses this issue by updating the new data as they arrive as single files or in batches to the dataset.

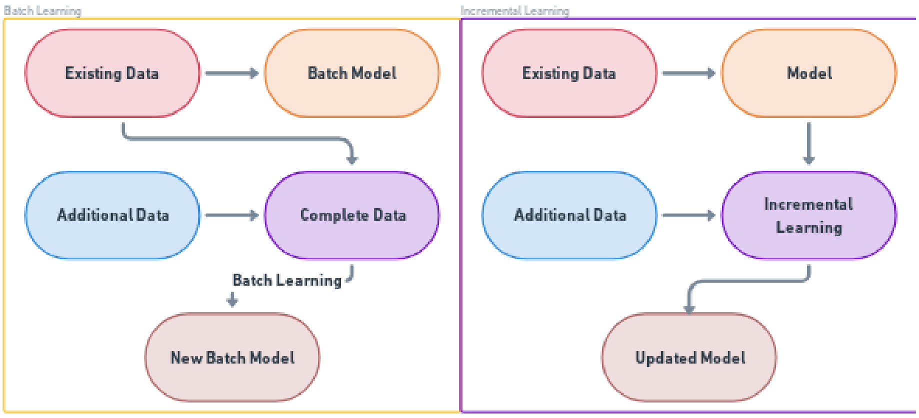

Fig 2.1: Process of Batch Learning vs Incremental Learning

There are different types of Incremental Learning which can be used to Implement a Face Recognition Model based on the kind of Dataset we have, whether it is labeled or unlabeled.

Primarily, Incremental Learning can be classified into 4 categories as given below:

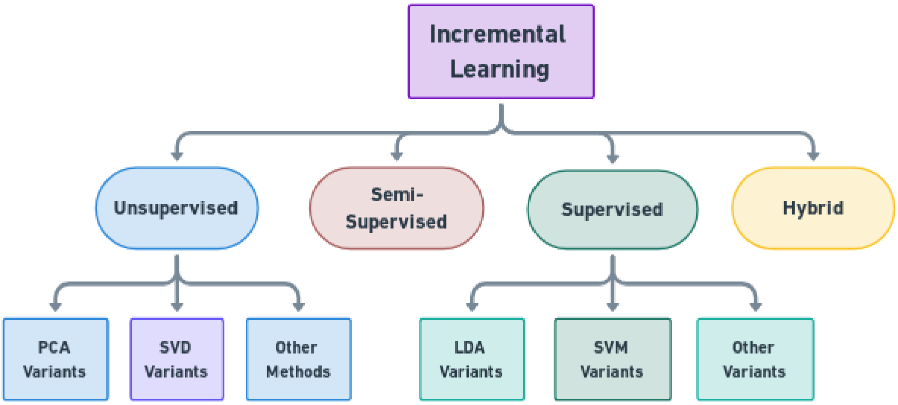

Fig 2.2: Different Types of Incremental Methods

Supervised Learning

In the case of Supervised Learning, we have a labeled dataset which means class information for each image. Supervised Learning tends to perform better than Unsupervised Learning in most cases as it has a goal to achieve i.e., class. That's why it is called Supervised Learning.

LDA Variants

The aim of the LDA (Linear Discriminant Analysis)is to distinguish between two or more classes by discovering the linear projections of the whole data assuming that all the classes have equal covariance gaussian structures. LDA is a widely adopted and successful method for dimension reduction and feature extraction. The challenging part in the case of LDA is that with the increase in the capability of handling complex data and the accuracy, the complexity in computation also increases. There are many variants of LDA proposed to address and encounter these challenges: NDA (Non-Parametric Discriminant Analysis), ILDA (Incremental LDA), GSVD-ILDA (Generalized SVD based Incremental LDA), DSLDA (Dual Space LDA), DLDA (Decremental LDA), etc.

SVM Variants

For Classification problems, SVM (Support Vector Machine) tried to find a hyperplane that exits in an N-Dimensional Space and is able to distinguish the data points on the basis of their classes. The N-Dimensional Space depends upon the number of features. This algorithm makes use of Support Vectors which are the data points close to the hyperplane. They influence the characteristics of the hyperplane. In the case of Incremental SVM, we discard the old data while keeping the support vectors and then train on the new data points added. So basically, "The key is to retain the Kuhn-Tucker (KT) conditions on all previously seen data, while adiabatically adding a new data point to the solution". Space complexity is a big challenge in SVM which can lead to an increase in training time. Some Variants of SVM are Incremental SVM with the use of DCT (Discrete Cosine Transformation) for preprocessing, Incremental SVM with Sigmoid Based and EVT (Extreme Value Theory) Calibration.

Unsupervised Learning

Unsupervised Learning deals with training on Unlabeled data where there is no information about the class of observation and recognizing the pattern among different observations on the basis of similarityand dissimilarities between them. These are cost-efficient methods as they don't require any manual labor to label the data.

PCA Variants

It is one of the most widely adopted dimensionality reduction techniques. It reduces the number of variables in a data (especially for the large and complex datasets) by transforming them into components while retaining the most amount of information in the components. Its goal is to simplify the complex data so it can be interpreted and visualized well as well as to avoid the curse of dimensionality.In the case of Incremental PCA (IPCA), the transformation coefficients matrix is updated on the fly for each new sample, eliminating the need to retain all of the samples in memory and IPCAalso tackles the memory issue when the dataset is too large to fit. These are some variants of Incremental PCA – Decay Based IPCA, Incremental 2D Reduction PCA, Incremental Bidirectional PCA, Batch Incremental PCA, etc.

SVD Variants

Singular Value Decomposition (SVD) is also a famous Dimension Reduction Technique and it is used to calculate the matrix inverse and other matrix-relatedoperations. It is used in linear regression (least squares), denoising the data, and as well as to perform compression of image data. Some of the SVD Variants are (RowIncremental Singular Value Decomposition), and Incremental Grassmann Kernel Learning based on ISVD which tackles the variation in expression, pose and lighting, etc.

Semi-Supervised Learning

Supervised Learning requires hand-labeled data which is rather a costly procedure whereas Unsupervised Learning doesn't require labeled data but its performance is worse and its range of application is limited as compared to the Supervised Learning, these disadvantages of both types of Learning are addressed by the Semi-Supervised Learning which is kind of a middle ground. It trains on the mixture of labeled and unlabeled data with more proportion of unlabeled data to keep the expenses of hand labeling as low as possible. Firstly, all the observations are clustered into clusters and then classes are assigned to the unlabeled data according to the labeled data within a cluster. Some proposed Incremental Semi-Supervised Learning Algorithms are Growing Neural Gas (GNG), Incremental SVM using PCA (One vs All), and Self-Organizing Incremental Neural Net (SONIN) based Incremental SVM, etc.

Hybrid Learning

Hybrid Learning is a step forward in the machine learning workflow that smoothly incorporates algorithms, methods, or procedures from comparable or dissimilar domains of knowledge or application areas with the goal of complementing each other. It employs different algorithms to handle the different processes in which they perform well. Some examples of Incremental Hybrid Learning are RAN-LTM (Resource Allocation Network with Long-Term Memory) Adaptive Ensemble of Classifiers based on IBC (Iterative Boolean Combination), CCIPCA (Candid Co-Variance Free Incremental PCA), MMPA (Min-Max Projection Analysis), STM-LTM, etc.

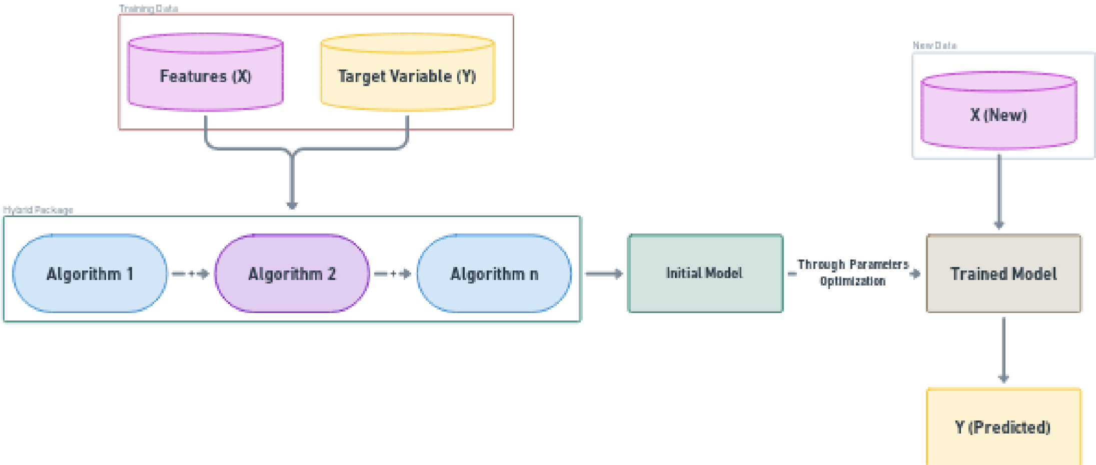

Fig 2.3: The Process of Hybrid Learning

METHODOLOGY

DATASETS

- **AR -**Martinez and Benavente generated this dataset in the Computer Vision Center (CVC) in 1998. It includes 126 photographs (70 males and 56 females) that capture illumination and expression. Its main feature is occlusions variation.
- **CACD–**created in 2015 by Chen et al. It features over 160k images of celebrities between the age of 16 to 62. Age variation is its main feature.
- **CASIA-WebFace -**Yi et al. (2014) created this dataset from the CBSR in 2014. There are 494,414 photos in the dataset, representing 10,575 people. It captures the variation in backgrounds.
- **CMU PIE –** Published from Carnegie Mellon University in 2001, PIE (Pose Illumination and Expression) has 41368 images of 68 individuals varying in illumination, pose and expressions.
- **FERET –** Compiled in 1993, It contains 14126 images of 1199 different people.
- **INDIA –** Created in 2011 contains variations in expression and pose of Indian Students.
- **LFW –** "Labelled Faces in the Wild" contains over 13k images of around 1680 individuals collected from the internet, it was created in 2007.
- **UCI –** It contains only 640 images equally distributed for 32 individuals having variations in facial features, expressions and poses. It was compiled in 1997.
- **YALE A/YALE B–** As suggested by the name the dataset was created by the Yale University. It has 576 photos of only 10 people. Its popular for pose and illumination variations as each individualhave 6 poses and 64 Illuminations. It was created in 1997.
- **EXTENDED YALE B–**Extension of the previous iterations, it has more quantity of images (161280 of 28 individuals. It was compiled in 2001.

ALGORITHMS

Various Incremental Algorithms which were introduced earlier in this study have been used for Performance Analysis on these mentioned Face Datasets in a comparative way.

RESULTS

Comparative Analysis of Different Incremental Algorithms on Different Face Datasets

Dataset	Feature Extraction Method	Classifier	Recognition Accuracy (%)
AR	DSLDA	Optimizationbased technique in	96.53
AR	Incremental 2D Two-Directional PCA	SVM	97.75
AR	IPCA	Neural Classifier	76.4
CACD	ISVM	Active Learning based SVM	91
CASIA-WebFace	ISVM	Active Learning based SVM	77
CMU PIE	Semi-supervised DiscriminantAnalysis	Semi-supervised DiscriminantAnalysis	99.5
CMU PIE	Bidirectional PCA	NearestNeighborClassifier (NNC)	99
CMU PIE	Maximum Margin Criterion	NNC with Cosine similarity	89
CMU PIE	Generalized SVD—ILDA	Minimum distance classifier	81
FERET	ISVD—Grassman Manifold mapping	N/R	99.37
FERET	2DPCA	Frobenius Distance Classifier	78
INDIA	ILDA	NNC with Euclidean distance	97
LFW	ISVM	SVM	84
LFW	ISVD—Grassman Manifold mapping	N/R	84

UCI	Incremental NDA	NNC with Euclidean Distance	98.91
Yale A / Yale B	ISVD—Grassman Manifold mapping	N/R	95.26
Yale A / Yale B	Incremental NDA	NNC	89.9
Extended Yale B	ILDA	N/R	99.9
Extended Yale B	2DPCA	NNC	56.56

CONCLUSION

This study introduces the various methods of Increment Learning for Face Recognition and shows its advantages over Batch Learning Methods. Most of the Traditional Machine Learning uses the Batch Learning Methods but in reality, all the data required to train a robust model is just impractical to get prior to training. Incremental Learning solves this issue where there is no need to retrain the entire model with the addition of new data. We have compared results (recognition accuracy) of different Incremental learning methods which were trained and evaluated on different Face datasets and compared them which clearly shows that Incremental Algorithms have high performance and they have advantage of high speed which makes them the perfect candidates for the implementation in various Real-Time Applications in a variety of fields like Video Surveillance, Online Gaming, Security and safety, Anomaly Detection, etc. There are four types of Incremental Methods used that are Supervised, Unsupervised, Semi-Supervised and Hybrid Learning based. They were implemented according to the nature (labeled or unlabeled) and complexity (Small or Large) of the dataset used. The challenging parts are the variations in Pose, Expressions, Face, Occlusions, Background, Illumination, etc. which can be accounted for by the use of specific datasets and various preprocessing steps can also help overcome these challenges.

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