

# Traditional Dimensionality Reduction Techniques using Deep Learning



K.M.Monica , R.Parvathi

**Abstract:** From the analysis of big data, dimensionality reduction techniques play a significant role in various fields where the data is huge with multiple columns or classes. Data with high dimensions contains thousands of features where many of these features contain useful information. Along with this there contains a lot of redundant or irrelevant features which reduce the quality, performance of data and decrease the efficiency in computation. Procedures which are done mathematically for reducing dimensions are known as dimensionality reduction techniques. The main aim of the Dimensionality Reduction algorithms such as Principal Component Analysis (PCA), Random Projection (RP) and Non Negative Matrix Factorization (NMF) is used to decrease the inappropriate information from the data and moreover the features and attributes taken from these algorithms were not able to characterize data as different divisions. This paper gives a review about the traditional methods used in Machine algorithm for reducing the dimension and proposes a view, how deep learning can be used for dimensionality reduction.

**Keywords:** dimensionality reduction, Principal Component Analysis, Non Negative Matrix Factorization, Random projection, variables, deep learning.

## I. INTRODUCTION:

Dimension Reduction is referred as the method of converting a cluster of data with many dimensions into the data with lesser dimensions ensuring that it conveys alike information in a brief way. These techniques are characteristically used for solving a machine learning problem which is a subset of Artificial intelligence to obtain better features for regression task and for classification. When dealing with data of high dimension, statistical and machine reasoning methods face many problems and generally the variables that are given as input are reduced prior to the application of data mining algorithm.

It is been found that dimension reduction is done in two ways, one is by holding the most appropriate variables from the original set of data which is known as feature selection and the other one is by exploiting the redundancy of the data which is taken as input and also by finding a very small group of latest variables where each reflect a group of the input variables, contains generally the same and similar old information as the input variables which is known as dimensional reduction.[22]

Compared with feature selection, feature extraction has gained attention and more interest in the quiet few years, and several branches have shown extensive progress, including algorithms like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Non-negative Matrix Factorization (NMF), Locally Linear Embedding (LLE), etc.[23]. Supervised and unsupervised are the two different approaches of Dimensionality Reduction. [10]

The most probable functions that plot input data to the target outputs can be done by Machine learning. In case of redundant attributes or noise in the input data, the facility of generalizing the input using Machine Learning algorithms will be affected unconstructively, and hence feature extraction and dimension reduction techniques like PCA, NMF and RP are used to preprocess the training data to have a better and efficient performance. Though data analytics has found application in many sectors, it causes its own problems and one of them is known as “curse of dimensionality” and dimensionality reduction is used to overcome this problem.

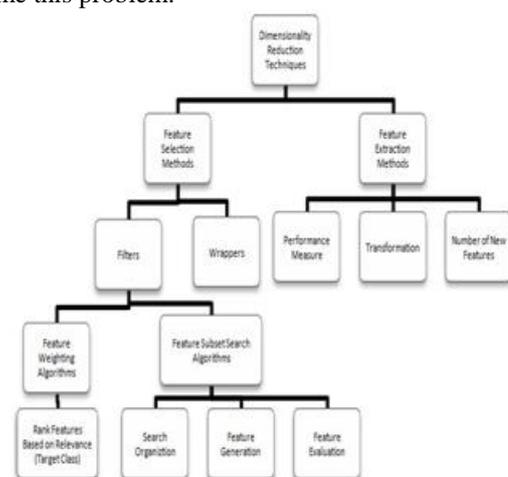


Fig 1: Hierarchical Structure of Dimensionality Reduction Techniques.

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## II. TRADITIONAL DIMENSIONALITY REDUCTION TECHNIQUES:

It is noted that dimension reduction is the process of dropping several random variables for consideration, to obtain a set of principal variables. Dimensionality reduction approaches in a traditional way fall into two major categories as feature extraction and feature selection.

Based on these approaches some of the traditional dimensionality reduction techniques are discussed.

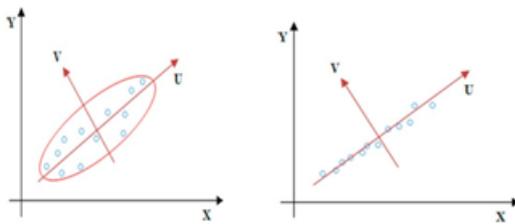
1. PCA - Principal Component Analysis
2. NMF - Non Negative Matrix Factorization
3. RP - Random Projection
4. SVD -Singular Value Decomposition
5. AE - Auto Encoder

### A.Principal Component Analysis:

Dimensionality reduction is the process of reducing random variables of the dataset, where reducing the variables may lead to information loss and this is where DR techniques are used. PCA is a holistic based algorithm which is an example for feature extraction method.

- PCA allows projection of data towards the directions where the data vary.
- Once it is projected these directions are captured by the eigen vectors of the covariance matrix which is found equivalent to the large Eigen values.
- Size of the Eigen values corresponds to the variance of the data all along the vector directions.

In case of finding the features or attributes of a distributed dataset based on the variance, it is considered PCA to be the statistical method. In X-Y coordinate system multivariate distributed data is given (Fig. 2), PCA first tries to find the utmost changes in the given data sets and later the data points are anticipated to a newly formed axis called UV coordinate system. The direction which is produced by this U and V-axis is known as principal components.



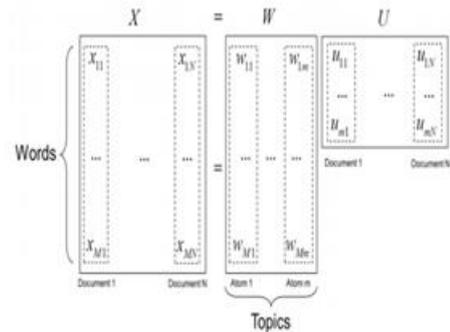
**Fig 2: PCA: (a) adjusted axis (b) variable v is discarded**

In U-axis the data variation is shown and followed by the orthogonal direction, V-axis is also shown (a). The data points on V- axis are seen very close to zero shown in Figure 2 (b), the data set can be represented by only one variable U and the variable V is remaining. [17]

### B.Non Negative Matrix Factorization:

Feature vectors with negative components are produced which is considered as a drawback for many dimensionality reduction techniques. This algorithm matrix V is factorized into matrices as W and H having the feature where the three elements of the matrices don't have any negative elements

and hence this effect makes the matrices result easier to examine. It is considered to be novel paradigm for dimensionality reduction and it obtains part based representation.[26] The main objective of NMF is to factorize a matrix into two non negative matrices where the product reconstruct the original data matrix which is used highly in main domains like signal processing, machine learning, deep learning, text mining and so on. The two important properties of NMF are sparsity and interpretability. [43] NMF is also termed as parts based algorithm that achieves dimensionality reduction by projecting the data towards the positive basis matrix by retaining and holding the commonly occurring parts among the data. [1] It is distinguished from other methods like PCA and SVD by its feature of non negativity constraint. It is advantageous for applications involving large matrices. [44] Nonnegative Matrix Factorization (NMF) is one of the most promising behaviors for dimension reduction in unsupervised learning, and is extended from two-matrix to triple-matrix factorization. The Standard Decomposition Dictionary  $X=WU$  is taken in which W is considered as dictionary, (of size  $M * m$  its columns which are named as atoms of the dictionary) and U (of size  $M * m$ ) is referred as the expression of the observations in the subspace. [24]



**Fig 3: Every document is decomposed as linear combination which is given by the weights in U of the topics (atoms) contained in W.**

### C.Random Projection:

The reason behind the original data with high dimension which is projected towards onto a lower dimensional space by a random matrix is because of random projection which is found to be computationally efficient. It is proved to be a precise approach for dimension reduction with high dimensional data set. RP is considered as one of dimensionality reduction tool which is used on high dimensional image and text data.[34] Random Projection consist of Gaussian Random Vectors which has been normalized to unit norm and the theoretical based results indicate that RP can preserve the gap between any data points as well as the structure of data. [35]

### D.Auto Encoder:

It is defined as unsupervised machine learning algorithm which is applied for back propagation by setting the target values to be equal to the inputs. The input is represented as a code that is described inside the hidden layer.

Autoencoder [32] is a structure with unique neural network which is made up of three layers namely input, output and hidden layer. By some implementation of training methods it adjust the weights of the layer that are hidden to enable the input and output value to be seen as close to each other which makes the hidden layer to realize unsupervised feature extraction which is considered as one of the important feature.

Autoencoders are similar to the Principal Component Analysis (PCA), which can reduce dimensions of data [33]. Though auto encoder belongs to neural network, they are closely related to PCA as said earlier. It can represent both linear and non linear transformation in encoding. It can be layered to form deep learning network due to its network representation.

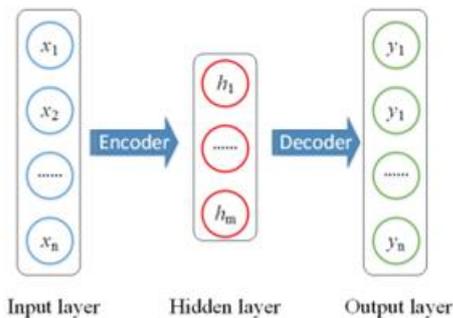


Fig 4: Autoencoders framework

In the above figure Autoencoders framework is shown that has the input layer as  $(X_1, X_2, \dots, X_n)$ , hidden layer  $(H_1, H_2, \dots, H_m)$ , and output layer  $(Y_1, Y_2, \dots, Y_n)$  and the weights of hidden layer symbolize attributes of the input signal.[31]

**E.Singular Value Decomposition:**

SVD leads data from high dimensional representation to a low dimension through matrix and hence it is considered to be an important algorithm. Since less number of dimensions is chosen, the less accurate will be the approximation. So SVD gives an appropriate representation of any matrix that is chosen where it is found effortless to eliminate a reduced amount of important parts of that matrix representation so that it turns out to be a fairly accurate representation with any desired number of dimensions. [41]

Consider  $M$  which denotes  $m \times n$  matrix, and the rank of  $M$  is named as  $r$ . The rank of a matrix is found to be the largest number of rows (or equivalently columns) where we can choose linear combination of the rows is all-zero vector  $0$  (we say a set of such rows or columns is independent). Then we can easily find the matrices  $U$ ,  $\Sigma$ , and  $V$  as shown in Figure 5 by considering the following properties listed below.

1.  $U$  is considered as  $m \times r$  column-orthonormal matrix; that is, each of its columns is a unit vector and the dot product of any two columns is 0.
2.  $V$  is considered as  $n \times r$  column-orthonormal matrix. It is noted as  $V$  is used as transposed form, so it is the rows of  $V^T$  that are orthonormal.
3.  $\Sigma$  is a diagonal matrix since all elements not on the main diagonal. The elements of  $\Sigma$  are called the singular values of  $M$ . [42]

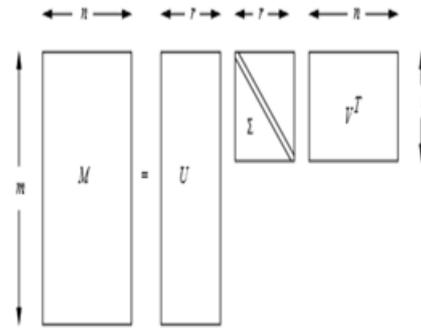


Fig 5: Singular-value decomposition form

**III. DIMENSIONALITY REDUCTION TECHNIQUES USING DEEP LEARNING:**

**A. Flownet: Deep learning framework:**

[8] A group of streamlines or stream surfaces are taken which is generated from flow field data set, the approach of flownet is to convert the data set into binary volumes and autoencoder is used to learn their latent feature descriptors. Once it is reconstructed, feature descriptors can represent flow lines in latent space. Dimensionality reduction is then performed for these feature descriptors and accordingly the projection results are clustered. This paper generates the feature descriptors generated from flownet and dimensionality reduction is done with the input of distance matrix and then similar objects are grouped via clustering. Mapping of 3D to 2D images for network training can be explored efficiently in future.

**B. Multiple Imputations:**

[7]Recently many embedding Dimensionality Reduction methods were developed to arrest the ‘Curse of Dimensionality’, but these methods cannot directly employ on data sets that are incomplete. The limitations are addressed by developing general methods for non linear dimensionality reduction with missing data. A high dimension extension of Gaussian Mixture Model is applied on the incomplete data set and then later employed under multiple imputation paradigms and thus the cost function expectation is minimized. The fitting of these Gaussian mixtures are difficult in High Dimensional spaces and therefore efficient HD extensions exist for reducing their number of parameters. Here the missing data in dimensionality reduction is processed under the multiple imputation paradigms and hence this provides a meaningful Low dimensional representation of each data point, though it seems missing values.

**C. Extreme Machine Learning Algorithm:**

[1]Extreme Learning Machine which is efficient is hierarchical learning which is proposed to train single hidden layer feedforward neural networks. The outputs that are generated from ELM hidden nodes are referred as ELM feature mapping and can be used for reducing the dimensions.

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Dimension reduction framework is introduced up to some extent where data is represented as different divisions, which has fast learning speed. This tries to reduce the distances of data points belonging to the same cluster. This algorithm learns features more localized than PCA, while not localized as NMF.

### D. Local Deep feature Alignment Algorithm:

In this paper for dimension reduction a framework unsupervised deep learning framework is used naming local deep feature alignment (LDFA).[3] This approach of local deep algorithm is used to map a newly formed data sample and learn about low dimensional subspace. Experimental results in this paper show that LDFA method is competitive and give accurate results when compared to other several well known dimensionality reduction techniques. This algorithm LDFA is used as a preprocessing step for image visualization, clustering and mainly for classification.

### E. Ensemble Discriminative Local Metric Learning:

[2]Hyperspectral images of high dimensional data space many times results in ill conditioned formulations. To overcome this problem Distance Metric Learning is applied for reducing the dimensions. But this was not appropriate for all training samples, therefore proposed an algorithm called as (EDLML) Ensemble Discriminative Local Metric Learning for hyperspectral images. Based on much experimental analysis, the distance metric used data region by region, it confirms the effectiveness and efficiency of proposed EDLML algorithm when compared with other Dimensionality reduction methods. With fewer training samples EDLML algorithm provided better quality classification performances to the traditional dimensionality reduction. By this algorithm optimization can be improved.

### F. Soft Margin Support Vector Machine Algorithm:

Various Dimensionality reduction methods such PCA, LDA AND KLDA are used and the difference between each methods lies in their optimization objective [6]. To improve the optimization objective, the margin between different classes is maximized, after projecting the original features into low dimensional subspace. This is implemented with the help of Soft Margin Support Vector Machines. Since the experiment is based on real world datasets, in addition of reducing redundant information it is also robust to noise. It is a promising dimensionality reduction method that is simple and effective in reducing the dimensions.

### G. Dimensionality reduction using Covariance Operators:

[14]In real valued multivariate labels, it is considered that the problem of dimensionality reduction is treated as Dimensionality Reduction for Regression (DRR), aims to discover a low dimension illustration, which is considered as the central subspace of input data that gives protection to the correlation with targets. A novel method is proposed as Covariance Operator Inverse Regression (COIR).This proposed method overcomes the problem that arises in DRR which exploits the notion of IR (Inverse Regression) and also other IR techniques that depend on explicit output space slicing. This paper shows a link between COIR and other

DRR techniques. Based on this a new solution is found to the problem of DR for regression in this paper.

### H. Intrinsic Dimension Estimation:

[27]In knowledge discovery in database, dimensionality reduction is considered to be an important step. In earlier cases, the two common methods used for intrinsic dimension estimation are box counting and correlation dimension. But the robustness in these methods was not evidently considered. Hence a clear picture about the robustness of these two methods with respect to data sample size is shown in this paper. It is noted that there will not be any change in the intrinsic dimension by adding up or removing the redundant variable completely in or from a dataset. Hence based on this observation an algorithm named Supervised Feature Selection can be developed for continuous output variables. Experiments based on the dimensionality reduction on data sets which have collected from real world have demonstrated the effectiveness and efficiency of feature selection method based on intrinsic dimension estimation.

### I. Data imputation using Deep Belief Network:

[28]In case of the handling the process in industry, while collecting some data, there occur a data loss because of human error, noise during the transmission, which have an effect on the entire quality of data. In addition to this, the data that are collected is usually composited with a large volume of data with high dimension. Many features are examined from DBNs (Deep Belief Network) because they can clearly express high dimension non linear function from a variety of variables. Hence it is used to crack the problem of data processing in industrial control system. Apart from this, Denoising is proposed and used in DBNs model to resist the noise from the various data which is incomplete. This paper concludes with the statement that DBN algorithm along with denoising can be used in case of missing value imputation and also for the dimensionality reduction in industrial process control systems.

### J. Dimensionality Reduction based on Ant Colony Algorithm:

This paper proposes a co operative search technique known as ant colony algorithm which is used in dimensionality reduction and classification for hyper spectral remote sensing image [30]. The transformation taken place from high dimensional data space into low dimensional data space is done by an algorithm named as Ant Colony. In this paper PCA is also used in subspace for extracting features. The main objective in decomposition of data space by using Ant Colony Algorithm is to strengthen the correlation intra bands. ACA is mainly benefitted for data clustering. The classification experiment results done in this paper shows the accuracy improvement by comparing with the standard PCA method. The results are proved to be better when comparing with the standard PCA.

**K. Dimensionality Reduction in Multiple antenna wireless networks:**

[36]In this paper, a distributed wireless network is considered and its crisis of Multi Antenna Source Detection with dimension reduction is taken. The distributed algorithm is designed in this wireless network which reduces the computational burden in case of maintaining high detection algorithm by projecting the unprocessed data into low dimensional data. For this purpose, a sketching matrix is constructed in this paper, which transmits the data into the

fusion center for source detection. From the survey it is seen that two stage dimension reduction techniques is adopted. In the first stage low dimensional sketching is constructed and in the second stage subspace method is used for the transformation of low dimensional matrix into vector. It is been concluded in this paper the proposed method Multiple antenna wireless networks maintains a very high detection performance. The simulation method showed the effectiveness on dimension reduction in the proposed method.

**TABLE 1: Dimensionality Reduction Techniques in Deep Learning**

Paper Details	Input	Output	Method	Advantages	Future Gap
Jun Han, Jun Tao, IEEE	Image with high dimension	Image with reduced dimension	A single deep learning framework called as FlowNet.	Proposed method is able to analyze hidden features of stream surface inside a single framework which is done in unsupervised learning.	In future this paper can explore a design of deep neural that learn the complicated relationship between input and output.
Cyril de bodt, Dounia mulder, Michel Verleyesen, IEEE	Text with missing data	Low Dimensionality data	Parametric multiple imputations	It minimizes cost function expectation.	The proposed method is not most efficient in facing extremely HD data. Due to increase in parameters, Gaussian mixtures find difficult. Hence alternate model is developed to deal with inherent sparsity of very HD spaces.
Jian Zhang, Jun Yu, Dacheng Tao, IEEE	Digits, Images	Low dimensionality of digits and images	Local Deep Feature alignment	This method studies both local and global features and attributes from data sample set	This method can be proposed for text in future.
Shaung Zhou, Junping Zhang, Baoku Su	Remote sensing Image	Dimension reduced Image	Ant Colony Algorithm	The method has higher Classification accuracy.	This method can be proposed for text in future.
Minyoung Kim, Vladimir Parloric	Image	Reduced dimension image	Covariance Operator Inverse Regression	This method appears as a congested form of solution to the problem of dimension reduction for regression	This method was not applicable for text and hence in future it can be explored.

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Liyaanaaracchi Lekamalage chamara kasunm, Yan yang, Guang Bin Huang, zhengyou zhang, IEEE	Data with noise and irrelevant information.	Data with reduced dimension.	Extreme Machine Learning.	The methods learn features more localized than PCA.	This method can be applied for image reduction in future.
Yanni Dong, Bo Du,Liangpei zhang, Lefei zhang	Hyperspectral images	Image with reduced dimension	Ensemble discriminative Local Metric learning.	This method provides better-quality classification performance with very few samples to the traditional dimensionality reduction.	Future work focuses on how to improve the optimization in order to increase the computational efficiency and classification accuracy.
Ruipeng Dong, Huo Meng, Zhiguo Long, Hailiang zhao	Real world data set containing numeric characters.	Data with dimension reduced	Soft Margin Support Vector Machine.	This method improves the performance on classification and also it is robust to noise.	Future work can be applied to image and text.
Xinwei Jiang, Junbin Gao, Tianjiang Wang,Daming	Iris data set	Dimension reduction by 2D visualization	Thin Plate Spline Latent Variable Model	Compared to other models it is best suited to low dimensional smoothing problems, such as data visualization in 2D/3D space.	TPSLVM can be used in computer vision tasks like face recognition and modeling human motions.

**Table 2: Traditional Dimension Reduction Techniques**

ALGORITHM	FEATURES	DRAWBACKS
PCA(Principal Component Analysis)	<ol style="list-style-type: none"> <li>1. Versatile technique</li> <li>2. Fast, simple to implement</li> <li>3. Offers several variations and extensions.</li> </ol>	<ol style="list-style-type: none"> <li>1. not interpretable</li> </ol>
LDA(Linear Discriminant Analysis)	<ol style="list-style-type: none"> <li>1. Improves predictive performance of extracted features.</li> </ol>	<ol style="list-style-type: none"> <li>1. not interpretable</li> <li>2. Requires labeled data</li> <li>3. Not appropriate for real time practical datasets</li> </ol>

AE(Auto Encoder)	1. They perform well on image and audio data	1. Require more data to train. 2. Not used as general purpose DR algorithm.
RP(Random Projection)	1. Simple yet powerful technique 2. Computationally efficient.	1. It doesn't have universal approximation capability.
NMF(Non negative Matrix Factorization)	1. Improves performance on non linear dimensionality reduction.	1. It is mathematically unjustified
SVD(Single Value Decomposition)	1. Useful in machine learning and in both descriptive and predictive statistics.	SVD is not an algorithm, it is just matrix decomposition and hence, its speed and quality cannot be defined.

### III CONCLUSION:

The prime objective that is found from this survey paper is to make available about the information on different kinds of Dimensionality Reduction techniques that is used and identify various methods that are used to reduce the dimensions in order to improve the accuracy of algorithms in Machine Learning. Therefore it is observed and noted that in order to select an appropriate method for reducing the dimensions, the dataset type and specific requirement of algorithms in machine learning, should be measured. The intent at the back of this survey is to provide an absolute and clear understanding of different kinds of algorithms used in Dimension Reduction and to have an idea about how to evaluate the rising importance of this field during the few years ago. In this paper we have randomly analyzed different methods used in diverse papers, where each of these methods requires different criteria. At the same time it is found that all these methods have same goal of reducing the complexity and also deliver an appropriate form of the information. This paper also gives understandable initiative of comparison of some dimensional techniques. The quality of big data will extend to enlarge over time and this is factual for data collected from large surveys. It is believed that dimension reduction techniques provide an efficacious strategy for the study of data.

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