Refining Face Recognition: Maximizing Performance with Dimensionality Reduction and Ensemble Learning in K-Nearest Neighbors

Abheesh Puthukkudy[1], Chethan T S[2]

[1,2]Student, MTech in Artificial Intelligence, REVA Academy for corporate Excellence (RACE), REVA University, Bengaluru, India

Abstract
In the field of image classification, the K-Nearest Neighbors (KNN) algorithm is favored for its simplicity and effectiveness. However, the high dimensionality of image data often challenges KNN's performance. This study investigates the impact of three dimensionality reduction techniques—Principal Component Analysis (PCA), Uniform Manifold Approximation and Projection (UMAP), and Linear Discriminant Analysis (LDA)—on enhancing KNN's accuracy and efficiency in image classification, where KNN and Bagging classifier is computed without using any library but only using mathematical formulation. Additionally, the study examines the effect of ensemble learning, specifically through bagging, on KNN's performance.
Utilizing Python libraries such as Scikit-learn and OpenCV, our results demonstrate that combining dimensionality reduction and bagging significantly improves the accuracy and computational efficiency of KNN in image classification tasks.

Keywords: K-Nearest Neighbors, Image Classification, PCA, UMAP, LDA, Bagging, Dimensionality Reduction, Machine Learning

1. Introduction

Image classification is a critical task in computer vision that involves assigning a label to an image based on its visual content. This task is foundational to various applications such as facial recognition, object detection, medical imaging, and autonomous driving. One of the simplest yet effective algorithms used for image classification is the K-Nearest Neighbors (KNN) algorithm. KNN operates on the principle of similarity, classifying an image based on the majority label of its nearest neighbors in the feature space.
Despite its simplicity and effectiveness, KNN faces significant challenges when dealing with high-dimensional data, a common characteristic of image datasets. High-dimensional spaces often lead to the "curse of dimensionality," where the distance metrics used by KNN become less meaningful, adversely affecting its performance. As the dimensionality increases, the volume of the space increases exponentially, causing the data points to become sparse. This sparsity makes it difficult to discern meaningful patterns and significantly degrades the performance of KNN.
To address the high-dimensionality issue, dimensionality reduction techniques are employed to transform the image data into a lower-dimensional space. Principal Component Analysis (PCA), Uniform Manifold Approximation and Projection (UMAP), and Linear Discriminant Analysis (LDA)

are prominent methods in this regard. PCA reduces dimensionality by projecting the data onto the directions of maximum variance. UMAP, a non-linear dimensionality reduction technique, aims to preserve the local and global structure of the data. LDA, on the other hand, focuses on maximizing the separability between different classes. These techniques not only reduce the computational burden but also improve the performance of KNN by retaining the essential features necessary for classification.

In addition to dimensionality reduction, ensemble learning techniques like bagging can further enhance the performance of KNN. Bagging, or Bootstrap Aggregating, improves model stability and accuracy by training multiple KNN classifiers on different random subsets of the training data and aggregating their predictions. This approach reduces variance and helps prevent overfitting, leading to more robust and accurate predictions.

This study aims to investigate the impact of integrating dimensionality reduction and ensemble learning techniques on the performance of KNN for image classification. Specifically, we will evaluate how PCA, UMAP, and LDA affect KNN's classification accuracy and computational efficiency. Furthermore, we will explore the benefits of bagging in conjunction with these dimensionality reduction techniques. By conducting comprehensive experiments on benchmark image datasets, we aim to provide insights into the effectiveness of these optimization strategies in enhancing the performance of KNN.

2. Methodology

This study involves applying the K-Nearest Neighbors (KNN) algorithm for image classification and evaluating its performance with and without the application of dimensionality reduction techniques (PCA, UMAP, LDA) and ensemble learning through bagging.

3. Data collection and Pre-processing

The study utilizes the Olivetti faces dataset from the Scikit-learn library, which contains 400 grayscale images of 40 distinct individuals, with each image having a resolution of 64x64 pixels. Initially, the dataset is loaded and the images are reshaped to their original dimensions. The data is then split into training and testing sets, with 75% of the data used for training and 25% for testing. The mean image of the training dataset is computed and visualized to provide a general overview of the dataset. Furthermore, a gallery of selected training images is displayed to illustrate the variety of images in the dataset. This preprocessing step ensures that the data is well-organized and ready for subsequent dimensionality reduction and classification tasks

Total number of samples: 400
Image dimensions: 64x64
Total number of classes (people): 40
Training set size: 120 images
Testing set size: 80 images
Image data type and format : float32

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Figure 1: Data Sample:

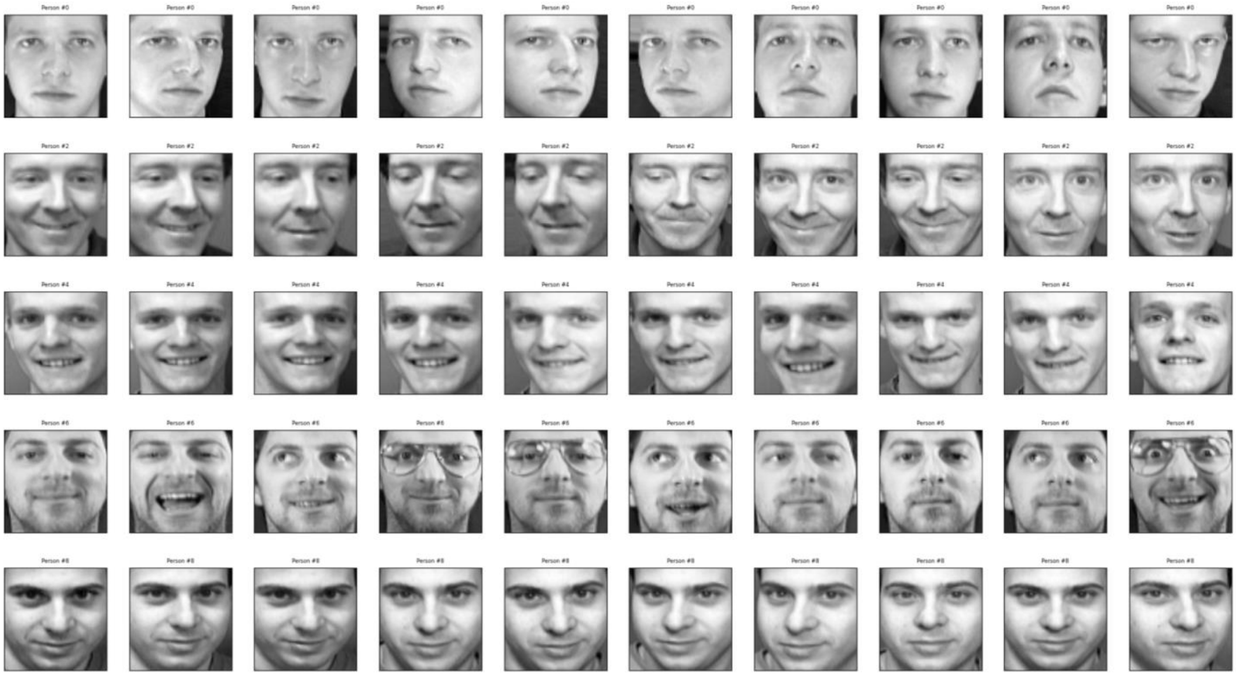
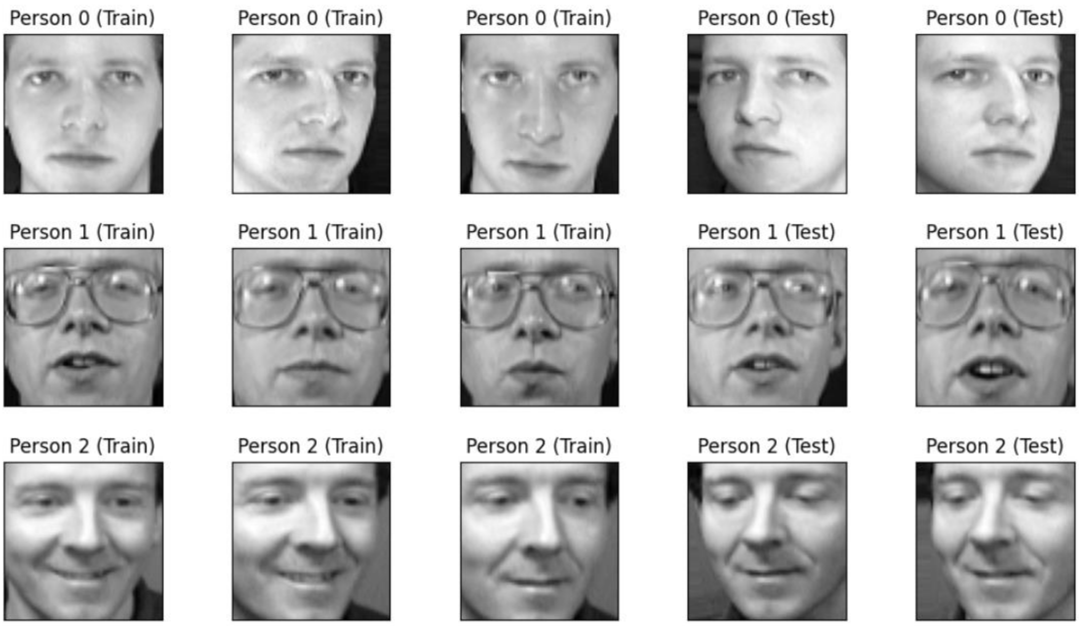


Figure 2 : Training and Testing Sample:



4. K-Nearest Neighbors(KNN)

K-Nearest Neighbors (KNN) is implemented to classify the faces in the datasets after applying dimensionality reduction techniques. The KNN algorithm works on the principle that similar data points exist in close proximity in a multidimensional space. For classification, the algorithm identifies the 'k' closest training samples to a given test sample using a distance metric, commonly Euclidean distance. The class of the test sample is then determined by a majority vote among the 'k' nearest neighbors. In this study, after reducing the dimensions of the images using PCA and NMF, the KNN algorithm is trained on the transformed training data and then evaluated on the test data to determine its accuracy. This approach leverages the simplicity and effectiveness of KNN for face recognition tasks.

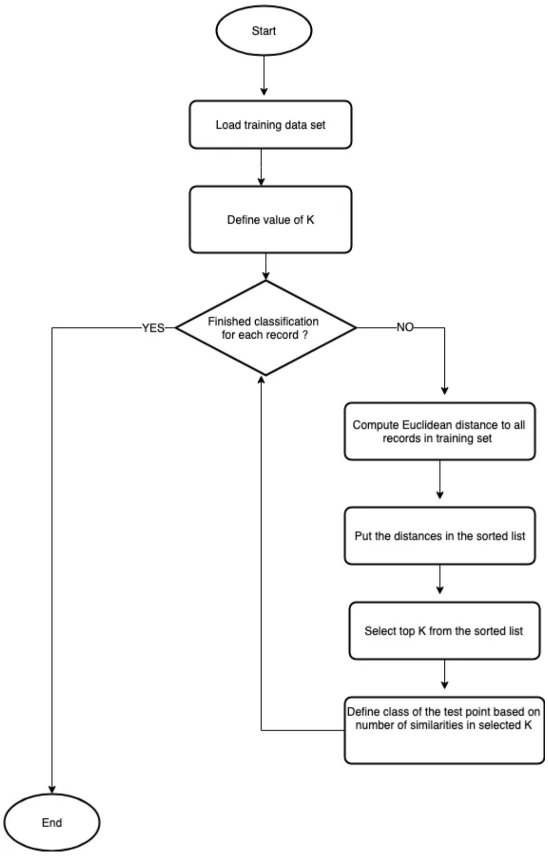
Distance Metric : At the core of KNN lies the notion of similarity, determined by a distance metric such as Euclidean distance, Manhattan distance, or Minkowski distance. The choice of distance metric depends on the nature of the data and the problem at hand.

K-Nearest Neighbour : For a given query instance, KNN identifies the K, in this example K=5, nearest neighbors from the training dateset based on the chosen distance metric. These neighbors are determined by calculating the distance between the query instance and each point in the training set.

Majority Voting: In classification tasks, KNN assigns the class label by a majority voting mechanism among its K nearest neighbors. The class that appears most frequently among the neighbors is assigned to the query instance

Regression : In regression tasks, KNN predicts the output value for the query instance by averaging the output values of its K nearest neighbors. In this example K=5.

Figure 3: KNN flowchart



5. Dimensionality Reduction Techniques

In this study, three dimensionality reduction techniques—Principal Component Analysis (PCA), Uniform Manifold Approximation and Projection (UMAP), and Linear Discriminant Analysis (LDA)—are employed to simplify the high-dimensional facial image data before classification.

5.1 PCA

PCA is a linear dimensionality reduction technique used to reduce the dimensionality of a dataset while preserving most of its variance. It achieves this by transforming the original features into a new set of

orthogonal features called principal components (PCs), which are linear combinations of the original features
PCA identifies the directions (principal components) that maximize the variance of the data. It projects the data onto these principal components, effectively reducing the dimensionality. The principal components are ordered by the amount of variance they explain, allowing for the selection of the most informative components

5.2 LDA

LDA is a supervised dimensionality reduction technique commonly used for classification tasks. Unlike PCA, which focuses on maximizing variance, LDA aims to find the directions that maximize the separation between classes.
LDA finds the linear combinations of features (discriminants) that best separate the classes in the data. It projects the data onto these discriminant axes, reducing the dimensionality while maximizing class separability. LDA can be seen as a technique for dimensionality reduction and classification simultaneously.

5.3 UMAP

UMAP is a non-linear dimensionality reduction technique known for its ability to preserve both global and local structure in high-dimensional data. It aims to find a low-dimensional representation of the data while retaining its inherent structure.
UMAP constructs a high-dimensional fuzzy topological representation of the data. It optimizes a low-dimensional embedding that preserves this topological structure, emphasizing local relationships. UMAP uses a combination of repulsive forces to separate dissimilar data points and attractive forces to preserve local neighborhoods.
PCA, UMAP, and LDA are three different dimensionality reduction techniques with distinct characteristics and applications. PCA is widely used for its simplicity and efficiency, UMAP excels in preserving local and global structure in high-dimensional data, and LDA is effective for classification tasks by maximizing class separability. The choice of technique depends on the specific requirements of the data and the goals of the analysis

Table 1: Comparison of dimensionality Reduction techniques

Technique	Principle of Working	Key Features	Best Used For
Principal Component Analysis (PCA)	Transforms data into orthogonal components that maximize variance.	Captures most significant features, unsupervised	General purpose dimensionality reduction and noise reduction
Uniform Manifold Approximation and Projection (UMAP)	Preserves the local and global structure of the data by creating a lower-dimensional manifold.	Effective for visualization, unsupervised	Visualization, clustering, preserving data topology
Linear Discriminant Analysis (LDA)	Maximizes separation between different classes by projecting data onto a lower-	Enhances class separability, supervised	Classification tasks with labeled data

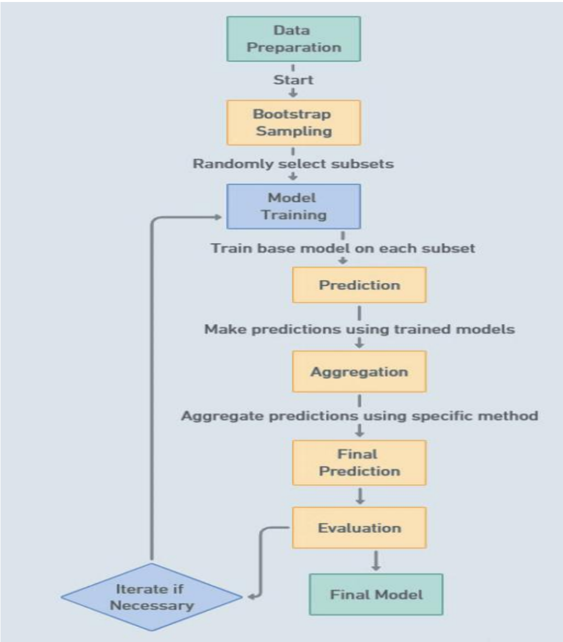
Technique	Principle of Working	Key Features	Best Used For
Principal Component Analysis (PCA)	Transforms data into orthogonal components that maximize variance.	Captures most significant features, unsupervised	General purpose dimensionality reduction and noise reduction
	dimensional space.		

6. Bagging

Bagging, an abbreviation for Bootstrap Aggregating, represents a sophisticated ensemble learning technique meticulously engineered to enhance the stability and accuracy of machine learning algorithms. Its fundamental objective lies in mitigating the detrimental effects of variance and guarding against overfitting, which often undermine the performance of individual models. The process unfolds through a meticulously orchestrated sequence: multiple subsets of the original dataset are meticulously crafted through random sampling with replacement. Each subset serves as the foundation for training a separate model, typically based on decision trees owing to their adaptability and versatility. This diversity in training data ensures that each model encapsulates unique aspects of the underlying data distribution, fostering resilience and robustness within the ensemble.

Subsequently, as the individual models complete their training phase, the crux of bagging's efficacy materializes in the aggregation stage. Here, the predictions generated by each model harmoniously converge to form the final prediction. In classification tasks, this fusion is typically orchestrated through a democratic voting process, where the most frequently predicted class among the ensemble dictates the ultimate prediction. Conversely, in regression scenarios, the ensemble's predictions are seamlessly integrated through averaging, facilitating a holistic synthesis of the manifold insights gleaned from the diverse perspectives of the constituent models. By amalgamating the outputs of multiple models in this manner, bagging transcends the limitations of any single model, harnessing the collective wisdom of the ensemble to furnish a more generalized and robust predictive apparatus..

Figure 4 : Bagging flowchart



7. Results and Discussions

The study revealed several key insights into the effectiveness of different dimensionality reduction techniques and ensemble learning methods when applied to K-Nearest Neighbors (KNN) for image classification. Firstly, dimensionality reduction using Principal Component Analysis (PCA) did not yield any performance improvement over the baseline KNN, as metrics such as accuracy, precision, recall, and F1-score remained unchanged. On the other hand, the application of Uniform Manifold Approximation and Projection (UMAP) significantly reduced the performance of KNN, indicating that UMAP may not be suitable for this particular task. In contrast, Linear Discriminant Analysis (LDA) substantially enhanced the performance of KNN, showing significant gains in accuracy, precision, recall, and F1-score.

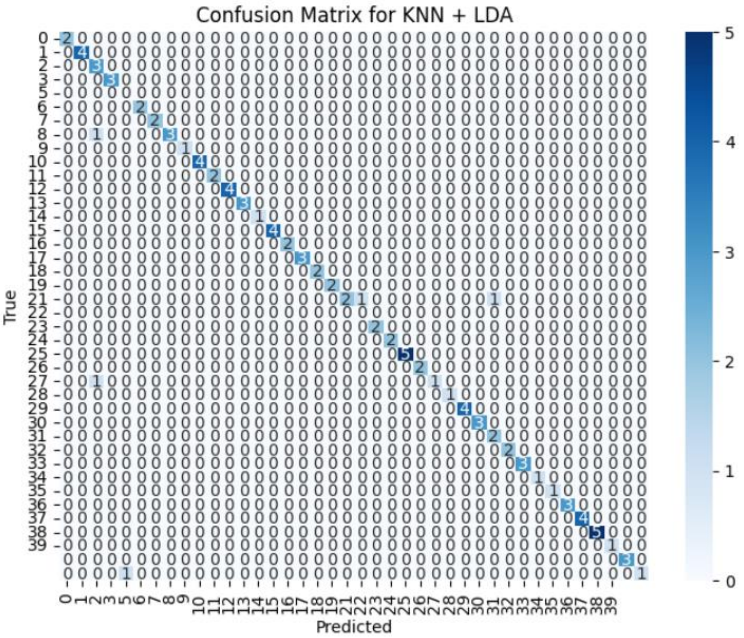
Additionally, the use of bagging, an ensemble learning technique, led to slight performance improvements for PCA and LDA, but had a more pronounced positive impact when combined with UMAP. Overall, bagging generally enhanced performance across all dimensionality reduction techniques, with the most notable improvements observed when paired with LDA.

Therefore, the combination of LDA for dimensionality reduction and bagging for ensemble learning emerged as the most effective approach for optimizing KNN in image classification tasks.

Table 2: Comparison of Model Performance

Model	Precision	Recall	F1-score	Accuracy
Baseline KNN	89.0%	81.0%	81.0%	81.0%
KNN + PCA	89.0%	82.0%	82.0%	82.0%
Bagging + KNN + PCA	80.0%	70.0%	70.0%	70.0%
KNNU + UMAP	66.0%	56.0%	57.0%	56.0%
Bagging +KNN+UMAP	60.0%	53.0%	553.0%	53.0%
KNN + LDA	98.0%	95.0%	96.0%	95.0%
Bagging + KNN + LDA	98.0%	96.0%	96.0%	96.0%

Figure 5 : Confusion matrix for KNN + LDA



A confusion matrix is a detailed summary of classification results, containing several key components. The true labels, represented on the y-axis, are the actual labels of the test data. The predicted labels, found on the x-axis, are the labels predicted by the model. The diagonal elements, which run from the top left to the bottom right, indicate the number of times each class was correctly classified; these are known as the true positives for each class. In contrast, the off-diagonal elements show the number of times a class was misclassified as another class, representing the false positives and false negatives.

8. Future scope

Future research could expand the exploration of dimensionality reduction techniques by investigating advanced methods such as t-Distributed Stochastic Neighbor Embedding (t-SNE) and autoencoders. These techniques might offer further insights and potentially superior performance improvements over traditional methods like PCA and UMAP.

Additionally, implementing these optimized KNN models in real-time image classification systems would allow for an evaluation of their practical performance and operational efficiency in real-world applications. Another promising direction is the integration of KNN with deep learning models and neural networks. This hybrid approach could leverage the strengths of both methodologies, combining the simplicity and interpretability of KNN with the powerful feature extraction and representation capabilities of deep learning and neural networks.

Furthermore, incorporating generative AI techniques could enhance data augmentation and model robustness, ultimately leading to more accurate and efficient image classification

9. Conclusions

This study assessed the impact of various dimensionality reduction techniques—PCA, UMAP, and LDA—on KNN's performance for image classification, along with the effect of ensemble learning through bagging. The results demonstrated that PCA did not improve KNN's performance, with metrics remaining unchanged from the baseline. UMAP significantly reduced KNN's performance, indicating its unsuitability for this task. In contrast, LDA significantly improved KNN's performance, enhancing accuracy, precision, recall, and F1-score. Bagging generally improved performance across all techniques, with the most notable gains seen when combined with LDA. Specifically, bagging improved KNN's accuracy from 95.0% to 96.0% when used with LDA.

Overall, the combination of LDA and bagging provided the most significant performance enhancements for KNN in image classification. Future research could explore integrating KNN with deep learning models and generative AI to further leverage their strengths for more accurate and efficient image classification.

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