CME LIVE OPEN ACCESS

Electrical Electronics Engineering: Open Access

Case Report

Evaluating the Impact of Kernel PCA on Machine Learning Performance Insights from Mnist Digit Classification

Amir Mehrabinezhad[1*], Mohammad Teshnehlab[2] and Arash Sharifi[1]

[1]Department of Computer Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran.

[2]Faculty of Electronic and Computer Engineering Department, K.N Toosi University of Technology, Tehran, Iran.

Corresponding Author: Amir Mehrabinezhad, Department of Computer Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran.

Received: 2024 Aug 13 **Accepted:** 2024 Sep 02 **Published:** 2024 Sep 09

1. Introduction

Kernel Principal Component Analysis (Kernel PCA) is an advanced dimensionality reduction technique that extends the classic Principal Component Analysis (PCA) to handle non-linearly separable data by applying kernel methods. This approach has been particularly influential in machine learning, especially in the context of complex datasets where traditional linear methods fall short. In this report, we evaluate the impact of Kernel PCA on machine learning performance, specifically focusing on MNIST digit classification, a standard benchmark in the field of machine learning.

Kernel Pca: A Brief Overview

Kernel PCA leverages kernel functions to map input data into a high-dimensional feature space, where linear PCA can be applied. This transformation allows Kernel PCA to capture intricate patterns and non-linear relationships in the data that traditional PCA might miss. Common kernels include the polynomial kernel, the radial basis function (RBF) kernel, and the sigmoid kernel. By projecting the data into this high-dimensional space, Kernel PCA can uncover hidden structures and relationships that are critical for enhancing classification performance [1].

Impact on Mnist Digit Classification

The MNIST dataset, comprising 70,000 handwritten digits (60,000 training and 10,000 test images), provides a comprehensive challenge for machine learning algorithms. Each image is a 28x28 pixel grayscale image, resulting in a 784-dimensional feature space. Given the high dimensionality and the complexity of the data, Kernel PCA offers a compelling method to reduce dimensionality while preserving crucial features [2].

Dimensionality Reduction and Feature Extraction

Kernel PCA can significantly reduce the dimensionality of the MNIST dataset while preserving the essential characteristics of the digit images. By transforming the data into a higher-dimensional space and then applying PCA, Kernel PCA can identify a lower-dimensional representation that captures non-linear structures. This process can lead to more efficient computation and potentially improve the performance of subsequent machine learning algorithms. For instance, applying Kernel PCA with an RBF kernel can reveal clusters of digits that are not linearly separable, thus aiding in better feature extraction [3].

Performance Improvement

The impact of Kernel PCA on performance is often measured in terms of classification accuracy, computational efficiency, and generalization. For MNIST digit classification, Kernel PCA typically improves the accuracy of machine learning models compared to those using raw pixel data or standard PCA. This improvement is attributed to the ability of Kernel PCA to capture non-linear patterns that are crucial for distinguishing between similar digits. Empirical studies have shown that classifiers such as Support Vector Machines (SVMs) or Neural Networks trained on Kernel PCA-reduced features can achieve higher accuracy compared to models trained on the original [4].

Computational Efficiency

While Kernel PCA offers significant improvements in classification accuracy, it is essential to consider its computational cost. Kernel methods can be computationally intensive, especially for large datasets like MNIST. The transformation of data into a high-dimensional space and the subsequent dimensionality reduction process can be resource-intensive. However, the trade-off between computational cost and classification performance often justifies the use of Kernel PCA, especially when dealing with complex datasets that benefit from non-linear extraction [4, 5].

2. Conclusion

Kernel PCA represents a powerful tool for enhancing machine learning performance, particularly in the context of

Citation: Mehrabinezhad, A., Teshnehlab, M., Sharifi, A. (2024). Evaluating the Impact of Kernel Pca on Machine Learning Performance Insights from Mnist Digit Classification. Electrical Electronics Engineering: Open Access. 1(1), 1-2.

complex datasets like MNIST. By addressing the limitations of linear PCA and capturing non-linear structures in the data, Kernel PCA can lead to significant improvements in classification accuracy and feature extraction. However, the computational cost associated with kernel methods should be carefully managed. Overall, Kernel PCA's ability to reveal intricate patterns and improve performance makes it a valuable technique in the machine learning toolkit, offering notable benefits for tasks such as digit classification and beyond [6,7].

References

1. Chin, T. J., Suter, D. (2007). Incremental kernel principal component analysis. IEEE transactions on image processing, 16(6), 1662-1674.
2. Njue, M., Franklin, B. (2020). Dimensionality Reduction on MNIST dataset using PCA, T-SNE and UMAP.
3. Hoffmann, H. (2007). Kernel PCA for novelty detection. Pattern recognition, 40(3), 863-874.
4. Plesovskaya, E., Ivanov, S. (2022). Hierarchical classification on the mnist dataset using truncated side and kernel density estimation. Proceeded Computer Science, 212, 368-377.
5. Shinde, A., Sahu, A., Agley, D., Runger, G. (2014). Preimages for variation patterns from kernel PCA and bagging. Iie Transactions, 46(5), 429-456.
6. Mehrabinezhad, A., Teshnehlab, M., Sharifi, A. (2024). A comparative study to examine principal component analysis and kernel principal component analysis-based weighting layer for convolutional neural networks. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 12(1), 2379526.
7. Tonin, F., Tao, Q., Patrinos, P., Suykens, J. A. (2024). Deep Kernel Principal Component Analysis for multi-level feature learning. Neural Networks, 170, 578-595.

Citation: Mehrabinezhad, A., Teshnehlab, M., Sharifi, A. (2024). Evaluating the Impact of Kernel Pca on Machine Learning Performance Insights from Mnist Digit Classification. Electrical Electronics Engineering: Open Access. 1(1), 1-2.