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# PCA METHOD IMPACT ANALYSIS ON DEEP NEURAL NETWORKS ACCURACY AND ARCHITECTURE FOR IMAGE CLASSIFICATION

**Anastasiia NESKORODIEVA**
PhD student,
Cherkasy State Technological University,
Cherkasy, Ukraine.
e-mail: neskorodieva.a@gmail.com.
https://orcid.org/0000-0002-8591-085X

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*The growth of visual data in modern information systems creates a need to reduce the computational complexity of classification methods. This paper presents the impact study of data preprocessing by the Principal Component Analysis (PCA) method on the effectiveness of training and classification ability of deep neural networks. The focus is on a comparative analysis of two architectures — the Multilayer Perceptron (MLP) and the Convolutional Neural Network (CNN). The work is aimed at solving the urgent scientific and practical problem of optimizing computing costs in computer vision systems operating in conditions of limited hardware resources. Based on the analysis of experimental data obtained on the MNIST image set, a comparative analysis of four architectural approaches was performed: classical MLP, classic CNN, hybrid PCA+MLP, and hybrid PCA+CNN. The effect of loss of spatial locality during image transformation by the PCA method, which leads to deterioration of the results of CNN-based models, as opposed to reduction of computational complexity of MLP-based models while maintaining classification accuracy, is studied. The paper provides a combined image classification method, an analysis of the obtained accuracy metrics and loss function, as well as a justification of the observed phenomena. The conducted study allows us to draw conclusions about the feasibility of using the PCA method in image classification problems in combination with MLP. The results show the importance of aligning data preprocessing methods with the architectural features of machine learning models. In both hybrid models, the number of parameters was reduced by 4 times, while the PCA+MLP training time was reduced by 2 times with an accuracy of 97.87%, and the PCA+CNN training time was reduced by 8 times with an accuracy of 95.02%. The PCA+MLP hybrid model is found to have 4 times lower computational complexity and 12 times less training time than CNN, with a small accuracy loss of 1.5%.*

*Keywords: convolutional neural network, multilayer perceptron, principal component analysis, combined image classification method, deep learning.*

## Introduction

The task of image classification is one of the key ones in modern information systems. It underlies many application solutions in the fields of computer vision, medical diagnostics, security systems, autonomous vehicles and intelligent information and analytical systems. The rapid growth of visual data, as well as the increase in image resolution, leads to a complication of computational processes associated with their processing and analysis. In this context, the problem of ensuring high accuracy of classification under conditions of limited computing resources is of relevance.

Deep learning methods, in particular CNN, today demonstrate the highest accuracy rates in image classification problems [1]. At the same time, such models are characterized by a significant number of parameters, high requirements for computing resources and memory, as well as a long training time. This limits the possibilities of their application in real-time systems, embedded devices and mobile platforms. In this regard, there is a need to find approaches that reduce the complexity of deep learning models without a critical loss of classification quality.

The urgent task of modern data science is to find the optimal balance between classification accuracy and computational efficiency. One of the promising areas for solving this problem is the use of methods to reduce the dimensionality of data before feeding it to the input of a neural network.

The principal component method (PCA) is a classic statistical tool that allows you to project multidimensional data into a space of smaller dimensionality while maintaining maximum variance. The hypothesis of this study is that the combination of PCA with deep neural networks can allow the creation of compact models that can work efficiently on devices with limited resources.

This paper examines the impact of PCA on two fundamentally different architectures: MLP, which treat the image as a plane vector, and convolutional networks, which consider the local topology of the image [2, 3]. Attention is paid to analyzing the trade-off between classification accuracy and computational complexity of models, as well as quantifying the impact of dimensionality reduction on the efficiency of different neural network architectures.

Previous experimental studies have confirmed the effectiveness of MLP and CNN for classification tasks in rhythmic gymnastics, demonstrating consistently high recognition results on current samples [4,5,6]. However, with the projected growth of training data, optimizing the architectural complexity of the algorithms used becomes important. Therefore, future research should focus on finding a balance between increasing the model's dimensionality and maintaining its computational efficiency to ensure real-time performance.

The remainder of this paper is structured as follows: related works, proposed technique, experimental results, discussion, conclusions.

## Related Works

The principal component method has traditionally been seen as a powerful tool for decorating variables and eliminating noise. In papers comparing the efficiency of classical algorithms (SVM, k-NN) on MNIST, it is often noted that the use of PCA can reduce training and inference time, and in some cases increase accuracy by eliminating multicollinearity between pixels. For example, studies show that reducing the dimensionality of feature space can have a positive effect on the performance of classifiers sensitive to the "dimensionality curse", such as k-NN, where distances in multidimensional space lose their discriminative capacity [7].

However, with the advent of deep learning, the focus of research has shifted to the integration of PCA with neural networks. There are works suggesting hybrid architectures such as PCANet, where PCA is used to train convolutional layer filters, effectively replacing the backpropagation step of the error in the feature extraction stage. This approach allows you to achieve fast convergence and high accuracy on simple data sets. Another line of research concerns the use of PCA to compress activations in the deep layers of the network or to initialize scales, which helps to stabilize the learning process [8].

However, the question of using PCA as an input preprocessing method for CNN remains controversial. Several researchers point out that the linear transformation carried out by the PCA destroys the spatial structure of the image. Since the main components are linear combinations of all the pixels in the image, they do not store the pixel neighborhood information that is fundamental to the convolution operation. In papers devoted to the analysis of hyperspectral images, PCA is often used to reduce spectral dimensionality (number of channels) while maintaining spatial dimensionality (width and height), which allows for efficient application of 2D or 3D CNN [9]. This is fundamentally different from the approach where PCA is applied to spatial coordinates, converting a two-dimensional image into a one-dimensional feature vector, effectively destroying the object's topology.

The paper proposes a hybrid model combining PCA and CNN using transfer learning based on DenseNet [10]. The authors demonstrated that the integration of the pre-trained DenseNet model avoids overtraining and achieves an accuracy of 89.82% on the CIFAR-10 dataset, which is higher than that of the conventional PCA-CNN architecture.

Comparative studies on the Fashion-MNIST dataset confirm that CNNs consistently outperform MLP and other methods due to their ability to automatically learn the hierarchy of spatial features [11]. At the same time, studies on the effects of PCA on MLP demonstrate that for MLP, reducing the dimensionality of the input vector can be positive because it reduces the number of parameters of the first layer, preventing overtraining and speeding up computation. This creates an interesting dichotomy: what is positive for one architecture (MLP) can be detrimental to another (CNN).

It is also important to note the works analyzing the effect of the number of main components on the accuracy of classification. It has been empirically established that there is a certain threshold for the number of components, after which the addition of new features does not lead to a significant improvement in the result, and sometimes even worsens it due to the addition of noise. For the MNIST dataset, this threshold is often in the range of 40 to 200 components, allowing more than 90% variance to be stored.

Thus, the existing literature points to the complex and ambiguous nature of the interaction of dimensionality reduction methods with deep neural networks. This study aims to systematize this knowledge and provide clear quantitative evidence of the impact of PCA on different types of architectures in the context of the image classification problem, filling a gap in understanding the mechanisms of information loss when spatial locality of data is violated.

Despite the above, no study has conducted a systematic side-by-side quantitative comparison of all four configurations (MLP, CNN, PCA+MLP, PCA+CNN) on identical hardware under identical conditions, which is precisely the gap this work addresses.

## Proposed technique

The combined approach to image classification, proposed in this paper, involves the sequential execution of two stages of data processing. At the first stage, the dimensionality of the input images is reduced using the main component method. In the second stage, the resulting compact representations are fed to the input of a neural network, which performs a direct classification.

The Principal Component Analysis method is a dimensionality reduction technique that projects data from a high-dimensional space into a lower-dimensional space, maximizing the variance of the data along new axes (principal components) [12,13].

Let $X$ be an input matrix of dimension $N \times D$, where $N$ is the number of images (samples) and $D$ is the number of features (pixels). For the MNIST set, N = 60000, D = 28 × 28 = 784.

The PCA algorithm includes the following steps:

1. Mean Centering: You need to move the data distribution center to the origin.

$$X_{centered} = X - \mu \tag{1}$$

where $\mu$ is the vector of average values.

2. The covariance matrix Σ describes the paired correlations between pixels calculated using the formula:

$$\Sigma = \frac{1}{N-1} X_{centered}^{T} X_{centered} \tag{2}$$

The dimension Σ is $D \times D$ (784×784). The $\Sigma_{ij}$ element shows how much the brightness of the $i$-th pixel changes with the $j$-th pixel.

3. The SVD method is used to find the eigenvectors $v$ and the eigenvalues $\lambda$ of the matrix Σ.

$$\Sigma \mathrm{v} = \lambda v \tag{3}$$

The eigenvectors (Eigenvectors) determine the directions of the principal components, and the eigenvalues (Eigenvalues) determine the amount of data variance along these directions.

4. The selection of components occurs by sorting eigenvectors in descending order of eigenvalues. To reduce the dimensionality, the first k vectors are chosen, which explain the required percentage of variance (for example, 95% or a fixed number of k=196)

$$W_k = [v_1, v_2, \dots, v_k] \tag{4}$$

5. Projection: The input data is projected onto a new subspace

$$X_{reduced} = X_{centered} \cdot W_k \tag{5}$$

The result (1-5) is a matrix $X_{reduced}$ of dimension $N \times k$ (60000×196). In this study, the number of principal components was determined by retaining 96.5% of the total variance in the training data, which resulted in k=196 components for the MNIST dataset. We use k components that are square (e.g. $14^2 = 196$) to provide a square shape to feed into the CNN.

The software implementation of the proposed combined classification method is performed in the Python programming language in the Jupyter Notebook interactive computing environment, consisting of an AMD EPYC 7B12 CPU (2 CPUs, 1 core per socket, 2 threads per core, 2249.998 MHz) with 12 GiB of RAM and an NVIDIA Tesla T4 GPU with 15 GiB of VRAM (CUDA 13.0). For the construction, training, and validation of neural networks, the functional API of the Keras library (as part of the TensorFlow framework) was used, and the tools of the Scikit-learn library were used for data preprocessing and the implementation of dimensionality reduction algorithms [14, 15]. To conduct the experiment, a MNIST dataset was selected, which contains 60,000 images for training and 10,000 images for testing [16]. Each image is a black-and-white drawing of a handwritten number measuring $28 \times 28$ pixels. Previous data processing involved normalizing pixel values to the range [0, 1], which is a standard procedure for accelerating convergence of gradient optimization methods.

Step-by-step process of integrating PCA with neural networks. First, the MNIST dataset is loaded, and the input images are flattened from 28×28 matrices into one-dimensional vectors of 784 elements and normalized to the [0, 1] range. Next, a PCA model is fitted exclusively on the training set, retaining 96.5% of total variance, and the resulting transformation is applied to both the training and test sets — yielding compressed representations of dimension k=196. For the PCA+CNN configuration, the compressed vectors are subsequently reshaped into 14×14 two-dimensional matrices to match the expected input format of the convolutional layers. The class labels are one-hot encoded into categorical vectors of dimension 10, after which the neural network is trained and evaluated on the transformed data.

## Experiments

Presented in Fig. 1 visualization of step-by-step data processing demonstrates the impact of reducing dimensionality on the structure of visual information. The top row displays the original reference images from the MNIST dataset, which are characterized by high definition and preserved spatial topology, where adjacent pixels form intelligible geometric primitives. The bottom row shows the result of the reverse reconstruction of objects to the original space, where the recovered digits retain their global structure and recognizability, but lose high-frequency detail and boundary clarity, confirming the nature of the PCA method as a lossy compression algorithm that isolates the most significant data variations by filtering out noise and fine details.

In the study, four different architectural configurations were developed and tested, which differ in the way data input is presented. All models were trained using the Adam optimizer with hyperparameters (learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\varepsilon$ = 1e-07), a batch size of 64 samples, for 10 epochs, with a validation split of 20% of the training data. Training data was shuffled before each epoch. Model evaluation was performed on the test set using the same size batch of 64. The first model was a CNN working directly with a three-dimensional image tensor. The architecture of this network consists of a sequence of two convolutional blocks.

The first block contains a convolution layer with 4 filters and a subsampling layer (MaxPooling), which reduces the spatial dimensionality of feature maps to 14 by 14, Fig. 2 (c). The second unit expands the number of channels to 16 filters, further reducing the dimension to 7 by 7. The obtained features are transformed into a one-dimensional vector and fed to a MLP layer with 256 neurons, followed by the initial classification layer. The total number of parameters of this model is 205250, which provides a balance between network capacity and learning speed.

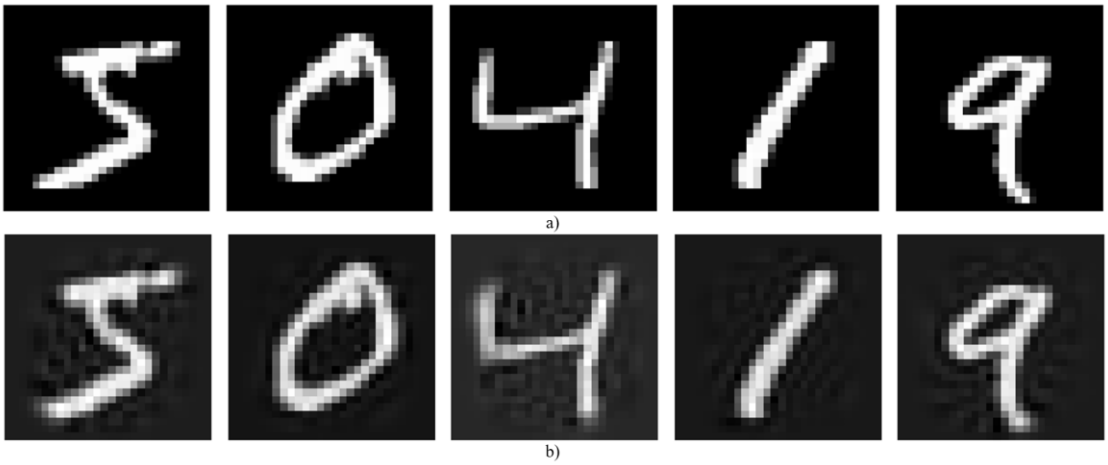

**Fig.1. a) samples of handwritten digits from the MNIST dataset; b) samples of handwritten digits from the MNIST dataset after reconstruction with 196 principal components.**

For the CNN model, the accuracy and loss plots for the training and validation samples during training are shown in Fig. 3 (a).

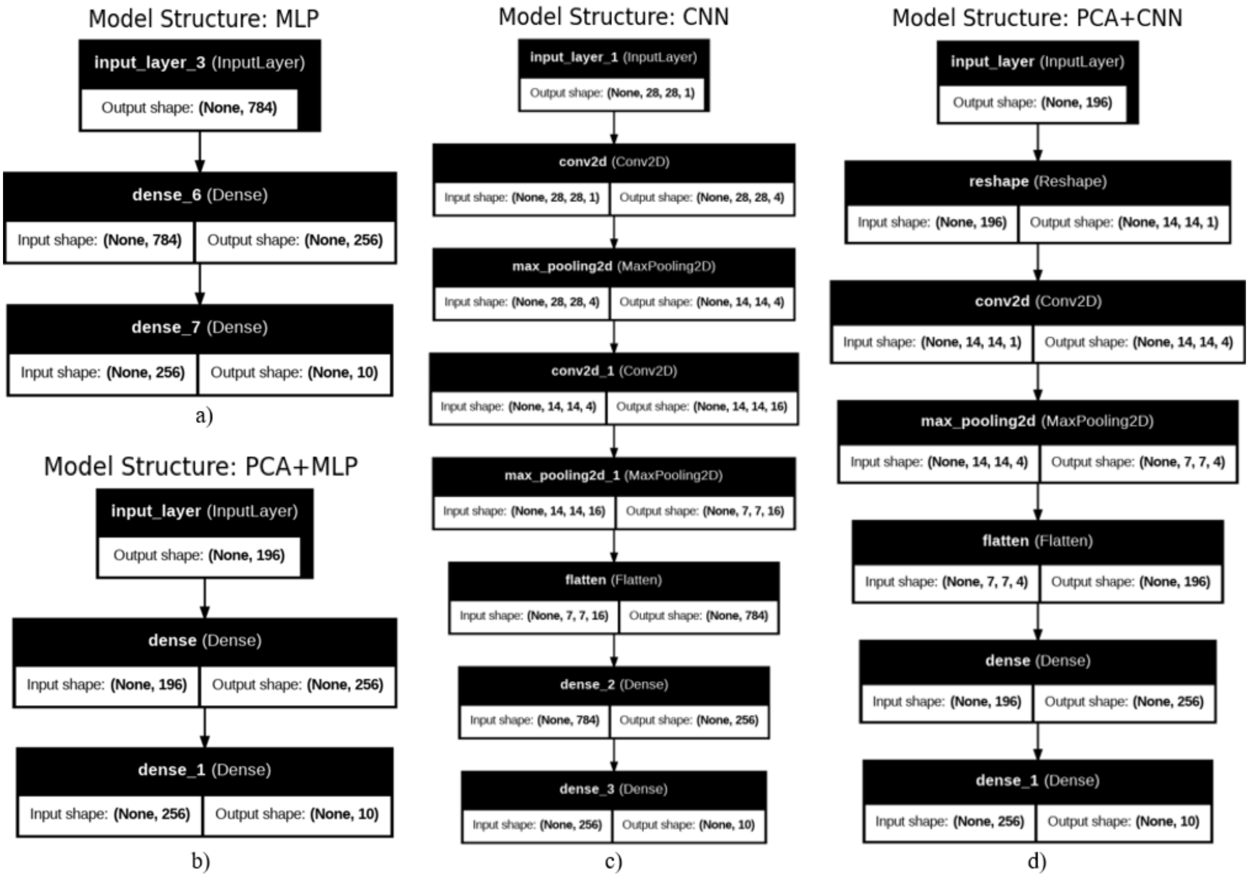


**Fig.2. Model Structure: a) MLP; b) PCA+MLP; c) CNN; d) PCA+CNN**

An alternative to the convolutional approach is the classical MLP, which takes a vectorized image with a length of 784 elements as input, Fig. 2 (a). Due to the lack of a local perception mechanism and shared weights characteristic of CNN, the first hidden layer of this model is forced to form connections with each pixel of the input image. This leads to an high computational complexity, in the number of parameters to 203530, increasing the risk of overtraining and increasing the requirements for computing resources. For the MLP model, the accuracy and loss plots for the training and validation samples during training are shown in Fig. 3 (b).

To investigate the effect of dimensionality reduction on learning performance, the PCA was used. The number of components was limited to 196, equivalent to a 14×14 dimension, which is a quarter of the original dimension of the feature space, Fig. 2 (b). The PCA+MLP hybrid model receives a compressed feature vector as input, which made it possible to reduce the number of network parameters to 53002, almost four times less compared to the basic version. This solution is aimed at filtering noise and isolating the most variable features even before the stage of training the neural network. For the PCA+MLP model, the accuracy and loss plots for the training and validation samples during training are shown in Fig. 3 (d).

The most experimental approach was the PCA+CNN architecture, where the vectors of the main components were artificially reconstructed (reshaped) into two-dimensional matrices measuring 14 by 14, Fig. 2 (d). The purpose of this conversion was to use efficient convolutional filters on compressed data. Since pooling operations are applied to an already reduced input space, this model has 50106 parameters. However, this approach introduces specific distortions into the data topology, since the proximity of elements in the matrix of principal components is statistical, not spatial in nature, which affects the ability of convolutional nuclei to distinguish geometric primitives. For the PCA+CNN model, the accuracy and loss plots for the training and validation samples during training are shown in Fig. 3 (c).

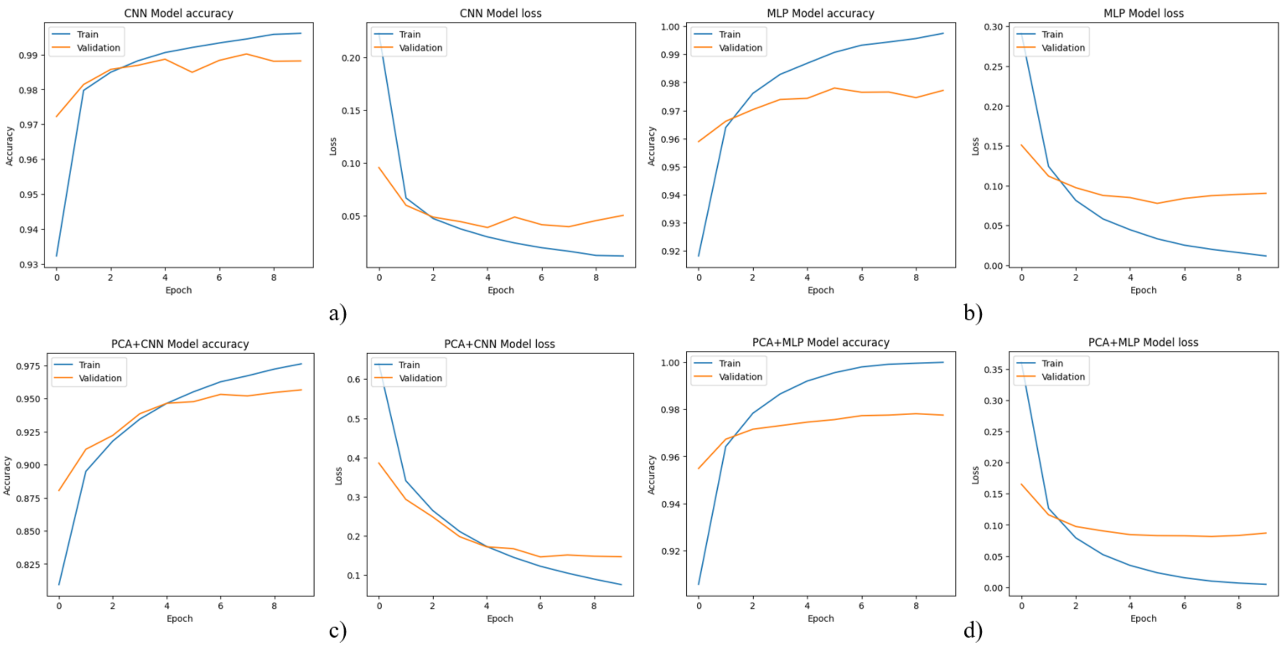


**Fig.3. Accuracy and loss graphs for the training and validation sets during training for the models: a) CNN; b) MLP; c) PCA+CNN; d) PCA+MLP**

A separate criterion for the effectiveness of the studied architectures is their computational complexity, which is the execution time of one training step (ms per step), which reflects the load on hardware resources. The analysis of the obtained metrics demonstrates a clear hierarchy of performance, where the leaders are MLP architectures: the basic MLP model shows a time of 6-8 ms per step, and its modification with PCA+MLP preprocessing reaches the range of 3-8 ms per step, which is explained by a decrease in the dimensionality of the input vector and the absence of resource-intensive convolution operations. In contrast, classic CNN proved to be the slowest (50-64 ms per step) because sliding window operations on full-size $28 \times 28$ images require a significant number of floating-point calculations. At the same time, the use of the main component method for the CNN reduced the training time by almost eight times, to 8-9 ms per step, which is a direct consequence of the reduction of the input feature space to the $14 \times 14$ matrix and confirms the hypothesis of the possibility of accelerating convolutional models due to the loss of part of the information capacity of the input data.

## Discussion

Analyzing the data in table 1, you can trace the following patterns. The CNN full data demonstrated the highest accuracy among all models, achieving an accuracy of 99.11% ±0.5% on the test set with repeated retraining.

This supports the thesis that CNN architecture is the most adapted to work with visual data due to its ability to consider spatial dependencies between pixels.

Table 1

| Model | Image shape | Total Params | ms per step | Train Accuracy | Train Loss | Val Accuracy | Val Loss | Test Accuracy | Test Loss |
|---|---|---|---|---|---|---|---|---|---|
| MLP | 28x28 | 203 530 | 6-11 | 0.9974 | 0.0108 | 0.9768 | 0.0871 | 0.9789 | 0.0705 |
| CNN | 28x28 | 205 250 | 50-64 | 0.9957 | 0.0128 | 0.9882 | 0.0453 | 0.9911 | 0.0342 |
| PCA + CNN | 14x14 | 53 106 | 8-9 | 0.9770 | 0.0759 | 0.9536 | 0.1547 | 0.9502 | 0.1610 |
| PCA + MLP | 14x14 | 53 002 | 3-8 | 0.9999 | 0.0042 | 0.9784 | 0.0802 | 0.9787 | 0.0740 |

The MLP model, working with full-size 28 × 28 images, required the creation of a network with 203530 parameters to achieve an accuracy of 97.89% ±1%. At the same time, the use of PCA to reduce the input dimension to 14 × 14 made it possible to reduce the number of parameters by almost 4 times — to 53002. At the same time, classification accuracy did not change significantly and amounted to 97.87% ±1%. Change in quality less than 0.02% indicates an insignificant difference in the accuracy of the models MLP and PCA+MLP when the computational complexity is reduced by 4 times.

A completely different picture is observed when analyzing the PCA+CNN model. Reducing the dimensionality of input data led to a decrease in the number of parameters to 53106. However, this was accompanied by a drop in classification accuracy to 95.02%, which is the worst result among all four models. The explanation for this effect lies in the fundamental principles of convolutional networks. CNNs are based on a convolution operation that scans local areas of an image to detect patterns such as lines, angles, and textures. The PCA method, by converting the pixel space into the space of the main components, destroys the natural spatial structure of the image. The resulting 196 components are linear combinations of all pixels of the original image and, being artificially formed into a 14 × 14 matrix, do not retain the topological neighborhood that existed in the original. Adjacent elements in the new 14 × 14 matrix can be statistically independent, making the application of local convolution filters inefficient. Thus, the combination of PCA and CNN is architecturally the least efficient among the models considered, since preprocessing destroys exactly the information (spatial locality) that the network is intended to use.

Analysis of the confusion matrices corroborates the quantitative findings reported in Table 1 and provides additional insight into the class-level error distribution across architectures. The standard CNN Fig. 4 (a), MLP Fig. 4 (c) and PCA+MLP Fig. 4 (d) models exhibit highly concentrated diagonal structures with negligible off-diagonal mass, indicating stable predictions for all classes. A detailed comparison of the MLP and PCA+MLP models across classes shows that MLP demonstrates higher across-class accuracy for classes {3, 5, 6, 8, 9}, while PCA+MLP achieves higher correct classification rates for classes {0, 1, 2, 4, 7}, confirming that the classification accuracy of these models is not significantly different. The PCA+CNN Fig. 4 (b) model exhibits the most pronounced error clusters, most notably confusing true digit 9 with predicted 4 in 67 cases, and true 5 with predicted 3 in 27 cases — suggesting that the destruction of spatial locality by PCA disproportionately harms the recognition of structurally similar, curved digits whose distinguishing features rely on fine local geometry that convolutional filters can no longer reliably detect.

A comparative example is a paper [17] proposing a hybrid architecture combining convolutional networks, hidden Markov models, and autoencoders for recognition tasks, which demonstrated higher accuracy than convolutional neural networks. However, such architecture relies on GPU acceleration to meet real-world processing requirements. This makes PCA+MLP a viable and lightweight alternative to more complex hybrid architectures.

Note the following limitations. It should be noted that the conclusions drawn in this study are specific to the MNIST dataset, which consists of balanced classes with 6,000 training samples per digit — a condition that may not hold in real-world scenarios where a minimum of 100 images per class is considered a practical lower bound for reliable model generalization. Furthermore, the applicability of the proposed combined method to datasets of greater visual complexity, such as CIFAR-10 or ImageNet, where inter-class variation is substantially higher and spatial high-frequency features carry greater discriminative weight, requires separate verification.

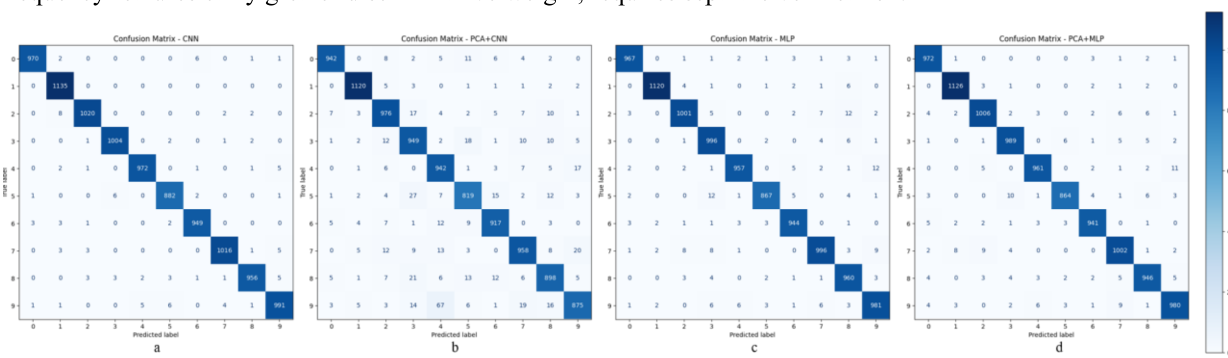


**Fig.4. Confusion matrix: a) CNN; b) PCA+CNN; c), MLP; d) PCA+MLP**

## Conclusions

In both hybrid models, the number of parameters was reduced by 4 times, while the PCA+MLP training time was reduced by 2 times with an accuracy of 97.87%, and the PCA+CNN training time was reduced by 8 times with an accuracy of 95.02%. The PCA+MLP hybrid model is found to have 4 times lower computational complexity and 12 times less training time than CNN, with a small accuracy loss of 1.5%.

The conducted study allows us to draw conclusions about the feasibility of using the PCA dimension reduction method in image classification problems depending on the selected neural network architecture. First, it has been established that for classic MLP, PCA preprocessing is an efficient approach. It allows you to reduce the computational complexity of the model and the amount of memory required, while maintaining accuracy. This approach is appropriate for systems with limited resources, where the use of large models is not possible. Second, use of PCA as a preprocessing step for CNNs leads to a deterioration in classification accuracy. The loss of spatial data structure due to projection onto the main components negates the main advantages of convolutional architecture, leading to a deterioration in the quality of recognition. The results show the importance of aligning data preprocessing methods with the architectural features of machine learning models. It is advisable to direct further research into the study of nonlinear methods of dimensionality reduction and their combination with deep neural networks, as well as to expand the experimental base due to more complex and diverse data sets.

## ADDITIONAL INFORMATION

### AUTHOR CONTRIBUTIONS

Conceptualization A.N.; methodology A.N.; validation A.N.; formal analysis, A.N.; investigation, A.N.; writing-original draft preparation, A.N.; writing -review and editing, A.N.; visualization, A.N.; project administration, A.N.

### DECLARATION ON THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS

In preparing this work, the author used Grammarly for: grammar and spelling checks. After using this tool/service, author reviewed and edited the content and take full responsibility for the content of this publication.

## REFERENCES

1. Sharma S., Guleria K.. Deep Learning Models for Image Classification: Comparison and Applications. 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022. P. 1733-1738, https://doi.org/10.1109/ICACITE53722.2022.9823516
2. Kruse R., Mostaghim S., Borgelt C., Braune C., Steinbrecher M. Multi-layer Perceptrons. Computational Intelligence. Texts in Computer Science. Springer, Cham. 2022. P. 53–124. https://doi.org/10.1007/978-3-030-42227-1_5.
3. Zhao X., Wang L., Zhang Y. et al. A review of convolutional neural networks in computer vision. Artif Intell Rev. 2024. Vol. 57. https://doi.org/10.1007/s10462-024-10721-6.
4. Neskorodieva A. Classification of rhythmic gymnastics sport elements by video. Automation of Technological and Business Processes. 2024 Vol. 16, No. 2. P. 103-112. https://doi.org/10.15673/atbp.v16i2.2845
5. Smirnov O. et al. Intellectual Classification method of Gymnastic Elements Based on Combinations of Descriptive and Generative Approache. Colins Vol. 1. 2024. P. 11-23. https://doi.org/10.31110/colins/2024-1/002
6. Neskorodieva A. et al. Real-time Classification, Localization and Tracking System (Based on Rhythmic Gymnastics). 2023 IEEE 13th International Conference on Electronics and Information Technologies (ELIT). IEEE. 2023. P. 11-16. https://doi.org/10.1109/ELIT61488.2023.10310664
7. Rana Md., Kabir Md Humayun, Sobur A. Comparison of the Error Rates of MNIST Datasets Using Different Type of Machine Learning Model. North American Academic Research. 2023 May. Vol. 6, No. 5. P. 173-181. https://doi.org/10.5281/zenodo.8010602.
8. Ganeshkumar M., Sowmya V., Gopalakrishnan EA., Soman KP. Unsupervised deep learning approach for the identification of intracranial haemorrhage in CT images using PCA-Net and K-Means algorithm. Studies in Autonomic, Data-Driven and Industrial Computing. 2022. P. 23-31. https://doi.org/10.1007/978-981-16-7771-7_3
9. Fırat H., Asker ME., Hanbay D. Classification of hyperspectral remote sensing images using different dimension reduction methods with 3D/2D CNN. Remote Sensing Applications Society and Environment. 2022. Vol. 25:100694. https://doi.org/10.1016/j.rsase.2022.100694
10. Haris M. A., Dzeaulfath M., Wasono R. Principal Component Analysis on Convolutional Neural Network Using Transfer Learning Method for Image Classification of Cifar-10 Dataset. Jurnal Ilmiah Teknologi Sistem Informasi. Dec. 2024. Vol.

10. No. 2. P. 141-150. https://doi.org/10.26594/register.v10i2.3517

11. Shen K., Jobst B., Shishenina E., Pollmann F. Classification of the Fashion-MNIST dataset on a quantum computer. arXiv.org. 2024 March 4. https://doi.org/10.48550/arXiv.2403.02405.

12. Wang L., Wang J., Li RC. Sparse PCA via matrix (2, 1) - norm regularization with an application to feature selection. Results in Applied Mathematics. 2025 Nov 1; Vol. 28. https://doi.org/10.1016/j.rinam.2025.100676.

13. Zou H., Hastie T., Tibshirani R. Sparse principal component analysis. Journal of Computational and Graphical Statistics. 2006 May 15; Vol. 15, No. 2. DOI: 10.1198/106186006X113430.

14. Team K. Keras: Deep Learning for humans. URL: https://keras.io/ (last access: 13.01.2026).

15. TensorFlow. URL: https://www.tensorflow.org/ (last access: 13.01.2026).

16. Rastogi R. et al. Knowledge Extraction in Digit Recognition Using MNIST Dataset. International Journal of Knowledge Management. Sept. 2021, Vol. 17, No. 4, P. 1–24. https://doi.org/10.4018/ijkm.2021100103.

17. Naji D., Elhattab K., Joumad A., Ider A. Ouisaadane A., Idhmad A. Hybrid convolutional networks, hidden Markov models, and autoencoders for enhanced recognition. IAES International Journal of Artificial Intelligence. Vol. 15. No. 1. P. 780, Feb. 2026. https://doi.org/10.11591/ijai.v15.i1.pp780-787

Аанастасія НЕСКОРОДЄВА
Черкаський державний технологічний університет

# АНАЛІЗ ВПЛИВУ МЕТОДУ PCA НА ТОЧНІСТЬ ТА АРХІТЕКТУРИ ГЛИБОКИХ НЕЙРОМЕРЕЖ КЛАСИФІКАЦІЇ ЗОБРАЖЕНЬ

*Зростання візуальних даних у сучасних інформаційних системах створює потребу в зменшенні обчислювальної складності методів класифікації. У цій роботі представлено дослідження впливу попередньої обробки даних методом аналізу головних компонентів (PCA) на ефективність навчання та здатність класифікації глибоких нейронних мереж. Основна увага приділяється порівняльному аналізу двох архітектур — багатошарового персептрона (MLP) і згорткової нейронної мережі (CNN). Робота спрямована на вирішення актуальної науково-практичної проблеми оптимізації обчислювальних витрат у системах комп'ютерного зору, що працюють в умовах обмежених апаратних ресурсів. На основі аналізу експериментальних даних, отриманих на наборі зображень MNIST, проведено порівняльний аналіз чотирьох архітектурних підходів: класичного MLP, класичного CNN, гібридного PCA+MLP та гібридного PCA+CNN. Досліджено вплив втрати просторової локальності під час трансформації зображень методом PCA, що призводить до погіршення результатів моделей на основі CNN, на відміну від зменшення обчислювальної складності моделей на основі MLP при збереженні точності класифікації. У статті представлено комбінований метод класифікації зображень, аналіз отриманих показників точності та функції втрат, а також обґрунтування спостережуваних явищ. Проведене дослідження дозволяє зробити висновок про доцільність використання методу PCA в задачах класифікації зображень у поєднанні з MLP. Результати демонструють важливість узгодження методів попередньої обробки даних з архітектурними особливостями моделей машинного навчання. В обох гібридних моделях кількість параметрів зменшено в 4 рази, при цьому час навчання PCA+MLP зменшено в 2 рази при точності 97,87%, а час навчання PCA+CNN зменшено у 8 разів при точності 95,02%. Встановлено, що гібридна модель PCA+MLP має в 4 рази меншу обчислювальну складність і в 12 разів менше часу на навчання, ніж CNN, при незначній втраті точності в 1,5%.*

*Ключові слова: згорткова нейронна мережа, багатошаровий персептрон, аналіз головних компонент, комбінований метод класифікації зображень, глибоке навчання.*