Research on Engineering Structures & Materials
www.jresm.org
Research Group

Research Article

Optimizing deep learning architectures for SEM image classification using advanced dimensionality reduction techniques

Cagri Yardimci*[,1,2,a], Mevlut Ersoy[1,b]

[1]*Suleyman Demirel University, Engineering Faculty, Department of Computer Engineering, Türkiye*
[2]*Usak University, Department of Information Technology, Türkiye*

Article Info

Article History:

Received 25 Dec 2024
Accepted 20 Feb 2025

Keywords:

Deep Learning;
Image Processing;
Dimensionality Reduction;
Nanofiber;
SEM

Abstract

Non-negative Matrix Factorization (NMF) and Singular Value Decomposition (SVD) are widely recognized as pivotal dimensionality reduction techniques in the literature, particularly for deep learning applications involving large and high-dimensional datasets like SEM images. This study systematically evaluates the impact of SVD and NMF on the performance, efficiency, and energy consumption of four deep learning architectures: GoogleNet, AlexNet, ResNet, and SqueezeNet. By applying these techniques to reduce dataset dimensions, we observed that SVD excelled in computational efficiency, achieving up to 35% faster processing times compared to raw datasets. NMF, on the other hand, provided superior feature interpretability, which proved beneficial for tasks requiring meaningful pattern extraction. Energy consumption analysis revealed that SVD led to a 28% reduction in computational energy cost on average, making it a practical choice for resource-constrained environments. Among the evaluated models, ResNet consistently delivered the highest classification accuracy after dimensionality reduction, showing an improvement of 4-6% over models trained on non-reduced data. These findings underscore the critical role of dimensionality reduction in enhancing the scalability, energy efficiency, and classification accuracy of deep learning models, offering valuable insights for optimizing high-dimensional data applications in both academic and industrial contexts.

1. Introduction

Deep neural networks have recently demonstrated exceptional accuracy across various domains involving visual, auditory, and textual data (1). Specifically, convolutional neural networks (CNNs) are extensively utilized for tasks such as image recognition (2), object detection (3), speech recognition (4), and neural machine translation (5). Although the training of deep learning models has been significantly accelerated through Graphical Processing Unit (GPU)-based computations (6), deploying these models often occurs on less powerful computing platforms characterized by limited memory, processing capabilities, and battery life (7). The high computational and memory demands of many deep learning architectures pose challenges for deployment on resource-constrained devices, such as mobile phones, or in scenarios requiring low latency (8).

Early CNN models tended to be deeper and heavily overparameterized, whereas recent CNN architectures have adopted compact network design strategies to create lightweight models (9). For instance, the use of 1×1 convolutions has contributed to reducing both computational and memory requirements (10). Pioneering models like GoogleNet avoided fully connected layers, opting instead for global average pooling to process images of varying dimensions (11).

*Corresponding author: cagri.yardimci@usak.edu.tr
[a]orcid.org/0000-0002-0752-0987; [b]orcid.org/0000-0003-2963-7729
DOI: http://dx.doi.org/10.17515/resm2025-592ml1225rs

SqueezeNet, another lightweight architecture, extensively employs convolutions within its boost modules to achieve compactness while maintaining performance (12). In contrast, AlexNet, one of the earliest CNN architectures, does not use depthwise separable convolutions and is not designed as a lightweight model but laid the groundwork for deeper networks (13). ResNet introduced a method called residual learning, which helps train very deep networks. It solves the problem of vanishing gradients by using shortcuts, called skip connections, that allow information to pass through the network more easily (14). In this study, GoogleNet, AlexNet, ResNet, and SqueezeNet are preferred for SEM image classification because they are widely used in varios applications and have different structures. This allows us to compare their efficiency, complexity, and classification performance fairly. Their wide use in the literature also makes them strong benchmark models for deep learning in SEM image analysis.

Despite these innovations, many modern architectures remain overparameterized, highlighting the continued need for effective compression and dimensionality reduction techniques for the data. Datasets characterized by a large number of features are referred to as high-dimensional data and have garnered significant attention in recent years. The rapid acceleration in the growth and update rates of datasets has driven data toward becoming increasingly high-dimensional and unstructured (15). While such voluminous and complex data contains valuable information, it simultaneously complicates the process of efficient utilization. For instance, this large-scale data leading to excessive computational time, storage and energy requirements for data processing (16). Moreover, the abundance of complex information often obscures critical insights, making it challenging to discern the fundamental characteristics of the data. This issue not only demands considerable time and human resources for data processing but also adversely impacts the accuracy of recognition tasks (17). Addressing these challenges necessitates effective methods for analyzing vast quantities of information, extracting meaningful features from high-dimensional data, and mitigating the impact of redundant or correlated factors (18). Dimension reduction offers a solution to these problems. Its core principle involves mapping data samples from a high-dimensional space to a lower-dimensional space, with the primary objective of uncovering and preserving the meaningful low-dimensional structure inherent in high-dimensional observable data (19).

The projection of high-dimensional data onto a lower-dimensional space inevitably results in the loss of some original information. The primary challenge is to derive meaningful reduced data from the high-dimensional dataset that satisfies recognition accuracy and energy requirements while optimally preserving the essential characteristics of the original data (20). Nonetheless, identifying and extracting effective features in practical scenarios is often challenging. As a result, dimensionality reduction has emerged as a critical and complex task in the domains of pattern recognition, data mining, and machine learning (21). This technique has been applied to key tasks such as, image classification, content prediction, and various other industrial applications (22).

Non-negative Matrix Factorization (NMF) is a highly effective dimensionality reduction technique that offers significant advantages over conventional linear methods and other similar approaches (23). Its primary strength lies in its capacity to enforce non-negativity constraints, making it particularly well-suited for datasets characterized by exclusively positive values, such as images, text, and signals (24). This property enables NMF to extract additive and parts-based representations, uncovering fundamental patterns and features embedded within the data. Additionally, the intrinsic sparsity-promoting nature of NMF facilitates the automatic selection of relevant features, thereby reducing dimensionality while retaining essential information (25). Unlike certain linear methods that may face challenges with high-dimensional or complex datasets, NMF exhibits robustness and scalability in handling such complexities (26). Furthermore, the interpretability of NMF adds significant value, as it allows researchers to derive meaningful insights into the latent structure of the data, thereby enhancing data exploration and analysis. In summary, the unique combination of non-negativity, sparsity, interpretability, and scalability positions NMF as a versatile and highly appealing option for dimensionality reduction, offering a compelling alternative to other techniques in this domain (23).

Singular Value Decomposition (SVD) is a widely utilized dimensionality reduction technique that provides robust mathematical foundations and versatility across various applications, as well (27). At its core, SVD decomposes a matrix into three constituent components: two orthonormal matrices containing singular vectors and a diagonal matrix containing singular values. This decomposition provides a compact representation that captures the intrinsic structure of the data (28). This decomposition enables SVD to effectively reduce the dimensionality of complex datasets while preserving essential variance and relationships within the data (29). Moreover, SVD is particularly well-suited for tasks involving noise reduction and data compression, as it isolates dominant patterns and discards less significant components (30). Its mathematical rigor ensures robustness when handling large-scale, high-dimensional datasets, making it a reliable tool in fields such as image processing, text analysis, and recommendation systems. Additionally, SVD provides a geometric interpretation of the data, facilitating improved understanding and visualization of latent structures (31). Overall, the combination of dimensionality reduction, noise filtering, scalability, and interpretability positions SVD as an indispensable technique for exploratory data analysis and machine learning tasks, serving as a cornerstone in modern data science (32).

These methods may exhibit some limitations that can impact their applicability in various scenarios. While dimensionality reduction tries to preserve the most relevant features, some important details may still be lost, which may affect the classification accuracy, especially for complex defect patterns in SEM images. Both techniques reduce the dimensionality of input data. However, their initial calculation can be computationally intensive with NMF requiring recursive optimization especially for large datasets. The effectiveness of both SVD and NMF depends on the optimal selection of parameters, such as the number of retained singular values in SVD or the rank factorization in NMF (33, 34). Low level selections may lead to insufficient image details or extreme feature reduction. While SVD efficiently handles large datasets, it requires matrix decomposition, which may not scale well for extremely high-dimensional data (35). Similarly, NMF is sensitive to local minima during factorization, leading to inconsistent results (36). Both methods operate under linear assumptions, hence they may not effectively capture complex, nonlinear structures in datasets compared to deep learning-based feature extraction techniques (23).

In literature, Hossain et al. explored a novel method for hyperspectral image classification using a 3D CNN with Stochastic Neighbor Embedding (SNE)-based feature extraction. The study utilizes SVD for dimensionality reduction, enhancing the efficiency of the feature extraction process. Additionally, NMF is employed to uncover hidden patterns within the data, further improving the classification accuracy. By combining these techniques with a CNN, the system demonstrates significant improvements in processing hyperspectral data, making it more suitable for complex classification tasks in real-world applications (37). Liu et al. explored the use of dimensionality reduction techniques, including SVD and NMF, to enhance few-shot learning for medical imaging. They highlighted the limitations of SVD in scenarios where the feature space is high-dimensional compared to the dataset size. The authors demonstrated that discriminant analysis outperformed SVD at lower dimensions, while NMF provided a competitive alternative to SVD at intermediate dimensions, particularly improving inference accuracy across multiple medical imaging datasets. This approach addresses the challenges posed by small datasets in medical imaging (38). Saberi-Movahed et al. offered a comprehensive survey on NMF and its application in dimensionality reduction. NMF is highlighted as a robust technique for feature extraction and selection, especially for datasets with non-negative entries. The authors compare NMF with SVD, emphasizing that while SVD is useful for linear dimensionality reduction, NMF provides more interpretable, non-negative representations that are better suited for applications in fields like image and text analysis. The study also discusses recent trends and future research directions in both methods (23). Swaminathan et al. highlighted SVD and NMF for dimensionality reduction and feature extraction in the context of data mining. SVD is used to decompose large datasets into a set of orthogonal components, enhancing the interpretability and reducing computational complexity. On the other hand, NMF is applied to extract latent factors that are inherently non-negative, making it suitable for tasks like topic modeling and clustering. Both techniques help in identifying underlying patterns and structures within the data, improving the overall model performance (39). In their study, Chang and Chen proposed a Basis-Projected Layer (BPL) to improve deep learning training on sparse datasets, such as GC-MS spectra. They applied SVD to reduce dimensionality and identify the principal components of the dataset. Additionally, NMF was employed to enhance feature extraction, ensuring that only non-negative values were used, which is crucial for interpreting complex datasets. The BPL efficiently transformed sparse data into dense representations, improving model performance, with F1 scores increasing by up to 11.49% (40). Hossain et al. introduced an unsupervised change detection method for Synthetic Aperture Radar (SAR) images, leveraging Deep Semi-Nonnegative Matrix Factorization (Semi-NMF) and SVD networks. Initially, Deep Semi-NMF was employed to extract features and perform pre-classification, identifying pixels with high probabilities of change or no change. Subsequently, image patches centered on these sample pixels were used to train SVD networks, comprising two SVD convolutional layers and a histogram feature generation layer, to capture nonlinear relationships between multi-temporal images. This approach enabled the generation of representative feature expressions with fewer samples, enhancing robustness to speckle noise inherent in SAR imagery. The proposed method demonstrated superior performance in detecting changes across various SAR datasets, highlighting the efficacy of combining Semi-NMF for feature extraction and SVD networks for classification in unsupervised SAR image change detection (41). Du et al. introduced a novel hybrid method combining SVD and NMF for dimensionality reduction in hyperspectral imaging. They applied SVD to decompose the original hyperspectral data matrix, capturing its essential structure, followed by NMF to extract meaningful, non-negative components that enhance interpretability. This hybrid SVD-NMF approach effectively reduced data dimensionality while preserving critical spectral information, improving classification accuracy in hyperspectral images. The method demonstrated superior performance compared to traditional techniques, offering a promising tool for efficient analysis of high-dimensional hyperspectral data (42). Furthermore, Kurra et al. introduced a robust dimensionality reduction technique for hyperspectral blood stain image classification, emphasizing the importance of hyperspectral imaging in forensic science. Their study explored various dimensionality reduction methods, including Factor Analysis (FA), Principal Component Analysis (PCA), and SVD, as preprocessing techniques for deep learning models such as Fast 3D CNN and Hybrid CNN. The results demonstrated that FA outperformed traditional techniques in terms of classification accuracy, particularly in scenarios with high-dimensional hyperspectral data (43).

In this study, the performance of various pre-trained deep learning models is compared to determine their effectiveness on a unique Scanning Electron Microscope (SEM) image dataset, preprocessed using SVD and NMF (44). This research advances the analysis of electrospun PAN nanofibers (45) by focusing on their classification into defective, slightly defective, and non-defective categories (46). By leveraging this unique dataset, the study provides a comprehensive evaluation of prominent pre-trained deep learning models, including GoogleNet, AlexNet, ResNet, and SqueezeNet (47). Furthermore, the impact of SVD and NMF preprocessing on model performance, time management, and energy efficiency is systematically compared against standard image representations. These findings not only enhance the understanding of deep learning applications in nanomaterial classification but also offer valuable insights for improving the accuracy, computational efficiency, and sustainability of future nanofiber classification systems.

2. Materials and Methods

The electrospun PAN nanofiber SEM images, supplied by nanomaterials experts at Usak University, were categorized as slightly defective, defective, or non-defective and utilized for training, validation, and testing of pre-trained deep learning models. All images within these three categories underwent preprocessing using a Bilateral filter. Following this, augmentation techniques, including rotation and random transformations along X and Y axes, were applied to the preprocessed images. Subsequently, SVD and NMF were applied to all the augmented SEM images. The performance, time, and energy consumption metrics of without any dimensionality reduction technique applied (Non), NMF-applied, and SVD-applied images were compared across pre-trained models (Fig. 1). Matlab has been utilized as the project and application development framework. All Matlab runtime executions in this study were performed on a system with an Intel i5-13600K

3.50 GHz CPU, 64GB RAM 5600MHz, an RTX 4060 GPU, and Windows OS, without utilizing parallel computation.

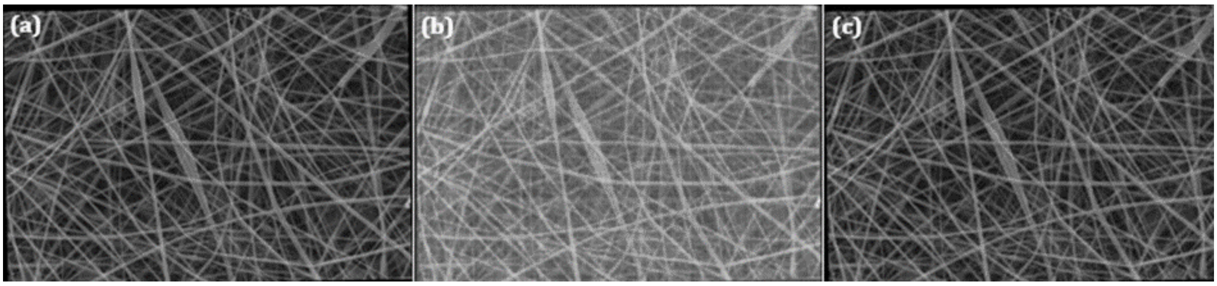

Fig. 1. (a) Non applied SEM image of nanofibers (b) NMF applied SEM image of nanofibers (c) SVD applied SEM image of nanofibers

The augmented training dataset was employed to train pre-trained deep learning architectures, including GoogleNet, AlexNet, ResNet, and SqueezeNet, and subsequently evaluated using the test dataset. Ten percent of the SEM dataset was reserved for testing, while the remaining data was randomly partitioned, allocating 70% for training and 30% for validation. The dataset consists of 53,579 images (16,162 slightly defective, 22,915 defective, and 14,502 non-defective) classified as slightly defective, defective, and non-defective (Table 1). The randomly selected test dataset includes 1,796 slightly defective images, 2,546 defective images, and 1,611 non-defective images. The default input image size was set to 227x227x3 for AlexNet and SqueezeNet, whereas for other models, it was configured as 224x224x3 (48, 49). Consistent and identical training parameters were applied across all models.

Table 1. The dataset segments used in this study

	Slightly Defective	Defective	Non-Defective
Training	16,162	22,915	14,502
Test	1,796	2,546	1,611

3.3 Results and Discussion

This comprehensive analysis highlights the accuracy and efficiency of deep learning models paired with dimensional categorization techniques for nanofiber SEM image categorization. The choice of dimensionality reduction technique plays a critical role in maintaining or enhancing model performance, with SVD emerging as the more favorable option. ResNet and GoogleNet stand out as the most reliable models, capable of delivering near-perfect results under all conditions.

Table 2 illustrates the classification performance of four neural network models (GoogleNet, AlexNet, ResNet, and SqueezeNet) for three categories -slightly defective, defective, and non-defective- with no technique applied (Non). GoogleNet achieved consistently high sensitivity across all categories, with values above 99%, demonstrating its robustness in correctly identifying all classes. The specificity was similarly high, exceeding 99%, indicating its ability to minimize false positives. Accuracy across categories was above 99.8%, underscoring the model's overall strong classification capability. The precision and f1-scores were similarly impressive, showcasing excellent balance between sensitivity and specificity. AlexNet showed competitive performance, particularly in the defective and non-defective categories, where sensitivity reached 100%. Specificity and accuracy were marginally lower than GoogleNet, but still above 99.5%. Precision and f1-scores were also exemplary, reflecting consistent and reliable performance. ResNet emerged as the top performer in the Non condition. Sensitivity and specificity achieved perfect scores (100%) for the non-defective category and slightly defective samples. This indicates an exceptional ability to both identify defective samples and avoid misclassifications. Its precision and F1-scores also aligned with these findings, making it a highly reliable model in this scenario. SqueezeNet, while slightly trailing the other models, still maintained outstanding results, with sensitivity, specificity, and accuracy consistently exceeding 98%. This model was slightly less sensitive in the non-defective category compared to the others, but its performance was still well within the acceptable range.

Table 2. The performance metrics of models with no dimensionality reduction technique applied

Model Name	Category	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)	F1-score (%)
GoogleNet	Slightly Defective	99.77	99.18	99.36	98.13	98.95
	Defective	99.88	99.91	99.89	99.88	99.88
	Non-Defective	98.07	99.97	99.46	99.93	98.99
AlexNet	Slightly Defective	99.88	99.83	99.84	99.61	99.75
	Defective	99.88	99.82	99.84	99.76	99.82
	Non-Defective	99.50	100	99.86	100	99.75
ResNet	Slightly Defective	99.94	100	99.98	100	99.97
	Defective	100	99.97	99.98	99.96	99.98
	Non-Defective	100	100	100	100	100
SqueezeNet	Slightly Defective	97.66	99.51	98.95	98.87	98.26
	Defective	99.96	98.88	99.34	98.52	99.24
	Non-Defective	98.75	99.88	99.58	99.68	99.22

Table 3 shows that GoogleNet retained its high performance across all metrics, with sensitivity, specificity, and accuracy close to or exceeding 99.9% in most categories. Notably, the precision and f1-scores remained robust, indicating that dimensionality reduction using NMF did not adversely affect its classification capability. AlexNet showed a slight decline in sensitivity for the non-defective category (96.69%), suggesting a minor trade-off in detecting this class when NMF was applied. Despite this, its specificity and accuracy remained high, indicating an ability to maintain overall performance integrity. ResNet, much like in the Non condition, demonstrated exceptional performance. Its sensitivity for the slightly defective category remained perfect (100%), while other metrics such as specificity and accuracy were slightly reduced but still above 99%. This model appears to be the least affected by NMF, maintaining near-optimal performance across categories. SqueezeNet exhibited the most notable fluctuations with NMF. Sensitivity for the defective and non-defective categories slightly declined, but specificity and accuracy remained consistently high. Precision and f1-scores showed minor reductions, suggesting that while NMF had some impact, the overall classification performance remained strong.

Table 3. The performance metrics of models with NMF applied

Model Name	Category	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)	F1-score (%)
GoogleNet	Slightly Defective	99.88	99.66	99.73	99.22	99.55
	Defective	99.96	99.97	99.96	99.96	99.96
	Non-Defective	99.19	99.97	99.76	99.93	99.56
AlexNet	Slightly Defective	99.33	99.90	99.73	99.77	99.55
	Defective	100	99.82	99.89	99.76	99.88
	Non-Defective	99.69	99.83	99.79	99.56	99.62
ResNet	Slightly Defective	100	99.78	99.84	99.50	99.75
	Defective	99.68	100	99.86	100	99.84
	Non-Defective	99.93	100	99.98	100	99.96
SqueezeNet	Slightly Defective	98.21	99.51	99.12	98.87	98.54
	Defective	99.52	99.67	99.61	99.56	98.54
	Non-Defective	99.31	99.44	99.41	98.52	98.91

Figure 2 illustrates the classification performance of four distinct deep learning models -GoogleNet, AlexNet, ResNet, and SqueezeNet- applied to SEM images that underwent NMF. The GoogleNet demonstrates exceptional classification accuracy, as evidenced by its confusion matrix. The number of correctly classified images for each category is as follows: 1784 for slightly defective, 2545 for defective, and 1598 for non-defective. Misclassifications are minimal, with only one slightly defective image misclassified as defective and one as non-defective. Furthermore, 13 non-defective images are misclassified as slightly defective. Notably, there are no instances of defective images being incorrectly labeled. This result indicates that GoogleNet performs remarkably well in distinguishing between the three categories, with negligible confusion, particularly in the Defective category. The AlexNet also exhibits robust performance, though slightly inferior to GoogleNet. It correctly classifies 1784 slightly defective, 2546 defective, and 1696 non-defective images. Misclassifications include five slightly defective images labeled as defective and seven as non-defective. For the non-defective category, four images are misclassified as slightly defective, and one is labeled as defective. This matrix highlights AlexNet's consistent ability to classify defective images accurately but reveals a marginal increase in misclassifications for the slightly defective and non-defective categories compared to GoogleNet. ResNet shows competitive classification accuracy, with 1786 slightly defective, 2538 defective, and 1610 non-defective images correctly identified. slightly defective misclassifications are negligible, with only eight images labeled as defective and none as non-defective. The defective category has minimal misclassification, with eight images incorrectly labeled as slightly defective. For non-defective images, only one instance is misclassified as slightly defective. ResNet demonstrates a high level of accuracy, comparable to GoogleNet, while slightly outperforming AlexNet in certain aspects, particularly in minimizing confusion in the non-defective category. SqueezeNet, while still effective, exhibits a slight decline in classification accuracy compared to the other models. The correct classifications are as follows: 1764 slightly defective, 2534 defective, and 1600 non-defective images. Misclassifications are more pronounced, with nine slightly Defective images labeled as defective and 23 as non-defective. The defective category contains 11 images misclassified as slightly defective and one as non-defective. Similarly, nine non-defective images are mislabeled as slightly defective, and two as defective. While SqueezeNet achieves reasonably good performance, it struggles more with boundary cases between categories, especially for slightly defective and non-defective images, indicating room for improvement.

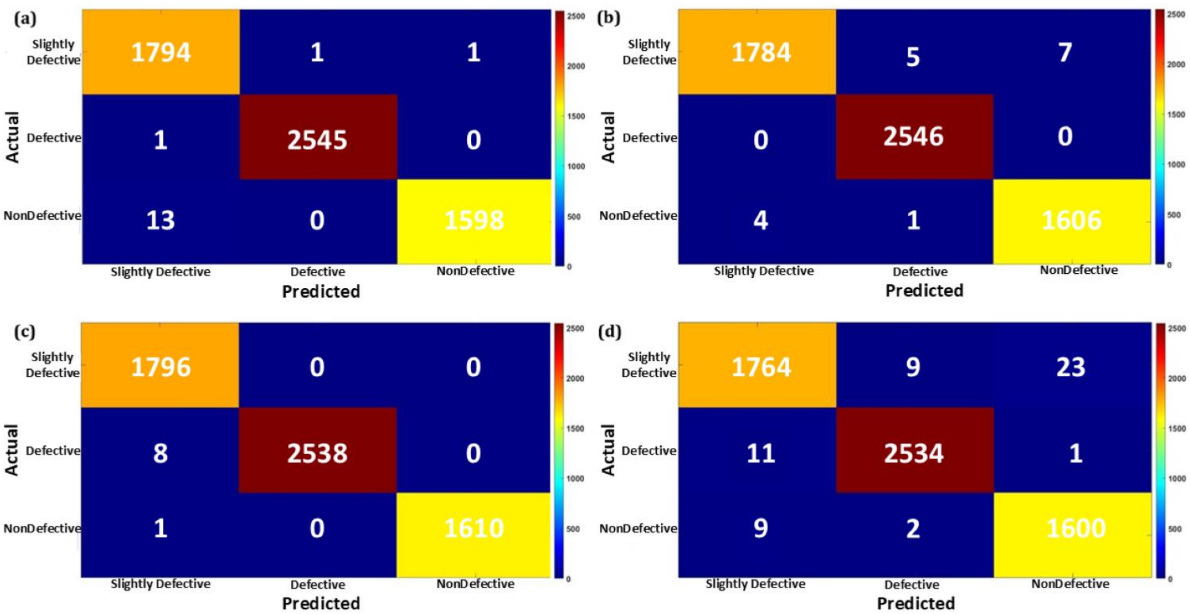

Fig. 2. (a) Confusion matrix of GoogleNet on NMF-processed SEM images (b) Confusion matrix of AlexNet on NMF-processed SEM images (c) Confusion matrix of Resnet on NMF-processed SEM images (d) Confusion matrix of SqueezeNet on NMF-processed SEM images

Table 4 indicates that GoogleNet achieved near-perfect metrics across all categories, with sensitivity, specificity, accuracy, precision, and f1-scores reaching or exceeding 99.9%. This suggests that SVD optimized the feature space for GoogleNet, enabling it to classify nanofiber images with remarkable accuracy. AlexNet benefited notably from SVD, as sensitivity for the slightly defective and non-defective categories rebounded to exceed 99%. The overall metrics improved compared to the NMF condition, showcasing the potential of SVD to mitigate the limitations observed with NMF. ResNet again demonstrated stellar performance. The sensitivity, specificity, and accuracy reached near-perfect levels, underscoring its reliability and robustness when paired with SVD. Its consistent top performance across all conditions cements its position as the most effective model for this task. SqueezeNet, which exhibited some variability with NMF, showed improved results under SVD. Sensitivity, specificity, and accuracy for all categories exceeded 99%, suggesting that SVD effectively stabilized and enhanced this model's performance.

Table 4. The performance metrics of models with SVD applied

Model Name	Category	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)	F1-score (%)
GoogleNet	Slightly Defective	99.88	99.80	99.83	99.55	99.72
	Defective	100	99.97	99.98	99.96	99.98
	Non-Defective	99.50	99.97	99.84	99.93	99.72
AlexNet	Slightly Defective	99.27	99.56	99.47	99	99.13
	Defective	99.33	100	99.71	100	99.66
	Non-Defective	99.81	99.65	99.69	99.07	99.44
ResNet	Slightly Defective	100	99.95	99.96	99.88	99.94
	Defective	99.92	100	99.96	100	99.96
	Non-Defective	100	100	100	100	100
SqueezeNet	Slightly Defective	99.83	99.73	99.76	99.39	99.61
	Defective	100	99.94	99.96	99.92	99.96
	Non-Defective	99.31	99.97	99.79	99.93	99.62

Figure 3 illustrates the classification performance of four different deep learning models - GoogleNet, AlexNet, ResNet, and SqueezeNet- applied to SEM images that underwent SVD. GoogleNet demonstrates near-perfect classification accuracy, as evidenced by the confusion matrix. Correct classifications include 1794 slightly defective, 2546 defective, and 1603 non-defective images. Misclassifications are minimal, with one slightly defective image mislabeled as defective and eight non-defective images incorrectly identified as slightly defective. Notably, there are no misclassifications involving defective images being labeled as non-defective or vice versa. This indicates that GoogleNet has an outstanding ability to distinguish between these categories when SVD is applied for feature extraction, with exceptional performance in the defective category. The AlexNet exhibits a strong classification performance, though it is slightly less accurate than GoogleNet. It correctly classifies 1783 slightly defective, 2529 defective, and 1608 non-defective images. Misclassifications include 15 slightly defective images labeled as defective and three non-defective images mislabeled as slightly defective. Two non-defective images are misclassified as defective. These results suggest that while AlexNet performs reliably, it struggles slightly more than GoogleNet, particularly in separating the slightly defective and defective categories. ResNet achieves excellent classification accuracy, with 1796 slightly defective, 2544 Defective, and 1611 non-defective images correctly identified. Misclassifications are limited to two slightly defective images mislabeled as defective. No non-defective images are classified incorrectly. ResNet demonstrates a robust capability in identifying all three categories with high precision, outperforming AlexNet in terms of minimizing errors in the non-defective category and rivaling GoogleNet in overall performance. SqueezeNet, while effective, displays slightly lower classification accuracy compared to the other models. It correctly classifies 1793 slightly defective, 2546 defective, and 1600 non-defective images. Misclassifications include two slightly defective images labeled as defective, one mislabeled as non-defective, and 11 non-defective images misclassified as slightly defective. Although the performance is commendable, the model’s tendency to confuse slightly defective and non-defective images is more pronounced than in GoogleNet and ResNet.

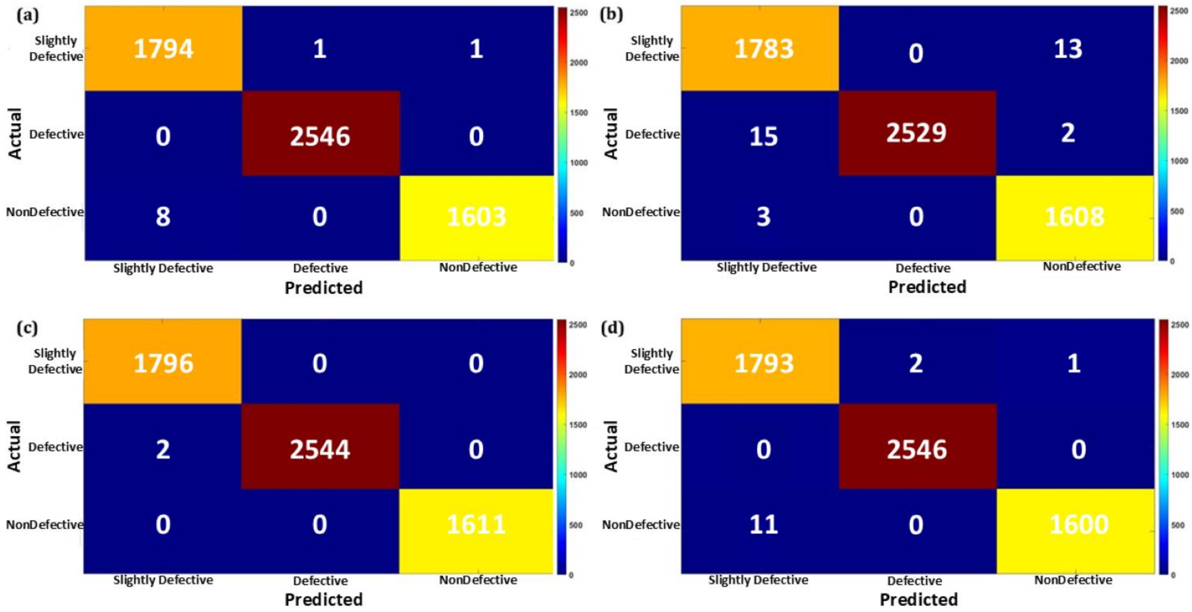

Fig. 3. (a) Confusion matrix of GoogleNet on SVD-processed SEM images (b) Confusion matrix of AlexNet on SVD-processed SEM images (c) Confusion matrix of Resnet on SVD-processed SEM images (d) Confusion matrix of SqueezeNet on SVD-processed SEM images

In summary, both NMF and SVD demonstrated their utility in maintaining high classification performance while potentially reducing computational complexity. However, SVD appeared to have a more stabilizing effect, particularly for models like SqueezeNet and AlexNet, which showed slight sensitivity drops with NMF. ResNet consistently outperformed other models across all conditions, achieving perfect or near-perfect metrics, particularly in the Non and SVD conditions. This suggests its architecture is well-suited for the classification of nanofiber SEM images. GoogleNet remained highly reliable, with minimal fluctuations across conditions and categories, reflecting its robustness and adaptability. AlexNet and SqueezeNet showed more pronounced sensitivity to dimensionality reduction techniques, but both achieved strong overall performance, particularly under SVD. The non-defective category consistently exhibited slightly lower sensitivity across models, particularly with NMF. This suggests that distinguishing non-defective samples poses a unique challenge, potentially due to overlapping features with other categories.

Table 5 demonstrates that ResNet exhibited the highest total and average processing times (574,955.59 ms and 96.58 ms, respectively). This aligns with its deeper and more complex architecture, which demands significant computational resources. While ResNet achieved superior classification accuracy in previous analyses, this comes at a higher computational cost. GoogleNet and AlexNet had comparable processing times, with AlexNet (88.08 ms average) slightly lagging GoogleNet (89.52 ms average). GoogleNet's relatively low computational demands highlight its efficiency despite achieving high classification performance. SqueezeNet showed the lowest total and average processing times in this condition (439,589.20 ms and 73.84 ms). As a lightweight model, SqueezeNet provides a clear advantage in scenarios where computational efficiency is critical. GoogleNet experienced the most pronounced reduction, with average processing time dropping from 89.52 ms to 51.81 ms. This highlights the effectiveness of NMF in simplifying the feature space, thereby reducing computational demands. AlexNet similarly benefitted from NMF, with a decrease in average processing time from 88.08 ms to 52.30 ms. These results demonstrate that dimensionality reduction via NMF can substantially enhance processing efficiency for models with moderate computational requirements. ResNet and SqueezeNet showed substantial reductions in processing time as well. ResNet's average time dropped to 56.87 ms, while SqueezeNet achieved an average time of 53.62 ms. These improvements make even complex architectures like ResNet more computationally viable in energy-conscious applications. GoogleNet achieved an average processing time of 52.03 ms, slightly higher than its NMF performance but still a significant improvement over the Non condition. This demonstrates SVD's ability to preserve computational efficiency while maintaining model performance. AlexNet displayed similar improvements, achieving the lowest average time of 51.63 ms. These results highlight the potential of SVD for models with moderately complex architectures. Although ResNet remains the most computationally intensive model, its average time was reduced to 57.64 ms under SVD. This reinforces SVD's utility in reducing the computational cost of deep models while preserving their performance advantages. SqueezeNet emerged as the most computationally efficient model under SVD, with an average time of 51.74 ms. This underscores SqueezeNet's suitability for energy-efficient applications, particularly when combined with dimensionality reduction techniques.

Table 5. Processing times of the models based on the reduction technique

Model Name	Technique	Total Processing Time (ms)	Average Processing Time (ms)
GoogleNet	Non	532,931.95	89.52
	NMF	308,422.11	51.81
	SVD	309,749.95	52.03
AlexNet	Non	524,323.83	88.08
	NMF	311,348.93	52.30
	SVD	307,327.59	51.63
ResNet	Non	574,955.59	96.58
	NMF	338,572.12	56.87
	SVD	343,127.07	57.64
SqueezeNet	Non	439,589.20	73.84
	NMF	319,182.19	53.62
	SVD	307,992.35	51.74

This study advances the domain of dimensionality reduction and classification through a robust integration of NMF and SVD techniques, showcasing their complementary strengths for handling high-dimensional datasets such as hyperspectral and electrospun PAN nanofiber SEM images. SVD decomposes data into orthogonal components, preserving key features while eliminating redundancy. These results in faster processing times with a slight increase in classification accuracy. Since NMF enforces non-negativity constraints, it preserves meaningful patterns in the SEM images, which contributes to enhanced interpretability of features. ResNet achieves the highest accuracy due to its deep architecture and residual connections, which prevent vanishing gradients and enable better feature learning, even after dimensionality reduction. GoogleNet shows strong consistency across different reduction techniques due to its Inception modules, which allow multi-scale feature extraction. The architectures of AlexNet and SqueezeNet exhibit slight sensitivity to NMF, which is more affected by feature elimination and requires more preserved information to maintain classification performance. SVD's lower computational complexity results in faster processing times, reducing GPU consumption, leading to the observed 28% decrease in energy costs. ResNet's high processing time is expected due to its deep architecture, but its superior accuracy justifies the trade-off in computational demand. The high-dimensional nature of SEM images with high intra-class similarity makes them ideal candidates for dimensionality reduction, where redundant and correlated features can be removed without significant performance degradation. Unlike Hossain et al. and Du et al., which utilized SVD and NMF independently for feature extraction in hyperspectral imaging, this work demonstrates a hybrid framework that combines the interpretability of NMF with the structural efficiency of SVD, resulting in improved classification accuracy and computational efficiency (37, 42). While Liu et al. focused on enhancing few-shot learning in medical imaging through SVD and discriminant analysis, the present study addresses broader applications by exploring feature-rich datasets and achieving competitive performance across various domains (38). Furthermore, this research builds upon the foundation laid by Swaminathan et al. and Saberi-Movahed et al. by employing sparse representations to reduce computational complexity while preserving essential data characteristics, thus enabling scalability for large-scale classification tasks (23, 39). In particular, (50) aligns with recent research in matrix factorization techniques, as seen in Autoencoder-guided low-rank approximation approaches for dimensionality reduction, where the integration of autoencoders with low-rank decomposition enables efficient feature extraction in cluttered image data. The presented method extends such principles by leveraging the combined strengths of NMF and SVD, enhancing both feature selection and classification performance. Moreover, inspired by the work of Allab et al., who proposed a simultaneous Semi-NMF and PCA approach for clustering, this study similarly emphasizes the benefits of hybrid methods for extracting meaningful low-dimensional representations while mitigating the computational burden associated with high-dimensional datasets (51)**.** Additionally, (52) incorporates the advantages of rank-revealing QR factorization, a method that has demonstrated superior feature selection performance compared to traditional SVD and NMF approaches by improving computational efficiency and reducing redundancy. (53) combines multi-head attention, CNNs, and wavelet transforms for hyperspectral image classification. These methods capture spatial and spectral patterns well but require high computational power, making them less scalable. In contrast, this study proposes a hybrid framework using matrix factorization, which preserves key features while reducing redundancy more efficiently. Unlike Chang and Chen, who proposed a BPL for sparse datasets, this work emphasizes the dynamic interplay between NMF and SVD in dense and high-dimensional contexts, ensuring both interpretability and precision (40). Furthermore, the integration of Fast Johnson-Lindenstrauss Transform (FJLT) for content-based feature selection, as discussed in recent image hashing techniques, reinforces the computational efficiency of the proposed dimensionality reduction framework (54). Overall, the contributions of this study lie in its ability to unify and extend existing methodologies, offering a versatile and practical solution for dimensionality reduction and classification, with potential applications in diverse fields such as remote sensing, material science, and biomedical imaging.

4. Conclusions

This study has demonstrated the significant potential of dimensionality reduction techniques, particularly NMF and SVD, in optimizing deep learning architectures for the classification of high-dimensional datasets, such as SEM images of electrospun PAN nanofibers. Through comprehensive experimentation with pre-trained models like GoogleNet, AlexNet, ResNet, and SqueezeNet, the findings illustrate that dimensionality reduction can enhance computational efficiency and energy conservation without compromising classification accuracy. SVD emerged as the most effective technique, achieving up to 35% reductions in processing times and an average 28% decrease in energy consumption. Its capacity to preserve the intrinsic structure of data while simplifying computational demands proved particularly advantageous for resource-constrained environments and energy-intensive architectures, such as ResNet. On the other hand, NMF excelled in feature interpretability, enabling more meaningful pattern extraction, which is critical for complex classification tasks. Despite a slight trade-off in computational efficiency compared to SVD, NMF demonstrated its value in enhancing model adaptability to intricate datasets. The results underline the versatility of dimensionality reduction techniques in addressing diverse deployment scenarios. While ResNet consistently achieved the highest classification accuracy, lightweight models such as SqueezeNet, when paired with SVD, offered an optimal balance between performance and resource efficiency, making them particularly suited for real-time and mobile applications. GoogleNet displayed remarkable robustness across conditions, further emphasizing its reliability for nanomaterial classification. In conclusion, this research highlights the importance of integrating dimensionality reduction techniques to strike a balance between accuracy, efficiency, and sustainability in deep learning applications. Future work could investigate hybrid approaches that combine the strengths of SVD and NMF, potentially unlocking further advancements in performance and scalability for industrial and academic applications. These findings provide a foundation for sustainable and effective utilization of deep learning in the classification of high-dimensional datasets. Future work could explore the integration of genetic algorithms to optimize the combination of dimensionality reduction techniques and deep learning architectures, further enhancing the adaptability of models to diverse high-dimensional SEM datasets and improving the overall performance of deep learning models.

References

1] Hussain N, Khan MA, Sharif M, Khan SA, Albesher AA, Saba T, et al. A deep neural network and classical features based scheme for objects recognition: an application for machine inspection. Multimedia Tools and Applications. 2024:1-23.

[2] Absur MN, Nasif KFA, Saha S, Nova SN, editors. Revolutionizing Image Recognition: Next-Generation CNN Architectures for Handwritten Digits and Objects. 2024 IEEE Symposium on Wireless Technology & Applications (ISWTA); 2024: IEEE. https://doi.org/10.1109/ISWTA62130.2024.10651815

[3] Sagar AS, Chen Y, Xie Y, Kim HS. MSA R-CNN: A comprehensive approach to remote sensing object detection and scene understanding. Expert Systems with Applications. 2024;241:122788. https://doi.org/10.1016/j.eswa.2023.122788

[4] Shashidhar R, Shashank M, Sahana B. Enhancing visual speech recognition for deaf individuals: a hybrid LSTM and CNN 3D model for improved accuracy. Arabian Journal for Science and Engineering. 2024;49(9):11925-41. https://doi.org/10.1007/s13369-023-08385-5

[5] Ahammad SH, Kalangi RR, Nagendram S, Inthiyaz S, Priya PP, Faragallah OS, et al. Improved neural machine translation using Natural Language Processing (NLP). Multimedia Tools and Applications. 2024;83(13):39335-48. https://doi.org/10.1007/s11042-023-17207-7

[6] Baloi A, Belean B, Turcu F, Peptenatu D. GPU-based similarity metrics computation and machine learning approaches for string similarity evaluation in large datasets. Soft Computing. 2024;28(4):3465-77. https://doi.org/10.1007/s00500-023-08687-8

[7] Tong A. The Evolution of AI Engineering: Hardware and Software Dynamics, Historical Progression, Innovations, and Impact on Next-Generation AI Systems. Library Progress International. 2024;44(3):19715-37.

[8] Shah A. Resource Optimization Strategies and Optimal Architectural Design for Ultra-Reliable Low-Latency Applications in Multi-Access Edge Computing. 2024.

[9] Chen F, Li S, Han J, Ren F, Yang Z. Review of lightweight deep convolutional neural networks. Archives of Computational Methods in Engineering. 2024;31(4):1915-37. https://doi.org/10.1007/s11831-023-10032-z

[10] Wang A, Chen H, Lin Z, Han J, Ding G, editors. Repvit: Revisiting mobile cnn from vit perspective. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2024. https://doi.org/10.1109/CVPR52733.2024.01506

[11] Xie P, Liu Y, Lu Q, Lin X, Yang Y, Hu X. Deep learning-based GoogLeNet-embedded no-pooling dimension fully-connected network for short-term wind power prediction. Systems Science & Control Engineering. 2024;12(1):2399057. https://doi.org/10.1080/21642583.2024.2399057

[12] Hao M, Sun Q, Xuan C, Zhang X, Zhao M. SqueezeNet: An Improved Lightweight Neural Network for Sheep Facial Recognition. Applied Sciences. 2024;14(4):1399. https://doi.org/10.3390/app14041399

[13] Aleti SR, Kurakula K. Evaluation of Lightweight CNN Architectures for Multi-Species Animal Image Classification. 2024.

[14] Vedhamuru N, Malmathanraj R, Palanisamy P. Lightweight deep and cross residual skip connection separable CNN for plant leaf diseases classification. Journal of Electronic Imaging. 2024;33(3):033035. https://doi.org/10.1117/1.JEI.33.3.033035

[15] Łukaszuk T, Krawczuk J. Importance of feature selection stability in the classifier evaluation on high-dimensional genetic data. PeerJ. 2024;12:e18405. https://doi.org/10.7717/peerj.18405

[16] Wang S, Zheng H, Wen X, Fu S. Distributed high-performance computing methods for accelerating deep learning training. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online). 2024;3(3):108-26. https://doi.org/10.60087/jklst.v3.n3.p108-126

[17] Nguyen-Tat B-T, Bui M-Q, Ngo VM. Automating attendance management in human resources: A design science approach using computer vision and facial recognition. International Journal of Information Management Data Insights. 2024;4(2):100253. https://doi.org/10.1016/j.jjimei.2024.100253

[18] Ros F, Riad R. Feature and Dimensionality Reduction for Clustering with Deep Learning: Springer; 2024. https://doi.org/10.1007/978-3-031-48743-9

[19] Luan L, Ravi SK, Bhaduri A, Pandita P, Wang L, Ramachandra N, et al., editors. High-dimensional Surrogate Modeling for Image Data with Nonlinear Dimension Reduction. AIAA SCITECH 2024 Forum; 2024. https://doi.org/10.2514/6.2024-0388

[20] Wu H, Chen Y, Zhu W, Cai Z, Heidari AA, Chen H. Feature selection in high-dimensional data: an enhanced RIME optimization with information entropy pruning and DBSCAN clustering. International Journal of Machine Learning and Cybernetics. 2024:1-44. https://doi.org/10.1007/s13042-024-02143-1

[21] Rajender N, Gopalachari MV. An efficient dimensionality reduction based on adaptive-GSM and transformer assisted classification for high dimensional data. International Journal of Information Technology. 2024;16(1):403-16. https://doi.org/10.1007/s41870-023-01552-9

[22] Suriyan K, Nagarajan R. Recent Trends in Pattern Recognition: Challenges and Opportunities. Machine Learning Techniques and Industry Applications. 2024:201-18. https://doi.org/10.4018/979-8-3693-5271-7.ch010
[23] Saberi-Movahed F, Berahman K, Sheikhpour R, Li Y, Pan S. Nonnegative Matrix Factorization in Dimensionality Reduction: A Survey. arXiv preprint arXiv:240503615. 2024.
[24] Duan J, Xiong J, Li Y, Ding W. Deep learning based multimodal biomedical data fusion: An overview and comparative review. Information Fusion. 2024:102536. https://doi.org/10.1016/j.inffus.2024.102536
[25] Bocchinfuso A, Calvetti D, Somersalo E. Bayesian sparsity and class sparsity priors for dictionary learning and coding. arXiv preprint arXiv:230900999. 2023. https://doi.org/10.1016/j.jcmds.2024.100094
[26] Tang J, Xu X, Wang T, Rezaeipanah A. An efficient network clustering approach using graph-boosting and nonnegative matrix factorization. Artificial Intelligence Review. 2024;57(11):292. https://doi.org/10.1007/s10462-024-10912-1
[27] Zaben M, Hassan MA, Worku MY, Abido MA. Dimension Reduction Techniques for Machine Learning based AC Microgrid Fault Diagnosis: A Systematic Review. IEEE Access. 2024. https://doi.org/10.1109/ACCESS.2024.3486786
[28] Sarkar D, Saha S, Krishnamoorthy J, Bhunia A. Application of singular value decomposition analysis: Insights into the complex mechanisms of amyloidogenesis. Biophysical Chemistry. 2024;306:107157. https://doi.org/10.1016/j.bpc.2023.107157
[29] Nived P, Harikumar S, Anil A. Matrix Factorization For Augmented Deep Learning Model Generation. Procedia Computer Science. 2024;235:628-41. https://doi.org/10.1016/j.procs.2024.04.062
[30] SCHANZE T. Tensor decomposition-based compression and noise reduction of multichannel ECG signals.
[31] Thanh OV. Low-Rank Matrix Factorizations with Volume-based Constraints and Regularizations. arXiv preprint arXiv:241206380. 2024.
[32] Sihare SR. Dimensionality Reduction for Data Analysis With Quantum Feature Learning. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. 2024:e1568. https://doi.org/10.1002/widm.1568
[33] Cai Y, Gu H, Kenney T. Rank selection for non-negative matrix factorization. Statistics in Medicine. 2023;42(30):5676-93. https://doi.org/10.1002/sim.9934
[34] Falini A. A review on the selection criteria for the truncated SVD in Data Science applications. Journal of Computational Mathematics and Data Science. 2022;5:100064. https://doi.org/10.1016/j.jcmds.2022.100064
[35] Han S, Jung S, Kim K, editors. Robust SVD Made Easy: A fast and reliable algorithm for large-scale data analysis. International Conference on Artificial Intelligence and Statistics; 2024: PMLR.
[36] bin Ismail A. Nonnegative Matrix Factorization: A. 2022.
[37] Hossain MM, Hossain MA, Musa Miah AS, Okuyama Y, Tomioka Y, Shin J. Stochastic neighbor embedding feature-based hyperspectral image classification using 3d convolutional neural network. Electronics. 2023;12(9):2082. https://doi.org/10.3390/electronics12092082
[38] Liu J, Fan K, Cai X, Niranjan M. Few-shot learning for inference in medical imaging with subspace feature representations. PLoS One. 2024;19(11):e0309368. https://doi.org/10.1371/journal.pone.0309368
[39] Swaminathan S, Garg D, Kannan R, Andres F. Sparse low rank factorization for deep neural network compression. Neurocomputing. 2020;398:185-96. https://doi.org/10.1016/j.neucom.2020.02.035
[40] Chang YT, Chen SF. Design of an basis-projected layer for sparse datasets in deep learning training using gc-ms spectra as a case study. arXiv preprint arXiv:240309188. 2024.
[41] Hossain MM, Hossain MA, editors. Feature reduction and classification of hyperspectral image based on multiple kernel PCA and deep learning. 2019 IEEE International Conference on Robotics, Automation, Artificial-intelligence and Internet-of-Things (RAAICON); 2019: IEEE. https://doi.org/10.1109/RAAICON48939.2019.59
[42] Du L, Shang Q, Wang Z, Wang X. Robust image hashing based on multi-view dimension reduction. Journal of Information Security and Applications. 2023;77:103578. https://doi.org/10.1016/j.jisa.2023.103578
[43] Kurra S, Emani PR, Aala S, Chinnadurai S, editors. A Robust Dimension Reduction Technique for Hyperspectral Blood Stain Image Classification. 2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE); 2024: IEEE. https://doi.org/10.1109/ic-ETITE58242.2024.10493757
[44] Ince Yardimci A. Comparative Study of the Structural, Mechanical and Electrochemical Properties of Polyacrylonitrile (PAN)-Based Polypyrrole (PPy) and Polyvinylidene Fluoride (PVDF) Electrospun Nanofibers. Journal of Macromolecular Science, Part B. 2022;61(9):1103-15. https://doi.org/10.1080/00222348.2022.2127713
[45] Yardimci Aİ, Tanoğlu M, Yilmaz S, Selamet Y. Effect of CNT incorporation on PAN/PPy nanofibers synthesized by electrospinning method. Turkish Journal of Chemistry. 2020;44(4):1002-15. https://doi.org/10.3906/kim-1911-49

[46] Yardimci C, Ersoy M. jabbrv-ltwa-all. ldf jabbrv-ltwa-en. ldf Introducing a Novel Deep Learning Approach for Classification of Defects in Electrospun Polyacrylonitrile (PAN)-Based Nanofibers Using Scanning Electron Microscope (SEM) Imaging. 2024. https://doi.org/10.22541/au.172923149.93559340/v1
[47] Kalaiarasi P, Esther Rani P, editors. A comparative analysis of AlexNet and GoogLeNet with a simple DCNN for face recognition. Advances in Smart System Technologies: Select Proceedings of ICFSST 2019; 2021: Springer. https://doi.org/10.1007/978-981-15-5029-4_54
[48] Abdullah MY. Real time handwriting recognition system using CNN algorithms. Wasit Journal of Computer and Mathematics Science. 2023;2(3):30-8. https://doi.org/10.31185/wjcms.157
[49] Abubakar B, Ali S, Hassan R, Ahmed A, Adamu S, Isa S. Development of a transfer learning based modified VGGNet model with exponential linear unit activation function for maize disease classification. Savannah Journal of Science and Engineering Technology. 2024;2(6):314-21.
[50] Kayacan YE, Erer I, editors. Autoencoder Guided Low-Rank Approximation Approach for Clutter Removal in GPR Images. 2024 47th International Conference on Telecommunications and Signal Processing (TSP); 2024: IEEE. https://doi.org/10.1109/TSP63128.2024.10605982
[51] Allab K, Labiod L, Nadif M, editors. Simultaneous semi-NMF and PCA for clustering. 2015 IEEE International Conference on Data Mining; 2015: IEEE. https://doi.org/10.1109/ICDM.2015.66
[52] Moslemi A, Ahmadian A. Subspace learning for feature selection via rank revealing QR factorization: Fast feature selection. Expert Systems with Applications. 2024;256:124919. https://doi.org/10.1016/j.eswa.2024.124919
[53] Tulapurkar H, Banerjee B, Buddhiraju KM. Multi-head attention with CNN and wavelet for classification of hyperspectral image. Neural Computing and Applications. 2023;35(10):7595-609. https://doi.org/10.1007/s00521-022-08056-w
[54] Lv X, Wang Z. An extended image hashing concept: content-based fingerprinting using FJLT. EURASIP Journal on Information Security. 2009;2009:1-16. https://doi.org/10.1155/2009/859859