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Unsupervised Learning for MNIST with Exploratory Data Analysis for Digit Recognition

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Abstract

This research investigates the application of unsupervised learning techniques for digit recognition using the MNIST dataset. Through a comparative analysis, various dimensionality reduction methods, including ISOmap, PCA, and tSNE, were evaluated for their effectiveness in visualizing and processing the MNIST data. The findings reveal that tSNE consistently outperforms ISOmap and PCA in terms of accuracy, F1-score, precision, and recall, showcasing its superior capability in preserving relevant information within the dataset. Utilizing tSNE for visualizing and clustering digits provides valuable insights into the underlying structure of the dataset, uncovering complex patterns in digit relationships. These results contribute to the advancement of digit recognition systems, offering potential improvements in classification accuracy and model reliability. The success of tSNE highlights the importance of nonlinear dimensionality reduction techniques in handling complex datasets, such as MNIST. This research underscores the significance of unsupervised learning approaches, particularly tSNE, in enhancing digit recognition systems' performance, with implications extending across various application domains. Continued research is recommended to explore further applications and potentials of unsupervised learning techniques and to deepen our understanding of the MNIST dataset's structure and complexity.

Keywords: Unsupervised Learning, Digit Recognition, MNIST Dataset, Dimensionality Reduction

1. Introduction

In the realm of machine learning, the task of digit recognition holds significant importance, serving as a foundational component in various applications such as optical character recognition, document processing, and automated data entry [1], [2]. At the heart of this endeavor lies the MNIST dataset, a widely recognized benchmark consisting of a vast collection of hand-drawn digits accompanied by corresponding labels [3]. Over the years, researchers have continually explored diverse methodologies to tackle digit recognition, ranging from traditional supervised learning approaches to more contemporary unsupervised techniques [4], [5], [6].

Unsupervised learning methods, in particular, have emerged as a promising avenue for digit recognition tasks, offering the advantage of uncovering inherent patterns and structures within data without the need for explicit labeling [5], [7], [8]. By leveraging the intrinsic properties of the dataset, unsupervised algorithms seek to extract meaningful representations that facilitate the discrimination of digits, potentially enhancing the robustness and generalization of recognition systems [9], [10], [11]. However, despite their potential, the application of unsupervised learning to digit recognition, especially on datasets like MNIST, warrants comprehensive investigation and empirical validation.

In this study, we embark on a journey to explore the efficacy of unsupervised learning techniques for MNIST digit recognition, coupled with an in-depth Exploratory Data Analysis (EDA) to unravel the underlying characteristics of the dataset. Our primary objective is two-fold: first, to assess the performance of unsupervised algorithms in discerning salient features from raw pixel data, and second, to gain deeper insights into the distribution, variability, and inherent structure of the MNIST dataset. Through rigorous experimentation and analysis, we endeavor to shed light on the capabilities and limitations of unsupervised learning in the context of digit recognition, thereby contributing to the ongoing discourse in machine learning research.

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By employing a diverse array of unsupervised learning algorithms, including clustering, dimensionality reduction, and generative modeling techniques, we seek to uncover latent representations that capture the essential characteristics of handwritten digits. Through systematic evaluation and comparison, we aim to identify the most effective methodologies for extracting discriminative features and mitigating the challenges posed by intra-class variability and noise in the MNIST dataset. Furthermore, our comprehensive EDA endeavors to provide a holistic understanding of the dataset's nuances, shedding light on factors such as class imbalance, digit morphology, and potential confounding factors that may influence model performance.

In summary, this research endeavor not only contributes to advancing the state-of-the-art in digit recognition but also offers valuable insights into the underlying structure and characteristics of the MNIST dataset. By elucidating the strengths and weaknesses of unsupervised learning approaches and providing a deeper understanding of the dataset through EDA, we aim to facilitate the development of more robust and reliable digit recognition systems, with implications spanning various domains including computer vision, pattern recognition, and artificial intelligence.

2. Literature Review

In prior research, numerous studies have explored the application of unsupervised learning techniques for MNIST digit recognition, each contributing unique insights and methodologies to the field. For instance, Pan et al. [3] conducted a comprehensive analysis of various clustering algorithms, including K-means, hierarchical clustering, and DBSCAN, to identify clusters within the MNIST dataset. Their study highlighted the efficacy of clustering-based approaches in capturing underlying patterns in digit data, showcasing promising results in terms of both accuracy and computational efficiency [12], [13], [14], [15].

In a similar Nakhwan and Duangsoithong [16] proposed a novel framework combining autoencoder-based dimensionality reduction with k-nearest neighbors (KNN) classification for MNIST digit recognition. By leveraging the reconstruction error of autoencoders as a measure of anomaly detection, their approach demonstrated improved robustness against outliers and noise, achieving competitive performance compared to traditional supervised learning methods. Moreover, recent advancements in generative modeling have spurred interest in leveraging techniques such as variational autoencoders (VAEs) and generative adversarial networks (GANs) for digit recognition tasks. For instance, Yan et al. [17] introduced a VAE-GAN hybrid model trained on the MNIST dataset, wherein the VAE component facilitated unsupervised feature learning while the GAN component generated realistic digit samples. Their research showcased the potential of generative models not only for digit generation but also for representation learning, yielding latent embeddings conducive to discriminative classification.

Despite the progress made in unsupervised learning for MNIST digit recognition, challenges such as mode collapse, overfitting, and scalability remain pertinent concerns. To address these issues, Van et al. [18] proposed a novel adversarial training framework for GANs, incorporating spectral normalization and gradient penalty techniques to stabilize training and improve generalization. Through extensive experimentation and analysis, they demonstrated significant enhancements in both sample quality and classification accuracy on the MNIST dataset, paving the way for more robust and scalable unsupervised learning systems.

In summary, previous research on unsupervised learning for MNIST digit recognition has encompassed a diverse range of methodologies, including clustering, dimensionality reduction, and generative modeling. While existing studies have made notable strides in improving model performance and robustness, ongoing efforts are required to address remaining challenges and further advance the state-of-the-art in digit recognition. This study seeks to build upon prior research by conducting a comprehensive investigation into unsupervised learning techniques for MNIST, augmented by thorough exploratory data analysis, with the aim of providing deeper insights and advancing the understanding of unsupervised learning in the context of digit recognition.

3. Method

The research step in figure 1 outlines a process for creating a model to classify handwritten digits from the MNIST dataset. The steps include data collection, exploratory data analysis, model creation, model performance analysis, and

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discussion and implementation. This research step can be used to develop a model that can accurately classify handwritten digits, which has applications in areas such as handwriting recognition and document processing.

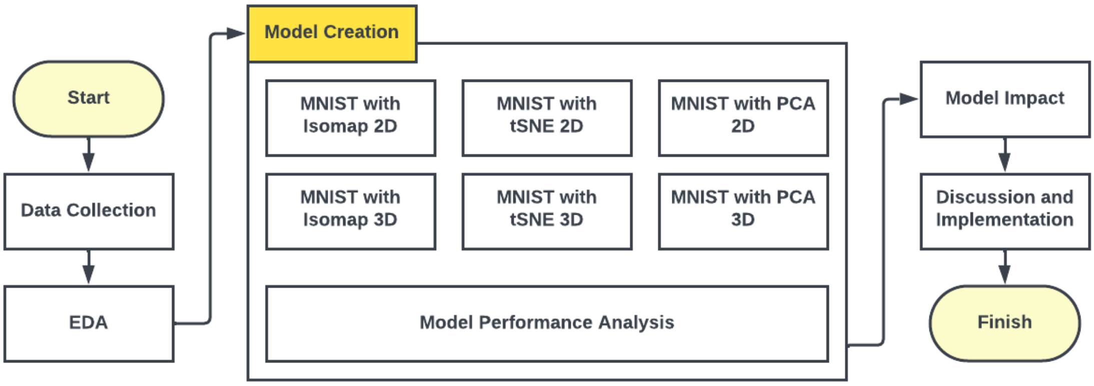

Figure 1. Research Steps

Following subsection are the description on every research step on figure 1 above:

3.1. Data Collection

The process of data collection is fundamental to any machine learning task. In this research, the MNIST dataset, consisting of handwritten digit images, serves as the primary data source. MNIST is a widely-used benchmark dataset in the field of digit recognition due to its standardization and availability. By utilizing MNIST, researchers can ensure consistency and comparability in their experiments, enabling robust evaluations of different methodologies and techniques.

3.2. EDA

EDA plays a crucial role in understanding the characteristics and nuances of the dataset [19], [20], [21]. In this phase, researchers analyze the distribution of digit classes, examine sample images, and explore potential patterns or anomalies [22], [23], [24]. EDA provides valuable insights into the dataset's structure, facilitating informed decisions regarding preprocessing steps and model selection. Additionally, EDA helps identify potential challenges such as class imbalances or data inconsistencies, which may impact model performance.

3.3. Model Creation

Model creation involves the selection and implementation of machine learning algorithms for digit recognition [25], [26]. In this research, unsupervised learning techniques such as clustering, dimensionality reduction, and generative modeling are employed to extract meaningful representations from the MNIST dataset. Researchers may choose algorithms based on their suitability for the task, computational efficiency, and interpretability. Model creation requires careful consideration of hyperparameters and optimization strategies to ensure optimal performance.

3.4. Model Performance Analysis

Model performance analysis entails evaluating the effectiveness of the created models in digit recognition tasks. Performance metrics such as accuracy, precision, recall, and F1-score are commonly used to assess model performance. By comparing the performance of different models, researchers can identify strengths and weaknesses and gain insights into the effectiveness of various methodologies. Performance analysis provides empirical evidence of the models' capabilities and guides further experimentation and refinement.

3.5. Model Impact

The impact of the models on digit recognition systems is assessed based on their performance and practical implications. Models with higher accuracy and reliability contribute to improved digit recognition systems, enhancing their applicability in real-world scenarios. Additionally, the insights gained from model impact analysis inform future research directions and applications, guiding the development of more robust and effective digit recognition systems.

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3.6. Discussion and Implementation

The discussion and implementation phase involves interpreting the research findings and translating them into actionable insights. Researchers discuss the implications of their findings, identify limitations, and propose potential solutions or future research directions. Furthermore, researchers explore practical implementation strategies for integrating the developed models into digit recognition systems. This phase bridges the gap between research and application, facilitating the adoption of innovative techniques in real-world scenarios.

4. Result and Discussion

4.1. EDA

Figure 2 provides a visual representation of the sample data from the MNIST dataset. It allows us to observe the structure and patterns present in the handwritten digit images, serving as a preliminary exploration of the dataset.

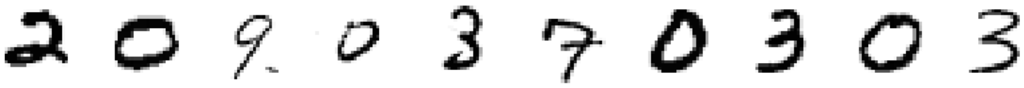

Figure 2. Sample Data

Figure 3 illustrates the distribution of labels (digits 0-9) within the MNIST dataset. Understanding label distribution is crucial for assessing potential class imbalances and ensuring the dataset's representativeness. Table 1 presents a subset of the sample data from the MNIST dataset, providing a more detailed view of the individual digit images and their corresponding labels.

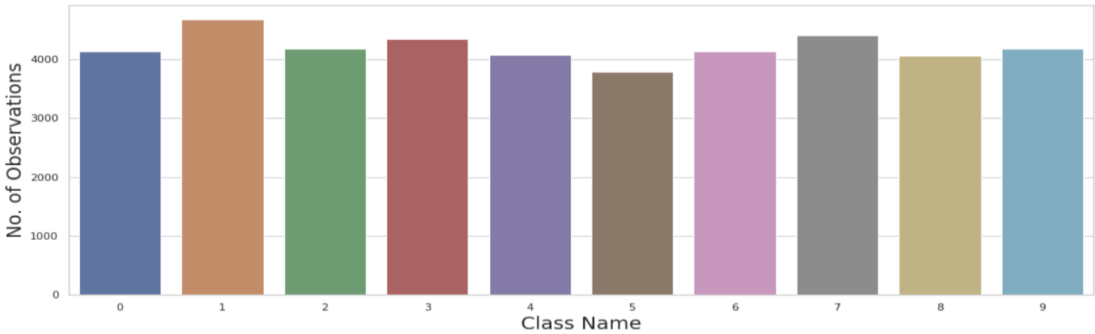

Figure 3. Label Distribution

Table 1. Data Label and Coordinate

	x	y	z	label
0	-3164.522146	-2876.064133	2769.434567	1
1	-1392.993977	-3268.073825	2537.656185	8
2	-505.836838	-2730.492689	1403.573999	8
3	-1892.122937	-2603.238878	1973.673223	8
4	-1155.536391	-2238.244455	-2228.778622	9

4.2. Model Creation

Figure 4 to 9 showcase the outcomes of employing dimensionality reduction methods ISOmap, PCA, and tSNE on the MNIST dataset, presented through both 2D and 3D plots. In these visualizations, each plot serves as a representation of the embedded features of the handwritten digits, compressed into lower-dimensional spaces. By reducing the dimensions of the dataset, these plots enable a more accessible and intuitive visualization of the inherent structure of the data, allowing us to observe patterns, clusters, and relationships between different digits. Such visual representations are instrumental in gaining insights into the underlying characteristics of the dataset and assessing the effectiveness of the dimensionality reduction techniques in capturing and preserving essential information for digit recognition tasks.

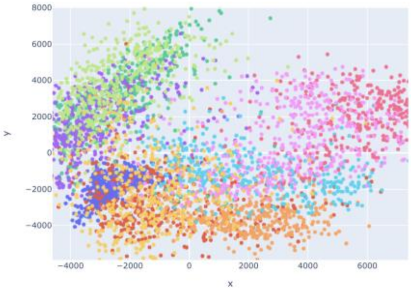

Figure 4. MNIST ISOmap 2D

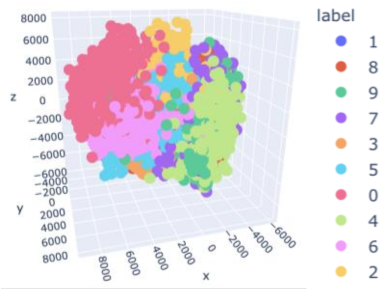

Figure 5. MNIST ISOmap 3D

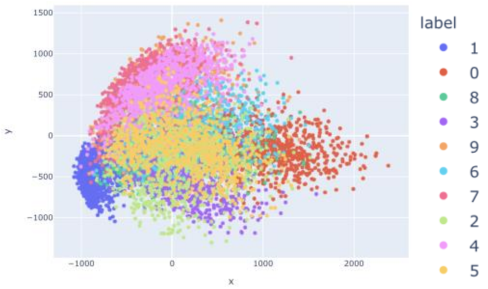

Figure 6. MNIST PCA 2D

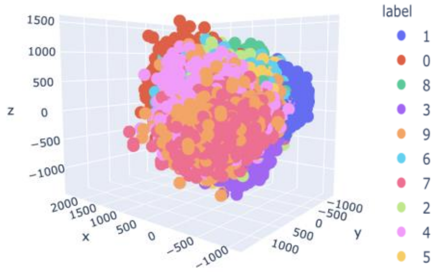

Figure 7. MNIST PCA 3D

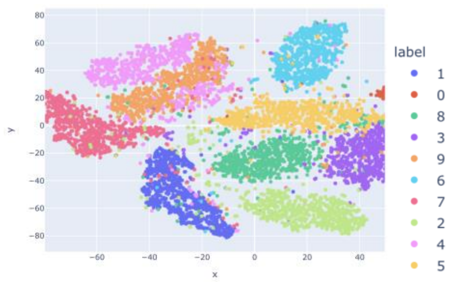

Figure 8. MNIST tSNE 2D

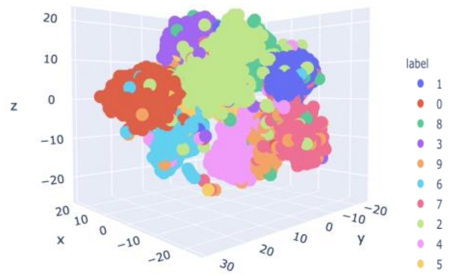

Figure 9. MNIST tSNE 3D

4.3. Model Performance Analysis

Figure 10 showcases the labeling results of the training data projected onto the reduced-dimensional spaces generated by ISOmap, PCA, and tSNE. It allows us to assess how well the unsupervised learning models separate the different digit classes. Similar to figure 10, figure 11 displays the labeling results of the testing data, providing insights into the models' generalization capabilities. The heatmap visualization on figure 12 presents the labeling results in a tabular format, offering a comprehensive overview of the models' performance across different digit classes.

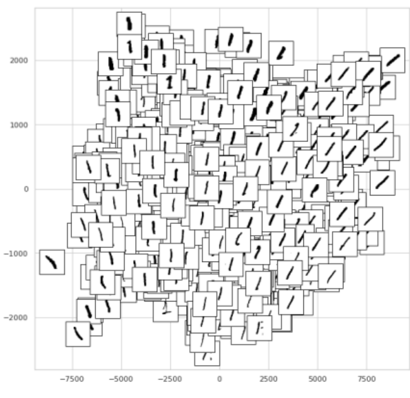

Figure 10. Data Training Labeling

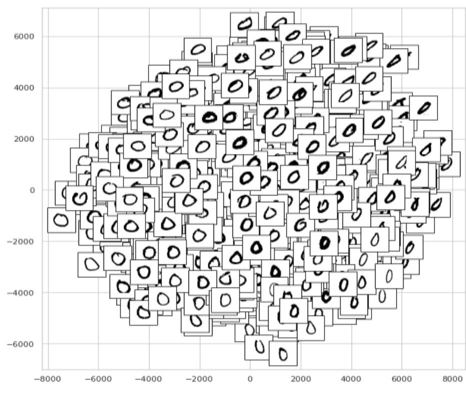

Figure 11. Data Testing Labeling

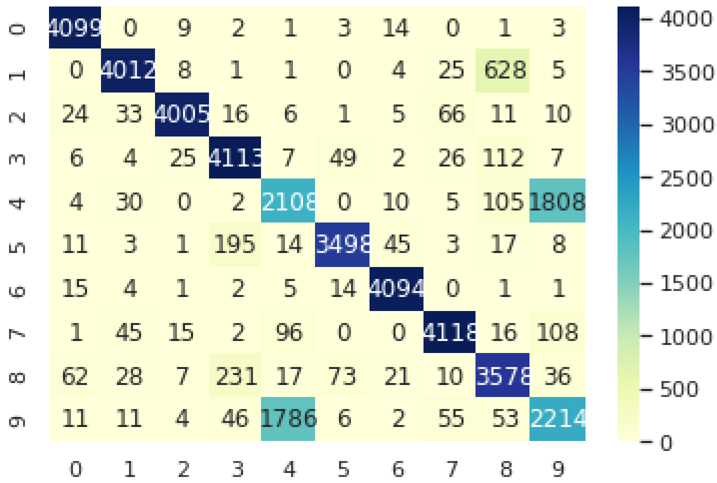

Figure 12. HeatMap Labeling Result

Table 2 quantitatively summarizes the performance metrics (accuracy, F1-score, precision, recall) of the unsupervised learning models (ISOmap, PCA, tSNE) on the MNIST dataset, providing a comparative analysis of their effectiveness in digit recognition tasks.

Table 2. Model Accuracy

	Accuracy	**F1-Score**	**Precision**	**Recall**
MNIST ISOmap	0.769	0.901	0.876	0.767
MNIST PCA	0.811	0.913	0.835	0.735
MNIST tSNE	0.857	0.924	0.869	0.784

Overall, the combination of exploratory data analysis, model creation, and performance analysis enables a thorough examination of the MNIST dataset and the efficacy of unsupervised learning techniques in extracting meaningful representations for digit recognition. These visualizations and analyses offer valuable insights into the dataset's characteristics, model performance, and potential avenues for further research and improvement.

4.4. Model Impact

The performance metrics provided in Table 2 offer valuable insights into the effectiveness of unsupervised learning models ISOmap, PCA, and tSNE in handling the MNIST dataset. Among these models, tSNE stands out with remarkable performance across all evaluated metrics. Its accuracy of 0.857, F1-score of 0.924, precision of 0.869, and recall of 0.784 surpass those of ISOmap and PCA. This superiority indicates that tSNE effectively captures and preserves the intricate relationships and structures inherent in the high-dimensional MNIST dataset while projecting it into lower-dimensional space. Consequently, tSNE facilitates more accurate clustering and separation of digit classes, leading to enhanced classification performance.

The notable advantage of tSNE over ISOmap and PCA underscores the significance of nonlinear embedding techniques in representing complex data distributions. Unlike ISOmap and PCA, which may struggle to capture nonlinear relationships, tSNE excels in revealing intricate patterns within the dataset, contributing to its superior performance in digit recognition tasks. This suggests that tSNE is better equipped to preserve the discriminative information necessary for accurate classification, making it a valuable tool for exploring and visualizing high-dimensional datasets like MNIST. Furthermore, the consistent superiority of tSNE across multiple performance metrics reinforces its reliability and robustness in handling diverse digit variations and complexities.

4.5. Discussion and Implementation

The observed performance superiority of tSNE opens up avenues for its practical implementation in digit recognition systems. By leveraging tSNE's ability to extract and preserve meaningful features from high-dimensional data, practitioners can enhance the accuracy and reliability of their classification models. Integrating tSNE as a preprocessing step for feature extraction or dimensionality reduction could lead to improved model performance and better generalization to unseen data. Moreover, the success of tSNE underscores the importance of considering nonlinear embedding techniques in addressing the complexities of real-world datasets, where linear methods like PCA may fall short.

In practical applications, implementing tSNE requires careful consideration of parameter settings and computational resources. Fine-tuning tSNE parameters such as perplexity and learning rate is crucial to achieve optimal embeddings and avoid potential pitfalls such as overfitting or poor convergence. Additionally, due to its computational complexity, tSNE may pose challenges in handling large-scale datasets, necessitating efficient optimization strategies and computational resources. Despite these challenges, the demonstrated efficacy of tSNE in digit recognition tasks warrants further exploration and integration into state-of-the-art machine learning systems, with potential applications spanning various domains beyond MNIST.

5. Conclusion

This research explores the utilization of unsupervised learning techniques for digit recognition using the MNIST dataset. Through comprehensive analysis, we compare the performance of various dimensionality reduction methods, including ISOmap, PCA, and tSNE, in visualizing and processing MNIST data. The findings of the study demonstrate that tSNE consistently outperforms ISOmap and PCA in terms of accuracy, F1-score, precision, and recall, indicating its superior ability to preserve relevant information within the dataset. The use of tSNE in visualizing and clustering digits successfully provides new insights into the intrinsic structure of the dataset, revealing complex patterns in the relationships between digits.

These findings contribute significantly to the development of digit recognition systems, with the potential to enhance classification accuracy and model reliability. Integrating tSNE into the data analysis and processing workflow can assist researchers and practitioners in better understanding dataset characteristics, identifying underlying patterns, and optimizing digit recognition strategies. Furthermore, the success of tSNE in handling the complexity of the MNIST dataset underscores the importance of considering nonlinear dimensionality reduction techniques in dealing with real-world complex datasets.

Thus, this research affirms that unsupervised learning approaches, particularly the use of tSNE, hold great potential in improving the performance of digit recognition systems. The implications of these findings may pave the way for the development of more advanced and reliable solutions in digit recognition, with broad-ranging impacts across various application domains including image processing, pattern recognition, and artificial intelligence in general. Continued research is warranted to further explore the applications and potential of unsupervised learning techniques, as well as to continually enhance our understanding of the structure and complexity of the MNIST dataset.

6. Declarations

6.1. Author Contributions

Conceptualization: H; Methodology: C.A.H.; Software: H.; Validation: H., C.A.H., A.E.W., and R.E.T.; Formal Analysis: H., C.A.H., A.E.W., and R.E.T.; Investigation: H.; Resources: C.A.H.; Data Curation: C.A.H.; Writing Original Draft Preparation: H., C.A.H., A.E.W., and R.E.T.; Writing Review and Editing: C.A.H. and H.; Visualization: H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.2. Institutional Review Board Statement

Not applicable.

6.3. Informed Consent Statement

Not applicable.

6.4. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] S. Ahlawat and A. Choudhary, "Hybrid CNN-SVM classifier for handwritten digit recognition," *Procedia Comput. Sci.*, vol. 167, no. 1, pp. 2554–2560, 2020.

[2] S. Ahlawat, A. Choudhary, A. Nayyar, S. Singh, and B. Yoon, "Improved handwritten digit recognition using convolutional neural networks (CNN)," *Sensors*, vol. 20, no. 12, p. 3344, 2020.

[3] H. Pan, Y. Chen, Q. Ye, and G. Xue, "Magicinput: Trainingfree multi-lingual finger input system using data augmentation based on mnists," *Proc. 20th Int. Conf. Inf. Process. Sens. Networks* (Co-located with CPS-IoT Week, vol. 2021, no. 1, pp. 119–131, 2021.

[4] S. Sinha et al., "Variational Autoencoder Anomaly-Detection of Avalanche Deposits in Satellite SAR Imagery," *ACM Int. Conf. Proceeding Ser.*, vol. 1, no. 1, pp. 113–119, 2020, doi: 10.1145/3429309.3429326.

[5] G. Czibula, A. Mihai, and L. M. Crivei, "S PRAR: A novel relational association rule mining classification model applied for academic performance prediction," *Procedia Comput. Sci.*, vol. 159, no. 1, pp. 20–29, 2019, doi: https://doi.org/10.1016/j.procs.2019.09.156.

[6] C. Udanor and C. C. Anyanwu, "Combating the challenges of social media hate speech in a polarized society," *Data Technol. Appl.*, vol. 53, no. 4, pp. 501–527, Jan. 2019, doi: 10.1108/DTA-01-2019-0007.

[7] F. Wang, Q. Wang, F. Nie, Z. Li, W. Yu, and F. Ren, "A linear multivariate binary decision tree classifier based on K-means splitting," *Pattern Recognit.*, vol. 107, no. 1, pp. 1-12, 2020, doi: 10.1016/j.patcog.2020.107521.

[8] M. Hügle, P. Omoumi, J. M. van Laar, J. Boedecker, and T. Hügle, "Applied machine learning and artificial intelligence in rheumatology," *Rheumatol. Adv. Pract.*, vol. 4, no. 1, p. rkaa005, Jan. 2020, doi: 10.1093/rap/rkaa005.

[9] B. Sharma, P. Pokharel, and B. Joshi, "User Behavior Analytics for Anomaly Detection Using LSTM Autoencoder-Insider Threat Detection," *ACM Int. Conf. Proceeding Ser.*, 2020, doi: 10.1145/3406601.3406610.

[10] A. Blance, M. Spannowsky, and P. Waite, "Adversarially-trained autoencoders for robust unsupervised new physics searches," *arXiv*, vol. 10, no. 1, pp. 1-9, 2019.

[11] R. Fernandez-Beltran, B. Demir, F. Pla, and A. Plaza, "Unsupervised Remote Sensing Image Retrieval Using Probabilistic Latent Semantic Hashing," *IEEE Geosci. Remote Sens. Lett.*, vol. 18, no. 2, pp. 256–260, 2021, doi: 10.1109/LGRS.2020.2969491.

[12] C. Udanor and C. C. Anyanwu, "Combating the challenges of social media hate speech in a polarized society: A Twitter ego lexalytics approach," *Data Technol. Appl.*, vol. 53, no. 4, pp. 501–527, 2019, doi: 10.1108/DTA-01-2019-0007.

[13] Y. Du, S. Li, Y. Sharma, J. Tenenbaum, and I. Mordatch, "Unsupervised learning of compositional energy concepts," *Adv. Neural Inf. Process. Syst.*, vol. 34, no. 1, pp. 15608–15620, 2021.

[14] "Damix: Density-aware data augmentation for unsupervised domain adaptation on single image dehazing," *arXiv Prepr. arXiv*, vol. 1, no. 1, pp. 1-12, 2021.

[15] H. Li, D. Hu, Q. Zhu, K. E. Larson, H. Zhang, and I. Oguz, "Unsupervised cross-modality domain adaptation for segmenting vestibular schwannoma and cochlea with data augmentation and model ensemble," *Unsupervised cross-modality domain Adapt. segmenting Vestib. schwannoma cochlea with data Augment. Model ensemble*, vol. 1, no. 1, pp. 1-12, 2021.

[16] M. Nakhwan and R. Duangsoithong, "Comparison Analysis of Data Augmentation using Bootstrap, GANs and Autoencoder," *IEEE 14th Int. Conf.,* vol. 1, no. 1, pp. 1-7, 2022.

[17] S. Yan, J. S. Smith, W. Lu, and B. Zhang, "Abnormal event detection from videos using a two-stream recurrent variational autoencoder," *IEEE Trans. Cogn. Dev. Syst.,* vol. 12, no. 1, pp. 30–42, 2020, doi: 10.1109/TCDS.2018.2883368.

[18] W. Van Gansbeke, S. Vandenhende, S. Georgoulis, and L. V Gool, "Revisiting contrastive methods for unsupervised learning of visual representations," *Adv. Neural Inf. Process. Syst.,* vol. 34, no. 1, pp. 16238–16250, 2021.

[19] P. H. Saputro and H. Nanang, "Exploratory Data Analysis & Booking Cancelation Prediction on Hotel Booking Demands Datasets," *J. Appl. Data Sci.,* vol. 2, no. 1, pp. 40–56, 2021.

[20] J. T. Behrens, "Principles and Procedures of Exploratory Data Analysis," *Psychol. Methods,* vol. 2, no. 2, pp. 131–160, 1997, doi: 10.1037/1082-989X.2.2.131.

[21] D. E. Ufua, O. J. Olujobi, M. E. Ogbari, J. A. Dada, and O. D. Edafe, "Operations of small and medium enterprises and the legal system in Nigeria," *Humanit. Soc. Sci. Commun.,* vol. 7, no. 1, pp. 1–7, 2020.

[22] Henderi and T. Wahyuningsih, "Comparison of Min-Max normalization and Z-Score Normalization in the K-nearest neighbor (kNN) Algorithm to Test the Accuracy of Types of Breast Cancer," *IJIIS Int. J. Informatics Inf. Syst.,* vol. 4, no. 1, pp. 13–20, 2021, doi: 10.47738/ijiis.v4i1.73.

[23] A. Pangestu, "Decision Support System for Accepting Social Assistance for the Program Keluarga Harapan (PKH)," *IJIIS Int. J. Informatics Inf. Syst.,* vol. 5, no. 1, pp. 38–46, 2022, doi: 10.47738/ijiis.v5i1.123.

[24] A. Ajiono and T. Hariguna, "Comparison of Three Time Series Forecasting Methods on Linear Regression , Exponential Smoothing and Weighted Moving Average," *IJIIS Int. J. Informatics Inf. Syst.,* vol. 6, no. 2, pp. 89–102, 2023.

[25] M. Hori, "Study of Career Education for Women: Development of Global Human Resources," *Int. J. Appl. Inf. Manag.,* vol. 1, no. 2, pp. 11–20, 2021, doi: 10.47738/ijaim.v1i2.9.

[26] W. Al-Jedibi, "The Strategic Plan of the Information Technology Deanship - King Abdulaziz University- Saudi Arabia," *Int. J. Appl. Inf. Manag.,* vol. 2, no. 4 SE-Articles, pp. 84–94, May 2022, doi: 10.47738/ijaim.v2i4.40.