Assignment No. 2

Seminar And Technical Communication

Title: Assignment on analysing the latest technical topic through literature survey; this assignment may include progress of the topic from last few years like contents from review reports, journals or research papers related to selected topic for seminar work. Students should keep records of all the resources and use citation.

Topic of seminar : Autoencoders.

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Date of Submission :

➤ LITERATURE SURVEY:

Name of Paper	Author(s)	Year	Description	Drawback(s)
1. Autoencoders Based Deep Learner for Image Denoising	Komal Bajaja, Dushyant Kumar Singhb, Mohd. Aquib Ansaric	2020	This paper presents an autoencoder-based deep learning model for image denoising. The model effectively removes noise from images by learning noise patterns from training data and applying them to clean novel images.	A potential drawback is that the model may perform suboptimally when dealing with other noise types like Salt and Pepper or Poisson noise, as the focus is solely on Gaussian noise
2. AN INTRODUCTION TO AUTOENCODERS	Dibyendu Barman, Abul Hasnat, Rupam Nag	2022	Autoencoders are neural networks used to learn data encodings in an unsupervised manner, often for dimensionality reduction or feature extraction. They work by compressing input data into a latent space and then reconstructing it back to its original form.	A drawback of autoencoders is their susceptibility to overfitting, especially with complex models and insufficient training data, which can limit their performance on unseen data
3. Auto-Encoders in Deep Learning—A Review with New Perspectives	Shuangshuang Chen	2023	Auto-encoders are a type of neural network used in deep learning to perform unsupervised learning by encoding input data into a compressed representation and then decoding it to reconstruct the original input. They are valuable for tasks like feature extraction, pattern recognition, and data generation.	Auto-encoders is their tendency to overfit when the model has too much capacity, leading to the model learning to simply copy the input data instead of extracting meaningful features

4. Autoencoders and their applications in machine learning: a survey	Kamal Berahmand1 · Fatemeh Daneshfar2 · Elaheh Sadat Salehi3 · Yuefeng Li1 · Yue Xu1	2024	Autoencoders are a type of neural network used for dimensionality reduction and feature extraction by learning efficient representations of data	Autoencoders is their sensitivity to hyperparameters like the size of layers and the learning rate, which can affect performance and may require significant trial and error to optimize
5. Autoencoder-Based Risk-Neutral Model for Interest Rates	Andrei Lyashenko1, Fabio Mercurio2 and Alexander Sokol3	2024	Autoencoders are neural networks designed for unsupervised learning, where the goal is to encode input data into a compressed form and then decode it to reconstruct the original data, typically used for tasks like dimensionality reduction and anomaly detection.	A key drawback of autoencoders is their tendency to overfit, especially when trained on small datasets, and their difficulty in preserving meaningful structure when noise or outliers are present.

➢ **DESCRIPTION :**

Reference paper 1 : Autoencoders Based Deep Learner for Image Denoising

Limitations:

1. **Focus on Gaussian Noise**: The model primarily addresses Gaussian noise, leaving other types of noise like Salt and Pepper or Poisson noise for future exploration.
2. **Performance Trade-offs with SSIM**: While the model excels in PSNR, the SSIM (Structural Similarity Index) scores are sometimes lower compared to other models, indicating a trade-off in maintaining the structural integrity of the image.
3. **Dataset-specific**: The performance is based on specific datasets like STL-10 and SET5, which may not generalize well to all types of images, particularly those with different characteristics than those found in these datasets.

4. **Hardware-dependent Training**: The model relies on GPU acceleration (NVIDIA GEFORCE 920 MX) for training, which may be a limitation for users without access to such hardware.

Advantages:

1. High Performance in Denoising: The proposed autoencoder-based model outperforms conventional denoising models, especially in terms of PSNR (Peak Signal-to-Noise Ratio), which suggests improved image quality after noise removal.
2. Efficiency with Gaussian Noise: The model is specifically designed for Gaussian noise, showing significant improvements over other models like CDDNN and RED30 when tested with different noise densities.
3. Skip Connections: The use of skip connections helps in recovering finer details of the image and improves backpropagation, making the training process more efficient.
4. Deep Learning-based Solution: Leveraging convolutional denoising autoencoders allows for better handling of complex noise patterns, offering a more robust solution than traditional methods.
5. Utilizes Unsupervised Learning: The model uses a self-taught learning approach with the STL-10 dataset, providing flexibility in handling large-scale datasets without the need for labeled data.

Reference paper 2 : An Introduction To Autoencoders

Limitations:

1. The model's focus on Gaussian noise limits its effectiveness in handling other types of noise, such as Salt and Pepper or Poisson noise.
2. While PSNR is improved, the Structural Similarity Index (SSIM) sometimes decreases, indicating a potential compromise in maintaining the structural integrity of the image

Advantages:

1. The autoencoder-based model effectively removes Gaussian noise while preserving essential image details, enhancing the Peak Signal to Noise Ratio (PSNR) compared to conventional models.
2. The skip connections in the architecture help recover fine image details, improve color smoothing, and make backpropagation easier, improving the learning process

<u>Reference paper 3 :</u> Auto-Encoders in Deep Learning—A Review with New Perspectives

<u>Limitations:</u>

1. Optimization Challenges: Many AE models suffer from optimization challenges, especially when dealing with deep networks, as they may fall into poor local minima or require pre-training, which can be computationally intensive.
2. Overfitting and Reconstruction Problems: If the encoder and decoder have excessive capacity, AEs can simply learn to copy the input, failing to generalize well. This is especially problematic in over-complete representations.
3. Sparse Representations Complexity: Regularization techniques like sparsity constraints in Sparse AEs require careful tuning to balance representation learning and generalization, which can be laborious.
4. Blurred Outputs: Some advanced variants, such as VAEs, tend to produce blurry outputs when generating new data, particularly in the case of natural images.
5. Computational Complexity: Fully connected AEs like SAE and DAE introduce computational complexity and can become inefficient for handling high-dimensional data, unlike convolutional AEs that scale better but have other challenges like increased model complexity.

<u>Advantages:</u>

1. **Wide Applicability**: Auto-encoders have been successfully applied to many fields like image classification, data generation, recommender systems, and medical image analysis.
2. **Unsupervised Learning**: AEs can extract meaningful features from unlabelled data, enabling non-linear feature extraction, making them useful in environments where labelled data is scarce.
3. **Variants of AE**: Various AE variants such as Denoising Auto-Encoders (DAE), Sparse Auto-Encoders (SAE), and Variational Auto-Encoders (VAE) offer flexibility in learning robust feature representations.
4. **Dimensionality Reduction**: Basic AEs can act as a more powerful nonlinear alternative to Principal Component Analysis (PCA), offering better dimensionality reduction, especially when equipped with non-linear encoder functions.
5. **Advanced Models**: Some advanced models, such as the Wasserstein Auto-Encoder (WAE) and Adversarial Auto-Encoder (AAE), achieve better quality samples and more expressive encoders using adversarial training and optimal transport techniques.

Reference paper 4 : Autoencoders and their applications in machine learning: a survey

Limitations:

1. The paper notes that autoencoders are highly sensitive to hyperparameter tuning, which can affect their performance and may require extensive trial and error to optimize.
2. Autoencoders may struggle with robustness when handling noisy or corrupted data, leading to poor performance in certain real-world scenarios

Advantages:

1. It provides a comprehensive overview of different autoencoder architectures, offering a new taxonomy that helps categorize modern autoencoder methods effectively, which serves as a useful guide for researchers and developers in machine learning.
2. It highlights the wide applications of autoencoders across various fields, such as data compression, anomaly detection, and feature learning, showcasing the versatility and significance of these models in solving complex machine learning tasks.

Reference paper 5: Autoencoder-Based Risk-Neutral Model for Interest Rates

Limitations:

1. Hyperparameter Sensitivity: Autoencoders require careful tuning of hyperparameters, such as learning rate and the number of layers. This sensitivity can lead to suboptimal performance if not well-calibrated.
2. Overfitting & Lack of Robustness: Autoencoders are prone to overfitting, especially when trained on small datasets. They also may not handle noisy or incomplete data well, impacting the quality of reconstructions.

Advantages:

1. Versatility Across Applications: The paper highlights how autoencoders are widely applicable across various domains like computer vision, natural language processing, network analysis, and more. They provide effective solutions for tasks such as anomaly detection, data denoising, and dimensionality reduction.

2. Data Compression & Feature Learning: Autoencoders are particularly beneficial for data compression and feature extraction, helping systems manage high-dimensional data while preserving essential information. They also enhance anomaly detection by quantifying reconstruction errors to identify irregularities, the same technology can be applied, making it scalable and adaptable to different agricultural contexts.

Conclusion : Hence we have successfully studied the literature survey , limitations and advantages of five reference papers related to topic "Autoencoders".

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