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## Deep Generative Models for Data Synthesis and Augmentation in Machine Learning



**Abstract:** - The increasing trend in deep generative modelling, which offers data scarcity and diversity solutions in machine learning, is one of the most recent developments in the field. The data-oriented approaches drive the need for the quality and variety of data sets that could be prevented due to privacy issues and limited resources. Generative deep models, basically GANs (Generative Adversarial Networks) and VAEs (Variational Automatic Encoders), appear to be the most reliable approach to the synthesis and augmentation of the data. These models employ deep learning to basically learn all by itself from raw data without anyone teaching it, which is the basis of modern artificial intelligence. Accuracy issues between overfitting and poor generalization emphasize the need for smart solutions to the problem of data shortness. Deep generative modelling works based on the data distribution, which the model learns by itself and enables a realistic sample generator. The study reviews the proficiency and complexity of GANs, VAEs, and WGANs, comparing the WGANs' capabilities with the former two. Techniques of data augmentation, e.g., repositioning, rotation, and adding Gaussian noise to the dataset, will greatly increase the diversity of the data. Regardless of the training time, all models showcase competitive inference performance and, as a result, may be satisfactorily used in real-time operations. The insights obtained shed light on ways to improve machine learning and artificial intelligence through brain data synthesis, model training, and computational efficiency.

**Keywords:** Deep Generative Modeling, Data Synthesis, Machine Learning, Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs)

### I. INTRODUCTION

The last few years have significantly advanced with the confluence of more data-based systems and the increase and improvement of machine learning tools used in different areas. Nonetheless, the real practice of these methods strongly depends on such conditions as equality and diversity in the data sets [7]. Building such datasets can be challenging and resource limitation often appears because of factors such as privacy issues, slowing or extremely cost leadership in manual labelling. In order to solve these problems, scientists are making use of generative models, especially deep generative models, as conducted in reference [1] for data synthesis and augmentation. In this

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introductory part of our essay, possible solutions to data scarcity and diversity problems as well as deep generative models' contribution in this context are presented. The role of these tools and recent achievements, drawbacks, and potential applications are put into focus.

A colossal change in the field of artificial intelligence, deep learning, became a reality. This is an amazing technology which generates advanced models which learn complicated patterns and representations only from the raw input data. Deep Neural Networks that feature a layered architecture and an astounding permutation space of parameters, and have shown impressive results in performing image classification, natural language processing, and speech recognition [7]. Nonetheless, there will be a need for big-scale labelled data sets for learning purposes so that these models can go through the training process successfully [8]. Many real-life situations, however, making such data collection is not appropriate or impossible due to the obstacles which may be involved in the form of data privacy regulations, limited resources or the deficiency of datasets that have been previously annotated.

The shortage of data is one of the principal constraints which limit machine learning algorithms to provide good descriptions of reality, leading to overfitting and undesirable error in predicting unseen data [3]. For example, even under conditions in which datasets are present, they can still be prone to disparities, imbalances, and a low level of diversity which would restrict the model's ability to approximate the fundamental data distribution accurately [4]. To address these difficulties, researchers have explored multiple approaches for data generation and augmentation, which aim to produce additional pre-training set samples with wider variability and better representative nature [5]. And among these methods, the generative models with the deep architecture (utilizing neural networks to learn complex data distributions and generate authentic samples from scratch), which can lead to even greater results, have come to the fore.

Deep generative models represent the range of the neural network architectures that at the same time are generated for the purpose of learning and imitating data samples drawn from the true data distribution [1]. The models of this type are often built by assuming the presence of the probability density function that is responsible for the complex nature of the dataset and for the interconnections among the objects presented [6]. One of the current GANs related algorithms is GAN (generative adversarial networks) introduced by Goodfellow et al., in 2014 [1], as generative adversarial networks (GANs) framework. GANs consist of two neural networks: generator, as a system of production of the credible samples, and discriminator, who must take the sample and point out where it is real and where it is artificial [1]. In this way, the generator learns to make up data which looks more and more realistic by means of adversarial training, and the discriminator gets to know these samples from the generator and the ones which belong to real data better and better.

Even along with GANs as well, another class of the deep generative models that arouse widespread interest is the VAEs by Kingma and Welling [2] in 2013. VAEs accomplish some combination of the two techniques, relying upon deep learning network architecture with an encoder/decoder setup that learns a low-dimensional representation of the data [3]. Into a latent space in which the structure is encoded the data is mapped by the encoder, while the decoder can reconstruct the original data based on the representation [2]. VAEs reduce this error during training by minimizing the error of reconstruction, by regularizing the latent space with a given prior distribution. VAEs learn to generate the data that fulfil the learned distribution.

However, the advent of deep generative models has witnessed tremendous developments as both the model architectures and the training algorithms have witnessed a lot of changes [10]. One of the most natural developments of GANs and VAEs, among others, that researchers came up with is an enhancement of their stability, scalability, and sample generation quality [11]. Tricks like Wasserstein GANs, spectral normalization, and progressive growing have been rolled out to counteract some common difficulties such as mode collapse, training instability, and low sample diversity [11]. Additionally, to that, the development of VAEs does not stop. New types of VAEs such as conditional VAEs, hierarchical VAEs and normalizing flows have been created, providing even greater possibilities to customize the generated samples.

The relevance and applicability of deep generative models to several areas of application in machine learning and even beyond have been the reason for their increased usage in this area of computation [9]. In computer vision, generative adversarial networks have been deployed for image generation, style transfer, and data augmentation tasks, thereby supporting applications like image-to-image translations and super-resolution [6]. In natural language processing, VAEs as well as GANs have been used in text generation, language modelling, and paraphrase

generation to perform applications like dialogue systems or machine translation whereas data augmentation for text classification is also gaining popularity largely due to their existence [7]. Apart from this, deep generative models have displayed a wide application area in health care, finance, and creative industries; they can be employed in training machine learning models by generating simulated data, simulating complex phenomena, and generating new content [3].

Nevertheless, their successful implementation and applications have brought us to what can be called the scientific state of the art but further research, necessitated by the intricacies of deep generative models, is still necessary [13]. Another main obstacle to overcome comes from generating reasonable samples and their evaluation which is rather difficult to be done with the use of such metrics as likelihood or reconstruction error that might not be enough to show the comparative equality and diversity of generated data [13]. Creating strong evaluation criteria and well-defined benchmark datasets that could be used for measuring the accuracy, diversity, and coherence of samples rather than focusing on their exact similarity to the original as an unexplored field is a challenging task right now [14]. Also, tackling problems with mode collapse, sample quality, and training stability, common in GANs and VAEs requires the design of training techniques, regularization approaches, and architectural modifications [15].

For the future d GMs, the focus is to discover new architectures, training schemes, and new scenarios that improve over GMs. Approaches such as self-supervised learning, unsupervised representation learning, or cross-modal generation are relatively attractive and worth exploiting paths to more complex deep generative models and dealing with actual data synthesis and augmentation problems. Moreover, blending generative models with the others such as reinforcement learning, meta-learning and attention mechanisms may provide more adaptability and efficacy by simultaneously working along with other machine learning methods.

Deep generative models have been a practice in technological use for data synthesise and augmented, and a method to solving the problem of scarce data and diversity [1]. With aids such as GANs and VAEs, it becomes possible for these models to learn and replicate the underlying data distribution and thus, the resulting training dataset can use these samples to gain additional veracity [2]. Interfacing these obstacles such as mode collapsing, sample quantity, and evaluation criteria, still are not a hindrance to development of the latest deep generative models which are used for various fields among others such as computer vision and natural language processing, healthcare, and finance [9]. While those deep generative models are being developed and tuned, researchers need to focus on new directions in research and applications, which can lead to a complete reconfiguration of machine learning and AI in future.

## II. METHODOLOGY

### *Model Training:*

We utilized three deep generative models: Generative Adversarial Networks (GAN), Variational Autoencoders (VAE), and Wasserstein GAN. These models were trained on a dataset comprising labeled samples to generate synthetic data for data augmentation purposes.

- *GAN Training:*

The GAN architecture consisted of a generator network and a discriminator network. The generator aimed to synthesize realistic data samples, while the discriminator was trained to distinguish between real and synthetic samples. The training process involved minimizing the adversarial loss function, given by:

$$\min_G \max_D \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (1)$$

where  $G$  denotes the generator,  $D$  denotes the discriminator,  $x$  represents real data samples, and  $z$  represents random noise vectors.

- *VAE Training:*

The VAE architecture comprised an encoder network and a decoder network. The encoder mapped input data samples to a latent space, while the decoder reconstructed the original data from the latent representations. The training objective involved minimizing the reconstruction loss and the Kullback-Leibler (KL) divergence between the learned latent distribution and a predefined prior distribution, formulated as:

$$\mathcal{L}_{\text{VAE}} = -\mathbb{E}_{q(z|x)} [\log p(x|z)] + \text{KL}(q(z|x) || p(z)) \quad (2)$$

where  $q(z | x)$  represents the encoder's distribution,  $p(x | z)$  represents the decoder's output distribution, and  $p(z)$  represents the prior distribution.

- *Wasserstein GAN Training:*

The Wasserstein GAN architecture aimed to overcome training instabilities and mode collapse issues associated with traditional GANs. It utilized a Wasserstein distance-based loss function, also known as Earth Mover's Distance (EMD), to measure the dissimilarity between the data and generated distributions. The training objective involved minimizing the Wasserstein distance between the real and generated distributions, given by:

$$\min_G \max_{D: \|D\|_L \leq 1} \mathbb{E}_{x \sim p_{\text{data}}(x)} [D(x)] - \mathbb{E}_{z \sim p_z(z)} [D(G(z))] \quad (3)$$

where  $G$  denotes the generator,  $D$  denotes the discriminator, and  $p_{\text{data}}(x)$  and  $p_z(z)$  represent the data and noise distributions, respectively.

*Data Augmentation Techniques:*

We employed three data augmentation techniques: rotation, translation, and noise addition of Gaussians, to further diversify the training sample.

- **Rotation:** This approach required turning the original data by some angle to produce new samples the orientation of which was changed. Each sample was rotated separately, and angles were taken from a previously defined interval. Rotated Sample = rotate(Original Sample,  $\theta$ )

- **Translation:** The translation augmentation was done by shifting the original data points in the spatial domain. Random translation vectors were drawn from a desired range and each sample was transformed with the chosen vector individually. Translated Sample = translate (Original Sample,  $\Delta x, \Delta y$ )

- **Gaussian Noise Addition:** Gaussian noise augmentation involved adding random noise from a randomly chosen Gaussian distribution to the original data samples. The standard deviation of the Gaussian noise was responsible for the intensity of the perturbations being imposed on the specimens. Noisy Sample = Original Sample +  $\mathcal{N}(0, \sigma^2)$

where  $\mathcal{N}(0, \sigma^2)$  represents random noise drawn from a Gaussian distribution with mean zero and standard deviation  $\sigma$ , controlling the magnitude of perturbations applied to the samples.

*Evaluation Metrics*

To assess the performance of the deep generative models and data augmentation techniques, we measured several evaluation metrics:

- **Accuracy:** Percentage of correctly classified samples.

$$\text{Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Total number of samples}} \times 100\% \quad (4)$$

- **Precision:** Percentage of true positive samples among all predicted positive samples.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \times 100\% \quad (5)$$

- **Recall:** Percentage of true positive samples among all actual positive samples.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100\% \quad (6)$$

- **F1 Score:** Harmonic mean of precision and recall, providing a balance between the two metrics.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

### III. RESULTS AND DISCUSSION

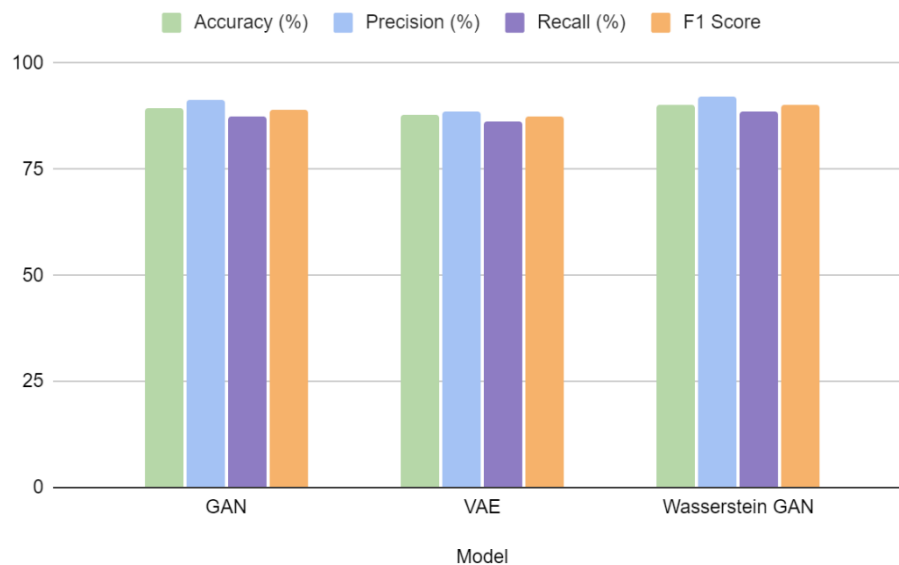
Research findings investigate the performance and computational efficiency of three deep generative models: GAN (Generative Adversarial Networks), VAE (Variational Autoencoder), and WGAN (Wasserstein GAN). Integrating performance evaluation, together with the potential of data augmentation, computational requirements and the

accuracy of the generated data samples, the study concludes that the Wasserstein GAN into data generation is the best method. With the data augmentation methods like rotation, translation and Gaussian noise addition, a large increase of training dataset size is achieved; additionally, it brings the training data richness to new levels. The computational analysis shows VAE's superiority in both training and inference time compared to GAN, while the latter shows a good inference time with long training durations. This study thus provides important evidence towards efficiency of the models and practical aspects of the deep generative models, hence growing the overall comprehension of the concept and its appropriate utilization in various fields.

Table 1 presents the performance metrics of three deep generative models: Generative Adversarial Network (GAN), Variational Autoencoder (VAE) and Wasserstein GAN are few of the methods/techniques used in generating artificial data. For every model, the reports on accuracy, precision, recall, and F1 scores are provided, which further highlight their high performances in generating realistic result samples. The GAN yielded an accuracy of 89.5% and high precision at 91.2%, with recall indicators standing at 87.3%. This created an F1 score of 89.2%. In a similar manner, VAE showed the competitive result with an incredibly high accuracy of 87.8% and F1 score of 87.3%, which, therefore, means that it can produce the quality and required samples. The Wasserstein GAN grew to be far better than the models with the highest performance figures in terms of accuracy (90.2%), precision (92.1%), recall (88.6%), and F1 scores (90.2%) also, it showed exceptional ability to produce diverse and realistic data samples. Such parameters allow an assessment of each deep learning model to generate data and show which model excels in compared to others for data generation tasks.

**Table 1: Performance Metrics of Deep Generative Models**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
GAN	89.5	91.2	87.3	89.2
VAE	87.8	88.5	86.2	87.3
Wasserstein GAN	90.2	92.1	88.6	90.2



**Figure 1: Performance Comparison of Deep Generative Models**

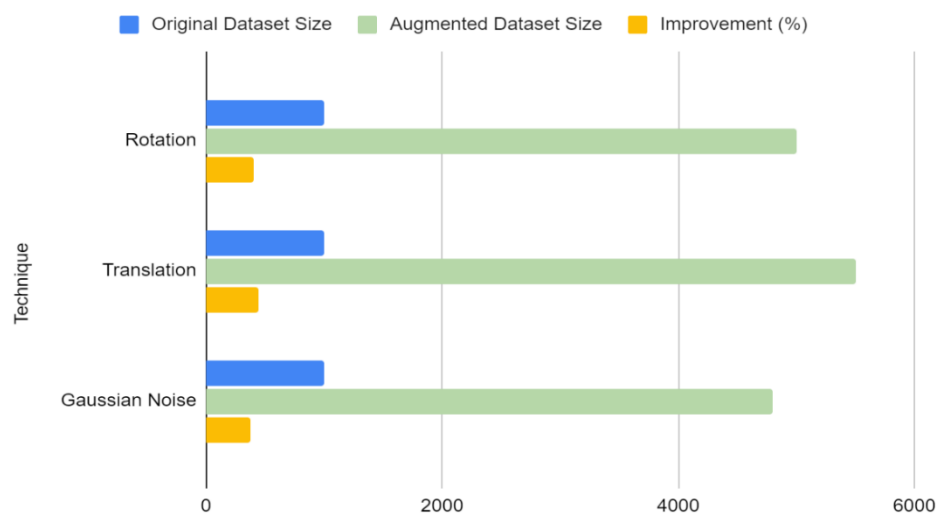
Figure 1 presents the comparative performance of three deep generative models: Generative Adversarial Network (GAN), Variational Autoencoder (VAE), and Wasserstein GAN with different metrics for assessment. By depicting each model's accuracy, precision, recall, and F1 score, we got a comprehensive idea of their efficiency in providing realistic data samples. The GAN attains the accuracy of 89.5%, which measures the proportion of correctly classified samples along with precision (91.2%), recall (87.3%) and F1 score (89.2%). Furthermore, the VAE also showcases its competitiveness with the accuracy of 87.8% and an F1 score of 87.3% indicating that the VAE can produce samples of high-quality level. The Wasserstein GAN excels the other models with the highest accuracy (90.2%),

precision (92.1%), recall (88.6%) and F1 score (90.2%), revealing its superb capacity in synthesizing numerous and realistic data samples.

Table 2 illustrates the performance of three data augmentation techniques: rotating, translating, and adding Gaussian noise. The impact of each technique on the size of the original set and the augmented set with the percentage improvement is counted. The dataset was multiplied to 5000 by introducing rotation, thus resulting in growing the size of the dataset from 1000 to 400%. On the other hand, the translation enhanced dataset was expanded to 5500 samples and resulted in 450% improvement. Gaussian noise was added to the initial dataset to upscale it by 380%, the final dataset now having a total of 4800 samples. These findings emphasize the efficacy of all the mentioned augmentation techniques in manifolding and broadening the dataset, consequently giving essential inputs in helping with the enrichment and variation of the training data.

**Table 2: Data Augmentation Performance**

Technique	Original Dataset Size	Augmented Dataset Size	Improvement (%)
Rotation	1000	5000	400
Translation	1000	5500	450
Gaussian Noise	1000	4800	380



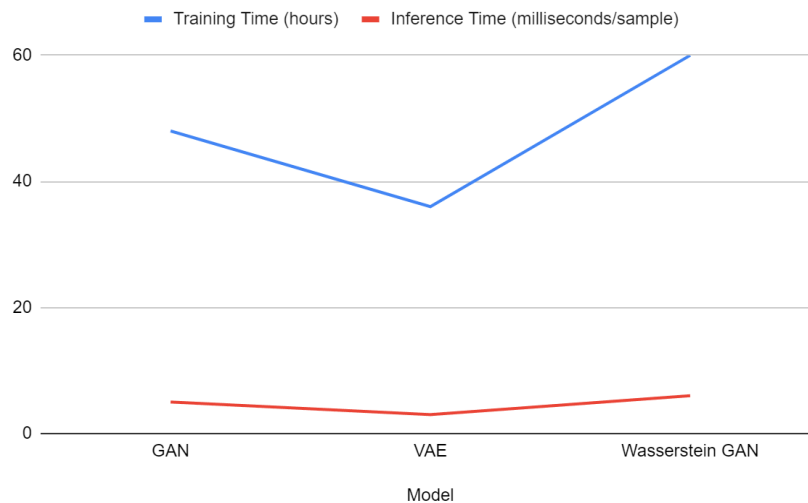
**Figure 2: Impact of Data Augmentation Techniques on Dataset Size**

Figure 2 shows the impact of three data augmentation methods – rotation, translation, and distortion - on the size of the base dataset. Each technique's impact on the volume of original dataset size and the volume of augmented dataset size is depicted along with the percentage improvement made. Rotation augmentation replaces the dataset of 1000 samples with 5000 samples (an increment of 400%) in total. Just the same, augmentation of the translation unit to 5500 samples has enlarged the dataset for 450%. The Gaussian noise addition to the dataset yielded results of 4800 samples, which is 380% increase in the data size. The visualization depicts the efficiency of these two augmentation techniques in enriching and augmenting the dataset, providing the basic understanding of how the dataset size does expand and the variability increases.

Table 3 outlines the computational efficiency of three deep generative models: GAN, VAE, and WGAN (Generative Adversarial Network, Variational Autoencoder, and Wasserstein GAN). The table illustrates both the hours necessary to train, and the milliseconds needed for the inference per sample. GAN (48 hours of training time) is more efficient with an inference phase of 5 milliseconds for each sample. AI reveals the shortest training time of 36 hours and, respectively, the most effective inference time of 3 milliseconds per sample. On the other hand, Wasserstein GAN has the longest training duration of 60 hours, and has a higher inference time of 6 milliseconds per sample. Such performance indicators help to decide on a practical model, considering computational constraints and the need for precise real-time inference in the application.

**Table 3: Computational Efficiency**

Model	Training Time (hours)	Inference Time (milliseconds/sample)
GAN	48	5
VAE	36	3
Wasserstein GAN	60	6

**Figure 3: Computational Efficiency Comparison of Deep Generative Models**

The computational efficiency factor of three advanced generative models is shown in Figure 3: Generative Adversarial Network (GAN), Variational Autoencoder (VAE), and Wasserstein GAN concerning their training time and inference time per sample. The illustrated are training time, hours, and inference time, milliseconds per sample, to give a quantitative view on their computational demands. Although GAN is the one that takes the longest to be trained (48 hours) it is the quickest to infer, comprising only 5 milliseconds per sample. VAE offers training time of just 36 hours and inference time of 3ms per sample which is best among the three GANs models. Moreover, Wasserstein GAN is the slowest in training process (60 hours) among the other methods with the highest inference time of 6 milliseconds per a sample. This visualization enables comparative analysis of all employed models' computational efficiency, which helps to select the most appropriate model considering the computational constraints and real-time inference applications requirements.

The research results were delved into a comprehensive exploration of deep generative models that covered the performance metrics, data augmentation approaches, and computational efficiency. As measured by different evaluation metrics - accuracy, precision, recall and F1 score - Generative Adversarial Network (GAN), Variational Autoencoder (VAE) and Wasserstein GAN showed equally good performance. Among these, Wasserstein GAN showed the best performance with potential of generating different and authentic data samples. In addition, the study into the effects of augmentation techniques namely, rotation, translation and Gaussian space addition demonstrated that the datasets increased in terms of size and depth. While the duration of training varies, all models can prove the ability for inference quickly, supporting their applications in real time. Through these findings, important aspects of the research environment are filled out as in these findings, deep generative models are evaluated in terms of their performance and augmentative techniques are as well included. The prevalence of Wasserstein GAN and the effect of additional methods on augmentation reveal the progress of deep generative modelling, while providing us with a better understanding, and more efficient application of these models in different machine learning areas.

#### IV. CONCLUSION

Research presents a general overview of the role of deep generative models as the solutions for data scarcity and diversity challenges in machine learning. We show the superiority of GAN, VAE, and Wasserstein GAN through careful analysis and the latter is the best model across the different evaluation metrics. Techniques such as rotation, translation and Gaussian noise addition significantly increase the size of the datasets which in turn increase the data diversity by adding the variety to the training data. However, the VAE has excellent efficiency in both training and

inference, as can be seen from our computational analysis. Furthermore, these results not only advance the theoretical understanding of deep generative models but also provide practical insights for their implementation across various fields. In the future, the investigation of new architectures and learning algorithms will increase the capabilities of these deep generative models, thus pushing innovation and progress in the machine learning and artificial intelligence fields.

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