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A COMPREHENSIVE STUDY ON TEXT-TO-IMAGE SYNTHESIS USING GENERATIVE ADVERSARIAL NETWORKS(GAN's)

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Abstract: *Using automated image generation from textual descriptions, this work introduces a novel way to text-to-image synthesis. Our approach leverages sophisticated neural networks, such as Generative Adversarial Networks (GAN's), to overcome multi-modal learning issues. It does this by improving visual realism, handling many scenes, guaranteeing semantic consistency, and facilitating style transfer. The architecture combines a sophisticated text encoder, flexible generator network, larger datasets , conditional discriminator, and painstaking detail-oriented design. Its potential significance is highlighted by rigorous evaluation measures and a variety of applications, which pave the way for further improvements and signal a paradigm change in the capabilities of text-to-image synthesis.*

Keywords: *Text-to-image synthesis, Generator network, Enhanced text encoder, Conditional discriminator, Generative models.*

INTRODUCTION

Text-to-image synthesis is an exciting and rapidly evolving field within the realm of artificial intelligence. Its primary objective is to develop automated models that possess the ability to understand and interpret detailed textual descriptions, subsequently generating corresponding visual representations. This task is inherently intricate due to the necessity of seamlessly merging the realms of natural language processing and computer vision, thereby demanding a sophisticated level of creativity and ingenuity.

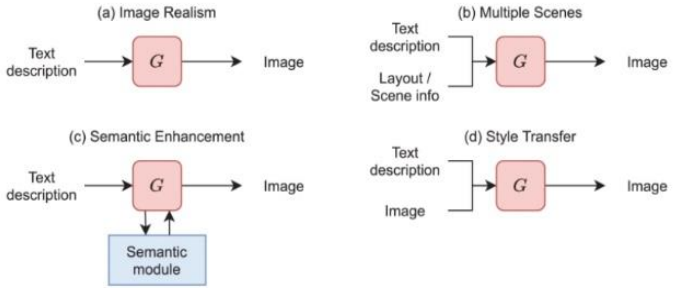
Despite its immense potential, text-to-image synthesis remains relatively underexplored compared to other well-established domains within machine learning, such as object recognition. The complexity of this field stems from its inherent requirement to integrate and reconcile multimodal information, effectively combining textual cues with visual inputs.

Generative Adversarial Networks (GANs) have emerged as a powerful and versatile architecture for text-to-image synthesis. GANs consist of two primary components: a generator network tasked with producing images, and a discriminator network responsible for assessing the authenticity of these generated images.

One of the significant advancements in text-to-image synthesis has been the introduction of conditional variations within GANs, known as conditional GANs (cGANs). These models have the capability to incorporate additional inputs, such as class labels or textual descriptions, enabling them to generate images that align more closely with the semantics of the provided textual input.

Despite these advancements, several challenges persist within the realm of cGAN-based approaches. These challenges include the imperative of maintaining semantic coherence between textual descriptions and generated images, preserving fine details during the synthesis process, and effectively handling diverse object classes and scenes within a single image.

In summary, while significant progress has been made in the field of text-to-image synthesis, there still exist numerous opportunities for further research and development aimed at addressing these challenges and Unleashing the complete capabilities of this revolutionary technology.



2.LITERATURE SURVEY

[1] Scaling Up GANs for Text-to-Image Synthesis (2023) by Minguk Kang and crew presents GigaGAN, an adaptable text-to-image synthesis model based on StyleGAN. The results show competitiveness, though it falls short of achieving photorealism compared to some counterparts. Summary: This work focuses on scaling GANs and demonstrates the

ability to generate high-resolution images but highlights limitations in achieving photorealistic quality.

[2] TextControlGAN: Image Synthesis with Controllable Generative Adversarial Networks (2023) by Hyeeun Ku and Minhyeok Lee leverages the ControlGAN framework to enhance synthesis on the Caltech-UCSD Birds-200 dataset. Summary: This method introduces control mechanisms to improve synthesis quality, resulting in improved Inception Score and reduced FID.

[3] CapGAN: Text-to-Image Synthesis Using Capsule GANs (2023) by Maryam Omar and crew employs CapGAN, based on capsule networks. Summary: CapGAN shows superior performance on complex datasets like Oxford-102 Flowers, Caltech-UCSD Birds 200, and ImageNet Dogs by leveraging capsule networks for better feature representation.

[4] StyleGAN-T: Unlocking the Power of GANs for Fast Large-Scale Text-to-Image Synthesis (2023) by Axel Sauer and others introduces StyleGAN-T, which allows for smooth interpolations and various styles without additional training, specifically using the MSCOCO dataset. Summary: This model is noted for its efficiency and flexibility in style transfer, offering significant improvements in training speed and diversity.

[5] DF-GAN: A Simple and Effective Baseline for Text-to-Image Synthesis (2022) by Ming Tao and associates proposes DF-GAN, which outperforms newer rivals on the CUB bird and COCO datasets. Summary: DF-GAN establishes a strong baseline with simplified architecture, achieving high performance on benchmark datasets.

[6] Vector Quantized Diffusion Model for Text-to-Image Synthesis (2022) by Shuyang Gu and others presents VQ-Diffusion, a non-autoregressive text-to-image model that excels in complex settings across CUB-200, Oxford-102, and MSCOCO datasets. Summary: This work highlights the advantages of non-autoregressive models in handling diverse and intricate text-to-image tasks.

[7] Improving Text-to-Image Synthesis Using Contrastive Learning (2021) by Hui Ye and others investigates the impact of various techniques, achieving superior performance over AttnGAN and DM-GAN on CUB and COCO datasets. Summary: The paper demonstrates how contrastive learning can enhance the quality of synthesized images.

[8] DAE-GAN: Dynamic Aspect-aware GAN for Text-to-Image Synthesis (2021) by Shulan Ruan and colleagues focuses on enhancing realism by incorporating aspect knowledge, excelling in text-to-image synthesis authenticity on CUB and COCO datasets. Summary: DAE-GAN introduces dynamic aspect modeling, significantly improving image authenticity.

[9] Cycle-Consistent Inverse GAN for Text-to-Image Synthesis (2021) by Hao Wang and others presents CI-GAN, which integrates text-to-image synthesis and guidance, performing exceptionally well on Recipe1M and CUB datasets. Summary: CI-GAN uses cycle-consistency for better alignment between text and image domains.

[10] Unsupervised Text-to-Image Synthesis (2021) by Yanlong Dong and others adopts visual concepts in AttnGAN, showing superior performance in a single background using the MSCOCO dataset. Summary: This work explores unsupervised learning techniques to improve text-to-image synthesis.

[11] Text to Image Synthesis for Improved Image Captioning (2021) by MD. ZAKIR HOSSAIN and others examines the intersection of text-to-image synthesis and image captioning, demonstrating artificial figures surpassing conventional methods on the MSCOCO dataset. Summary: This paper highlights the benefits of integrating synthesis techniques into image captioning tasks.

[12] A Survey and Taxonomy of Adversarial Neural Networks for Text-to-Image Synthesis (2020) by Jorge Agnese and others reviews and categorizes various methods, including Conditional GAN, DC-GAN, MC-GAN, StackGAN, and AttnGAN. Summary: This comprehensive survey provides a detailed taxonomy of existing GAN-based methods for text-to-image synthesis.

[13] KT-GAN: Knowledge-Transfer Generative Adversarial Network for Text-to-Image Synthesis (2020) by Hongchen Tan and associates features AATM and SDM, achieving superior synthesis on CUB Bird and MS-COCO datasets. Summary: KT-GAN leverages knowledge transfer to enhance synthesis quality.

[14] Efficient Neural Architecture for Text-to-Image Synthesis (2020) by Douglas M. Souza and others presents novel approaches like GAN-INT-CLS, GAWWN, StackGAN, and HDGAN, exploring various enhancements with single-stage training on Caltech-UCSD Birds (CUB) and Oxford-102 datasets. Summary: This paper explores efficient architectures and training methods to improve synthesis performance.

[15] Generative Adversarial Text to Image Synthesis (2016) by Scott Reed and others significantly contributed by enhancing CUB text-to-image synthesis, with applications extending to MS-COCO, targeting higher resolutions.

Summary: This foundational work laid the groundwork for modern text-to-image synthesis methods, demonstrating the potential of GANs in this domain.

Comparison of Methods:

- Performance: DF-GAN and VQ-Diffusion demonstrate superior performance on standard datasets like CUB and MSCOCO.
- Innovation: GigaGAN and StyleGAN-T introduce scalability and stylistic flexibility, respectively.
- Complexity: CapGAN and DAE-GAN address complex representation tasks with capsule networks and dynamic aspect modeling.

Challenges and Future Directions:

- Photorealism: Achieving photorealistic quality remains a challenge for models like GigaGAN.
- Efficiency: Improving training efficiency and reducing computational costs are ongoing concerns.
- Generalization: Enhancing model generalization to handle diverse and unseen text descriptions.

Visualization and Results:

- DF-GAN: Notable for clear and high-quality bird images.
- VQ-Diffusion: Excels in generating detailed images in complex scenarios.
- StyleGAN-T: Demonstrates smooth style interpolations with minimal training.

Technical Details:

- GigaGAN: Based on StyleGAN with enhanced scalability.
- TextControlGAN: Utilizes ControlGAN framework for better synthesis control.
- CapGAN: Integrates capsule networks for improved feature representation.

Table 1: Techniques used in various research

S.NO.	Author	Dataset	Methodology	Result
1	Axel Sauer, Tero Karras, Samuli Laine, Andreas Geiger, Timo Aila	MSCOCO dataset	StyleGAN-T	"StyleGAN-T demonstrates smooth interpolations and diverse styles without extra training."
2	Hyeeun Ku and Minhyeok Lee	Caltech-UCSD Birds-200 (CUB) dataset	Conditional GANs (cGANs), Auxiliary Classifier GAN (ACGAN), AttnGAN, DM-GAN	"TextControlGAN enhances text-to-image synthesis, improving Inception Score, reducing FID."
3	Maryam Omar, Hafeez Ur Rehman, Omar Bin Samin, Moutaz Alazab, Gianfranco Politano and Alfredo Benso	Oxford-102 Flower, Caltech-UCSD Birds 200, ImageNet Dogs datasets	CapGAN	"CapGAN, based on capsules, excels in complex image synthesis tasks."
4	Minguk Kang, Jun-Yan Zhu, Richard Zhang, Jaesik Park, Eli Shechtman Sylvain Paris, Taesung Park	MSCOCO dataset	StyleGAN	"GigaGAN: Scalable text-to-image synthesis, competitive but not as photorealistic"
5	Ming Tao, Hao Tang, Fei Wu1 Xiaoyuan Jing, Bing-Kun Bao Changsheng Xu	CUB bird and COCO	Deep Fusion GAN (DF-GAN)	"Proposed DF-GAN for superior text-to-image synthesis, outperforming state-of-the-art on CUB and COCO datasets."
6	Shuyang Gu,Dong Chen,Jianmin Bao,Fang Wen,Bo Zhang,Dongdog Chen,Lu Yuan,Baining Guo	CUB-200, Oxford-102, and MSCOCO datasets	StackGAN, AttnGAN	"VQ-Diffusion: Non-autoregressive text-to-image model for complex scenes, surpassing GANs."
7	Hui Ye, Xiulong Yang, Martin Takac, Rajshekhar Sunderraman, Shihao Ji	CUB and COCO datasets	DM-GAN	"Improved text-to-image models with contrastive learning, outperforming AttnGAN and DM-GAN."
8	Shulan Ruan, Yong Zhang, Kun Zhang, Yanbo Fan, Fan Tang, Qi Liu, Enhong Chen	CUB-200 and COCO datasets	DAE-GAN	"DAE-GAN leverages aspect info, excelling in text-to-image synthesis realism."

9	Hao Wang, Guosheng Lin, Steven C. H. Hoi, Chunyan Miao	Recipe1M and CUB datasets	Cycle-consistent Inverse GAN (CI-GAN)	"CI-GAN unifies text-to-image and manipulation, excelling in diverse synthesis."
10	Yanlong Donga, Ying Zhang, Lin Mac, Zhi Wang, Jiebo Luo	MSCOCO dataset	AttnGAN	"Unsupervised text-to-image synthesis using visual concepts, outperforming supervised models."
11	Md. Zakir Hossain, (Student Member, IEEE), Ferdous Sohel, (Senior Member, IEEE), Mohd Fairuz Shiratuddin, Hamid Laga, and Mohammed Bennamoun, (Senior Member, IEEE)	MSCOCO dataset	AttnGAN	"Synthetic images enhance image captioning, outperforming baseline and state-of-the-art methods."
12	Jorge Agnese, Jonathan Herrera, Haicheng Tao, Xingquan Zhu	MNIST, Oxford-102, COCO, CUB, CIFAR-10	Conditional GAN, DC-GAN, MC-GAN, Resolution Enhancement GANs,StackGAN, AttnGAN, HDGAN, ACGAN, TAC-GAN,Text-SeGAN	"Surveyed advanced text-to-image synthesis methods, proposing taxonomy and evaluating architectures"
13	Hongchen Tan, Xiuping Liu, Meng Liu, Baocai Yin and Xin Li, *Senior Member, IEEE*	CUB Bird dataset MS-COCO dataset	AttnGAN	"KT-GAN employs AATM and SDM, excelling in text-to-image synthesis quality."
14	Douglas M. Souza, Jonatas Wehrmann, Duncan D. Ruiz	CUB and Oxford-102 datasets	GAN-INT-CLS, GAWWN, StackGAN, StackGAN++, TAC-GAN, HDGAN	"Novel text-to-image approach with single-stage training, exploring diverse enhancements."
15	Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran Bernt Schiele, Honglak Lee	Oxford-102 Flowers dataset, MS COCO dataset, MS-COCO dataset	GAN-CLS	"Enhanced CUB text-to-image, generalized to MS-COCO, targeting higher resolution."

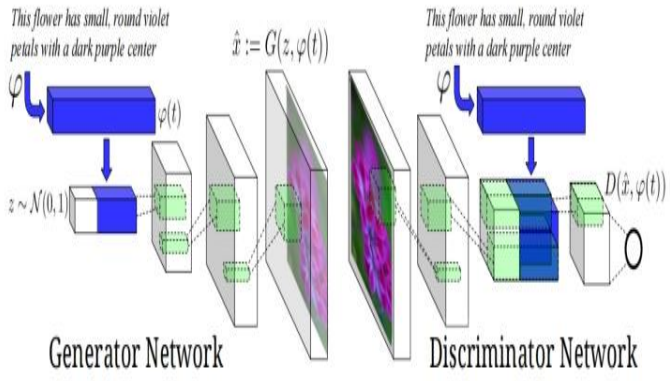
3.METHODOLOGY USED

In our project, we employ a sophisticated deep learning model, specifically a deep convolutional generative adversarial network (DC-GAN), to combine textual descriptions with image synthesis. This model is trained on a dataset of handwritten documents and utilizes a combination of character-level convolutional and recurrent neural networks. This section outlines the methodology employed, detailing the network architecture and the techniques used to enhance the training process.

3.1 Network Architecture

The generator network (G), defined as $G:R^Z \times R^T \rightarrow R^D$, is designed to generate images from text inputs. Conversely, the discriminator network (D), defined as $D:R^D \times R^T \rightarrow \{0,1\}$, differentiates between real and generated images.

Here, T represents the length of the text input, D is the dimension of the generated image, and Z is the dimension of the noise input to G.The architecture begins by sampling noise z from a standard normal distribution $z \in R^Z \sim N(0,1)$.The text input t is encoded using a text encoder ϕ. The encoded text $\phi(t)$ is then compressed and concatenated with the noise vector zz. The generator uses this combined input to produce an artificial representation $x^{\wedge}$.



3.2 Matching-Knowledgeable Discriminator (GAN-CLS)

The Matching-Knowledgeable Discriminator (GAN-CLS) enhances traditional GAN training by incorporating real images paired with different text descriptions. Unlike conventional GANs, which treat (quote, expression) pairs as joint observations, GAN-CLS introduces a secondary reference type, using real images corresponding to varied text passages. This method helps distinguish unrealistic expressions from realistic images of the wrong class, refining the conditioning information's accuracy.

3.3 GAN-CLS Training Algorithm

The GAN-CLS training algorithm involves multiple steps to boost performance:

1. Encoding the text and its alternatives to produce representations that capture the textual essence.
2. Sampling random noise and combining it with the encoded text to generate fake images.
3. Calculating scores for real and fake inputs, allowing the discriminator to learn and improve face/passage matching.
4. Updating the discriminator and generator based on the discriminator loss (LD) and generator loss (LG), respectively.

3.4 Learning with Manifold Interpolation (GAN-INT)

GAN-INT uses the characteristics of deep networks to create additional text embeddings by interpolating between training set captions. This method enhances the model's ability to interpolate between various textual descriptions, thus improving the generation of realistic images.

3.5 Inverting the Generator for Style Transfer

For style transfer, a convolutional network is trained to invert the generator, regressing from generated samples back to the latent space. A squared loss function trains the style encoder, allowing the model to predict the style and generate images accordingly. This technique enables the transfer of styles from one image to another while maintaining content integrity.

4. PROPOSED SYSTEM

The proposed system represents a significant advancement in the field of text-to-image synthesis, aiming to redefine the capacities and outlook of existing models. It addresses the limitations of traditional approaches that often struggle with producing images confined to specific classifications. Our goal is to create a more adaptable and comprehensive system capable of generating concepts across a wide spectrum, including mammals and human subjects. This innovative system is underpinned by an advanced GAN design, attention mechanisms, and an improved dataset, each contributing to its pioneering proficiencies.

Our proposed system incorporates an advanced text encoder, serving as the intelligent nucleus of the architecture. Unlike traditional encoders, our enhanced variant boasts a broader understanding of textual inputs, achieved through

progressive techniques in natural language processing. This nuanced understanding guarantees accurate representation of complex textual descriptions, facilitating faithful image synthesis.

At the heart of our system lies the versatile generator network, designed for flexibility and equipped with advanced deconvolutional layers and attention mechanisms. These architectural innovations enable seamless transition between generating images across diverse subjects based on textual input. The flexibility of the generator ensures adaptation to a wide range of textual inputs, facilitating the production of contextually appropriate and realistic concepts.

Our system includes a conditional discriminator, critical for evaluating the authenticity and coherence of generated images within diverse contexts. Unlike traditional discriminators, which may struggle with heterogeneous inputs, our conditional discriminator is adept at handling a broad spectrum of subjects. This critical component ensures that generated images seamlessly align with the intended textual descriptions across various categories, enhancing the fidelity and realism of the synthesized images.

Attention mechanisms play a crucial role in our system, emphasizing the importance of capturing fine-grained details and accurate representations in generated images. These mechanisms guide the synthesis process, enabling the model to focus on relevant features mentioned in textual descriptions. This meticulous attention to detail elevates the quality of the generated images, imbuing them with a heightened sense of realism and authenticity.

The performance of our proposed method is rigorously evaluated using a versatile approach that includes both quantitative and qualitative metrics. Quantitative assessments, including Inception Score and Frechet Inception Distance (FID), offer valuable insights into the model's quantitative performance, shedding light on its fidelity and diversity. Qualitative evaluations involve human annotators, providing feedback on the realism and coherence of the generated images, ensuring alignment with human perceptual standards.

4.1 DATASET USED

The Microsoft Common Objects in Context (MS-COCO) dataset is a widely-used resource in the field of computer vision, particularly in tasks such as text-to-image synthesis using generative adversarial networks (GANs). It consists of over 200,000 images, each annotated with detailed descriptions and labels for objects within the scene. This rich and diverse dataset serves as a foundational resource for training GAN models to generate realistic images from textual descriptions. By leveraging the MS-COCO dataset, researchers and developers can create sophisticated AI systems capable of understanding and generating complex visual content.

4.2 REQUIREMENTS

4.2.1 Hardware Requirements:

1) Processor: Intel Core i7 or higher
2) GPU: NVIDIA GTX 1080 Ti or higher
3) RAM: 16 GB or more
4) Storage: 1 TB SSD for fast read/write operations
5) Internet Connection: High-speed for downloading datasets

4.2.2 Software Requirements

1) Operating System: Windows 10, macOS, or Linux (Ubuntu 18.04 or higher)
2) Python Version: Python 3.7 or higher
3) Deep Learning Frameworks: TensorFlow 2.x, Keras
4) Other Libraries: NumPy, Matplotlib, Pillow, Flask, Requests, TQDM, PyCOCOTools

4.2.3 System Specifications

Development Environment: Jupyter Notebook or any preferred Python IDE

Version Control: Git for tracking changes and collaboration

4.3 ADVANTAGES

1. High-Quality Image Synthesis: The use of DC-GAN allows for the generation of high-quality, realistic images from text descriptions.

2. Flexibility: The architecture can be adapted to various datasets and text inputs, improving generalizability.

3. Advanced Techniques: Incorporation of methods like GAN-CLS and GAN-INT enhances the model's robustness and interpolation capabilities.

4.4 DISADVANTAGES

1.Computationally Intensive: Training GANs, especially with advanced techniques, requires significant computational resources and time.

2.Complexity: The architecture and training algorithms are complex, requiring deep understanding and expertise in deep learning.

3. Overfitting Risk: Without adequate data and regularization, the model may overfit, reducing its generalizability.

5.CONCLUSION

In this work, we have developed a fundamental and practical model for generating images based on detailed visual descriptions. Our model successfully synthesizes various possible visual interpretations of given textual captions, demonstrating its capability to handle diverse and complex content descriptions.

One of the key enhancements in our approach is the manifold expansion regularizer, which significantly improved the text-to-image synthesis performance on the CUB dataset. This regularizer allows the model to generate a wide range of visual outputs, capturing the detailed nuances and variations described in the text. Our experiments showed that the model could effectively disentangle design and content, enabling features such as bird pose and background transfer from reference images onto text descriptions. This highlights the model's ability to maintain coherence and accuracy in generating contextually appropriate images.

Furthermore, we demonstrated the generalizability of our approach by generating images containing multiple objects and varying backgrounds using the MS-COCO dataset. This shows the model's robustness and versatility in handling complex scenes and multiple object scenarios, making it suitable for a wide range of applications in visual content creation.

Our results on the MS-COCO dataset, which includes diverse objects and scenes, underscore the model's potential for real-world applications. The model maintained high-quality visual outputs across different scenarios, demonstrating its adaptability and effectiveness in generating images from complex textual inputs.

In future work, we aim to scale up the model to generate higher resolution images. This will involve refining the current architecture and incorporating advanced techniques to manage increased computational demands while maintaining image quality. Additionally, we plan to extend the model's capabilities to include a broader range of content types, ensuring it can handle even more diverse textual descriptions and generate corresponding visual outputs with greater detail and accuracy.

We also intend to explore the integration of more sophisticated context-aware mechanisms to improve the coherence and relevance of generated images in complex scenes. Leveraging advancements in natural language processing and computer vision, we aim to enhance the model's understanding of context and semantics, leading to more meaningful and contextually appropriate visual outputs.

Furthermore, we will investigate the potential of incorporating user feedback mechanisms to fine-tune and personalize the image generation process. This will enable users to guide and refine the outputs based on their specific preferences and requirements, making the model more interactive and user-friendly.

Overall, our work lays a solid foundation for future advancements in text-to-image synthesis, paving the way for more sophisticated, high-resolution, and context-aware image generation models. The promising results achieved in this study demonstrate the potential of our approach to revolutionize the way visual content is created, offering new possibilities for creative expression and practical applications in various domains.

6. REFERENCES

[1] Rameen Abdal, Yipeng Qin, and Peter Wonka. Image2stylegan: How to implant concepts into the stylegan hidden scope? In IEEE International Conference on Computer Vision (ICCV), 2019. 3

[2] Martin Arjovsky, Soumith Chintala, and Leon Bottou.´Wasserstein Generative Adversarial Networks. In International Conference on Machine Learning (ICML), 2017. 4

[3] Th Brandt, Johannes Dichgans, and Ellen Koenig. Differential belongings of principal against visual field on individualistic and exocentric motion understanding. Experimental intellect research, 16(5):476–491, 1973. 2

[4] Kevin Chen, Christopher B Choy, Manolis Savva, Angel X Chang, Thomas Funkhouser, and Silvio Savarese. Text2shape: Generating shapes from human language by knowledge joint embeddings. In Asian Confernce on Computer Vision, pages 100-116. Springer, 2018-1

[5] Jun Cheng, Fuxiang Wu, Yanling Tian, Lei Wang, and Dapeng Tao. 2020. RiFeGAN: Rich Feature Generation for Text-to-Image Synthesis From Prior Knowledge. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.

[6] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-preparation of deep bidirectional transformers for terminology understanding. arXiv published document arXiv:1810.04805 (2018).

[7] Samek, W.; Wiegand, T.; Müller, K.-R. Explainable machine intelligence: Understanding, visualizing and defining deep education models. arXiv 2017, arXiv:1708.08296.

[8] Lee, Y.-L.; Tsung, P.-K.; Wu, M. Techology flow of edge ai. In Proceedings of the 2018 International Symposium on VLSI Design, Automation and Test (VLSI-DAT), Hsinchu, Taiwan, 16–19 April 2018; pp. 1–2.

[9] Ongsulee, P. Artificial intelligence, machine intelligence and deep education. In Proceedings of the 2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE), Bangkok, Thailand, 22–24 November 2017; pp. 1–6.

[10] RoyChowdhury Aruni, Chakrabarty Prithvijit, Singh Ashish, Jin SouYoung, Jiang Huaizu, Cao Liangliang, and Learned-Miller Erik. Automatic acclimatization of object detectors to new rules utilizing self-preparation. In CVPR, 2019.

[11] Munjal Bharti, Galasso Fabio, and Amin Sikandar. Knowledge distillate for end-to-end man search. In BMVC, 2019.

[12] Li Bowen, Qi Xiaojuan, Lukasiewicz Thomas, and H. S. Torr Philip. Controllable textbook-to-countenance creation. In NeurIPS, 2019.

[13] W. Li, P. Zhang, L. Zhang, Q. Huang, X. He, S. Lyu, J. Gao, Object-compelled quotation– to-concept combining by way of opposing preparation, in: CVPR, 2019, pp. 12174–12182.

[14] T. Xu, P. Zhang, Q. Huang, H. Zhang, Z. Gan, X. Huang, X. He, Attngan: Fine– grained document to representation creation accompanying attentional fruitful opposing networks, in: CVPR, 2018, pp. 1316–1324.

[15] N. Zhou, J. Fan, Automatic figure–theme adjustment for big netting representation indexing and recovery, Pattern Recognit. 48 (1) (2015) 205–219.

[16] Y. Liu, Y. Guo, L. Liu, E.M. Bakker, M.S. Lew, Cyclematch: a phase-constant implanting network for representation-paragraph corresponding, Pattern Recognit. 93 (2019) 365–379.

[17] Abdal, R., Zhu, P., Mitra, N. J., and Wonka, P. StyleFlow: Attribute-trained survey of StyleGANgenerated concepts utilizing dependent constant normative flows. ACM Trans. Graph., 40(3), 2021. 1

[18] Amir, S., Gandelsman, Y., Bagon, S., and Dekel, T. Deep VIT visage as thick able to be seen with eyes descriptors. CoRR, antilock braking system/2112.05814, 2021. 5

[19] Balaji, Y., Nah, S., Huang, X., Vahdat, A., Song, J., Kreis, K., Aittala, M., Aila, T., Laine, S., Catanzaro, B., and others. eDiff-I: Text-to-representation spread models accompanying an ensemble of expert denoisers. CoRR, antilock braking system/2211.01324, 2022. 2, 7, 8

[20] Wenbo Li, Pengchuan Zhang, Lei Zhang, Qiuyuan Huang,Xiaodong He, Siwei Lyu, and Jianfeng Gao. Object-compelledquotation-to-countenance combination by way of opposing preparation. In Proceedings of the IEEE Conference on Computer Vision and PatternRecognition, pages 12174–12182, 2019. 1, 6