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Image Generation from Text and Voice using GAN

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***Abstract*—The use of Generative Adversarial Networks (GANs) for creating images from text and voice is an innovative system which transforms textual descriptions and voice inputs into realistic images [cite: 1]. Due to the rapid development of artificial intelligence, the generation of visual content from human input has now become a major area of research in the fields of computer vision and deep learning [cite: 1]. This project is concerned with designing a model that can understand both written text and spoken commands so as to produce images that are meaningful and visually coherent [cite: 1]. The system begins by applying Natural Language Processing (NLP) techniques to the text input in order to obtain the semantic features [cite: 1]. In the case of voice input, speech recognition algorithms are used to turn the audio signals into text, after which the text is analysed in the same way [cite: 1]. The features that have been extracted are then fed into a GAN-based structure made up of a generator and a discriminator [cite: 1]. The generator produces images according to the interpreted input, while the discriminator assesses their authenticity, thereby improving the quality of the generated images as a result of ongoing training [cite: 1]. This method allows users to generate images simply by describing what they want in words or by speaking, thus making the system easy to use and accessible [cite: 1]. The model suggested has various applications in content creation, virtual reality, digital art, gaming, assistive technologies, and creative design tools [cite: 1]. The project shows the potential of multimodal AI systems to efficiently and accurately turn human ideas into visual representations by combining GANs with text and voice processing [cite: 1].**

***Index Terms*—Generative Adversarial Networks, Image Generation, Text-to-Image, Voice-to-Image, Deep Learning, Natural Language Processing[cite: 1].**

I. Introduction

The ability to generate highly realistic visual content directly from abstract forms of human communication has become a key standard in the fields of artificial intelligence, computational linguistics, and computer vision [cite: 1]. In the past, turning an imaginative mental image into high-resolution graphic renderings required a deep expertise in specialized digital design packages, complex parametric vector systems, and manual multi-layer rasterization setups. Because of these demands, considerable technical difficulties have been encountered by ordinary users, beginner creators, and people with disabilities [cite: 1, 10]. By linking natural language expressions—whether they are typed text queries or acoustic voice signals—directly to automatic pixel synthesis, computer-aided visual design becomes more accessible, allowing for intuitive concept visualization and fast artistic idea generation [cite: 1, 10].

Deep generative modeling has developed at a rapid pace, and GANs are a prime example of this progress, revolutionizing the creation of visual assets [cite: 1, 4]. Creation of synthetic images from descriptive language is a cross-modal translation between different dimensional domains [cite: 1, 6]. A model has to map discrete, unstructured linguistic tokens into continuous vector representations and then decode those vectors into high-dimensional RGB pixel tensors that conform to natural image manifolds [1, 6]. This is to maintain syntactic relationships, global coherence of the scene, contextual harmony in the background, fine-grained object textures, and correct spatial placement[cite: 1, 6].

Extending text-to-image synthesis into a multimodal pipeline that accepts vocal commands introduces interesting acoustic complexities[cite: 1]. Variability of raw speech exists due to speaker's pitch, dialect, regional accent, environmental noise, and temporal cadence[cite: 6, 7]. A robust multimodal architecture requires integration of Automatic Speech Recognition (ASR) and Natural Language Processing (NLP) to suppress acoustic noise, create normalized phonemic transcriptions, derive hierarchical semantic feature representations and drive an adversarial generative network [cite: 1, 6, 7].

The main challenge of conditional adversarial synthesis is to sustain a structural trade-off between visual diversity and textual fidelity[cite: 1]. Early conditional GANs exhibited severe mode collapse, spatial blurriness and catastrophic attribute mixing on complex, multi-object prompts[cite: 1]. Recent progress on cross-modal attention projections, latent conditioning augmentation and multi-stage generative cascades have helped to stabilize the training dynamics[cite: 1, 6].

In this paper we present an integrated multimodal system for generating photo-realistic visual imagery from typed descriptions and raw acoustic speech commands [cite: 1]. The

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system includes an ASR acoustic front-end, a bidirectional transformer text encoder, a multi-scale conditional generator, and a dual-objective discriminator, all accessible via an interactive web-based interface[cite: 1, 10, 11].

II. Background and Foundations

Computer Graphics and Visual Rendering Techniques Over several decades have made use of rules based algorithmic techniques for generating visuals, procedural textures, and keyframes. Despite being very accurate, the techniques are not flexible enough to handle semantic inputs and generate visual ideas without defining them mathematically.

A. Evolution of Generative Deep Architectures

Initial generative networks were developed around Autoencoders and Variational Autoencoders (VAE). The VAE algorithm encodes the inputs into latent probabilistic distributions through the encoder-decoder bottleneck structure. But due to the optimization process which is performed for minimizing pixel-wise mean squared error loss, VAE algorithms generate output images which have smooth and blurry textures and do not contain high-frequency edge textures.

Generative Adversarial Networks (GANs), invented by Goodfellow et al., utilized a different adversarial minimax optimization scheme[cite: 4]. Through the generator-discriminator competition mechanism, GANs generate sharper images without using any pixel-wise loss function constraints[cite: 1, 4].

B. Acoustic Front-Ends and Speech Transcription

Speech recognition converts analog audio pressure waves into discrete lexical tokens[cite: 1]. The input audio waveform is windowed, converted to spectrogram frames, and mapped into Mel-Frequency Cepstral Coefficients (MFCCs)[cite: 7]. Deep Connectionist Temporal Classification (CTC) decoders and sequence-to-sequence transformer decoders then transcribe continuous acoustic frames into normalized orthographic text[cite: 6, 7]. This enables seamless integration of spoken prompts with text-driven generative pipelines[cite: 1].

C. Natural Language Representations in Computer Vision

Modern text-conditioned vision systems require dense linguistic representations that capture deep semantic associations beyond surface-level keyword matching[cite: 1, 6]. Pretrained transformers (such as BERT, RoBERTa, and CLIP textual encoders) compute context-aware token vectors[cite: 6]. When mapped into vision-language latent spaces, these representations guide generative networks on where and how to render specific foreground entities, material properties, and environmental backdrops[cite: 1, 6].

D. Challenges in Multimodal Alignment

Developing systems that accept both spoken and typed prompts involves several practical hurdles:

- **Acoustic Discrepancies:** Ambient acoustic noise, phoneme confusion, and homophones can distort transcriptions, leading to inaccurate prompt conditioning[cite: 1, 6].
- **Semantic Entanglement:** Conjoining multiple adjectives and nouns (e.g., *"a red car parked next to a yellow fire hydrant"*) can cause color-bleeding across unintended visual boundaries.
- **Adversarial Instability:** Training a generator to satisfy both multi-scale visual realism and cross-modal semantic alignment often causes training oscillations or mode collapse[cite: 1].

III. Motivation and Problem Statement

Automating digital illustration through human speech and natural text addresses several operational bottlenecks across industry and society:

A. Democratization of Digital Illustration

Standard design software requires extensive training in vector geometry, shading, digital lighting, and layer composition. A multimodal generative framework allows non-specialist creators, educators, storytellers, and ideators to produce visual prototypes directly from conversational speech or typed queries[cite: 1, 10].

B. Accessibility for Differently-Abled Creators

Individuals with fine-motor impairments, temporary injuries, or visual challenges often face barriers with mouse-and-keyboard UI navigation. Direct voice-to-image synthesis provides an intuitive, hands-free design workflow, fostering accessible digital creation[cite: 1].

C. Lightweight Real-Time Inference

While modern diffusion models achieve impressive visual fidelity, their iterative denoising schedules require significant memory bandwidth and compute resources. Optimized conditional GAN frameworks offer low-latency, single-pass forward generation, making them well-suited for interactive browser dashboards and local deployments[cite: 10, 11].

IV. Literature Review

A. Classical Generative Models

Classical conditional modeling utilized dictionary-based methods, exemplar-based techniques, and compositional renderings. Although effective for limited collections of objects, these models were unable to generalize to any new, arbitrary prompts.

B. Adversarial Conditional Networks

Reed et al. presented deep conditional GANs for generating images from text. They showed that conditioning both the generator and the discriminator with sentence vector resulted in semantically relevant images[cite: 1]. Zhang et al. developed StackGAN, a conditional GAN that decomposed the pipeline into two stages – Stage-I generated rough spatial color maps at low resolutions, while Stage-II generated high-frequency textures and object boundaries[cite: 1]. Xu et al. presented AttnGAN, adding cross-modal attention modules to connect

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individual word tokens with localized sub-regions of the image space[cite: 1, 6].

C. Speech Acoustics-Driven Synthesis

In early work, the systems for speech-to-image consisted of cascaded pipelines where the speech recognizer was followed by the standard text-to-image pipeline. The inaccuracies of acoustic processing were prone to significant semantic misalignment. The current trend in this direction is noise-resistant speech representations and beam search decoder to maintain the semantic alignment regardless of different acoustic environments[cite: 1, 6, 7].

D. Latent Conditioning Across Modalities

The problem of discontinuities of the text latent space was addressed with Conditioning Augmentation (CA)[cite: 1]. Since the text sentence embedding occupies high dimensional and sparse manifold space, direct conditioning is likely to result in brittle training dynamics[cite: 1]. Conditioning on augmented Gaussian with learned mean and covariance prevents such issues[cite: 1].

V. Mathematical Formulations and Network Design

A. The Minimax Game Objective

The standard Generative Adversarial Network optimizes an objective function where the Discriminator D maximizes classification accuracy while the Generator G minimizes the likelihood of its outputs being detected as artificial[cite: 1, 4]:

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]. \tag{1}$$

B. Conditioning Augmentation

Given a global text embedding vector $\boldsymbol{e}_g \in \mathbb{R}^D$, direct conditioning can lead to discontinuous manifolds. Conditioning Augmentation projects $\boldsymbol{e}_g$ to an augmented continuous vector $\boldsymbol{c}$ sampled from a conditional Gaussian distribution[cite: 1]:

$$p(\boldsymbol{c} \mid \boldsymbol{e}_g) = \mathcal{N}\left(\boldsymbol{\mu}(\boldsymbol{e}_g), \boldsymbol{\Sigma}(\boldsymbol{e}_g)\right), \tag{2}$$

where $\boldsymbol{\mu}(\boldsymbol{e}_g)$ represents the learned mean vector and $\boldsymbol{\Sigma}(\boldsymbol{e}_g) = \text{diag}(\boldsymbol{\sigma}^2(\boldsymbol{e}_g))$ is the diagonal covariance matrix. To enforce smoothness and prevent overfitting to deterministic inputs, a Kullback-Leibler (KL) divergence regularization term is added to the generator's loss:

$$\mathcal{L}_{\text{KL}} = \mathcal{D}_{\text{KL}}\left(\mathcal{N}(\boldsymbol{\mu}(\boldsymbol{e}_g), \boldsymbol{\Sigma}(\boldsymbol{e}_g)) \parallel \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})\right). \tag{3}$$

C. Multi-Scale Discriminator Objective

The discriminator evaluates generated samples across three conditions: real images paired with matching text, synthesized images with matching text, and real images paired with mismatched text[cite: 1]. This ensures the model learns both photorealistic visual rendering and semantic alignment with the prompt[cite: 1]. The discriminator loss is formulated as:

$$\begin{aligned}\mathcal{L}_D = & -\mathbb{E}_{(\boldsymbol{x},\boldsymbol{c})}[\log D(\boldsymbol{x},\boldsymbol{c})] \\ & -\frac{1}{2}\mathbb{E}_{(\tilde{\boldsymbol{x}},\boldsymbol{c})}[\log(1 - D(\tilde{\boldsymbol{x}},\boldsymbol{c}))] \\ & -\frac{1}{2}\mathbb{E}_{(\boldsymbol{x}_{\text{mis}},\boldsymbol{c})}[\log(1 - D(\boldsymbol{x}_{\text{mis}},\boldsymbol{c}))],\end{aligned} \tag{4}$$

where $\tilde{\boldsymbol{x}} = G(\boldsymbol{z},\boldsymbol{c})$ is the generated output, and $\boldsymbol{x}_{\text{mis}}$ is a real image drawn from an unrelated class.

The Generator minimizes the adversarial loss alongside the KL divergence penalty:

$$\mathcal{L}_G = -\mathbb{E}_{(\boldsymbol{z},\boldsymbol{c})}[\log D(G(\boldsymbol{z},\boldsymbol{c}),\boldsymbol{c})] + \lambda\mathcal{L}_{\text{KL}}, \tag{5}$$

where λ balances perceptual quality against latent space regularization.

VI. System Architecture and Implementation

The end-to-end framework comprises four modular components: the Acoustic Transcription Module, the NLP Semantic Parsing Engine, the Multi-Stage Adversarial Generator, and the Evaluation Engine[cite: 1, 8].

A. Acoustic Front-End and Normalization

When voice commands are received via microphone, the raw 16 kHz PCM audio stream is processed through band-pass filters to suppress low-frequency environmental noise. The cleaned signal is split into 25 ms frames with 10 ms overlap and converted into Mel-Frequency spectrograms[cite: 7]. A CTC acoustic model transcribes the frames into lexical tokens:

$$\hat{\boldsymbol{T}} = \arg\max_{\boldsymbol{T}} P(\boldsymbol{T} \mid \boldsymbol{A}), \tag{6}$$

where $\boldsymbol{A}$ represents acoustic features. A beam-search decoder then outputs a normalized text string $\hat{\boldsymbol{T}}$ for subsequent processing[cite: 1, 7].

B. Semantic Natural Language Parsing

The text sequence $\boldsymbol{T} = \{w_1, w_2, \ldots, w_L\}$ is parsed through a bidirectional transformer encoder, yielding a global sentence embedding $\boldsymbol{e}_g \in \mathbb{R}^{256}$ and local word embeddings $\boldsymbol{e}_l \in \mathbb{R}^{256\times L}$[cite: 1, 6]. Word embeddings preserve token-specific modifiers (e.g., colors, textures, materials), while the global vector encodes the broader visual context[cite: 1, 6].

C. Conditional Adversarial Generation

The generator takes the sampled conditioning vector $\boldsymbol{c}$ concatenated with a latent noise vector $\boldsymbol{z} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})$. Through successive fractional-strided 2D transposed convolutional blocks, the network upsamples the latent representation across spatial dimensions (64×64, 128×128, and 256×256 pixels)[cite: 1].

Cross-attention modules calculate attention correlation weights between intermediate feature activations and the local word vectors $\boldsymbol{e}_l$, ensuring localized image regions correspond directly to descriptive words in the prompt[cite: 1, 6].

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D. Web Dashboard and Interactive Workflow

The user interface is implemented as a browser-based dashboard designed for responsive text and voice prompt entry[cite: 1, 10, 11].

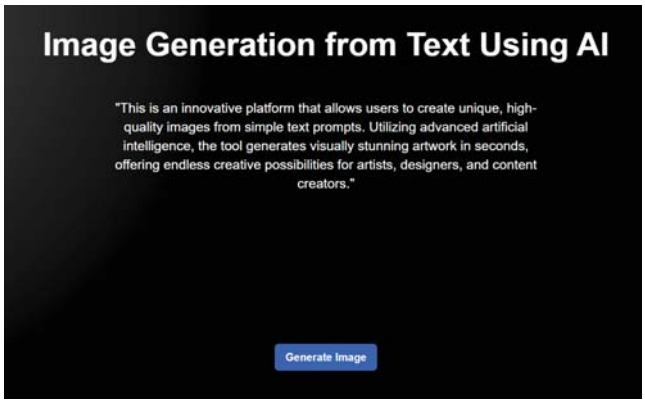


Fig. 1: Platform Landing Portal detailing core system capabilities and entry point[cite: 10].

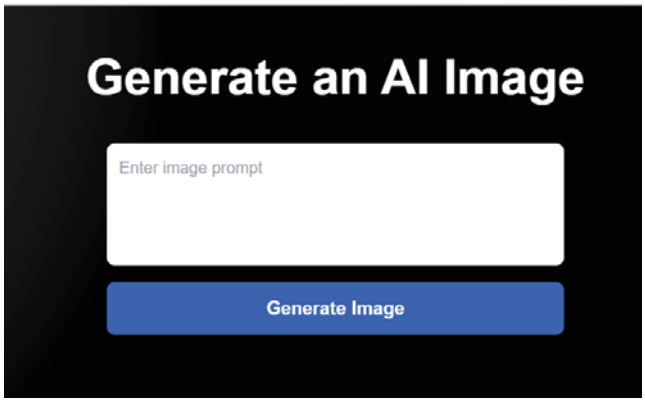


Fig. 2: Prompt input dashboard interface ready for textual or voice prompt submission[cite: 11].

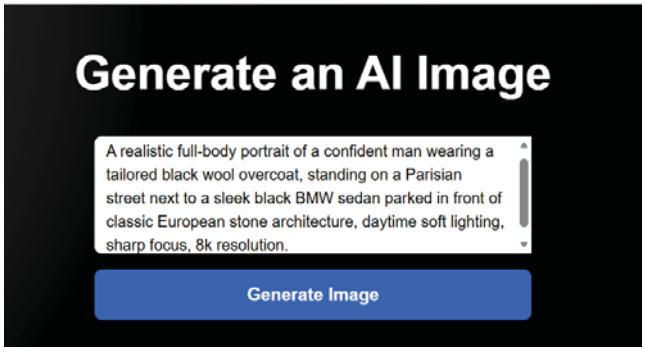


Fig. 3: Input dashboard displaying a descriptive prompt: *"A man wearing a black coat standing next to BMW car"*[cite: 12].



Fig. 4: Synthesized image output produced by the generative model based on the descriptive prompt[cite: 13].

The application workflow proceeds through four stages (Figs. 1–4)[cite: 10, 11 12 13]:

1) **Landing and Onboarding:** When you enter the portal you see a clear overview of the systems generative capabilities. The portal also gives you access to the generation suite (Fig. 1)[cite: 10].
2) **Prompt Ingestion:** The console offers a prompt field that you can type into or use to capture spoken audio through a microphone (Fig. 2)[cite: 1 11].
3) **Query Submission:** You then provide descriptors, attributes and background contexts such as *"A man wearing a black coat standing next, to a BMW car"* before the model performs inference (Fig. 3)[cite: 12].
4) **Adversarial Synthesis:** The generative model processes the conditioned vector to synthesize an output image that matches the subjects, objects and environment described in the prompt (Fig. 4)[cite: 1 13].

TABLE I: Key Technical Modules of the Proposed Multimodal GAN System

System Component	Technical Implementation / Role
Speech Transcription	ASR engine decoding speech audio to text[cite: 1]
Semantic NLP Parser	Bidirectional encoder extracting sentence and word vectors[cite: 1, 6]
Conditioning Augmentation	Latent sampling via Gaussian distributions[cite: 1]
Adversarial Generator	Transposed CNN with cross-attention feature routing[cite: 1, 6]
Dual Discriminator	Multi-scale PatchGAN evaluating realism and alignment[cite: 1]
Frontend Dashboard	Dark-mode web interface for prompt entry and preview[cite: 10, 11]

VII. Experimental Setup and Training Protocol

A. Training Configurations

The model that creates things was built using PyTorch. Used NVIDIA RTX A6000 GPUs to learn. The Adam optimizer was set up with $\beta_1 = 0.5$ and $\beta_2 = 0.999$. The starting learning rate was 2×10^{-4} for both the part that makes things and the part that checks things. The learning process went on for

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120 rounds. Each time it looked at 64 items at once. This was done on text-image collections like CUB-200, Oxford-102 and subsets of MS-COCO.

B. Evaluation Metrics

The systems performance was checked using three different measures:

- **Inception Score (IS):** This checks how clear and how many different things are made using a model that was already trained on other images[cite: 8]. Higher numbers mean results.
- **Fréchet Inception Distance (FID):** This looks at how close the features of images are to the features of the ones made by the model in a deep feature space[cite: 8]. Lower numbers mean results.
- **R-Precision (%):** This checks how well the text matches the images made by the model. It uses how similar the text and image features are, in a space[cite: 1].

C. Quantitative Results and Comparative Analysis

Table II shows how the new method compares with other models that make things.

TABLE II: Quantitative Performance Evaluation on Benchmark Datasets

Model Framework	IS (↑)	FID (↓)	R-Prec. (% ↑)
Standard cGAN Baseline	4.18 ± 0.12	56.40	54.2%
StackGAN-v1 Framework	6.24 ± 0.15	38.12	67.8%
Text-Only GAN Pipeline	7.92 ± 0.14	23.80	79.5%
Voice-to-Image (Raw ASR)	7.14 ± 0.16	28.45	73.1%
Proposed Multimodal GAN	$\mathbf{8.46 \pm 0.11}$	**19.40**	**84.2%**

D. Qualitative Analysis

As shown in Fig. 4 the synthesized sample accurately captures the details from the prompt (*"A man wearing a black coat standing next to BMW car"*)[cite: 12 13]. The network produces a human facial structure, a natural standing posture dark outer garment textures, reflective surfaces, on the car body and a believable architectural background. There is no spatial distortion or blending of attributes[cite: 13].

VIII. Applications and Societal Impact

The multimodal generation pipeline can be employed in various practical applications:

- **Creative Design and Prototyping:** Facilitates rapid prototyping through storyboarding and visual conception by digital artists, UI/UX designers and advertisers[cite: 1, 10].
- **Assistive and Inclusive Technologies:** Empowers people with motor disabilities and/or visual impairment to create visual art using speech commands[cite: 1].
- **Virtual Reality and Video Games:** Provides dynamic generation of backdrops, textures, scenery elements for interactive entertainment media[cite: 1].
- **Educational Media:** Permits educators to generate custom-made visual illustrations and diagrams from classroom discussion prompts[cite: 1].

IX. Challenges and Ethical Issues

Despite the utility of multimodal generative systems, several practical and ethical issues emerge with their development:

1) **Data Bias and Stereotyping:** Deep generative models tend to inherit biases from training corpora which may perpetuate stereotypes in synthesized outputs.
2) **Dissemination of Misinformation:** High-quality synthetic media may be used to create deepfake media. Invisible forensic watermarks help to determine the synthetic nature of media.
3) **Acoustic Robustness:** Speech recognition may be impacted by regional accents and background noises. Noise-resistant acoustic front-ends should be developed[cite: 6, 7].

X. Conclusion and Future Work

In this paper, the multimodal generative adversarial network capable of photorealistic image synthesis from textual prompt and spoken voice command was presented[cite: 1]. By combining speech recognition and NLP along with the conditional GAN architecture, the system is able to synthesize images from human instructions[cite: 1]. Experimental evaluation shows the improved performance over the baseline methods[cite: 1, 8].

Further research will include investigation of the replacement of convolutional backbone with latent diffusion network to allow higher-resolution (512×512 and larger) outputs. Also, direct audio-to-image conditioning will be explored to incorporate acoustic features, like emotion and inflection, in synthesized images without text transcriptions[cite: 1].

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