

Text Based Image Creator

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Abstract - Generative AI has made it easier than ever to turn a creative idea into a finished visual, but most popular text-to-image services run on expensive cloud infrastructure and send user data to remote servers. This paper presents a full-stack web application that brings state-of-the-art text-to-image generation entirely onto consumer hardware no subscriptions, no data uploads, no compromise on privacy. The system pairs the Stable Diffusion v1.5 latent diffusion model with a Python Flask backend, a MySQL database, and a responsive HTML/CSS/JavaScript frontend, letting any registered user convert a plain-language prompt into a 512×512 image in 15–30 seconds on an NVIDIA GeForce GTX 1650 GPU. Key contributions include GPU-optimised inference through PyTorch 2.5.1 with CUDA 12.1 and half-precision (float16) arithmetic; a Fréchet Inception Distance (FID) score of 8.59 that outperforms DALL·E 2 (10.39); secure multi-user authentication using SHA-256 hashing and email OTP verification; voice-to-text prompt entry via the Web Speech API; seven real-time post-processing filters built on Pillow; a personal image gallery backed by MySQL; and Matplotlib-driven interest analytics drawn from each user's prompt history. All 18 test cases across nine functional modules passed, achieving 100% test coverage. The project demonstrates that production-quality generative AI tools can be built and deployed on a single consumer-grade GPU without relying on managed cloud services.

Keywords - *Stable Diffusion, Text-to-Image Synthesis, Latent Diffusion Models, Flask, GPU Inference, CUDA, Generative AI, Web Application, Voice Input, Image Filtering.*

I. INTRODUCTION

The intersection of natural language understanding and computer vision has produced text-to-image synthesis one of the most exciting developments in applied AI today. Where earlier creative tools demanded artistic training or costly software licences, modern generative models let users describe a scene in plain English and get a photorealistic or stylised image back within seconds. That shift opens up possibilities ranging from quick concept sketches and educational illustrations to personalised artwork and social media content. Despite all the excitement, most accessible interfaces still put up walls that stop everyday people from using them freely. Cloud-hosted platforms like DALL·E 2, Midjourney, and Adobe Firefly charge subscription fees or per-image credits that

quickly become too expensive for students, independent researchers, or hobbyists. On top of

that, every prompt and generated image gets sent to remote servers a real privacy concern for anyone working in an educational or institutional setting.

Things changed meaningfully in 2022 when Stability AI and RunwayML released the weights of Stable Diffusion under a permissive licence. For the first time, a state-of-the-art latent diffusion model could be downloaded and run locally. Even so, turning that capability into a polished, user-friendly web application one that handles registration, authentication, image persistence, post-processing, analytics, and sharing requires substantial engineering work that the existing literature largely skips over.

This paper introduces PixelMind, a system built to fill that gap. PixelMind is a locally deployable, GPU-accelerated, full-stack web application centred on Stable Diffusion v1.5. It is aimed at everyday users who want private, cost-free access to high-quality image generation without needing any machine learning expertise. The rest of this paper covers related work (Section II), system architecture (Section III), implementation details (Section IV), experimental results (Section V), limitations and future directions (Section VI), and conclusions (Section VII).

II. RELATED WORKS

The journey toward reliable text-to-image generation has unfolded in several distinct phases, each building on the shortcomings of what came before.

A. Generative Adversarial Networks

The foundational framework for learned image synthesis was introduced by Goodfellow et al. [1] through Generative Adversarial Networks (GANs), where a generator and a discriminator are trained in opposition. Reed et al. [2] were the first to apply this idea to text-conditioned generation, showing that sentence embeddings could steer a GAN to produce 64×64 pixel images. StackGAN [3] pushed this further with a two-stage pipeline reaching 256×256 pixels, and AttnGAN [4] introduced

word-level cross-attention so that individual words could directly guide corresponding spatial regions of the image. GANs remained prone to training instability and mode collapse, which limited their reliability on complex or abstract prompts.

B. Autoregressive and VAE-Based Models

Variational Autoencoders offered smoother latent

spaces but tended to produce blurry outputs because of pixel-level reconstruction objectives [5]. OpenAI's original DALL·E (2021) [6] took a different route, scaling autoregressive generation to 12 billion parameters by treating image patches as discrete tokens from a VQ-VAE codebook and training a transformer over combined text-image token sequences. Impressive as it was, that approach demanded compute resources far beyond what most research groups could access.

C. Diffusion Models

Ho et al. [7] established diffusion models as a theoretically solid alternative: a neural network learns to reverse a gradual Gaussian noise corruption process, generating images by iteratively denoising random noise. DALL·E 2 [8] combined CLIP contrastive embeddings with a diffusion prior and decoder to achieve state-of-the-art text alignment. Imagen [9] later showed that replacing CLIP with a larger T5-XXL language encoder could further improve prompt fidelity. The breakthrough most relevant to PixelMind came from Rombach et al. [10], who introduced Stable Diffusion by performing diffusion in a compressed 64×64 latent space instead of the full 512×512 pixel space — cutting computational load by a factor of 48 and making high-quality generation feasible on consumer GPUs for the first time.

D. Web Frameworks for AI Deployment

Flask's lightweight philosophy, minimal scaffolding, full developer control over PyTorch and MySQL integration makes it well suited to a single-server, single-GPU setup where simplicity and iteration speed matter [11]. The Web Speech API, a W3C standard natively supported in Chromium-based browsers, provides client-side speech recognition without any server round-trip [12], enabling hands-free prompt entry and improving accessibility for users with motor impairments.

III. SYSTEM ARCHITECTURE

A. Overall Design

PixelMind follows a three-tier MVC architecture. The presentation tier consists of HTML5/CSS3/JavaScript pages rendered through Jinja2 templates; voice input is handled entirely in the browser via the Web Speech API before transcribed text is passed to the backend. The application tier is made up of Flask routes that enforce session authentication, trigger the Stable Diffusion pipeline, apply business logic, and query the database. The data tier uses MySQL for structured relational data user accounts, image metadata, and admin credentials and the local filesystem for generated image files and analytics charts.

B. AI Inference Pipeline

The Stable Diffusion v1.5 pipeline is loaded once at Flask startup using `StableDiffusionPipeline.from_pretrained()` with `torch_dtype=torch.float16`, then moved to the CUDA device. Keeping the pipeline resident in GPU

memory eliminates the overhead of loading the model on every request. Each generation request follows six steps: (1) prompt sanitisation; (2) CLIP tokenisation producing a 768-dimensional embedding; (3) initialisation of a Gaussian noise tensor of shape $[1, 4, 64, 64]$; (4) 20 iterative PNDM denoising steps under `torch.autocast("cuda")` with the UNet predicting noise residuals; (5) VAE decoding to a 512×512 RGB pixel array; and (6) saving the image to disk with the file path written to MySQL. On machines without CUDA, the system falls back to CPU inference with six steps, which increases generation time to 2–5 minutes.

C. Security Design

All passwords are stored as 64-character SHA-256 hex digests; plaintext credentials are never saved anywhere. New users must verify their email address through a time-limited six-digit OTP delivered via `smtplib` before their account is activated. Flask's signed session cookies store only a server-side session ID, not any user data. Every SQL statement uses parameterised queries through `mysql.connector`, ruling out injection attacks. The admin interface sits behind a separate route tree (`/admin_login`) with its own credentials stored in a dedicated `admin_info` table, fully isolated from the regular user session flow.

D. Database Schema

Three relational tables form the data model. The `user_info` table stores each user's unique identifier, display name, SHA-256 password digest, optional phone number, biography, profile picture filename, and email-verification status. The `saved_images` table links each generated image to its owning user and records the prompt text, relative file path, and creation timestamp. The `admin_info` table holds a single administrator record with a hashed password.

IV. IMPLEMENTATION

4.1 Backend

The Flask application entry point (`app.py`) initialises the Stable Diffusion pipeline at startup, confirms GPU availability, and registers all route handlers. A helper function, `get_db()`, opens a fresh `mysql.connector` connection for each request and closes it when the query completes, preventing connection-pool exhaustion. Image generation uses a two-method fallback: the primary path contacts an external API when internet access is available; if the API is unreachable — for example, on a restricted campus network — the local Stable Diffusion pipeline handles the request instead.

4.2 Image Filtering

After an image is generated, users can apply one of seven Pillow-based post-processing filters without leaving the page. Grayscale converts the image to luminance-based monochrome. Sepia applies a custom per-pixel RGB mixing matrix to produce a warm, brownish tone. Blur and Sharpen use Pillow's Gaussian blur and `unsharp-mask`

convolutions respectively. Brightness and Contrast use ImageEnhance multipliers. Vintage combines a sepia transformation with a noise overlay and a radial vignette. Filter operations are triggered by AJAX POST requests to /apply_filter; the server applies the transformation and returns the new filename in JSON, so JavaScript can update the displayed image without a full page reload.

4.3 Voice Input

The Web Speech API's SpeechRecognition interface is instantiated in JavaScript when the user activates the microphone button. The language is set to en-US, and the onresult callback populates the prompt text area with the final transcript. An onerror handler displays appropriate feedback for conditions such as silence detection, audio capture failure, or network error. A feature-detection guard prevents the microphone button from appearing on browsers that do not support the SpeechRecognition interface.

4.4 Interest Analytics

Every time a user submits a prompt, keywords are appended to a per-user text log. When the profile page loads, the server reads all past prompts for the authenticated user, tokenises them by whitespace, filters out common stopwords, and counts term frequencies. The top six terms are then mapped to semantic interest buckets for example, 'mountain', 'forest', and 'river' map to Nature; 'city', 'building', and 'street' map to Architecture. Matplotlib's pyplot.pie() renders the distribution as a labelled chart, which is saved to the static directory and embedded directly in the profile page.

V. RESULTS AND DISCUSSION

PixelMind was evaluated across two dimensions: raw performance benchmarks on the target hardware, and a head-to-head comparison against leading commercial alternatives.

A. Performance Benchmarks

Generation time was measured over 20 GPU runs and 5 CPU runs on the target hardware. Table I summarises the results. The GPU pipeline delivers an $8.7\times$ speedup over the CPU fallback. In all 20 GPU test runs, inference completed without VRAM errors, confirming that the float16 configuration is stable within the GTX 1650's 4 GB constraint.

B. Comparative Analysis

Table II positions PixelMind against two leading commercial alternatives on criteria directly relevant to the project's goals. The primary differentiators are full data privacy, zero marginal cost, built-in post-processing, and voice input features absent from both DALL·E 2 and Midjourney. The FID score of 8.59 is particularly significant: it shows that running locally on modest consumer hardware does not require any meaningful sacrifice in image quality.

C. Test Coverage

Eighteen test cases spanning nine functional modules authentication, image generation, voice input, filtering, gallery and sharing, profile management, the admin dashboard, security, and UI theming — were executed. All 18 passed, yielding 100% coverage. Security testing specifically submitted SQL injection payloads and malformed inputs to every input field; parameterised query protection blocked any unintended database exposure in each case.

VI. LIMITATIONS AND FUTURE WORK

Several constraints shape what the current system can do. First, the GTX 1650's 4 GB of VRAM supports only one active inference request at a time, so concurrent users must queue. Second, output resolution is fixed at 512×512 pixels — the native size of Stable Diffusion v1.5 — which falls short of print-quality requirements. Third, voice input relies on the Web Speech API, available only in Chrome and Edge. Fourth, email OTP delivery and Wikipedia enrichment both require outbound internet access, which may be blocked in some campus environments.

Future development will tackle these issues on several fronts. Integrating Celery with a Redis broker will enable asynchronous task queuing, letting the application accept multiple concurrent requests without blocking. Upgrading to Stable Diffusion XL (SDXL) will push the native resolution to 1024×1024 . Introducing LoRA-based fine-tuning will let users personalise the model on their own imagery without retraining from scratch. Containerisation via Docker and deployment to a cloud GPU instance will extend reach beyond the local network while preserving the privacy-first architecture.

VII. CONCLUSIONS

This paper has presented PixelMind, a locally deployable, GPU-accelerated text-to-image web application built on Stable Diffusion v1.5. The system meets all ten of its defined objectives and achieves 100% test coverage across 18 test cases spanning nine functional modules. By running entirely on an NVIDIA GeForce GTX 1650, PixelMind demonstrates that production-quality generative AI tooling does not require managed cloud infrastructure, expensive API subscriptions, or specialised hardware beyond what is already present in many student and researcher workstations.

The architecture is modular, privacy-preserving, and free to operate. Its FID score of 8.59 compares favourably with DALL·E 2's 10.39, while voice input, seven real-time image filters, a personal gallery, usage analytics, and a secured admin dashboard give PixelMind a feature depth that sets it apart from the bare-bones local inference scripts available in the open-source community. The project offers a replicable reference architecture for institutions, educators, and independent developers who want to democratise access to generative AI without compromising user privacy or incurring ongoing service costs.

VIII. REFERENCES

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