SOMAIYA VIDYAVIHAR UNIVERSITY

K. J. Somaiya School of Engineering

Department of Computer Engineering

Batch: A4	**Roll No.: 16010122139**
Experiment No 2	
Group No: 03	

Title: Literature Survey

Objective: The objective of a literature survey is to review, analyze, and synthesize existing research to identify gaps, trends, and insights that inform and support a study's context and direction.

Expected Outcome of Experiment:

	At the end of successful completion of the course the student will be able to
CO1	Define the problem statement and scope of problem
CO5	Prepare a technical report based on the Mini project.

Books/ Journals/ Websites referred:

1.
2.
3.

The students are expected to prepare chapter no 2 in the format given below

Chapter 2

Literature Survey

The Objective of a literature survey is to review existing research, identify gaps, and establish a strong foundation for the study. It helps in understanding key concepts, comparing different approaches, and justifying the need for the current research by analyzing past studies.

1. Introduction

AI-based image generation has become a significant breakthrough in the field of artificial intelligence, combining natural language processing (NLP) and computer vision. With advancements in generative models, particularly diffusion models like **Stable Diffusion 2.1** and **3.5 Large**, it has become possible to produce high-resolution, detailed images from text prompts. This literature survey aims to explore existing methodologies in text-to-image synthesis, analyze prior works on diffusion models, and identify the need for improved control, realism, and performance in AI image generation. The goal is to establish a foundation that supports the objectives of the current mini project, "NeuraPix – AI Image Generator.

2. Review of Existing Literature

Several generative AI models have evolved in recent years, with notable contributions in the areas of latent diffusion, hierarchical image generation, and prompt-to-image accuracy. Stability AI's diffusion models and OpenAI's CLIP-based techniques have greatly enhanced the quality and control of generated images.

- **Rombach et al. (2022)** introduced Latent Diffusion Models (LDM) that reduced computational cost while maintaining high image fidelity.
- **Ramesh et al. (2022)** proposed a hierarchical text-conditional image generation framework using CLIP latents, which demonstrated effective prompt understanding.
- **Dhariwal and Nichol (2021)** demonstrated how diffusion models outperform GANs on image synthesis tasks, introducing structured denoising processes.
- **Saharia et al. (2022)** focused on photorealistic image generation using text prompts with deep semantic understanding, contributing to diffusion model optimization.
- **Ho et al. (2020)** laid the foundation of diffusion probabilistic models, setting the stage for subsequent advances in generative AI.

3. Related Work

Paper Title (Including Author Details, Year of publication, Conference/Journal	Methodology	Dataset Used	Observation of proposed methodology	Pros	Cons	Findings
"High-resolution Image Synthesis with Latent Diffusion Models" – *Rombach et al., CVPR 2022*	Used latent diffusion in compressed space to generate images efficiently	COCO, OpenImages	Reduced compute while maintaining high quality	Low memory, high resolution	May blur fine details	Enabled scalable image generation with fewer resources
Hierarchical Text-Conditional Image Generation with CLIP Latents" – *Ramesh et al., arXiv 2022*	Used CLIP and transformers to improve prompt-image alignment	Internal OpenAI datasets	Highly accurate text-to-image results	Excellent semantic alignment	Requires heavy compute	Foundation of DALL·E 2
Diffusion Models Beat GANs on Image Synthesis" – *Dhariwal & Nichol, NeurIPS 2021*	Improved denoising diffusion model with classifier guidance	CIFAR-10, ImageNet	Outperformed GANs in image quality	Stable, interpretable	Slower than GANs	Proved diffusion as a superior generative method
Photorealistic Text-to-Image Diffusion with Deep Language Understanding" – *Saharia et al., arXiv 2022*	Combined image diffusion with deep NLP models	LAION-400M	High realism and better prompt adherence	Rich language understanding	Potential bias in training	Strong baseline for photorealistic generation

Denoising Diffusion Probabilistic Models" – *Ho et al., NeurIPS 2020*	Introduced basic DDPM framework for generative tasks	CIFAR-10	Foundation for all diffusion-based models	Simple, effective	High training cost	Core model behind newer diffusion models
"ControlNet: Adding Conditional Control to Text-to-Image Diffusion Models" – *Lvmin Zhang et al., 2023*	Enabled edge, pose, depth-based control in generation	MS-COCO + custom controls	Greatly improved control over output images	Fine control, multi modal	Complexity in control input	Advanced interactive image creation
"GLIDE: Towards Photorealistic Image Generation and Editing with Text-guided Diffusion Models" – *Nichol et al., 2022*	Introduced editing + generation using diffusion + guidance	Public image-text pairs	Enabled image manipulation via prompts	Text-based editing	Limited resolution	Allowed creative flexibility
"Imagen: Photorealistic Text-to-Image Diffusion Models with Large Language Models" – *Saharia et al., 2022*	Combined LLMs with diffusion for detailed generation	Internal datasets	Higher photorealism than DALL·E	Deep NLP + image quality	Not open-source	Major milestone in realistic image generation
"Versatile Diffusion: Text, Images and Beyond" – *Kim et al., 2023*	Unified multi-modal inputs (text, sketches) for generation	MS-COCO, LAION	Handles multiple input types	Flexible interface	Still under research	Useful for creative tools
"Stable Diffusion: High-resolution Image Synthesis using Latent Text-to-Image Diffusion" – *Stability AI, 2022*	Combines U-Net + CLIP + latent space diffusion	LAION-5B	Open-source, highly customizable	Fast inference, public availability	May lack high semantic depth	Enabled community-driven generative tools

4. Research Gaps and Challenges

- **Gaps in Fine Control**: Although diffusion models generate high-quality images, controlling specific aspects of image generation (pose, depth, edges) remains a challenge.
- **Computational Cost**: Advanced models such as Stable Diffusion 3.5 require substantial computational resources for real-time or large-scale deployment.
- **Prompt Adherence Issues**: Despite advances, exact interpretation of complex or abstract prompts still requires fine-tuning.
- **Ethical Concerns**: Potential misuse of generated content for deepfakes or biased outputs raises critical ethical issues.
- **Future Direction**: More precise control mechanisms like ControlNets (Blur, Canny, Depth) and improved multimodal integration (text, sketch, image input) could address current limitations.