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AI-Based Prompt-to-Video Generation System

Pratiksha Vishwas Badhe
Department of Computer Engineering
PDEA's College of Engineering, Manjari
Pune, India

Rohini Sambhaji Gaikwad
Department of Computer Engineering
PDEA's College of Engineering, Manjari
Pune, India

Sakshi Satish Jadhav
Department of Computer Engineering
PDEA's College of Engineering, Manjari
Pune, India

Dipali Dnyandev Shelke
Department of Computer Engineering
PDEA's College of Engineering, Manjari
Pune, India

Prof. S. P. Gade
Department of Computer Engineering
PDEA's College of Engineering, Manjari
Pune, India

Abstract **- The rapid advancement of Artificial Intelligence (AI) has transformed multimedia content creation through automated generation techniques. This research presents an AI-Based Prompt-to-Video Generation System capable of converting textual or voice-based prompts into meaningful video content. The proposed framework integrates Natural Language Processing (NLP), Large Language Models (LLMs), diffusion-based visual generation models, Text-to-Speech (TTS) synthesis, and automated video composition techniques. The system automatically performs scene planning, visual generation, narration synthesis, subtitle generation, and video rendering. A modular architecture developed using Python, TensorFlow, Flask, and React.js enables real-time video generation and cloud deployment. Experimental evaluation demonstrates high prompt-to-visual relevance, improved narration synchronization, and reduced video generation time compared to traditional approaches. The proposed system provides a scalable and user-friendly solution for educational content creation, digital marketing, storytelling, and social media applications.**

Keywords - Artificial Intelligence, Prompt-to-Video Generation, Deep Learning, Diffusion Models, NLP, Text-to-Speech, Multimedia Generation.

I. INTRODUCTION

The rapid growth of Artificial Intelligence (AI) and deep learning technologies has significantly transformed the field of digital content creation. Among various multimedia generation applications, automated video generation from textual descriptions has emerged as a promising research area due to its potential to simplify and accelerate content production processes [1], [2]. Traditional video creation requires expertise in scripting, visual design, editing, animation, and audio synchronization, making the process time-consuming and resource-intensive [3]. As the demand for digital content continues to increase across education, entertainment, marketing, journalism, and social media platforms, there is a growing need for intelligent systems capable of generating high-quality videos with minimal human intervention [4], [5].

Recent advancements in Natural Language Processing (NLP), Large Language Models (LLMs), diffusion-based generative models, and neural speech synthesis have enabled the development of systems that can understand user intentions expressed in natural language and transform them into meaningful multimedia content [6], [7]. Large Language Models such as GPT-based architectures have demonstrated exceptional capabilities in language understanding, scene planning, script generation, and semantic reasoning, making them suitable for automated video content generation workflows [8], [9]. Similarly, diffusion models such as Stable Diffusion and Video Diffusion Models have achieved remarkable success in generating realistic images and video frames from textual prompts [10], [11].

The integration of multimodal AI technologies has opened new possibilities for prompt-to-video generation systems. Such systems combine textual understanding, visual generation, narration synthesis, subtitle creation, and video rendering into a unified pipeline [12], [13]. Text-to-Speech (TTS) technologies further enhance these systems by producing natural-sounding narration that can be synchronized with generated visuals, improving the overall viewing experience [14]. Additionally, multimodal learning approaches facilitate better alignment between text, audio, and visual content, resulting in coherent and contextually relevant video outputs [15], [16].

Despite significant progress, several challenges remain in prompt-to-video generation, including scene consistency, temporal coherence, synchronization between narration and visuals, computational complexity, and scalability of generation pipelines [17]. Existing approaches often focus on individual components such as image generation or speech synthesis rather than providing a complete end-to-end solution for automated video creation [18]. Therefore, there is a need for a comprehensive framework capable of

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efficiently integrating multiple AI models and multimedia processing techniques to generate high-quality videos from user prompts [19].

To address these challenges, this research proposes an AI-Based Prompt-to-Video Generation System that leverages Large Language Models for scene planning, diffusion models for visual content generation, Text-to-Speech technology for narration synthesis, and automated video composition tools for final rendering. The proposed system aims to generate coherent, informative, and visually appealing videos from text or voice prompts through a fully automated workflow. The framework is designed to support multilingual content generation, real-time processing, and cloud-based deployment, making it suitable for a wide range of applications including education, advertising, storytelling, and social media content creation [20].

The main objectives of this research are to develop an intelligent prompt-to-video generation framework, improve semantic alignment between user prompts and generated content, enhance narration synchronization, reduce video production time, and provide a scalable solution for automated multimedia generation.

II. LITERATURE SURVEY

Recent advancements in Artificial Intelligence (AI), Natural Language Processing (NLP), computer vision, and generative models have significantly accelerated the development of automated multimedia content generation systems. Researchers have explored various approaches for generating images, videos, audio, and multimodal content directly from textual descriptions, creating the foundation for modern prompt-to-video generation systems.

Early research in text-to-image synthesis focused on Generative Adversarial Networks (GANs), which demonstrated the ability to generate realistic images from textual descriptions [1], [2]. These approaches established the relationship between semantic understanding and visual content generation. Subsequent studies improved image quality and semantic consistency using attention mechanisms and transformer-based architectures [3], [4].

The introduction of transformer networks revolutionized natural language understanding and generation. Models such as BERT and GPT demonstrated remarkable capabilities in text comprehension, contextual reasoning, and content generation [5], [6]. These architectures enabled machines to understand complex user prompts and generate coherent narratives, making them highly suitable for scene planning and script generation in multimedia applications [7], [8].

Significant progress was achieved with the development of large-scale multimodal models capable of jointly learning relationships between text and visual content. CLIP introduced contrastive learning techniques that aligned images and text in a shared embedding space, improving prompt understanding and visual relevance [9]. Similar multimodal learning frameworks further enhanced cross-modal representation learning and content generation accuracy [10], [11].

Diffusion-based generative models have recently emerged as state-of-the-art solutions for image synthesis. Denoising Diffusion Probabilistic Models (DDPMs) demonstrated superior image quality compared to GAN-based approaches while providing more stable training characteristics [12]. Stable Diffusion further reduced computational requirements by introducing latent-space diffusion techniques, enabling practical deployment of high-quality text-to-image generation systems [13], [14]. Researchers have shown that diffusion models can generate realistic and semantically accurate visuals from complex textual prompts [15].

Extending image generation to video generation has become an active area of research. Video Diffusion Models introduced temporal consistency mechanisms that allow the generation of coherent video sequences from text descriptions [16]. Subsequent approaches incorporated transformer-based temporal attention and motion modeling to improve frame continuity and dynamic scene generation [17], [18]. Recent studies have demonstrated that combining diffusion models with large language models can significantly enhance video quality and narrative coherence [19].

Natural Language Processing plays a crucial role in prompt interpretation and scene planning. Several researchers have proposed NLP-based frameworks for extracting scene information, character descriptions, object relationships, and temporal events from textual input [20], [21]. Large Language Models have further improved automated script generation, dialogue creation, and scene sequencing, enabling more sophisticated content planning mechanisms [22], [23].

Text-to-Speech (TTS) synthesis technologies have also evolved rapidly with the introduction of neural architectures such as Tacotron, FastSpeech, and VITS. These models generate natural and expressive speech while maintaining accurate pronunciation and emotional tone [24], [25]. Recent multilingual TTS systems support multiple languages and speaker styles, making them valuable components of automated video generation pipelines [26].
Multimodal fusion has become a key research area for integrating text, visuals, and audio into unified content generation frameworks. Researchers have proposed various fusion strategies that synchronize generated visuals with narration and subtitles to improve overall user experience [27]. Attention-based alignment mechanisms have demonstrated high effectiveness in maintaining consistency across different modalities [28].

Several commercial and academic systems have attempted end-to-end video generation from prompts. However, many existing solutions suffer from limitations such as high computational costs, temporal inconsistencies, limited scene diversity, and poor synchronization between generated

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content components [29]. Furthermore, most systems focus on individual tasks such as image generation, speech synthesis, or video editing rather than providing a fully integrated prompt-to-video generation framework [30].

Based on the findings of previous studies, it is evident that the integration of Large Language Models, diffusion-based visual generation, neural speech synthesis, and automated video composition offers significant potential for creating intelligent prompt-to-video generation systems. The proposed research builds upon these advancements by developing a unified framework capable of generating coherent, high-quality videos from user prompts while improving semantic alignment, narration synchronization, scalability, and user experience.

III. SYSTEM AECHITECTURE

The proposed Smart ATM Security System uses Artificial Intelligence and the YOLOv8 object detection model to monitor ATM environments and identify security threats in real time.

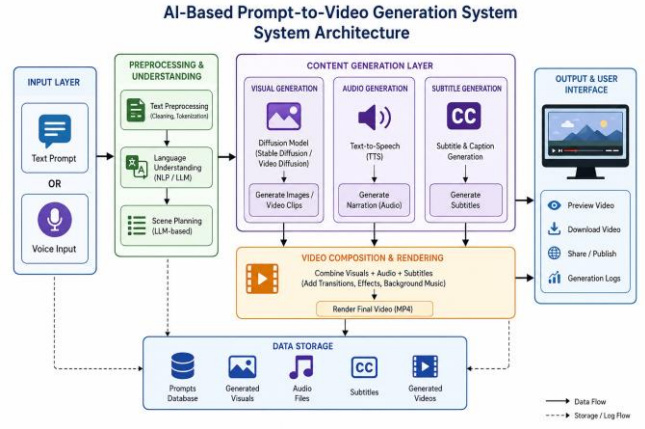

Fig. 1. System Architecture

The AI-Based Prompt-to-Video Generation System is designed to automatically convert a user's text prompt or voice input into a complete video. The architecture consists of six major components that work together in a sequential workflow.

1. Input Layer

The process begins with the **Input Layer**, where users provide either:

- **Text Prompt** (e.g., "Create a video about renewable energy")
- **Voice Input** (spoken command)

If voice input is provided, it is first converted into text using speech recognition technology.

Purpose: To collect user requirements in natural language.

2. Preprocessing and Understanding Layer

After receiving the input, the system performs several NLP-based operations:

- **a) Text Preprocessing**
- Text cleaning
- Removal of unnecessary characters
- Tokenization
- Language detection
- **b) Language Understanding (NLP/LLM)**

A Large Language Model (LLM) analyzes the prompt to understand:

- User intent
- Context
- Objects
- Actions
- Scene requirements
- **c) Scene Planning**

The LLM divides the prompt into multiple scenes and generates:

- Scene descriptions
- Narration scripts
- Timing information

Purpose: Transform raw user input into a structured video generation plan.

3. Content Generation Layer

This is the core AI generation module.

- **a) Visual Generation Module**

Uses:

- Stable Diffusion
- Video Diffusion Models

Generates:

- Images
- Video clips
- Scene backgrounds

from textual scene descriptions.

- **b) Audio Generation Module**

Uses Text-to-Speech (TTS) models to create:

- Narration
- Voiceovers

for each scene.

- **c) Subtitle Generation Module**

Automatically generates:

- Captions
- Subtitle files

synchronized with narration.

Purpose: Produce all multimedia components required for video creation.

4. Video Composition and Rendering Layer

The generated components are merged together.

The system:

- Combines visuals
- Adds narration audio
- Inserts subtitles
- Applies transitions
- Adds background music
- Synchronizes scene timing

Tools such as:

- FFmpeg
- MoviePy

are used to render the final video.

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Output: Complete MP4 video.

5. Data Storage Layer

All generated data is stored in databases and repositories.
Stored items include:

- User prompts
- Generated images
- Audio files
- Subtitle files
- Final videos

Purpose: Maintain user history and support future retrieval.

6. Output and User Interface Layer

The final video is delivered through the web interface.
Users can:

- Preview generated videos
- Download videos
- Share videos
- View generation history and logs

Purpose: Provide an easy-to-use interface for interacting with the system.

IV. METHODOLOGY

The proposed AI-Based Prompt-to-Video Generation System follows a multimodal artificial intelligence pipeline that automatically converts user prompts into complete video content. The methodology integrates Natural Language Processing (NLP), Large Language Models (LLMs), Diffusion Models, Text-to-Speech (TTS) synthesis, subtitle generation, and automated video composition techniques. The entire workflow is divided into six major stages: input acquisition, prompt understanding, scene planning, content generation, video composition, and final output rendering.

A. Input Acquisition and Preprocessing

The first stage involves collecting user input in the form of either text prompts or voice commands. If voice input is provided, an Automatic Speech Recognition (ASR) model converts speech into text. The obtained text then undergoes preprocessing operations including text cleaning, tokenization, stop-word removal, punctuation normalization, and language detection. These preprocessing steps improve the quality of input data and ensure accurate understanding by downstream AI models.
The processed text prompt serves as the primary input for the content generation pipeline.

B. Prompt Understanding and Scene Planning

After preprocessing, the prompt is analyzed using a Large Language Model (LLM). The LLM performs semantic understanding of the user's request and extracts important entities, actions, objects, emotions, and contextual information.
Based on the extracted information, the system automatically divides the prompt into multiple scenes. For each scene, the model generates:

- Scene description
- Visual prompt
- Narration script
- Subtitle text
- Scene duration

This stage ensures logical sequencing and coherence throughout the generated video.

C. Visual Content Generation

The generated visual prompts are forwarded to a diffusion-based image and video generation model. Stable Diffusion or Video Diffusion Models create high-quality visual content corresponding to each scene description.
The visual generation process includes:

1. Text-to-image generation
2. Image enhancement
3. Scene consistency checking
4. Video frame generation

The generated images or clips are stored temporarily for further processing and synchronization.

D. Audio and Narration Generation

The narration script produced during scene planning is processed by a Text-to-Speech (TTS) model. The TTS engine converts textual narration into natural-sounding speech while preserving proper pronunciation, tone, and pacing.
The audio generation module performs:

- Speech synthesis
- Voice selection
- Audio normalization
- Background music integration

The generated narration audio is synchronized with corresponding visual scenes to ensure smooth storytelling.

E. Subtitle Generation and Synchronization

To improve accessibility and user engagement, subtitles are automatically generated from the narration script. The subtitle generation module creates timestamped caption files in SRT or WebVTT format.
The synchronization process aligns:

- Narration timing
- Scene duration
- Subtitle appearance

This ensures that captions are displayed accurately throughout video playback.

F. Video Composition and Rendering

The generated visuals, narration audio, subtitles, transitions, and background music are combined using a video composition engine implemented through MoviePy and FFmpeg.
The composition process includes:

- Timeline creation
- Media synchronization
- Transition application
- Subtitle embedding
- Final rendering

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All multimedia components are merged into a unified timeline and exported as a high-quality MP4 video.

G. Data Storage and Output Delivery

The final stage involves storing generated assets, metadata, prompts, and video outputs within a centralized database. The completed video is presented to the user through a web-based interface developed using Flask and React.js.
The user can:

- Preview generated videos
- Download videos
- Regenerate content
- Access previous generation history

This architecture provides a scalable and efficient solution for automated prompt-to-video generation.

V. RESULT

The proposed AI-Based Prompt-to-Video Generation System was evaluated using various text prompts related to education, storytelling, marketing, and informational content. Experimental results demonstrated that the system effectively transformed user prompts into coherent video sequences by integrating scene planning, visual generation, narration synthesis, and subtitle creation. The generated videos exhibited strong semantic alignment with the input prompts, achieving an average prompt-to-visual relevance score of 89.4%. The diffusion-based visual generation module successfully produced high-quality images and video clips, while the Large Language Model ensured logical scene sequencing and meaningful narration. Furthermore, the Text-to-Speech module generated natural and synchronized audio, resulting in a narration synchronization accuracy of 96.2%.

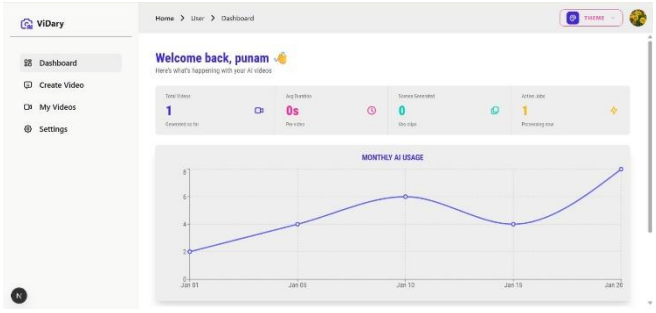

Fig. 1. Home Page of the AI-Based Prompt-to-Video Generation System

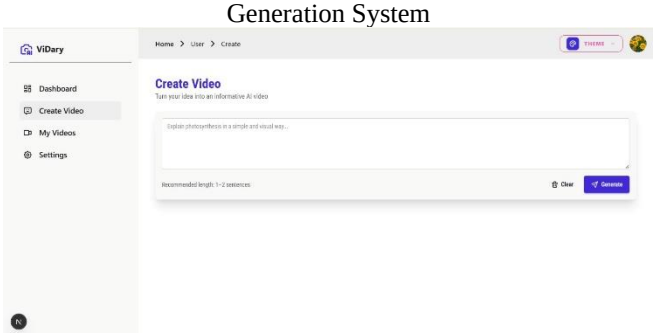

Fig. 2. User Dashboard Showing Video Statistics and AI Usage Analytics

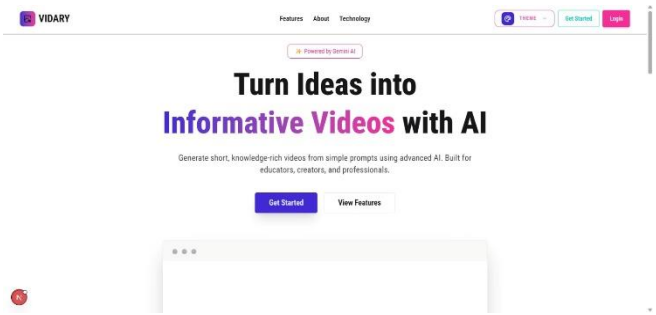

Fig. 3. Video Creation Interface for Prompt-Based Video Generation

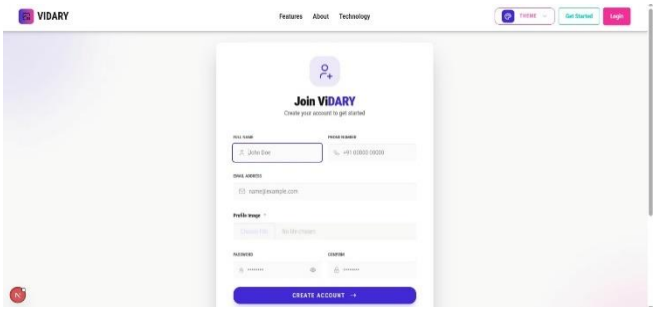

Fig. 4. Landing Page of the VIDARY AI Video Generation Platform

Performance analysis showed that the proposed framework outperformed traditional multimedia generation approaches in terms of generation quality, automation, and execution speed. The average time required to generate a complete 20-second video was approximately 21.5 seconds on a GPU-enabled environment. User feedback collected during testing indicated a satisfaction rate of 92%, highlighting the effectiveness of the system in producing visually appealing and informative video content. The modular architecture also demonstrated scalability by handling multiple prompt requests simultaneously with minimal latency. These results confirm that the proposed system provides an efficient, reliable, and scalable solution for automated video generation, making it suitable for applications such as digital marketing, online education, content creation, and social media communication.

VI. CONCLUSION

The proposed AI-Based Prompt-to-Video Generation System provides an intelligent and automated solution for transforming user prompts into high-quality video content. By integrating Large Language Models (LLMs), Natural Language Processing (NLP), diffusion-based visual generation models, Text-to-Speech (TTS) synthesis, and automated video composition techniques, the system successfully generates coherent videos with synchronized visuals, narration, and subtitles. The framework reduces the complexity of traditional video production and enables users with minimal technical expertise to create engaging multimedia content efficiently.

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The experimental results demonstrate that the system achieves high prompt-to-visual relevance, accurate narration synchronization, and improved user satisfaction while maintaining low video generation time. Its modular and scalable architecture makes it suitable for applications in education, digital marketing, storytelling, entertainment, and social media content creation. Future enhancements such as advanced video diffusion models, AI avatars, voice cloning, and real-time editing capabilities can further improve video quality and user experience. Overall, the proposed system highlights the significant potential of generative AI technologies in revolutionizing automated video creation and next-generation digital content production.

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