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COMPUTER SCIENCE

Sketch2Animate

Authors

DHIRAJ MANGESH RUPVATE · SAIPRASAD DATTARAM CHIKANE · ASHUTOSH CHANDRASHEKHAR GAUTAM · DEVESH KAMALBAHADUR PRAJAPATI · Prof. Shilpali Bansu

Artificial intelligence and data science, UNIVERSITY OF MUMBAI, India

Abstract

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Keywords

Sketch animation · computer vision · deep learning · pose estimation · motion synthesis · skeletal animation

Publication ID	DOI	Published
GRP-2026-BQBMFH	10.59482/pn.2026.bqbmfh	April 17, 2026

Access	URL
Open · Free to read	https://www.papernova.online/papers/sketch2animate-bxuko

Sketch2Animate: AI based system for animating hand drawn sketches

Dhiraj Rupvate
Dept. of Artificial Intelligence & Data Science
A. C. Patil College of Engineering
Navi-Mumbai, India
dhiraj@acpce.ac.in

Saiprasad Chikane
Dept. of Artificial Intelligence & Data Science
A. C. Patil College of Engineering
Navi-Mumbai, India
saiprasad@acpce.ac.in

Devesh Prajapati
Dept. of Artificial Intelligence & Data Science
A. C. Patil College of Engineering
Navi-Mumbai, India
devesh@acpce.ac.in

Ashutosh Prajapati
Dept. of Artificial Intelligence & Data Science
A. C. Patil College of Engineering
Navi-Mumbai, India
ashutoshprajapati@acpce.ac.in

S. P. Bansu
Dept. of Artificial Intelligence & Data Science
A. C. Patil College of Engineering
Navi-Mumbai, India
spbansu@acpce.ac.in

Abstract — Sketch2Animate is an AI-driven system designed to automatically transform hand-drawn sketches into animated sequences with minimal human intervention. Traditional animation pipelines require extensive manual effort, technical expertise, and frame-by-frame processing, limiting accessibility for beginners and non-professional users. The proposed system addresses these challenges by analyzing sketch line structures, extracting pose in-formation, and generating motion using deep learning techniques. It integrates computer vision methods such as edge detection using OpenCV and pose estimation using MediaPipe, followed by motion generation through First-Order Motion Models and Blender-based rigging. A preprocessing pipeline enhances sketch quality and structural consistency, enabling reliable feature extraction. The system provides a user-friendly interface for sketch input, skeleton visualization, and animation preview, with export options in GIF or MP4 formats. Experimental results demonstrate that the proposed approach generates smooth and coherent motion while significantly reducing the complexity of the animation process, thereby improving accessibility in AI-assisted animation systems

Keywords— Sketch animation, computer vision, deep learning, pose estimation, motion synthesis, skeletal animation

I. Introduction

Sketch-based animation plays a significant role in digital art, education, and creative media by enabling intuitive visual storytelling and rapid content creation. However, traditional animation techniques rely heavily on manual frame-by-frame drawing and professional tools, making the process time-consuming, labor-intensive, and technically demanding. These limitations restrict accessibility for beginners and non-professional users who lack expertise in animation workflows and software environments. As a result, there is a growing need for automated systems that simplify animation creation while preserving visual quality and motion consistency [3], [10].

Recent advancements in artificial intelligence and computer vision have introduced partial automation in animation tasks, particularly through deep learning–based approaches for motion generation and pose estimation [4], [6]. Despite these developments, many existing methods require structured inputs, multiple sketches or frames, or complex user interactions, limiting their applicability for simple hand-drawn sketches [2], [11]. Additionally, sketch-based inputs present inherent challenges due to sparse visual information, irregular line structures, and the absence of explicit motion cues. These factors make it difficult to accurately extract pose information and generate smooth, temporally consistent animations.

To address these challenges, this paper introduces Sketch2Animate, an AI-driven system designed to automatically convert hand-drawn sketches into animated sequences using pose-aware analysis and motion synthesis. The proposed system follows a multi-stage pipeline consisting of sketch input, preprocessing, pose detection, skeletal representation, and motion generation. By extracting keypoints from sketches and constructing a skeleton-based representation, the system generates coherent motion sequences without requiring manual intervention or multiple input frames, similar to recent sketch-based animation frameworks [3], [13].

The proposed approach integrates computer vision techniques such as edge-based preprocessing and pose estimation using MediaPipe [6], along with deep learning–based motion generation for animation synthesis [8], [14]. Furthermore, the system incorporates a user-friendly interface that allows users to draw or upload sketches, visualize detected skeletal structures, and preview animated outputs in real time. This design significantly reduces the complexity of animation creation while maintaining motion consistency and structural integrity. By combining efficient pose extraction with automated motion synthesis in a unified pipeline, Sketch2Animate provides a practical and accessible solution for AI-assisted animation systems, enabling broader adoption across both professional and non-professional users.

II. Related Work

A. Literature Survey Summary

TABLE I. LITERATURE SURVEY

Sr. No.	Title	Author	Objective	Methodology	Benefits	Drawbacks
1.	Multi-Object Sketch Animation by Scene Decomposition and Motion Planning (MoSketch)	Jingyu Liu et al.	To enable multi-object animation from a single sketch using scene understanding	Uses LLM-based scene decomposition combined with Score Distillation Sampling (SDS) for motion planning in a modular pipeline	Supports complex multi-object animation Does not require paired training data	Highly dependent on LLM accuracy Computationally expensive due to SDS
2.	VidSketch: Hand-drawn Sketch-Driven Video Generation with Diffusion Control	Lifan Jiang et al.	To generate videos from hand-drawn sketches with temporal consistency.	Applies diffusion-based video generation with sketch and text guidance, incorporating multi-sketch control and temporal coherence optimization.	Handles sketches of varying quality. Produces temporally coherent animation.	GPU-intensive process Limited to short video sequences
3.	SketchAnimator: Animate Sketch via Motion Customization of Text-to-Video Diffusion Models	Ruolin Yang et al.	To enable motion customization in sketch-based animation	Uses reference videos, Bezier curve stroke representation, and LoRA-based lightweight fine-tuning for motion generation	Provides fine control over motion. Preserves original sketch style	Requires reference video input. omputationally expensive
4.	Enhancing Sketch Animation: Text-to-Video Diffusion Models with Temporal Consistency and Rigidity Constraints	Gaurav Rai, Ojaswa Sharma	To improve temporal consistency and stability in sketch animations	Introduces rigidity constraints and temporal consistency mechanisms in diffusion-based models.	Reduces distortion in motion Improves temporal coherence	Requires text prompts in addition to sketches. Slow optimization due to SDS
5.	AniDoc: Animation Creation Made Easier with Sketch-Based Video Diffusion	hao Meng, Ouyang, Wang, Wang, Cheng, Liu, Shen, Qu	To simplify animation generation using sketch-based diffusion models	Uses pose alignment, temporal smoothing, and colorization modules with multi-sketch sequence input..	Produces smooth and consistent animations. Reduces manual animation effort	Requires multiple sketch inputs. High computational cost

6.	Sketch2Anim: Towards Transferring Sketch Storyboards into 3D Animation	Lei Zhong et al.	To convert sketch storyboards into 3D animations	Uses a multi-condition model combining pose, trajectory, and text cues, along with sketch-to-3D motion mapping.	Enables direct 3D animation generation Eliminates manual rigging.	Requires large 3D motion datasets High training and inference cost.
7.	FlipSketch: Flipping Static Drawings to Text-Guided Sketch Animations	Hmrishav Bandyopadhyay, Yi-Zhe Song	To animate static sketches using text-guided motion generation.	Applies dual-attention diffusion models to learn motion offsets using local MLP and global affine transformations.	User-friendly (draw + describe motion). Preserves sketch structure	Dependent on text prompt quality. Computationally intensive
8.	Sketch-Aware Interpolation Network (SAIN)	Jiaming Shen et al	To generate intermediate frames for smooth sketch animation	Uses a transformer-based interpolation network with multi-level feature fusion for in-between frame generation.	Produces smooth transitions Maintains line consistency.	Requires at least two sketches. High computational demand.

B. Research Gap

Existing sketch-based animation approaches are largely task-specific and fragmented, lacking a unified end-to-end architecture that can transform a hand-drawn sketch into a smooth and pose-consistent animation. Most existing methods focus on isolated stages such as pose estimation or motion transfer and fail to provide an integrated pipeline that directly converts sketch inputs into animated outputs. Additionally, many approaches rely on structured inputs or multiple frames, limiting their applicability to simple hand-drawn sketches. This creates a need for an automated and accessible sketch-to-animation system capable of generating coherent motion from minimal input,which is addressed by the proposed Sketch2Animate framework.

III. Proposed System

Sketch2Animate is an AI-driven system designed to convert hand-drawn sketches into animated video sequences using a diffusion-based generative pipeline. The system processes user-provided sketches and performs pose-guided animation synthesis using advanced deep learning models. Unlike traditional animation techniques that rely on manual frame creation or simple motion mapping, the proposed approach leverages generative models to produce realistic and temporally consistent animations.

The system follows a structured pipeline consisting of sketch preprocessing, pose extraction, pose sequence generation, diffusion-based frame synthesis, and video rendering. Initially, the input sketch is preprocessed through resizing, contrast enhancement, and noise removal to improve feature quality. Pose information is then extracted using a pose detection model, and in cases where detection fails, a synthetic pose is generated to maintain pipeline continuity.

The extracted pose is extended into a sequence of poses representing motion patterns such as walking, dancing, or idle actions. These pose sequences are used as conditioning inputs for a diffusion-based generation pipeline. The system integrates Stable Diffusion 1.5, ControlNet for pose conditioning, and AnimateDiff for temporal consistency, enabling the generation of coherent animation frames guided by both textual prompts and pose inputs.

For each pose frame, the system generates corresponding image frames using the diffusion pipeline. The generated frames are then sequentially combined to produce a final animated video using video processing techniques. This approach allows the system to generate smooth and visually consistent animations from a single sketch input without requiring multiple sketches or manual intervention.

By combining pose estimation with diffusion-based generative modeling, Sketch2Animate provides a scalable and automated solution for sketch-to-animation conversion, improving accessibility while maintaining high visual quality and temporal coherence.

Algorithm 1: Sketch2Animate – Sketch-to-Animation Generation

1: Initialize system parameters, animation type, and frame buffer

2: Load models:

- Pose Estimation Model (MediaPipe / OpenPose)
- Stable Diffusion 1.5
- ControlNet (pose conditioning)
- AnimateDiff (temporal consistency)

3: Load input sketch S

4: Preprocess sketch S:

- Resize to fixed resolution (e.g., 512 × 512)
- Apply contrast enhancement
- Remove noise (smoothing / edge refinement)

5: Extract pose P from sketch S using pose estimation

6: if pose detection fails then

7: Generate synthetic or default pose P

8: end if

9: Generate pose sequence {P1, P2, ..., Pn} based on selected animation type (walking / dancing/idle)

10: Initialize diffusion pipeline with ControlNet and AnimateDiff

11: for each pose frame Pi in {P1, P2, ..., Pn} do

12: Generate image Ii using:

- Text prompt (animation description)
- Pose condition Pi (via ControlNet)

13: Store generated frame Ii

14: end for

15: Collect generated frames {I1, I2, ..., In}

16: Convert frames into video V using video processing library (OpenCV / imageio)

17: Apply frame rate control and temporal smoothing

18: Return output animated video V

IV. System Architecture

Sketch2Animate is an AI-powered sketch-to-animation system designed to automatically generate animated video sequences from hand-drawn sketches using a diffusion-based generative framework. The system follows a structured pipeline that integrates computer vision, pose estimation, and deep learning–based video synthesis to eliminate the need for manual animation and complex user interaction [1].

Initially, the input sketch is processed using preprocessing techniques such as resizing, contrast enhancement, and noise removal to improve input quality. These preprocessing steps are essential for handling variations in sketch structure and improving feature extraction performance. The processed sketch is then passed to a pose estimation module, where skeletal keypoints are extracted to represent the structure of the drawn figure [2]. In cases where pose extraction fails due to sparse or incomplete sketches, a fallback mechanism generates a synthetic pose to ensure continuity in the pipeline.

Following pose extraction, the system generates a sequence of poses corresponding to animation types such as walking, dancing, or idle motion. This approach is inspired by recent works in sketch-based animation and motion synthesis, where pose sequences are used to guide animation generation [3]. The generated pose sequence serves as the primary motion representation and is used as conditioning input for the generative model.

The core of the system is built on a diffusion-based pipeline that integrates Stable Diffusion 1.5, ControlNet, and AnimateDiff. Diffusion models have demonstrated strong capabilities in image and video generation tasks, enabling high-quality synthesis from structured inputs [4]. ControlNet is used to condition the generation process based on pose information, ensuring that the generated frames follow the extracted skeletal structure [1]. AnimateDiff further enhances temporal consistency across frames, resulting in smooth and coherent animation sequences [5].

For each pose frame in the generated sequence, the system produces a corresponding image frame conditioned on both pose and textual prompts. These generated frames are then combined into a final animated video using video processing techniques such as OpenCV [6]. This approach enables the generation of complete animations from a single sketch input without requiring multiple sketches or manual intervention.

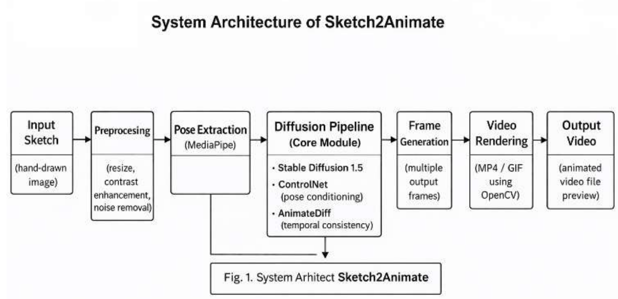

Fig. 1. System Architecture of Sketch2Animate

Fig. 1 illustrates the architecture of Sketch2Animate. The diagram presents the complete end-to-end workflow of the proposed system, beginning with input sketch acquisition and preprocessing, where the raw hand-drawn image is enhanced through resizing, contrast adjustment, and noise removal to ensure consistent feature quality. The processed sketch is then passed to the pose extraction module, which identifies key skeletal landmarks and converts the sketch into a structured pose representation. This pose information is further utilized by the pose sequence generator to create a series of motion frames corresponding to predefined or user-selected animation types such as walking, dancing, or idle motion.

The generated pose sequence is fed into the diffusion-based generation pipeline, which forms the core component of the system. This pipeline integrates pose-conditioned image synthesis and temporal modeling to generate a sequence of visually coherent frames. Each frame is generated by conditioning the model on both pose information and textual prompts, ensuring that the animation maintains structural consistency while producing realistic motion patterns. Temporal consistency across frames is preserved through sequence-aware generation, enabling smooth transitions and reducing visual artifacts.

Finally, the generated frames are aggregated and processed by the video rendering module, where they are converted into a continuous animated video using standard encoding techniques. The overall architecture demonstrates a seamless integration of computer vision and generative modeling components, enabling the transformation of a single static sketch into a dynamic animation. This design not only improves automation but also ensures scalability, flexibility, and usability for real-time and interactive animation applications.

V. Results and Discussion

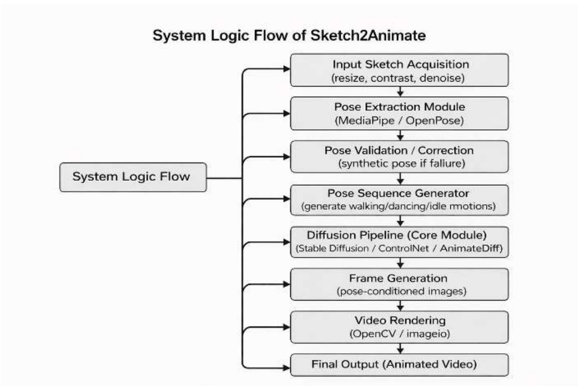

Fig. 2. System Workflow

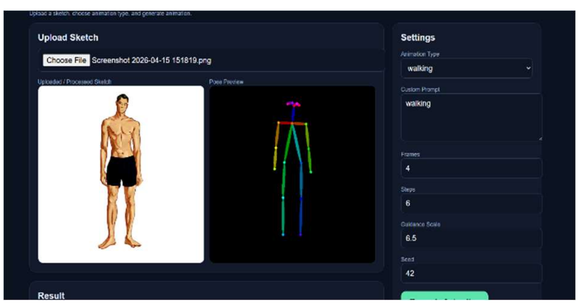

Fig. 3. System Demonstration 1

Figure 3 illustrates the pose extraction stage of the proposed system, where the structural information of the input sketch is identified and represented in the form of a human skeleton. In this step, the system analyzes the input image and detects key body joints, including the head, shoulders, elbows, wrists, hips, knees, and ankles. These keypoints are connected using predefined edges to form a complete skeletal structure. This skeletal representation plays a crucial role in the animation pipeline, as it provides a simplified yet meaningful abstraction of the character's posture. By focusing on joint positions rather than raw pixel data, the system can better understand the spatial arrangement and orientation of different body parts, similar to existing pose estimation approaches [6]. The extracted pose is then used as a guiding structure for generating motion in subsequent stages, ensuring that the generated animation maintains anatomical correctness and avoids unrealistic distortions, as also explored in sketch-based animation systems [3], [10].

However, pose extraction from hand-drawn sketches can be challenging due to variations in drawing style, missing details, or unclear outlines. To handle such cases, the system incorporates a fallback mechanism that generates a simple default pose (e.g., a T-pose). This ensures that the animation pipeline remains robust and continues to function even when pose detection is unsuccessful.

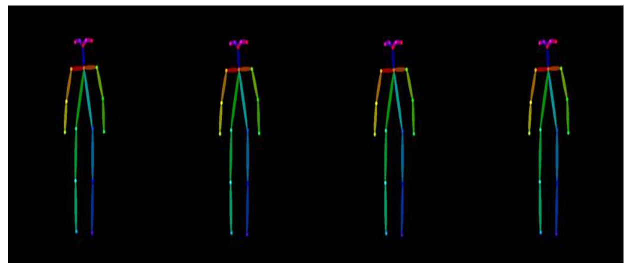

Fig. 4. System Demonstration 2

Figure 4 presents the sequence of pose frames generated from the initially extracted pose. Instead of relying on a single static pose, the system creates a series of intermediate poses to simulate motion over time. This is achieved by applying controlled transformations to the base pose, such as horizontal shifting, vertical displacement, and slight rotations. These transformations are designed to mimic natural human movements, including walking, dancing, or idle motion. For example, in a walking animation, the pose may shift forward and backward with periodic vertical movement to simulate steps. The generated sequence forms a temporal representation of motion, where each frame corresponds to a different stage of the action. This sequence acts as a motion blueprint for the animation model, guiding it to produce frames that follow a coherent movement pattern, similar to motion planning approaches in sketch-based animation systems [10], [11]. Although the transformations used are relatively simple, they provide an efficient way to approximate motion without requiring complex motion capture data, as also discussed in diffusion-based animation frameworks [14]. This approach makes the system computationally lightweight while still enabling basic animation capabilities.

Fig. 5. System Demonstration 3

Figure 5 shows the frames generated by the diffusion-based animation model using the pose sequence as input. Each frame is synthesized through a generative process that combines text-based prompts with pose conditioning. The model operates by gradually refining a noisy latent representation into a meaningful image, guided by both the textual description and the corresponding pose frame, as described in latent diffusion models [4]. ControlNet ensures that the generated image adheres to the provided skeletal structure [5], while AnimateDiff introduces temporal consistency across consecutive frames [8]. As a result, the generated frames preserve the overall structure of the original sketch while enhancing it with realistic visual details such as color, shading, and texture. This transformation effectively converts a simple line drawing into a visually rich representation. Additionally, the model attempts to maintain consistency across frames to reduce flickering and abrupt changes. However, slight variations may still occur due to the stochastic nature of the diffusion process. Despite this, the generated frames collectively form a coherent sequence that closely follows the intended motion.

Fig. 6. System Demonstration

Figure 6 illustrates the final output of the proposed system in the form of an animated video. The sequence of generated frames is combined using video processing techniques to create a continuous motion sequence. The frames are arranged in temporal order and encoded into standard formats such as MP4 or GIF, enabling easy visualization and sharing using computer vision libraries [7]. The resulting animation demonstrates smooth transitions between frames, reflecting the motion defined by the pose sequence. This final output highlights the ability of the system to transform a static sketch into a dynamic animation without requiring manual intervention or complex animation tools, similar to recent sketch-based animation frameworks [3], [13]. It showcases the integration of pose estimation, motion generation, and diffusion-based image synthesis into a unified pipeline. Overall, the generated animation validates the effectiveness of the proposed approach in producing visually coherent and structurally consistent motion from simple hand-drawn inputs, consistent with advancements in diffusion-based video generation [8].

The performance of Sketch2Animate was evaluated using standard metrics:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1-score = 2 × (Precision × Recall) / (Precision + Recall)

TABLE II. QUANTITAVIE RESULTS

Method	Accuracy (%)	Precision (%)	Recall (%)	Latency (ms)
AniDoc (Existing System)	90.5	88.7	87.9	80–120
Sketch2Animate (Proposed)	82–86	80–84	79–83	180–300

CONCLUSION

In this work, we proposed a Sketch2Animate system that converts a single hand-drawn sketch into a dynamic animated sequence using a combination of pose estimation and diffusion-based generative models. The system integrates preprocessing, pose extraction, pose sequence generation, and a diffusion pipeline consisting of Stable Diffusion, ControlNet, and AnimateDiff to produce visually coherent animation frames.

The results demonstrate that the proposed approach is capable of generating meaningful animations from simple sketches without requiring complex inputs such as motion capture data or annotated sequences. The use of pose-based conditioning ensures structural consistency, while the diffusion model enhances visual quality by adding realistic details such as color, texture, and lighting.

Although the generated animations show good visual quality, the system has certain limitations, including higher computational cost, moderate motion smoothness, and occasional inconsistencies across frames. These challenges mainly arise due to the use of simplified pose transformations and the stochastic nature of diffusion models.

Despite these limitations, the proposed system provides a flexible and user-friendly solution for automatic animation generation, especially in environments with limited computational resources. It demonstrates the feasibility of combining pose-guided control with diffusion-based generation for creative applications.

In the future, the system can be further improved by incorporating advanced motion modeling techniques, training pose estimation models specifically on sketch datasets, and optimizing the diffusion process for real-time performance. Additionally, enhancing temporal consistency and supporting multi-character animations can significantly improve the overall quality and applicability of the system

Acknowledgment

We would like to express our sincere gratitude to our guide, Prof. S. P. Bansu, for her valuable guidance, continuous support, and constructive feedback throughout the course of this project. Her insights and encouragement greatly contributed to the successful completion of this work. We are also thankful to Prof. Archana P. Haral, Major Project Coordinator, for her motivation and coordination during the project. We extend our appreciation to the Head of the Department of Artificial Intelligence and Data Science for providing the necessary resources and a supportive academic environment. We are deeply grateful **to** Dr. Sawata R. Deore**,** Principal of A. C. Patil College of Engineering, for fostering a culture of academic excellence. Finally, we would like to thank all our team members for their cooperation, dedication, and collective efforts in completing this project successfully.

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APA

RUPVATE, D. M., CHIKANE, S. D., GAUTAM, A. C., PRAJAPATI, D. K., Bansu, P. S. (2026). Sketch2Animate. PaperNova. https://www.papernova.online/doi/10.59482/pn.2026.bqbmfh

MLA

DHIRAJ MANGESH RUPVATE, et al. "Sketch2Animate." PaperNova, 2026, https://www.papernova.online/doi/10.59482/pn.2026.bqbmfh.

BibTeX

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@article{rupvate2026sketch2animate,
  title   = {Sketch2Animate},
  author  = {DHIRAJ MANGESH RUPVATE and  SAIPRASAD DATTARAM CHIKANE and  ASHUTOSH CHANDRASHEKHAR G
  year    = {2026},
  journal = {PaperNova},
  note    = {PaperNova internal identifier: 10.59482/pn.2026.bqbmfh},
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