

FaceVid-1K: A Large-Scale High-Quality Multiracial Human Face Video Dataset

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Figure 1: Overview of the proposed FaceVid-1K dataset. The FaceVid-1K dataset comprises over 200,000 video clips featuring more than 150,000 unique identities, with 80% representing Asian individuals. We have collected approximately 700 hours of face videos and integrated other related public datasets, such as HDTF (Zhang et al. 2021), TalkingHead-1KH (Wang, Mallya, and Liu 2021), CelebV-HQ (Yu et al. 2023), and CelebV-Text (Yu et al. 2023), filtering out noisy and low-quality data to create a large-scale, evenly distributed, multiracial dataset. We maintain this enhanced resource will significantly support research tasks related to human face videos. Please zoom in to observe the facial details.

Abstract

Generating talking face videos from various conditions has recently become a highly popular research area within generative tasks. However, building a high-quality face video generation model requires a well-performing pre-trained backbone, a key obstacle that universal models fail to adequately address. Most existing works rely on universal video or image generation models and optimize control mechanisms, but they neglect the evident upper bound in video quality due to the limited capabilities of the backbones, which is a result of the lack of high-quality human face video datasets. In this work, we investigate the unsatisfactory results from related studies, gather and trim existing public talking face video datasets, and additionally collect and annotate a large-scale dataset, resulting in a comprehensive, high-quality multiracial face collection named **FaceVid-1K**. Using this dataset, we craft several effective pre-trained backbone models for face video generation. Specifically, we conduct experiments with several well-established video generation models, including text-to-video, image-to-video, and unconditional video generation, under various settings. We obtain the corresponding performance benchmarks and compared them with those trained on public datasets to demonstrate the superiority of our dataset. These experiments also allow us to investigate empirical strategies for crafting domain-specific video generation tasks with cost-effective settings. We will make our curated dataset, along with the pre-trained talking face video generation models, publicly available as a resource contribution to hopefully advance the research field.

Introduction

Generating talking face videos (Xu et al. 2024b) has become one of the most popular video generation tasks in recent years. There are several different downstream tasks for creating talking face videos with various conditions, such as using text prompts (Li et al. 2021; Zhang et al. 2022; Wang, Dai, and Lundgaard 2023; Jang et al. 2024), reference images (Hong and Xu 2023; Chu et al. 2024; Ye et al. 2024), driven audio (Liu et al. 2023; Gan et al. 2023; Zhong et al. 2023; Tan, Ji, and Pan 2024; Tan et al. 2024; Drobyshev et al. 2024) or face landmark sequences (Feng et al. 2024) as inputs to generate guided video results. Current popular research on talking face video generation primarily consists of two branches: GANs (Goodfellow et al. 2014) and Diffusions (Ho, Jain, and Abbeel 2020; Song, Meng, and Ermon 2021). Due to the advantages of diffusion-based methods, which offer higher quality and greater diversity (Dhariwal and Nichol 2021), in this work, we mainly focus on the diffusion-based branch.

Current diffusion-based methods (Shen et al. 2023; Stypułkowski et al. 2024; Wei, Yang, and Wang 2024; Ma et al. 2024b) primarily focus on adopting pre-trained universal video generation backbone models, e.g., Diffusion Transformer (Peebles and Xie 2023) and Stable Video Diffusion (Blattmann et al. 2023) or image generation model (Stable Diffusion (Rombach et al. 2022)) and further optimizing the

control mechanisms to generate talking face videos. However, it is well-known that the ultimate success of video generation tasks (Wang et al. 2023; Jin et al. 2024) heavily depends on the capability of the pre-trained backbone model. Compared to other generative domains such as Text-to-Image (Ramesh et al. 2021) and Text-to-3D (Ding et al. 2024), developing a well-performing universal video generation backbone model is significantly more challenging due to the lack of large-scale, high-quality datasets and the inevitable massive computational burden, which cannot be adequately addressed in the current era.

We buy in the successful experience from other generative domains, *e.g.*, Large Language Model (Touvron et al. 2023) and Image Generation (Saharia et al. 2022) that training a specialized pre-trained video generation model on an extensive, high-resolution dataset is a more effective and efficient strategy (Blattmann et al. 2023) for addressing the challenge of generating high-quality talking face videos. Nevertheless, there are still two key research questions (**RQ**) that lack empirical research: **RQ1: Data Scale Requirement**. Taking the task of face video generation as an example, what is the cost-effective required scale of high-quality data and the corresponding number of model parameters needed to train a well-performing backbone model for a specific domain? **RQ2: Difference of Backbones**. What are the performance and cost differences among various widely-adopted video generation models, such as the Diffusion Transformer related models and Stable Video Diffusion?

To investigate these two questions, in this work, we first gather relevant public datasets of human talking face videos, *i.e.*, HDTF (Zhang et al. 2021), TalkingHead-1KH (Wang, Mallya, and Liu 2021), CelebV-HQ (Zhu et al. 2022), and CelebV-Text (Yu et al. 2023) and filter out noisy data. Additionally, as shown in Figure 1, we collect and annotate cropped videos over 700 hours from public video websites, resulting in a comprehensive, high-quality, multi-ethnic dataset of about 1,000 hours in total, named **FaceVid-1K**. Based on this collected large-scale, high-quality video dataset, we conduct extensive experiments under different settings to address the questions mentioned above regarding training the video generation backbone model. Furthermore, we derive several empirical insights for training video generation backbone models and compare the performance of models trained on our dataset with those trained on public datasets under the same settings. We evaluate these models on various tasks, including Text-to-Video, Image-to-Video, and unconditional video generation, and obtain the corresponding performance benchmarks. These extensive experiments demonstrate that our collected dataset is capable of enhancing the performance of related tasks and can serve as a benchmark for future research in this area. Overall, the contributions of this work can be summarized as follows:

- We make a large-scale, high-quality, multi-ethnic human face video dataset (FaceVid-1K) public to serve as a valuable resource;
- We conduct extensive experiments on training video generation backbone models to investigate the two research questions mentioned above, drawing empirical conclu-



Figure 2: We identify several common issues in existing public human face video datasets that significantly contribute to the poor quality of videos generated by the corresponding trained models. These issues have been largely neglected in previous works.

sions to guide the development of pre-trained backbone video generation models for specific domains;

- Based on our collected dataset and the pre-trained backbone model, we demonstrate that these pre-trained models can improve performance on related tasks, establishing a series of new benchmarks for the future work.

FaceVid-1K Dataset

In this section, we first outline the current challenges associated with existing public datasets and explain the motivation behind the collection of our new extensive dataset. We then provide detailed information on the collection and pre-processing methods employed. Finally, we present statistical properties of our collected dataset and compare them with those of other public datasets.

Motivation and Challenge

High-quality face video datasets are crucial for the training of generative models. However, existing public datasets are not only too small in scale to support the training of a well-performing video generation model but also often suffer from several significant quality issues. As illustrated in Figure 2, we briefly summarize several common problems found in public datasets: (a) Low definition and resolution, with issues such as violent shaking or smearing, often resulting in the model generating blurry outputs; (b) Multiple faces appearing in a single frame, making the generated video perplexing; (c) Hands or other objects intermittently entering the frame, causing the model to introduce extraneous elements; (d) Presence of text or noise within the frame, leading the model to generate noisy artifacts. These problems are highly detrimental and fail to meet the high-quality standards required for video generative models. Moreover, to the best of our knowledge, public datasets lack sufficient Asian human face data, which prevents generative models from producing satisfactory multi-racial face videos. To address these issues, we curated existing human face video datasets, including HDTF (Zhang et al. 2021), TalkingHead-1KH (Wang, Mallya, and Liu 2021), CelebV-HQ (Zhu et al. 2022), and CelebV-Text (Yu et al. 2023) by selecting high-quality and talking head videos, resulting in approximately 300 hours of satisfactory footage. We additionally collect

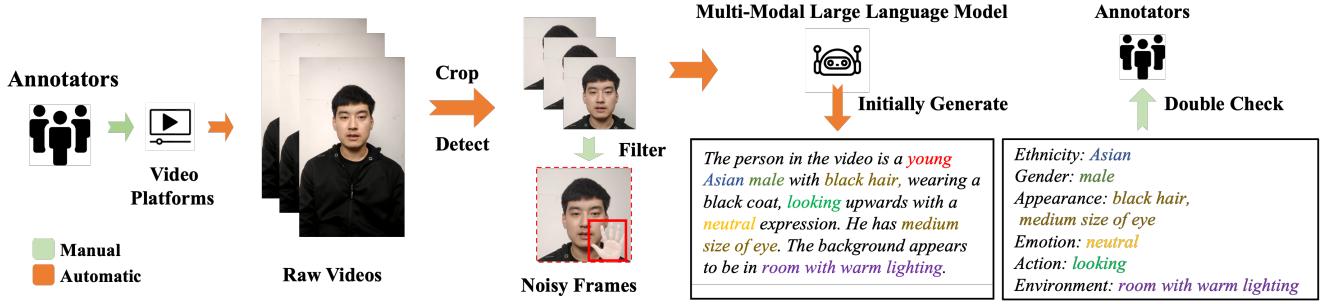


Figure 3: Illustration of the processing pipeline for our collected dataset includes the following main steps: collecting raw videos, detecting and cropping to the face region, filtering out noisy clips, and generating video descriptions.

and process over 700 hours of Asian face videos. This effort resulted in a large-scale, high-quality, multi-racial video dataset exceeding 1,000 hours in total, facilitating training of backbones for Text-to-Video and Talking Head Generation.

Collection and Processing

To ensure the scale and diversity of the proposed dataset, we primarily collected data from several popular video websites where users upload their own content. The raw video data we gathered predominantly had resolutions exceeding 1080p, and the content mainly consisted of interview programs and vlogs. As shown in the processing pipeline in Figure 3, we firstly utilized the Dlib (King 2009) to detect facial regions in the videos. We filtered out raw data containing multiple faces in the same frame and cropped the videos to focus on single face regions, while allowing for natural face or head movement within an acceptable range. The cropped videos primarily included the full face and the upper shoulder area. After cropping, we employed approximately 100 annotators over 6 months to manually filter out most videos containing hands, text, and other extraneous noise. Note that although we made significant efforts to collect a sufficient quantity of high-quality Asian faces, we encountered issues with resolution compression from the video platforms. After cropping and resizing to 512×512 , some videos remained blurry. To enhance these videos (less than 4% of total data), we applied the CodeFormer (Zhou et al. 2022) method.

After obtaining the high-quality videos, we proceeded to generate detailed video content descriptions. We used a pre-trained video captioning model (Xu et al. 2024a) to automatically generate initial annotations. Unlike (Yu et al. 2023), which employs description templates for semi-automatic annotation generation, we leveraged prompt-based techniques similar to those used in large language model (LLM) interactions to enhance effectiveness. The captioning model was tasked with generating single-sentence descriptions of the characters in the videos, detailing their ethnicity, gender, age, appearance attributes (*e.g.*, hairstyle, hair color, and eye size), emotional state, actions (predominantly talking or speaking with occasional singing), background environment, and lighting conditions. To capture the dynamic actions of characters in the videos (*i.e.*, head movements), we randomly sampled non-consecutive frames while generating captions. In our experiments, we set $n = 3$ to balance text

accuracy and processing efficiency. To ensure the accuracy of the generated video descriptions, we employed over 100 annotators to manually double-check and cross-check the annotations. This rigorous process resulted in a high-quality, multi-racial, large-scale face video dataset **FaceVid-1K** with precise annotations.

Properties and Comparison

The final version of our collected FaceVid-1K contains 213,500 video clips, including 35,150 clips from trimmed public datasets and 178,350 clips from collected videos. In total, our dataset spans over 1,000 hours of video, with 80% of the clips depicting Asian faces. Specifically, as shown in Table 1, our dataset includes six annotated labels and video content descriptions, initially generated by PLLaVA (Xu et al. 2024a) and subsequently reviewed and corrected by annotators. Note that the video resolutions for HDTF, CelebV-HQ, CelebV-Text, and our dataset are all 512×512 or higher. In contrast, TalkingHead-1K contains many low-quality and low-resolution videos, which are not as valuable. Therefore, we filter out and retain only the videos with resolutions of 512×512 or higher from TalkingHead-1K and then performed statistical analysis on the remaining data. Overall, our collected dataset FaceVid-1K surpasses these datasets by a large margin across all statistical metrics. Next, we introduce the statistics of these attributes and compare them in detail with other public datasets.

Ethnicity, Gender, and Age. One of the key motivations for proposing FaceVid-1K is to address the lack of Asian faces in current public datasets. As shown in Figure 4 (e), over 80% of the faces in this dataset are Asian. The remaining approximately 20% consists of 11% White, 4% African, and 5% from other ethnicities, including Latin and Middle Eastern. In terms of gender distribution, our dataset is split with 55% male and 45% female. Regarding age distribution, our dataset comprises 15% minors, 73% adults, 25% middle-aged individuals, and 2% elderly persons.

Appearance. The statistical analysis of our dataset regarding appearance attributes can be observed as follows: FaceVid-1K contains a total of 30 appearance attributes, as shown in Figure 4 (a). Among these, 11 attributes (*i.e.*, No Beard, Straight Hair, Young, Black Hair, Male, Anchored Eyebrow, Short Hair, Eyeglasses, Brown Hair, Rosy Cheeks,

Table 1: Comparison of our collected **FaceVid-1K** with four related public datasets. “#” indicates the number. “Etnh.”, “Gen.”, “Emo.”, “Act.”, and “Env.” stand for Ethnicity, Gender, Emotion, Action, and Environment, respectively.

Datasets	#. Samples	Meta Information Resolution	Duration	Etnh.	Gen.	Appr.	Emo.	Act.	Env.	Text
HDTF (Zhang et al. 2021)	368	512×512	15.8h	-	-	-	-	-	-	x
TalkingHead-1KH (Wang, Mallya, and Liu 2021)	80,000	512×512	160h	-	-	-	-	-	-	x
CelebV-HQ (Zhu et al. 2022)	35,666	512× 512	68h	x	x	✓	✓	✓	x	✓
CelebV-Text (Yu et al. 2023)	70,000	512×512+	279h	x	✓	✓	✓	✓	x	✓
FaceVid-1K	213,500	512×512+	1003h	✓	✓	✓	✓	✓	✓	✓

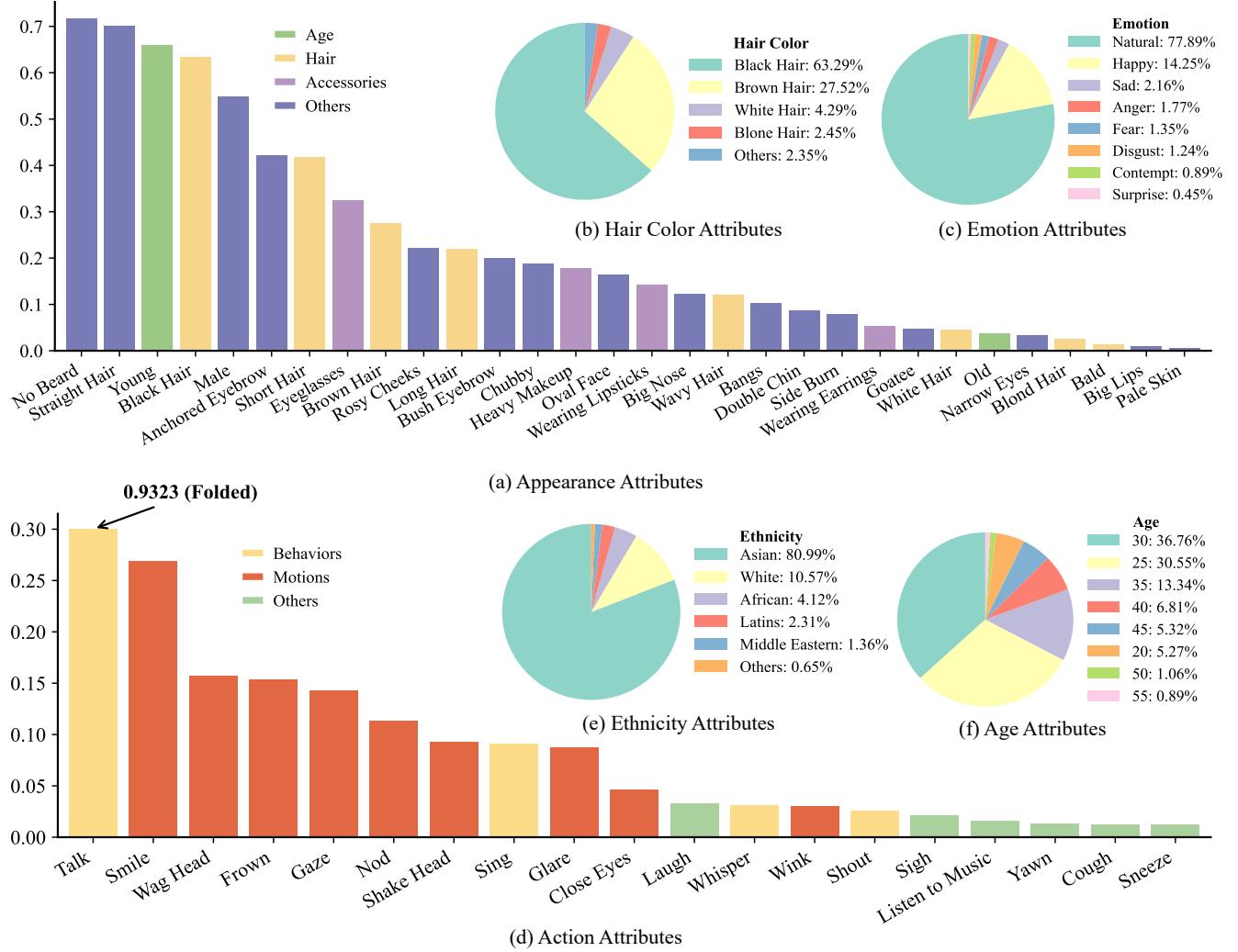


Figure 4: Distributions of general appearances, hair colors, emotions, actions, ethnicity, and age.

Long Hair) each account for more than 20%, while 8 attributes (*i.e.*, Bush Eyebrow, Chubby, Heavy Makeup, Oval Face, Wearing Lipsticks, Big Nose, Wavy Hair, Bangs) each account for between 10% and 20%. We aim for our dataset to contain as much diversity as possible. The overall attribute distribution exhibits a long tail, with some attributes accounting for less than 4%. Given that FaceVid-1K contains an overwhelming number of Asian faces (over 80%), appearance characteristics typical of Asians (such as black straight hair and sparse beard) appear with higher frequency, whereas attributes like blonde hair and baldness occur less

frequently. As depicted in Figure 4 (b), the majority of identities have black hair.

Emotion. The distribution of emotional attributes is illustrated in Figure 4 (c). Given that the raw data predominantly originates from conversational videos and vlogs, “Neutral” emotions constitute the majority, followed by “Happy”, “Angry”, “Surprised”, and other naturally expressed emotions during conversations.

Action. FaceVid-1K predominantly includes the action of “Talking”. It also contains other actions commonly performed during conversations, such as “Smiling”, “Wagging

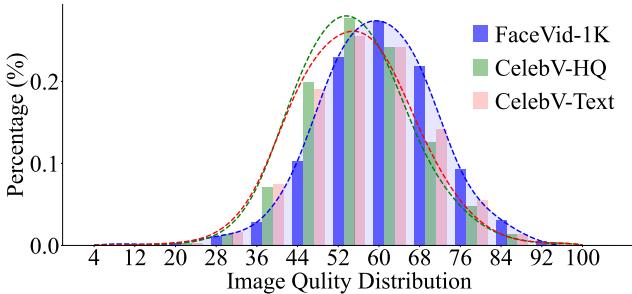


Figure 5: Comparison of the image quality between the highest-quality public datasets and ours.

head”, “Nodding”, and “Frowning”. Our primary objective during data collection was to facilitate the training of backbone models for text-driven talking video generation. To ensure the diversity of the dataset, we included actions such as “Singing” and “Whispering”, thereby enabling the trained model to generate corresponding action videos. The proportions of these actions are illustrated in Figure 4 (d).

Environment and Text Description. Leveraging the power of the multi-modal pre-trained model, *i.e.*, PLLaVA (Xu et al. 2024a), we generate text descriptions for the given videos. Different descriptions of the environment can affect lighting, shadows, background, and other related visual features. Since these descriptions are in natural language, we do not perform statistical analysis on them. However, we assert that they are important for the final performance of the generative models. Initially generated by the MLLM model and double-checked by human annotators, we believe these accurate, high-quality text descriptions are also an advantage of our dataset for further fine-tuning via text prompt.

Video Quality. We adopted the same evaluation method used by CelebV-Text (Zhu et al. 2022) to assess the quality of the videos. Specifically, we used BRISQUE (Mittal, Moorthy, and Bovik 2012) to evaluate the quality of each frame of the video segments and calculated the average value. In Figure 5, we compare FaceVid-1K with datasets from (Zhu et al. 2022) and (Yu et al. 2023). Evaluation results indicate that our dataset outperforms the other datasets.

Experiments

In this section, we conduct experiments on public human face video datasets and our collected FaceVid-1K dataset across three popular video generation tasks: Text-to-Video, Image-to-Video, and unconditional video generation. We use widely accepted evaluation metrics for all three tasks, namely FVD (Unterthiner et al. 2018) and FID (Heusel et al. 2017), to assess temporal consistency and single frame quality, respectively. Additionally, for the task of text-to-video generation, we employ the CLIPScore (Hessel et al. 2021) to evaluate video-text similarity of the generated videos. Both qualitative and quantitative results demonstrate the effectiveness and superiority of the proposed FaceVid-1K for these three human face video generation tasks. Additionally, we draw empirical insights to answer the two research questions (*i.e.*, RQ1: Analysis for Data Scale Requirement and RQ2: Difference of Backbones) proposed in previous sections.

Table 2: Quantitative results on Text-to-Video generation. We adopt Open-Sora for this task and keep the same settings to compare the performance across different datasets.

Dataset	FVD (\downarrow)	FID (\downarrow)	CLIPScore (\uparrow)
HDTF	94.72	18.26	0.9037
TalkingHead-1KH	236.85	47.02	0.7831
CelebV-HQ	175.79	27.53	0.7924
CelebV-Text	151.31	25.18	0.8215
FaceVid-1K	38.01	8.71	0.9365

Table 3: Quantitative results on Image-to-Video and unconditional video generation tasks. We respectively adopt Stable Video Diffusion and Latte for these two experiments and maintain the same settings to compare the performance across different datasets.

Task	Image-to-Video		Unconditional Video	
	FVD (\downarrow)	FID (\downarrow)	FVD (\downarrow)	FID (\downarrow)
HDTF	203.56	9.69	81.25	13.42
TalkingHead-1KH	523.56	30.09	201.87	35.54
CelebV-HQ	351.39	10.18	151.31	25.18
CelebV-Text	316.11	9.65	149.52	21.83
FaceVid-1K	168.32	9.35	68.01	10.96

Experiments on Text-to-Video Generation

We conduct experiments to demonstrate the effectiveness of FaceVid-1K for Text-to-Video generation, using the state-of-the-art Open-Sora Plan model (Lab and etc. 2024). Although Open-Sora Plan is not specifically designed for face video generation, fine-tuning with high-quality face video datasets transforms it into a robust Text-to-Face-Video model. As shown in Figure 6, we compare our dataset with the highest-quality public dataset, CelebV-Text. Both models, trained on these datasets, generate face videos based on text prompts. However, the model trained on CelebV-Text struggles with generating high-quality Asian faces due to limited data and often produces artifacts like “hands flashing into the frame.” In contrast, the model trained on FaceVid-1K avoids these issues and shows superior performance in synthesizing teeth and lips. Quantitative results in Table 2 show that while both models achieve competitive scores across three metrics, our model outperforms due to the careful filtering of low-quality data, which enhances training outcomes.

Experiments on Image-to-Video Generation

In this experiment, we use the widely-adopted Image-to-Video model, Stable Video Diffusion (SVD) (Blattmann et al. 2023), to compare the performance of models trained on the highest-quality public dataset, CelebV-Text, and our dataset. The quantitative results reported in Table 3 show that the model trained on our dataset outperforms the one trained on CelebV-Text across the two evaluation metrics by a large margin. For qualitative experiments, since images inherently provide more detailed information compared to the ambiguous textual prompts of natural language descriptions, both models are able to generate Asian face videos that re-

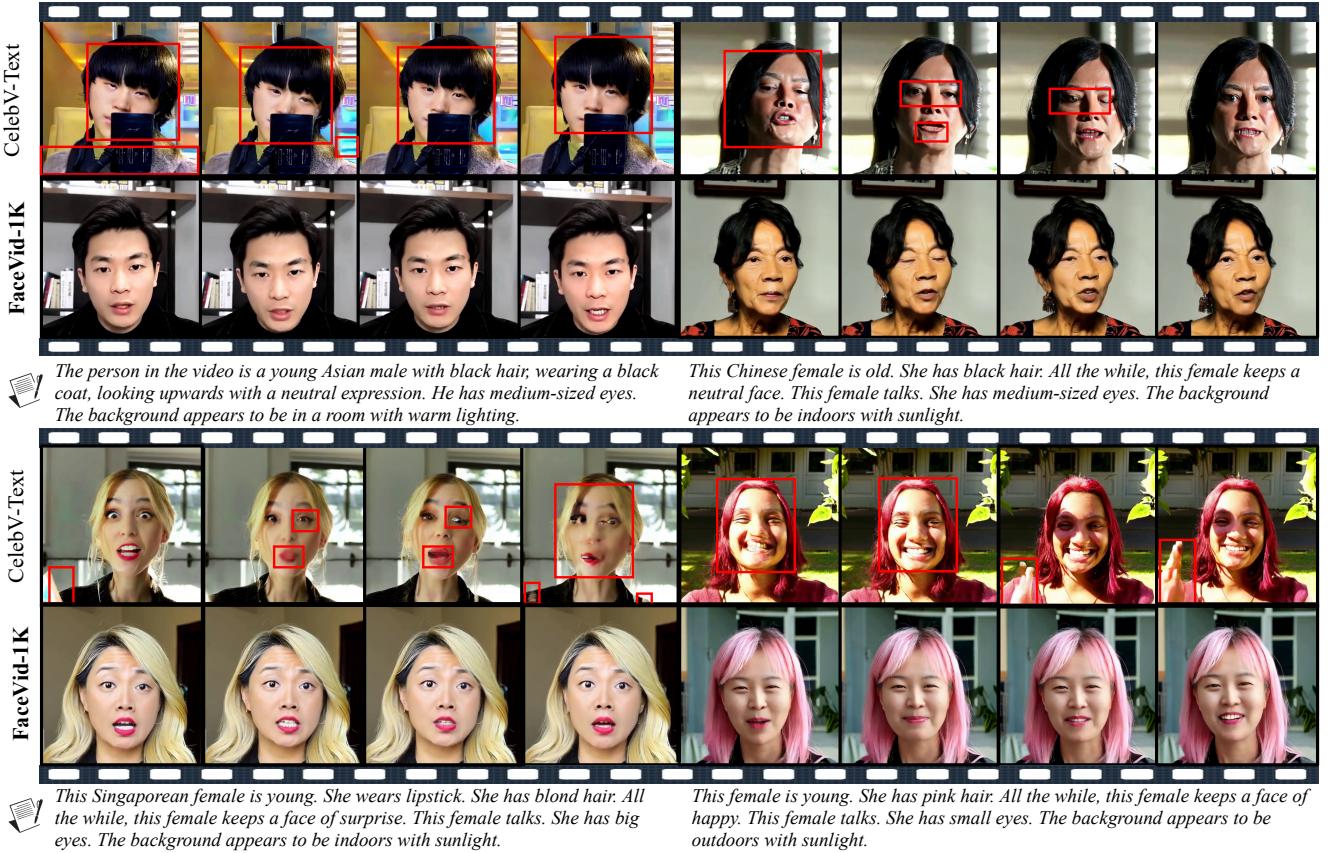


Figure 6: **Text-to-Video.** Using the same video generative model (*i.e.*, Open-Sora Plan) trained respectively on the best publicly available dataset (CelebV-Text) and our collected dataset (FaceVid-1K), we conduct a qualitative comparison of the videos generated by the two models, both under identical settings and text prompts. Please zoom in to observe the facial details.

tain the input face characteristics. However, as shown in Figure 7, the model trained with FaceVid-1K exhibits superior performance in facial details, such as the teeth and eyes. The model trained with FaceVid-1K generates a wider range of natural facial motions and expressions due to the dataset’s higher quality and diversity.

Experiments on Unconditional Video Generation

We apply Latte (Ma et al. 2024a) for experiments on unconditional video generation. The generated videos have a resolution of 256×256 and a length of 16 frames. From the quantitative results reported in Table 3, the model trained on our dataset outperforms the model trained on CelebV-Text across both FVD and FID metrics, indicating higher video quality and higher image quality, respectively. From the qualitative results shown in Figure 8, we can observe that the model trained with FaceVid-1K outperforms the one trained on CelebV-Text. Specifically, the model trained on CelebV-Text suffers from artifacts in the mouth and eye regions. Due to the low frame rate of videos generated by Latte (8 frames per second), the model trained on CelebV-Text exhibits reduced temporal consistency, noisy and collapse view, primarily because of significant head movements within the dataset. In contrast, the model trained on our dataset is capable of addressing these issues effectively.

RQ1: Analysis for Data Scale Requirement

We conduct a series of experiments for investigating this research question, using the Text-to-Video model, Open-Sora Plan (Lab and etc. 2024), as the evaluation task. We randomly sample a series of training videos (*i.e.*, 100h, 200h, 400h, 600h, 800h, and 1000h) from our collected dataset and performed identical training experiments with different parameter configurations of the model. All models are trained with the same learning rate, batch size, and other hyperparameters for 100k steps. The results, evaluated using FVD (Unterthiner et al. 2018), FID (Heusel et al. 2017), and CLIPScore (Hessel et al. 2021), are summarized in Table 4. Based on these results, we observe that smaller models often perform well initially on small-scale datasets. However, as the dataset size increases, these models struggle to handle the more diverse and challenging data. This is reflected in the deterioration of FVD and FID, with CLIPScore showing a significant decline. Specifically, we observed that a 1B-parameter model trained on a 100-hour dataset produced highly similar videos when given similar prompts. Through these experiments, we conclude that for a 1B-scale DIT-based backbone video generation model, a dataset size of around 300 hours strikes a good balance between diversity and quality in the generated videos. On the other hand, larger models struggle to converge on small datasets as effectively

Table 4: Quantitative experiments on the text-to-video task with varying model parameters and different scales of training data to investigate the cost-effective scale of training data for different parameter models.

Param.	1B			3B			6B		
Duration	FVD (\downarrow)	FID (\downarrow)	CLIPScore (\uparrow)	FVD (\downarrow)	FID (\downarrow)	CLIPScore (\uparrow)	FVD (\downarrow)	FID (\downarrow)	CLIPScore (\uparrow)
100h	147.88	31.83	0.8436	255.06	49.70	0.8219	343.52	65.17	0.8128
200h	106.18	25.73	0.8612	156.33	31.01	0.8533	266.43	51.83	0.8471
400h	87.62	16.60	0.8605	99.52	18.16	0.8952	200.99	38.25	0.9014
600h	129.59	25.07	0.8174	55.14	10.15	0.9372	113.25	21.83	0.9235
800h	159.67	30.11	0.7533	98.52	17.50	0.9025	89.63	16.05	0.9187
1000h	152.92	31.95	0.6957	102.27	20.91	0.8840	38.01	8.71	0.9365



Figure 7: **Image-to-Video.** Using the same video generative model (*i.e.*, Stable Video Diffusion) trained respectively on the best publicly available dataset (CelebV-Text) and our collected dataset (FaceVid-1K).

as their smaller counterparts. For instance, a 3B-parameter model trained on the optimal 400-hour dataset configuration for the 1B model fail to achieve comparable performance. The training process is unstable, the generated results often contain noise, and the model’s performance deteriorates as training progresses. We attribute this to a mismatch between the dataset size and the model’s parameter scale. By analyzing FVD, FID, and CLIPScore, along with a manual evaluation, we reveal that the 6B-parameter model trained on the full FaceVid-1K dataset performs best.

RQ2: Analysis for Difference of Backbones

There are two main commonly used video generation frameworks in our experiments: the Diffusion-based Stable Video Diffusion (SVD) (Blattmann et al. 2023) and the DiT-based Open-Sora Plan (Lab and etc. 2024). Although the types of prompts are different, simply considering the generated image quality and video quality, we can observe that the DiT-

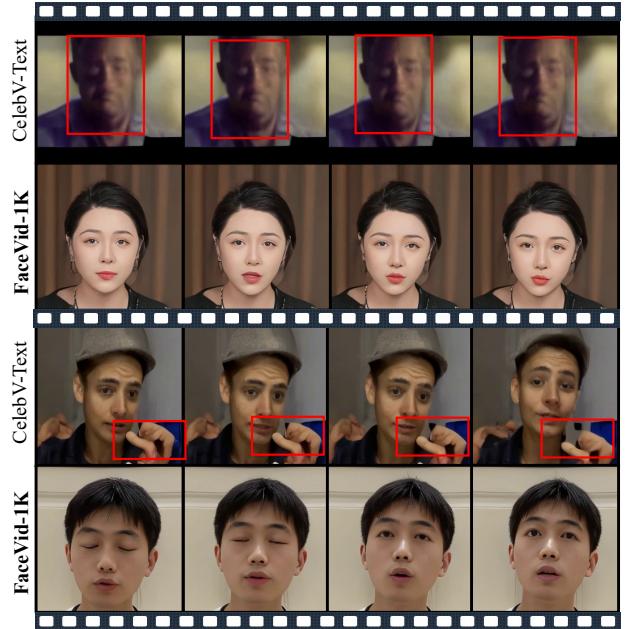


Figure 8: **Unconditional Video Generation.** Using the same video generative model (*i.e.*, Latte) trained respectively on the best publicly available dataset (CelebV-Text) and our collected dataset (FaceVid-1K).

based model respectively outperforms SVD in the metrics of FVD (Unterthiner et al. 2018) and FID (Heusel et al. 2017), as reported in Table 2 and Table 3. Experiments show that SVD converges faster than Open-Sora Plan. However, Open-Sora Plan produces higher quality and more diverse videos, and its inference speed is faster due to the stacked attention block architecture.

Conclusion

In this work, we introduce our collected large-scale, high-quality, multi-racial human face video dataset, FaceVid-1K. We assert that this resource can meet the demands of research tasks related to human face video generation. We have also conducted extensive experiments on the dataset, yielding several valuable empirical insights. In the future, we plan to further expand the dataset and contribute more pre-trained backbone video generation models to the research community.

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