NFT1000: A Cross-Modal Dataset for Non-Fungible Token Retrieval

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Abstract

With the rise of "Metaverse" and "Web 3.0", Non-Fungible Token (NFT) has emerged as a kind of pivotal digital asset, garnering significant attention. By the end of March 2024, more than 1.7 billion NFTs have been minted across various blockchain platforms. To effectively locate a desired NFT, conducting searches within a vast array of NFTs is essential. The challenge in NFT retrieval is heightened due to the high degree of similarity among different NFTs, regarding regional and semantic aspects. In this paper, we will introduce a benchmark dataset named “NFT Top1000 Visual-Text Dataset” (NFT1000, as shown in Fig.1), containing 7.56 million image-text pairs, and being collected from 1000 most famous PFP [1] NFT collections[2] by sales volume on the Ethereum blockchain. Based on this dataset and leveraging the CLIP series of pre-trained models as our foundation, we propose the dynamic masking fine-tuning scheme. This innovative approach results in a 7.4% improvement in the top1 accuracy rate, while utilizing merely 13% of the total training data (0.79 million *vs.* 6.1 million). We also propose a robust metric Comprehensive Variance Index (CVI) to assess the similarity and retrieval difficulty of visual-text pairs data. The dataset will be released as an open-source resource. For more details, please refer to: https://github.com/ShuxunoO/NFT-Net.git

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[1] PFP is an abbreviation for “Profile Picture”, representing a category of NFTs primarily used as avatars in social media contexts.
[2] An NFT collection represents an NFT project, which contains the same batch of media files and metadata data.

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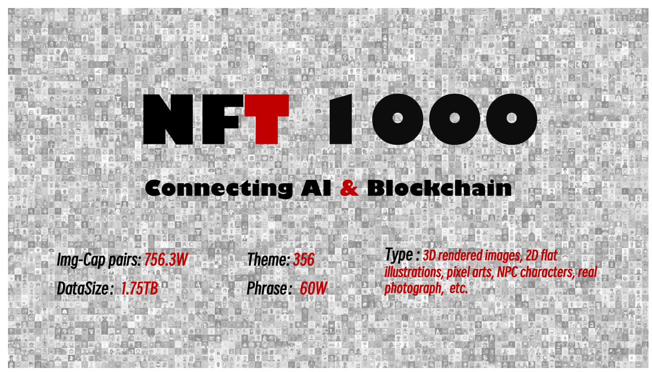

Figure 1: NFT1000 is the first NFT dataset within the field of computer vision. The proposed dataset encompasses the most renowned 1,000 avatar-based NFT projects on the Ethereum mainnet, comprising 7.563 million image-text pairs.

CCS Concepts

• **Computing methodologies** → *Image representations.*

Keywords

Cross-Modal Retrieval, Blockchain, NFT, CLIP, AIGC

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1 Introduction

With the emerging concept of the “Metaverse” [16, 26] and “Web3.0" [13], NFT [25] has entered the public eye as a significant digital asset within this space. The NFT, standing for Non-Fungible Token, is a unique cryptocurrency token on blockchain [29] representing digital assets such as images, videos, tickets, inscription, etc. NFT is coveted for its characteristics of provenance, high liquidity, and rarity. NFT possesses immense value; for instance, the renowned NFT project CryptoPunks has amassed a trading volume of $2.78 billion since its launch[3]. Statistical data[4] indicates that by the end of March 2024, the cumulative number of NFT minted on different blockchain platforms has exceeded 1.7 billion. When purchasing NFTs, people often gravitate towards tokens that align with their personal style or match their preferences, aiming to fulfill their desire for personalized expression in virtual spaces. However, both the academic and industrial sectors lack effective and precise methods or toolkits for the retrieval of NFT data due to the high degree of regional and semantic similarity among NFTs (Fig.2). This represents a novel research area that requires our exploration.

Given the lack of a dedicated NFT dataset for scientific research in the field of computer vision, we firstly construct the NFT1000. It is composed of the top 1000 PFP NFT collections by sales volume on the Ethereum blockchain with the ERC-721 [5] standard. Each project contains an average of 7500 image-text pairs. In total, the dataset includes 7.56 million image-text pairs, with a data volume of 1.75TB. It is suitable for various downstream tasks such as retrieval, generation and so on.

Under the background of NFT-type data retrieval and leveraging the NFT1000 dataset, we introduce a task focused on large-scale, high-similarity image-text retrieval, representing a potential approach in the intersection of AI and blockchain research. This task aims to retrieve target images from a massive collections of highly similar pictures by using tokens' descriptions. Although CLIP models are pre-trained using 400 million image-text pairs from the Internet, their performance on fine-grained classification tasks is somewhat lacking. This indicates that CLIP's training approach struggles to capture the local semantic information of image-text pairs. To address the limitation, we propose a dynamic masking fine-grained contrastive learning scheme. Through analysis of input images, its dynamic masking module probabilistically masks certain component areas of the image and the corresponding captions. This subtractive approach from the global semantics more fully exposes the local features of the image-text pairs, allowing the model to more specifically align the detailed information of the visual-caption pairs. Our experimental results demonstrate that it is possible to train a model that surpasses the total data's top1 accuracy by 7.4% using only 13% of its training data. This significantly reduces the training overhead and enhances the effectiveness of data utilization.

To quantitatively assess the similarity between a set of images and texts, rather than relying on subjective human judgment, we propose the Comprehensive Variance Index(CVI). It comprehensively considers the similarity within images, captions, and the degree of match between images and texts. Our empirical evidence demonstrates a clear correlation between this index and retrieval accuracy.

Our main contributions are: (1) We construct the first NFT visual-text dataset in the field of computer vision. (2) We introduce a task of large-scale, high-similarity image-text retrieval. (3) We design an effective training method for NFT data, using less data but training better models. (4) We propose the Comprehensive Variance Index, a universal metric designed to measure the similarity between images and texts.

Figure 2: Randomly selecting seven projects and choosing seven images from each to create an average image (as shown in the red-framed picture), we can observe that the average image has clear contours and distinct content. This indicates that the batch of images randomly selected from the same project possesses a high degree of regional similarity.

2 Related Work

2.1 About NFT

NFT [25], short for Non-Fungible Token, is a kind of unique virtual digital asset based on blockchain [29]. As a fundamental component of the metaverse, NFT plays a significant role in various domains, such as social interaction, finance, sports, gaming copyright verification, *etc.* NFT is a broad concept encompassing a diverse array of forms, including images, videos, text, audio, code, and more. Each form of NFT is unique, making them distinct from more common, interchangeable tokens like cryptocurrencies (e.g. Bitcoin [17] and Ethereum [1]). However, the most widely accepted forms of NFT currently are multimedia formats such as images and videos.

NFT is highly valued due to its unique combination of scarcity, verifiability, liquidity, and the ability to fulfill people's social status needs. NFT is scarce because each one is unique or limited in quantity, making it sought after in a market where people are willing to pay more for rare items. Its possession is verifiable through blockchain technology, which provides a secure, transparent record of each NFT's history and ownership, ensuring authenticity and reducing the risk of fraud. Furthermore, NFT offers high liquidity compared to physical assets; it can be easily bought, sold, or traded on global platforms with minimal transaction costs, making it attractive to investors looking for quick and efficient asset turnover. Lastly, owning an NFT, especially those created by famous artists or those that are particularly rare, can convey social status, as it signifies wealth, taste, and exclusivity. This desire for social recognition through unique digital assets drives demand and increases its value. Collectively, these factors make NFT valuable in today's digital economy, appealing to collectors, investors, and those seeking social distinction alike. According to statistical data[6], prominent

[3] As of April 12, 2024, 22:00, the data is sourced from site of https://nftgo.io/macro/market-overview

[4] https://www.nftscan.com/

[5] ERC-721 stands for Ethereum Request for Comment #721. It is a universal NFT standard protocol that defines a series of interfaces for NFT token transactions. For more details, please visit:https://eips.ethereum.org/EIPS/eip-721.

[6] As of April 12, 2024, https://nftgo.io/discover/top-collections

NFT projects have achieved significant trading volumes: Bored Ape Yacht Club has sold \$3.66 billion, CryptoPunks has amassed \$2.78 billion, Mutant Ape Yacht Club has make \$2.51 billion, etc.

As the metaverse continues to develop, NFT will increasingly become a digital commodity for trading. As previously mentioned, an NFT can significantly represent the taste of its holder. Therefore, consumers often prefer those that are renowned and align with their personal style. However, with billions of NFT entries, finding one that suits an individual's needs is challenging. Additionally, the high degree of similarity among NFTs adds considerable complexity to their retrieval. Thus, the task of retrieving an NFT is both a critical need and highly challenging, meriting in-depth research and exploration.

2.2 Cross-Modal Retrieval

Cross-modal Image-text Retrieval (ITR) is to retrieve the relevant samples from one modality while the queries are expressed in another modality, usually consists of two subtasks: image-to-text (i2t) and text-to-image (t2i). ITR has been witnessed great success in recent years [4, 11, 19] thanks to the rapid development of deep language-vision models [3, 5, 23] and various large-scale multimodal pre-trained models [8–11, 19, 21, 27]. Most ITR systems deployed in real-world applications are built upon pre-trained models that have been fine-tuned. Generally speaking, the pre-trained models can be divided into two categories according to the their architectures: 1) Fusion-structure models: ALBEF [11] and BLIP [10]. 2) Dual-encoder models: CLIP [19], META-CLIP [27] and ViLEM [2]. The fusion-structure models process text and image inputs simultaneously through a unified network architecture. In these models, image and text data are merged at an early stage and the entire model propagates forward through a single data stream. The drawback of fusion-structure models is their low-efficiency and inflexibility due to the computation of similarity between queries and whole data of another modality during retrieval. While dual-encoder models encode image and text in parallel by independent models and align them by self-supervised contrastive learning. Compared with fusion-structure models, dual-encoder models are more flexible and are much more efficient at zero-shot inference [19]. Dual-encoder models align image and text semantic features into a consistent high-dimensional feature space and the encoders are generally pre-trained models. Besides, the computed semantic features of each branch can be stored for fast inferring during retrieval. These advantages make dual-encoder models efficient and flexible to deploy. In this work, we will fine-tune a series of dual-encoder models on our NFT1000 dataset.

2.3 Image-Text Dataset

In the realm of computer vision and natural language processing, datasets like Flickr30K [18], COCO [12] and LAION-5B [20] offer vast amount of image-text pairs for diverse applications. Flickr30K is an image-caption dataset widely used in computer vision and natural language processing research. It consists of 31,000 images sourced from the online photo-sharing platform Flickr. Each image in the dataset is paired with five English captions, which provide descriptive annotations written by human annotators. The COCO dataset provides over 200,000 labeled images with detailed instance annotations and The LAION-5B encompasses 5.85 billion CLIP-filtered image-text pairs, making the training of large-scale multimodal models plausible.

However, Most of the data in the above datasets are collected from the real world, which inherently exhibits significant distributional differences compared to NFT data. In addition to this, images from one NFT project, although different, have fine-grained semantic similarity because they are permutations and combinations of fixed components, as we will discuss in Section3.2, this is a distinctive feature that the aforementioned datasets do not possess. To our knowledge, iCartoonFace benchmark [28] has similar situation with NFT1000, it is a large-scale, high-quality, richly annotated cartoon face recognition dataset, containing 389,678 images of 5,013 cartoon characters. However, this dataset lacks captions corresponding to each image, making it difficult to meet the requirements for cross-modal retrieval.

Given the absence of a dedicated NFT dataset in the computer vision field, in this work, we construct the first benchmark dataset consisting of NFTs, designed to support NFT retrieval and generation tasks.

3 Properties of NFT1000

3.1 Inherent Image-Text Pair Format

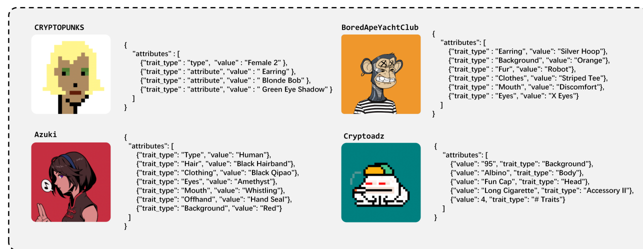

Figure 3: In the NFT1000 dataset, each image within every collection naturally comes with an accompanying JSON file, which introduces the attributes of the image in a key-value pair format.

Each NFT in the dataset is associated with a metadata resource file, which typically exists in the form of a JavaScript Object Notation (JSON) format. This file uses key-value pairs to describe the attributes of the NFT token(Fig.3).

3.2 Fixed-Components Permutation and Combination

The essential reason for the high degree of similarity among NFT images within a same project lies in the fact that all images are permutations and combinations of fixed components. As shown in Fig.4: (a) Images contain a clothing layer named "Navy striped tee"; (b) Pictures include the same "3D glasses" layer. (c) Every image features the same "Bored bubblegum mouth". (d) All photos are adorned with a same "Commie hat". However, it is important to note that in projects initiated after the removal of identical image covers, no two images within a project are the same.

3.3 Abstract Description

NFT can be considered a form of crypto arts, but the definition of these artworks by artists often include subjective elements. This

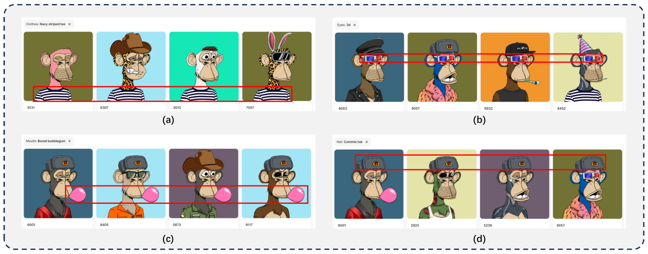

Figure 4: All images within the same collection are blended from a specific set of components arranged in various combinations, resulting in pixel-level uniformity in image regions.

leads to the abstract description issue, which can be understood as the image itself being difficult to comprehend or the image description lacking clear semantic information. From Fig.5, we can observe intuitively that the No.0 token from the *Superlative Secret Society* project is particularly hard to comprehend, or rather, there is no obvious correlation between its image and caption. It is noteworthy that this situation is common in NFT projects.

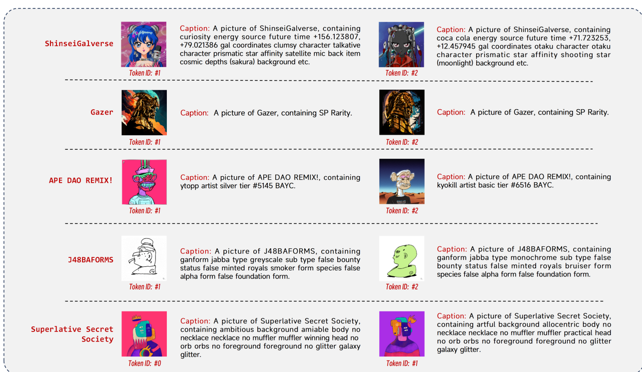

Figure 5: Show case of abstract images and their abstract descriptions.

4 Constructing NFT1000

4.1 Clarifying the Download Targets

Among various NFT categories, PFP NFT collections account for over 60% of the market share[7]. Besides, in avatar-type NFT, the JSON file accompanying each image relatively effectively describes its own attributes. Ethereum is the birthplace of NFT and the most flourishing blockchain for NFT crypto arts. Therefore, we select the top 1000 PFP NFT projects on the Ethereum blockchain, based on sales volume, as our download targets.

4.2 Downloading and Filtering

We utilize resources from the Web3.0 domain such as NFTScan[8], Alchemy [9] and IPFS [10], leveraging the basic resource links provided in the smart contracts [11] of each NFT project. This enabled us to piece together the complete links for the media resource and JSON data of each token for downloading and collection. In fact, we have downloaded resources from a total of 1250 projects for purpose of selection.

Among all the collections that have been fully downloaded, we exclude those with completely duplicated media data (or all images being identical covers), projects with an insufficient total number of tokens (set as fewer than 500), and those lacking a JSON file or where the JSON file contains no substantive semantic information.

4.3 Standardization

Standardize File Format and Dimensions. Native NFT data, encompassing static image formats such as JPG, PNG, SVG and WebP, are uniformly transformed into the PNG format (This conversion is primarily due to PNG being the predominant format in most NFT collections, and the choice is intended to maximally retain the original fidelity of the data). For dynamic media formats, including GIF and MP4, a representative frame is randomly selected and converted into PNG format. The standardized resolution for these images is set to a width of 512 pixels, with a proportionally adaptive height to maintain aspect ratio integrity. Employing this method, we have reduced the original data size from 14TB to 1.75TB.

Caption Extraction. For the original key-value pairs formatted attribute lists, there are two methods for generating captions(Fig.6): one is based on large language models (ChatGPT, LLAMA-13B [22]), using prompt engineering to create descriptions according to the attribute list corresponding to the image; the other way involves using predefined sentence templates to concatenate attributes into a single caption. By using large language models, we generate 30,000 descriptions for 10,000 randomly selected images, while also creating 10,000 captions using language templates. Subsequently, we utilize OpenAI's CLIP-ViT-L pretrained model for zero-shot inference and compared the retrieval accuracy of captions obtained via the two methods (Fig. 7). The result indicates that the large language model can generate better image descriptions, but overall, the performance of the two methods **does not differ significantly.** Lastly, considering the former method would consume considerable time and computational resources, we ultimately opt for generating captions using sentence templates.

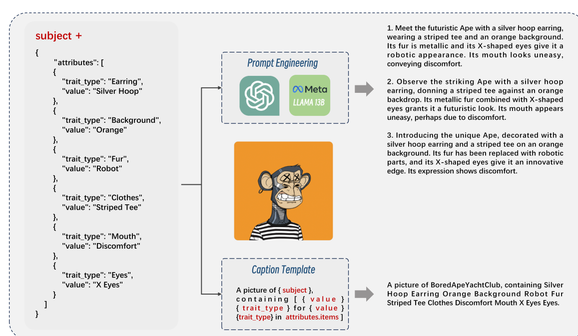

Figure 6: Illustration of two methods for generating captions

[7]Please refer to the "Category Market Cap" entry on the Web: https://nftgo.io/analytics/market-overview
[8]https://www.nftscan.com/
[9]https://www.alchemy.com/
[10]https://ipfs.tech/
[11]Smart contracts on blockchain are self-executing scripts with the terms written in code.

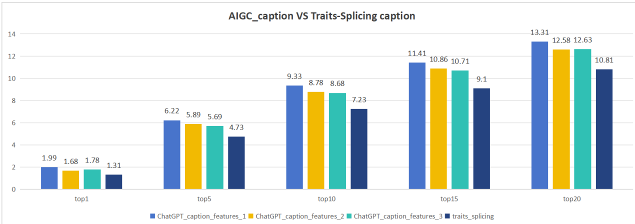

Figure 7: The CLIP model's zero-shot retrieval accuracy in comparing captions generated by large language models *vs.* those produced by sentence template.

Data Partitioning. Due to the presence of identical components and descriptions in images within the same project, internal division of training and test sets in a NFT collection may result in "data leakage." Consequently, we adopt the project as the fundamental unit for data division, allocating the entire dataset into training, validation, and test sets in an 80:5:15 ratio.

Dataset Statistics. The NFT1000 dataset comprises 1000 outstanding PFP NFT projects, each containing approximately 7500 image-text pairs, encompassing a total of 7.56 million image-text pairs with a collective data volume of 1.75TB. In the dataset, the training set includes 800 projects with 6,178,249 image-text pairs. The validation set comprises 50 projects with 383,916 image-text pairs, and the test set consists of 150 projects with 1,000,838 image-text pairs. The content spans a diverse range of artistic types, including 3D rendered images, 2D flat illustrations, pixel arts, NPC characters, real photographs,etc. It covers a total of 356 different content themes and 595,504 unique descriptive phrases. For more details about each NFT project, please refer to Appendix Table.

5 Fine-Grained Contrastive Learning

The CLIP models gain fame for achieving state-of-the-art (SOTA) performance through zero-shot inference on various datasets, following its training on a dataset of 400 million image-text pairs using a straightforward contrastive learning strategy. We sequentially use OpenAI's CLIP-ViT-B-32, CLIP-ViT-L-14 pretrained models and META's META-CLIP-ViT-L-14 [27] for zero-shot inference and fine-tuning. The experimental results are presented in Table 1. This table reveals that these pretrained SOTA models have almost never encountered data from the NFT1000 dataset, indicating that the data distribution in NFT1000 is unique and novel. Despite the noticeable improvement (with an average increase in top1 accuracy of about 10%), the overall effectiveness remains suboptimal.

Table 1: Comparison of zero-shot inference and fine-tuning inference accuracy of different models on the NFT1000 test set.

model-type	zero-shot			fine-tuning		
	top1	top5	top10	top1	top5	top10
CLIP-VIT-B-32	0.01	0.02	0.03	10.63	20.32	25.19
META-CLIP-VIT-L-14	0.00	0.01	0.02	13.06	23.68	28.81
CLIP-VIT-L-14	0.06	0.25	0.42	15.36	27.55	33.26

As discussed in Section 3.2, all images within an NFT project are permutations and combinations of fixed components. Given that the CLIP model is not particularly adept at focusing on the local semantic information of images, we hypothesize that the prerequisite for precise retrieval is accurate cognition. If we could fine-tune the CLIP model at the component level, it might address the issue of the fine-tuned model not achieving satisfactory recall performance. To verify this hypothesis, we propose a fine-grained fine-tuning strategy based on dynamic masking.

5.1 Component Separation

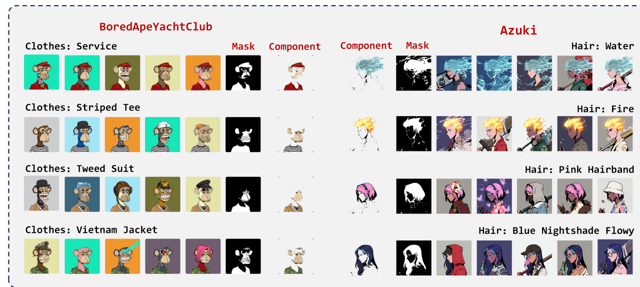

Figure 8: Illustration of component separation. The results demonstrate that, through a process of initial differentiation followed by superposition, components can be separated into relatively clean and complete entities, even in the presence of overlapping among them.

Given the pixel-level consistency within the same area of images containing the same component in an NFT project, we adopt a strategy of differentiation followed by superposition to isolate the various distinct components. The specific approach is as follows:

(1) Identify which images share a same component, achievable through analysis of the NFT's accompanying JSON file.
(2) Randomly select a set of images, using the first image as a template, and perform image differencing operations with the subsequent images to get the shared regions and their mask representations.
(3) Repeat step 2 multiple times, ultimately assembling the fragmented components into a relatively complete component and its mask.

Experiments show that performing differencing operations on 4 images at one time and repeating this process 8 times is a good choice. This combination balances execution efficiency and also results in relatively complete and clean components and masks, as shown in Fig. 8.

5.2 Dynamic Masking

Before the model loads the training image-text pairs data, we firstly analyze the image to identify its constituent components. With probability p, a component's corresponding mask is randomly selected to perform a masking operation on the original image. Simultaneously, the tag of the selected component is removed from the full caption. This process results in a new image-text pair that lacks certain local pixels and descriptive information, thereby allowing the detailed information of the image-text pair to emerge from the global semantics. By subtracting from the original image-text pairs in this manner, the model is encouraged to fully comprehend the correspondence between components and their names, thereby achieving fine-grained feature alignment with NFT data. A dynamic visualization of the masking process is shown in the Fig. 9.

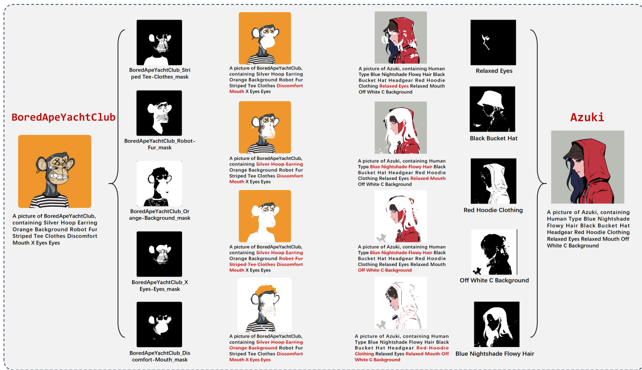

Figure 9: Illustration of the generation process of dynamic masks. Through this method, a single NFT image-text pair can generate new pairs with varied semantic richness.

6 Experiments On NFT1000

In this chapter, we will conduct a series of experiments to validate the effectiveness of the dynamic masking fine-tuning method and the application potential of the NFT1000 dataset, focusing on four aspects: the selection of the dynamic masking probability p, the generalizability of the dynamic masking approach, the metric Comprehensive Variance Index (CVI) and NFT generation.

In the classical contrastive learning framework, we introduce a dynamic masking unit capable of analyzing the composition of sampled image-text information. This unit applies masks to components of an NFT image with a specific probability, thereby eliminating certain semantic information from the global image-text context. For the remaining training pipeline, we employ the same training strategy as the original CLIP to fine-tune models. Specifically, we utilize image and text encoders to extract features from images and captions. Subsequently, we use contrastive loss to optimize the parameters of the image and text encoders, aiming to progressively align NFT images and their corresponding captions within the same semantic space. The training pipeline is illustrated in Fig. 10.

6.1 Mask Selection Probability

During the process of generating dynamic mask, a component mask is selected with a probability p. The larger the value of p, the more areas of the original image are masked, resulting in finer semantic granularity but also a more fragmented image; conversely, the smaller the value of p, the fewer areas are masked, leading to coarser semantic granularity and a more rough correspondence between components and captions. Therefore, selecting an appropriate p is a critical issue.

To swiftly determine the appropriate probability, we construct a smaller dataset from the complete dataset, called NFT1000mini. This subset consists of a training set with 800 projects, a bitch of 1000 image-text pairs are randomly extracted from per project, totaling 794,698 pairs; and a test set comprising 150 projects, each with 1000

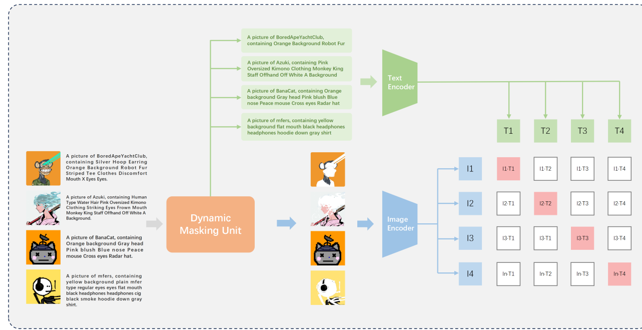

Figure 10: Illustration of the fine-tuning pipeline. The integration of the dynamic masking unit allows for the highlighting of local information within NFT image-text pairs, thereby facilitating fine-grained alignment of the model with NFT data.

Table 2: Comparison of data sizes between NFT1000mini and NFT1000

	NFT1000mini		NFT1000	
	NFT project number	image-text pairs	NFT project number	image-text pairs
training set	800	794,698	800	6,178,249
validation set	50	49, 738	50	383,916
test set	150	147,615	150	1,000,838

random image-text pairs, totaling 147,615 pairs. The comparison of data sizes between NFT1000mini and NFT1000 is shown on Table 2. Subsequently, we conducted a series ablation studies by using the pre-trained CLIP-ViT-B-32 model on the NFT1000mini training set with the same training parameters but varying p for model fine-tuning. With results shown in Table 3 . From the table, we can observe that the relationship between p and accuracy forms a convex function, peaking near $p = 0.5$. This indirectly suggests that the more random the mask selection, the better the training effect of the model. Unless otherwise specified, we set $p = 0.5$ in subsequent experiments.

Table 3: The impact of different mask selection probabilities on model retrieval performance.

probability	top1	top5	top10
p=0	16.93	29.99	36.17
p=0.3	22.79	36.86	42.87
p=0.5	22.68	37.17	43.51
p=0.7	21.59	35.71	41.88

6.2 Generalizability of Dynamic Masking

To verify whether we can fine-tune the model more efficiently under the condition of fine-grained semantic alignment, we compared the inference performance on the NFT1000mini test set of different models trained with and without dynamic masking on the NFT1000mini training set, as well as those trained on the entire NFT1000 training dataset. Subsequently, we obtained surprising results, as shown in Table 4. It is evident that under the same training set conditions (NFT1000mini training set), the use of dynamic masking leads to at least a 10% improvement in accuracy. Compared with the CLIP-ViT-L-14 model, which achieves SOTA performance using the NFT1000 training set, there's a 7.44% increase in top1 accuracy. This conclusively demonstrates the effectiveness of the dynamic masking training method.

In addition to conducting instance-level searches across the entire dataset, we also compared the search results within a specific NFT project by zero-shot and fine-tuning inference, with data presented in Table 5. It displays the retrieval results for the top 5 and bottom 5 NFT projects, with the data for the top 5 achieving nearly 100% in the top 10 accuracy. However, we can also directly observe that the bottom 5 NFT projects show almost no improvement in accuracy before and after model fine-tuning. This issue arises from the abstract definitions discussed in section 3.3. Consequently, how to retrieve NFT data with abstract definitions will be a focal point of our future work.

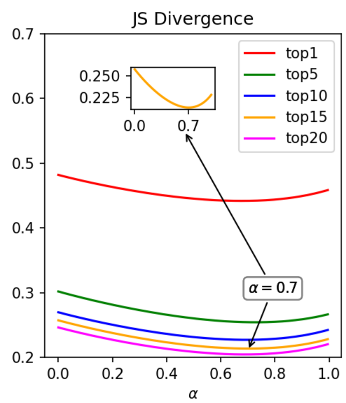

Figure 11: After L1 normalization, the trend of the JSD between the CVI distribution and the TopK distribution varies with changes in alpha. When α approaches 0.7, the JSD approximately reaches its lowest point and CVI can most accurately serves as a measure of image-text similarity.

6.3 Comprehensive Variance Index

To quantitatively measure the similarity between a set of image-text pairs, rather than just relying on subjective human judgment (for example: "not very similar," "somewhat similar," "very similar", *etc.*), we propose the Comprehensive Variance Index. In the current realm of deep learning, a commonly used approach [14] for image-text retrieval involves employing pretrained visual and language encoders to extract image and text features, known as embeddings. Subsequently, dot product operations are conducted to obtain the cosine similarity between the images and texts. The similarity scores are then sorted in descending order to yield the final topk results. For any given model, the most hard retrieval scenario occurs when all probabilities are identical, forcing the model to make a blind selection.

Based on this observation, we propose a concept originating from the probability distribution of vector cosine similarities. This concept posits that if a batch of images exhibits a more uniform distribution of cosine similarity probabilities (in a certain sense, the smaller the variance in the distribution of cosine similarity), the features of these images are more similar. This similarity manifests in semantic and regional aspects of the images, concurrently increasing the difficulty of image retrieval.

Drawing from the preceding discussion, we propose the Comprehensive Variance Index. $\boldsymbol{I} \in \mathbb{R}^{N \times M}$ represents the feature vectors of a batch of images, in which N represents the number of images and M denotes the dimensionality of the feature vectors. Then $\boldsymbol{S_{II}} \in \mathbb{R}^{N \times N}$ is given by $\boldsymbol{S_{II}} = \boldsymbol{I} \cdot \boldsymbol{I}^\top$. Similarly, we can obtain the inner product of the corresponding texts' feature vectors, denoted as $\boldsymbol{S_{TT}} \in \mathbb{R}^{N \times N}$, and the inner product of the text-image feature vectors, denoted as $\boldsymbol{S_{TI}} \in \mathbb{R}^{N \times N}$. Following, CVI of a batch of image-text pairs is defined as

$$\begin{aligned} CVI = \frac{1}{2N}\Big(\alpha \sum_{i=1}^{N} \mathrm{var}(\boldsymbol{S_{II\_i}}) \\ + (1-\alpha)\sum_{i=1}^{N} \mathrm{var}(\boldsymbol{S_{TT\_i}}) + \sum_{i=1}^{N} \mathrm{var}(\boldsymbol{S_{TI\_i}})\Big) \end{aligned} \quad (1)$$

where i represents a row in the matrix, α stands for the bias index, indicating the overall metric's preference for the similarity between images and the similarity between captions.

Jensen-Shannon divergence (JSD) [15] is a popular method for measuring the similarity between two probability distributions. It is a symmetrized and smoothed version of the Kullback-Leibler divergence (KLD) [24]. Given two probability distributions P and Q, the JSD is mathematically defined as:

$$JSD(P \parallel Q) = \frac{1}{2}D(P \parallel M) + \frac{1}{2}D(Q \parallel M) \quad (2)$$

where $M = \frac{1}{2}(P+Q)$. One of the key properties of JSD is its boundedness, as it ranges from 0 to 1. A value of 0 indicates that the two distributions are identical, while a value of 1 signifies complete dissimilarity.

Experiments show that when α is approximately 0.7 (Fig.11), CVI best fits the experimental data. This also suggests that the information contained in images is more significant than that in captions and should therefore have a greater weight in similarity measurements. We randomly selected some projects from NFT1000 and some categories from COCO [12] to conduct zero-shot inference using a pretrained CLIP model and to calculate the corresponding CVI values. The results are shown in Table 6, we can see that the lower CVI value, the more similar the batch of image-text pairs is, indicating a higher retrieval difficulty; conversely, a higher CVI value signifies easier retrieval. This also demonstrates that data retrieval within the NFT1000 dataset is indeed a challenging task.

6.4 Applications of the dataset

We developed a NFT retrival system based on the models we have trained and use it for piracy detection task for NFTs, illustrated in Fig.12(a), which aids in copyright protection for well-known NFT projects.

As discussed in Section 3.1, NFT data inherently comes with a descriptive JSON file, and most NFTs fall within the category of artworks, making them particularly suitable for generative tasks. Leveraging diffusion models [6] and LoRA [7], we also trained several LoRA plugin models for the Azuki Fig.12(b) and Akutars

Table 4: Inference results of different models on the NFT1000mini test set under various training methods.

model_type	zero-shot			FT-NFT1000mini			FT-NFT1000			FT-NFT1000mini-with-dynamic-mask		
	top1	top5	top10	top1	top5	top10	top1	top5	top10	top1	top5	top10
CLIP-VIT-B-32	0.03	0.10	0.15	12.10	23.66	29.54	20.33	34.47	40.74	22.68 ↑2.35	37.17 ↑2.7	43.51 ↑2.77
META-CLIP-VIT-L-14	0.01	0.05	0.11	20.53	35.05	41.67	23.07	37.08	43.01	31.83 ↑8.76	47.29 ↑10.21	53.47 ↑10.46
CLIP-VIT-L-14	0.33	1.02	1.55	20.43	34.78	41.13	26.66	41.91	48.22	34.10 ↑7.44	50.21 ↑8.3	56.41 ↑8.19

Table 5: The recall rate within NFT project before and after fine-tuning the CLIP-ViT-L-14 model.

collection	item_num	zero-shot			fine-tuning		
		top1	top5	top10	top1	top5	top10
Stoner Ape Club	6666	1.08	2.81	4.29	91.31	98.93	99.61
Junglebayapeclub	5555	0.90	2.65	4.14	89.79	98.56	99.23
Cool Ape Club	5555	0.59	1.39	2.32	88.17	97.95	99.05
Fat Rat Mafia	7777	0.03	0.27	0.63	83.27	96.18	98.06
0xAzuki	9999	0.85	3.25	5.48	80.73	95.44	97.82
......	......	......	......	......	......	......	......
ShinseiGalverse	8889	0.01	0.16	0.35	0.19	0.75	1.31
Gazer	2100	0.00	0.24	0.43	0.05	0.19	0.43
APE DAO REMIX!	5528	0.02	0.14	0.22	0.04	0.18	0.36
J48BAFORMS	4848	0.04	0.10	0.21	0.12	0.27	0.54
Superlative Secret Society	11110	0.02	0.05	0.08	0.02	0.08	0.21
all_collections	1000838	0.06	0.25	0.42	21.04	34.40	40.16

Table 6: Comparison table of retrieval accuracy and CVI between NFT1000 and COCO datasets.

	Collection/Category	Top1	Top5	Top10	CVI
NFT1000	Savage Droids	0.0365	0.1823	0.3646	0.0003
	Hor1zon	0.0286	0.1429	0.4858	0.0005
	CyberTurtles	0.3060	0.7201	1.3141	0.0007
	SpriteClub	0.4758	1.7359	2.9574	0.0009
	Tasty Bones	1.4656	3.7433	5.9418	0.0011
COCO	person	10.3192	25.6125	37.2309	0.0034
	car	13.2463	36.3806	50.0000	0.0037
	broccoli	18.0556	37.5000	56.9444	0.0038
	backpack	24.8908	52.8384	68.1223	0.0042
	cell phone	26.0465	50.2326	60.4651	0.0044

Fig.12(c) NFT projects. They demonstrate the capabilities of generative models for the open-ended creation of NFTs with varying styles and the editable generation of NFTs within the same style.

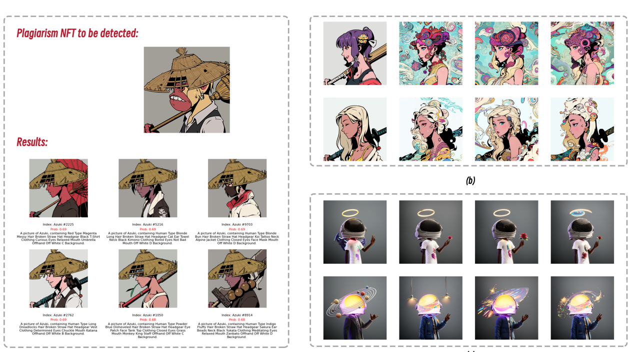

Figure 12: The potential applications based on the NFT1000

7 Discussion and Future Work

7.1 Efficient Utilization of Data

As shown in Table 4, using just 13% of the training dataset, we trained a superior model. This raises the question: What is the minimum data needed for accuracy? Efficient data use requires further exploration, as does retrieving NFT projects with abstract definitions, as discussed in Section 3.3.

7.2 Continuing to Expand the Dataset

NFT1000 is an ambitious project. In the future, we plan to broaden our scope beyond Ethereum to include more collections of outstanding NFTs from other public blockchains like Solana, Polygon, BNB Chain, Klaytn, etc. We aim to scale the data to the level of hundreds of millions, striving to build an ImageNet equivalent in the NFT domain, thereby making a significant contribution to both the academic and industrial communities.

7.3 Exploring Further Potential of NFT1000

NFT holds significant untapped potential for development. In the future, we plan to explore the use of generative models to create a wider array of NFT artworks.

8 Conclusion

In this work, we construct the first NFT visual-text dataset in the field of computer vision. Furthermore, we propose an effective training method for NFT-type data, called dynamic masking fine-tuning scheme, and have trained several models as our baseline. To quantify image-text similarity, we introduce the Comprehensive Variance Index, which accounts for the similarities within images and texts, as well as the degree of image-text matching. Finally, we also explore the application of NFT data in the image generation field.

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Table 7: Details of NFT collections in the NFT1000 dataset

index	NFT_name	collected_tokens	index	NFT_name	collected_tokens	index	NFT_name	collected_tokens	index	NFT_name	collected_tokens	index	NFT_name	collected_tokens
1	BoredApeYachtClub	10000	2	CRYPTOPUNKS	10000	3	MutantApeYachtClub	19482	4	Azuki	10000	5	CloneX	19485
6	Moonbirds	10000	7	Doodles	10000	8	BoredApeKennelClub	9597	9	Cool Cats	9965	10	Beanz	19950
11	PudgyPenguins	8888	12	Cryptoadz	7024	13	World Of Women	10000	14	CyberKongz	5000	15	0N1 Force	7777
16	MekaVerse	8888	17	HAPE PRIME	8192	18	mfers	10000	19	projectPXN	10000	20	Karafuru	5555
21	Invisible Friends	5000	22	FLUF	10000	23	Milady	10000	24	goblintown	9999	25	Phanta Bear	10000
26	CyberKongz VX	14672	27	KaijuKingz	9999	28	Prime Ape Planet	7979	29	Lazy Lions	10000	30	3Landers	9981
31	The Doge Pound	10000	32	DeadFellaz	10000	33	World Of Women Galaxy	20789	34	ALIENFRENS	10000	35	VOX Series 1	8889
36	Hashmasks	16355	37	Psychedelics Anonymous Genesis	9595	38	VeeFriends Series 2	55554	39	RENGA	8898	40	CoolmansUniverse	10000
41	Art Gobblers	9988	42	SupDucks	9916	43	Jungle Freaks	10000	44	Sneaky Vampire Syndicate	8888	45	SuperNormalbyZipcy	8851
46	Nakamigos	20000	47	Impostors Genesis	10420	48	Potatoz	9999	49	CryptoSkulls	10000	50	Moonbirds Oddities	10000
51	RumbleKongLeague	10000	52	MURI	10000	53	Galactic Apes	9998	54	Lives of Asuna	9997	55	My Pet Hooligan	8888
56	Murakami.Flowers	10105	57	Kiwami	10000	58	SHIBOSHIS	10000	59	Sappy Seals	10000	60	DEGEN TOONZ	8888
61	Killer GF	7777	62	CryptoMories	9583	63	Crypto Bull Society	7777	64	CryptoBatz by Ozzy Osbourne	9666	65	Quirkies	5000
66	Robotos	9999	67	Tubby Cats	20000	68	Chain Runners	10000	69	MutantCats	9698	70	Boss Beauties	9999
71	OnChainMonkey	9501	72	Rektguy	8814	73	Desperate ApeWives	10000	74	DigiDaigaku	2022	75	DeGods	9066
76	apekidsclub	9999	77	The Humanoids	9901	78	Sevens Token	7000	79	Akutars	15000	80	HypeBears	10000
81	Hero	5205	82	KIA	9998	83	inbetweeners	10777	84	C-01 Official Collection	8887	85	Imaginary Ones	8888
86	ZombieClub Token	5478	87	Groupies	10000	88	Valhalla	9000	89	MOAR by Joan Cornella	5555	90	Wizards & Dragons Game	45519
91	the littles NFT	10000	92	The Heart Project	9931	93	CryptoDads	10000	94	Chimpers	5555	95	Crypto Chicks	9970
96	VOX Series 2	8473	97	WonderPals	10000	98	LilPudgys	21243	99	a KID called BEAST	9631	100	Akuma	5553
101	G'EVOLs	9886	102	Tasty Bones	5049	103	Animetas	10101	104	ALPACADABRAZ	9666	105	KILLABEARS	3333
106	loomlocknft	12345	107	Metasaurs	9999	108	Dour Darcels	10000	109	Slotie	9953	110	Party Ape Billionaire Club	5160
111	WinterBears	10000	112	SlimHoods	4999	113	Shinsekai	10000	114	EveraiDuo	7708	115	MoodRollers	5000
116	EightBit	8888	117	Apocalyptic Apes	8888	118	X Rabbits Club	2544	119	GalaxyFightClub	9994	120	(B)APETAVERSE	10000
121	Swampverse	9599	122	Boonji Project	10056	123	Shiba Social Club	7772	124	Acrocalypse	10389	125	Wicked Apes	8270
126	Crypto Coven	9768	127	Anonymice	10000	128	CatBloxGenesis	9999	129	TEST NFT	10000	130	Dippies	8888
131	Habbo Avatars	11600	132	Starcatchers	9998	133	TheWickedCraniums	10762	134	Kanpai Pandas	8959	135	FoxFam	10000
136	Gutter Dogs	2955	137	CryptoonGoonz	6968	138	BASTARD GAN PUNKS V2	11303	139	HeadDAO	552	140	Vogu	7777
141	Boki	7777	142	Gray Boys	10000	143	Cool Monkes	10000	144	Little Lemon Friends	9999	145	Genuine Undead	9999
146	The Other Side	8887	147	Los Muertos	10000	148	Ethlizards	5050	149	Sipher INU	10000	150	Fishy Fam	9999
151	FOMO MOFOS	8008	152	Gh0stlyGh0sts	6809	153	Space Punks	10000	154	DystoPunks V2	2076	155	RareApepeYachtClub	10000
156	The Doggies	10000	157	Divine Anarchy	9929	158	Loser Club	10000	159	Fang Gang	8888	160	FrankenPunks	10000
161	Holoself	8888	162	Weirdo Ghost Gang	5555	163	Monster Ape Club	6133	164	HOWLERZ	5000	165	Yakuza Cats Society	8929
166	Gooniez Gang	8888	167	ShinseiGalverse	8889	168	Women Rise	10000	169	Incognito	9995	170	Project Godjira Generation 2	3332
171	Superlative Secret Society	11110	172	Women and Weapons	10000	173	Loneley Aliens Space Club	10001	174	Kubz	8260	175	Angry Ape Army	3333
176	APE DAO REMIX!	5528	177	Feudalz	4444	178	Genesis	9200	179	Alpha Kongs Club	8887	180	8liens	10001
181	0xApes	10146	182	Thingdoms NFT Official	10000	183	Kitty Crypto Gang	7858	184	Gutter Birds	2955	185	Dapper Dinos	9997
186	Cosmic Labs	9000	187	8SIAN	8888	188	The Surreals	10000	189	Grandpa Ape Country Club	5000	190	Prime Kong Planet	9797
191	CakedApes	8888	192	Crypto Cannabis Club	10000	193	Gen-F	10000	194	Pixelated Llama	3999	195	ShitBeast	10000
196	FlowerGirls	10000	197	uwucrew	9670	198	Habibiz	4900	199	Dented Feels	11111	200	Fat Ape Club	9999
201	Undead Pastel Club	9999	202	Mindblowon	6968	203	DeadHeads	10000	204	Moonrunners	9257	205	MetaBillionaire	7778
206	Anata NFT	1993	207	Meta Eagle Club	12000	208	Mocaverse	8888	209	Hero Galaxy Heroes	5554	210	CreatureToadz	8888
211	Doge Pound Puppies	7241	212	ZooFrenzToken	6666	213	AIMoonbirds	10000	214	Bored Mummy Waking Up	8888	215	NOUNDLES	7464
216	Goopdoods	7998	217	ExpansionPunks	9959	218	Clementine's Nightmare	5000	219	The Indifferent Duck	10000	220	KILLAz	6614
221	CROAKZ	6969	222	Monfters Club	8000	223	Toxic Skulls Club	9995	224	Bears Deluxe	6416	225	Meta-Legends	12345
226	BullsOnTheBlock	10000	227	Goons	9697	228	BearX	3695	229	Omnimorphs	8167	230	Alpha Girl Club	9860
231	Claylings	4039	232	NotOkayBears	10000	233	CryptoZunks	9991	234	Purrnelopes Country Club	10000	235	Koda	3348
236	Kumo x World	6651	237	Stoner Ape Club	6666	238	T Thugs	7777	239	Pop Art Cats	10000	240	GenesisApostle	7363
241	Fatales	10000	242	Hedgies by dYdX	3330	243	CryptoPhunksV2	10000	244	Goofy Oversized Optics People	9999	245	Weirdos	10000
246	HalloweenBears	9979	247	SoulZ Monogatari	7776	248	Toy Boogers	3334	249	Axolittles	10000	250	Rogue Society Bots	15777
251	Akumu Dragonz	10000	252	Girlies	10000	253	NAH FUNGIBLE BONES	10004	254	Society of Derivative Apes	9998	255	Timeless	9411
256	Beeings	10000	257	DuskBreakers	10000	258	Bamboozlers	9996	259	Sidus NFT Heroes	5998	260	CryptoHoots Steampunk Parliament	2491
261	Coodles	8888	262	BEANS - Dumb Ways to Die	10000	263	Party Penguins	9995	264	Isekai Meta	7777	265	Knights of Degen	8874
266	Super Cool World	5080	267	Gutter Clone	19549	268	ZombieToadz	5555	269	ZenApe	4998	270	illogics	8888
271	Ghost Boy	6666	272	Noodles	5555	273	Mutant Shiba Club	10000	274	OogaVerse	7757	275	YOLO Bunny	9999
276	TheProjectURS	9983	277	Mutant Hounds	7011	278	0bits	7132	279	FameLadySquad	8888	280	Squishy Squad	8888
281	Chill Frogs	6000	282	DystoApez	4444	283	Women Ape Yacht Club	10000	284	Meta Angels	10000	285	Avastar	26493
286	Whiko NFT	3577	287	Woodie	9736	288	Anatomy Science Ape Club	8000	289	Long Lost	10000	290	Kitaro World	7777
291	0xVampire	7213	292	Superlative Apes	4444	293	BBRC OFFICIAL - IVY BOYS	7755	294	KREEPY CLUB	9999	295	Haki	5000
296	GhostsProject	10000	297	Larva Lads	5001	298	Fluffy Polar Bears	9441	299	Squishiverse	6617	300	Unemployables	5000
301	Ninja Squad	8888	302	FroyoKittens	10000	303	Regulars	10000	304	Space Poggers	12000	305	PeopleInThePlaceTheyLove	1000
306	TrippyToadz	6969	307	Matr1x 2061	2061	308	PolkamonOfficialCollection	7447	309	Hedz	1000	310	SympathyForTheDevils	4261
311	Yung Ape Squad	6318	312	The Possessed	10000	313	Bubblegum Kids	10001	314	Spooky Boys Country Club	13000	315	GOATz	5019
316	Peacefall	8192	317	Finiliar	9449	318	Fomo Dog	777	319	GossApeGirl	7000	320	Wulfz	8188
321	SmallBrosNFT Official	8888	322	Magic Mushroom Clubhouse	9200	323	Sad Girls Bar	10000	324	Deez Nuts	10000	325	ChubbyKaijuDAO	9999
326	CosmodinosOmega	8888	327	Visitors of Imma Degen	9999	328	Sad Frogs District	6995	329	Hikari	5375	330	Queens+KingsAvatars	6451
331	Seizon	7573	332	CHIBI DINOS	10000	333	ChiptoPunks	512	334	Notorious Frogs	10000	335	Moshi Mochi	8000
336	TheAlienBoy	10000	337	Elderly Ape Retirement Club	5000	338	Apes In Space	9999	339	UninterestedUnicorns	6900	340	DigiDaigakuHeroes	1928
341	Women Tribe	10000	342	TronWars	8883	343	JunkYardDogs	7978	344	META KONGZ	9550	345	Big Cats	5109
346	Bunny Buddies	8888	347	Fly Frogs	9999	348	DeFiApes	9998	349	Super Creators By IAC	2221	350	CREYZIES	9965
351	Alien Frens Evolution	12175	352	Alien Secret Society	9999	353	alinft-official	6578	354	Private Jet Pyjama Party	5267	355	The Plague	10999
356	Wall Street Bulls	10000	357	Tsuki	10000	358	Champions	8888	359	DeadFrenz	9509	360	ALPACADABRAZ 3D	19969
361	Cosmic Cats	8887	362	Video Game Dev Squad	5555	363	Cosmic Wyverns	2881	364	YuGiYn	8886	365	INNOCENT CATS	9025
366	Skulltoons	7777	367	Satoshibles	5000	368	FVCK_AVATAR	10656	369	COOLDOGS	5000	370	Rebel Seals	10000
371	NonFungibleHeroes	8888	372	Angry Ape Army Evolution Collection	5544	373	Ascended NFT	8872	374	CryptoSimeji	10000	375	KaijuMutant	3496
376	Rebel Society	7000	377	MadRabbitsRiotClub	7500	378	Blvck Genesis	9998	379	Villagers of XOLO	14704	380	ThePicaroons	10000
381	Outlaws	10001	382	Super Puma	10000	383	Lil Baby Ape Club	5000	384	Quirklings	10000	385	Ape Reunion	9997
386	UninterestedUnicorns	6900	387	Space Riders	8888	388	Satoshi Runners	7777	389	PLUTO	9998	390	MegaPunksPOP	10000
391	Avarik Saga	8888	392	Demonized Azuki	8888	393	Savage Nation	7777	394	Slotie Junior	9937	395	Tigerbob	1000
396	Lucky Zeros NFT	2226	397	Pablos	10000	398	BAP GENESIS BULLS	10500	399	Chibi Apes	3000	400	DinoBabies	5500
401	Bibiz	6959	402	Sipher NEKO	9990	403	WizNFT	8750	404	Degenz	11110	405	Looki	7794
406	Steady Stack Titans	2125	407	The Lobstars	7777	408	MekaApeClub	5638	409	Chubbies	9433	410	Kibatsu Mecha	2211
411	StreetMachine	1922	412	Women of Crypto	8888	413	Space Boo	8888	414	Sacred Skulls	8888	415	Supreme Kong	2000
416	COVIDPunks	10000	417	Super Ordinary Villains	8886	418	GOBLIN GRLZ	5000	419	Chubbiverse Frens	8888	420	GoldHunter	39996
421	Bad Bunnies NFT	5480	422	Loopy Donuts	10000	423	Coalition Crew 2.0	3974	424	BladeRunner Punks	10000	425	Galaktic Gang	5555
426	Angry Pitbull Club	10000	427	1,989 Sisters	1989	428	Long Neckie Ladies	3333	429	The Lost Glitches	10000	430	CryptoFoxes	10586
431	Weather Report	10000	432	HUXLEY Robots	1000	433	RiverMen	9996	434	troll-town.wtf	9999	435	DIOs Genesis	4000
436	For the Culture	6969	437	Waifus	5066	438	Lofi Originals	5555	439	RubberDuckBathParty	10000	440	Dope Shibas	9899
441	The Moon Boyz	11110	442	Chungos	8888	443	RareBunniClub	5500	444	SchizoPosters	5555	445	NeoTokyoPunks	2222
446	Heroes	3333	447	OctoHedz	888	448	nbayc	5000	449	Based Ghouls	5677	450	Dogs Unchained	3553
451	Lunartics	10000	452	Genzee	9983	453	Cyber Gorillas	2412	454	Artie	4445	455	Shonen Junk	9001
456	AlphaBetty Doodles	10000	457	TheEnigma	7771	458	CryptoShack	3501	459	LoudPunx	2435	460	FastFoodFrens	5509
461	GenX by HOK	9998	462	Monkes	3333	463	YOLO	10000	464	Cool Ape Club	5555	465	GUNSLINGERS	7777
466	AnonymiceBreeding	2978	467	ZombieCats	9999	468	VIVID	8888	469	House Of Legends	9993	470	AotuNFT	2254
471	HOPE	5192	472	Karma	7742	473	Nudie Community	10000	474	Mr.Rich	998	475	sunnies	9141
476	Tripsters	5555	477	Never Fear Truth	3850	478	BlockchainBikers	11111	479	DormantDragon	5000	480	The Royal Cubs	8888
481	Cozy Penguin	10000	482	Fortune Friends Club	8888	483	SMOWL	4201	484	Exosama	10000	485	Cats	10000
486	ThorGuards	9999	487	ElectricSheep	7000	488	Joker Charlie Club Genesis	555	489	Iron Paw Gang	4000	490	Wicked Hounds	11104
491	Nyolings	7777	492	RoaringLeaders	6575	493	Savage Droids	2743	494	The Rebels	10101	495	Dirtybird Flight Club	9090
496	Metakages	3000	497	Dreamlands	10000	498	RugBurn	999	499	Whiskers	5555	500	NounPunks	9969
501	Dead Army Skeleton Klub	6969	502	ape mfer	8888	503	Leave Me Alone	10000	504	Squiggles	5000	505	LO-FI PEPE	6969
506	Shellz Orb	8947	507	STARKADE	7015	508	DumpsterDorks	5000	509	Kureiji	5555	510	The Jims	2047
511	LordSocietyNFT	7777	512	Imps	8211	513	Kahiru	6907	514	LonelyPop	10000	515	Hall Of Fame Goat Lodge	10000
516	mems	6000	517	Cartoons	7777	518	Bastard Penguins	9614	519	Ordinal Kubz	10000	520	Moon Ape Lab	8000
521	OkayBearsYachtClub	7777	522	MadMeerkatBurrow	777	523	the dudes	512	524	krazykoalas	9900	525	Bad Face Bots	5496
526	Ape Invaders	5500	527	Paradise Trippies	9996	528	TheWhitelist	10000	529	8 BIT UNIVERSE	8888	530	Super Shiba Club	10010
531	Lucky Lion CLub	4000	532	mfer chicks	5555	533	Derpy Birbs	8192	534	Moose	10000	535	The Evolving Forest	9312
536	SpriteClub	7777	537	ShatteredEon	10000	538	Doodled Punks	2070	539	TCG World Dragons	10000	540	Lonely Frog Lambo Club	10000
541	Women From Venus	5555	542	Keepers V2	10001	543	Skvllpvnkz Hideout	9999	544	Shabu Town Shibas	9998	545	KaijuFrenz	6666
546	ALTAVA Second Skin Metamorphosis	2785	547	DAPE	2444	548	Castle Kid	9987	549	Loomi Heads	5555	550	Oddstronauts	9872
551	Pirates of the Metaverse	10000	552	CryptoPochi	732	553	Bapes Clan	2499	554	MurMurCats	759	555	BabyDoge	10000
556	UnStackedToadz	9999	557	COBI	10000	558	MOODIES BY HANUKA	7401	559	Psychonaut Ape Division	7777	560	Strong Ape Club	4999
561	FoxyFam	3331	562	Chill Bear Club	5544	563	Encryptas	10000	564	Catbotica	12000	565	ForgottenRunesWarriorsGuild	16000
566	Regenz	2538	567	SpikySpaceFish United	10000	568	DigiDaigakuSpirits	2022	569	CrashTestJoyride	4444	570	Tennis Champs Genesis Series	3333
571	SamuraiCats by Hiro Ando	4747	572	Nickelodeon	3871	573	Goat Soup	3744	574	Aki Story	5555	575	My Homies In Dreamland	10420
576	Floppy	10000	577	JPunks OG-Rex	7776	578	TOKYO PUNKS by SABET	755	579	Travel Tiger Club	1000	580	PLUR	8585
581	BULLSEUM	4999	582	BoomGala	6072	583	BlankFace	9999	584	WannaPanda	10001	585	DemiHuman	10000
586	Based Fish Mafia	10000	587	Fudders	6464	588	Rareland	10000	589	Dr.Ji	2502	590	Apiens	4229
591	The Uncanny Country Club	5000	592	Uncool Cats	6969	593	The Divine Order Of the Zodiac	10000	594	Angry Boars	10000	595	CryptoZombiez	5555
596	Murakami Lucky Cat Coin Bank	4674	597	Dodoor NFT	1000	598	shroomz	8591	599	The ModZ	5555	600	Robopets	6485
601	Goobers	14577	602	Sneaky Vampiress Syndicate	12345	603	Polymorphs	527	604	Blockchain Bandits	3334	605	Larva Doods	8887
606	GIToadz	6956	607	Not Your Bro	10000	608	Ethereans	11000	609	Monkey Legends	6572	610	y00ts Yacht Club	10000
611	Outside Yacht Club	5556	612	the pixels	5062	613	Derage	4201	614	CanineCartel	9918	615	CyberRonin Haruka	5555
616	Outkast	9465	617	Candy Hunters	10000	618	CyberFrogz	5555	619	hobotown	6900	620	WunksV2	6000
621	CryptoMutts	10000	622	Juicebox Frens	6969	623	BitMates	10000	624	posers	5000	625	Tropical Turtles	1200
626	Angry Cat	10000	627	FULL SEND X Alien Frens	1001	628	Yakuza Inc.	3223	629	The Blitnauts	1539	630	Ethermonkeys	10000
631	R Planet	8889	632	Frenly Pandas	10000	633	Gaming Ape Club	6550	634	Crypto Bear Watch Club	3000	635	0xAzuki	9999
636	BeanBagFrens	7777	637	Forest Spirits	8888	638	Social BEES University	13084	639	CouncilOfKingz	5277	640	AlphieWhales	7777
641	Crookz	9999	642	xmfers	6969	643	Hor1zon	6999	644	Colonists	24999	645	Lazy Bunny NFT	5555
646	Froggy Friends	4434	647	Glitches	4517	648	CosmicCowGirls	6969	649	CryptoHodlers	10000	650	ApesOfSpace	10000
651	Choadz	3558	652	MegaKongs	6000	653	Baby Shiba Social Club	8882	654	CrazySkullz	10000	655	ChinaChic NFT	2600
656	Rich Baby	5105	657	Hasbulla NFT	10000	658	Turtle Town	10000	659	Pixelady Maker	10000	660	Riot Girls	636
661	Zombie Mob Secret Society	10000	662	XANA Genesis	9909	663	METASAMURAI	3333	664	The Wild Bunch	4000	665	NFT Worlds Genesis Avatars	11839
666	Etherbananas	749	667	Kindergarten BabyApes	3691	668	DopeApeClub	10000	669	Ghost Child	3334	670	Soul Cafe	3333
671	MEGAMI	5414	672	Spookies	8888	673	WoW Pixies	5536	674	KPK Project	1000	675	676	Pixls
681	Variant	3333	682	WaveCatchers	3334	683	Superfuzz The Good Guys	7511	684	SpaceBoysNFT	8888	685	HolyCows	5000
686	Planktoons	4411	687	Cheers UP	3929	688	DogeArmy	10000	689	Broskees	1691	690	BearsOnTheBlock	9102
691	Doge Club	10000	692	Billionaire Coyote Cartel	2222	693	Band Bears	1130	694	Ririsu	5554	695	Verb	6500
696	MetaTravelers Nibiru	7777	697	WAGMI ARMY	9993	698	Toad Punks	6969	699	The Ninja Hideout	8888	700	Neko	7703
701	Murder Head Death Club	6275	702	Alpha Elementary	3000	703	Mini Supers	6969	704	Sora's Dreamworld	10000	705	Idol	9999
706	Ethaliens	7500	707	Voyager	2057	708	LuckyManekiNFT	14158	709	Metaclubbers	6000	710	Divine Wolves	3800

index	NFT_name	collected_tokens	index	NFT_name	collected_tokens	index	NFT_name	collected_tokens	index	NFT_name	collected_tokens	index	NFT_name	collected_tokens
711	Phoenixes	8888	712	Astroheads	8845	713	HAPE EXODUS	8120	714	ChillRx	9795	715	Party Grandpa Retirement Club	6000
716	Scholarz	2500	717	CyberTurtles	5555	718	Silks Genesis Avatar	7302	719	Star Wolvez	8780	720	Mooncatz	5555
721	Crypto Bears	7546	722	Onigiri Pepes	6198	723	The Council	1337	724	OctoHedz V2	7998	725	IROIRO	5000
726	CryptoApes	6969	727	Cypher Collection	3362	728	Bibos	1111	729	Pixel Interfaces	4003	730	Lazy Ape Yacht Club	10001
731	Rare Bears	2333	732	MeemosWorld	6666	733	DizzyDragons	2717	734	Broadcasters	7777	735	SuperGeisha	6776
736	Space Yetis	3333	737	CRYPTONINJA WORLD	7808	738	LostSoulsSanctuary	9999	739	Japanese Born Ape Society	6883	740	Permies	555
741	Mecha Melters	6000	742	Non Fungible Frens	1001	743	GoldSilverPirates	1125	744	KumaVerse	2010	745	Tie Dye Ninjas	7777
746	Lil Brains	7778	747	CornTown	10000	748	Slumdoge Billionaires	10000	749	FortuneDao	658	750	Forever Fomo Duck Squad	7638
751	OKOKU	3403	752	ENS Maxis	10000	753	AngelsDevilsNFT	10000	754	Avius Animae	9991	755	XXD34D	6420
756	nobody	3210	757	Junglebayapeclub	5555	758	The Dori Samurai	888	759	Tokenmon	10420	760	Qzuki	10000
761	Rowdy Roos	9993	762	BaoSociety	3887	763	KevinPunks	555	764	The Weirdos Battle Royale	9272	765	We All Survived Death	9992
766	Okay Duck Yacht Club	5555	767	Easy Demons	6666	768	MindFulls	1111	769	Cheebs NFT	10000	770	J. Pierce & Friends	4000
771	CockaDoodles	4444	772	PixelBeasts	9998	773	STRAWBERRY.WTF	9954	774	zombietown.wtf	7777	775	VRFuture	7776
776	Bad Bears	5555	777	CryptoPolz	9696	778	Wickens	6666	779	Lamb Duhs	8500	780	Love Addicted Girls	3997
781	DenDekaDen Spirit Key Avatars	7743	782	LEGION	7777	783	Apocalyptic Queens	8887	784	STARCATS	1512	785	Crecodiles	8888
786	Basic Bored Ape Club	10000	787	J48BAFORMS	4848	788	baby goblinz	4999	789	Metathugs	10000	790	TRAVELBIRBS	2000
791	Persona Lamps	4443	792	Barn Owlz	3000	793	Hunnys	10000	794	Project Shura	5499	795	Dopey Ducklings	2044
796	Rug Radio Faces of Web3 by Cory Van Lew	20000	797	Save the Martians	13412	798	Blocky Doge 3	10001	799	Untamed Elephants	7500	800	Larva Chads	5000
801	Gummies Gang	6970	802	Moonbirds2	9999	803	Bad Kids Alley	8888	804	BapesFuture	10000	805	NOT NASA	1093
806	Sports Rollbots	9647	807	Starlink PixelNauts	10000	808	Afro Droids	12101	809	The Chimpsons	7000	810	Flower Fam	6954
811	SeKira	3201	812	Character	1000	813	Binkies	10001	814	Shark Boy Fight Club	8883	815	Doodle Dogs	10000
816	Creepz by OVERLORD	8937	817	Space Dinos	9079	818	Bad Influence	6373	819	Mutant Ape Planet	6799	820	AuctionMintContract	8988
821	Casual Sloths	4444	822	NuoChip	2069	823	DSC E_MATES 4 DA NEXT LEVEL	7968	824	Meta Penguin Island	3581	825	Ey3k0n	10000
826	Angry Apes Society	9999	827	Steady Stack Legends	8726	828	Private Jet Pyjama Party First Ladies	3333	829	poobs	5382	830	Proof of Narnian NFT	3333
831	GalaXY Kats	10000	832	Funcles	3333	833	Aiko Virtual	8888	834	ByteBear	888	835	Buzzed Bear Hideout	9999
836	Deathbats Club	10000	837	Rare Ghost Club	5000	838	Mutant Floki	4199	839	RUDE KIDZ	7748	840	Project Draca	996
841	Lucky Ducky	7777	842	Gazer	2100	843	Pepe Ape Yacht Club	7777	844	Miningverse	1249	845	Pixel Foxes	10000
846	Dogs of Elon	9997	847	Remarkable Women	6000	848	Earpitz	6969	849	Metakrew	6196	850	MegaToads	844
851	Primate Social Society	10000	852	HashGuiseGenOne	9999	853	ElysianFields	567	854	TheWickedStallions	8952	855	Lobby Lobsters	10000
856	HPPRs	6476	857	MonsterShelter	5521	858	Strxngers	6666	859	Lofi Kitties	9999	860	The Americans	10000
861	GameDisease	7601	862	Fun Apes	8887	863	Karma Collective	555	864	Broadside	7290	865	Curious Addys Trading Club	4896
866	NyokiClub	2732	867	HypnoDuckzGenesis	555	868	Spicy Pumpkins	4340	869	TORIX	5563	870	DigiDaigakuDarkSpirits	4037
871	CryptoTitVags	2240	872	Average Creatures	7728	873	TheBirdHouse	6000	874	MoonbirdsMfers	9000	875	PixelGlyphs	553
876	BONEHEADS	10000	877	Tribe Quokka	8000	878	Chum Chums	5699	879	Bufficorn Buidl Brigade	10000	880	ESION	6000
881	PunkX	3067	882	Infinity Frogs	10000	883	Immortalz	4517	884	Strange Times	7777	885	The Connors	2000
886	Kryptoria Alpha Citizens	10000	887	ProjectAtama	666	888	VoltedDragonsSailorsClub	9998	889	Crypto Tech Women	8830	890	Dirt Birds	10000
891	SaltyPirateCrew	2964	892	Bad Baby Dinos	7777	893	Rainbow Cats	4999	894	InfamousAgents	1902	895	The Donut Shop	5432
896	NonconformistDucks	9994	897	Babyrareapepeyc	5554	898	DeBox Guardians Penguin	2048	899	OnChainBirds	10000	900	Who Is Samot	3095
901	Meka Rhinos	3333	902	Meta Bounty Huntress	8888	903	PugFrens	8787	904	ShadesOfYou	7000	905	Stoned Ape Saturn Club	6969
906	Darkflex	6666	907	SemiSupers	5555	908	Sewer Rat Social Club	8886	909	Tribe Odyssey	6810	910	Cyclops Monkey Club	6666
911	WhiteRabbitOne	8765	912	DigiDaigakuDarkHeroSpirits	3653	913	Ethereal Art NFT	4969	914	Muppeth	6969	915	2545	9995
916	Oni Squad	6666	917	Skullx	10000	918	SameToadz	6970	919	YOLO Fantasy	3333	920	Ibutsu	3333
921	The Billionaire Bunker	4444	922	Grumpets	3600	923	Baller Bears	4444	924	reepz	5000	925	Wealthy Ape Social Club	7777
926	RSTLSS texttimes CrypToadz	2208	927	Geisha Tea House	10000	928	Moonlings	10000	929	doodlefrens	10000	930	HeeDong	5555
931	League of Sacred Devils	10000	932	Aneroverse	6334	933	Cypher City	8887	934	EpicEagles	7676	935	Kidzuki	5556
936	Ghost Buddy NFT	5555	937	Quacky Ducks	8888	938	DOGE DASH	4120	939	Spunks NFT	10000	940	Ordyugapunk	1234
941	RichKids	7389	942	Honk	5556	943	Slacker Duck Pond	6000	944	Bagner	6966	945	Fat Rat Mafia	7777
946	Yin Yang Gang	8977	947	The Last Raptor	1923	948	The Squids	2000	949	Rink Rat Ice Club	7777	950	Tokyo Alternative Girls	9658
951	FullBodyApeClub	1111	952	COSMIQS	5555	953	E_Shell	9450	954	Raccoon Mafia	3333	955	Bit Monsters	6667
956	MaskBillionaireClub	3333	957	Lora Of Flower Garden	2000	958	Shikibu World	10000	959	Astrobot Society	3950	960	MistfitsNFT	8000
961	Bored y00ts Ape Club	6969	962	WizardsOfTheTowerShade	10000	963	Sad Bots	3067	964	Shiba Shelter	5555	965	ToonSquad	9939
966	Droplets	6500	967	AI Rein	2999	968	Wafuku	11111	969	Yurei	1111	970	EnterDAO Sharded Minds	5000
971	ReconRams	4246	972	Tsubasa	1423	973	EVERYBODYS	10000	974	Bushidos	8888	975	NICE NFT	9996
976	Cosmos	6060	977	AKCPETS	11999	978	WOAW	5553	979	MuleSquad	690	980	HUGO x IO	738
981	Wojakians	2733	982	Ghidorah Godz	5999	983	Cyber Hornets Colony Club	8888	984	SynthHeads	3030	985	Azuki Mfer	10000
986	MetaStonez	1221	987	Chibi Galaxy	3500	988	Baby Ape Mutant Club	6666	989	Chad	10000	990	Dobies Collection	7591
991	Cyber Snails	3333	992	MUTANT PUNKS CITY	3609	993	Reflections NFT	3333	994	AllStarsClub	2500	995	MoonPepes	4197
996	Pluto2	10000	997	ChippysWorld	2500	998	Superfuzz The Bad Batch	777	999	Soulda	7777	1000	Women Unite - 10k Assemble	6991
1001	BanaCat	9710												