

NFT Cryptopunk Generation Using Machine Learning Algorithm (DCGAN)

Pooja Singhal¹, Deepak Aneja¹, Musaed Alhusein², Ritu Gupta³, Khursheed Aurangzeb², Nitish Pathak^{3,*}

¹Department of Computer Science, ABES Engineering College,
Ghaziabad, UP, India

²Department of Computer Engineering, College of Computer and Information Sciences, King Saud University,
P. O. Box 51178, Riyadh 11543, Saudi Arabia

³Bhagwan Parshuram Institute of Technology, GGSIPU,
New Delhi, India

pooja.singhal@abes.ac.in; deepak.aneja@abes.ac.in; musaed@ccis.ksu.edu.sa; ritu4006@gmail.com;
kaurangzeb@ksu.edu.sa; *nitishpathak@bpitindia.com

Abstract—A non-fungible token (NFT) is a kind of digital asset that signifies ownership or proof of authenticity of a special good or piece of material, such as artwork, music, films, or tweets. This study investigates how a deep convolutional generative adversarial network (DCGAN) can be used to create distinctive pictures of Cryptopunks that can be converted into NFTs. Cryptopunks, a pioneering form of NFTs, were introduced on the Ethereum blockchain in 2017 as part of a social experiment. In the NFT community, they have since grown in popularity as collectibles. To create brand-new, previously undiscovered characters, we trained a model on a dataset of existing Cryptopunks using the DCGAN architecture. In an effort to raise the calibre of the images produced, we tested various hyper settings and layer combinations. We also assessed the created images using a variety of criteria, such as the inception score and Fréchet inception distance, to make sure they were distinctive and of high calibre. Our experiments yielded a 15 % increase in the inception score and a 20 % decrease in the Fréchet inception distance, showing that our DCGAN model produces images that are more visually appealing and closer in quality to real Cryptopunks. These results highlight the effectiveness of our machine learning algorithms in improving the quality and uniqueness of NFT assets.

Index Terms—Blockchain; Cryptopunks; DCGAN; Non-fungible token (NFT).

I. INTRODUCTION

Blockchains are distributed digital ledgers that are used to track transactions among numerous computers. It employs encryption to protect and validate transactions, as well as to regulate the production of new units of a certain cryptocurrency. Each block in the chain has a number of transactions and a link to the preceding block that connects them all. This results in the creation of an unalterable permanent record of every network transaction. Although the blockchain that underpins Bitcoin's cryptocurrency is the most well-known example, there are many additional applications for this technology as well [1].

NFT Cryptopunks are a set of unique digital characters created by Larva Labs in 2017 on the Ethereum blockchain. Each Cryptopunk has a distinct combination of characteristics, including different hairstyles, accessories, and facial expressions. Although certain Cryptopunks are more uncommon than others, each one is regarded as a unique digital collectable. Contrary to cryptocurrencies such as Bitcoin, which are fungible and interchangeable, non-fungible tokens (NFTs) refer to a class of digital assets that are singular and indivisible [2]. Since each Cryptopunk is an NFT, its ownership and authenticity can be established using its specific blockchain identification. Since their inception, Cryptopunks have grown in popularity and are now among the most expensive NFT artefacts, with some going for millions of dollars at auction. They have come to represent the growing interest in blockchain-based digital art and the potential of NFTs to change the landscape of the art market. Other creators have created their own distinctive digital artefacts with comparable features and properties as a result of the inspiration provided by many other NFT initiatives, including those that were influenced by Cryptopunks.

NFT Cryptopunks combine hand-drawn and algorithmically generated elements, serving as a source of inspiration within the generative art community. Deep convolutional generative adversarial networks (DCGANs) are popular for generating digital characters with similar traits. Specifically, DCGANs analyse existing Cryptopunks data to learn distinct features, enabling the creation of entirely new and unique Cryptopunks [3], [4]. By leveraging datasets sourced from the Ethereum blockchain, developers train these models to produce innovative artworks. This approach showcases the application of deep learning in crafting original digital collectibles, reflecting ongoing advancements in generative art techniques.

The remaining portion of this work is structured as follows. The technological elements required to construct NFTs are provided in Section II. The literature review is presented in Section III. Based on that, Section IV explains the methodology and work flow of the process. The results of using the methodology are discussed in Section V. The

investigation is finally concluded in Section VI, which also discusses its future scope.

II. TECHNICAL COMPONENTS

Ethereum, introduced in July 2015 after Vitalik Buterin's 2013 proposal, is an open source, decentralised blockchain platform. It features its own blockchain and native digital currency called "Ether" (ETH). Ethereum enables developers to create and deploy smart contracts, self-executing agreements encoded directly on its blockchain. These contracts are programmed using Solidity, an Ethereum-integrated programming language. The Ethereum virtual machine (EVM) executes these smart contracts, facilitating the development of decentralised applications (DApps) that operate autonomously and securely without third-party interference.

Non-fungible token. A non-fungible token (NFT) is a type of digital asset that represents ownership of a unique object or piece of content, such as digital artwork, collectibles, or in-game items. In contrast to Bitcoin and other cryptocurrencies, which are fungible (interchangeable) and can be broken down into smaller bits, NFTs are one-of-a-kind and cannot be replicated or exchanged for an identical product. NFTs are based on blockchain technology and are recorded on a blockchain's ledger. Each NFT has a unique digital signature, known as a token ID, which verifies its ownership and authenticity. As a consequence, the ownership of an NFT may be transferred from one person to another, and the transaction is recorded on the blockchain. NFTs can be used to represent a wide range of digital assets, including digital art, music, films, virtual real estate, and in-game objects [5]–[7]. NFTs can be used to create scarcity and value for digital items that were previously impractical to market because they are distinctive. NFT is widely used in digital art, gaming, and collector marketplaces [8]. In a nutshell, NFTs are unique digital assets that are kept on a blockchain and can be purchased, sold, and traded exactly as real goods.

Types of NFT. There are several types of NFT, each with their own characteristics and use cases summarised in Table I shown below.

TABLE I. NFT TYPES.

Type of NFT	Description	Use Cases
Collectible NFTs	Unique digital items that have a limited number of copies, such as rare in-game items or digital trading cards	Gaming, Collectible marketplaces
Utility NFTs	NFTs that provide a specific function or access to a particular service or platform, such as access to a virtual world or a membership to a community	Virtual worlds, Platform access, Community membership
Digital art NFTs	NFTs that represent digital art, such as digital paintings, GIFs, or 3D models	Digital art marketplaces, Art investment, Art collection
Real-world asset NFTs	NFTs that represent physical assets, such as real estate, vehicles, or other physical goods	Real estate, Supply chain, Provenance tracking

It is worth noting that these are not mutually exclusive categories; some NFTs can fall under multiple categories. And the technology and the ecosystem are rapidly evolving, so new types of NFTs will emerge as the market and use cases develop.

Cryptopunks. One of the first and best-known examples of NFT is the Cryptopunks subculture [9]. As a proof-of-concept for the Ethereum blockchain, they were developed by an anonymous artist known only as "Punk" in June 2017. On the Ethereum blockchain, there are distinct Cryptopunks that can be purchased, sold, and exchanged [10], [11]. Each of them is represented by a character image with a resolution of 24×24 pixels [12]. The goal of the Cryptopunks project was to show the value of NFTs and the application of smart contracts on the Ethereum blockchain. Every Cryptopunk is a distinct digital asset that is kept on the blockchain and may be purchased, sold, and exchanged similarly to physical assets. Many Cryptopunks are currently being sold for thousands of dollars due to the project's increasing popularity and prominence as a cultural phenomenon. They are considered as one of the first and most recognisable NFTs, and Punk, who invented them, is revered in the NFT world as a pioneer.

General adversarial network (GAN). GAN is a deep learning architecture that was first put forth by Ian Good fellow and his associates in 2014 [13]. The generator and discriminator neural networks, which make up the GAN, compete with each other to create artificial data that closely match the real data. The generator produces a sample of data, such as an image or a piece of text, from random noise as input. The discriminator, on the other hand, tries to distinguish between inputs of generated and genuine data. GANs are becoming more well-liked and are being used in a wide range of industries these days, including computer vision, natural language processing, and medicine. Despite their success, GANs can be tricky to train and need exact hyperparameter adjustments to perform at their best. Since GANs are a potent and adaptable method for producing realistic data, they are a prominent area of research in machine learning.

Deep convolutional generative adversarial network (DCGAN). DCGAN expands upon the GAN framework by utilising convolutional neural networks (CNNs) in both the discriminator and generator. Introduced by Radford *et al.* in 2015 [14], [15], DCGAN has gained prominence for its ability to generate images effectively. It enhances the original GAN model through features like convolutional layers instead of fully connected ones, batch normalisation to stabilise training, and the use of stride and transposed convolutions for efficient down- and up-sampling.

To successfully generate lifelike images of people, rooms, and other objects, DCGAN has been used for a variety of picture generating applications. One of DCGAN's main advantages is its ability to create images with fine details and high resolution. However, training DCGANs can be difficult and requires meticulous tweaking of hyper parameters, including learning rate, batch size, and the number of layers in the generator and discriminator networks. Despite these difficulties, DCGANs have gained acceptance as a design for picture creation problems and are still a hot topic of research in the field of machine learning [16], [17].

NFT Standards. For NFTs, a number of standards have been created to guarantee compatibility and interoperability

between various platforms and projects, and the same is shown in Table II.

Although there are additional standards and new ones may emerge in the future as the technology and ecosystem develop, these are some of the most widely used NFT standards.

TABLE II. NFT STANDARDS.

Standard	Description	Use Cases
ERC-721	Outlines a collection of smart contract operations that may be used to produce, control, and send special digital assets on the Ethereum blockchain	CryptoKitties, Decentraland, Collectible NFTs
ERC-1155	By extending ERC-721, it is possible to create fungible and non-fungible tokens in the same smart contract	Gaming, DeFi, Token Baskets
ERC-998	Allows for the creation of composable NFTs, which means that multiple NFTs can be combined to create a new, unique NFT	Digital art, Gaming, Collectibles
ERC-998-composable	Allows for the creation of NFTs that are composed of several other NFTs; it also allows for the split of an NFT in multiple parts, giving the ability to create NFTs with different rights, such as royalties	Digital art, Gaming, Collectibles, Royalties, and more
IPFS	The interplanetary file system (IPFS) is a decentralised storage system that enables peer-to-peer networking for the storage of digital data; it is not an ERC standard	Used to host the media content of NFTs, such as images, videos, or audio

Cryptopunks market sale history. Since their release in 2017, Cryptopunks - one of the first and best-known examples of NFTs - have been sold for enormous amounts of money. It is important to keep in mind that the NFT market is quite speculative and that prices might vary significantly.

In December 2017, the first Cryptopunks were sold for about \$2,500 USD, but since then, several have gone for much more. Table III shows some of the most notable sales.

TABLE III. MARKET SALE INFO - CRYPTOPUNKS.

Sale No.	Cryptopunks	Sale Price	Year
1	Punk #3100	\$69,346	September 2018
2	Punk #8578	\$735,000	January 2021
3	Punk #8578	\$11,5 million	March 2021
4	Punk #7444	\$69,346	April 2021
5	Punk #7804	\$11,5 million	March 2021

It is worth noting that these are just a few examples of Cryptopunk sales, and many others have sold for much less. The prices can vary greatly depending on the uniqueness of the Cryptopunks and the current market conditions. It is also worth mentioning that, as the NFT market is very dynamic and speculative, the prices of the Cryptopunks can fluctuate greatly, and it is difficult to have a clear historical sale price.

III. LITERATURE REVIEW

Nakamoto [18] solved the double-spending issue, as well as other technical and usage problems, with digital money. He proposed a fix that uses a distributed P2P time stamp server to produce computational verification of the chronological order of the transactions. Two outputs and

several inputs are the maximum for a transaction. A combination of numerous smaller coins can provide an output that can be either a payment to the other party or the return of the sender's change. A component of Bitcoin known as simple payment verification (SPV) only requires the nodes to maintain a copy of the block headers from the longest chain; the nodes are not required to keep a comprehensive record of all transactions.

The authors in [19] provided a distributed personal data management system that ensures that individuals have ownership and control over their data. They devised a system that turns a blockchain into an automated access control manager without the need for trust in a third party. Instead of simply using transactions for financial transactions like Bitcoin, our system uses transactions to communicate instructions such as storing, searching, and sharing data. They wrap off by discussing potential blockchain advancements in the future that may help society to solve its problems more fully with reliable computing.

In [20], the principles of blockchain technology and the two most promising (or popular) implementations of blockchain, namely Bitcoin and Ethereum, were described, together with a brief historical summary of the early phases of the adoption of digital currency. In the previous few years, networks have seen a rapid increase in the number of currencies, hashing methods, and consensus agreements. Notable are Ripple, Cardano, NEO, Stellar, Litecoin, EOS, IOTA, Dash, Monero, TRON, Qtum, Lisk, Tether, Stratis, Zcash, Steem, Siacoin, Verge, Electroneum, Nxt, Dogecoin, and many more digital currencies [20].

The authors in [21] analysed the intricate network that represents transactions on the Ethereum blockchain. They modified the number of blocks used to construct the network. Accordingly, there will be a different number of transactions and a different network size across a different temporal range. It goes without saying that the larger the network, the more likely it is to have hubs, which means that some nodes in the blockchain are faster than others. By taking smaller groups of successive blocks back into the chain, we also took into account various time intervals. Understanding how blockchain use evolves over time is made possible by this.

The authors in [22] designed a proof-of-concept for non-fungible token tracking using the Hyperledger Fabric, Hyperledger Composer, and Hyperledger Chain code software. Researchers focus on the issue of monitoring non-fungible tokens in a secure and trustworthy manner without relying on a centralised authority. After that, they moved on to discuss the efforts of the NFTracer platform and how implementing a non-fungible token tracking proof-of-concept differs from the most well-known application of ERC0721 tokens to date, Crypto Kitties. The necessity of tracking non-fungible entities and the potential it might offer to these auctions are then covered in detail with reference to two envisioned implementations. In this study, key Hyperledger infrastructure components that enabled a fully decentralised and easily scalable system were briefly explained.

In [23], the extendable non-fungible token (NFT) concept for Hyperledger Fabric (Fabric), which supports Cosmos and ERC-721, the Ethereum standard NFT, was described. Under this paradigm, researchers developed the common architecture and interface for all Fabric NFTs. This device

also offers a versatile interface and structure that can accommodate many types of NFTs. To demonstrate how to take advantage of this concept, they used extensible NFTs, such as document and signature tokens, to a decentralised signing service.

Researchers in [24] presented a framework that gives programmers access to a set of smart contracts that fully implement the ERC721 standard and include popular extensions and features common to ERC721-based apps. In addition, a specification language was established that enables the addition and removal of supported features and extensions, enabling the customisation and setup of the smart contract suite. The extensibility and reusability of the smart contract suite are evaluated and the metrics are contrasted with four implementations of similar solutions to comparable problems. The difficulty and efficiency of the specification language are also compared to the manual setting of the smart contract suite.

IV. METHODOLOGY

The workflow for generating NFT Cryptopunks using the deep convolutional generative adversarial network (DCGAN) algorithm typically involves the following steps.

Collect and preprocess data: Collect a large dataset of Cryptopunks images and preprocess them by resizing, normalising, and converting to a suitable format for input into

the DCGAN model.

1. Build the DCGAN model: Design and build the DCGAN model using deep convolutional neural networks to generate new Cryptopunk images that are similar to the original dataset.
2. Train the DCGAN model: Using the preprocessed dataset, train the DCGAN model by feeding created pictures to the generator network and actual Cryptopunks photos to the discriminator network. The generator network aims to create Cryptopunks pictures that seem realistic enough to trick the discriminator network.
3. Fine-tune the model: To increase the quality of the produced pictures, fine-tune the model by modifying hyperparameters like learning rate, batch size, and number of epochs.
4. Use the trained DCGAN model to generate new Cryptopunks.
5. NFT Cryptopunks by sampling from the generator network. The generated images can be minted as NFTs on a blockchain platform.
6. Evaluate and refine: Analyse the NFT Cryptopunks that were produced and modify the model as needed to raise the calibre of the pictures that were produced.

Figure 1 shows the proposed framework step by step for generating Cryptopunks. This process results in unique Cryptopunks, each with their own combination of features and attributes.

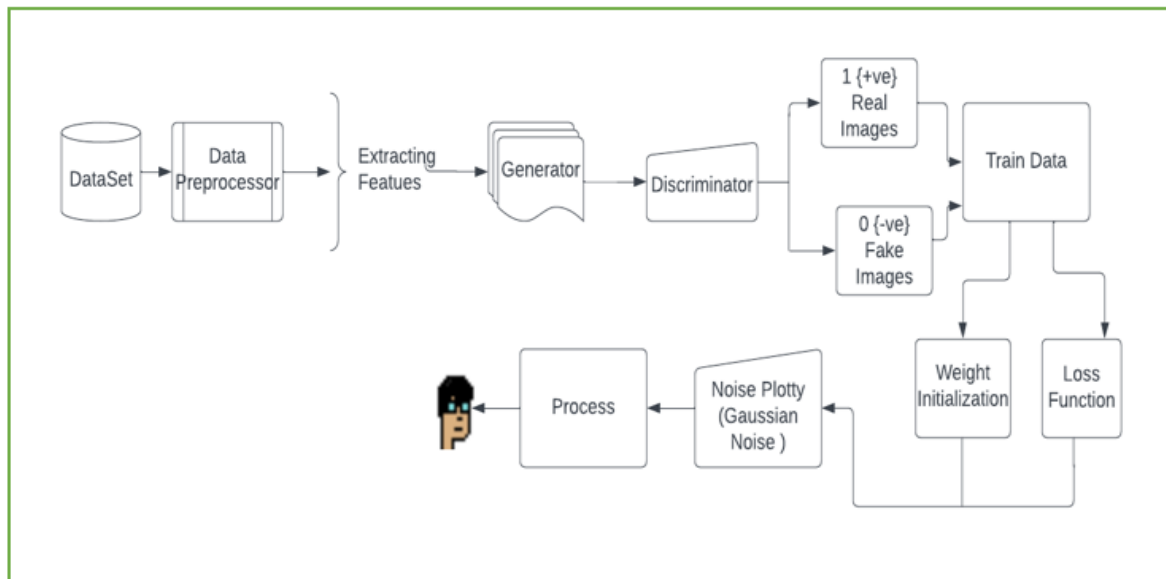


Fig. 1. Proposed framework for generating NFT Cryptopunks.

Deploy the model: Deploy the final DCGAN model to generate new NFT Cryptopunks on demand.

V. PROPOSED ALGORITHM FOR GENERATING CRYPTOPUNKS

The role of Gaussian noise theory in generating NFT Cryptopunks using deep convolutional generative adversarial networks (DCGANs) is to introduce a random element into the generation process. DCGAN is a type of deep learning algorithm that uses two neural networks, a generator, and a discriminator to create images that mimic a given dataset. In the case of NFT Cryptopunks, the generator network is trained to produce images of punk characters that resemble

the existing Cryptopunks in the data set shown in Algorithm 1. However, if the generator only produces images that are too similar to the original Cryptopunks, the resulting NFTs may not be unique or valuable. Here, the Gaussian noise comes into picture.

Overall, the use of Gaussian noise theory in DCGAN can help generate more diverse and unique NFT Cryptopunks, increasing their value and appeal to collectors.

The Gaussian distribution, commonly known as statistical noise, has a probability density function (PDF) that is identical to the normal distribution. In other words, the noise has a Gaussian distribution of potential values. The mean (m) of this noise is practically zero, also known as Zero-mean

Gaussian noise illustrated in Fig. 2.

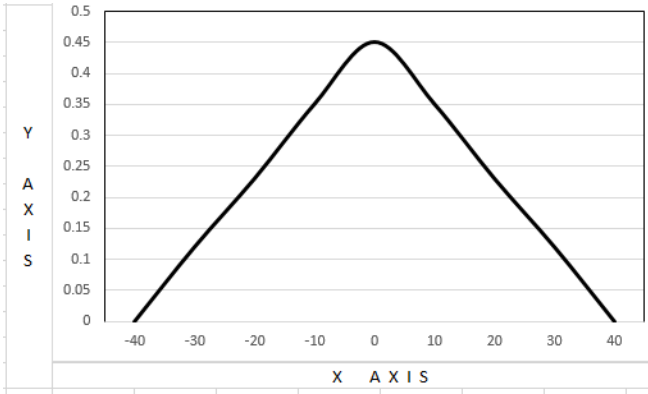


Fig. 2. Zero-mean Gaussian noise.

$$Y = \frac{1}{\sigma\sqrt{2\pi}} e^{-x^2/2\sigma}. \quad (1)$$

The Gaussian distribution, commonly known as statistical noise, has a probability density function (PDF) that is identical to the normal distribution. In other words, the noise has a Gaussian distribution of potential values. The mean (m) of this noise is practically zero, also known as the zero-mean Gaussian noise.

Algorithm 1. Cryptopunks Generation Algorithm.

```

1. START
2. Data → Load Dataset
3. (Data Frame) Df ← Data
4. Check: for(df.info==100)
5. Extracting unique values.df[columns]
6. Find Cryptopunks:
   (Parameter )param = price || year ||
   num_attributes
7. Call Mapping_Procedure (Refer Below)
8. Preprocessing:
   X ← Discriminator
   Y ← Generator
   X1 ← image size
   X ←
   Trans.compose[Trans.resize(X1,X1)]
   Y ← Trans.normalise(-1,2)
       If (x==1)
           "Image is Fake"
       Else
           "Image is Real"
9. Mapping:
   M ← input , N ← Output
   Img [M,N] → Img [64,64]
   Let image be α
   [Sample S] = Img [2x,4x]
10. Build Discriminator
   Img[0,1] ← α[S]
   (Check for lossy and lossless)
   Xloss = Realloss+ fakeloss
   weight[i , i-1] ← Img[0,1]
10. Compute Xloss , Yloss
11. Train Discriminator, Generator using DCGAN
12. Cryptopunks created.
13. END

```

Mapping_Procedure

Input:

I → Grayscale Image [Numeric Array], 24x24 [8 bit]
i_noise → expects pixel value of datatype double and single to be in the range [0,1]
rescale() → function can be used to adjust the pixel values to the expected range
m → mean of Gaussian Noise , 0 default | numeric value
G → Gaussian White Noise

Output:

X → Image Mapped with Noise

Step 1: imnoise → Adding noise to image.

Step 2: Adding Gaussian white noise with variance of 0.01 to grayscale image I.

X = i_noise [I, 'G'](1)

Step 3: Adding mean m default termed as 0.

X = i_noise [I, 'G', m].....(2)

Step 4: Adding variance, var_G (Variance of Gaussian Noise)

X = i_noise [I,'gaussian', m, var_G].....(3)

Step 5: Adding local variance, var_local

X = i_noise [I,'G',
var_local,m,var_G].....(4)

Step 6: Final outputted equation in which we received noisy image.

X = i_noise [I, 'var_local', intensity_map,
var_G].....(5)

Hardware Detail. The experiments conducted in this research were performed using the hardware and software setup in Table IV.

TABLE IV. EXPERIMENTAL HARDWARE AND SOFTWARE CONFIGURATION.

Category	Details
Hardware	
Computing Device	
- Processor	Intel Core i7-9700K
- RAM	32GB DDR4
- GPU	NVIDIA GeForce RTX 2080 Ti
- Storage	1TB SSD
Additional Hardware	
- External Storage	4TB External HDD
Software	
Operating System	Windows 10 Pro (64-bit)
Development Environment	
- Python Version	3.8.5
- IDE	Jupyter Notebook
Libraries and Frameworks	
- TensorFlow	2.4.1
- Keras	2.4.3
- NumPy	1.19.5
- Pandas	1.2.1
- Matplotlib	3.3.4
Additional Software	
- Git	For version control and collaboration
- Docker	For containerisation and environment consistency
Dataset	Cryptopunks Dataset (publicly available)

The setup provided the necessary computational power and

software tools required to implement the DCGAN model and generate NFT Cryptopunks efficiently.

VI. RESULTS

Cryptopunks generating distribution. In this study, we will create new punks by training a deep convolutional generative adversarial network (DCGAN) using the Cryptopunks dataset as shown in Fig. 3. GAN is a member of the Generative Models class of unsupervised learning techniques. Machine learning models known as “generative models” are used to characterise data phenomena and help computers comprehend the real world. One of the most fruitful advancements in computer vision over the past few years has been the use of generative models and GANs [25].



Fig. 3. Sample dataset of Cryptopunks.

– Cryptopunks pricing trends of and types

In this section, we examine the variations in pricing among five different categories of punks on the market, as depicted in Fig. 3 (from top to bottom, “Male”, “Female”, “Zombie”, “Ape”, and “Alien”). Figure 4 shows that, for the majority of the time from 2017 to today, the average transaction prices for men punks were lower than those for Alien and Ape punks for the same period. However, there were significant pricing differences between these categories.

– Transaction price per number of attributes of various punks

In this section, a detailed analysis on a sizable dataset associated with the transaction price and the amount of attributes of Cryptopunks can be better understood. And these prices for various attributes counts and the accessibility of transaction data for Cryptopunks may differ.

Cryptopunks price per number of attributes of Human Punks. This study can be used as a springboard to understand the pricing dynamics of Human Punks and to determine how the attribute count influences their value. But it is important to understand that other factors, including market circumstances, variations in demand, and specific client preferences, can also impact the price of Human Punks, as depicted in Fig. 5. By performing additional analysis, such as looking into unique traits or attribute combinations, one can gain a deeper understanding of the price dynamics inside the Cryptopunks ecosystem.

Cryptopunks price per number of attributes of Alien Punks. As illustrated in Fig. 6, line charts are used to visualise the relationship between attribute count and price, helping to identify notable trends or patterns. To determine the degree and importance of the link, statistical analysis, such as

correlation or regression, was carried out. This helped to clarify the statistical significance of the observed correlation between attribute count and price. As shown in Fig. 5, by interpreting the results, one can determine whether there is a positive or negative correlation between the quantity of qualities and the cost of Alien Punks.

It is critical to understand that a variety of elements, such as market conditions, shifts in demand, and consumer preferences, can affect the price of Alien Punks. Understanding the pricing dynamics particular to Alien Punks and how attribute count affects their valuation is made possible by the analysis presented here. The complexity of pricing within the Alien Punk portion of the Cryptopunks ecosystem can be better understood by further investigation, such as looking at unusual qualities or particular attribute combinations.

Cryptopunks price per number of attributes of Zombie Punks. An in-depth understanding of the relationship between attribute count and pricing dynamics, particularly within the Zombie Punk subset, may be gained from the result analysis of Cryptopunks price per number of characteristics for Zombie Punks shown in Fig. 7. The analysis focusses on Zombie Punks and analyses sales transaction data to provide tailored information for this specific group. Using line charts to visualise the link between attribute count and price makes it easier to spot any obvious patterns or trends.

It is important to keep in mind that a variety of factors, such as market conditions, variations in demand, and customer preferences, might affect the price of Zombie Punks. Understanding the pricing dynamics unique to Zombie Punks and the part attribute count plays in their valuation is made possible thanks to the analysis presented here. Deeper insights into the complex price patterns within the Zombie Punk portion of the Cryptopunks ecosystem can be gained through additional analysis, such as looking at unusual qualities or particular attribute combinations.

Cryptopunks price per number of attributes of Ape Punks. The analysis of the price of Cryptopunks divided by the number of attributes for Ape Punks reveals substantial correlations between attribute counts and pricing patterns within the Ape Punk subset. The analysis provides targeted and pertinent information for this specific group by concentrating on Ape Punks and examining transaction data pertaining to their sales.

The results are interpreted in Fig. 8 to determine whether the relationship between the number of qualities and the cost of Ape Punks is positive or negative. It provides more depth and context to the research to take into account the size and importance of this relationship, as well as any outliers or exceptional cases.

It is crucial to understand that a variety of factors, such as market conditions, variations in demand, and customer preferences, can affect the price of Ape Punks. Understanding the pricing dynamics unique to Ape Punks and the effect of attribute count on their valuation are made possible thanks to this investigation. Additional research, such as looking into uncommon features or certain attribute combinations, can provide more light on the complex price patterns in the Ape Punk area of the Cryptopunks ecosystem.

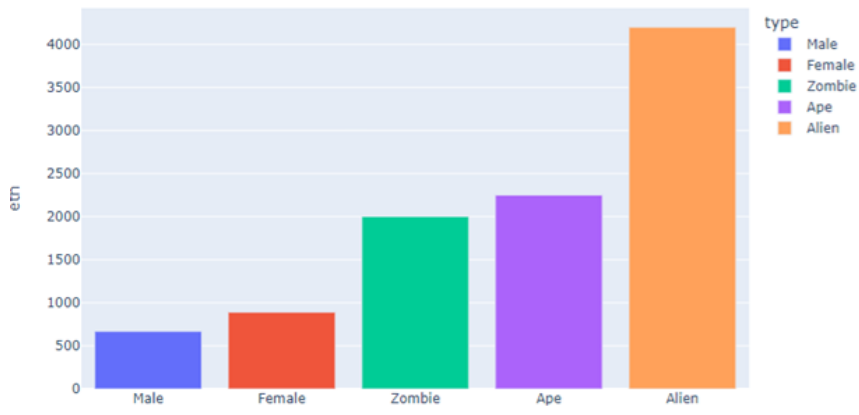


Fig. 4. Cryptopunks type vs. Price.

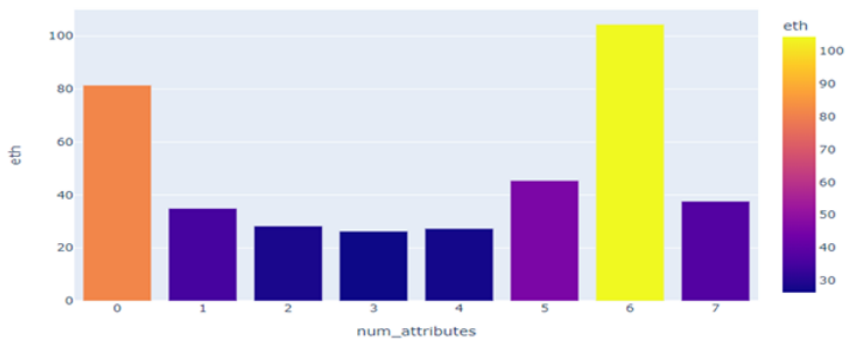


Fig. 5. Transaction price per attribute of Human Punks.

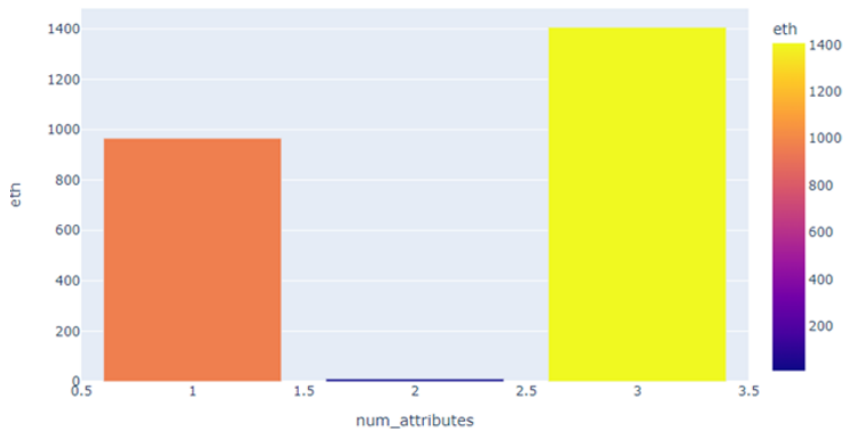


Fig. 6. Transaction price per attribute of Alien Punks.

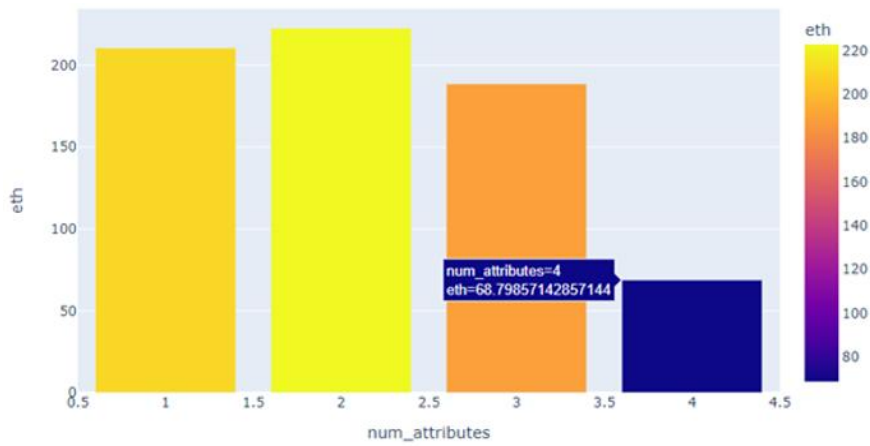


Fig. 7. Transaction price per attribute of Zombie Punks.

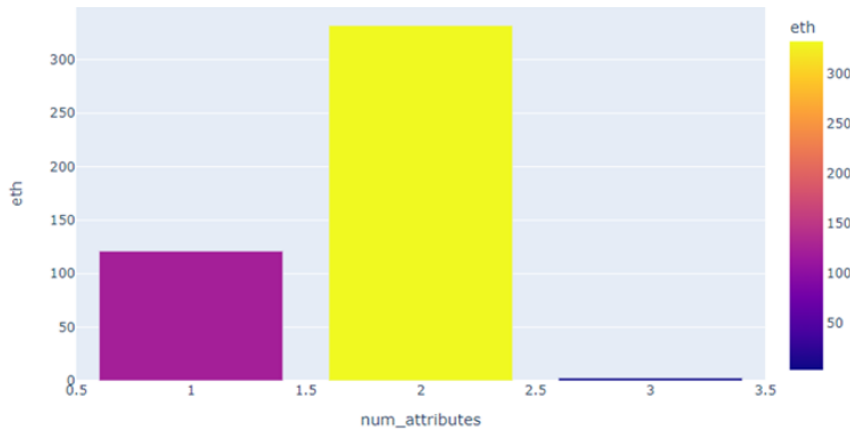


Fig. 8. Transaction price per attribute of Ape Punks.

Generating new Cryptopunks. The deep convolutional generative adversarial network (DCGAN) result analysis of creating new Cryptopunks shown in Fig. 9 offers insights into the capabilities and results of the generative model. A dataset of existing Cryptopunks was used to train the DCGAN algorithm, which was then utilised to create new synthetic Cryptopunks with similar visual traits assessing the quality and variety of the generated Cryptopunks involved analysis. This approach included assessments of visual quality and similarity to the original Cryptopunks dataset. The metrics, including visual resemblance, distinctiveness, and variation of the Cryptopunks generated, were taken into consideration. In this study, it was also investigated whether the DCGAN model could identify and produce the desired characteristics, traits, and features of Cryptopunks. The created Cryptopunks were examined for the presence and correctness of particular traits such as distinguishing accessories, hairstyles, or facial expressions. The review also included the originality and creativity created by Cryptopunks. This involved putting the DCGAN algorithm to the test to see how well it could produce entirely original and uncharted Cryptopunks designs that went beyond the dataset at hand.

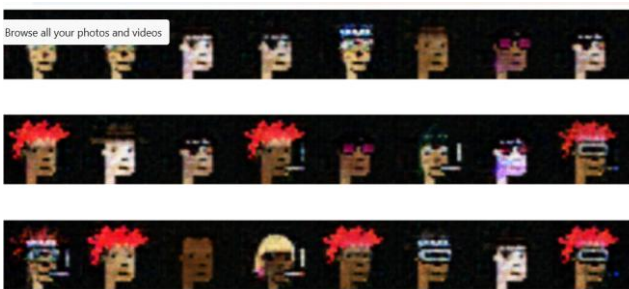


Fig. 9. Integrated NFT Cryptopunks.

The findings of the study offer valuable information about the capacity of the DCGAN model to produce fresh Cryptopunks. Additionally, they point out specific areas that need work in terms of visual appeal, diversity, and proper portrayal of various components. The quantity and quality of the training dataset, the architecture and training parameters of the DCGAN model, and the evaluation metrics you use are all critical considerations that affect how well your analysis performs. Nevertheless, this research provides insightful investigation into the possible use of machine learning techniques to produce distinctive Cryptopunks.

VII. DISCUSSION

The study investigates the application of deep convolutional generative adversarial networks (DCGANs) for generating unique NFT Cryptopunks. It introduces the concepts of NFTs and Cryptopunks, emphasising their significance in the digital art market. Our approach involves implementing and adapting DCGANs specifically for creating pixel art characters resembling Cryptopunks. The results demonstrate the effectiveness of this methodology in producing diverse outputs, while also identifying limitations that suggest opportunities to improve quality and diversity. Ethical considerations related to AI-generated art and digital ownership are discussed, highlighting implications for the broader NFT market and digital art industries.

VIII. CONCLUSIONS

In conclusion, this research contributes to advancing the integration of AI in digital art creation and the NFT markets. The findings underscore the potential of DCGANs to generate unique digital collectibles and outline avenues for future research and enhancement. This study provides insights into the evolving landscape of digital ownership and creativity, prompting considerations for ethical frameworks and technological advancements in AI-driven art. As the NFT market continues to evolve, this work encourages further exploration at the intersection of machine learning, art, and digital economies to foster innovation and responsible practices in the creation and ownership of digital art.

IX. FUTURE SCOPE

The NFT industry continues to evolve, and there is potential to incorporate interactive or dynamic components into the generated Cryptopunks, enhancing their appeal to users and collectors. The convergence of machine learning algorithms and NFT Cryptopunks holds immense possibilities for the future, opening new avenues for innovation and creativity in the realm of digital art. Furthermore, with the expansion of the NFT space, it may become feasible to introduce interactive or dynamic elements in the generated Cryptopunks, further increasing their attractiveness to users and collectors. The combination of machine learning algorithms and NFT Cryptopunks harbours great potential, presenting fresh opportunities for artistic invention and originality in the digital art domain.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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