# IITP-VDLand: A Comprehensive Dataset on Decentral Parcels

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#### Abstract

This paper presents IITP-VDLand, a comprehensive dataset of Decentraland parcels sourced from diverse platforms. Unlike existing datasets which have limited attributes and records, IITP-VDLand offers a rich array of attributes, encompassing parcel characteristics, trading history, past activities, transactions, and social media interactions. Alongside, we introduce a key attribute in the dataset, namely Rarity score, which measures the uniqueness of each parcel within the virtual world. Addressing the significant challenge posed by the dispersed nature of this data across various sources, we employ a systematic approach, utilizing both available APIs and custom scripts, to gather it. Subsequently, we meticulously curate and organize the information into four distinct segments: (1) Characteristics Data-Fragment, (2) OpenSea Trading History Data-Fragment, (3) Ethereum Activity Transactions Data-Fragment, and (4) Social Media Data-Fragment. We envisage that this dataset would serve as a robust resource for training machine- and deep-learning models specifically designed to address real-world challenges within the domain of Decentraland parcels. The performance benchmarking of more than 20 state-of-the-art price prediction models on our dataset yields promising results, achieving a maximum  $R^2$  score of 0.8251 and an accuracy of 74.23% in case of Extra Trees Regressor and Classifier. The key findings reveal that the ensemble models performs better than both deep learning and linear models for our dataset. We observe a significant impact of coordinates, geographical proximity, rarity score, and few other economic indicators on the prediction of parcel prices.

# 1 Introduction

Embarking on an innovative journey in 2017 by the visionary founders, Esteban Ordano and Ari Meilich, Decentraland [38] has emerged as one of the most popular Metaverse platform in the present day. This pioneering venture allows users to be part of a shared digital experience where they can play games, socialize, create, buy, or sell digital items. Few of the key components of Decentraland include LAND (virtual real estate), Parcels (individual units of LAND), Estates (clusters of LAND for collaborative purposes), Avatars (virtual user representations), and the Builder tool for creating 3D content. Notably, the popularity of Decentraland surged when virtual parcels were traded for almost \$1 million in June 2021, followed by a notable transaction of cryptocurrency worth \$2.4 million, with the buyer being the crypto investor Tokens.com. As reported in [35], in 2022, Decentraland experienced around 8000 daily active users with large number of repeat visitors to explore and spend time on the platform. This series of events played a crucial role in propelling the market capitalization to a noteworthy \$903,847,923 in the recent year [7]. Unlike other Metaverse platforms, Decentraland is

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governed by the DAO, a Decentralized Autonomous Organization, that utilizes off-chain voting for community engagement.

As the Decentraland experiences a surge in popularity and an expanding user-base, a plethora of interesting research avenues emerge. Among these, notable research problems include predicting parcel prices and forecasting their future values, classifying high-valued parcels, and tracking intricate trends within the Decentraland ecosystem. Recent research efforts in the literature aimed at understanding the impact of various features on the dynamic pricing behavior of Decentraland Non-Fungible Tokens (NFTs) [14, 19, 53, 36, 15, 44, 39, 29, 32, 8, 5, 33]. However, the datasets used in their training phases contain a limited number of records and attributes of Decentraland parcels, therefore lacking the comprehensive representation necessary for analyzing the multifaceted influences on parcel dynamics within Decentraland. Specifically, out of the four publicly available datasets [36, 32, 28, 41], two contain a maximum of 6,141 records with 37 attributes, while the other two contains social media comments/discussions. This underscores the pressing need for a comprehensive dataset encompassing Decentraland parcels along with their detailed attributes, which are currently fragmented and scattered across diverse sources.

To this aim, this paper is dedicated to the development of a comprehensive dataset, called IITP-VDLand, tailored specifically for the virtual realm of Decentraland parcels. Our extensive compilation encompasses a diverse array of attributes, spanning parcels' characteristics and their trading history, as well as transaction-specific details recorded on the Ethereum blockchain including social media data. Drawing from various sources such as Decentraland [38], OpenSea [17], Etherscan [50], Google BigQuery [20], Discord [13], Telegram [51], and Reddit [42], this dataset serves as a robust resource for training machine- and deep-learning models specifically designed to address real-world challenges within the domain of Decentraland parcels.

In particular, our dataset comprises in total 92,598 parcels with 81 attributes. These parcels are associated with various characteristics attributes including their coordinates, geographical proximity from prominent locations, visual link, unique Id, and rarity score. This is worth emphasizing that, for the first time, we use one of the most popular rarity meters, namely Rarity.tools, to calculate the rarity score of the parcels, which measures the uniqueness of each parcel in comparison to others. To capture the market dynamics of Decentraland, we leverage the extensive trading history available on OpenSea, the largest secondary marketplace. This allows us to access offers prices and sales prices for each parcel over a specified time period. Since Decentral and operates on the Ethereum blockchain, to delve into the specifics of Ethereum on-chain transactions, we aim to include transaction details such as gas prices, bidding history, and parcel-related activities. These attributes encompass details like invoked methods, block-specific information, mining specifics, and more. In essence, we seek to comprehensively analyze Ethereum transactions within Decentral and by capturing a broad spectrum of relevant data points, facilitating deeper insights into user interactions and the ecosystem's dynamics. We also dive into social media platforms to get a gist of people's views and sentiments. These distinctive attributes significantly enrich our dataset, offering a novel perspective for research and academic exploration. By delving into the economic dimension of Decentraland, researchers can gain a profound understanding of this virtual world. To enhance clarity, we've organized our dataset into four segments: (1) Characteristics Data-Fragment, (2) OpenSea Trading History Data-Fragment, (3) Ethereum Activity Transactions Data-Fragment, and (4) Social Media Data-Fragment.

To the best of our knowledge, this is the first benchmark dataset that is in-depth and tailor-made for various machine- and deep-learning applications of Decentraland parcels. Unlike existing Decentraland NFT datasets which are notably incomplete and lack critical attributes, IITP-VDLand sets a new standard encompassing details ranging from parcels' metadata, transactional details to social media data.

To summarize, the major contributions of our paper are:

- We introduce IITP-VDLand, an extensive dataset comprising Decentraland's parcel NFTs sourced from diverse platforms, including *Decentraland* [38], *OpenSea* [17], *Etherscan* [50], *Google BigQuery* [20], *Discord* [13], *Telegram* [51], and *Reddit* [42]. This dataset serves as a robust resource for training machine- and deeplearning models tailored to tackle real-world challenges within the Decentraland NFT domain.
- We meticulously curate the data, creating four distinct segments: (1) Characteristics Data-Fragment, (2) OpenSea Trading History Data-Fragment, (3) Ethereum Activity Transactions Data-Fragment, and (4) Social Media Data-Fragment. Alongside the existing data, we also introduce a significant attribute of Decentral parcels in the dataset, namely Rarity score, which quantifies the uniqueness of each parcel within the virtual world.
- We conduct a performance benchmarking of more than 20 state-of-the-art price prediction models on our novel dataset, aiming at assessing their predictive performance and determine which models are best suited for our dataset. The results demonstrate that ensemble models perform better than both deep learning and linear models for our dataset, achieving highest  $R^2$  score of 0.8251 and accuracy of 74.23% in case of Extra Trees Regressor and Classifier. Furthermore, the ablation study reveals the importance of various attributes present in our dataset, demonstrating the substantial influence of coordinates, geographical proximity, rarity score, and few other economic indicators on parcel price prediction.

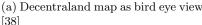
The structure of the rest of the paper is organized as follows: In Section 2, we provide a preliminary background about Decentraland Metaverse platform. In Section 3, we present an overview of previous research endeavors and publicly available datasets in the literature. A detailed description of our proposed dataset is provided in Section 4, emphasizing its composition, sourcing methodology, and inherent attributes. Section 5 conducts an exploratory data analysis, highlighting key insights and patterns in our dataset. Section 6 outlines the empirical results from the performance benchmarking of our dataset using over 20 state-of-the-art price prediction models. Finally, in Section 7, we discuss our key findings and highlight the potential future avenues.

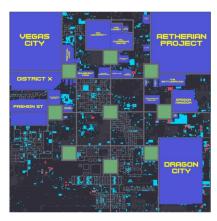
# 2 Decentraland: A Quick Tour

Decentraland [38] is designed as Metaverse, a shared digital universe built on the Ethereum blockchain where users can create, buy, sell and develop virtual real estate and digital assets. The virtual real estate in Decentraland, known as "LAND", is divided into parcels. Each parcel is a unique NFT that can be bought, sold and developed by users. Users have creative freedom to build on their parcels, and the content they create can range from virtual business, events, concert and art galleries to interactive experiences. They can even create customizable avatars to represent themselves as a virtual host in Decentraland. While the primary focus remains on the current parcel offerings, Decentraland aims to streamline and enhance the development process, catering to both novice enthusiasts with its user-friendly drag-and-drop tools and allows land owners rent out their virtual property to other users of the platform for a predefined time which empower users to earn residual income from their Metaverse assets.

Decentral and is meticulously governed by a total of 126 smart contracts, with 101 deployed on the Ethereum network and an additional 25 deployed on the Polygon network. It operates through two primary tokens: LAND and MANA. LAND, a non-fungible digital asset, is a finite traversable 3D virtual space, whereas MANA, a fungible token, is the cryptocurrency associated with the Decentral and to be utilized for purchasing parcels and availing various services within the ecosystem. While MANA is built upon ERC20 fungible token standard, LAND token follows ERC721 standard. Decentral and is divided into parcels with unique cartesian coordinates  $\boldsymbol{x}$  and  $\boldsymbol{y}$  which lies in range







(b) Decentral and map of diverse landscape [49]

Figure 1: Decentral Map

between (-150 to 163) and (-150 to 158) respectively within the Decentraland map. Each parcel size is  $16 \times 16$  m ( $52 \times 52$  ft), are spread across the map with a total of 92,598 identical-sized parcels, as shown in the Decentraland Map in Figure 1. The map shows location of all the parcels including both private owners and themed community districts. The evolution of the maps indicated by the colored keys [49] is as follows:

- PARCELS (Dark Grey): Privately owned parcels available for purchase and sale on the Marketplace. It includes 44480 square spaces.
- DISTRICTS (Purple): Privately owned thematic communities that are not available for sale. It includes 35092 square spaces.
- PLAZAS (Large Green Squares): Designated map areas where player respawns and generate high footfall. Plazas are not for sale. There are total 9 plazas including 3588 square spaces.
- ROADS (Light Grey, Straight Lines): It includes 9438 square spaces and are not for sale.

An association of two or more directly adjacent parcels is called Estate. These parcels must be directly adjacent and can not be separated by a road, plaza or another parcel. At present 2,645 estates of different sizes have been created. Figure 1 presents the Decentraland map showcasing diverse lanscape of districts, plazas, roads, and parcels. The uniqueness of Decentraland parcels stem from their distinctive adjacency feature, setting them apart from conventional web domains. These parcels demand contiguity, facilitating the spatial exploration of content and the establishment of thematic districts. Unlike web domains with boundless hyperlinks, Decentraland parcels possess a finite number of adjacencies, offering content visibility from neighboring parcels at a distance. This structure fosters the creation of districts that attract targeted traffic, allowing users to immerse themselves in themed experiences and engage within vibrant neighborhoods. The constrained availability of parcels amplifies this exploration process, compelling developers to strategically acquire parcel in high-traffic regions, thereby spurring the emergence of secondary markets centered around parcel ownership and rentals.

The value of parcel in Decentral and derives from its adjacency to attention hubs, its capability to host applications, and its role as an identity mechanism. Developers and content creators actively pursue parcel to construct and engage their target audience. Despite the standardized exchange rate (1000 MANA = 1 Parcel) for unclaimed parcels, each one is distinctive, potentially trading at varying prices on the secondary market. This variability is rooted in differences in adjacencies and traffic, reflecting the unique attributes and desirability of each parcel [3].

Decentraland operates several essential smart contracts, including LANDRegistry and MANAToken, which manage LAND and MANA tokens, respectively. Transactions are executed on the Ethereum blockchain mainnet through various smart contracts such as LANDProxy, LANDAuction, and ERC721Bid for parcel transactions, as well as EstateRegistry and EstateProxy for estate transactions. When purchasing parcels, MANA is exchanged by utilizing the MANABurner smart contract, where the burn function is utilized to consume MANA and record the transactions in the LANDRegistry. The Marketplace smart contract on Ethereum facilitates the creation of orders for selling parcels, estates, names, and legacy wearables, while the Polygon smart contract is dedicated to order wearables and emotes.

# 3 Overview of Prior Efforts

There have been number of attempts to solve various research problem related to Decentraland. In this section, we first provide an overview of the existing research efforts addressing various applicative aspects of Decentraland. Then we discuss the details about the Decentraland datasets available so far and their utilities.

#### 3.1 Literature Review

Mitchael Dowling in his early study [14] highlighted the pricing behaviour of Decentral Land NFTs. Interestingly, it is observed that, despite of having a discrepancy of the pricing behaviour in the early stage of market, the value of NFT was continuously on rise. Later, Goldberg et al. [19] identified that the pricing of the NFTs, which has not been considered in [14], is closely linked with the location of the parcels, particularly the locations close to the center part or have some memorable addresses tend to have higher price. Further, Christopher Yencha [53] considered spatial characteristics of Decentral parcels to provide an evidence of the effects of locations on the price, similar to the real estate market.

To map the market trends and the trade network after NFT market experienced a record sale in 2021, Nadini et al. [36] used statistical properties of the market and showed how visual features and sales history are good predictors for the price of Decentraland as well as other NFTs. As cryptocurrency pricing behaviour is an important factor for the market of NFTs, the authors in [15] presented a wavelet coherence analysis between NFT pricing and cryptocurrency. Observably, a spillover index showed only limited volatility transmission effect between cryptocurrency and NFTs.

Rachel Schonbaum in [44] envisioned the possibility of improved market efficiency in Decentraland's LAND market, which in turn has positive implications for NFT usage on the Metaverse. According to them, the NFT-world is likely to change in the next decade, bringing a lot of potential for positive changes in the near future.

Few significant research attempts demonstrating the impact of social media on the pricing of popular NFT's, including Decentraland is reported in [39, 29, 32]. Christian Pinto-Gutiérrez et al. [39] showed how the change in cryptocurrency market (Bitcoin and Ether) draw attention of the investors of NFT's, such as Decentraland and Cryptopunk, by examining the data of Google search trends. A time series analysis on Google trends data of cryptocurrency prices for NFT's is presented in [29]. Junliang Luo et al. [32] performed tweet keyword analysis based on Decentraland along with other top 18 NFT projects, demonstrating the impact of feature word extraction to influence the price of NFTs.

To predict NFT performance by solely relying on images and description, the authors in [8] proposed a multimodal representation based learning by considering Decentral and transactions data along with other NFTs. S.C.Brunet et al. [5] provided a detailed

study to show how the factors related to the revenue-generating potential of the Decentraland parcels are more likely to play a role in its pricing, rather the user traffic on the parcel. J.Luo et al. [33] analysed user behavior in Decentraland using graph analysis technique, along with an examination of the user traffic and transactions. This is observed that interaction in virtual world is different from the traditional social-media platform. Majority of the interaction is based on economic incentive, rather than socializing. Some people even may not wish to join due to the lack of knowledge about blockchain technology.

## 3.2 Available Datasets

Let us mention below the list of publicly available Decentraland datasets.

- Dataset-1 [36]: Nadini et al. created a dataset to give a general overview of NFT market, consisting of 6.1 million trades of 4.7 million NFTs in 160 cryptocurrencies, covering the period between June 23, 2017 and April 27, 2021. The dataset was primarily obtained from Ethereum and WAX blockchains, using various open source APIs: Cryptokitties sales, Gods-unchained, Decentraland, OpenSea and Atomic API. They considered different NFTs and grouped them in six categories, i.e Art, Collectible, Games, Metaverse, Utility and Other. Decentraland was one of the NFT to be grouped in Metaverse category. The Decentraland dataset contains total 16,944 records categorized as: ens-839, estate-1,368, parcel-6,141 and wearable-8,645, sold in between June 2017- April 2021. The attributes of this dataset is depicted in Table 1a. This dataset is suitable for simple regression and classification models for predicting the price and NFT secondary sales (resold chances a NFT) using past history sale and visual features. Since their primary goal was to give an overview of the market, they did not explore other methods such as feature extraction from images and price prediction models.
- Dataset-2 [32]: Unlike previous dataset, Luo et al. explored the relationship between the NFT social media communities and the NFT price in term of the tweet number and the content of the tweets. They collected top 19 NFT token trade transactions and tweets, one of them was the Decentraland transactions data with 2,09,737 records, publicly available in Google BigQuery. Table 1b depicts various attributes of this transaction dataset. This transaction dataset is suitable for time series analysis and machine learning models for predicting the influence of social media (Twitter) on NFT market price.
- Dataset-3 [28]: This is Decentraland NFT Virtual Estate dataset including NFT land price and features, which is publicly available on Kaggle. The data is categorized into various estates according to their features depicts in 1c. Few notable use of this dataset includes price prediction of Land NFTs and Decentraland token, finding most profitable land based on their features, and so on. However, this collection is limited to only 1,999 records with highest sales count and less number feature for a perfect analysis. Kaggle has not mentioned about any study that uses this dataset for analysis.
- Dataset-4 [41]: This is a social media dataset which contains total 3,481 users' comments about Decentral NFTs on Reddit and is publicly available on Kaggle. Even though this dataset is not being used by any researcher yet, we believe that it would be appropriate for analyzing the impact of social media on the price of Decentral NFTs. The attributes of the dataset is depicted in Table 1d.

A comparative summary of the existing related datasets and the proposed IITP-VDLand are shown in Table 2.

#### 3.3 Why New Dataset?

The existing datasets, as discussed earlier, lack a comprehensive representation of records and attributes necessary for analyzing the multifaceted impact of various factors

Table 1: Publicly Available Decentraland datasets

#### (a) Skeleton of Dataset-1

#### (b) Skeleton of Dataset-2

Column	Description	Column	Descrip
name		name	
id	Unique ID for a given NFT	address	This is t
category	Category in which NFT belongs to.	is_erc 721	Ethereun
nft	Details about the NFT with their unique		standard
1116	ID, token ID, contract address, token		to repres
	URL, name (if they have any), image link	is_erc 20	Ethereun
	in PNG.		standard
	Search order history, search parcel his-		represent
	tory, coordinates, estate size, search wear-	from_address	It is a wa
	able history.		the funds
nftAddress	Unique address of the NFT	to_address	It is a w
txHash	Transaction Hash that is generated when-		wallet fu
	ever transaction is performed.	value	It is repr
owner	Owner ID for the given NFT		est
buyer	Buyer ID for the given NFT	transaction	It is the u
price	Price of the NFT	hash	action
status	Information about the status of the NFT	transaction	It is the
	whether it was sold or not	value	
block	It is a numerical value used to desig-	hash	It is the
Number	nated the order of a block added to the	log_index	Use to id
	blockchain.	block times-	It is the
expiresAt	The time when the NFT expired	tamp	plete inf
createdAt	The time when the NFT created		minutes
updatedAt	The time when the NFT updated		block wa

Description
This is the unique address of an NFT
Ethereum request for comment is a data
standard for creating non-fungible token
to represent digital assets
Ethereum Request for comment is a data
standard for creating fungible token to
represent a variety of assets
It is a wallet address to show from where
the funds were sent
It is a wallet address to show to which
wallet funds were sent
It is represented as a token ID of the ass-
est
It is the unique identifier(ID) of the trans-
action
It is the price of the asset in Eth or wei
It is the hash function for a given NFT
Use to identify unique events logs
It is the Unix timestamp that has com-
plete information about dates, hours,
minutes & seconds(in UTC) when the
block was created

# (c) Skeleton of Dataset-3

#### (d) Skeleton of Dataset-4

Column	Description
name	<del>-</del>
contract address	Contract address is a unique address allocated when a smart contract is deployed.
Token_id	A Token ID is the unique identifier code for an NFT
sales_price	The price at which an NFT being sold
timestamp	Timestamp represents the Unix timestamp and ensure accurate and reliable transaction record
owner_id	Current owner (buyer) unique identifier code for a given NFT
bids_count	A list of total number of bids that determining the price a user willing to pay to buy an NFT
sales_count	This is the count of how many time an NFT has been sold
parcels_list	This List has the coordinates of parcels
parcels_cour	t This list consist a LAND NFT's total number of parcels count
status (la- bel)	It shows the label if a piece of land is parcels, road or a plaza
adjacency [road, district, plaza]	The smallest distance of parcel to a road, district and plaza
coordination	- A mean estimation of parcel coordinates
est	in parcel list
mana_price	Mana token (Decentral and project's base currency) value at the moment of transaction
land_price	The price of a Land NFT obtained by the product of mana price and sales price in USD

Column	Description
name	
submission	A list of user IDs to post or comment on
	Reddit
subreddit	Category within Reddit to focus on a spe-
	cific topic
author	The username who post a content in sub-
	reddit
created, re-	Unix timestamps of creation, retrieval,
trieved and	and modification respectively
edited	
pinned	Whether a post gets pinned by the com-
	munities as information aggregators
archived	Indicates how many posts are being
	archieved.
locked	Whether the post is locked.
removed	Whether removed by the automoderator,
	or the spam filter, or by the Reddit entity
deleted	whether deleted by the user.
is_self/	whether the submission is in a text/video
is_video	format
is_original	Whether the submission is set as original
content	content
title	The title of the submission
link_flair_text	Text content which acts as a link flair for
	a submission
upvote_ratio	The percentage of upvoted from all votes
	on the submission
score	The number of upvotes for the given sub-
	mission
gilded	Represents overall count of gilded awards
	on submission
total_awards	The number of awards received by the
received	submission
num_comment	,
crossposts	crossposts on the submission.

on parcel dynamics within Decentraland. While dataset-1 and dataset-3 provide limited insights, focusing solely on parcels sales activities, dataset-2 and dataset-4 are designed to explore the influence of social media on the parcels prices. The comparative summary in Table 2 underscores the inadequacies of these existing datasets and underscores the

Table 2: Comparison Between Existing and Proposed Datasets

Dataset Source(s) Record(s)		Pagord(s)	Attribute (s)						Attributes Count	Social Media
			Geographical Proximity	Rarity Score	Visual Link	Sales Data	Offers Data	Ethereum Transactions Data	Attributes Count	Data
Dataset - 1 [36]	Decentraland	Decentraland Parcel: 6141	0	×	· ·	~	×	×	37	×
Dataset - 2 [32]	Google BigQuery, Twitter	Decentral Tweets: 51692 Decentral Transactions: 209737	×	×	×	×	×	•	11	~
Dataset - 3 [28]	Ethereum Blockchain Decentraland	Decentraland Parcel: 1999	•	×	×	•	0	×	14	×
Dataset - 4 [41]	Reditt, Pushshift	Comments: 3481	×	×	×	×	×	×	-	~
HTP-VDLand (Proposed)	Decentraland, OpenSea, Google BigQuery, Etherscan, Discord, Telegram, Reddit	Parcel's Characteristics : 92598 Parcel's OpenSea Sales : 20092 Parcel's OpenSea Offers : 2246545 Parcel's Ethereum Biddim; : 40566 Parcel's Ethereum Sales : 20092 Parcel's Other Activity Transactions : 202136 Social Media : 317801	V	~	V	V	V	V	81	V

(Note: ♠) = Partially Available, ✓ = Available, × = Not Available, - = Not mentioned)

need for a more encompassing dataset.

In order to address this gap, a dataset related to Decentral is invaluable as it serves as a comprehensive repository of information crucial for understanding virtual land market dynamics, facilitating asset valuation and investment analysis. However, assembling such a dataset poses significant challenges due to fragmented information scattered across diverse sources, making it difficult to obtain a holistic view of Decentral and's past and present.

Our study addresses this challenge by introducing the IITP-VDLand dataset, a novel and comprehensive resource dedicated to Decentraland's Parcel NFTs. As delineated in Table 2, our dataset incorporates several pivotal features, including:

- Rarity score: A metric quantifying the uniqueness of NFTs within a collection, influencing users' purchasing decisions.
- Geographical proximity: Detailing the spatial relationships between parcels, providing insights into clustering and neighborhood dynamics.
- Blockchain- and transaction-specific details: Offering a granular understanding of transaction histories and blockchain attributes, crucial for discerning patterns and behaviors.
- Comprehensive activity tracking: Enabling a complete view of all transactions and activities within Decentraland parcels, facilitating deep-dive analyses into specific events and trends.

To enhance usability across diverse applications, we segment the dataset according to various criteria, tailoring it to meet specific analytical needs. This segmentation facilitates targeted analyses and promotes wider adoption across the Decentraland community and beyond.

## 4 Our Dataset: IITP-VDLand

In this section, we present IITP-VDLand, an expansive dataset of Decentraland's parcel NFTs, which are gathered from diverse sources such as Decentraland [38], OpenSea [17], Etherscan [50], Google BigQuery [20], Discord [13], Telegram [51], and Reddit [42]. This dataset serves as a robust resource for training machine- and deep-learning models specifically designed to address real-world challenges within the domain of Decentraland NFTs.

In our data collection process, we harness all possible relevant data sources and APIs to collect and compile our dataset. In particular, we obtain parcels metadata using *Decentraland API 'tiles'* [12] and 'parcels' [11] which offers an up-to-date characteristics information, such as unique Id, name, coordinates, geographical proximity, rarity score, and visual link about each parcel. For a deeper understanding of lands' sales history and offers received, we seamlessly integrate the *OpenSea API 'Get Events (by NFT)'* [17], which covers temporal perspectives. Tracking gas prices, a pivotal aspect in Ethereum transactions, is facilitated through *Google BigQuery* [20], supplying information on Decentraland transactions' costs. Additionally, to extract essential details regarding the activities initiated through these transactions, we leverage *Etherscan* [50], which contributes to a well-labeled dataset. Subsequently, we expand our data

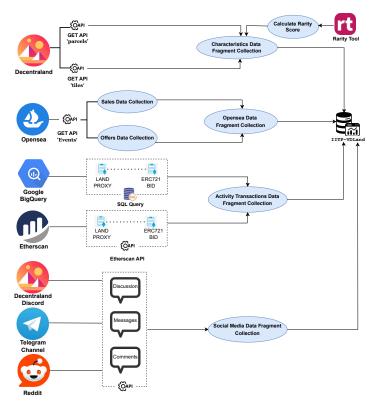


Figure 2: Overview of Data collection process

scope to prominent social media platforms, including *Discord* [13], *Telegram* [51], and *Reddit* [42]. We systematically collect individuals' comments and opinions pertaining to Decentraland providing invaluable insights within the online community. Our thorough data collection process ensures that IITP-VDLand is well-equipped to support diverse analytical and predictive endeavors within the Decentraland virtual ecosystem. A global overview of our data collection process and its corresponding pseudoalgorithm are shown in Figure 2 and Algorithm 1, respectively.

Our dataset comprises 92,598 parcels, serving as a rich source for analysis. Among them, 9,220 parcels are linked with historical sales data which creates a valuable time series encompassing 20,092 records. In connection with these parcels, we collect in total 2,62,423 records from both Google BigQuery and Etherscan, out of which 40,195 records represent bidding information, 20,092 records represent sales information, and 2,02,136 records represent other activities (such as minting, creating estate, claiming rewards, delisting parcels, etc.) over the Decentraland. Apart from these, we also collect 3,17,801 pieces of content from social media platforms that provide valuable information to predict the rise and fall of demands in parcel pricing. Furthermore, the dataset contains a substantial 22,46,545 records of offer information associated with these parcels, enabling an unrestricted examination of buying and selling activities within the OpenSea marketplace.

According to the nature of information linked to the parcels, we divide our dataset into the following four segments:

- 1. Characteristics Data-Fragment
- 2. OpenSea Trading History Data-Fragment
- 3. Ethereum Activity Transactions Data-Fragment
- 4. Social Media Data-Fragment

A high-level view of various data-fragments and their relations in our dataset is depicted

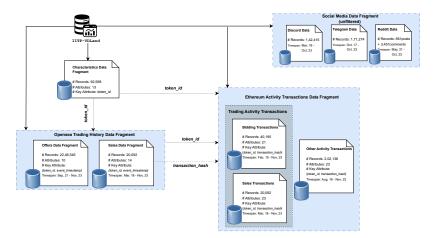


Figure 3: Highlevel view of different data-fragments and relations

in Figure 3. Let us now delve into the details of each of the fragments.

#### Algorithm 1 Data Extraction Pseudoalgorithm

Input: token\_id, smart\_contract, transaction\_hash, keyword

Output: parcels details, transactions details, texts

- {ids, type, coordinates} ← Decentral and . GetTiles()
- {name, description, point\_of\_interests, image\_link } 

  Decentraland.GetParcels(coordinates)
- {rarity\_score} ← Rarity.tools(coordinates, point\_of\_interests)
- 4: Characteristics Data← {ids, type, coordinates} ∪ {name, description, point\_of\_interests, image\_link }  $\cup$  {rarity\_score}
- 5: offers-details← OpenSea.GetEvents(token\_id, "offer")
- 6: sales-details← OpenSea.GetEvents(token\_id, "sale")
- OpenSea Trading History← offers-details ∪ sales-details
- {transaction\_hash, block\_details, addresses, Txnfees, status, ErrCode, method }← Etherscan(ERC721Bid Smart Contract)
- $\{transaction\_details, \ gas\_details, \ token\_id, \ input, \ duration\} \leftarrow \ \texttt{EtherscanAPI.GetABI}(ERC721Bid \ Smarter and Sma$  $Contract) \, \cup \, \mathtt{web3.eth}(GetTransaction, \, contract.decode\_function\_input)$
- {transaction\_details, block\_details, gas\_details, addresses, token\_id, method, GoogleBigQuery.runSQL(LANDProxy Smart Contract)  $\cup$  Etherscan(LANDProxy Smart Contract) 10: {transaction\_details,
- $11. \ \textbf{Ethereum Activity Transactions} \leftarrow \{\text{transaction\_details, block\_details, gas\_details, addresses, token\_id, addresses}\}$
- 12: {id, text\_content, author\_details, timestamp} \leftarrow \texttt{DiscordAPI}() \cup \texttt{RedditAPI}() \cup \texttt{TelegramAPI}()
- 13: Social Media Data← {id, text\_content, author\_details, timestamp}
  14: IITP-VDLand← Characteristics Data ∪ OpenSea Trading History ∪ Ethereum Activity Transac $tions \cup Social Media Data$

#### 4.1 Characteristics Data-Fragment

Our data collection journey commence with the utilization of the Decentral API 'tiles' [12] which furnishes us with a broad range of information covering essential characteristic attributes of total 92,598 virtual parcels. These attributes include unique Id, name, coordinates, owner-ID, etc. The proximity of a parcel to significant locations and landmarks within the Decentraland virtual world is a crucial aspect for many users, influencing its demand and supply. Keeping this in mind, we gather geographical proximity corresponding to these points of interest by using the Decentral API 'parcels' [11]. Furthermore, we add an important parcel attribute, called Rarity score, which refers to the degree to which a particular digital asset is unique or scarce within a specific collection or series of NFTs [1]. While all parcels are inherently unique, their trade value can vary significantly based on this rarity factor.

We measure rarity score for our collections by applying one of the most popular rarity meter, namely Rarity.tools [40]. This computes individual scores for all traits (features) and provides the resulting rarity as their sum, defined below:

Total Number of Items in Collection  Observe that Rarity.tools is suitable for our data as it also considers all none traits present, whereas many of the other rarity score meters [45] tend to overlook none traits. Interestingly, the higher the Rarity score is, the rarer the asset is.

**Attribute Details.** Below we outline the list of attributes with their respective details linked to this parcels' characteristics data-fragment:

- token\_id: This is the unique id given to every parcel.
- name: This is the name of the parcel given by the owner, default name is its coordinates.
- x, y: This is the coordinate of the parcel, where  $x \in [-150, 163]$  and  $y \in [-150, 158]$ .
- type: This is the division of the parcel into district, owned, plazas, and road.
- estate\_id: This is the unique id given to an estate(collection of parcels).
- owner\_id: This is the unique address of the owner.
- description: This is the description of the parcel given by the owner.
- updated\_at: This is the timestamp mentioning the last activity performed at that parcel.
- image\_link: This is the link of the image of a given parcel.
- DistanceToDistrict: This is the distance, measured in terms of the number of parcels away, from the nearest District. Observe that the value 10 indicates that the distance of the parcel is *greater than or equal to* 10.
- DistanceToRoad: This is the distance of a parcel from the nearest Road. This is measured in the similar way as of 'DistanceToDistrict'.
- DistanceToPlaza: This is the distance of a parcel from the nearest Plaza. This is measured in the similar way as of 'DistanceToDistrict'. As Plaza is always surrrounded by roads the minimum distance is 1.
- rarity\_score: This is the attribute indicating rarity score of a parcel.

#### 4.2 OpenSea Trading History Data-Fragment

In our relentless pursuit of historical trading data within Decentral and ecosystem, we use the OpenSea API 'Get Events (by NFT)' [37]. This API allows us to delve deeper into the current market dynamics of parcels, gathering historical data about the bids and sales of parcels among the sellers and buyers. The process of trading Decentral and parcels commences with sellers listing their parcels on the market place, specifying the initial price. Then, interested buyers place bids during a specified auction duration and at the end of the auction, the highest bid wins the right to purchase the parcel. This entire sale process is facilitated by a local smart contract hosted on OpenSea network, which supports several tasks such as the transfer of ownership, release of payment, and verification. Therefore, we divide this trading data-fragment into two parts, as follows:

#### 4.2.1 Offers Dataset:

This critical data furnishes us with information about the offers proposed during the bidding process of parcels by the potential buyers. It is worthwhile to note that, while offering prices signify buyer interest, they don't guarantee successful sales. The dataset at hand is tied to OpenSea and exists within the off-chain domain of Ethereum. OpenSea employs a smart contract, named as 'seaport', to empower users to offer prices for any parcels. OpenSea doesn't follow staking of bidding amount and hence save user from paying transaction fees and staking ether. The 'confirmation of bid' is a wallet signature (EIP-712) necessary to make the process trustless. No one will be able to steal tokens by forging offers. This unique functionality of this seaport automatically execute sales when a user secures the highest bid. This off-chain dataset, encapsulates the dynamic interplay of user-initiated bids, the pricing mechanism, and the automated execution of sales, offering a far-reaching snapshot of trading activities within the OpenSea marketplace. As a result, there are a total of 22,46,545 offer records corresponding to 92,593 parcels spanning over a time period from September 04, 2021 to November 03, 2023.

**Attribute Details** Below we outline the list of attributes with their respective details linked to this parcels' offers received:

- token\_id: This is the unique id given to every parcel.
- event\_timestamp: This is the timestamp when the bid was offered.
- bid\_amount: This is the specific amount that a bidder is willing to pay for the parcel.
- starting\_price: This is the minimum bid amount required for participants to enter the auction.
- ending\_price: This is the highest bid at which the parcel is sold when the auction concludes.
- payment\_token\_symbol: This is the payment token in which parcel was bid which includes MANA, ETH, USD, and WETH.
- decimals: This is the number of decimal places corresponding to given payment token to be used while calculating the price in USD or ETH  $(10^{-decimals})$ .
- eth\_price: This is the exchange rate of the payment token to Ether at the time of bid
- usd\_price: This is the exchange rate of the payment token to USD at the time of bid.
- from\_account: This is the address of the sender of the transaction.

#### 4.2.2 Sales Dataset:

This dataset offers a complete historical sales details of the parcels which are sold atleast once. As mentioned earlier, out of 92,598 parcels, only 9,220 parcels belong to this category comprising a total of 20,092 sales-records over a time period March 19, 2018 to November 03, 2023. This information plays a crucial role in several applications such as forecasting the prices of next sale of the parcel, finding out the probability of a parcel to be sold again, understanding temporal patterns of resale, average number of days it takes for the parcels to be resold, tracking price fluctuation over time, identifying recurring behaviors of any user or any particular parcel over a time period, etc. Since there exists a correspondence between the Offers dataset and the Sales dataset, one can relate these two datasets through the common attribute 'token\_id' and 'event\_timestamp'.

**Attribute Details** Below we outline the list of attributes with their respective details linked to this parcels' sales data:

- token\_id: This is the unique id given to every parcel.
- listing\_time: This is the time when the current parcel was listed.
- auction\_type: This categorizes the auctions of the parcels into the following two categories: English Auction (which offers the sales to the highest bidder) and Dutch Auction (where the value declines until a buyer emerges).
- event\_timestamp: This is the timestamp when the sale occurred.
- sale\_price: This is the numerical value at which the parcel was sold.
- payment\_token\_symbol: This is the payment token in which parcel was sold, which includes MANA, ETH, USD, and WETH.
- decimals: This is the number of decimal places corresponding to given payment token to be used while calculating the price in USD or ETH  $(10^{-decimals})$ .
- eth\_price: This is the exchange rate of the payment token to Ether at the time of transaction.
- usd\_price: This is the exchange rate of the payment token to USD price at the time of transaction.
- from\_account: This is the address of the sender of the transaction.
- to\_account: This is the address of the receiver of the transaction.
- transaction\_hash: This is the unique hash of the transaction.
- seller\_address: This is the address of the seller.

• winner\_address: This is the address of the winner of the auction.

## 4.3 Ethereum Activity Transactions Data-Fragment

As we delve into the transactions associated with Decentraland parcels, which operates on the Ethereum blockchain, our focus turn towards extracting relevant information from the transaction dataset available on Etherscan [50] and Google BigQuery [20]. Etherscan is a popular and widely used blockchain explorer and analytic platform specifically designed for the Ethereum blockchain. It provides a range of tools and services to explore, analyze, and interact with the Ethereum blockchain, making it an invaluable resource for Ethereum users, developers, researchers, and enthusiasts. Google BigQuery, on the other hand, is a high-performance and scalable platform for querying and analyzing vast datasets. To this aim, we consider the following two smart contract addresses [10] deployed on the Decentraland mainnet, particularly linked with the parcels related services, and we extract all relevant transactions from both Etherscan and Google BigQuery:

- 1. ERC721Bid: 0xe479dfd9664c693b2e2992300930b00bfde08233
- $2. \ LANDProxy: 0xf87e31492faf9a91b02ee0deaad50d51d56d5d4d$

'ERC721Bid' smart contract facilitates auction based transaction for parcels, allowing users to place bids, withdraw bids, and finalize auctions whereas 'LANDProxy' smart contract acts as an intermediary for parcel ownership and management within Decentraland, providing a standardized interface for interacting with parcels and enabling various functionalities such as transfers, estate creation, and access control. Our SQL query is meticulously crafted to target and extract intricate transaction details associated with the Decentraland ecosystem, utilizing addresses mentioned earlier. We subdivide our collected data into three distinct components: bids, sales and other associated transactions of the parcels. By segregating the data in this manner, we aim to facilitate targeted analysis of each facet of the trading ecosystem. This data fragment primarily contains transaction- and blockchain-specific information, including transaction-hash, block-number, log-index, gas consumption, services provided, etc. This acts as an important data resource for the development of AI tools for applications such as predicting users activity trends, correlation between gas price fluctuation and parcels' price dynamics, periods of increased or decreased transaction volume, anomaly detection, and many more.

#### 4.3.1 ERC721Bid Dataset

This transaction dataset is the on-chain bids received by the parcels that serve as a real-time reflection of market sentiment and demand. The whole bidding process is initiated by invoking the 'placeBid' function on the Bids-contract and the parcel owner has the authority to accept any active bids, provided they are not expired, and the bidder possesses sufficient amount for the transaction. To approve a bid, the asset owner needs to transfer the parcel to the Bids-contract using the 'safeTransferFrom' function of the parcel contract, including additional data containing details of the accepted bid. Upon receiving the parcel, the Bids-contract verifies in its on 'ERC721Received' function that the bid is still valid, and the bidder has adequate funds. If all conditions are met, the parcel transfers to the bidder, and the caller of the 'safeTransferFrom' function is compensated with the declared amount from the bid. This dataset holds paramount importance in determining fair market values, establishing competitive pricing strategies, assessing bid success rates, gauging parcel popularity, and more. As a result, there are a total of 40,195 bid records spanning over a time period from February 26, 2019 to November 03, 2023.

**Attribute Details** Below we outline the list of attributes with their respective details linked to the transaction data associated with the contract address of 'ERC721Bid':

- transaction\_hash: This is the unique hash of the transaction.
- transaction\_index: This is the integer of the transactions index position in the block.
- transaction\_type: This is the transaction type (0 = Regular Transactions, 1 = Contract Creation, 2 = Contract Interaction).
- from\_address: This is the address of the user or entity initiating the interaction with the smart contract for token transfer operation.
- to\_address: This is the address of the receiver of the token transfer operation.
- token\_id: This is the unique id given to every parcel.
- block\_timestamp, block\_number, block\_hash, nonce: These are the block-specific information where the transaction is stored.
- value\_in\_wei: This is the value transferred in Wei.
- gas: This is the gas fee provided by the sender.
- gas\_price: This is the gas price provided by the sender in Wei.
- TxnFee (ETH), TxnFee (USD): These are the total costs including gas and priority fee incurred by a user for executing a transaction in Ether and USD, respectively.
- historical\_price (USD/Eth): This is the historical price of Ether in terms of USD at the time of each respective transaction.
- status: This is the status of the transaction. Observe that empty cells indicate success.
- ErrCode: This is the error reason for unsuccessful transactions like bad instruction, out of gas, reverted, execution reverted.
- duration: This is the duration until which the bid is valid.
- method: This is the activity performed by the transaction.
- input: This is the data sent along with the transaction.

#### 4.3.2 LANDProxy Dataset

This dataset is extracted using the smart contract address 'LandProxy'. It contains all the activities related to parcels ranging from create estate, transfer land, execute order, claim rewards and many more. In order to separate the sale dataset, the transaction\_hash of this dataset is matched with the sales dataset of *OpenSea* to maintain the uniformity that includes 20,092 sales records of 9,220 parcels. This sale process is initiated through the 'createOrder' function, once an order has been created on-chain, the asset will be listed for sale so that any user can buy it. This order is executed by calling the 'executeOrder' function in the marketplace smart contract and then the exchange of amount and parcel take place between the two users. The rest 2,02,136 records are considered as other activities till November 03, 2023.

**Attribute Details** Below we outline the list of attributes with their respective details linked to the transaction data associated with the contract address of 'LANDProxy':

- log\_index: This is the log index in the token transfer receipt.
- from\_address\_b: This is the source address of all transactions in a block.
- to\_address\_b: This is the target address of all transactions in a block. It shows null when its a contract creation transaction.
- max\_fee\_per\_gas: This is the total gas fee that covers both base and priority fees.
- max\_priority\_fee\_per\_gas: This is the fee given to miners to incentivize them to include the transaction.
- receipt\_cumulative\_gas\_used: This is the total amount of gas used when this transaction was executed in the block.
- receipt\_gas\_used: This is the amount of gas used by this specific transaction alone.
- receipt\_effective\_gas\_price: The actual value per gas deducted from the senders account.

Observe that, in addition to the above attributes, there are some common transaction-

and block-specific attributes, similar to the 'ERC721Bid Dataset'.

# 4.4 Social Media Data-Fragment

Social media platforms, with their extensive reach and influential presence, have become pivotal in shaping the pricing dynamics of Decentraland parcels. Community engagement and hype are among the primary ways in which social media impacts parcel pricing. Platforms such as Discord [13], Telegram [51], and Reddit [42] serve as gathering points for Decentraland enthusiasts, facilitating discussions, showcasing insights, opinions regarding the latest trends, developments, and market movements within Decentraland. As these communities expand and interact, they generate excitement around specific collections, driving up demand and consequently influencing their prices. To gain deeper insights into parcel pricing movements, we gather data from the aforementioned platforms by accessing their APIs. The data spans from October 20, 2017 to October 28, 2023, encompassing discussions, comments, and posts related to the parcels. In total, we collect 3,17,801 pieces of content that could provide valuable information for understanding the various impacts on parcel pricing.

# 5 Exploratory Data Analysis

In this section, we provide an insightful information about the intricate patterns, relationships, and characteristics inherent in our dataset. As mentioned earlier in section 2, the map of Decentraland is subdivided into different point of interests: Districts, Plazas, Roads, and Parcels. We analyze the relationship between the distances of parcels from the point of interests, exploring their impact on the number of sales. In Figure 4, it is evident that the majority of parcels are situated at a considerable distance from their respective point of interests. However, when evaluating the percentage of sales, it indicates that users exhibit a tendency to acquire parcels in closer proximity to various landmarks resembling the real estate world.

In Figure 5, we conduct time series analysis on the value of parcels over the time. The highest sale value of \$784,124.0 was reached in 2018, but there is a constant decrease in the value of parcels throughout the subsequent years. It is likely to be influenced by a combination of market factors, platform developments, economic conditions, and changes in user behavior and preferences.

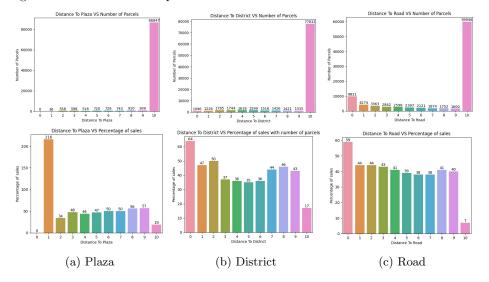


Figure 4: Comparison of number of parcels and percentage of parcels sold with respective distances to geographical proximity

To understand the interest of people, we examine the number of user activities and

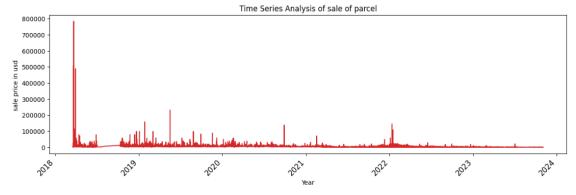


Figure 5: Sale Price History of Decentraland parcels

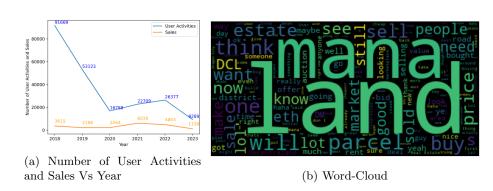


Figure 6: Impact of user activities on sale and the Buzz-words of Decentraland

sales over the years, and we extract the buzz words centering around Decentraland. We can see in Figure 6a, there is a sharp decline in user-activities from 2018 to 2020, which eventually impact the number of sales. In contrast, during pandemic (2020 to 2022) the significant surge in the popularity of virtual worlds leads to the demand for parcels, contributing to the evaluation of Decentral and. However, as the world opened up, the interest to buy parcel is decreased in 2023 (till November 3, 2023), prompting the downfall in demand that describes the high volatility. Notably, social media discussions play a crucial role in shaping parcel pricing. Figure 6b specifically focuses on discussions within Discord channels, showcasing the enthusiasm and hype among enthusiasts regarding land-related topics. This underlines the impact of social media engagement on the dynamics of parcel pricing. Our dataset also uncover that 100 seller addresses initiate and transfer transactions, with nearly 8,280 receipt addresses. This presents an opportunity to conduct a study on the network dynamics and interconnections among these addresses, similar to [36], but specifically tailor for Decentraland parcels. In our dataset, 4,150 parcels are sold only once between 2018-2023, while 5,070 parcels are resold twice or more. Further analysis is required to identify the tendency of a parcel to be resold multiple times. While there are numerous potential analyses that could provide valuable insights into the Decentral and ecosystem, we have chosen to focus our efforts to showcase the practical applications of our dataset in the next sections. By applying machine- and deep-learning approaches, we aim to demonstrate the importance and usefulness of our dataset through tasks such as price prediction and binary classification of parcels. This targeted approach allows us to highlight the rich information encapsulated within our dataset, shedding light on various dynamics within the Decentral ecosystem.

# 6 Benchmark Evaluation: Parcels valuation and pricing

In our benchmark, we consider a diverse range of state-of-the-art price prediction models, encompassing both regression and classification tasks across various NFTs and cryptocurrencies. Table 3 presents a brief summary of these models. Our primary objective is to utilize these baseline models to evaluate their performance on our proposed dataset. While we adopt regression task aiming at predicting the price of Decentraland parcels, the classification task enables us to assess the likelihood of parcels for being resold. The experiments are conducted on a system equipped with Intel core i5  $10^{th}$  gen CPU with Windows 10 Pro operating system, 16GB of RAM and a 256GB SSD.

#### 6.1 Data Preprocessing

In order to evaluate the models on our proposed dataset, we seamlessly integrate the characteristics and OpenSea sales data fragment based on 'token.id' and 'last sale price' of parcels, with the latter being designated as the prediction target. From the total 92,598 parcels, only 9,220 parcels are identified as being sold at least once. These selected parcels are then merge with the Ethereum activity transactions data fragment, utilizing the 'transaction\_hash' to incorporate the gas price incurred during the trading. The parcel price and gas price associated with each transaction are converted to USD, shedding light on the effective transaction costs incurred in the buying and selling of parcels. To streamline our experiments, we exclusively retain numerical features, eliminating irrelevant attributes containing text, links, IDs, and dates. The refined set of features primarily includes coordinates, geographical proximity to the points of interest, exchange rates in USD and Ether for the payment tokens, gas fees, calculated rarity scores and the most recent sale price of the parcels. As depicted in Figure 5, the prices of parcels in our dataset exhibit significant volatility. To mitigate the influence of outliers, we adopt the outlier removal methodology outlined in [30]. Specifically, we categorize the dataset into four tiers based on asset value: 'Extreme' (greater than \$100,000), 'High' (exceeding \$10,000), 'Mid' (falling between \$1,000 and \$10,000), and 'Low' (below \$1,000). This results 147 assets in the low-value category, 8,391 in the mid-value range, 673 classified as high-value assets, and 9 identified as extreme-value assets. Subsequently, we opt to disregard extreme, high-, and low-value assets as outliers, focusing solely on mid-value assets as a more representative set of the data. Following this, we perform normalization of the target price through Min-Max scaling [43, 16], according to the following equation:

$$X_{std} = \frac{X - X.min(axis = 0)}{X.max(axis = 0) - X.min(axis = 0)}$$

$$\tag{1}$$

$$X_{scaled} = X_{std} * (max - min) + min$$

Furthermore, motivated from the findings in [18, 48], we expand our analysis by integrating crucial external data, which act as economic indicators [24, 21], including Ether-, Bitcoin-, Crude oil-, Gold-prices and Google trend, which has already been proven to have a significant impact on the NFT marketplace. This strategic feature selection process aims to maintain focus and potentially enhance the accuracy of predictions by aligning with the critical factors influencing pricing dynamics within our dataset.

## 6.2 Performance Metrics

As the target variable is price, a continuous variable, we have chosen several regression evaluation metrics to validate our experimental results. These include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE),  $R^2$  score, Root Mean Squared Log Error (RMSLE), and Mean Absolute Percentage Error

Table 3: Brief summary of the state-of-the-art price prediction models for NFTs and cryptocurrencies  $\frac{1}{2}$ 

Ct -t C	G. L. C. L. N. L. D. C. C.					
State-of- the-Art	Year	Brief Summary	ML/DL models used			
proposals						
Henriques et	2023	Forecasted NFT coin prices using machine	Random Forest, Extremely			
al. [22]	2025	learning approach.	Randomized Trees, Tree			
[]			Boosting, SVM, Lasso, Naive			
			Bayes			
Seabe et al.	2023	Forecasted cryptocurrency prices using deep	LSTM, GRU, Bi-Directional			
[46]		learning approach.	LSTM			
Z. wang et al.	2023	Predicted NFT sale price fluctuations on	AdaBoost, Random Forest			
[52]		OpenSea.				
Brunet et al.	2023	Explored different Metaverse platforms and	Spearman correlation, XG-			
[5]		created an analysis tool using machine learn-	Boost			
D 1 4 1	2000	ing model.	I LIGDIA GAD A VO			
Dawod et al.	2023	Evaluated machine learning algorithms to ap-	LightGBM, CatBoost, XG-			
[9]		praise NFT real-price based on characteristics, market event information, and rarity score.	Boost, RF, TabNet, Polynomial, LR, SVM, Ridge, Lasso,			
		market event information, and rarity score.	ElasticNet			
J. Luo et al.	2023	Demonstrated NFT price movement through	Support vector machine, multi-			
[32]	2020	tweets keywords analysis.	layer perceptron, Transformer			
Ghosh et al.	2023	Predicted and interpreted NFT and DeFi	Isometric mapping - GBR, Uni-			
[18]		prices through ensemble machine learning.	form manifold approximation			
			and projection - RF, Decision			
			Tree, Support Vector Regres-			
			sor, ARIMA, SARIMA			
Kin-Hon-Ho	2022	Highlighted the intricate interplay between	XG BOOST			
et al. [23]		rarity and utility in determining prices of play-				
Branny et al.	2022	to-earn gaming NFTs on Axie Infinity.  Forecasted NFT sale prices using multiple	Linear Regression, Decision			
[4]	2022	multivariate time series datasets containing	Tree, Bayesian Ridge, LSTM			
[+]		features related to the NFT market space.	Tree, Bayesian Riage, Borni			
Kapoor et al.	2022	Predicted NFT asset value with Twitter and	Logistic Regression, SVM,			
[30]		OpenSea Interaction Analysis.	Random Forest, Light gbm,			
			XG Boost			
Jain et al. [25]	2022	Examined the correlation between NFT valua-	RNN, Linear Regression			
		tion and various features: market data, meta-				
NT 1: 1 1	0001	data and social trends data.	T: D : All :			
Nadini et al. [36]	2021	Analyzed market trades to predict NFT sales using simple machine learning approach.	Linear Regression, Adaboost, PCA, AlexNet			
Chen et al. [6]	2020	Considered the sample's granularity and fea-	Logistic Regression, Random			
Chen et al. [0]	2020	ture dimensions for Bitcoin price prediction.	Forest, XGBoost, LSTM, SVM			
JAY et al. [27]	2020	Introduced a stochastic module to capture	MLP, LSTM			
		markets' reaction and observed feature activa-	,			
		tions of neural networks to stimulate market				
		volatility.				
Felizardo et al.	2019	Comparative study of Bitcoin price prediction	ARIMA, SVM, Random Forest,			
[16]	2010	using different machine learning approach.	LSTM, WaveNets Linear Regression, Random			
Saad et al. [43]	2019	Built a machine-learning model to analyze the market of cryptocurrency for highly accurate	Linear Regression, Random Forest, Gradient Descent			
[±0]		prediction.	Torest, Gradient Descent			
Lahmiri et al.	2019	Detected chaos and fractal characteristics	LSTM, GRNN, LLE, DLNN			
[31]		along with LSTM to predict price of cryp-	, ,,			
' '		tocurrencies using the largest Lyapunov Expo-				
		nent (LLA) and Detrended Fluctuation Anal-				
		ysis (DFA).				
Mcnally et	2018	Predicted price of Bitcoin in USD.	RNN, LSTM, Arima			
al.[34]	0016	A (	VOD / DANI LOTA			
Laura et al.	2018	Anticipated the short-term evolution of the	XGBoost, RNN, LSTM			
[2]		cryptocurrency market using two ensemble models of regression trees.				
JANG et al.	2017	Predicted Bitcoin price using BNN, based on	BNN, Linear Regression			
[26]	2011	blockchain information.	Divir, Ellical Regression			
Sin et al. [47]	2017	Explored the dependencies of next day price	MLP, GASEN			
		on Bitcoin features.	<u> </u>			
			•			

(MAPE) [error metric]. Let  $y_i$ ,  $\hat{y}_i$ ,  $\bar{y}$ , N be the actual value, predicted value, mean value, and the number of observations, respectively.

MAE is a risk metric corresponding to the expected value of the absolute error loss

which is also known as L1 norm loss is define as:

$$MAE = \frac{\sum_{i=0}^{N-1} |y_i - \hat{y}_i|}{N}$$
 (2)

MSE (Mean Squared Error) is a risk metric that corresponds to the expected value of the squared (quadratic) error loss and is defined as follows:

$$MSE = \frac{\sum_{i=0}^{N-1} (y_i - \hat{y}_i)^2}{N}$$
 (3)

Root Mean Squared Error (RMSE) measures the average difference between values predicted by a model and the actual values define as:

RMSE = 
$$\sqrt{\frac{\sum_{i=0}^{N-1} (y_i - \hat{y}_i)^2}{N}}$$
 (4)

The coefficient of determination,  $R^2$ , serves as an indicator of the model's ability to predict future samples. With a best possible score of 1.0, it can also take on negative values, indicating a model that performs arbitrarily worse. The definition includes a constant model, predicting the expected value of y regardless of input features, define as:

$$R^{2} = 1 - \frac{\sum (y_{i} - \hat{y}_{i})^{2}}{\sum (y_{i} - \bar{y})^{2}}$$
 (5)

RMSLE evaluate the performance of a model when the target variable is skewed or has a large range of values. It is similar to RMSE, but it is calculated using the logarithmic difference between the predicted values and the actual values as follow:

RMSLE = 
$$\sqrt{\frac{1}{N} \sum_{i=0}^{N-1} (\log_e (1+y_i) - \log_e (1+\hat{y}_i))^2}$$
 (6)

MAPE is a metric that gauges the average of the absolute percentage errors across entries in a dataset. It quantifies the accuracy of forecasted quantities by measuring the disparity between these forecasts and the actual quantities defined as:

MAPE = 
$$\frac{100}{N} \sum_{i=0}^{N-1} \frac{y_i - \hat{y}_i}{y_i}$$
 (7)

Similar to the regression task, we select specific classification metrics to validate our experimental results to provide insights into the performance of our classification models. These include Accuracy, Precision, Recall, and F1 score [error'metric]. Let TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative respectively.

Accuracy is a metric that calculates the ratio of correctly predicted instances to the total instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
 (8)

Precision measures the model's accuracy when it claims an instance as positive.

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

Recall calculates the ratio of correctly predicted positive observations to all actual positives. It measures the model's ability to capture all the positive instances.

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

The F1 Score provides a balance between precision and recall, making it a valuable metric for binary classification problems, especially when there is an imbalance between the classes. It ranges from 0 to 1, where 1 indicates perfect precision and recall, and 0 indicates the worst performance.

F1 Score = 
$$\frac{2*Precision*Recall}{Precision+Recall} = \frac{2*TP}{2*TP+FP+FN}$$
(11)

## 6.3 Training and Performance Evaluation

In this section, we present the experimental evaluation results obtained by applying the state-of-the-art regression and classification approaches, listed in Table 3, on our dataset. The aim is to assess their predictive performance and determine which models are best suited for our dataset. To conduct this evaluation, we randomly divided the dataset into two parts: a training set containing 80% of the parcels and a test set containing remaining 20% parcels.

Among the machine learning models applied for regression analysis, we observe that the Extra Trees Regressor, Light Gradient Boosting Machine, Random Forest Regressor, and Extreme Gradient Boosting consistently exhibit superior performance across multiple metrics, as depicted in Table 4a. Specifically, the Extra Trees Regressor achieves an  $R^2$  score of 0.8251, exhibiting the highest level of explanatory power among the models tested. The other ensemble models Light Gradient Boosting Machine, Random Forest Regressor, and Extreme Gradient Boosting follow closely with  $R^2$  score of 0.8211, 0.8195, and 0.8151 respectively showcasing their effectiveness in explaining the variance in the target variable. The underlying reason of Extra Trees Regressor performing better as compared to other models lies in its unique approach of randomly selecting subsets of features, leading to increase diversity among trees that helps to reduce variance and overfitting. We also find that Gradient Boosting and Decision Tree gives  $R^2$  score of 0.7364 and 0.6474 respectively that is relatively less than other ensemble models. These models while less susceptible to overfitting, still relies on the sequential addition of weak learners, which does not fully capture the underlying relationships in the data. Conversely, linear models such as Linear regression, Ridge regression, Lasso regression, Bayesian Ridge regression, Elastic Net, and AdaBoost exhibit comparatively poor performance across the evaluated metrics with  $R^2$  score lying around 0.36, due to the volatility and non-linearity inherent in our dataset.

We also observe a similar trend in the performance of the machine learning based classification approaches, as depicted in Table 4b. Notably, the Extra Trees Classifier stands out with the highest accuracy of 74.23%, and Random Forest Classifier model excel with an accuracy of 73.74%, achieving the highest Recall (81.25%), and F1 score (76.90%). These models indicate their ability to correctly classify instances across different classes while minimizing false positives and false negatives. Despite its slightly lower accuracy of 71.40%, the Light Gradient Boosting Machine exhibits a superior precision at 73.48%. Other models such as Extreme Gradient Boosting, Gradient Boosting Classifier, and Decision Tree also demonstrate commendable performance, with accuracies of 71.35%, 66.60%, and 64.46% respectively. Linear models like Adaboost, Ridge, Logistics Regression, and SVM with a linear kernel achieve satisfactory accuracy levels, with varying performances across different metrics. However, it is crucial to consider the trade-offs between different metrics base on the specific goals of the classification task. Overall, these results highlight the effectiveness of ensemble methods such as the

Table 4: Performance Evaluation using State-of-the-art Machine Learning Approaches

#### (a) Performance Analysis of Regression Models

Model	MAE	MSE	RMSE	R2	RMSLE	MAPE
Extra Trees Re-	549.9695	755238.1578	868.6787	0.8251	0.2309	0.1678
gressor [22]						
Light Gradient	591.9959	772802.0429	878.8025	0.8211	0.2375	0.1813
Boosting Machine						
[9, 30]						
Random Forest Re-	565.7065	779215.1271	882.0563	0.8195	0.2357	0.1726
gressor [22, 52, 18,						
30, 6, 16, 43, 9]						
Extreme Gradient	588.1852	798352.8312	892.8080	0.8151	0.2424	0.1807
Boosting [5, 9, 23,						
30, 6, 2]						
Gradient Boosting	752.5699	1139456.3378	1066.7778	0.7364	0.2886	0.2382
Regressor [18]						
Decision Tree Re-	724.2672	1521704.7801	1232.1022	0.6474	0.3154	0.2153
gressor [18, 4]						
Linear Regression	1257.0171	2742406.8567	1655.4335	0.3653	0.4605	0.4407
[36, 4, 43, 26, 9]						
Ridge Regression [9]	1260.2644	2746626.7865	1656.7530	0.3643	0.4607	0.4410
AdaBoost Regressor	1469.5244	2753052.8910	1658.5956	0.3628	0.5359	0.6201
[36, 52]						
Lasso Regression [9,	1260.8927	2753645.3368	1658.8414	0.3627	0.4609	0.4412
22]						
Bayesian Ridge [4]	1263.4940	2765753.7330	1662.4404	0.3600	0.4619	0.4426
Elastic Net [9]	1263.4951	2765622.9268	1662.4024	0.3600	0.4619	0.4427

#### (b) Performance Analysis of Classification Models

Model	Accuracy	Recall	Prec.	F1
Extra Trees Clas-	0.7423	0.8021	0.7284	0.7634
sifier [22]				
Random Forest Clas-	0.7374	0.8125	0.7303	0.7690
sifier [22, 52, 18, 30,				
6, 16, 43, 9]				
Light Gradient	0.7140	0.8072	0.7348	0.7646
Boosting Machine				
[9, 30]				
Extreme Gradient	0.7135	0.7744	0.7297	0.7512
Boosting [5, 9, 23,				
30, 6, 2]				
Gradient Boosting	0.6660	0.7921	0.6705	0.7261
Classifier[18]				
Decision Tree Classi-	0.6446	0.6658	0.6884	0.6767
fier [18, 4]				
Ada Boost Classifier	0.6349	0.7455	0.6517	0.6952
[36, 52]				
Ridge Classifier[9]	0.6101	0.7717	0.6218	0.6886
Logistic Regression	0.6011	0.7674	0.6146	0.6824
[30, 6]				
SVM - Linear Kernel	0.5650	0.7353	0.5342	0.6119
[22, 9, 32, 30, 6, 16]				

Extra Trees in accurately predicting the target variable in our dataset over the linear models.

Let us now consider the state-of-the-art deep learning models, including Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Multilayer Perceptron (MLP). In order to apply them on our dataset, we apply a standardized configuration across the board. This configuration consist of an input layer with 256 neurons, followed by two hidden layers with 128 and 64 neurons respectively. We utilize the Adam optimizer for optimization, with the Rectified Linear Unit (ReLU) serving as the activation function. MSE is employed as the loss function for regression task, while Binary Crossentropy is used for classification purpose. Setting the learning rate to 0.001, batch size to 32, and training epochs to 50 ensure that our models refine their parameters without overfitting or excessive computational costs. The evaluation results are shown in Table 5. Interestingly, our analysis reveals a spectrum of performance among the deep learning

models, ranging between traditional linear models and ensemble-based approaches. Notably, RNN achieves the highest  $R^2$  score of 0.7466, closely followed by LSTM of 0.7410, and MLP of 0.7210 for regression task. For classification task, MLP outperforms the others with an accuracy of 66%. These findings indicate a balanced performance across the models, demonstrating their capacity to capture intricate patterns within the data.

Table 5: Performance Evaluation using State-of-the-art Deep Learning Approaches

(	(a)	Performance	Analysis	of Dee	ep Learning	Models for	Regression

Model	MAE	MSE	RMSE	R2	RMSLE	MAPE
Recurrent Neural	701.2313	1117524.6744	1057.1303	0.7466	0.2738	0.1994
Network [2, 34, 25]						
Long Short Term	735.5871	1141768.2396	1068.5355	0.7410	0.2842	0.2246
Memory [16, 2, 31,						
34, 27, 6, 4, 46]						
Multilayer Percep-	730.0393	1211754.2753	1100.7971	0.7210	0.2881	0.2165
tron [47, 32, 27]						

(b) Performance Analysis of Deep Learning Models for Classification

Model	Accuracy	Recall	Prec.	F1
Multilayer Perceptron [47, 32, 27]	0.6600	0.7214	0.6981	0.6643
Recurrent Neural Network [2, 34, 25]	0.6548	0.6878	0.6845	0.6834
Long Short Term Memory [16, 2, 31, 34, 27, 6, 4, 46]	0.6198	0.6748	0.6523	0.6671

#### 6.3.1 Analysing Feature Importance:

In this section, we analyze the importance of various features under consideration, which contribute to the overall performance in both the tasks for Extra Trees models. As we can see in Figure 7a, for regression task, the prices of ether and bitcoin alongside their exchange-rates heavily influence the price of the parcel, thereby underscoring the interconnectedness of the cryptocurrency market, as highlighted in [18]. In addition, while the attribute 'DistanceToRoad' influences the sale prices of the parcels (Figure 7a), the parcels coordinates (x, y) play a pivotal role in assessing the likelihood of a parcel being resold (Figure 7b), as reported in [5]. Rarity score proves to be a strong predictor in classification task but shows reduced efficacy in regression. Gas prices do not significantly contribute to the price prediction but exhibit notable significance in parcel resale forecasts. Interestingly, google trend, crude oil- and gold-prices also make moderate contributions to both predictions. It is worth mentioning that other geographical proximities, such as 'DistanceToPlaza' and 'DistanceToDistrict', perform poorly in both of the tasks. This could be attributed to most parcels being far from plazas and districts, with a value of 10 as seen in Figure 4, thereby diluting their significance. These findings demonstrate the potential to analyze and predict market trends of Decentraland parcels. With the appropriate data and organization, researchers can gain valuable insights into the usage patterns and operational dynamics of this platform.

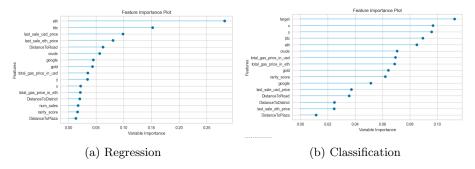


Figure 7: Feature Importance

# 7 Discussions and Future Research Scope

The Metaverse is frequently praised as the Internet's next evolutionary phase, representing a shared digital universe. While the Metaverse is still in its early stage, millions of users have already started interacting with it. As of 2024, one of the most common methods of joining the Metaverse is to purchase virtual land parcels and Decentraland platform stands out to be most popular one where users can buy and sell parcel, build experiences, and socialize [38]. With this surge, recent research attempts revealed insights into the pricing behavior of Decentraland NFTs and how various factors can influence their valuation [14, 19, 53, 36, 15, 44, 39, 29, 32, 8, 5, 33]. However, the existing datasets used in the study, lack details to encapsulate the full spectrum of attributes necessary for analyzing the subtle patterns that could significantly influence parcel sale and user engagement within the Decentraland. This deficiency extends beyond mere scarcity to encompass a lack of depth, breadth, and diversity in the available data sources.

To address this gap, this paper presents a comprehensive collection of parcel data of Decentral and IITP-VDL and over a span of five years. The dataset is collected from diverse sources, including Decentraland [38], OpenSea [17], Etherscan [50], Google Big-Query [20], Discord [13], Telegram [51], and Reddit [42], facilitating the inclusion of high-dimensional features, comprising characteristics, blockchain information, trading prices, transactions, and social media data. The salient features of our work which makes our dataset distinct from others are as follows: (1) inclusion of a novel attribute, called Rarity score, which measures the uniqueness of a parcel, (2) inclusion of gas-, mining-, and block-specific details of the transactions encompassing various activities (including parcel trading) by leveraging the 'web3.eth' package on Etherscan, (3) considering trading history over a most popular marketplace 'OpenSea', (4) providing a detailed bidding history for off-chain and on-chain, gathered from OpenSea and Etherscan. Furthermore, we also encompass peoples' sentiments about Decentraland parcels across various social media platforms, including Discord, Telegram, and Reddit. To ensure the dataset's efficacy across various disciplines we subdivide our dataset into four category naming it as: (1) Characteristics Data-Fragment (2) OpenSea Trading History Data-Fragment (3) Ethereum Activity Transactions Data-Fragment (4) Social Media Data-Fragment.

We envisage that our dataset, covering a broad spectrum of Decentral and parcels, would present a unique opportunity to unearth novel findings and enrich unexamined discoveries of the intricacies within the Decentral and parcels ecosystem. Through our analysis, we observe a notable correlation mirroring real-world scenario, wherein the sale of parcels decreases as the distances from point of interests increases. In addition, our examination also reveals a direct relationship between the volume of activities and number of sales. Aiming to showcase the richness of our dataset that can be used to solve plethora of applications including analysis of transaction costs, market liquidity, variance of gas prices, transaction delays, traders' speculative behaviors, supply and demand dynamics, pricing trends, and market sentiment etc., we limit ourselves as of now with a regression and a classification approach. In particular, we consider more than 20 state-of-the-art machine- and deep-learning models, to assess our prediction. Among all the other models, we observe Extra Trees algorithm achieves the highest  $R^2$ score of 82.51% to predict the parcel price and the highest accuracy of 74.23% to predict the probability of parcels being resold. Our results demonstrate the suitability of our dataset for ensemble models over deep learning and linear models revealing the complex nature of our data. We observe that, beside parcels' own features such as coordinates, geographical proximity, rarity score, other economic indicators (such as ether, bitcoin, crude oil, gold prices, google trend) help to increase the predictability as well.

Our research opens avenues for expansion to additional facets of Decentral and ecosystem, such as avatars, wearables, or other virtual experiences. To explore the predictabil-

ity of visual and textual features, one may explore additional techniques such as statistical methods (e.g., ARIMA) and neural network models (e.g., CNN and GNN). Moreover, the presence of data in multiple modalities (textual, visual, and social) enable us to adopt multimodal learning techniques, thereby enhancing precision. As mentioned earlier, beyond price prediction, the wide spectrum of attributes in our dataset also lead to solve numerous interesting research problems, including sentiment analysis, network dynamics between traders' speculative behaviors, tracking intricate trends within the Decentraland ecosystem.

# 8 Acknowledgement

This research is partially supported by the research grant provided by IIT Bhilai Innovation and Technology Foundation (IBITF).

# 9 Data availability

Data will be made available on request.

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