



Forecasting NFT Prices on Web3 Blockchain Using Machine Learning to Provide SAAS NFT Collectors

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Abstract

Non-Fungible Tokens (NFTs) are one-of-a-kind digital items with static or continuous visual and audio content. NFTs digitally represent any assets that may hold photos, gifs, audio, videos, or any other data-based storable material. These assets may come under a variety of asset groups, including art, in-game goods, and entertainment collecting units. What makes them appealing is their exclusivity, in the sense that each NFT is unique to itself, and ownership is determined by a digital certificate. In the first half of 2021, NFT sales totaled more than a billion. The NFT Software as a service (SAAS) based system is a one-of-a-kind offering and concept for thinking outside the box and presenting intellectuals and creative treasures and exhibiting these objects to ensure the security and integrity of digital assets. The existence of core decentralized networks allows for unrestricted access to this material as well as further analysis. Based on the Web3 Blockchain technology, these assets may be traded and represent next-generation ownership. In this paper, Adaptive Improved Convolutional Neural Networks (AICNN) are used to forecast NFT to provide a SAAS NFT collector. We also introduce Tree-seed Chaotic Atom Search Optimization (TSC-ASO) algorithm to optimize the forecasting process. The proposed method of NFT price forecasting is evaluated and compared with the existing forecasting methods. To produce an accurate report for NFT price forecasting, the proposed method will be effective.

Keywords: Non-Fungible Token (NFT); price forecasting; Web3 Blockchain technology; Adaptive Improved Convolutional Neural Networks (AICNN); Tree-seed Chaotic Atom Search Optimization algorithm (TSC-ASO)

1. Introduction

Non-Fungible Tokens (NFTs) are blockchain-reliant virtual assets that may hold photos, gifs, audio, videos, or any other data-based storable material. These assets may come under a variety of asset groups, including art, in-game goods, and entertainment collecting units. What makes them appealing is their one-of-a-kind nature, in which each NFT is unique to itself, and ownership is determined by digital certificates that belong alone to the owner [1].

Most of the present focus in the NFT sector is on art; however, this is not the exclusive focus. Assets are exchanged on online exchanges, where information on the kinds of NFTs sold and the number of NFTs sold is limited to top chart data. With their behaviors and material created, traders, producers, and assets constitute a full collection of hidden information. In recent years, the Non-Fungible Token industry has seen multi-million-dollar trading. It is getting more difficult to discern true NFT from fads and frauds as the NFT market environment evolves rapidly via technology, innovation, and decentralization. This article focuses on price formation, market structure, transparency, and applicability to other financial fields of the NFT market microstructure. Market manipulation in

the NFT markets has also been investigated in the context of wash-sale patterns. The essay finishes with recommendations for due-diligence activities that investors might use to reduce the danger of NFT trading [2]. Figure 1 displays the general illustration of the NFT.

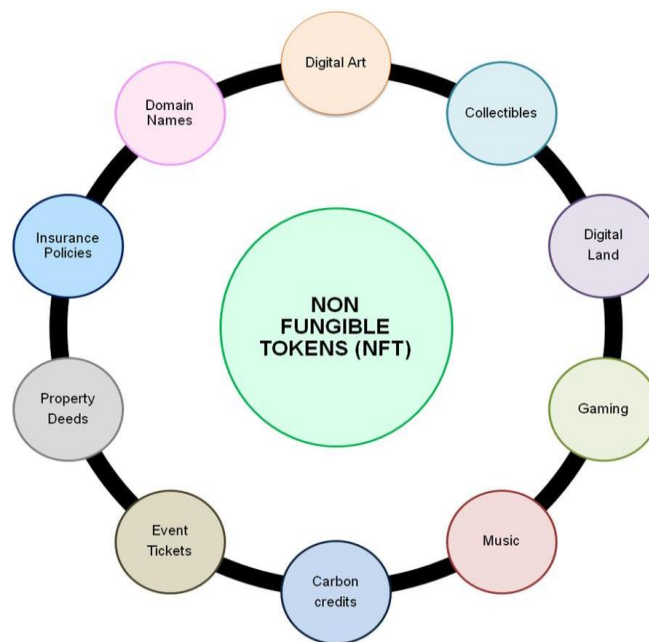


Figure 1: General illustration of the NFT

Three things determine the price of the NFT in general. These include aesthetic characteristics, previous NFT transactions, and the popularity of buyers and sellers. Colors, forms, and other visual characteristics of NFTs, digital assets, are determined using advanced computer vision algorithms. When it comes to prior sales, it's important to consider the market history of goods from the same collection. Finally, in the NFT network, the popularity of buyers and sellers is determined by the popularity of each trader. While these three elements have a part in deciding NFT art pricing, it is estimated that 50 percent of price swings are due to past artwork sales. The popularity of the traders accounts for 10% to 20% of the pricing, while visual elements contribute 10% to 20%. It is feasible to predict future price patterns based on these factors [3].

Investors might limit their risks by keeping these patterns in mind. Several variables influence NFT sales, including but not limited to visual content, trading conduct, and author reputation. It is feasible to remove unit assets, creators, and trader-based assets due to the market's immaturity and reliance on aesthetic elements intelligence to forecast future transactions. Sales may be linked to visual recognition-based decision-making, behavioral finance, the influence of macroeconomic factors on individual sales, and overall transactions, given the multidisciplinary character of the NFT area. Considering the number of transactions, predicting future transactions, or determining crucial criteria that determine whether NFTs are successful or not might suggest a value. Visual characteristics are mostly unknown as a solitary attribute. Online markets and transaction hosting websites hold visual material. The open sea is a transaction-focused marketplace that provides open API access for data retrieval with certain restrictions. Another possible data-gathering source is recent research [4].

Visual aspects of NFTs may be identified using recent advances in the computer vision area, and classification, grouping, or similarity ranking of these pictures can be performed. Neural network architectures will be utilized in this research to find trends in NFTs' visual content to better understand what makes some NFTs more valuable than others by removing possible biases. The artist's reputation, trader cluster behaviors, market manipulation activities, and NFT's tale outside of its digital material may all be sources of prejudice. Because they have the potential to influence and distort results, visual feature extraction will be used to thoroughly study and model them. Convolutional neural networks (CNNs) are expected to be the best methods for feature extraction and maybe picture categorization. AlexNET and ResNet are two of the most popular and commonly used CNNs, and they will

be useful in the scope of this research [5]. The fact that these models are pre-trained and open-source makes them easy to use and assess. A further part of this paper contains II) a Literature review III) a Proposed work IV) a Performance analysis V) a Conclusion.

2. Literature Review

The objective of [6] offers a novel approach for constructing an NFT Price Index that encompasses a whole new market. Furthermore, this index will enable us to analyze and diagnose the behavior and performance of NFT marketplaces. The goal of [7] is to look at the connections between NFT sales, NFT users, and Bitcoin and Ether prices. The results suggest that (larger) cryptocurrencies get an effect on the formation and expansion of the NFT industry, but no reverse link exists. In [8] a network of interconnections demonstrates that traders tend to specialize in NFTs and establish tighter groups with certain other traders who market the same items and are associated with identical products. Third, they organize things linked to NFTs into groups depending on unique aesthetic elements, indicating that groupings are made up of visually consistent components. Finally, they use basic machine learning methods to study the predictability of NFT sales and discover that selling history and, secondly, visual attributes are strong price predictors. They expect that these results will spur further study into NFT production, adoption, and trading in a variety of settings. According to [9] possible illegal trading trends in utilizing information from the 52 highest important collectors by quantity, NFT exchanges were tracked between January 2018 through mid-November 2021. Our findings suggest that 3.93 % of the locations in our survey, which handled 2.04 percent of all sales, arouse suspicion of stock manipulation. Nearly all collections are contaminated by flagged transactions, which may have inflated real trade volumes by as much as 149,5 million for the timeframe. The bulk of programmable found swing sometimes between accounts, indicating a preference for manually dialing. They feel the information presented here can be utilized as a minimum bound evaluation for the NFT wash trade on Ethereum. However, they believe such selling is less common than industry watchers previously believed. We show that speculative bubbles occur in both NFT and Defi markets, with NFT bubbles being more common and having larger magnitudes than Defi bubbles. Market excitement and more general cryptocurrency market uncertainties are closely connected with price bubbles in the NFT and Defi markets. They do encounter periods without bubbles, indicating that these markets have some underlying worth and should not be disregarded as mere bubbles [10]. In [11], the study looks at the instability features of NFT-based enterprises that are registered on the bitcoin marketplace. The investigation was sparked by a recent surge in NFT behavior among entrepreneurs, speculators, and dealers. They start by inventing a novel grading system for existing NFTs, which encompasses anything from NFT crypto to NFT metaverses to NFT Defi. According to the report, adding NFT infrastructure to present blockchains boosts their value on the market. In [12] investigates Foundation's operations and discovered numerous noteworthy underlying dynamics. Furthermore, we did social network analysis on a graph we established on Foundation using transmitted NFTs and then defined the graph's properties. Finally, we developed a similarity model based on neural networks for collecting and grouping comparable NFTs. We also demonstrated that the performance of most NFTs in auctions was similar to that of other NFTs in their cluster. The objective of [13] wants to know what the most important aspects are when it comes to valuing NFT assets. To achieve this goal, we created a first-of-its-kind dataset that captures social media profiles and connected NFT assets by combining Twitter and OpenSea (the biggest NFT marketplace). Our database contains 245,159 tweets by 17,155 individual customers, which are linked to 62,997 NFT significant assets of \$19 million on OpenSea. The information has already been made available to the general community. We look at the emergence of NFTs, the Twitter users who support them, and also the impact of Twitter characteristics on the virality of NFTs. We also test the usefulness of various social media and NFT platform features by using a variety of machine and deep learning models to estimate the value of an asset. Our findings suggest that including social media characteristics improves accuracy by 6% over using solely NFT platform data in baseline models. The number of user membership lists, as well as the number of likes and retweets, are key social media elements. The goal of [14] shows how marketplace design may have a big impact on market intelligence, especially when it comes to bidding expenses, which can vary a lot based on transaction fees, the number of bidding bots, and the user interface for making bids. We create an empirical model of the strategic interaction between sellers and bidders using data from the CryptoPunks marketplace. Counterfactual simulations indicate that lowering bidding prices has no effect on the number of sales, but it does raise the percentage of sales resulting from bids. As sellers anticipate more offers, listing prices rise, making items look more valuable. Rare and common asset listing and realized selling price ratios are shrinking, making the market look more uniform. Because of variations in bidding prices rather than differences in intrinsic worth, collections supplied by two distinct markets might have dramatically different market statistics. The findings have ramifications for how NFT market information should be interpreted. The

research [15] concentrates on a particular marketplace, NBA TopShot, which allows the buying and exchange of sports memorabilia in this research. Our goal is to create a system that can identify whether or not peer-to-peer transactions on the network are unusual. To accomplish our goal, we start by creating a model that calculates the profit that can be produced by selling a given item on the site. The mistakes from the profit models are then modeled using a random forest framework for the conditional density of the dependent variables. This phase enables us to calculate the likelihood of an unusual transaction. Finally, every transaction with a probability of less than one percent is classified as anomalous. Provided the lack of ground truth for testing the framework's transaction categorization, we examine the trade networks produced by these anomalous transactions and compare them to the platform's whole trade network. In [16] provides three parties from the business of the NFL's success, the paper discusses the digital art industry's future as well as the logical conduct of developers, artists, & even buyers. It comments on digital art investment behavior and the need for a solid long-term investment for a specialized group looking to fulfill their desire for distinctive items. The article focuses on how AI applications build successful marketplaces and act as a roadmap for digital art. The Non-Fungible Token sector has experienced multi-million-dollar trade in recent years. It is getting more difficult to discern true NFT from fads and frauds as the NFT market environment evolves rapidly via technology, innovation, and decentralization. This article focuses on price formation, market structure, transparency, and applicability to other financial fields of the NFT market microstructure. Market manipulation in the NFT markets has also been investigated in the context of wash-sale patterns. The essay finishes with recommendations for due-diligence activities that investors might use to reduce the danger of NFT trading [17]. In the financial business, AI systems, particularly Deep Neural Networks (DNN), have recently become popular for the stock price and motion forecasting. To construct AI-based solutions for the financial market, a daily based DNN training process for each stock is necessary, which needs collaboration among a huge number of businesses. Nevertheless, data security, the expense of AI processing, and a lack of desire to exchange information make it difficult. To address these challenges, the study [22] presents a revolutionary Blockchain-based design that enables the use of a decentralized network, federated learning, and master node. The researchers of [23] calculated many strategies in attempting to estimate historical market values and then analyzed their accuracy. The writers of [24] look at digital financial bubbles in the middle of the COVID-19 epidemic. They discover numerous bubbles spanning the analyzed crypto assets using a sample of 3 NFTs, Bitcoin, 9 DeFi tokens, and Ethereum. They also find DeFi and NFT-specific bubbles in the Summer of 2020, implying that these asset classes have different driving drivers. NFTs have recently attracted a lot of investor attention, with some NFTs attaining trading values that were formerly unfathomable for a non-fungible digital asset. Through the lens of the non-fungibility of a digital asset, it elevates intriguing queries about "value" and "scarcity" in relation to blockchain systems, and the paper [25] intends to highlight these queries as they would form an alternate solution to blockchain technologies and exchange in the future.

Problem statement

Some who have acquired digital products created by NFT believe that are storing securities. The relevance of leveraging digital assets is shown by the reality that NFT virtual masterpieces were auctioned from hundreds of thousands to millions of dollars. However, numerous analysts have compared the current mania for owning these assets to an economic bubble that would ultimately burst. Several non-fungible tokens, of course, have demonstrated their worth and growth potential. It's also worth noting that not all digital assets are valued at the same amount. In NFT investment, there is still the risk of over-speculation and herding.

3. Proposed Work

This paper gives a new method to forecast NFT price by web3 blockchain using machine learning to provide SAAS NFT collector. This paper discusses Adaptive Improved Convolutional Neural Networks (AICNN) used to forecast NFT price and we introduce Tree-seed Chaotic Atom Search Optimization (TSC-ASO) algorithm to optimize the forecasting process. The schematic representation of the suggested optimization is depicted in Figure 2.

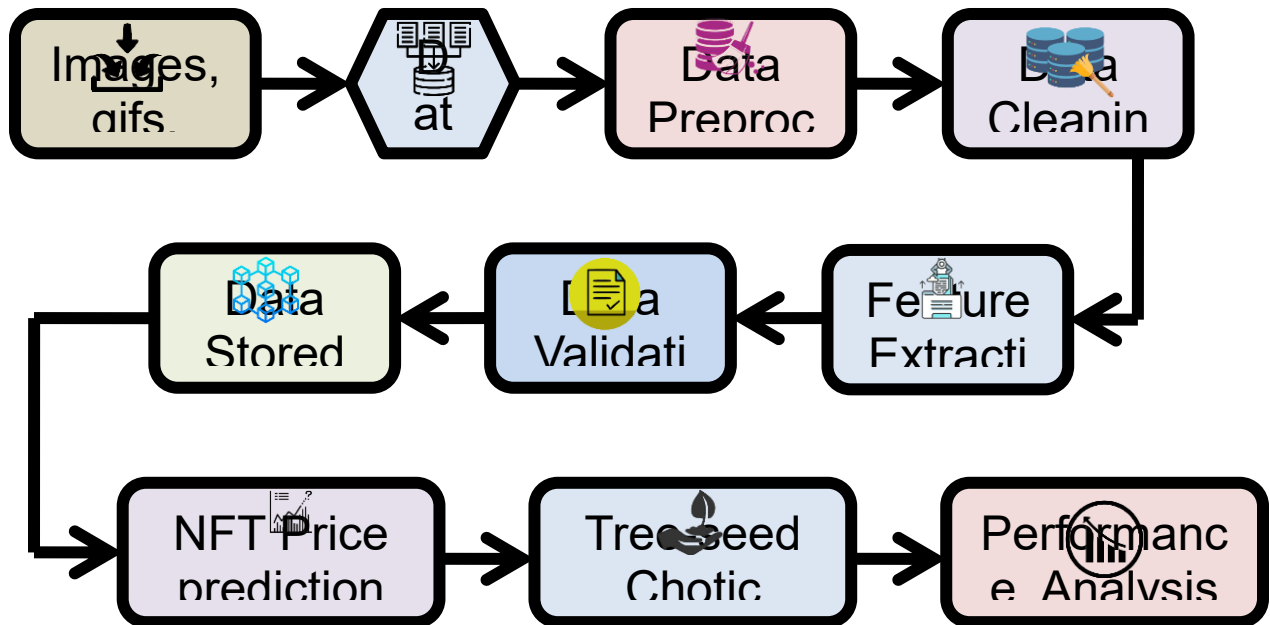


Figure 2: Schematic representation of the suggested optimization

Data collection

For every NFT in this dataset, researchers were able to rack up one URL that corresponds to a representation of the Nonfungible token material image (with less than 3,000 exceptions). Major image types and GIFs were examined, giving a sum of 1.2 million visual graphic objects and 4.7 million new NFTs. It's important mentioning that a single digital object shall be linked to several entities; for instance, similar material characteristics can be printed in extra versions, including one with a unique NFT. Having transformed animations to PNGs since our previous encounter by utilizing the optical extraction of features approach, which operates for fixed photographs, to recover the middle pixel of each GIF. We use a neural network to encode the visual elements that describe a picture into a latent space to convey them simply. AlexNet, based on neural network architecture designed initially in order, is implemented in PyTorch. AlexNet is started using parameters that have been pre-trained on Deep learning, a widely utilized labeled image data. AlexNet takes a photograph and transforms it via a series of steps. The hidden tier (before the classification stage) is a 4,096-valued vector that provides compact features of the input image in a higher-dimensional region. Resemblance sorting, combining, and categorization may all be done with these matrices. To minimize the complexity of AlexNet matrices, we used Principal Component Analysis (PCA) to extract the 5 least relevant essential parts. PCA reduces data variation by converting each high-dimensional pixel into a workspace with the required set of measurements. The dataset details are shown in Table 1.

Table 1: Dataset description

Division	Number of Buyers	Number of sellers	NFTs	Volume (106 USD)
Art	161,420	70,620	859,570	655.78
Collectible	62,200	67,175	1,344,449	109.65
Games	151,700	192,780	2,202,432	70.68
Metaverse	12,120	10,285	47,286	68.43
Utility	2,640	1,480	7,752	8.66
Other	34,645	22,310	242,990	21.83
Total	424725	364650	4704479	935.03

Data preprocessing using geometric transformation

The approaches deal with color and brightness/contrast. The placements of pixels in a picture are altered using geometric transformation, but the colors remain the same. Geometric transformations remove distortions that occur during the capture of a photograph. Geometric transformation processes include rotating, resizing, and deformation of images. Geometric transformations include two essential steps:

- Spatial change of the image's actual pixel rearrangement
- Grey level interpolation, in which the modified picture is assigned grey levels

Transformations include scaling, translation, rotating, shearing, affine transformation, and viewpoint transformation. Scaling is the process of resizing a picture. The altering of an object's position is known as translation. Rotating an item with theta degrees is all there is to it. Shearing is the process of horizontally shifting pixels. The mixture of the 4 transforms is known as an affine transformation. Those 3 transformations are typically integrated as one matrix instead of stating the transformation matrix, sheared factors, and angulation individually. Viewpoint Transformation is the process of changing the standpoint of a photograph or video to gain a better comprehension of the material. The spots on the picture from which you wish to obtain information by shifting the viewpoint must be specified here.

Data cleaning and categorization

Data cleaning is the process of removing erroneous, distorted, terribly written, redundant, or inadequate data from data. There are several possibilities for evidence to be replicated or incorrectly classified when integrating data from different sources. If the data is right, the results and approaches are dependable. If the information is incorrect, the results and procedures are untrustworthy. Because the methodology will differ from information to statistic, there is no one-size-fits-all approach for defining the exact processes in the collected data. Data categorization is the method of coordinating data into useful classifications so it can be used and protected more efficiently.

Feature extraction using linear discriminant analysis

Diffusion distance is used as a classification feature in this study. The difference between two 1E distributions, $e_1(y)$ and $e_2(y)$, may be defined as $e(y) = e_1(y) e_2(y)$. If $U(y, u)$ is an isolated temperature field, $U(y, 0) = e(y)$ when $u = 0$.

The heat diffusion equation is satisfied by the temperature in an isolated field, hence the formula to determine $U(y, u)$ is

$$U(y, u) = U_0(y) * \phi(y, u) \quad (1)$$

$$U_0(y) = U(y, 0) = e(y) \quad (2)$$

$$\phi(y, u) = \frac{1}{(2\pi)^{1/2}u} f^{-\frac{y^2}{2u^2}} \quad (3)$$

$U(y, u)$ may be thought of as a diffusion process that exchanges the distribution value to equalize e_1 and e_2 . As a result, a distance between e_1 and e_2 may be presented as a metric for measuring the process as the difference between two distributions. The space between us is defined as

$$\hat{L}(e_1, e_2) = \int_0^{\bar{u}} l(|U(y, u)|) eu \quad (4)$$

Where u is a positive constant, $l(e)$ is a norm that assesses how $U(y, u)$ departs from 0, and we pick the L1 norm since it requires less computation.

The definition of $L(e_1, e_2)$ for two m -dimensional distributions $e_1(y)$ and $e_2(y)$, where y is an m -dimensional matrix, is comparable to equation 4. Because aliasing is not produced during smoothing and subsampling in the Gaussian pyramid, it may effectively characterize the continuous diffusion process $U(y, u)$. As a result, a Gaussian pyramid-based diffusion distance is presented.

$$L(e_1, e_2) = \sum_{m=0}^M l(|e_m(Y)|) \quad (5)$$

Where

$$ee_0(Y) = e_1(Y) - e_2(Y) \quad (6)$$

$$ee_m(Y) = [ee_{m-1}(Y) * \phi(Y, \sigma)] \downarrow_2 \quad (m = 1, \dots, M) \quad (7)$$

$$\phi(Y, \sigma) = \frac{1}{(2\pi)^{n/2}\sigma} f^{-\frac{YUY}{2\sigma^2}} \quad (8)$$

Where M is the count of Gaussian pyramid units, the symbol "2" indicates half-size down sampling and is the Gaussian filter's constant standard deviation. The diffusion distance is defined as follows when using the M1 norm.

$$EE(e_1, e_2) = \sum_{m=0}^M |ee_l(Y)| \quad (9)$$

The size of y determines the value of M in this case.

Data validation using smart contracts

Data validation is the mechanism of verifying the integrity and precision of information. It's done by incorporating several tests into a program or reporting to ensure that inputs and recorded information are intellectually coherent. With no human interaction, information is entered into automated machines. Consequently, it's important to make sure that the information inputted is precise and satisfies the suitable quality requirements. If indeed the data isn't captured accurately, it won't be of much use and might lead to worse upstream reporting problems. Although if data information is supplied correctly, there will be costs associated with cleaning, transforming, and storing it.

NFT price prediction using Adaptive Improved Convolutional Neural Network (AICNN)

Improved Adaptive Convolutional although the effectiveness of neural networks increases as the quantity of neurons increases, the finding demonstrates that the benefit of growing network size outweighs the time needed if the system is grown blindly. This is because standard CNN design is constructed by trial and error, with no concept to guide variable choices, such as the number of hidden layers, neural size, and so on. We offer an AICNN that can create a network automatically using simple beginning network architecture and a set of provided parameters to solve some of the concerns stated above.

The AICNN algorithm works as follows:

Step 1 Network Initial population.

As seen in the diagram, the initial connection has only one branch. This branch has two neural networks and two sampled layers. Every one of the 4 layers has its own extracted features.

Backpropagation is used to update the network's weights (BP).

Despite CNN, the original system will be decided if it is convergent or just not after a certain amount of training cycles, which saves time. The converging tendency condition is described in this sentence.

$$fss_{initial} - fss_{present} \geq U \quad (10)$$

Where $fss_{initial}$ is the prior training's network median deviation, $fss_{present}$ is the current training's average error, and U is the convergence rate's threshold value, which is set at 0.1.

The average error rate in the system is fss .

$$fss = \frac{1}{2} \frac{\sum_{k=1}^b \sum_{j=1}^n (z - z_{label})^2}{b} \quad (11)$$

The whole number of training samples is a , while the number of output units is n . If equation 10 is true, the current network may be termed convergent, and it is trained until the average error of the system fulfills the condition. Otherwise, the current network will not converge, necessitating global growth.

Step 2: Expansion of the global network is the second step.

The worldwide network extension of a new branch C was built based on the first branch A. Before the expansion, the R_C of training and testing samples is kept separate at branch A's output layer, and R_B is superimposed on branch C's output layer. Branch C's output is specified as:

$$z = g(R_B + R_C)(12)$$

Only the weights of branch C are updated by CZ, while the weights of branch A remain fixed. Another global branch will be enlarged if the expanded branch cannot likewise be convergent within the required number of training sessions. When the convergent branch is found, it is trained until the system's average error approaches the goal. The AICNN global network has been fully learned. As can be shown, CNN's worldwide growth strategy is superior to ICNN's in terms of reducing human interference.

Step 3: Expansion of the local network is the third step.

The timing of global or local expansion and new is artificially set, as well as the necessary conditions for installations are like for overseas markets. When the system's average deviation will be less than the predefined threshold after international integration, but the recognition accuracy of training images still falls short of the aim, a local wireless expansion is necessary. To improve CNN accuracy, a merging of worldwide branching is recommended for localized area networks, as shown. Before expanding the network connection, the local features of each branching in the worldwide network are preserved as inputs, and the recommended fusion is done.

$$D1_{local} = g(T1_B * l_B + T1_C * l_C)(13)$$

Where $D1_{local}$ is the feature map of the local network's first convolutional layer, and $T1_B$ and $T1_C$ are the feature maps of branch B and C's layer D1. The convolutional kernels are k_A and k_B .

At the same time, R_{global} at the global network's output layer is kept and layered on the local branch's output layer. The local network's output is specified as:

$$R_{global} = R_b + R_c(14)$$

$$z = g(R_b + R_c)(15)$$

CP only updates the values of the nearest branch, whereas the values of the worldwide network remain constant. Whenever the detection performance of the training images reaches the necessary level, the retraining integrity of the entire system is completed, assuring AICNN correctness. Because there is no fusing whenever the worldwide network has only one branching, the subset of features at layer R1 of the worldwide network is usually combined using different convolutions. AICNN, on either hand, automates the creation of a network rather than depending on expertise. However, unlike CNN, ACNN trains the approach that relies on a preset technical error and detection rate, which cuts practice time and assures accuracy.

Tree seed chaotic atom search optimization algorithm (TSC-ASO)

Tree seed chaotic atom search optimization algorithm (TSCASO) comes from the seeds, and molecular modeling has a link. Trees disseminate their seeds in the environment. These seedlings will be nourished through time, and new trees will sprout from the seeds stated above. If the ground were considered a context for improving space, the positions of plants and seedlings may represent the solutions. Because this process comprises the search's core, the location of a seed produced from a tree is critical for the optimization problems. Equations 16 and 17 are suggested for this procedure. The tree seed chaotic atom search optimization algorithm (TSCASO) is a recently invented optimization technique that is based on fundamental molecular dynamics and is discussed. Only the most important formulae will be provided here.

Equation 16 improves the capacity of the supplied algorithm's local search or intensification. In addition, Equation 17 uses two different tree positions to create a fresh seed for the tree.

$$R_{j,k} = U_{j,k} + \alpha_{j,k} \times (A_k - U_{s,k})(16)$$

$$R_{j,k} = U_{j,k} + \alpha_{j,k} \times (U_{j,k} - U_{s,k})(17)$$

The algorithm utilized to calculate the placement of a new seedling is the most significant component to investigate. On a range of [0,1], a correction factor termed search tendency (ST) will be used to govern this choice. The greater the influence of search strategy and the quicker the divergence, the lower the amount of ST; the greater the influence of search query and the shorter the integration. Because the first three sites reflect possible approaches to the optimization problem, they are constructed utilizing equation 18 at the beginning of the investigation.

$$U_{j,k} = M_{k,min} + s_{j,k}(I_{k,max} - M_{k,min})(18)$$

where $M_{k,min}$ is the search space's lower limit, While the locations of fresh seeds for a tree are being formed, the number of seeds might be more than one, and this quantity is dependent on the size of the population. The quantity of seed produced in TSA is determined at random.

The location of atoms in ASO is updated by:

$$y_j(u + 1) = y_j(u) + w_j(u + 1)(19)$$

where $() J$ denotes the j^{th} atom's location in the u^{th} iteration, $y_j(u + 1)$ indicates the j^{th} atom's location in the $(u + 1)^{th}$ iterative process, & $w_j(u + 1)$ is the j^{th} atom's velocity in the $(u + 1)^{th}$ iteration and is computed as follows:

$$w_j(u + 1) = rand \times y_j(u) + b_j(u)(20)$$

Here $rand$ denotes an arbitrary number between 0 and 1, and $b_j(u)$ denotes the acceleration of the j th atom in the u^{th} iteration, computed as follows:

$$b_j(u) = -\eta(u) \sum_{k \in L_{best}} \frac{rand[2 \times (i_{jk}(u))^{13} - (i_{jk})^7]}{n_j(u)} \times \frac{y_j(u) - y_k(u)}{y_j(u) - y_k(u)_2} + \beta f^{-\frac{20u}{u}} \frac{y_{best}(u) - y_j(u)}{n_j(u)}(21)$$

Eqs. 22, 23, and 24 compute $(u), i_{jk}(u)$, and $n_j(u)$, respectively,

$$\eta(u) = \alpha \times \left(1 - \frac{u-1}{u}\right) \times f^{-\frac{20u}{u}}(22)$$

$$i_{jk}(u) = \begin{cases} i_{min} & \frac{s_{jk}(u)}{\sigma(u)} < i_{min} \\ \frac{s_{jk}(u)}{\sigma(u)} & i_{min} \leq \frac{s_{jk}(u)}{\sigma(u)} \leq i_{max} \\ i_{max} & \frac{s_{jk}(u)}{\sigma(u)} > i_{max} \end{cases}(23)$$

$$n_j(u) = \frac{N_j(u)}{\sum_{k=1}^O N_k(u)}(24)$$

What is the depth weight, and the distance among the j th and k th atoms at the u th iteration is $s_{jk}(u)$, and the values for i_{min} , i_{max} , (t) , and $n_j(u)$ are computed as follows:

$$i_{min} = h_0 + h(u)(25)$$

$$i_{max} = v \tag{26}$$

$$\sigma(u) = y_{jk}(u), \frac{\sum_{k \in L_{best}} y_{jk}(u)}{L(u)} \tag{27}$$

$$N_j(u) = e^{-\frac{Fit_j(u) - Fit_{best}(u)}{Fit_{worst}(u) - Fit_{best}(u)}} \tag{28}$$

$h(u)$ and $L(u)$ are estimated as:

$$h(u) = 0.1 \times \sin\left(\frac{\pi}{2} \times \frac{u}{U}\right) \tag{29}$$

$$L(u) = O - (O - 2) \times \sqrt{\frac{u}{U}} \tag{30}$$

O is the number of atoms in the system.

4. Performance Analysis

The performance of Web3 blockchain-based NFT price forecasting was analyzed in this paper. NFT data was stored in Web3 blockchain and the forecasting process was carried out by using an Adaptive improved conventional neural network (AICNN) this process was optimized by Tree Seed Chaotic Atom Search Optimization Algorithm (TSC-ASO). The performance of the proposed Web3 blockchain-based NFT price forecasting is compared with four other existing methods namely i) Linear regression (LR), ii) Visual feature Extraction (VFE), iii) Neural network (NN), and iv) Support vector machine (SVM).

Prediction error

Prediction Errors are an unavoidable part of predictive analytics, and they should be measured and provided with any model, normally in the context of a standard error that shows how accurate the model's predictions should be. The proposed method shows a very low level of prediction error when contrasted to other traditional approaches. Figure 3 shows the comparative analysis for prediction error.

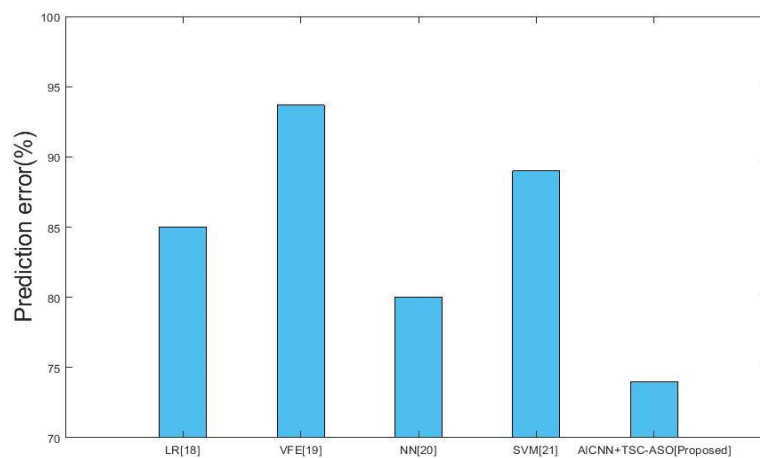


Figure 3: Comparative analysis for prediction error

Precision

Precision is defined as the interaction of a series of similar measurements obtained under the same conditions. When compared to current approaches, the suggested method provides a high degree of accuracy in measuring customer happiness. The suggested precision range approach is shown in Figure 4.

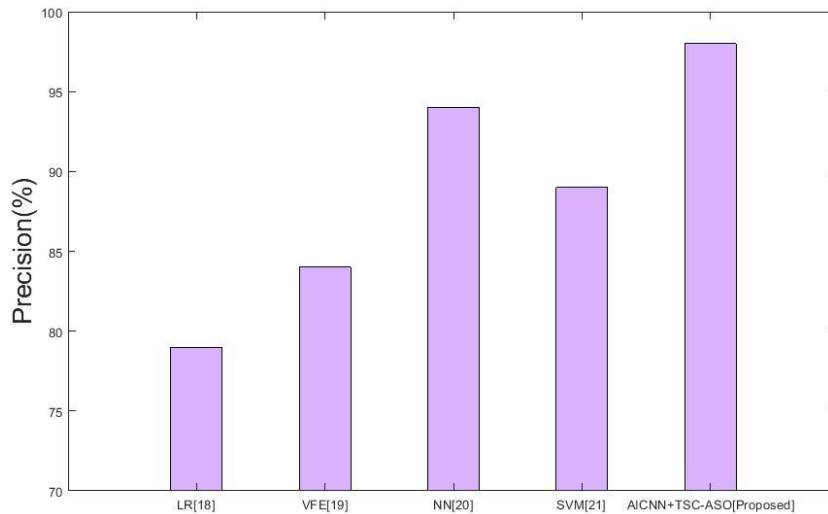


Figure 4: Comparative analysis for a precision range

Accuracy

The term "accuracy" refers to the assurance that the data is accurate and error-free. In NFT price prediction, the proposed method gives a high range of accuracy than the existing methods. Figure 5 depicts the comparative analysis for the accuracy of the proposed method vs the existing method.

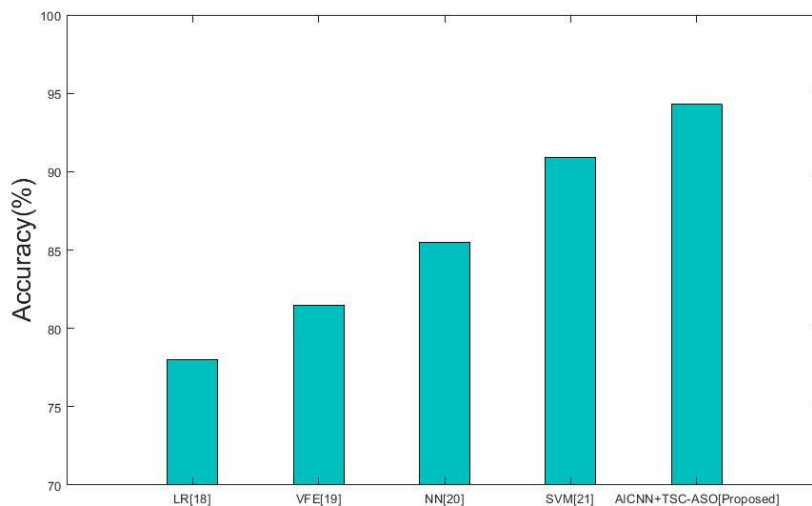


Figure 5: Comparative analysis for accuracy

Root Mean Square Error (RMSE)

The square root of the mean square errors the root means a square error of a population parameter estimator. The forecasted value of the square of the variation between the estimator and the variable is the MSE. The RMSE value for the suggested technique is less when contrasted to conventional methodologies. Figure 6 depicts the comparative analysis for RMSE of the proposed method vs the existing method.

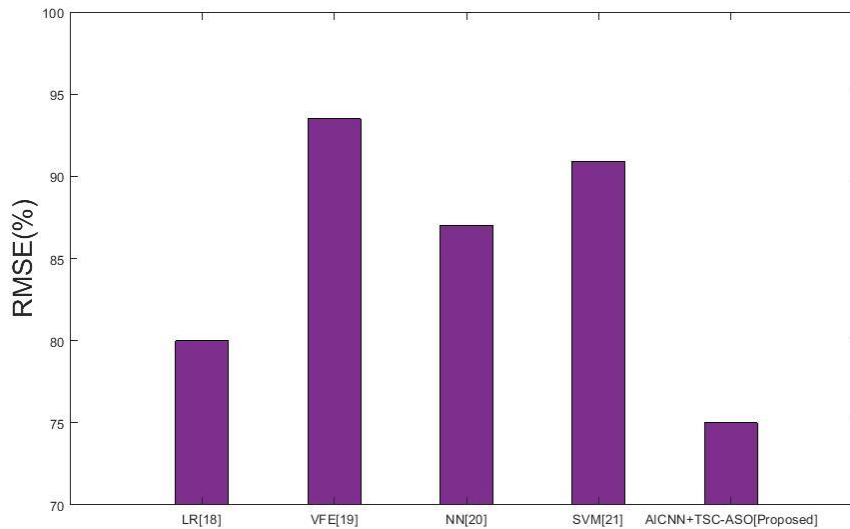


Figure 6: Comparative analysis for RMSE

Recall

The recall is a number that indicates how many precise positive measurements were obtained out of all potential positive readings. As previously mentioned, the accuracy and precision of the proposed measurement technique are better than those of existing methodologies. Consequently, the recall percentage of the proposed strategy is higher than that of previous methodologies. Figure 7 depicts the recall percentage of the recommended strategy.

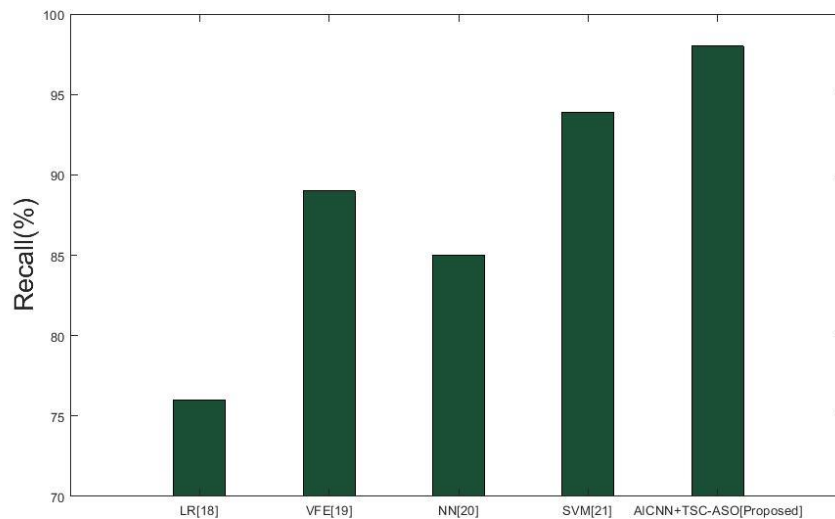


Figure 7: Comparative analysis for Recall

5. Conclusion

NFTs grow to promote e-commerce and royalty transfers simpler; more will emerge in the future. NFTs have proved to be crucial and life-saving tools for artists all over the globe throughout the pandemic and they address some of the most common and long-standing issues in the art market, such as provenance and ownership. In this paper, we have introduced a Web3 blockchain-based Adaptive Improved Convolutional Neural Network (AICNN) and Tree seed chaotic atom search optimization algorithm (TSC-ASO) for forecasting NFT price to provide NFT SAAS collector. To optimize the accuracy and advantages, this optimization is an effective use of technology that creates the exactness of forecasting NFT price. Through the provided, NFT SAAS collector users may quickly choose a digital wallet, and the auctions may stay at one price for sellers without any changes. Finally, the internet shop handles money and digital asset transfers. The secure transfer of digital assets and money is possible.

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