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Multi-Perspective Video Game Analysis on YouTube: A Hybrid Time Series-Based Bee Colony Optimization Approach (TSBBCOA)

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Abstract: Within the domain of digital media, YouTube functions as a flourishing centre for a wide range of content, encompassing evaluations, analyses, and demonstrations of video games. However, the existing constraints inherent in contemporary approaches for analysing video game material on the YouTube platform highlight an urgent need for a novel and innovative methodology. Introducing the Time Series-Based Bee Colony Optimization Algorithm (TSBBCOA), an innovative approach developed to tackle the limitations above effectively. The current systems encounter significant limitations, including difficulty capturing the wide range of perspectives and opinions expressed in YouTube videos, challenges in scaling up to accommodate the platform's rapid content expansion, and inability to handle temporal changes or process large amounts of data effectively. The constraints above highlight the need for an algorithmic approach such as TSBBCOA. This methodology leverages time series analysis and bee colony optimization to offer a comprehensive and precise understanding of the multifaceted landscape of video games on the YouTube platform. This research presents a conceptual framework of TSBBCOA, explores its mathematical modelling and algorithmic complexities, and illustrates its actual implementation, highlighting its effectiveness in addressing the limitations of existing systems. The TSBBCOA framework is a very effective solution urgently required to enable a thorough and intelligent video game content analysis from several perspectives in the current digital media era.

Keywords: ABC (Artificial Bee Optimization), Time Series-Based Bee Colony Optimization Algorithm (TSBBCOA), Video Marketing, YouTube, Time Series, Optimal Solution.

INTRODUCTION

A video view system has been set up to distinguish between legitimate views and the remainder because YouTube wants to ensure that its films are seen by actual humans and not a bot trying to inflate the view count. YouTube only records views when the conditions listed are satisfied.

To start the video, a user must physically press the play button. Playing the video for at least 30 seconds is required. Counting it as a "view" aids YouTube in determining that a viewer is doing so on purpose. This study represents a thorough investigation of video game-related content inside the expansive realm of the YouTube platform. This research study utilizes multiple perspectives and approaches to comprehensively examine the gaming phenomena observed on a widely-used video-sharing site. This study is expected to examine several facets of video game content, including evaluations of gameplay, content contributed by users, emerging patterns, and interactions within the gaming community. By employing a multi-perspective methodology, this study targets to offer a widespread understanding of the gaming culture and its influence on the diversified viewership of YouTube. The Multi-Perspective Video Game Analysis on YouTube is a scholarly effort to analyse and interpret the intricate realm of video games within the framework of the YouTube platform.

This initiative aims to provide valuable insights into the dynamic interplay between gamers, content creators, and their respective audiences in the digital landscape. The volume of the global optimal solution along with the chance of attaining the global optimal solution were both raised by this algorithm's use of Bloch coordinates for food source quantum bit encoding in the artificial colony approach. Then, a quantum rotation gate updated food sources. This work suggested a unique method known as Artificial Bee Colony [1]. To determine the connection between the two rotation phases in the quantum rotation gate. The proposed Integrated Probability Multi-search and Solution Acceptance Rule-based Artificial Bee Colony Optimization Scheme (IPM-SAR-ABCOS), which uses multi-search probabilistic parameters, tackles the procedure of comprehensive optimization in service configuration [2]. This work recommends a novel result update method intended for the basic ABC algorithm. The result updating rule is built on the normal distribution. The performance in addition to accuracy of the suggested way

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are assessed using 24 benchmark functions. The outcomes show that the strategy is real in resolving continuous optimization problems [3]. Before theoretically determining the absorption coefficient of the anisotropic fibrous material is investigated [4]. The chapter in [5] discusses the Artificial Bee Colony and Evolutionary Optimization Algorithm established on the foraging behaviour of bees.

LITERATURE REVIEW

The Artificial Bee Colony (or ABC) is a numerical strategy for optimization is based on the foraging behaviour of honey bees that were put out in this article [6]. The main objective of the project is to detect any accident locations and alert emergency services, law enforcement, and neighbouring citizens using the GSM (Global System For Mobiles) and GPS (Global Positioning System) networks [7]. The cardinality-constrained mean-variance portfolio optimization framework is analysed in this study as a mixed quadratic additional to an integer programming problem that can be solved using heuristic techniques [8]. This work employed an improved ABC optimization approach. The novel method was assessed against the well-known ABC Optimization and PSO [9]. The HACO-ABC-CHS—Hybrid Ant Colony with Artificial Bee Colony Optimization Algorithm—is a practical cluster head selection approach described in this paper [10]. The authors of this work picked two popular, contemporary algorithms from the evolutionary and swarm intelligence families and then tested them on high-dimensional function optimization problems [11]. Some of the subjects discussed by the authors in this study include PSO, ABC, Differential Evolution (DE), Solution Search Strategy, in addition to Scout Strategy [12]. The enhanced artificial bee colony method is suggested to create random frames for the implanting process. The watermarking the video sequence is the end product of the watermark entrenching procedure [13]. This research presents a combination of the ABC algorithm in addition to the BFGS algorithm to address the multi-modal optimization issue based on the benefits of the ABC and BFGS algorithms [14].

This study describes a HACO-ABC-CHS approach to choose cluster heads effectively. This technique does so by mutually removing the shortcomings of ACO and ABC [15]. A hybrid Dynamic Load Balancing Strategy (DLBS) ABC optimization technique has been developed for use in parallel computing environments [16]. This study describes a novel ABC algorithm and genetic algorithm hybrid. The suggested approach combines the basic ABC algorithm with crossover operations from Genetic Algorithms (GA). Crossover-based ABC (CbABC) is the name of the proposed technique [17]. A novel quantum optimization method was indicated by fusing quantum theory and the ABC algorithm to address sluggish convergence speed issues and readily enter a local optimal value for the ABC algorithm [18]. The ABC Optimization Algorithm was the foundation for developing a new algorithm that included the construction of a dynamic punishment function. The program ABCOA1.0 through hybrid discrete variables for the suggested approach was created using the MATLAB environment [19]. The persistence of this study is to investigate, develop, and analyse a feature selection technique for the categorization of various data sets using the Artificial Bee Colony methodology [20].

NOVELTY OF THE PROPOSED WORK

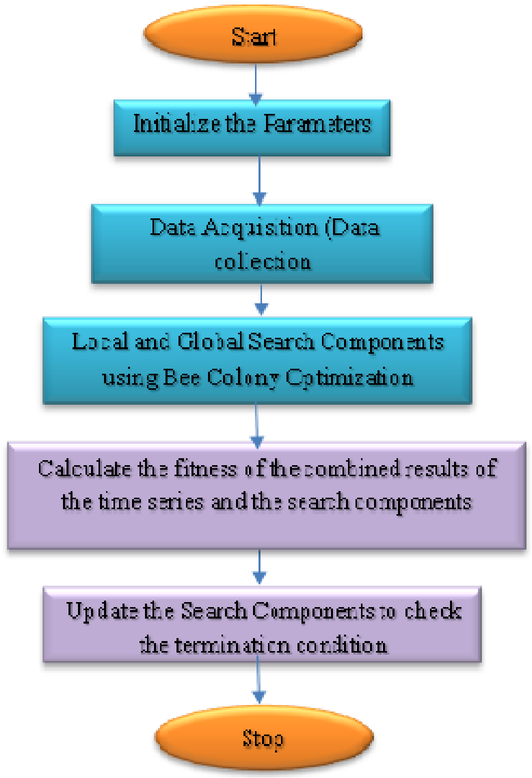
This research piece emphasizes various innovative aspects. First and foremost, this study sets itself apart by adopting a comprehensive multi-perspective methodology to analyse video game material on the YouTube platform. In contrast to traditional studies that frequently adhere to singular perspectives, this research delves into the multifaceted range of viewpoints, criticisms, and game-play experiences that are widespread within the YouTube gaming community. Furthermore, the originality of this approach is cantered on the use of the Time Series-Based Bee Colony Optimization Algorithm (TSBBCOA). The proposed hybrid algorithm integrates time series analysis and bee colony optimization, presenting a novel approach to video game analysis that enhances the precision and efficiency of sentiment and opinion extraction.

Furthermore, this study delves into temporal dynamics, recognizing how feelings change over time concerning gaming patterns. This aspect has frequently been disregarded in prior methodologies. TSBBCOA effectively tackles the critical concerns of scalability and efficiency, which are crucial given the ongoing expansion of YouTube's extensive collection of video game material. In summary, the research title exemplifies originality by employing a multifaceted approach incorporating algorithms and temporal awareness to analyse video game content on YouTube. This study aims to expand the scope of digital media analysis.

PROPOSED SYSTEM

Standard forecasting techniques call for rigid assumptions like normalcy and linearity. For real-world time series, it is difficult to meet these presumptions. Since time series methods do not call for strict assumptions, analyzing many real-world time series is simple. As a result, time series techniques have become increasingly appealing in recent years. Time series approaches have used artificial intelligence for a variety of purposes. In this research paper, a hybrid time series method is put forth that uses an ABC algorithm to formulate the solution to the problem. The following Figure 1 represents the process flow of the proposed system.

Figure 1: Process flow of the proposed TSBBCOA mod



New intelligent optimization method called Time Series-Based Bee Colony Optimization Algorithm (TSBBCOA) is inspired by honey bee colony feeding behaviors. In TSBBCOA, worker, observer, and scout bees are all involved in finding the greatest food source for the colony. The worker bees and observers are responsible for the local exploration, while the scout bees direct the wider exploration. The TSBBCOA algorithm may be summarized is given below.

Step 1: Initialization

- Initialize the population of the artificial bees as N with random solution in the solution space.
- The time t is initially set to 0.
- Create a default value for the border of positions by [Min, Max]
- The initialization function may be described as follows: each searching point C_j on the border is given a random initialization.

$$c_{ji} = Min + K_{ji} * (Max - Min) \qquad (1)$$

In Equation (1), $C_j = (c_{j1,}c_{j2}, \ldots .. c_{jT})$, and where $j = 1,2, \ldots ., GM,$ and where t means the optimization parameters, where K_{ji} is a random number within the given range of $[-1, 1]$.

- Start the worker bees out in the best possible place to begin their search by solving the initialization position matrix C^{GM*T} using the greedy strategy.

Step 2: Worker bee phase

- Worker bees use the following Equation (2) to come up with novel strategies.

$$y_{ji} = x_{ji} + \emptyset_{ji} * (c_{ji} - c_{ri}) \qquad (2)$$

- The potential solution to the following equation is denoted as y_{ji}, where $\mathrm{j,r} \in \{1,2, \ldots ., \mathrm{GM}\}$ and $i \in \{1,2, \ldots .. T\}$ are arbitrary indices, but $r \neq i$. In this case, $\emptyset_{ji}$ is a random integer between $[-1, 1]$.

- Using the greedy approach, choose the optimal answer from among the newly proposed candidate solutions y_{ji} and the most recent of the original solutions x_{ji}. Make the following calculations to determine the fitness values addition to the chance of selection using the Equation (3).

$$fit_j = \begin{cases} \frac{1}{1+l_j} if\ lj \geq 0 \\ 1 + epg(lj) if\ lj < 0 \end{cases} \qquad (3)$$

where fit_j is the fitness rate of the j^{th} solution in C_j, additionally, the l_j denotes the cost value of the j^{th} solution in C_j.

Step 3: Phase of the Onlooker bee

- Using the selection probability b_j is presented in the Equation (4), choose a novel solution from among all of the used bee solutions.

$$b_j = \frac{fit_j}{\sum_{r=1}^{GM} fit_r}$$

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \qquad (4)$$

Two primary areas of research focus for the proposed TSBBCOA are accelerating the pace of convergence and preventing the formation of local optima.

Step 4: Time Series Analysis

- Smoothing of the time-series data $Y_t$using the integrated approach is given in Equation (5).

$$Y_t = \int_0^x (\alpha * X_t + (1 - \alpha) * Y_{t-1})\, dx \qquad (5)$$

In the Equation (5), α denotes the smoothing parameter, X_t is the representation of the observed time series data, and Y_t is the smoothed time-series data.

- The objective function of the time-series analysis is represented in the Equation (6).

$$g(Y_t) = \int_0^x h(Y_t) dx \qquad (6)$$

In the above Equation (6), the complex function of the smoothed time series is denoted as $h(Y_t)$.

Step 5: Local Search Component

$$L(x_i(t)) = \Sigma_j \left(\nabla f(x_i(t)) * \nabla_g \left(x_{ij}(t) \right) \right), \quad j \neq t \tag{7}$$

- The above Equation (7) is the representation of the local search exploration using some of gradients to generate a local search component. $\nabla f\left(x_i(t)\right)$ denotes the gradient of the fitness function and $\nabla_g\left(x_{ij}(t)\right)$ is used to calculate the time series analysis function's gradient.

Step 6: Global Search Component

- For each bee's solution, a global search component is generated for global exploration using the Equation (8).

$$G(X_i(t)) = \int \int \phi(X_i(t), X_j)\, dX_i\, dX_j, j \neq i \tag{8}$$

In the above Equation (8), $\phi(X_i(t), X_j)$is the representation of interaction among the bee's solutions; whereas, X_j denotes the calculated solutions of other bees in the given population size.

RESULTS AND DISCUSSION

In order to evaluate how well the TSBBCOA model performs in comparison to the data from the real tests, it is necessary to choose some appropriate performance metrics. Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R2), Mean Absolute Percentage Error (MAPE), Mean Relative Error (MRE), and Recall are the statistical measures that have been selected for this study because of their widespread use among researchers. The suggested technique is contrasted with some of the more established approaches, such as the K-Nearest Neighbor (KNN) algorithm, the Extreme Learning Machine (ELM), along with the Support vector machine (SVR). Table 1 depicts the outcomes of MAPE, MRE, MSE and R2 for existing and proposed methodologies.

Table 1: Outcomes of MAPE, MRE, MSE and R^2

Algorithm	MAPE (%)	MRE (%)	MSE (%)	$R^{2\,(\%)}$
KNN	18	17	9	19
SVR	8	8	18	15
ELM	15	14	12	6
TSBBCOA [Proposed]	3	2	5	2

MAPE is the mean of the absolute percentage errors of prediction. According to performance evaluation,

Figure 2 shows that the proposed TSBBCOA is lower when evaluated to the existing methods.

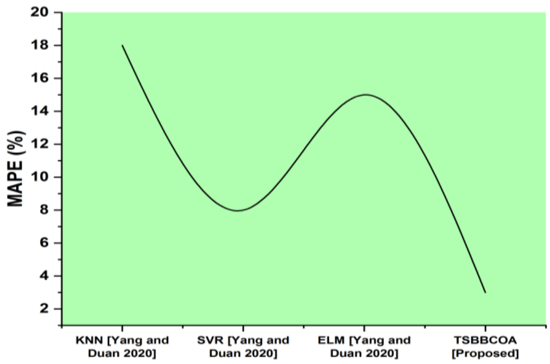


Figure 2: MAPE

A comparison of the MRE results of the proposed approach with those of the existing methods is shown in Figure 3. It is abundantly obvious that the MRE of the suggested approach is lower in comparison to the MRE of the existing methods. The Mean Squared Error (MSE) is a statistical technique utilized to assess the degree of correspondence between a regression line and a specific set of data points. The risk function is characterized by a numerical number corresponding to the predicted squared error loss and its expected value. The computation of mean square error entails determining the arithmetic mean of the squared discrepancies arising from data analysis regarding a specific function.

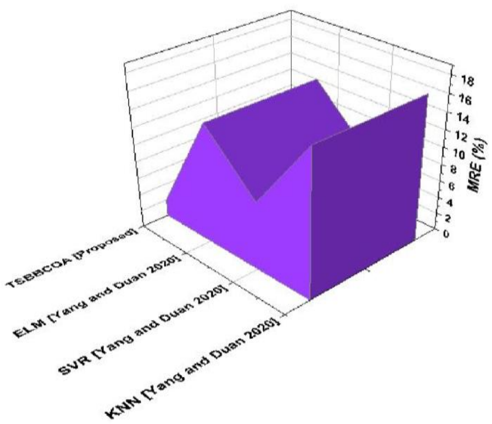


Figure 3: MRE Comparison

Figure 4 demonstrates, in accordance with the findings of the performance assessment, that the proposed TSBBCOA has a reduced MSE in comparison to the current approaches.

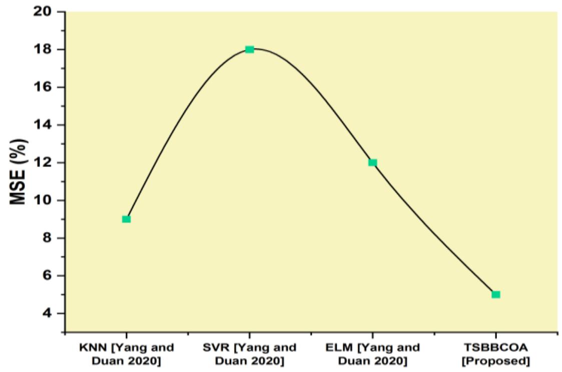


Figure 4: MSE comparison

The percentage of variation for a dependent variable can be depicted using a statistical measure referred to as R-squared (R^2). Figure 5 depicts the Comparative evaluation of R^2 in Suggested and Traditional Methods. It clearly shows that the proposed method is higher when compared to the existing methods.

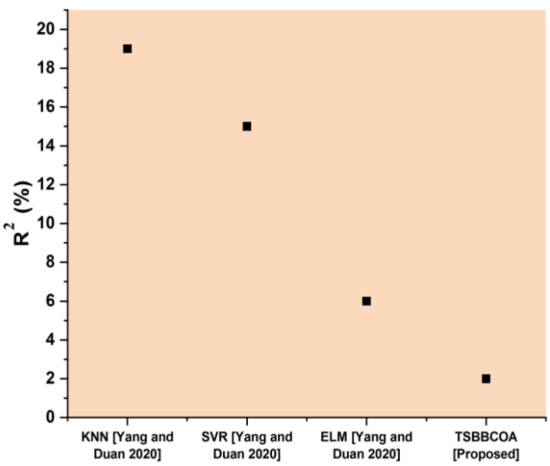


Figure 5: R^2 Comparison

Table 2 represents the outcomes of RMSE, recall and MAE for existing and proposed methodologies.

Table 2: Outcomes of RMSE, recall and MAE

Algorithms	RMSE (%)	Recall (%)	MAE (%)
KNN	18	65	93
SVR	16	72	75
ELM	5	88	84
TSBBCOA [Proposed]	3	94	60

CONCLUSION

It's crucial to remember that YouTube videos will only keep getting new views if they follow YouTube's rules. Therefore, placing a video on a website and setting it to play automatically will not result in countable views. Neither would be buying views using view bots. By utilizing these spam workarounds, risks are having the YouTube video deleted, losing your ability to monetize, or, even worse, having your account suspended. Therefore, one may quickly determine the number of views without spam using the hybrid Time Series Based Bee Colony Optimization Algorithm to assess numerous YouTube video game ideas.

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