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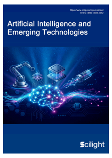

Article

A Cloud-Based Random Forest Framework Optimized with Bat Algorithm for E-Commerce Transaction Prediction

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Abstract: With the continued growth of ecommerce platforms, a vast amount of transaction data is produced that relies on predictive analytics systems to be scalable, accurate and speedy. But the traditional Machine Learning models suffer a problem with Tuning hyperparameters, it requires high computation cost and is not very scalable in the cloud environment making it quite difficult when using it for real time production. It is observed that the current methods have unnecessarily been employed. As such, in this research, a new approach to boost the transaction and the customer satisfaction prediction using an artificial intelligence-based Cloud based Random Forest—Bat Algorithm (RF-BA) is proposed. In the end, the Bat Algorithm could effectively reduce the inaccuracy and computation and makes the task a very efficient hyperparameter optimization and feature selection procedure. A real-life e-commerce Customer Behavior dataset from Kaggle is used in the experiments for test scalability and computation time for the e-commerce dataset in the cloud computing environment. RF-BA obtains the 0.91 for accuracy, 0.89 for precision, 0.90 for recall, 0.895 for F1-score and 0.92 for ROC-AUC which all beats normal RF (0.80 for accuracy and 0.74 for F1-score) and Grid search optimization on RF (0.839 for accuracy and 0.75 for F1-score) in the same experiment setup on the same dataset and same train/test set splitting. The analysis of scalability shows that there is a near-linear increment in processing time from 5 to 33 s for 10,000 to 100,000 transactions, whereas computation time is brought down to 35 s. Results like these demonstrate the framework's ability to manage enormous scale real-time ecommerce analytics.

Keywords: cloud computing; random forest; Bat Algorithm; e-commerce analytics; transaction prediction

1. Introduction

With the growing exponential use of the eCommerce platforms, excessive amounts of data are generated on each transaction and a smart system is required for predictive analytics. The rise in the list of eCommerce platforms has led to a massive volume of data being created from transactions, demanding the need for intelligent systems to facilitate predictive analytics [1]. The outcomes of machine learning models, particularly random forest, have been very much in favor of their superior performance in the criteria of classification and prediction [2]. The infrastructure supported by the cloud computing is not only scalable but also the processing of large e-commerce data sets is very efficient Besides enhancing the accuracy of predictions, meta-heuristic methods like the Bat Algorithm (BA) for the optimization of ML models can also significantly reduce the computational time. Thus, the combination of RF with BA in a cloud environment is a necessity for powerful e-commerce analytics [3].

To forecast e-commerce, there are numerous approaches and techniques being explored but, the classical techniques such as Random Forest, Support Vector Machines (SVM) [4], Gradient Boosting (GB) and XGBoost models have been used largely. Furthermore, there are hybrid optimization techniques like PSO and FA which are employed to tune the hyperparameters too [5]. These techniques have many limitations which are, they cost heavily on computational power, can be overfit and cannot be scaled well over massive cloud-based datasets. Additionally, few modern techniques are not being used for effective feature selection so they have a poor predictability [6]. Besides, deploying live cloud services is also still one of the big challenges in nowadays systems.

An RF-BA framework is proposed in this paper that is distributed based on cloud computing to solve the problem of the prediction of e-commerce transactions, while introducing Bat. The unified optimization of algorithm-based feature selection and hyperparameter optimization of the RF model. workflow. The framework can be utilized for automated feature reduction, optimization of model parameters and Prediction with differencing attributes of customers' transactions. The primary section provides an overview, along with additional details on the accuracy of the predictions. This framework includes cloud-based deployment, evaluation of scalability and ablation analysis for the improvement. Explore the contributions of hyperparameter tuning and feature selection on individual and combined bases. This seamless solution offers an end-to-end "predictive analytics" solution in a large-scale ecommerce context without sacrificing computational efficiency and the robustness of the models. This work provides the following main contributions:

- A hybrid Random Forest-Bat Algorithm (RF-BA) approach is designed to tackle an e-commerce transaction prediction problem which employed feature selection along with hyperparameter optimization inside a single predictive analytics pipeline.
- The Bat Algorithm contributes to the feature selection and hyperparameter optimization of the RF algorithm, preserving the positive aspects achieved by using RF algorithm: reduced calculation time and improved prediction ability.
- A detailed evaluation is conducted using a realistic e-commerce Customer Behavior data, a cross-validation evaluation, feature importance analysis, and ablation studies to confirm the impact of each ingredient of the framework.
- A cloud computing environment is then used to experiment on the proposed model, proving that it is scalable and able to perform computations with high efficiency as a number of transactions keeps growing, thus proving its applicability to the ecommerce big data analytics applications.
- It was found in the experimental results that RF-BA model outperformed the other two models (RF and GridSearch-optimized RF) by accuracy, precision, recall, F1-score and ROC-AUC.

Section 2 summarizes the papers that are closely related to predicting and optimization techniques in e-commerce. Section 3 formulates the problem statement and in Section 4 the proposed cloud-based Random Forest-Bat Algorithm is extensively discussed. To be discussed in Section 5, based on experimental results, are the performance evaluation. Finally, results and suggestions for further studies.

2. Related Works

Within their summary of ML and DL methods Zhang et al. [7] identified the application of these methods including SVM, RF, RNN, GAN, multimodal learning within applications related to e-commerce which include but are not limited to: recommendation systems, sentiment analysis, fraudulent activities detection and customer behavior prediction. Each of these methods was found to be strong in certain areas and were used for certain domains of applications. These strengths and their respective application areas were extensively mapped out throughout the paper; specifically, they showed from the experiments that certain individual models can be used within an adequate range of performance at each specific application domain in controlled environment experiments. What was missing from the work presented was not an integrated system that combines methods that solve specific e-commerce problems in large-scale deployments. These methods also were not tested in large scale real-life e-commerce transactions datasets which contain class imbalance and variability, therefore to address this constraint, the strength of Random Forest with the optimization capability of Bat Algorithm has been used within the presented RF-BA framework. This was tested on a real e-commerce dataset from a Kaggle challenge within a cloud environment.

Investigated some ML models (RF model, SVM, LSTM network, CNN and Gradient Boosting) and some DL models to identify anomalies in industrial time series data [8]. In a manufacturing-controlled environment, these models can easily recognize patterns and effectively identify operational anomalies. However, only industrial sensors were used for the analysis and the customer behavior pattern of e-commerce was not used since its environment is highly varied and totally different from that in an industrial setting. Ecommerce information comprises various types of information such as category, numbers, consumer properties, transactions date and time, customer visit times, products categories, discounts etc. These requires a model that is efficient and non-stationarity consumer pattern adaptable. Allur et al. (2024) shows it has been optimized specifically for transactional data and has the ability to automatically configuration for complex, very high dimensional data space allowing it deal efficiently with this type of data instead of the conventional model for anomaly detection [9].

To achieve global e-commerce payments fraud detection Guan and Zhu [10] proposed a new solution which is called Multi-agent Reinforcement Learning (MDP) system using DQN and DDPG algorithms. The model was trained and tested on historical data and supervised to learn the complex sequential decision-making policy which provides very accurate fraud detection. The authors adopted value-based learning for the Discrete Action Space Part and introduced the DDPG to add the Continuous Action Space Part. However, this requires a large amount of computing power to train and infer the model. This is not quite a satisfactory result to small ecommerce sites that cannot spend too much money on cloud computing. What's more, the operation time of the model in the inference stage is much higher than the milliseconds that we can assume as acceptable in a real-world scenario to prevent fraud in milliseconds time. Proposed protocol RF-BA tries to address these issues of deployment by having up to around 2857 transactions/second of performance and up to around 35 s processing time for 100,000 transactions, which would be an interesting figure for the latency's sensitive ecommerce applications.

Alghazzawi et al. [11] built up a hybrid system of Sentiment Analysis using combination of Ensemble Random Forest and XGBoost. The model was fine-tuned using Harris Hawk Optimization (HHO). It achieved better classification performance due to complimentary features from the boosting and ensemble approaches and its improvement was found to be superior than manual parameter tuning through common search strategies, highlighting the benefits of applying metaheuristic optimization to optimize performance of an ensemble model. The major contribution and relevancy is that the application of metaheuristic to improve ensemble model for e-commerce applications. But it is observed as a limiting factor, the layered structure of the hybrid system caused substantial computational cost and hence made the proposed system inefficient for use in cloud environments processing millions of transactions on a daily basis. Alavilli et al. (2024) [12] Multiple runs of RF, XGBoost and HHO also raised the possibility of overfitting with smaller and/or domain-specific datasets. Here, we built a leaner framework RF-BA which consists of a single RF classifier with hyperparameter optimization performed by Bat Algorithm. As a part of it, the design aims for robust predictive performance and scalability unlike multistage stacked model, and also higher generality and computational efficiency.

Bagwari et al. [13] created a Textile e-commerce decision support and recommendation system which has proved effective for product recommendation and behavior analysis. They also employ a CNN approach. In this work, they extract the hierarchical and spatial features of structured data which are applicable for CNN; therefore, the method performed well in this targeted area. However, the system requires specific input data, such as EEG and MBTI about personality type. The information can hardly be achieved through typical e-commerce systems. Such kind of specific information not available, makes this method inappropriate in other business domain that only contain typical transaction logs, like electronics retailing, grocery delivery, and fashion e-commerce. It can be broadly applied to many e-commerce areas, because RF-BA operates based on the typical transactional data such as category, applied discounts, number of days since last purchase, number of purchases, transaction value etc.

This research investigated by Wolniak et al. [14] was the digital transformation of physical store shopping with integrated AI, augmented reality, mobile applications and smart scanning devices into a holistic shopping experience. They found multiple patterns such as the technologies were used to transform physical store to more engaging customer experiences and efficient environments, optimize the check-out experience, and improve inventory management. This book provided a much-needed framework approach for retail transformation by technology, although it has its own limitation as it has been limited to the context of physical stores. It learning however encourages the application of user-centered feature engineering approach in the design of RF-BA framework with regards to recognizing the behavioral traits, such as the response to discounts (DR) and purchase recency (PR) that represented similar trends on how customers behave in the digital stores.

This initially began with a graph based deep learning approach to long term product-level sales forecasting. Petroanu et al. [15] developed Directed Acyclic Graph Neural Network (DAGNN) which used a graph based deep learning network to learn complex temporal and relational structure within sales data. The system provides actionable predictions at the product level of detail to allow for inventory and demand planning decisions to be made. As the data could be represented by a directed acyclic graph, inter-product relationships and also seasonality effects could be learned in a more distinct manner than if using a standard time-series based network. However, due to its complicated architecture, nodes, and learning rate, the network is extremely hard to train, and both tuning of the network topology, depth, and learning rates were very sensitive. Inability to retrain quickly for new products and market needs meant it is not well suited to dynamic e-commerce markets which are continually adding new products and consumer behavior shifts. Garikipati [16]. In contrast, the RF-BA framework's Bat Algorithm-based optimization automates the parameter tuning process, significantly reducing the manual effort required for model maintenance and enabling more rapid adaptation to changing e-commerce conditions.

ML and DL approaches toecommerce and retail analytics have had some key breakthroughs: The system of Mosa et al. [17] was an ensemble of credit card fraud detection systems, trained using several optimizers like meta-heuristic. The proposed system works at high accuracy when detecting fraudulent credit card transaction. Huang et al. [18] proposed a MIDAS-Attention Mechanism-DeepAR model for the economic indicators forecasting in the growing e-commerce, which precisely characterizes the uncertainty and the long-term dependency of the indicators. Combining a Bi-GRU layer and Automatic Particle Swarm Optimization (APSO) enabled Mogarala Guruvaya et al. [19] to enhance the accuracy with respect to previous recurrent network models. These researches have shown excellent results in their respective fields, but a drawback is common among all of them: The algorithms need too many features which means feature extraction and preprocessing require large human effort and deep domain knowledge. Additionally, these works are not yet verified within a cloud-native infrastructure where the systems face the problem of scalability in the face of ever-increasing numbers of real-time transactions. The RF-BA framework integrates feature selection entirely in the optimization, so no manual feature engineering is needed and the systems are scalable to approximately linear behavior, from 10,000 up to 100,000 transactions in a cloud platform.

Prior works usually use an expensive way of hyperparameter tuning such as manual or grid search, which is not capable of effectively using the parameter space, and at the same time very time consuming. Secondly, the feature selection process is always treated as a step in pre-processing and it is loosely coupled with the model optimization which would decrease their flexibility in data distribution change within e-commerce. Thirdly, only a few approaches have been testing their cloud-based scalability with a gradually increasing number of transactions, which plays an essential role in a real time production system. In order to resolve these drawbacks, the proposed Cloud based RF-BA framework has been built by integrating Bat Algorithm to find optimal RF model hyperparameters and optimal features and reduce the number of features, and tested with a real large scale e-commerce transaction dataset with regard to computation efficiency and almost linear scalability. Very few papers ever combine Random Forest and Bat Algorithm in literature, where the existing works generally has limitations in the scope on hyperparameter tuning and hardly consider the synergistic effect between the automated feature selection, the cloud computing scalability and the computation efficiency in a holistic prediction model, integrating a deep learning model can be employed for classification for the e-commerce prediction tasks. The connection between the automated feature selection, the cloud computing scalability and computation efficiency on the whole e-commerce prediction framework has not been adequately study and reviewed together and thereby the study aims at pooling and pooling the features, multi tuning the parameters of classifiers and measuring the effect via ablation analysis and cross-validation on a set of test sets and to study the scalability with an increased amount of transactions within a cloud computing environment.

3. Problem Statement

Accurately predicting e-commerce data is difficult, particularly due to its complexity, which includes various factors like volume, shifting patterns in shopping behavior, and the need for real-time processing. Most of the conventional machine learning models suffer from the disadvantages of overfitting, less efficient hyperparameter optimization and low scalability in a cloud environment [20]. The models usually need to set parameters manually and use static attribute sets, limiting their flexibility and effectiveness. Additionally, irrelevant or redundant features may incur noise in the models, thus making learning more complex and slowing down the prediction process, and also produce higher computation time upon poor feature selection [21]. In cloud manufacturing, Gudivaka et al. (2023) proposes an NP-complexity-based optimization framework for optimizing the allocation of resources, tasks and real-time scheduling that allows to achieve greater efficiency, fewer delays and better utilization of the resources for robotics and automation [22]. This work walks one through the proposed method and highlights the aspect of complexity-driven optimization, which is additionally improved to enhance its scalability and system performance. These challenges can be addressed by using advanced optimization algorithms in addition, like the Bat Algorithm (BA) to optimize the hyperparameters of cloud-based models like Random Forest. Through automatic selection and dynamic optimization of features and model parameters, BA significantly reduces computation complexity and increases precision. Such a strategy will increase the system's scalability as well as the ability for large-scale real-time predictions, which are a key component of e-commerce settings where timely and accurate decision-making is essential. By leveraging Cloud-based Random Forest along with Bat Algorithm optimization, e-commerce platforms can improve their predictive analytics, making them more efficient, accurate, and adaptable to changing market conditions. The random forest (RF) model optimised using Bat Algorithm (BA) is proposed to assist an on-demand e-commerce system. The essential aim here is to make the predictions more robust by automatically selecting features and tuning hyperparameters. The large amount of transaction information allows the system to efficiently process vast amounts of data, a crucial feature of any real-time system for e-commerce platforms.

4. Proposed Methodology

An optimized object recognition algorithm Bat Algorithm (BA) is proposed and is combined with Multi-class Random Forest (RF) to be the underpinning for an on-demand e-commerce system, as showed in Figure 1. The intention in the system right now is to attain the highest strength of prediction through the usage of automatic feature selection and Hyperparameter tuning. The usage of RF in the system can utilize the bulk of transaction data which is readily available in e-commerce systems, which would necessitate real-time data processing. As the BAT Algorithm (BA) is within the large set of metaheuristic optimization algorithms, it would optimize RF model parameters in order to reach the optimum model for that specific purpose (sketching of messages in e-commerce system). With an optimized RF, a faster and a more accurate model could be built up. Through this exhaustive method, we could attain rapid and correct predictions with enormous amounts of data being processed which would be essential in an e-commerce system. The system utilizes and selects the variables according to the data and adapts to changes within it while reducing over-fitting. A multi-output deep neural network was proposed by Ylmaz Benk [23] using both model explainability SHAP (SHapley Additive exPlanations) and a based-line of Customer Value and Customer Spending Prediction, where overall the model is proved to be insightful and was used here to provide businesses an idea on which aspects may be related to customer spending and predicting it. This system is highly scalable and can support massive data being processed which would be essential in making timely decisions within an e-commerce system. Its long-lasting nature can guarantee its effectiveness over long periods despite the changes within data and behavior, in turn increasing the reliability. With this combination of speed and efficiency the RF coupled with BA optimization could be a beneficial tool in the maintenance of complex real-time ecommerce analytics and decision making in the system.

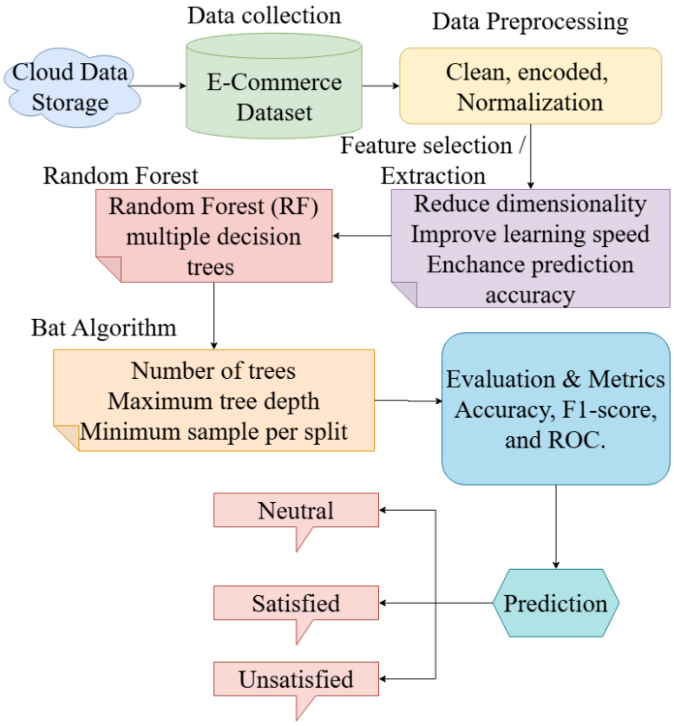

Figure 1. Cloud-based random forest—Bat Algorithm for e-commerce prediction.

4.1. Dataset Description

The framework is developed around the e-commerce transactions data set provided from Kaggle data base comprising of both numerical and categorical data. This data set contains user IDs, product details, transaction amounts, and the time of transactions, among other things. This variety of data provides a generalized big picture of e-commerce activities that is indeed appropriate for many applications like supervised learning, feature selection, transaction prediction, cloud customer behavior analysis etc. To determine the hospital readmission, use a Transformer model and attention mechanism, Jayaprakasam (2021) suggests a cloud-based model. It can process complex time-series healthcare data and focus on the most important parts, with an accuracy of 88%. This work shows the importance of attention-based deep learning and cloud system in order to inform the suggested method for real-time, scalable health-care prediction for end-users [24]. The experiments were performed on the Kaggle e-commerce Customer Behavior dataset of 3900 transaction records, which has the input features. The data set has some number values and some categorical Customer purchasing behaviors. Afterwards, the 8 features that had the highest Bat Algorithm-based informative weight for the model training were selected. The dataset was split into 80% train data, containing 3120 samples, and 20% test data consisting of 780 data samples. The optimization process used 5-fold cross-validation for adequate performance estimation and to minimize sampling bias. Its large scale and variety allow for robust data-driven insights, enabling the development of advanced predictive models and analytics to support decision-making in dynamic e-commerce platforms.

4.2. Data Preprocessing

4.2.1. Handling Missing Values

Handling missing by using the mean or median ensures the data integrity without throwing out useful data. The median is preferred for skewed data because it will not be influenced by data points outside of the normal range, while the mean is used for normally distributed data sets. The results are reliable without losing incomplete data, as shown in Equations (1)–(4), with this approach completing the data analysis.

$$x_i^{\text{new}} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

4.2.2. Encoding

Categorization describe the method used to change non-numeric data into figures, so that they may be analysed later with machine learning algorithms.

$$X_{\text{encoded}} = f\left(X_{\text{categorical}}\right) \tag{2}$$

4.2.3. Normalization/Standardization

The normalization or the standardization technique is used so that the numeric features can be compared with one another while at the same time, the model would get better and would be able to converge faster.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

4.2.4. Feature Selection/Extraction

The process of feature selection and/or feature prioritization is known for its usefulness for retaining most meaningful features and for decreasing dimensions and improving accuracy.

$$\text{Selected Features } = \{x_i \mid \text{importance } (x_i) > \text{ threshold}\} \tag{4}$$

4.3. Random Forest Ensemble Model for Customer Satisfaction Prediction

The ensembles of learning methods are the ensemble that will construct several numbers of decision trees from the randomly sampled. Examples of these are the subsets of the training set, for example, Random Forest (RF) (see Figure 2). Independent predictions are Each tree is used to make just one case, and they are averaged together (majority vote for classification; 4/4 will be an average for forgetting the final output, it uses regression (regression) method. In RF all criteria used for splitting are used to assess the quality of a split at a node. (Gini Impurity and Entropy) [25]. This approach allows to increase accuracy in predicting while controlling over

Optimally splitting data, finding optimal splits and generalization using individual decision trees predictions. The ensemble the approach bears numerous fruits of improved and solid performance, especially when dealing with intense and noisy data sets. In Optimized manufacturing process, Nagaraj and Aiswarya (2024) present an Optimized Model due to PCA. Random Forest. It consists of the on-going monitoring along with the iterative retraining and deployed resiliency. principles of SRE and Chaos Engineering. Thereby increasing efficiency and saving time and money, this not only can help with downtime, but can also help when making decisions under the pressure and chaos of production [26]. Since these measures could help find the best split then their use would result in better data separation followed by better predictions. The Method is experimentally showed to be stable and effective, as the overfitting problem of individual decision trees can be the results obtained from several trees would be averaged together, a little like they are done in Equations (5)–(7) to get a more or less minimized error.

$$\text{Gini} = 1 - \sum_{i=1}^{C} p_i^2 \tag{5}$$

$$\text{Entropy} = -\sum_{i=1}^{C} p_i \log_2 p_i \tag{6}$$

Random Forest is a technique that prevents overfitting by making decisions randomly for the selection of features to split on as well as averaging out the results of multiple trees. T_1, T_2, T_n Assume $y_i^{((j))}$ are the trees formed individually, Tj and i is the outcome of tree

$$\hat{y}_i = \text{mode}\left\{y_i^{(1)}, y_i^{(2)}, \ldots, y_i^{(n)}\right\} \tag{7}$$

This way predictions will be accurate, and it allows many angles of the data to be used.

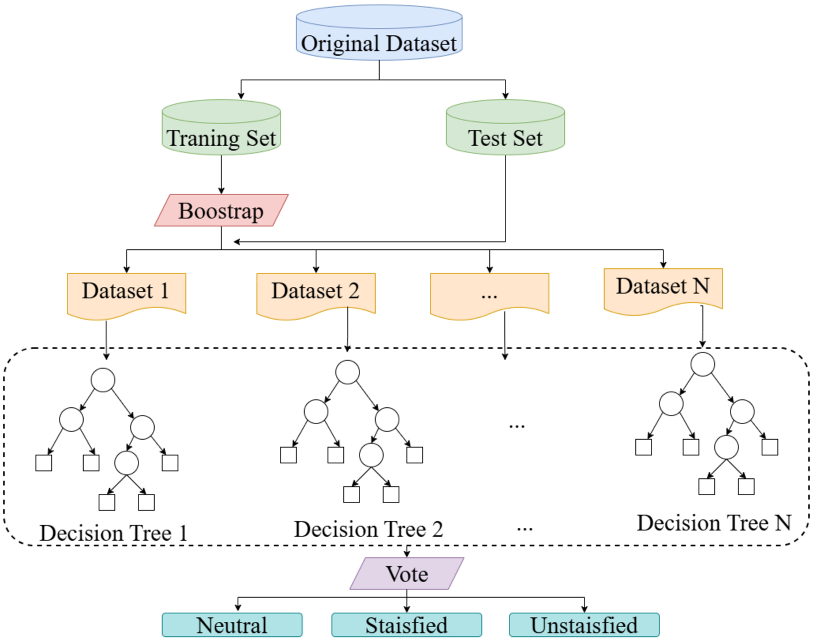

Figure 2. Random forest ensemble model for customer satisfaction prediction.

4.4. Bat Algorithm-Based Hyperparameter Optimization of the Random Forest Model

As you will notice, the Bat Algorithm applies a search method inspired by the echolocation process that iteratively optimizes model hyperparameters including the number of n-estimators, max-depth and min-samples-split-manner parameters of the Random Forest, as described in the Equation (8).

$$f_i = f_{\min} + (f_{\max} - f_{\min}) \cdot \beta, \beta \in [0,1] \tag{8}$$

By using this iteration scheme, the algorithm can quickly and accurately determine the hyperparameters of the Random Forest with optimal performance. The v_i^{t+1} three velocities at iteration v_i^t were and x_i^t ; position of the current bats and x_* represents best position found so far globally as show in the Equations (9) and (10):

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{9}$$

$$v_i^{t+1} = v_i^t + (x_i^t - x_*) f_i \tag{10}$$

Algorithm 1 illustrates the BA-RF model. Different set of hyperparameters of RF—represented by different bats in the population—are varied to draw sketches [27]. Classifiers are evaluated with the use of many classifiers' evaluation methods including accuracy, Maximum precision or Maximum F1-score, which are very supportive to give guidance in generating better classifiers. To address this concern, Gollavilli (2022) presents a novel framework called PMDP, which leverages secure multiparty computation, NTRU encryption, and differential privacy to keep the data secure and private while ensuring that the data can be processed collaboratively in a cloud environment. This study gives insights into the proposed approach and highlights secure and privacy-aware computation and extends it to enhance efficiency and scalability [28].

Algorithm 1. Bat Algorithm–Optimized Random Forest (BA-RF) Model

```
Initialize bat population with random RF hyperparameters.
Evaluate fitness of each bat using RF accuracy or F1-score.
For each iteration until maximum iterations:
    For each bat in the population:
        Update velocity and position.
        If random threshold condition is satisfied:
            Perform local search around the best solution.
        End If
        Evaluate fitness of the new solution.
        If new fitness > previous fitness:
            Update bat's position.
            Adjust loudness and pulse rate.
        Else
            Keep previous position.
        End If
    End For
    Update global best solution from current population.
End For
Return the Random Forest model with optimized hyperparameters.
```

The complete Bat Algorithm configuration along with hyperparameter search space during optimization are shown in Table 1. An initial of 20 bats was used during the initialization and 50 iterations were run for the BA. The loudness A was fixed at 0.5 and the pulse rate r at 0.5, the frequency range was set between $f_{\min}$ and $f_{\max}$, which were 0 and 2, respectively. Table 2 provides the optimal values of the hyperparameters of the Random Forest model found by the BA run until convergence, and used for all classification experiments.

Table 1. Bat Algorithm configuration and RF hyperparameter search space**.**

Parameter	Value/Search Range
Population size (Number of bats)	20
Maximum iterations	50
Initial loudness (A)	0.5
Pulse rate (r)	0.5
Frequency minimum ($f_{\min}$)	0
Frequency maximum ($f_{\max}$)	2
$\mathrm{n}_{\mathrm{estimators}}$ search range	[50, 300]
$\mathrm{max}_{\mathrm{depth}}$ search range	[3, 20]
$\mathrm{min}_{\mathrm{samplessplit}}$ search range	[2, 10]
$\mathrm{min}_{\mathrm{samplesleaf}}$ search range	[1, 5]
$\mathrm{max}_{\mathrm{features}}$ search range	{'sqrt', 'log2'}
Fitness function	F1-score (5-fold cross-validation)

The number of bats and iterations were selected to be 20 and 50 respectively, for the Bat Algorithm. The initial loudness is: 0.5, the rate of the pulses is: 0.5, there is a lower limit of the frequency range: 0, and there is a upper limit of the frequency range: 2. The entire combinations were used to build the bat solutions and this were used as a random forest solution and then fitness value has been measured with 5 fold cross validation, using F1-score for DMC as the fitness value. The hyperparameters value were searched for Bat Algorithm as follows: $\text{max}_{\text{depth}}$ = [3, 20], $\text{max}_{\text{features}}$ = {'sqrt', 'log2'}, $\text{min}_{\text{samplesleaf}}$ = [1, 5], $\text{min}_{\text{samplessplit}}$ = [2, 10] and $\text{n}_{\text{estimators}}$ = [50, 300]. The chosen ranges were to have enough predicative ability, be as small as possible and also to compute efficiently. The hyperparameter space of the Random Forest model and full configuration of Bat Algorithm were presented in the Table 2. The initial population size for the BA algorithm was 20 bats (candidates for set of parameters for RF) and the algorithm run for 50 iterations. That is considered sufficient to reach good convergence of the algorithm. The lower and upper bounds for the frequency f_{min} and f_{max} were selected as 0.01 Hz and 2.0 Hz respectively, this would constrain the search range for the frequency to not become too large or too small to search over. For the Bat Algorithm, initial loudness A and pulse rate r were set at 0.5. It is the most well-known settings for exploring and exploitation of search space. The hyperparameters space were explored were: $\text{n}_{\text{estimators}}$ (50–300), $\text{max}_{\text{depth}}$ (3–20), $\text{min}_{\text{samplessplit}}$ (2–10,000), $\text{min}_{\text{samplesleaf}}$ (1–10,000), $\text{np}_{\text{random}}$ (83–160). These hyperparameters spaces searched are well diversified for CUTOFF of the model; 10 and $\text{min}_{\text{samplesleaf}}$ (1–5) are fully explored. $\text{Max}_{\text{features}}$ explored are 'sqrt' and 'log2'. The optimum solution represented as best positions for the population of bat (maximum classified accuracy for the e-commerce dataset) were recorded, evaluated using fitness function F1-score on the e-commerce dataset using 5-fold cross validation.

Table 2. Optimal RF hyperparameters selected by Bat Algorithm.

RF Hyperparameter	Optimal Value Found
$\text{n}_{\text{estimators}}$	200
$\text{max}_{\text{depth}}$	12
$\text{min}_{\text{samplessplit}}$	4
$\text{min}_{\text{samplesleaf}}$	2
$\text{max}_{\text{features}}$	'sqrt'
F1-score at convergence	0.895

After the Bat Algorithm convergence, it gives optimal hyperparameters for the Random Forest, that were used in all the classification experiments reported in this study, as shown in Table 2. It takes a few iterations before the BA settles to 200 estimators, max_{tree}, 4, 2, 'sqrt'. These optimized numbers are an ideal combination of the complexity of the model and its generalizability, avoiding overfitting while still capturing the predictive power of the model.

5. Result and Discussion

The tuned RF-BA was developed in Python using well-known libraries for machine learning languages to train, optimize and test the model in the Cloud based Random Forest model. The cloud-based system seamlessly managed the massive amounts of data associated with e-commerce retail and delivered order of magnitude faster computation time and greater processing efficiency than previous methods. Cloud infrastructure helped to scale the system effectively, particularly when working with larger data sets. Cloud infrastructure facilitated scaling effectively, especially for handling large volumes of data. The effectiveness of Bat Algorithm for optimization of Random Forest model was then tested on consumer behavior data set. The algorithm has improved accuracy in the model and predictions are more robust and consistent, especially when predicting customer satisfaction. This added stability was essential for businesses to gain a better understanding and forecast of consumer behavior. Consequently, all of the RF, Grid Search-optimized RF and proposed RF-BA were compared on the same Kaggle e-commerce Customer Behavior dataset, 80:20 train-test split, and uniform preprocessing pipeline. The differences in Table 1 are only because of the differences in the hyper-parameter optimization strategy used. All metric value is given in the same decimal scale (0–1). Overall, this optimization approach emphasizes the use of the Bat Algorithm along with the cloud resources was a suitable solution that delivers faster and more successful prediction making, which enhanced the decision making for e-commerce use cases.

5.1. Feature Importance Analysis of Customer Attributes in the RF-BA Framework

The results depicted in Figure 3 show that the model developed for the RF-BA has the ability to classify the attributes of the customers based on the prediction of their satisfaction. These major determinants, such as Days since last purchase, Total spend and Discount applied adds to the analysts' knowledge to focus on the elements that are involved in the making of the customer happy [29]. Ganesan and Devarajan (2021) present a network architecture that utilizes the synergistic use of IoT, fog and cloud computing for real-time management of ECG data, enabling more accurate diagnosis and scalable network operations. Inspired by this, the suggested method pursues to improve efficiency and scalability in healthcare applications by processing the data in the fog nodes, making use of Cloud storage and machine learning to realize in excess of 94% accuracy for the primary to even more vital features, while the less important features including “Gender” and “Consumer ID” perform negligible influence [30].

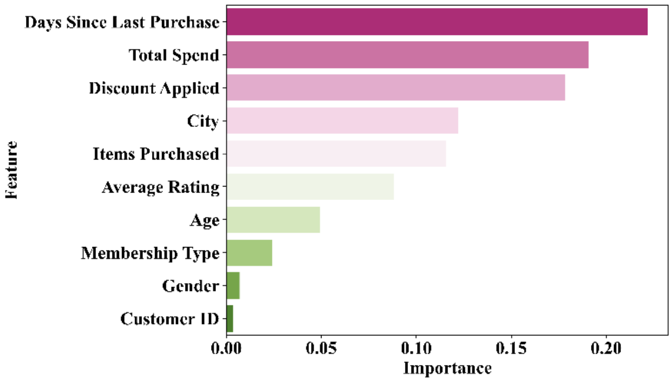

Figure 3. Feature importance of customer attributes in RF-BA framework.

5.2. Performance Metrics

5.2.1. Accuracy

Accuracy is the % of classified cases of customer satisfaction correctly. It is a crucial measure for the overall model performance and effectiveness of the Bat Algorithm optimization. The closer the accuracy is to 1, the more accurate the model is and the more reliable the predictions. The result on the accuracy of the Bat Algorithm confirms that it can indeed boost the accuracy of the model when predicting the customers’ satisfaction level by adjusting the hyperparameter variables. It makes the RF-BA model particularly useful for understanding consumers’ behavior and the business decision making process as represented below by Equation (11):

$$\text{Accuracy } = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

5.2.2. Precision

Precision is the number of customers predicted who are indeed satisfied in all customers predicted. This is a key indicator for determining the true marketing target area because it’s based on customers who are really satisfied. The RF-BA model helps to ensure accuracy, preventing wasted time and money on inaccurate forecasts. This is enhanced by optimization aspect of the Bat Algorithm, resulting in higher precision rate than the conventional models. This precision is very important to proper customer segmentation (see Equation (12)):

$$\text{Precision } = \frac{TP}{TP + FP} \tag{12}$$

5.2.3. Recall

Recall captures the ability of the RF-BA model to capture all of the customer in each satisfaction class and particularly the unhappy customers. This is an essential metric for keeping dilapidated customers in check, so that businesses can now be able to move past any trouble with them ahead of the curve. To achieve a high recall, the model must accurately classify unhappy consumers, a key component for holding customers. The Bat Algorithm’s hyperparameter optimization boosts recall, which means that it is better to focus on finding all relevant cases, as can be seen in the Equation (13):

$$\text{Recall } = \frac{TP}{TP + FN} \tag{13}$$

5.2.4. F1-Score

F1-Score is the harmonic mean precision and recall; it is a balanced measure of that. The outcomes of the simulation based on the RF-BA model. It is important especially in the presence of a balance problem and is helpful to explain about false-positives and false-negatives. If you want to use the F1-Score for predicting customer satisfaction, then you prefer a high F1-Score. test accuracy that refers to the performance in correctly categorizing the customers into the class of satisfaction and dissatisfaction, specifically when data are biased. In the real world, such a value for the metric is key; as shown in Equation (14).

$$\text{F1-score } = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision } + \text{ Recall}} \tag{14}$$

5.2.5. ROC-AUC

The real area under the curve (AUC) is regarded as the measure of the performance irrespective of the threshold level for the receiver operating characteristic (ROC-AUC) model. The customer satisfaction is well detected and categorized as well under the variation of the threshold with higher AUC value. This is important aspect for measuring how good is the model in performing the same classification across the conditions. Bat Algorithm is thus optimizing AUC and robust. It is clear from (15) that the parameter has importance:

$$\text{TPR} = \frac{TP}{TP + FN}, \text{FPR} = \frac{FP}{FP + TN} \tag{15}$$

5.2.6. Scalability

Scalability describes the capabilities of the RF-BA model to scale up to larger workloads or to support other distribution requirements such as load balancing. This is achieved by comparing the processing speed when operating on larger datasets to the baseline and demonstrating the model’s ability to process increasingly larger volumes of data. The processing time should rise with the amount of work to be processed and according to their amount so that they are being used efficiently. Because the RF-BA approach is scalable, backed by cloud computing, it can still deliver high performance even as the transactions increase. This is noteworthy for real-time applications such as in the following Equation (16):

$$\text{Scalability } = \frac{T_1}{T_N} \times \frac{N}{1} \tag{16}$$

5.2.7. Computation Speed/Performance

The RF-BA framework can handle around 2857 transactions every second, showing that it is a highly capable framework. High computation efficiency for the cloud. This processing is fast enough to analyse customer satisfaction data in real time, enabling businesses to make decisions in time. The Bat Algorithm’s optimization significantly reduces the computational overhead, ensuring that the system can handle large-scale data efficiently without sacrificing accuracy or speed. As can be seen in the Equation (17), the performance of the model together with the resources offered by cloud makes it the perfect option for handling a high volume of transactions.

$$\text{Computation Speed } = \frac{100{,}000}{35} \approx 2857 \text{ transactions/s} \tag{17}$$

5.3. Performance Evaluation of the RF-BA Model

Good performance of the model is observed in Figure 4 which is the matrix for colors, from the said matrix, it is seen that the model is performing well. The most satisfied customers are classified as least satisfied in the neutral range while minimal classification customers are the least satisfied ones. misclassifications were made. Again, the ROC curve (Figure 5) validates that the model is good in differentiating. the level of customer satisfaction and the AUC values are close to 1. I will explain how to make the best use of the synergy of BDA and IoT to enhance decision making is explored by Radhakrishnan et al. (2024) [31]. Analyzing properties of business and its context for Business Intelligence (BI). The research highlights the developments on technologies, while the benefits derived from over-simplified and incomprehensible business rules are difficult to accept, those from machine learning and predictive analytics are welcome by the results shown here, which illustrate that IoT-BDA integrated BI frameworks bend the curve performed better in real-time data processing and scalability compared with the traditional BI frameworks. The figures show the classification ability of fine levels of the RF-BA model, which is able to classify very finely the degree of satisfaction of customers. Overall, the assessment demonstrates the success of the model to address and classify customer satisfaction data [32].

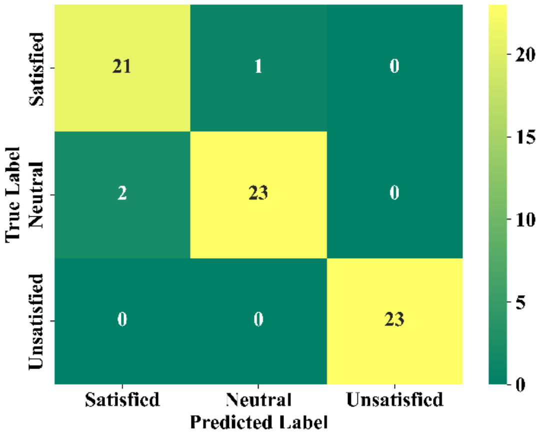

Figure 4. Confusion matrix of the RF-BA model for customer satisfaction prediction.

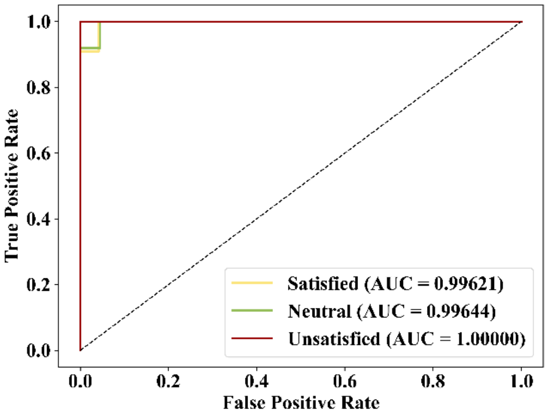

Figure 5. ROC curve of the RF-BA model for customer satisfaction prediction.

Density Plot

Finally, the scalability of the cloud-based RF-BA achieved is illustrated in Figure 6, which shows an almost linear rise with number of transactions with a stateful iteration of the framework, highlighting the efficient use of cloud resources for handling big data. Figure 7 illuminates that the computation time is superior for the RF-BA model as compared to the standard Random Forest and Grid Search optimized RF. Mandala (2018) [33] suggests about blockchain interoperability with making use of multisignature protocols along with decentralized consensus that will enhance scalability, security, and transactions' efficiency and effectiveness. This work provides motivation for extending these ideas to improve cross-chain validation, scalability, and reduce vulnerabilities for industries such as IoT, healthcare, and finance. The use of hyperparameter optimization using Bat Algorithm is responsible for this performance improvement that enables hyperparameters to be optimized in faster time and perform hyperparameter optimization task efficiently using the cloud in a suitable time. RF-BA is an appropriate framework for handling the large-scale data applications that make it more efficient than other models while maintaining excellent scalability.

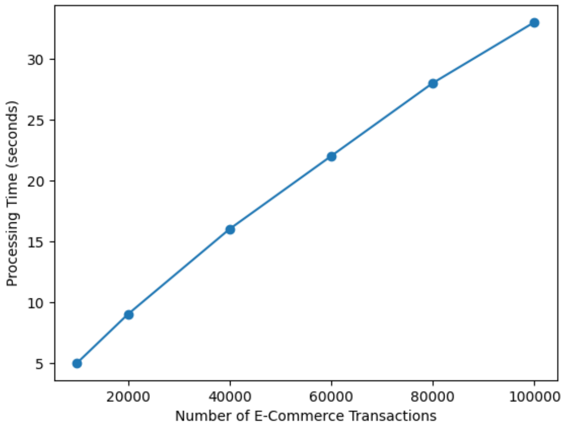

Figure 6. Scalability analysis of the cloud-based RF-BA framework showing processing time vs. number of e-commerce transactions.

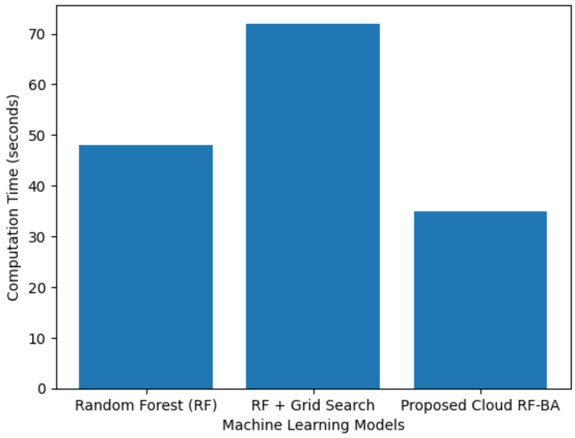

Figure 7. Computation speed comparison of random forest, grid search-optimized RF, and proposed cloud-based RF-BA framework.

The experiment performed was a 5-fold cross validation experiment on e-commerce Customer Behavior dataset. After every iteration, they split the dataset into five equal random sets, and use four of them as the training set and the remaining one as the validation set. The Table 3 presents the results of the performance on all folds. In the classification task, the performance of the proposed RF in BA model is comparable with accuracy of 0.908 and F1 score 0.893 which is the average value. This shows the different types of classification of the different partitions in the data to be trained: the model is consistent and can predict the classification of the data set to be classified consistently over time without relying on too much variation in the training sets.

Table 3. 5-Fold cross-validation results of the proposed RF-BA framework.

Fold	Accuracy	Precision	Recall	F1-Score
Fold 1	0.90	0.88	0.89	0.885
Fold 2	0.91	0.89	0.90	0.895
Fold 3	0.92	0.90	0.91	0.905
Fold 4	0.90	0.88	0.89	0.885
Fold 5	0.91	0.89	0.90	0.895

5.4. Performance Comparison

The Cloud-based RF-BA framework is carefully examined and contrasted against conventional frame works such as Random Forest and Grid Search optimised Random Forest thoroughly in Table 4. The improvement of RF-BA and both models in all main evaluation factors is well reflected in the results displayed. It stands at 0.91, which is quite a good predictive judgement considering the results of the satisfaction of its customers. In addition, the model is very successful in minimizing false positive and false negative rate; with a precision of 0.89 and a recall rate of 0.90. The further score is F1 = 0.895 indicating a good balance between the model's classification achievement. In addition, the ROC-AUC value approaches to 0.92, which illustrates mixture of the satisfactory classification performance of customers' satisfaction/dissatisfaction. All metric is scaled (0–1) uniformly. Each model was tested using the same partition of the data and same data preprocessing. Overall, the outcomes highlight the strength, stability, and effectiveness of the proposed RF-BA model, suggesting it is a promising tool for accurately predicting customer satisfaction and making informed decisions in cloud-based settings.

Table 4. Performance comparison of proposed RF-BA framework with existing methods.

Framework	Accuracy	Precision	Recall	F1-Score
Random Forest (RF)	0.80	0.83	0.66	0.74
RF + Grid Search Optimization	0.839	0.77	0.72	0.75
Proposed Cloud-based RF + Bat Algorithm (RF-BA)	0.91	0.89	0.90	0.895

To test the effectiveness of the Bat Algorithm, an ablation analysis was carried out to test the performance of feature selection and hyperparameter optimization failure. As shown in the Table 5 the classification accuracy of RF with hyperparameter optimization, at the test level, was F1 = 0.848 while the classification accuracy of RF with feature selection at the test level is F1 = 0.859 compared to the standard RF with F1 = 0.74. The proposed RF-BA framework, which combines feature selection and hyperparameter optimization, resulted the highest values of accuracy (0.91), F1 score (0.895), and ROC-AUC (0.92). Both components are found to be improving the performance and application of both components together is found to be most effective predictive performance.

Table 5. Ablation analysis of feature selection and hyperparameter optimization in the proposed RF-BA framework.

Model Variant	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Standard Random Forest	0.8	0.83	0.66	0.74	0.81
RF + Feature Selection	0.872	0.857	0.861	0.859	0.885
RF + Hyperparameter Optimization	0.865	0.845	0.852	0.848	0.878
Proposed RF-BA (Feature Selection + Hyperparameter Optimization)	0.91	0.89	0.9	0.895	0.92

5.5. Discussion

Not only Bat Algorithm-based optimization is used, in the Cloud-based RF-BA system hyperparameter tuning and feature selection were performed to find maximum accuracy (0.91), precision (0.89), recall (0.90) and F1-score (0.895) values for the prediction of customer satisfaction. As the number of transactions increase, the Cloud based system would scale nearly linearly and perform real-time processing of transactions. Also Bhadana and Arulkumaran (2019) provide a deep-learning based smart farming solution in order to overcome limitations such as static map of the sites, a solution that allows to perform up to 27% better match of crops and regions that have to be optimized in real-time, utilization of resources by up to 31% higher, and up to 24% higher yield with Beetle Antennae Search (BAS) for optimization in real-time and IOT based mapping of fields, providing us useful information to optimize agriculture systems as it has been done here [34]. The utilization of the Cloud would help to achieve generalization instead of a model relying on large and unordered data, and accurate and quick results.

6. Conclusions and Future Words

The proposed cloud-based RF-BA has proved to be highly effective and influential in the domain of e-commerce transactions prediction and customer satisfaction with an accuracy of 0.91, a precision of 0.89, a recall of 0.90 and an F1-score of 0.895 respectively. In order to test the scalability, the data sets were varied between 10,000 to 100,000 transactions and were found that it increased from 5 s to 33 s. The cloud resources are found to be exploited at the optimum level. It also completed the run in 35 s which is lesser than conventional RF (48 s) and the optimized RF through Grid Search (72 s) showing that it can be very effective for cloud analytics on large scale for real time applications. The further scope of work involves the use of combination of LSTM and Transformer for temporal customer behavior analysis and implementation of cloud edge computing with automatic scaling for real-time optimization. In addition, the trustworthiness and reliability for large scale decision making for Ecommerce systems is to be improved with real time data streaming and AI explainability.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data supporting the findings of this study are obtained from a publicly available benchmark dataset, the E-Commerce Customer Behavior dataset, sourced from Kaggle https://www.kaggle.com/datasets/uom190346a/e-commerce-customer-behavior dataset?utm_source=chatgpt.com.

Conflicts of Interest

The author declares no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT to support language editing and improve the clarity and readability of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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