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A Regional Feature Analysis Based Deep Learning Model for Improved Retail Management Using Block Chain

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Abstract. Modern human society and associated social factors are observed to have a great impact on the growth of the retail industry. Selection of production will be based on the rate of the sale, popularity etc. Though there are several models and methods devised by the conventional literatures, there are certain hurdles faced regularly while performing appropriate product selection. The present study has been formulated in order to address this issue. The present research has employed an effective Regional Feature Analysis based Deep Learning framework with Block Chain (RFDAM-BC) for improved performance of product selection and retail management. Several features and traces of retail have been extracted using Feature Centric Normalization (FCN) algorithm. The extracted features are fed to the Regional Feature Analysis method. By doing this, certain measures such as Regional Sale Support (RSS), Regional Popularity Support (RPS), Regional Affordability Support (RAS) and Regional Distribution Support (RDS) are estimated. With these measures, Product Selection Weight (PSW) is estimated, which helps in arranging and determining the best products and price in terms of region. The outcomes of the analysis are forwarded to the user by utilizing the block chain method that aids in encoding the data in various blocks which are decrypted from the receiver side. The proposed method improves the overall performance of retail development and management and in product selection.

Keywords: Retail Industry, Product Management, DLM, RFA, RFADM-BC, FCN, RPS, RSS, RDS, RAS, Block Chain.

1. Introduction

The modern society has great impact from information technology and their requirement has been continuously changing all the time. The lifestyle of the society lives in different region of any country differs with others. According to their lifestyle, the product being purchased by them also varies. Unlike earlier days, the customers purchase the products whatever they want through many E-commerce and M-commerce environments. The human society use mobile phones for most of their activities and carry out their day to day activity. The mobile phones become the most dominant entity in the common man's life now a day. The peoples explore the products they required through different E-Commerce solutions and they can purchase them through the environment.

The interest of the customers keep on varying at different time stamp. For example, wearing cotton cloths was a passion few years ago but in now a day, the people are moved towards other kind of fabrics. Similarly, using bicycles has been reduced in recent times like any other product. So, the interest of customers gets changing which challenges the manufacturer in making decision. The product manufacturer should always think about what the customer are looking for and what should be manufactured, where the market is and what the price should be. By analyzing all those factors only, the manufactured product can be distributed in the market. To perform this, market analysis is used to support the retail industry. Market analysis is the process of analyzing the products sale and selling rate and where the product has higher sale and analyze the popularity of the product.

The result of market analysis has been used in several problem. It has been used in growing the retail industry, finance sector and so on. By analyzing the purchase capability of the people living in the society, the growth of people's financial status can be measured. Similarly, the growth of retail industry can be analyzed by analyzing the purchase histories of any retail industry. However, to increase the product growth, it is necessary to analyze the retail data set and can identify which product has higher moving in the society. To perform this several approaches are available. Some of the methods uses the purchase frequency of specific product in measuring the growth, in some other approaches, popularity measures are used. However, the methods does not produce higher performance in the growth of retail sector.

Towards the scope, the region based features can be used in the growth of retail sector. The lifestyle of the peoples are differ at different regions and their purchase habits and capability also gets differ. So, by considering such regional features, the product growth analysis and retrial growth can be improved. By considering this, an efficient regional feature analysis based deep learning model is presented in this article. The market analysis is generally performed with the market trace using different approaches. The most commonly used approaches are K means clustering, SVM (Support Vector machine), Decision Tree and so on. The machine learning algorithms have great influence in various scientific problems. Similarly, the same algorithms are used in analyzing the market growth. However, there are many missing cases can be identified and the methods produces poor accuracy in achieving higher product growth. By considering all these, the proposed RFADM algorithm has been designed with the deep learning model which consider many features and works on huge data set. The method splits the data set according to regional features and train the model to estimate different regional support measures on different factors. The result of the deep leaning model has been used in product selection and product growth achievement.

The data security is the major concern in Mobile commerce where the user accesses various applications through the mobile device. So, the result of product analysis should be secured from illegal access. To perform this, various data encryption algorithms are available in literature, but has several issues. So, block chain technique is recently used which challenge the malicious user in tampering the cipher data. By adapting block chain method, the performance in terms of data security can be improved. The detailed approach is presented in the next section.

2. Related Works

Various approaches are described in existing researches towards the problem and this section details some the methods around the problem. A Functional Link Artificial Neural Network (FLANN) model has identified the rate of growth of different products towards various manufacturing industries. The method uses trigonometric features in analyzing the product growth (Bhatnagar, Majhi, & Devi, 2016). Towards the development of financial products, a regression analysis model is presented in (Wu & Wang, 2021), which analyze various factors which influence the purchase of various products towards generating recommendations to the students. A novel nonlinear dynamic diffusion analysis is presented in (Z. Tang & Zhu, 2020), which consider the consumer heterogeneity and uses the behavior features at micro level and macro level product purchase habits. In, (Y. Cui et al., 2022) a weighted statistical network modeling scheme is presented for analyzing the competition between various products. The method considers different product attributes and uses random graph model in analyzing the effect of various features in competitions. Towards product diffusion a mathematical model has been presented in (C. Li & Ma, 2020), which uses delay and coverage metrics of different products to perform diffusion of various new products. Bifurcation has been used in analyzing the products suitability.

A novel product screening and lifestyle analysis is designed in (Huang, 2014), which consider the lifestyle features and cultural features in generating recommendations to the users. Towards maintaining supply chain of different products a game analysis based information sharing scheme is presented in (Y. Li, Xu, & Zhao, 2021), which performs product modeling and behavior analysis of different enterprise groups involved in sharing information. Also, the method analyzes the income being achieved in sharing information to perform the selection of chain. Similarly, in (Javaid, Javed, Alanazi, & Alotaibi, 2021), a Generalized Sum Graphs based scheme is presented which computes Zagreb indices of different sum graphs at different operations at subdivision and strong product of graphs. According to that, the recommendations are generated. A dual product information diffusion analysis is presented in (Huo & Xie, 2020), which uses preferences of various products in analyzing the fitness of various products with Markov chains. The method analyzes the information with Monte Carlo simulation mechanism and uses critical threshold. Towards the development of agricultural economics, a fuzzy hybrid multi criteria based decision making model is presented in (M. Tang & Wang, 2021), which performs decision making according to the deficiency in supply and selection approaches. Towards incentive analysis in product development, a E-Tailer model is presented in (Dai, Liu, & Jian, 2021), which uses market information in analyzing the incentives for the product development.

A novel product placement approach is presented in (Y.-K. Chen, Chiu, & Yang, 2014), which places the products on the listing page towards maximizing the products. The method places the product according to the spatial arrangements of the product which increases the product influence. In (Zou & Tao, 2022), an dynamic modeling for creating virtual products on Open scene graph using artificial Intelligence is presented. The method uses the RTM (resin transfer molding) model is used to evaluate the process quality standard requirements of the Koji bowl shape.

A data augmentation method that based on the DNN-HMM (Deep Neural Network- Hidden Markov Model) has been depicted in the existing research (Waltner et al., 2015) that aids in classifying the speech based on the Random Forest method. The technique exhibits the classification mechanism at different level with the dysarthric speech. In order to support the access of situated information, an AR method used to be employed referred as MANGO which is an Austrian development. The framework is designed to assist the purchase of groceries and the framework fills the products such as vegetables and fruits based on the users' interest and profile. The interest of the user has been traced with the assistance of deep learning methods (X. Cui, Goel, & Kingsbury, 2015). The implementation of data-augmentation methods with the DNN has been illustrated in the conventional paper (Surv, Wanve, Kamble, Patil, & Katti, 2015) that works on the basis of the label information where the model considers the sparse data. It integrates both stochastic feature mapping (SFM) and vocal tract length perturbation (VTLP) schemes with DNN.

In (Gunjal, Gunjal, & Tambe, 2018), they presented a Cipher Text Policy Based ABE (CP-ABE) scheme, which enforce great integrity even at compromised nodes. The method enforces data security in attribute level which improves data security. In (Loukil, Ghedira-Guegan, Boukadi, Benharkat, & Benkhelifa, 2021), they propose a novel privacy-preserving IoT device management framework has been designed to work with the block-chain methodology. The technique has been observed to be capable enough in controlling the IoT devices based on the smart contracts that is reinforced during the connection establishment.

In the previous study (Yan, Peng, Feng, & Yang, 2021), the researchers have developed a lightweight consensus method on the basis of the Proof-of-trust (PoT) that optimally enhances the efficiency of the system when compared with other block-chain techniques. Another existing model has recommended a novel IoT management model that embraces the block-chain methodology to aid the organizations to frame the supply chain efficiently.

In the existing research (Song et al., 2021), the researchers have developed a consortium block-chain on the basis of the distributed secure search (CBDSS) scheme over the encrypted data in the ecommerce-environment. By combining searchable encryption model and blockchain technology, sensitive data can be protected efficiently.

In (Onoufriou, Bickerton, Pearson, & Leontidis, 2019) Nemesyst has been employment, which is a framework that utilizes the databases with the sequentialisation to leave the mechanisms to be fed in a unique manner and transformed data when necessary. The study illustrated that RNN and Generative Adversarial Networks along with Nemesyst framework seemed to perform better and flexible for further advancements that would be applied over time. In (Sui, Gosavi, & Lin, 2010), the existing investigator has recommended a method based on the reinforcement learning that is associated with the Bellman equation in order to find the replenishment policy in VMI system along with the consignment inventory.

Similarly, the existing research (Punia, Nikolopoulos, Singh, Madaan, & Litsiou, 2020) proposed a new forecasting mechanism that integrates both Random Forest (RM) and Long-Short Term Memory (LSTM). It has been reported that the recommended model can design complex relationships of both regression and temporal type which would return considerable accuracy over other forecasting techniques. Likewise, the existing investigator (Qi et al., 2022) has researched a data-driven multi-period inventory issue with uncertain vendor lead time and demand with the accessibility to a huge historical data. Without any intermediate step, the considered study recommended a one-step end-to-end model that utilizes the deep learning based model to return the recommended replenishment amount directly from the input features. In (I.-F. Chen & Lu, 2017) a clustering based forecasting framework has been employed by integrating the clustering and machine learning technique for computer retailing sales forecasting. The considered model initially employed the clustering method in order to segregate the training data into groups. Grouping the data with same feature or patterns in a cluster.

In (Jamil, Iqbal, Ahmad, & Kim, 2021) a blockchain based predictive energy trading platform for providing a day-head controlling, the real time support and generation scheduling of distributed energy resources. In order to estimate the people count in retail stores, a low-cost deep learning method has been used in (Nogueira Jr, Oliveira, Silva, Vieira, & Oliveira). The recommended has also been designed to visualize and detect the hotspots. With regard to the term low cost, the research has used an inexpensive RGB camera which is probably like a surveillance camera.

In (Amin, Badruddoza, & McCluskey, 2021), the existing method has used machine learning along with census tract data in order to predict the modified Retail Food Environment Index (mRFEI) that refers to the percentage of healthful food retailers in a tract and secularly extract the feature of no access which corresponds to a food desert and low access that corresponds to a food swamp.

All the techniques discussed in the prior context are observed to suffer in order to attain higher performance in analyzing the product development and produces higher false ratio.

3. Research Methodology

3.1 Regional Feature Analysis Based Deep Learning Model (RFADM-BC) with Block Chain Technique

The regional feature analysis based deep learning model (RFADM-BC) with block chain use the retail traces data set. The data set has been preprocessed with regional feature analysis algorithm (RFA) which removes incomplete records from the data set and extracts various features from the traces. Extracted traces are used in training the deep learning model. The neurons of the model are designed to compute Regional Popularity Support (RPS), Regional Sale Support (RSS), Regional Distribution Support (RDS), Regional Affordability Support (RAS) measures. The number of layers of the network is designed according to the number of regional data available. Finally, the estimated support measures are used in computing Product Selection Weight (PSW) value. According to the value of PSW, the technique sorts the products and finds the suitable products and prices in region wise. The result of analysis is send to the user by using block chain technique which encode the data in different blocks which has been decrypted at the receiver end.

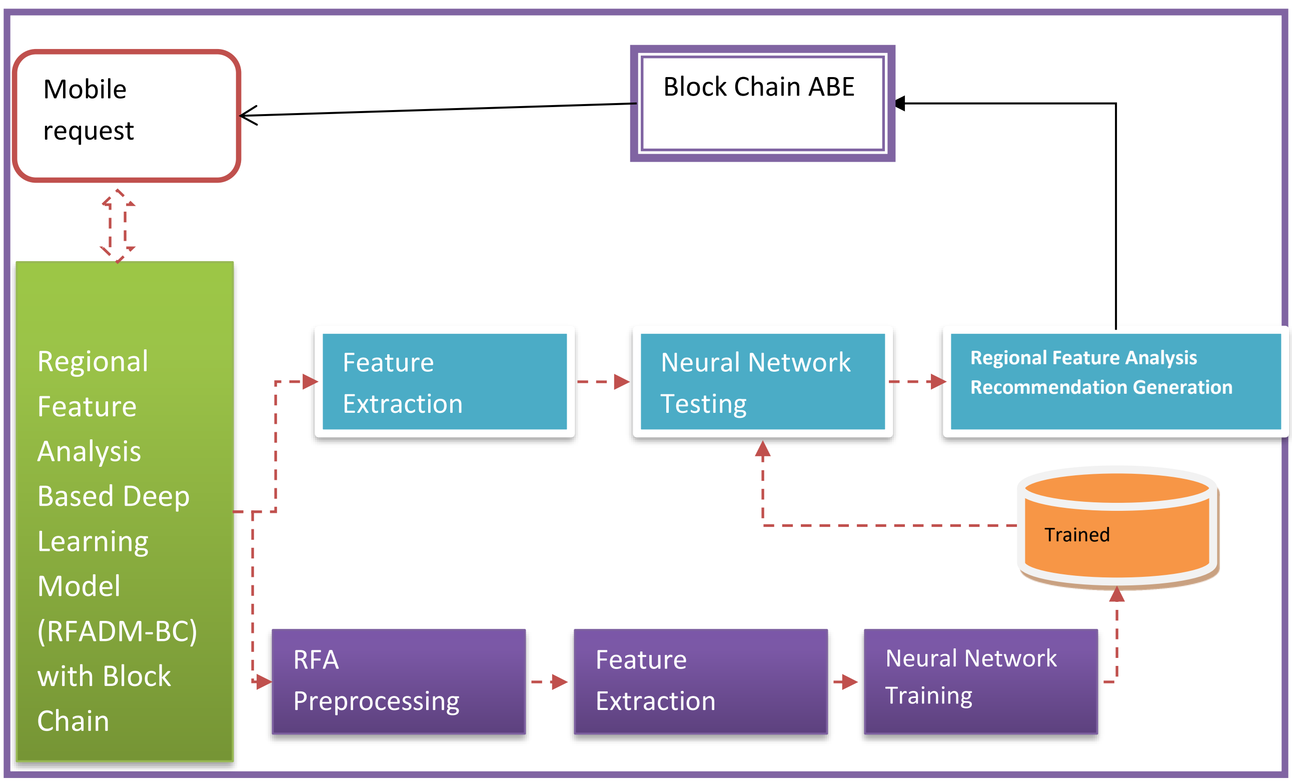

Fig. 1: Design of recommended RFADM-BC Model

The design of recommended RFADM-BC has been presented in Figure 1, and the details processes involved in the analysis is sketched in detail in this section.

3.2 RFA Preprocessing

The input retail trace has been fetched here for preprocessing. It contains number of traces and records belongs to the purchase made by various customers of different region of a country. So, in order to analyze the purchase behaviors and to improve the retail sector, it is necessary to group the traces according to the region they belongs to. In this way, the method first identify the set of region present in the records and split the records in regions. Also, the method finds the feature sets in the set and removes the traces with incomplete features. Such noise removed and region split data set has been used to perform further analysis.

RFA Preprocessing Algorithm:

Given: Retail Data set Rds.
Obtain: Region Set Rs.
Start
    Read Rds.
    Initialize Regional Trace Set RTs.
    Region set Regs = $\sum_{i=1}^{size(Rds)} Regs \cup (Rds(i).RegionID \ni Regs)$
    Find the features list Fes = $\sum_{i=1}^{Size(Rds)} Fes \cup (Rds(i).Features \ni Fes)$
    For each trace Ti
        For each feature Fi
            If Ti∈ Fi && Ti.Fi!=null then
            Else
                Flag=1
                Break
            End
        End
        If Flag !=1 then
        Rds = Rds∩ Ti
        End
    End
    For each region Ri
        Initialize region trace set Rs
        For each trace Ti from Rds
            If Ti.Region==Ri then
              Rs =Rs ∪ Ti
            End
        End
    End
Stop

The region feature approximation algorithm finds the feature set and region set from the data set given. According to the feature list identified, the traces has been identified for incomplete records and removed. Similarly, the method finds the set of regions to which the records are belongs to. According to that, the records or traces are split into different regions groups. Such region wise data has been used in further analysis.

3.3 Feature Extraction

The preprocessed and region wise data split by the RFA preprocessing algorithm has been used in feature extraction. The method extracts the features like region id, customer id, product, version, cost, profession, salary, and so on. Such feature extracted has been added to the concern region set. As, the method maintain the traces under different region set, the method extracts various features of the traces and convert them into feature vector. For each trace, the method generates a feature vector which has been stored with the features extracted. Generated feature vectors and stored in the region set has been used in feature analysis.

3.4 Neural Network Training

In the training phase, the method fetches the feature set or region feature set generated at the previous phase. The method first generates the neural network with number of layers N+2 where N represent the number of regions available and the value of 2 represent the input and output layers. Now for each layer the method generates number of neurons according to the number of feature vector available. Each neuron has been initialized with the features extracted from the traces. Similarly, the neurons are designed to measure different support measures. Such support measures on various factors are computed by the neurons at different layers which belongs to different regions. Such network has been used in training and analysis.

3.5 Neural Network Testing

The testing phase starts with the reception of the mobile request received from any M commerce application. From the request, the technique finds the service and extracts the features required. The product type identified has been used for the processing and once the features have been extracted, the method performs the neural network testing by submitting the product type. The neurons in the network trained have been to measure various support measures toward generating recommendation for the user. As the neurons at different layers measure Regional Popularity Support (RPS), Regional Sale Support (RSS), Regional Distribution Support (RDS), Regional Affordability Support (RAS) measures. Each layer will generate such four support measures and the output layer would receive N×4 number of values as results. Using this set of support values, the recommendation generation has been performed.

The neurons estimates the Regional Popularity Support value as follows: Consider, the region considered is Ri, and the product requested is P, then the value of RPS is measured accordingly.

$$RPS = \frac{\sum_{i=1}^{Size(RS(RI))} \sum_{j=1}^{size(Ri)} count(RI(j)==Ri) \&\& RI(j).Product==P}{\sum_{j=1}^{size(RS)} RS(j).Product==P}$$

Similarly, regional sale support (RSS) is measured according to the purchase frequency of product p in the region and what the other products frequency. The value of RSS is measured as follows:

$$RSS = \sum_{i=1}^{size(Rs)} Count(Rs(i).Product \equiv P \&\& Rs(i).Product != P) \Big/ Size(Rs) \quad \frac{\sum_{i=1}^{Size(RS(RI))} \sum_{j=1}^{size(Ri)} count(RI(j)==Ri) \&\& RI(j).Product==P}{Size(RI)} \times$$

Further, the value of regional distribution support RDS is measured according to the availability of product in the different region and why the other product is purchased. It measure the value based on the availability and unavailability factors. It has been measured as follows:

$$RDS = \frac{\sum_{i=1}^{Size(RS(RI))} \sum_{j=1}^{size(Ri)} count(RI(j)==Ri) \&\& RI(j).AlternateProduct==P}{Size(RI)} \times \sum_{i=1}^{size(Rs)} Count(Rs(i).ShopID = SI \&\& Rs(i).P.Available = No) \Big/ Size(Rs)$$

Finally, the method computes the Regional Affordability Support (RAS) according to the salary of different customers and average salary of peoples living and average salary of peoples who purchase the product. Employing these values the technique calculates the value of RAS. It has been measured as follows:

$$RAS = \frac{\sum_{i=1}^{Size(RI)} RI(i).Salary \&\& RI(i).Product==P}{size(RI)} \times \frac{1}{\sum_{i=1}^{Size(RI)} RI(i).Salary \Big/ Size(RI)}$$

Using the above mentioned support measures, the method performs recommendation generation.

3.6 Regional Feature Analysis Recommendation Generation

The regional feature approximation with recommendation generation algorithm, finds the product being requested and test the network for the result. The neurons in the model would estimate various support measures like RPS, RSS, RDS, RAS measures for various regions. The network generates such support sets at the output layer. Using the support values, the method computes the product selection weight (PSW) for various products in different region. According to the value of PSW, the technique orders the products for different regions.

Algorithm:

```
Given: Region Set Rs, Regional Popularity Support (RPS) set RPSS, Regional Sale Support (RSS) set
RSSS, Regional Distribution Support (RDS) set RDSS, Regional Affordability Support (RAS) set RASS.
Obtain: Recommendation Product Set RPS
Start
        Read Rs, RPSS, RSSs, RDSS, RASS.
        For each region R
                For each product P
                        Compute PSW = RPSS(P)/RDSS(p) × RSSS(p)/RASS(p)
                End
        End
        For each region R
                Recommendation R = Rank products according to PSW.
                Add to RPS.
        End
Stop
```

The above mentioned algorithm computes product selection weight for various products in the regions. According to that the products are ranked and produced as recommendations to the region.

3.7 Block Chain Attribute Based Encryption

The recommendations produced by the proposed model have been send to the user in form of block chain. From the block chain, the concern user can access the specific block. From the block available, the user can extract the data and perform data decryption to get the original recommendation. In this case, the method receives the recommendation and split them according to the region. For each region, the method selects a scheme and key according to the proactive information. Using the scheme and key, the method encrypts the data. Encrypted data has been placed in the block chain. The block chain has been generated with K number of blocks according to the number of regions. The user in term, can read the concern block and extract the hash code. The hash code represented mentions the region id. If the region id belongs to the user, then he can decrypt the data available in the data block. As the key and scheme to be used is proactively shared with the user, they can obtain the recommendations.

Algorithm:

```
Given: Recommendation set Recs, Scheme set Ss, Key set Ks
Obtain: Block chain Bc.
Start
        Read Recs, Ss, Ks.
```

Identify number of region NoR = size(Recs)
Generate block chain Bc = Block Chain (NOR)
For each block b
Cipher Text CText =
$size(Recs)$
$size(Scs)$
$size(ks)$
$Encrypt(Recs(i), Scs(i).RegionID == Recs.ID, Ks(j.RegionID == Recs.ID)$
$j = 1$
$i = 1$
$i = 1$
Add Ctext to block.
B.HashCode==Recs.ID.
End
Stop

The above discussed algorithm represents how the data encryption and block chain are generated with the recommendations. The user can receive the request and identify the concern block according to the hash code which represents the region of the user. From the detected block, the user is capable of decrypting the block data to retrieve the actual data.

4. Results

The recommended adaptive deep learning product growth analysis model has been applied and compared for its performance under different conditions. The performance of the technique has been measured with the results of various other approaches. The results obtained has been presented in this section.

Table 1: Details of Evaluation

Parameter	**Value**
No of Users	5000
No of Products	500
Total Records	1 million
Tool	Advanced Java

The details of evaluation being used towards performance analysis are presented in Table 1. The recommended framework has observed to perform effectively in different parameters which is estimated with outcomes of the other techniques.

Table 2: Analysis on Data Security

Analysis the performance in terms of Data Security			
	100 Users	**205 Users**	**500 Users**
HHE	72	74	78
CPABE	76	79	82
Blowfish-ECC	79	83	86
ABBR	82	87	89
FCDAM_BC	87	92	96
ADLPGM	89	94	97.6
RFADM-BC	91	96	98.7

The performance of techniques in attaining the higher data security has been estimated under the existence of various number of users in the environment. The performance of the techniques in accomplishing the optimal form of data security has been estimated on the presence of various number of users in the environment. The recommended RFADM-BC method has produced greater performance in terms of data security in all cased when compared with other existing methods.

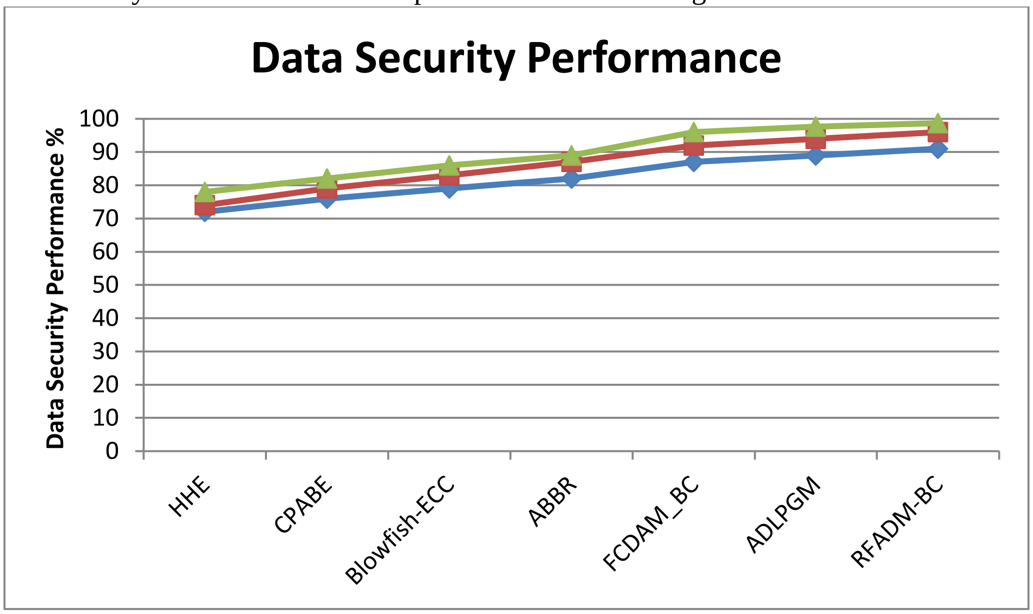

Fig. 2: Analyzing the performance in terms of data security

The performance of existing approaches in terms of data security have listed in the figure 2. The proposed RFADM-BC framework has resulted optimal performance in terms of data security in all cases when compared with other methods.

Table 3: Performance analysis on Recommendation generation

Investigating the Performance in terms of Recommendation Generation			
	100 Items	**250 Items**	**500 Items**
SDM	72	74	78
DNN-HMM	74	77	82
VLTP	79	83	86
MANGO	82	87	89
FCDAM-BC	87	92	96
ADLPGM	91	95	98
RFADM-BC	93	97	99.3

The results produced by the existing researches in terms of recommendation generation are estimated at the presence of various users in the environment. Comparatively, the recommended RFADM-BC has resulted with optimal accuracy and performs better when compared with other conventional methods.

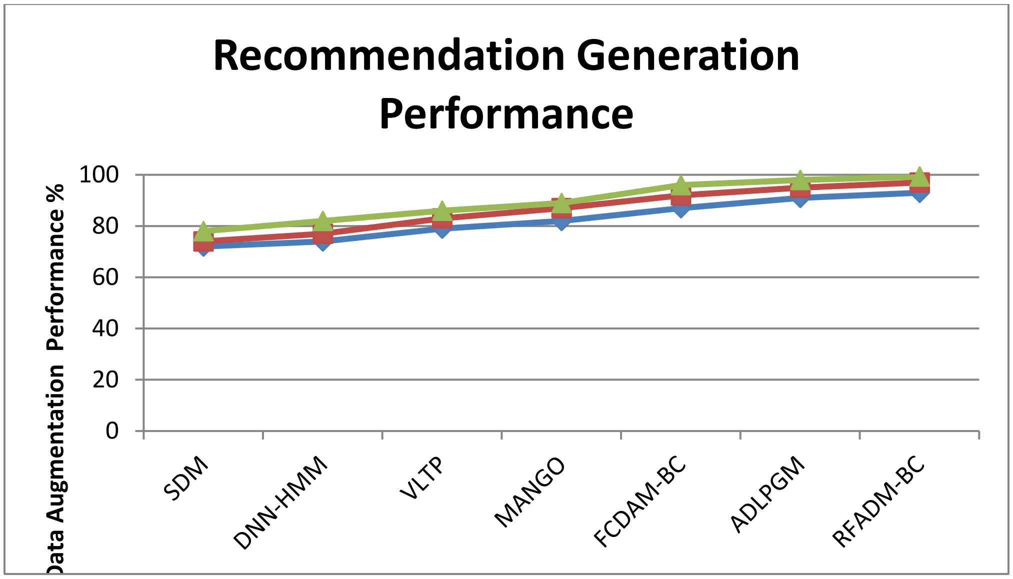

Fig. 3: Performance on Recommendation Generation

The results of the existing methods with regard to the recommendation generation has been compared in the presence of various items in the basket and estimated with the outcomes of other techniques. The proposed RFADM-BC has exhibited optimal performance in every case when compared with other existing methods.

Table 4: Performance analysis on Throughput

Performance analysis in terms of Throughput			
	100 Items	**250 Items**	**500 Items**
SDM	67	72	76
DNN-HMM	72	75	79
VLTP	75	79	82
MANGO	78	83	87
FCDAM-BC	87	92	96
ADLPGM	89	94	98
RFADM-BC	91	96	98.9

The performance exhibited by existing and the recommended RFADM-BC has been compared and listed in the table 4. It is clear that the proposed RFADM-BC has performed better in terms of higher throughput when compared with other existing techniques.

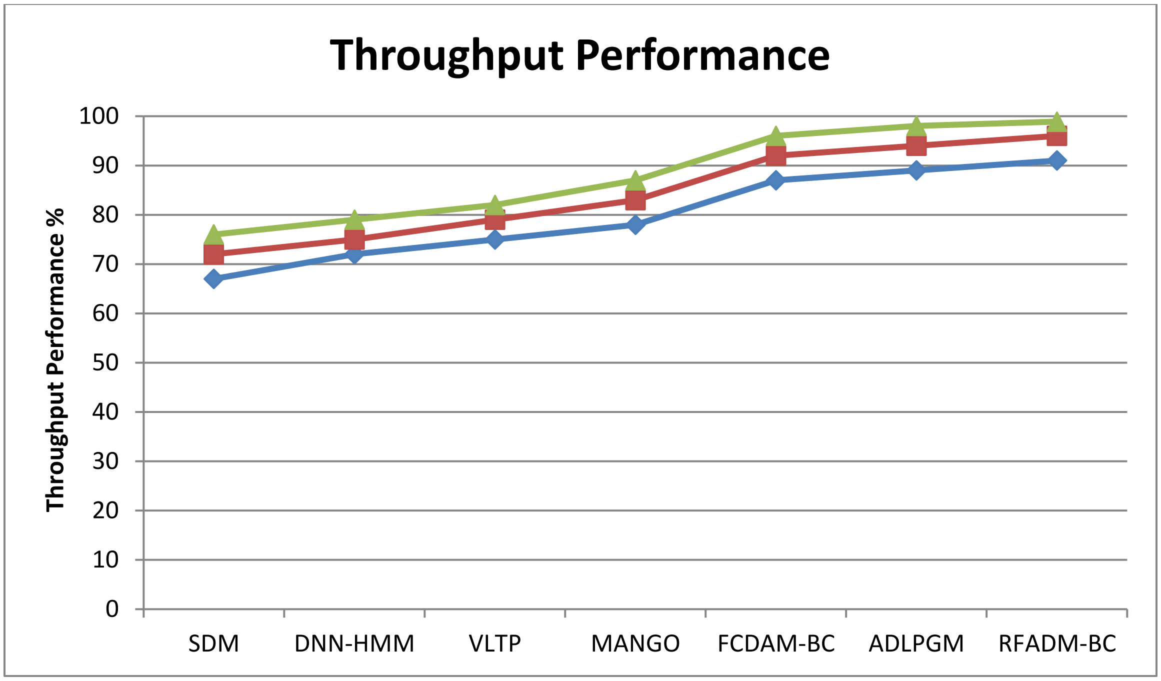

Fig. 5: Performance analysis on throughput

The results of the existing methods in terms of throughput and the proposed RFADM-BC have been compared and illustrated in the figure 5. The recommended RFDM-BC has been observed to exhibit optimal throughput performance when compared with other methods. From the overall results observed from the graphs and tables in the result section, it is obvious that that the proposed algorithm RFDM-BC has been observed to outperform when compared with other conventional algorithms such as SDM, DNN-HMM, VLTP, MANGO, FCDAM-BC and ADLPGM. Due to such efficient performance, the proposed model would obviously assist the retailers and the customers to choose the products in accordance with the ranks. This model would highly assist in developing the retailing industry by permitting them to select the standard products for their corresponding users.

5. Conclusion

The present research has presented a novel regional feature analysis based deep learning model with block chain (RFADM-BC) towards the growth of retail industry. The model preprocesses the input data and extracts several features to train the network mode. The network model has been designed to measure various regional support measures to compute product selection weight using which the method generates recommendations. The recommendations are encrypted using different scheme and key set being dedicatedly used by various regions. The cipher texts are placed in concern block and hash code is mentioned with the region id. The receiver in turn finds the region id from the hash code and extracts the cipher text and decodes using the same way. The technique exhibits higher performance in recommendation generation, data security and throughput performance. In spite of better performance, the proposed system lacks with regard to scalability as it relies on block chain concept. Hence, in future, suitable scalable algorithms have to be considered to further enhance the performance.

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