Computing, Information Systems, Development Informatics & Allied Research Journal
Vol. 15 No. 2, 2024 - www.cisdijournal.net

FePARM: The Frequency-Patterned Associative Rule Mining Framework on Consumer Purchasing-Pattern for Online Shops

[1]Malasowe, Bridget Ogheneovo, [2]Okpako, Abugor Ejaita, [3] Okpor, Margaret Dumebi,
[4]Ejeh, Patrick Ogholuwarami, [5]Ojugo, Arnold Adimabua & [6]Ako, Rita Erhovwo
[1]Department of Computer Science, University of Delta, Agbor, Nigeria
[2]Department of Cyber Security, University of Delta, Agbor, Nigeria
[3]Department of Cyber Security, Faculty of Computing, Delta State University of Science and Technology, Ozoro. Nigeria.
[4]Department of Computer Science, Dennis Osadebay University, Anwai-Asaba, Nigeria
[5] Department of Computer Science, Federal University of Petroleum Resources Effurun, Nigeria
[6] Department of Computer Science, Federal University of Petroleum Resources Effurun, Nigeria
E-mails: [1]bridget.malasowe@unidel.edu.ng; [2]ejaita.okpako@unidel.edu.ng; [3]okpormd@dsust.edu.ng,
[4] patrick.ejeh@dou.edu.ng; [5]ojugo.arnold@fupre.edu.ng, [6]ako.rita@fupre.edu.ng

ABSTRACT

Transaction data often is a true presentation of consumers' buying behavior, stored as a set of relational records, which properly harnessed via mining – can help businesses improve their sales volume as a decision support system. Managing such a system can pose many issues to biz such as feature evolution, concept evolution, concept drift, and infinite data length – and often makes it impractical to effectively store such big-data. To curb this, previous studies have assumed data to be stationary in using associative rule mining. This has deprived such systems of the flexibility and adaptiveness required to handle the dynamics of concept drift that characterizes transaction datasets. Our study thus proposes a basket frequent pattern growth trained associative rule mining model to handle large data. The dataset was retrieved from the Delta-Mall Asaba and consists of 556,000 transaction consumer records. The model consists of six-layers, and yields the best result with a 0.1 value for both the confidence and support level(s) at a 94% accuracy, sensitivity of 87%, and a specificity of 32% with a 20-second convergence and processing time.

Keywords: Big-Data Analysis, Feature Evolution, Inventory Model, Market Basket Analysis, Businesses, Transactional Data Streams, Concept Drift

CISDI Journal Reference Format
Malasowe, B.O., Okpako, A.E., Okpor, M.D., Ejeh, P.O., Ojugo, A.A. & Ako, R.E. (2024): FePARM: The Frequency-Patterned Associative Rule Mining Framework on Consumer Purchasing-Pattern for Online Shops. Computing, Information Systems, Development Informatics & Allied Research Journal. Vol 15 No 2, Pp 15-28. dx.doi.org/10.22624/AIMS/CISDI/V15N2P2-1. Available online at www.isteams.net/cisdijournal

1. INTRODUCTION

The Internet, which has today birthed the digital revolution alongside ensuring an unprecedented amount of data exchange between users daily – has also now allowed us to witness the enormous growth rate of data produced. This data (as scaled up) has skyrocketed in size from Tera-to-Peta bytes and continues to grow [1], [2] leading to the advancement of a field in informatics known as Big-Data.

In turn, it has necessitated increased attention to the issue of the velocity, veracity, and volume of data with its analysis, which enables its use as a decision-support framework for today's businesses and society at large [3]–[5]. Big-Data can refer to a large amount of data stored in a repository [6]. Compared to traditional dataset, a big-data consists of structured and unstructured data – making it requires a more critical, effective, authentic, and time-consuming mining process and investigation to effectively retrieve meaningful information to aid decision support systems [7]–[9]. Even with the plethora of tools, techniques, and methods that are available – the domain faces inherent challenges when dealing with data mining concerning its storage due to the lengthy size of the dataset, features evolution during its analysis, and concept evolution with the extraction of useful data [10], [11]. Mining a large collection of the dataset to extract meaningful data thus, often requires a great ordeal of improved technique, methods, and tools to aid in the effective management of the stored data vis-à-vis data generated with user access to the Internet daily [12]–[14].

Depending on the nature of such access to the Internet and for what purpose – data access of any kind is best described as a transaction. A transaction is an indivisible task or operation – whose processing is achieved via a transaction processing system (TPS). A transaction may either succeeds or fails, as a complete, indivisible segment [15]–[17]. Each transaction processed is an aggregation to classify any data into a minutiae, indivisible unit, or task. A TPS can be software or combined hardware and software that supports the processing of a transaction [18], [19]. A TPS is best suited for tasks to collect, modify, process, store and retrieve transactional data; while, offering greater performance, reliability, and consistency to support large volume(s) of data transaction(s) as used by large organizations and businesses. Thus, a TPS manages/automates large data processing via accurate tracking and the use of control procedures to efficiently extract useful data to support decision systems [20]–[22].

Despite the many benefits, basket analysis still faces lots of challenges in mining large transactional stream dataset. These include [23]–[25]:

1. Nature of the Dataset: Data mining systems are successfully grouped into the kind of data they do mine as knowledge. Based on a variety of functions such as characterization, evolution feat analysis, forecast, association affinity, and correlation. This proves to be more tedious due to the infinite length in the size of the dataset, and the issues of concept drift, concept evolution, and features evolution [26].
2. Classifying Transaction Data will continue to pose a challenge due to the phase-out of old items, advent of new products, replacement substitutes, etc. These yield infinite possibilities of cross-selling options – and make it impractical to utilize stored data for training. One solution is to know itemset in a basket, run algorithm to ascertain the most frequent pairs. This yields an impractical solution as many baskets contain a variety of itemset(s) pairs. We expect that some pair(s) maybe more popular than others. Thus, our need for a clustering model [27].
3. Naïve Solutions: Considering the nature of data, which is often infinite in length and ever-changing due to the itemset combination – it makes it tedious to store and adopt for model training. Many techniques and tools have proffered solutions; But, baskets are often an itemset with a billion combinations of a variety of items – the support model must be trained with each basket itemset as a pair, and stored such that the resulting platform can successively query and find the matching itemset. Some solutions engender many itemsets (pairs) in handling millions of basket transactions with different itemsets; Thus, plausible that specific pairs of itemsets are much more popular as proffered by the platform than others [28].

4. **Stationary Dataset**: Previous studies in handling such dataset via the use of associative rule mining – often assumes a stationary dataset in training/testing models on observed datasets acquired from the same population – and thus, yields the resultant decision support framework or platform. This deprives the ARM heuristic of the required flexibility and adaptiveness to non-existent data not present during training or from the outset as well as the needed robustness to handle the challenges of feature evolution, concept evolution, and concept drift inherent in the transactional dataset [29], [30].

We propose a frequent pattern growth trained associative rule mining (FePARM) model to handle transaction dataset – and resolves the issues of concept drift/evolution, feat evolution, and length-size of data, in a basket. The framework must flexibly exploit new itemset generated on the fly, and robustly cum easily reuse such a dataset with little (or no) modification to the system. This solution seeks to ensure: (a) distance between itemsets, is retained, (b) sales volume of two/more commonly purchased itemset, are positively correlated, (c) if/when itemsets sales volumes are observed at different timestamps, it generates a trend that must be similar in their upward/downward temporal patterns, with both trends assigned to same cluster – so that each cluster is a set of items analogous to an itemset in association rule mining [31]–[33].

2. METHOD AND MATERIALS

Problem Description and Formulation

Consider transaction logs of purchased items by a customer. The retailer seeks to maximize the **interestingness** of the items or products via their corresponding shelve placement and arrangement. Note that the location of the items on shelves and their clustering prevails and will help the retailer businesses maximize the cross-selling effect of these items. Previous studies have shown that shelve location of products can often impact the sales rate of items [34]. Thus, the preference function of depends on these parameters to include support/confidence level, selling benefit of each item pair, and the selling possibility of each item on the shelve, etc. These parameter(s) are integrated fused to yield Eq. 1 [35], [36] with m as number of items, p as number of shelves, C_{il} as confidence of a rule (item i ⟶ l), b_i as benefit to sell ith-item, v_{ik} as possibility to sell item i if placed on shelf k, and x_{ik} as decision variable (i.e. with the value of 1 if i is allocated to the shelf k; Else, the value sets as 0).

$$\mathrm{pf} = \sum_{i=1}^{m-1}\left[\sum_{l=i+1}^{m}\left[C_{il} + C_{li}\sum_{k=1}^{p}[b_i v_{ik} + b_i v_{ik} x_{ik} x_{lk}]\right]\right] \quad (1)$$

The capacity limit (cl) of a shelf can hinder the value of the preference function – and must be considered as a shock to yield Eq. (2) with U_k as limit of shelf k. A second feat to ensure support level of a rule (item i ⟶ l) must be greater than lower bounds of threshold [37]. Thus, it yields a non-linear goal function with a binary decision variable. This will also imply we are dealing with a feasible solution space that increases the chances our solution will be trapped at the local optimum. To avert this, we adopt the frequent-pattern growth clustering model as an alternative to train the associative rule mining heuristics [38], [39].

$$\mathrm{cl} = \sum_{i=1}^{m} x_{ik} \leq U_k \text{ with } k = 1,2,\ldots P \quad (2)$$

Numerical Example

Table 1 shows a binary-coded, itemset picked off a variety of shelves and dropped on to a basket at time t. Category 1 for item-1 has a prevalence of 0.81 (i.e. there is 81% chance items 1, 2, 6, and 8 will be selected from a shelf k and on to the basket to yield a transaction). With sales transaction dataset from Delta Mall used, the model notes that 8-items must be allocated to 4-shelves – and it is based on shelves' positions. The placement of these items on a different shelf will yield a varied impact on the possibility to sell good placed on such shelf. Such possibilities are computed, with choice of design evaluated economists/experts as in Table 1.

Table 1. The binary representation of 4-baskets/category values

Items	1	2	3	4	5	6	7	8	9	10	11	Weights
Cat. 1	1	1	0	0	0	1	0	1	0	0	0	0.823
Cat. 2	0	1	0	1	1	0	1	0	1	1	0	0.541
Cat. 3	0	0	1	0	1	0	1	1	0	1	0	0.239
Cat. 4	1	0	1	1	1	0	0	0	1	1	0	0.721
Cat. 5	0	1	0	0	0	1	1	1	0	0	1	0.902
Cat. 6	0	0	1	1	0	1	0	0	0	1	0	0.684

(Source: Authors' processing and translation)

This study builds on the frameworks [5], [40] to discover consumer purchase-patterns when/if there are multiple stores, and to optimize itemsets on shelf placement. We use a cluster frequent-pattern growth heuristic to train the associative rule mining algorithm. This will help ensure that: (a) items data obtained via cross-selling and combination will be grouped into families, and baskets classified as a weighted problem to help discover large item-patterns, (b) find a maximization task to ensure item-families and the family's location on a shelf is determined via a category catalog method that accounts for its impact/exploits on sales, and to yield maximal impact of shelf-layout, and (c) the profile clustering method will ensure that the cross-selling effect of items is accounted for and will help maximize expected total profit [41]–[43].

Associative Rule Mining with Market Basket: Related Literature

Associative rule mining (ARM) is used in retail marketing – to help business owners consciously and strategically place items on a shelf (location) so they are easily found by consumers. Thus, helps ensure that a set of items (itemset) can be purchased together. This, improves sales transactions and revenue generation. Items placement aids search and identification ease, enhances combined/cross-selling opportunities, helps managers to manage their inventory better, and optimize a store's layout [44]. As the most widely adopted method, ARM is suited for analyzing basket big-data that involves a large volume of transactions consisting of a high number of itemsets, phased-off items, new and replacement counterpart items, and timestamped demand-and-supply chain [45].

A market basket is the collection of data grouped as an itemset and stored as a pair. It provides a means of strategic modeling and data mining methods – that helps users discover interactions and relations between the items/products by generating rules that draw inferences on the possibility of these items occurring together in groups of specific types [46]–[48]. Basket analysis as mining technique – seeks to extract a group of items purchased within a transaction at time t. It outcomes a set of association rules used for the prediction of inventory of itemsets purchased within a single time-stamped transaction.

Each rule, is equipped with: (a) a support value to show the total number of transactions for which items A and B co-occurs, (b) a confidence value to show the accuracy with which item B appears in the same basket with item A already in it, (c) expected confidence value as the confidence on how frequent item A and B co-occurs given the number of times item B is already in a basket, and (d) lift measures how confident we are that item B is chosen with item A already in the basket [49]–[51]. Thus, for each rule given (A) and (B) – all variables combined yields a lift as in Eq. 1-4 respectively [52]–[54]:

$$P(h) = P(A, B) = \frac{\text{No. of Transactions A \& B}}{\text{No. of Transactions}} \quad (1)$$

$$P(B \mid A) = \frac{P(h)}{P(A)} = \frac{\text{No. of Transactions A \& B}}{\text{No. of Transactions A}} \quad (2)$$

$$P(A \mid B) = \frac{P(B)}{P(h)} = \frac{\text{No. of Transactions B}}{\text{Number of Transactions}} \quad (3)$$

$$\text{Lift} = \frac{\text{Confidence}}{\text{Expected Confidence}} \quad (4)$$

Many data mining methods have been adopted/adapted to market baskets [55]. ANN was used to predict stock, and offered benefits like computation efficiency, better accuracy, and saving time [56]. Even with evolutionary modeling, some cannot discover critical purchase patterns (in multiple stores). Other studies have sought to convert market baskets into the maximum-weighted problem as a means to discover large item-patterns [57]; while some have used optimization of shelf-space problem that grouped itemsets as families to help identify family-cluster-location via the cataloging mode. Location was found to impact on sales.

But, as study did not use purchase data – it failed to resolve cross-selling effect [52]. Also, [58], [59] in a bid to resolve this via shelf management, grouped the task into 2-parts: (a) a heuristic model to value shelf-layout impact on transaction, and (b) used simulated annealing to maximize expected total profit. This agrees with [60]–[62].

Also, [45] proposed a hierarchical memetic cluster model to retail itemsets using the 'distance' between items or items-family as in [24]. It yielded over 56-rules with elitist rules having a fitness of 0.865. Of the 22-of-56 rules have a profile itemsets so that rules can search for itemset(s) with 3 and above items in the basket [63]; Thus, increased the chance of detecting a basket, and improves the rules generally, and ensuring that new itemsets with generated rules can be added on to the rule-knowledgebase.

Also advanced by [64]; whereas, [10] used a moving average with fluctuating demand in itemsets to prove that the moving average can accommodate rapid changes/shocks in its dataset. While, the model proved suitable for companies with high variety of itemset (as products) and in retailing – it also proved less appropriate with long-term forecasts.

Theoretical Framework

To resolve the issue(s) – association rule mining is used on transaction dataset(s) to generate numerous itemsets that yield the purchasing behavior of a variety of customers via the following theories as thus:

1. Theory of Reasoned Action (RAT) – emphasizes behavior that is dependent on the consumer's attitude, behavioral choice, and public perception. It is a concept that is constantly influenced by the consumer's intentions, purported choice, and personal beliefs (forming external/internal shocks) that impact the decision to be made. Decisions are hinged on the fact that RATs are aligned with this theory [46], [65]. Its relevance is that a consumer can purchase items (online) if presented with specific expected results. The consumer can also change his/her mind, which impacts his/her decision cum actions taken, resulting in attitudinal and normative changes. These components include user-trust, user-confidence in a product, influence by a friend, experience with the product, etc. These, result in concept drift. Thus, applying this theory tests a consumer's action and attitude based on purpose so that consumers become more rational in line with their purpose that act in the best interest of their intentions.
2. Theory of Planned Behaviour – states that attitude towards a behavior, subjective norms, and perceived control often shapes a consumer's behavioral intents and in turn, his/her actions. This theory improves the analytical capability of RAT by including the perceived control of behaviors. Knowing that not all behavior is subject to a consumer's control – it is expedient to add the concept of perceived behavioral control – which implies that no matter the action is taken – a consumer's behavior is not only determined by the attitude and subjective norms; But also, via consumer perception about firm beliefs in control [66].
3. The Engel, Kollet, and Blackwell (EKB) model extends RAT – focusing on the mental activities the consumer is involved with before he decides to purchase a product. It bolsters on the RAT with a planned series of behaviors as thus: (a) consumer absorbs the advertised item(s), (b) consumer processes data gathered about the item via an advertising platform – and leverages experience to compare data with the expected outcome, and (c) consumer ponders on the decision to accept/reject the item, yielding a choice with balanced insight [67]. Thus, with the data input as the greatest prize – manufacturers of the items must seek to equip business managers with adequate data vis-à-vis the item that eventually drives the consumers to keep purchasing products' sales volumes up. This theory unveils the underlying feats that may cause a consumer-purchase shift in behavior. If a consumer is not adequately informed, s(he) may reject to buy the item as means to normalize a balance with the online data available. Thus, external shocks (i.e friends and item review ratings, be they fake or not) can/may influence the consumer to decide to either accept/reject the product.
4. Hawkins Stern Impulse Theory – notes that purchasing decisions are often influenced by impulse or the sudden buy of an item. They are a result of external shocks with no purpose and of no relations to the act of decision-making. They include: (a) pure impulse, (b) consumers reminded-impulse-buy, (c) suggested-impulse buy, and (d) consumer-makes-planned impulse buy (the consumer knows the product they wish to buy – though, they may be unsure about the product details). The relevance of the theory of impulse buying is that it provides a dimension in lieu of the irrational behavior in purchase drift as seen by their purchase-pattern. Thus, the fulcrum of this theory is enmeshed in an item's marketing – ranging from its packaging to advert and display over the shelf (and on e-store) with greater emphasis made on the various attributes of the product such as its features, cost, etc. All these will influence the buyer's impulse. Thus, an electronic description of an item should be sensitive to trigger such purchase drift on the consumer to like and accept the product – irrespective of their premonitions.

Our model exploits relations between varied components in transaction analysis to emphasize consumer purchase-pattern. With features-and-concept evolution arising from a vendor's quest to meet all consumer needs, this raises the concerns for concept drift. To resolve these, ARM is used on the appropriate data transactions to generate a variety of itemsets that adequately represents a consumer purchase-pattern. This, justifies our adoption of the adapted consumer behavior theories with adopted TRA/TPB that directly explains our research problem. To derive meaningful data via these theories, we visualized the consumers' behavior to help us resolve the issue of concept drift.

Big-Data Transactional Analytical Model for Customer Management

Figure 2 shows architecture for the proposed basket model with its components [68]–[72]:

i. Business Management Visualization studies all relevant consumer behavior and enables the inherent system use data analytics methods to boost customer retention; Thus, it resolves the challenges with conceptual drift.
ii. Interoperability helps improve transaction data analytics processing in retail marketing via the use of the Luigi v3.7. This software helped our proposed system to monitor conceptual drift in consumers by studying their buy-patterns using basket dataset with itemsets combination.
iii. Big Data Analytics platform is designed specifically for use by Delta Mall (ShopRite) to allow her study her consumer buying pattern. It creates inventory management that helps the mall to support decision-making activities as well as effectively manage existing consumer relations.
iv. Customer Management Strategy improves consumer-business relations by adequately studying buying-pattern in each consumer's transactions, and helping researchers aggregate the extent a consumer's consumption impacts their health. It also impacts basket analysis by assisting business managers enforce business policies/decisions as to the types of items to stockpile as means of inventory monitoring and control.

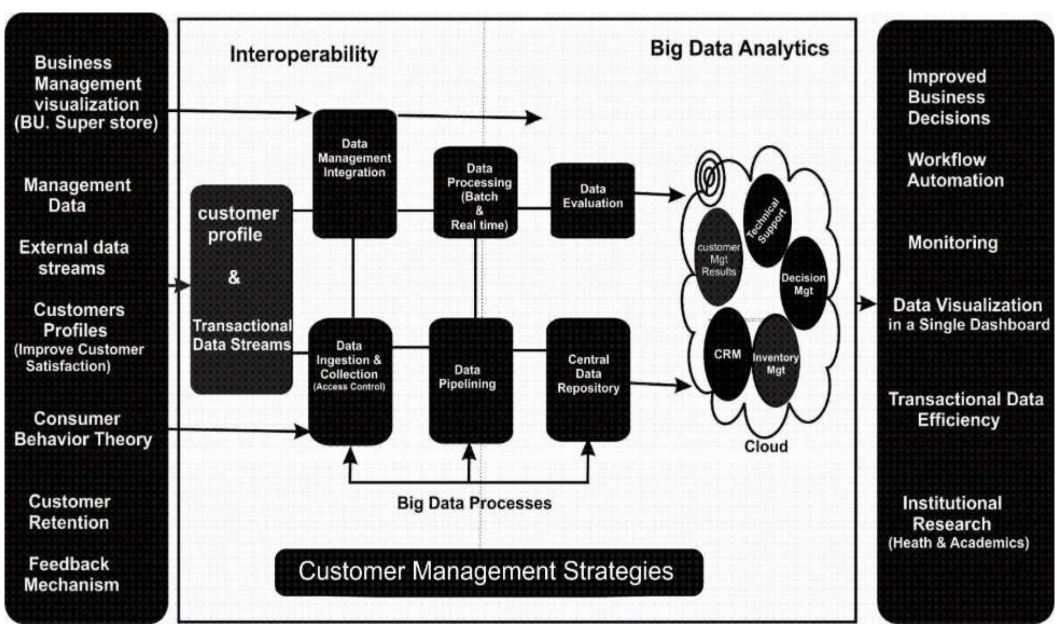
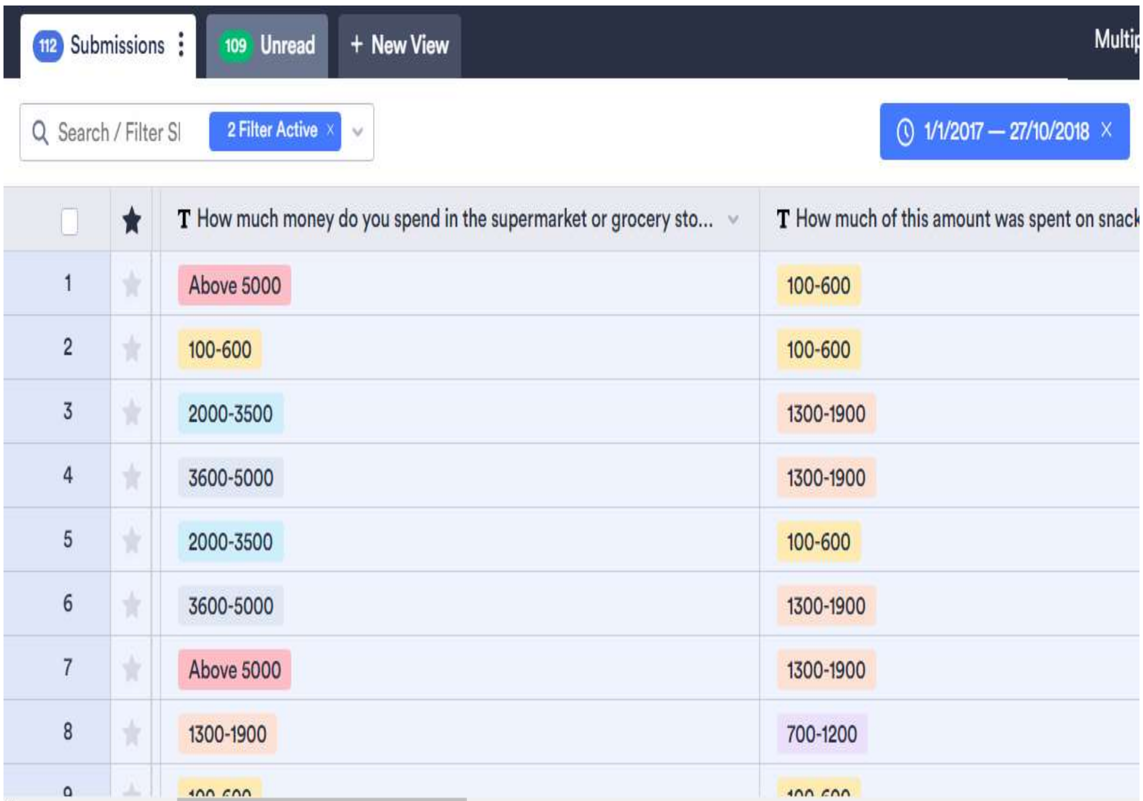


Figure 2. Big-Data Analytical Model for Customer Management

Applying The Calibev and Hovritz-Thompson Estimator

We applied Calibev and Hovritz-Thompson estimator (using Hadoop Data on tableau visualizer). These were analyzed using RapidMiner v8.1 to effectively calibrate a customer profile stream using a simple-random sampling without replacement (srswor) as in figures 3. The estimator ensures that only accurate data is processed with 2-sets of association rule mining rules generated via the apriori and frequent-pattern growth algorithm(s) as seen in Figure 4 [73]–[76].



	How much money do you spend in the supermarket or grocery sto...	How much of this amount was spent on snack
1	Above 5000	100-600
2	100-600	100-600
3	2000-3500	1300-1900
4	3600-5000	1300-1900
5	2000-3500	100-600
6	3600-5000	1300-1900
7	Above 5000	1300-1900
8	1300-1900	700-1200

Figure 3. The Calibev and Hovritz-Thompson Estimator on Tableau Data Analysis

Results and Discussion

3.1. Proposed Model Performance

To generate the rules – we employed two (2) association rule mining algorithm modes namely: (a) the Apriori algorithm mode, and (b) the Frequent Pattern growth algorithm. These were used to generate rules and analyzed using RapidMiner v8.1. The result of the performance was measured using minimum support and confidence level [77] as the matrices for evaluating the performance of ARM algorithms. The outcome of the analysis was implemented in the MBA transactional Big data Stream model designed for the bread status as in Figure 4.

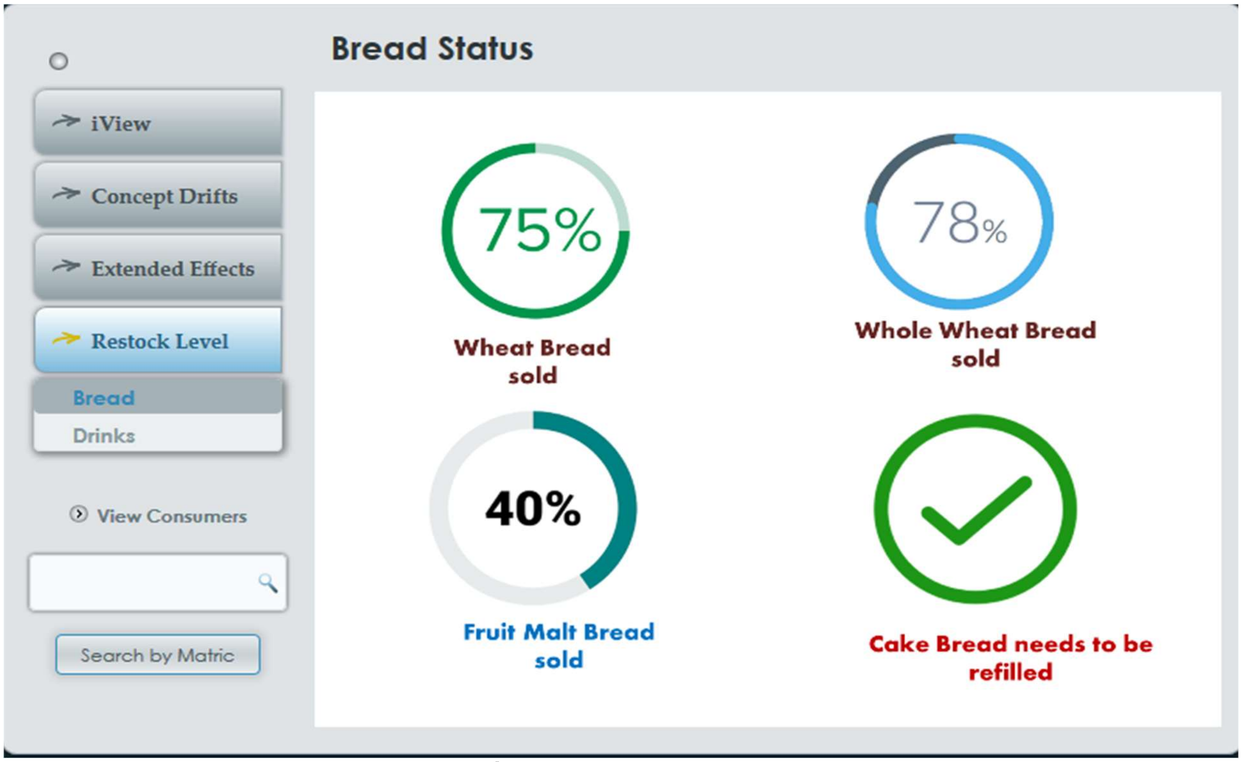


Figure 4. The bread basket analysis

Table 1: Summary Result of the Frequent-Pattern Growth Algorithm

Association Rules	Support	Confidence	Execution
DM Enriched Large Bread, DM Whole Wheat Bread → 7UP Pet Drink 50CL	0.026	0.194	18secs
DM Fruit Malt Bread, DM Enriched Cake Bread Large → C-Way Peach 500ML	0.006	0.214	
Enriched Large Bread; Enriched Cake Bread Large → Nutella Ferroro Hazelnut 350g	0.006	0.214	

3.2 Discussion of Findings

Results showed that ARM trained with the frequent-pattern growth algorithm performed better than the Apriori algorithm (in lieu of the rule transactions generated on the frequency of itemsets purchased by a consumer). The frequent itemsets represent the consumer's purchasing pattern and behavior for the system being modeled. With association rules mined and generated – the framework seeks to induce the basket analysis to study consumer's purchasing patterns and their frequency over time by resolving the issues of concept drift, concept evolution, and features evolution inherent in real-time transaction data-streams. This study agrees with [78] in provisioning consumer buying theories that sought to recognize reasons that contribute to a consumer's decision to purchase an itemset or product. These theories formed the basis to resolve the challenges presented in data-streams by concept drift and its association with basket analysis – which previous studies did not try to resolve.

The study notes that paramount to resolving the issues of concept drift with market baskets analysis – it is critical to use an enormous volume of transactional stream datasets collected over time. This will help to train the association rules to accurately predict the consumer purchasing/buying pattern cum behavior – even with the occurrences of a drift. The study agrees with [79] in our use of big-data analytics tools such as Spark to study customer's behaviors in market basket analysis.

4. CONCLUSION

The Big-Data basket model for managing conceptual drift was designed to interface with Delta-Mall data so as to effectively/efficiently monitor customers' purchases cum buy-pattern. It thus, enables business owners and store retail managers (in the Delta Mall Shopping complex – via their online platform) to manage their superstore. Provisioning them with amount in transaction on the frequecy of itemsets purchased and consumed by their customers. This will aid proper inventory planning and stock-piling of items, and also help in itemset shelve placement. Thereby, improving customer shopping experience and satisfaction. The implication is to help consumers know their consumption pattern and how it impacts on their health.

REFERENCES

[1] M. Christopher and H. Lee, "Mitigating supply chain risk through improved confidence," Int. J. Phys. Distrib. Logist. Manag., vol. 34, no. 5, pp. 388–396, Jun. 2004, doi: 10.1108/09600030410545436.

[2] A. E. Ibor, E. B. Edim, and A. A. Ojugo, "Secure Health Information System with Blockchain Technology," J. Niger. Soc. Phys. Sci., vol. 5, no. 992, pp. 1–8, 2023, doi: 10.46481/jnsps.2022.992.

[3] G. G. Akin, A. F. Aysan, G. I. Kara, and L. Yildiran, "The failure of price competition in the Turkish credit card market," Emerg. Mark. Financ. Trade, vol. 46, no. SUPPL. 1, pp. 23–35, 2010, doi: 10.2753/REE1540-496X4603S102.

[4] J. Obasi, Nwele, N. Amuche N, and U. Elias A., "Economics of Optimizing Value Chain in Agriculture Sector of Nigeria through Mechanised Crop Processing and Marketing," Asian J. Basic Sci. Res., vol. 02, no. 01, pp. 80–92, 2020, doi: 10.38177/AJBSR.2020.2109.

[5] A. A. Ojugo and R. E. Yoro, "An Intelligent Lightweight Market Basket Associative Rule Mining for Smartphone Cloud-Based Application To Ease Banking Transaction," Adv. Multidiscip. Sci. Res. J. Publ., vol. 4, no. 3, pp. 23–34, 2018, doi: 10.22624/aims/v4n3p4.

[6] N. Tomar and A. K. Manjhvar, "A Survey on Data Mining Optimization Techniques," IJSTE-International J. Sci. Technol. Eng. |, vol. 2, no. 06, pp. 130–133, 2015, [Online]. Available: www.ijste.org

[7] K. Vassil, M. Solvak, P. Vinkel, A. H. Trechsel, and R. M. Alvarez, "The diffusion of internet voting. Usage patterns of internet voting in Estonia between 2005 and 2015," Gov. Inf. Q., vol. 33, no. 3, pp. 453–459, Jul. 2016, doi: 10.1016/j.giq.2016.06.007.

[8] W. Pieters, "Acceptance of Voting Technology: Between Confidence and Trust," in International Conference on Trust Management, 2006, pp. 283–297. doi: 10.1007/11755593_21.

[9] A. A. Ojugo and A. O. Eboka, "Empirical Bayesian network to improve service delivery and performance dependability on a campus network," IAES Int. J. Artif. Intell., vol. 10, no. 3, p. 623, Sep. 2021, doi: 10.11591/ijai.v10.i3.pp623-635.

[10] T. Avinadav, "The effect of decision rights allocation on a supply chain of perishable products under a revenue-sharing contract," Int. J. Prod. Econ., vol. 225, p. 107587, Jul. 2020, doi: 10.1016/j.ijpe.2019.107587.

[11] A. A. Ojugo and O. D. Otakore, "Intelligent cluster connectionist recommender system using implicit graph friendship algorithm for social networks," IAES Int. J. Artif. Intell., vol. 9, no. 3, p. 497~506, 2020, doi: 10.11591/ijai.v9.i3.pp497-506.

[12] U. Usman, "Effects of Price & Non-Price Competition of Consumers Effects of Pricing and Non-Pricing Competition on Consumer Submitted By : Umair Usman Ghani Submitted To : Sir Raja Rub Nawaz Dated Preston University - Karachi Main Campus," no. February 2011, pp. 1–16, 2014.
[13] J. W. Hatfield, C. R. Plott, and T. Tanaka, "Understanding Price Controls and Nonprice Competition with Matching Theory," Am. Econ. Rev., vol. 102, no. 3, pp. 371–375, May 2012, doi: 10.1257/aer.102.3.371.
[14] N. A. Ananda, M. N. Fietroh, M. Mikhratunnisa, and R. M. Rizqi, "Theory Acceptance Model and Purchase Intention in Online Shopping," Proc. 1st Annu. Conf. Educ. Soc. Sci. (ACCESS 2019), vol. 465, no. Access 2019, pp. 165–169, 2020, doi: 10.2991/assehr.k.200827.042.
[15] A. A. Ojugo, A. O. Eboka, R. E. Yoro, M. O. Yerokun, and F. N. Efozia, "Hybrid model for early diabetes diagnosis," Math. Comput. Ind., vol. 50, no. 3–5, pp. 55–65, 2015, doi: 10.1109/MCSI.2015.35.
[16] S. Carbó, J. F. De Guevara, D. Humphrey, and J. Maudos, "Estimating the intensity of price and non-price competition in banking," Banks Bank Syst., vol. 4, no. 2, pp. 4–19, 2009.
[17] W. C. Kolberg, "Marketing Mix Theory: Integrating Price and Non-Price Marketing Strategies," SSRN Electron. J., no. 1993, pp. 1–35, 2011, doi: 10.2139/ssrn.986407.
[18] D. Acemoglu, K. Bimpikis, and A. Ozdaglar, "Price and capacity competition: Extended abstract," 44th Annu. Allert. Conf. Commun. Control. Comput. 2006, vol. 3, no. December, pp. 1307–1309, 2006.
[19] H. W. Ahmad, S. Zilles, H. J. Hamilton, and R. Dosselmann, "Prediction of retail prices of products using local competitors," Int. J. Bus. Intell. Data Min., vol. 11, no. 1, pp. 19–30, 2016, doi: 10.1504/IJBIDM.2016.076418.
[20] A. Farm, "Pricing and price competition in consumer markets," J. Econ. Zeitschrift fur Natl., vol. 120, no. 2, pp. 119–133, 2017, doi: 10.1007/s00712-016-0503-7.
[21] M. Armstrong and J. Vickers, "Patterns of Price Competition and the Structure of Consumer Choice," MPRA Pap., vol. 1, no. 98346, pp. 1–40, 2020.
[22] M. I. Akazue, R. E. Yoro, B. O. Malasowe, O. Nwankwo, and A. A. Ojugo, "Improved services traceability and management of a food value chain using block-chain network : a case of Nigeria," Indones. J. Electr. Eng. Comput. Sci., vol. 29, no. 3, pp. 1623–1633, 2023, doi: 10.11591/ijeecs.v29.i3.pp1623-1633.
[23] A. Shroff, B. J. Shah, and H. Gajjar, "Shelf space allocation game with private brands: a profit-sharing perspective," J. Revenue Pricing Manag., vol. 20, no. 2, pp. 116–133, Apr. 2021, doi: 10.1057/s41272-021-00295-1.
[24] A. Saxena and V. Rajpoot, "A Comparative Analysis of Association Rule Mining Algorithms," IOP Conf. Ser. Mater. Sci. Eng., vol. 1099, no. 1, p. 012032, Mar. 2021, doi: 10.1088/1757-899X/1099/1/012032.
[25] P. I. Tantawi, "The Variances of Consumers' Materialistic Personality Traits and Reduced Consumption Behavior Among Demographics in Egypt," J. Mark. Consum. Res., vol. 88, pp. 2020–2022, Jan. 2023, doi: 10.7176/JMCR/88-02.
[26] A. A. Ojugo and A. O. Eboka, "Signature-based malware detection using approximate Boyer Moore string matching algorithm," Int. J. Math. Sci. Comput., vol. 5, no. 3, pp. 49–62, 2019, doi: 10.5815/ijmsc.2019.03.05.
[27] P. Brunt, "Consumer behaviour in tourism," Tour. Manag., vol. 22, no. 5, pp. 579–580, 2001, doi: 10.1016/S0261-5177(01)00017-6.
[28] C. Panwar, "Consumer perceived risk in online shopping environment via Facebook as medium," Int. J. Eng. Technol., vol. 7, no. 4, pp. 2485–2490, 2018, doi: 10.14419/ijet.v7i4.11017.
[29] E. O. Buari, S. O. Salaudeen, and T. Emmanuel, "The Impact of Advertising Medium on Consumer Brand Preference for beverages in Osun State, Nigeria," J. Mark. Consum. Res., vol. 87, no. 2013, pp. 1–6, 2022, doi: 10.7176/jmcr/87-01.

[30] R. A. Debasish and K. N. Jena, "An analysis of Online Shopping of customers with special reference to Bhubaneswar," Mukt Shabd J., vol. 9, no. 5, pp. 4241–4252, 2020, [Online]. Available: https://www.researchgate.net/publication/341615464
[31] F. O. Aghware, R. E. Yoro, P. O. Ejeh, C. C. Odiakaose, F. U. Emordi, and A. A. Ojugo, "DeLClustE: Protecting Users from Credit-Card Fraud Transaction via the Deep-Learning Cluster Ensemble," Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 6, pp. 94–100, 2023, doi: 10.14569/IJACSA.2023.0140610.
[32] Y. Kang, M. Ozdogan, X. Zhu, Z. Ye, C. Hain, and M. Anderson, "Comparative assessment of environmental variables and machine learning algorithms for maize yield prediction in the US Midwest," Environ. Res. Lett., vol. 15, no. 6, p. 064005, Jun. 2020, doi: 10.1088/1748-9326/ab7df9.
[33] M. Kaur and S. Kang, "Market Basket Analysis: Identify the Changing Trends of Market Data Using Association Rule Mining," Procedia Comput. Sci., vol. 85, pp. 78–85, 2016, doi: 10.1016/j.procs.2016.05.180.
[34] H. Hasan, A. H. Harun, and Z. S. M. Rashid, "Factors That Influence Online Purchase Intention Of Online Brand," Conf. Pap., vol. 16, no. 10, pp. 1–10, 2018.
[35] P. M. Reyes and G. V. Frazier, "Goal programming model for grocery shelf space allocation," Eur. J. Oper. Res., vol. 181, no. 2, pp. 634–644, Sep. 2007, doi: 10.1016/j.ejor.2006.07.004.
[36] G.-J. Sheen, A. H. G. Nguyen, and Y. Yeh, "Category management under non-symmetric demands," Int. J. Syst. Sci. Oper. Logist., pp. 1–28, Jul. 2021, doi: 10.1080/23302674.2021.1951884.
[37] A. A. Ojugo and A. O. Eboka, "Modeling the Computational Solution of Market Basket Associative Rule Mining Approaches Using Deep Neural Network," Digit. Technol., vol. 3, no. 1, pp. 1–8, 2018, doi: 10.12691/dt-3-1-1.
[38] A. Bahl et al., "Recursive feature elimination in random forest classification supports nanomaterial grouping," NanoImpact, vol. 15, p. 100179, Mar. 2019, doi: 10.1016/j.impact.2019.100179.
[39] J. Jung, M. Maeda, A. Chang, M. Bhandari, A. Ashapure, and J. Landivar-Bowles, "The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems," Curr. Opin. Biotechnol., vol. 70, pp. 15–22, Aug. 2021, doi: 10.1016/j.copbio.2020.09.003.
[40] R. Shanthi and D. Kannaiah, "Consumers' Perception on Online Shopping," J. Mark. Consum. Res., vol. 27, pp. 30–34, 2015, [Online]. Available: www.iiste.org
[41] S. Khaki and L. Wang, "Crop Yield Prediction Using Deep Neural Networks," Front. Plant Sci., vol. 10, May 2019, doi: 10.3389/fpls.2019.00621.
[42] S. Khaki, L. Wang, and S. V. Archontoulis, "A CNN-RNN Framework for Crop Yield Prediction," Front. Plant Sci., vol. 10, Jan. 2020, doi: 10.3389/fpls.2019.01750.
[43] M. Rakhra, A. Bhargava, D. Bhargava, R. Singh, A. Bhanot, and A. W. Rahmani, "Implementing Machine Learning for Supply-Demand Shifts and Price Impacts in Farmer Market for Tool and Equipment Sharing," J. Food Qual., vol. 2022, pp. 1–19, Mar. 2022, doi: 10.1155/2022/4496449.
[44] A. A. Ojugo and R. E. Yoro, "Forging a deep learning neural network intrusion detection framework to curb the distributed denial of service attack," Int. J. Electr. Comput. Eng., vol. 11, no. 2, pp. 1498–1509, 2021, doi: 10.11591/ijece.v11i2.pp1498-1509.
[45] Y. Shiokawa, T. Misawa, Y. Date, and J. Kikuchi, "Application of Market Basket Analysis for the Visualization of Transaction Data Based on Human Lifestyle and Spectroscopic Measurements," Anal. Chem., vol. 88, no. 5, pp. 2714–2719, 2016, doi: 10.1021/acs.analchem.5b04182.
[46] M. Fatima and M. Pasha, "Survey of Machine Learning Algorithms for Disease Diagnostic," J. Intell. Learn. Syst. Appl., vol. 09, no. 01, pp. 1–16, 2017, doi: 10.4236/jilsa.2017.91001.
[47] Z. Sun, "Introduction to Business Intelligence and Database," Bus. Intell. A Mod. Approach, no. May, pp. 1–3, 2019, doi: 10.13140/RG.2.2.23711.61609.
[48] J. Zhao, A. Li, X. Jin, and L. Pan, "Technologies in individual animal identification and meat products traceability," Biotechnol. Biotechnol. Equip., vol. 34, no. 1, pp. 48–57, Jan. 2020, doi: 10.1080/13102818.2019.1711185.

[49] J. Zhao, Y.-W. Zhou, Z.-H. Cao, and J. Min, “The shelf space and pricing strategies for a retailer-dominated supply chain with consignment based revenue sharing contracts,” Eur. J. Oper. Res., vol. 280, no. 3, pp. 926–939, Feb. 2020, doi: 10.1016/j.ejor.2019.07.074.
[50] Q. Li et al., “An Enhanced Grey Wolf Optimization Based Feature Selection Wrapped Kernel Extreme Learning Machine for Medical Diagnosis,” Comput. Math. Methods Med., vol. 2017, pp. 1–15, 2017, doi: 10.1155/2017/9512741.
[51] A. A. Ojugo, P. O. Ejeh, C. C. Odiakaose, A. O. Eboka, and F. U. Emordi, “Improved distribution and food safety for beef processing and management using a blockchain-tracer support framework,” Int. J. Info. Comm. Technol., vol. 12, no. 3, p. 205, Dec. 2023, doi: 10.11591/ijict.v12i3.pp205-213.
[52] R. A. Russell and T. L. Urban, “The location and allocation of products and product families on retail shelves,” Ann. Oper. Res., vol. 179, no. 1, pp. 131–147, Sep. 2010, doi: 10.1007/s10479-008-0450-y.
[53] C. Coscia, R. Fontana, and P. Semeraro, “Market Basket Analysis for studying cultural Consumer Behaviour: AMTP Card-Holders,” Stat. Appl., vol. 26, no. 2, p. 73, 2016, [Online]. Available: researchgate.net/profile/Patrizia_Semeraro2/
[54] R. Nalini, R. Amudha, R. Alamelu, L. C. S. Motha, and V. Raja, “Consumer Perception towards Online Shopping.,” Asian Res. J. Bus. Manag., vol. 4, no. 3, pp. 335–342, 2017, doi: 10.24214/arjbm/4/3/113129.
[55] G. Martin-Herran, S. Taboubi, and G. Zaccour, “The Impact of Manufacturers’ Wholesale Prices on a Retailer’s Shelf-Space and Pricing Decisions*,” Decis. Sci., vol. 37, no. 1, pp. 71–90, Feb. 2006, doi: 10.1111/j.1540-5414.2006.00110.x.
[56] R. Y. Chenavaz and I. Pignatel, “Utility foundation of a Cobb-Douglas demand function with two attributes,” Appl. Econ., vol. 54, no. 28, pp. 3206–3211, Jun. 2022, doi: 10.1080/00036846.2021.2005238.
[57] X. Li, X. Qi, and Y. Li, “On sales effort and pricing decisions under alternative risk criteria,” Eur. J. Oper. Res., vol. 293, no. 2, pp. 603–614, Sep. 2021, doi: 10.1016/j.ejor.2020.12.025.
[58] M. I. Akazue, A. A. Ojugo, R. E. Yoro, B. O. Malasowe, and O. Nwankwo, “Empirical evidence of phishing menace among undergraduate smartphone users in selected universities in Nigeria,” Indones. J. Electr. Eng. Comput. Sci., vol. 28, no. 3, pp. 1756–1765, Dec. 2022, doi: 10.11591/ijeecs.v28.i3.pp1756-1765.
[59] A. A. Ojugo and D. A. Oyemade, “Boyer moore string-match framework for a hybrid short message service spam filtering technique,” IAES Int. J. Artif. Intell., vol. 10, no. 3, pp. 519–527, 2021, doi: 10.11591/ijai.v10.i3.pp519-527.
[60] A. Patil and P. Gupta, “A review on up-growth algorithm using association rule mining,” in 2017 International Conference on Computing Methodologies and Communication (ICCMC), Jul. 2017, pp. 96–99. doi: 10.1109/ICCMC.2017.8282605.
[61] R. E. Yoro, F. O. Aghware, M. . Akazue, A. E. Ibor, and A. A. Ojugo, “Evidence of personality traits on phishing attack menace among undergraduates in selected Nigerian universities,” Int. J. Electr. Comput. Eng., vol. 12, no. 6, 2022.
[62] R. E. Yoro, F. O. Aghware, B. O. Malasowe, O. Nwankwo, and A. A. Ojugo, “Assessing contributor features to phishing susceptibility amongst students of petroleum resources varsity in Nigeria,” Int. J. Electr. Comput. Eng., vol. 13, no. 2, p. 1922, Apr. 2023, doi: 10.11591/ijece.v13i2.pp1922-1931.
[63] A. A. Ojugo and R. E. Yoro, “Extending the three-tier constructivist learning model for alternative delivery: ahead the COVID-19 pandemic in Nigeria,” Indones. J. Electr. Eng. Comput. Sci., vol. 21, no. 3, p. 1673, Mar. 2021, doi: 10.11591/ijeecs.v21.i3.pp1673-1682.
[64] A. O. Eboka and A. A. Ojugo, “Mitigating technical challenges via redesigning campus network for greater efficiency, scalability and robustness: a logical view,” Int. J. Mod. Educ. Comput. Sci., vol. 12, no. 6, pp. 29–45, 2020, doi: 10.5815/ijmecs.2020.06.03.

[65] M. Cao and C. Guo, “Research on the Improvement of Association Rule Algorithm for Power Monitoring Data Mining,” in 2017 10th International Symposium on Computational Intelligence and Design (ISCID), Dec. 2017, pp. 112–115. doi: 10.1109/ISCID.2017.72.
[66] Z. Sun, “Big Data , analytics intelligence , and Data Science Big Data , analytics intelligence , and Data Science,” no. December, 2022, doi: 10.13140/RG.2.2.11911.47525.
[67] C. Li, N. Ding, H. Dong, and Y. Zhai, “Application of Credit Card Fraud Detection Based on CS-SVM,” Int. J. Mach. Learn. Comput., vol. 11, no. 1, pp. 34–39, 2021, doi: 10.18178/ijmlc.2021.11.1.1011.
[68] I. Ahmad et al., “Yield Forecasting of Spring Maize Using Remote Sensing and Crop Modeling in Faisalabad-Punjab Pakistan,” J. Indian Soc. Remote Sens., vol. 46, no. 10, pp. 1701–1711, Oct. 2018, doi: 10.1007/s12524-018-0825-8.
[69] J. Camargo and A. Young, “Feature Selection and Non-Linear Classifiers: Effects on Simultaneous Motion Recognition in Upper Limb,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 4, pp. 743–750, Apr. 2019, doi: 10.1109/TNSRE.2019.2903986.
[70] L. A. Belanche and F. F. González, “Review and Evaluation of Feature Selection Algorithms in Synthetic Problems,” Inf. Fusion, vol. 23, pp. 34–54, Jan. 2011.
[71] A. R. Bodie, A. C. Micciche, G. G. Atungulu, M. J. Rothrock, and S. C. Ricke, “Current Trends of Rice Milling Byproducts for Agricultural Applications and Alternative Food Production Systems,” Front. Sustain. Food Syst., vol. 3, Jun. 2019, doi: 10.3389/fsufs.2019.00047.
[72] G. B. Dela Cruz, B. D. Gerardo, and B. T. Tanguilig III, “Agricultural Crops Classification Models Based on PCA-GA Implementation in Data Mining,” Int. J. Model. Optim., vol. 4, no. 5, pp. 375–382, Oct. 2014, doi: 10.7763/IJMO.2014.V4.404.
[73] S. Iniyan, R. Jebakumar, P. Mangalraj, M. Mohit, and A. Nanda, “Plant Disease Identification and Detection Using Support Vector Machines and Artificial Neural Networks,” 2020, pp. 15–27. doi: 10.1007/978-981-15-0199-9_2.
[74] F. O. Aghware, R. E. Yoro, P. O. Ejeh, C. Odiakaose, F. U. Emordi, and A. A. Ojugo, “Sentiment Analysis in Detecting Sophistication and Degradation Cues in Malicious Web Contents,” Kongzhi yu Juece/Control Decis., vol. 38, no. 01, pp. 653–665, 2023.
[75] S. Mishra, R. Jain, and S. Dabas, Consumer Perception Towards-Online Shoping, vol. 12. 2019, pp. 1–14.
[76] P. M, “A Study on Consumer Perception Towards Digital Payment,” East Asian J. Multidiscip. Res., vol. 1, no. 6, pp. 1033–1044, Jul. 2022, doi: 10.55927/eajmr.v1i6.688.
[77] A. A. Ojugo, M. I. Akazue, P. O. Ejeh, C. Odiakaose, and F. U. Emordi, “DeGATraMoNN : Deep Learning Memetic Ensemble to Detect Spam Threats viap a Content-Based Processing,” Kongzhi yu Juece/Control Decis., vol. 38, no. 01, pp. 667–678, 2023.
[78] A. A. Izang, N. Goga, S. O., O. D., A. A., and A. K., “Scalable Data Analytics Market Basket Model for Transactional Data Streams,” Int. J. Adv. Comput. Sci. Appl., vol. 10, no. 10, 2019, doi: 10.14569/IJACSA.2019.0101010.
[79] A. Izang, S. Kuyoro, O. Alao, R. Okoro, and O. Adesegun, “Comparative Analysis of Association Rule Mining Algorithms in Market Basket Analysis Using Transactional Data,” J. Comput. Sci. Its Appl., vol. 27, no. 1, Aug. 2020, doi: 10.4314/jcsia.v27i1.8.