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Research Article

A Machine Learning-Based Double Token Weighted Clustering Approach for Online Product Recommendation

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ABSTRACT

Machine learning techniques have generated significant interest in the development of recommender systems. Given the vast array of direct and indirect variables that can be used to predict user preferences, there is a growing need for scalable, reliable algorithms and systems that offer high availability and scalability. In today's technologically advanced era, people have become more open-minded and increasingly depend on modern applications for daily needs such as purchasing accessories, watching movies, and more. The rising demand for online shopping and media consumption has led businesses to adopt machine learning-driven technologies to efficiently identify the most relevant products for users, with less effort compared to traditional marketing methods. Recommender systems (RS), particularly content-based filtering systems, play a vital role in both personal and professional contexts. These systems act as intermediaries between content providers—including social media platforms, e-commerce websites, and streaming services—and end users by suggesting items that match user preferences and past behaviors. Such personalized solutions are especially valuable when users are uncertain about what they want. Clustering is a key method in this space, which involves organizing a population or dataset into distinct groups, ensuring that data points within a single group are more similar to each other than to those in other groups. The goal is to identify users with similar characteristics and group them together in clusters associated with specific products. This research introduces a Double Token Weighted Clustering Model (DTWCM) designed to analyze and group relevant product recommendations sourced from multiple online recommendation systems. The model efficiently delivers high-quality suggestions to users. When compared with the traditional Adaptive Weights Clustering model, the proposed DTWCM demonstrates improved accuracy and scalability.

Keywords: Recommender System, Product Recommendation, Weighted Clustering.

INTRODUCTION

People's dependence on the internet has grown as a result of the growth in internet use and data availability [1]. Online shopping is the most popular service on the internet, with many companies selling their items via e-commerce platforms like Amazon and Myntra. In an e-commerce website, a big database of defined products is made available to a user for selection, leading to a problem of information overload [2]. With so much information available to them, the users in this environment are having a hard time making a selection about which product to buy. With the help of Recommender Systems, which learn from the behaviour of users and suggests goods that are comparable to their interests, this issue has been addressed [3]. As a result, the Recommender system aids customers in making the best possible purchasing decisions when shopping on e-commerce websites. Although there are numerous reasons to utilise a recommender system, firms typically use recommender systems for the following three reasons:

- To increase the sale of their goods
- To learn about the buying habits of customers to better serve them when it comes time to buy.
- By reducing a vast database to a manageable amount, recommendation systems help users get the information they're looking for.

The approaches shown in Fig. 1 are commonly used by recommendation systems.

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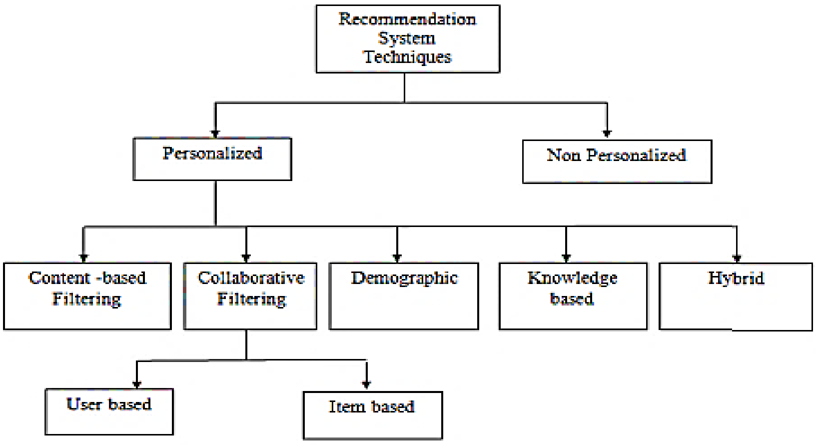

Fig 1: Recommendation System Techniques

Multiple fields, including e-commerce, tourism, health, and education, use Recommender Systems. E-commerce sites frequently employ these systems to suggest products to clients based on their previous purchases and interests [4]. Customers' purchasing habits are used to determine which things to recommend. Predictions about user preferences can also be formed using the analysis [5]. This method can be viewed as a form of personalisation because it aids customers in purchasing items that are of interest to them individually. If the suggestion is right, this technique can help build strong customer relationships [6] and enhance sales. The business community has taken notice of RS's work in e-commerce. The RS is used by Amazon to suggest books that customers are likely to buy. Although most RSs today are built on user, purchase histories, explicit ratings, and ownership data, no one system utilizes all of such at the same time in today's market [7].
The expansion of RS may have a positive impact on the tourism industry as well. They help travellers navigate the data of mountains and make wise travel choices [8]. Using this method, a suitable location can be recommended that has activities that fit their preferences. Many video and audio services use RSs as playlist generators. Walmart and social media sites such as Twitter and Facebook [9] use product recommenders. This approach is among the most effective uses of machine learning in the commercial world. This makes it easier for customers to make quick selections while transacting online and also enhances the overall quality of their buying [10]. This type of technology has also become important in healthcare, where, depending on their particular requirements, it may provide healthcare data recommendations to patients as well as health experts. With different ML models, the RS offers a chance in the medicinal domain [11]. Different ML methods may be utilized to efficiently address the most complicated problems involving unstructured data.
The field of recommender systems has seen a slew of research, including work in the movie recommendation, e-commerce, and healthcare sectors [12]. Providing learners with correct and up-to-date information is critical in an E-learning environment where recommendations play a vital role. Students and even adults' learning habits are being transformed by e-learning in the current scenario. Intentional students are frequently perplexed by the sheer volume of courses offered via the Internet, and it can be difficult to keep track of which courses are relevant [13]. Online recommendation systems can help students who are overwhelmed by the amount of information available to them due to the abundance of information available on the internet. An attempt will be made in this work to evaluate RS techniques, the application domains in which these techniques are applied, and the advantages and disadvantages of such techniques.

User suggestions are provided by recommender schemes, which are system software and procedures that make recommendations for a variety of items. User decision-making will be aided by the endorsements supplied by recommender systems [14]. Systems of recommender process data from a wide range of actively collected sources to make suggestions [15]. The type of recommendation systems dictated the type of data used in processing information. Using information that is simply accessible about the goods or commodities, or whatever else via online social networks, these recommender systems play an important part in making suggestions about the products or items. Using a cloud platform's Automatic Recommender System, users can get suggestions for products or services based

on the opinions or suggestions of the system [16]. People can use the cloud platform to express their thoughts and feelings about various products and services. The cloud-based system for the recommendation system will be provided by online social networks like Twitter and Facebook [17].
It encourages consumers to consider other people's perspectives and assists them in making decisions based on such perspectives [18]. Assessment mining also makes it possible to enhance items to meet the needs of advertising information and product comparison in the industrial sectors. As may be seen in Figure 2, the sentiment analysis procedure was carried out.Inthe first stage, all of the customer evaluations are screened for stop words and other irregular characters. To begin the classification process, positive and negative assessments are classified based on their moods. When it comes to buying things, people made better decisions when faced with extremes of opinion, whether favourable or negative.

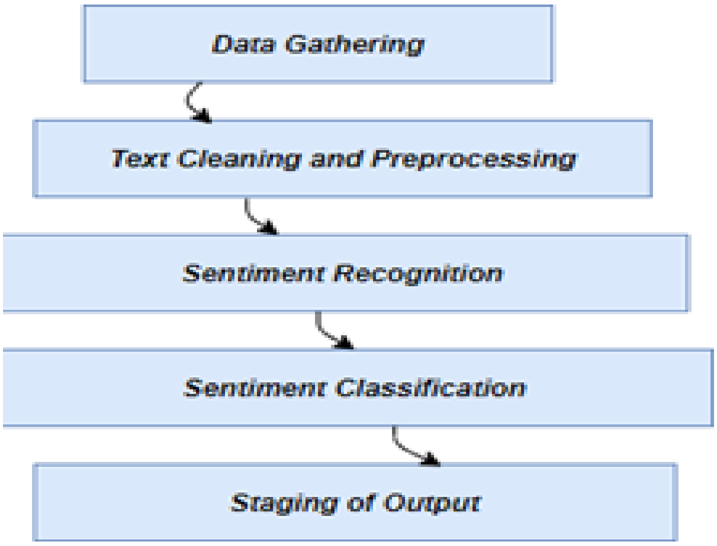

Fig 2: Sentiment Analysis Process

Data Gathering and Pre-Processing

The acquired material is examined for the recognition of opinions during the data collection and processing steps [19]. The words that communicate feelings will be removed in different ways, depending on the strategy used. After then, preprocessing is carried out to get rid of any useless viewpoints. It's critical for locating relevant keywords in the article because it provided a clear categorization [20].
Classification: Identifying the polarity of the content is done during the classification stage. Order is commonly divided into three categories, such as good, neutral, or negative. In addition to sentiment analysis, classification computations are also used in analysis of sentiment [21] in light of directed or unassisted methods using pre-checked representations. It's critical for building a classification model that uses domain-specific data [22].
Compilation and Display of Data: As part of the compilation and presentation process, the job or career measure result is combined with other data to determine the inclusive quality of the investigated text. As a result, the introduction to speaking about sentimental textual terms [23] is done quickly. The machine learning methods are quite helpful in classifying the gathered data and predicting the polarity of emotion as positive, negative, or neutral [24]. This article provides a machine-learning model used for sentiment analysis recommender systems [25].

LITERATURE REVIEW

G. Preethi et al. [1] suggested a recommendation system for online social classes based on Bayesian inference. In terms of performance, this suggestion performs better than the collaborative filtering and trust load recommendations. This system makes use of conditional probability to determine how similar two pieces of material

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are. The recommended method presents a Bayesian-inference-based commendation architecture using an accurate and tailored suggestion by exploiting integrated social makeup within a social network system.

An analysis of sentiment-based proposed approach for product rating was proposed by X. Yang et al. [2]. This algorithm compares retrieved tweets from Twitter to other classification methods like Nave Bayes and SVM and offers better accurate results. The dual prediction method and SVM text classifier adoption are two of this approach's major contributions. Twitter data is used for the evaluation, which yielded an accuracy rate of 82%.

According to Antoet al. [3], a recommender system based on sentiment analysis gives better recommendations by incorporating sentiment and faith inference from social networks into the decision-making process. This study presents a sentiment-based system and an implicit social trust paradigm. Real-time social information from Twitter was used to verify the architecture. This recommender system uses a combination of decision trees, neural networks, and regression models to provide suggestions. They engaged a stochastic erudition technique to classify the user's sentiments. Using the MAC address of the system, this recommender system can detect false reviews and disallows them. To overcome the limitations of classic recommender systems and enhance efficiency, this framework implements stochastic learning and a context-based engine.

Using lexicon-based approaches and ML tactics together, Rumelliet al. [5] created a novel model. An external word reference assigns a grade to each word in the phrase and the final extreme score is calculated by using additional substance score-based models as a naive technique for opinion analysis. Machine learning models are prepared to carry out exact evaluation explanations by applying highlights based on writings' extremity ratings. New Turkish texts have an accomplishment rate of 73% using the final supervised model, which does not require human intervention. Using an online business site, the data was compiled for this study.

The literary cry polls of organizations may be used to determine whether an evaluation is good or negative, according to Hemalatha et al. [7]. Information used in the estimating inquiry includes surveys of restaurants' food, management, cost, and atmosphere. The estimates are based on those results. Natural Language processing studies can benefit from the ML techniques in the Python NLTK package, and this work made considerable use of the library. Each computation has been compared to see which one is the most accurate.

For the analysis of literary information derived from digital assets, Chaturvedi et al. [8] recommend the use of presumption examination characterization as an effective technique. Sentiment analysis is an information mining approach that uses Artificial Intelligence (AI) to analyze literary data. To search, analyze, and combine customers' viewpoints for better decision-making, there is a huge amount of irreplaceable information available via web assets, such as assessments of customers, surveys, comments, and recommendations. Using sentiment analysis, customers may significantly influence a company area's dynamic cycle, which provides a convincing and competent assessment of them constantly.

According to Venkatesan et al. [10] research on the RS, the referral system is an effective instrument for making service recommendations to clients. Well-designed RS has shown that it can deliver reliable data to a wide number of clients via social media including Facebook, Google, Twitter, and Amazon, among others. Amazon.com frequently makes use of an item-based combined filtering algorithm. The number of objects as well as users can be counted separately using this method. When exhausting item-based combined filtering, we contrast the user's rated and bought items with similar items. The list of recommended purchases is then updated to include relevant goods.

Sharma et al. [12] showed that context awareness, neighbour transitivity loss, and sparsity are key issues in item-based RSs. Content-based, clustering algorithms, knowledge base, and hybrid approaches are the most often used RS categorization schemes. Users' past references are all that are used in content-based RS to build a profile and select recommended things. Collaborative filtering, on the other hand, looks at similar users' behaviour to identify potential items for inclusion. To match user requirements with potential objects of interest, the knowledge based RS consults knowledge of domain-specific. The hybrid recommendation system is a recommendation engine that employs several different methodologies to come up with a final recommendation. A better recommendation can be made by combining multiple methodologies. Clustering methods and hybrid techniques are commonly employed in tourist RSs.

To determine user interest, the majority of them employ both explicitly and implicitly related methods [13]. A semantic network that uses content-based filtering and combined filtering in this area suggests travel-related information. Location, type of attraction, cost, and travel time are just a few of the considerations. User's interests and ratings on attractions are identified and collected implicitly using a collaborative filtering approach, and the user's social network information is openly gathered. The recommended criteria take into account factors like the current date and hour, as well as the weather.

Leila Esmaeiliet al. [14] developed a new tourism recommendation system based on an information retrieval approach and implicit criteria. User pleasure must be maintained by using modern production space and performance optimization. These are the two fundamental challenges. RS can leverage user ratings, data, and feedback to produce suggestions using collaborative filtering. A common recommendation technique in collaborative filtering is the kNN(k-Nearest-Neighbors) recommendation algorithm. It's easy to use and can yield precise results. Although this technique has several advantages, the main disadvantages are its low scalability and sparsity. The kNN algorithm uses measures of similarity to determine how similar two sets of data are. When comparing two items or two users, the similarity computation was done between the two items, the user, and the user reviews.

Using metrics of similarity, comparable users are allocated to the user and the items as neighbors. Interactivity, adaptability, and personalization are three major shortcomings of the tourism RS. There is still a requirement for users to assist in manually planning their journey even if it suggests choices to them. The main issue here is the lack of autonomous travel planning. The user's social network and context may be used to help address the problem. Personal suggestions afflict major ways like collaborative, material, and demographic models. These issues of uniqueness can be addressed with hybrid techniques. To classify ailments using symptoms, Healthcare RS uses a collaborative filtering technique and then recommends provides to patients. Whether employing a collaborative filtering strategy or a mix one, the RS must gather info on users to develop recommendations. Support vector machines are a common machine learning method in the healthcare business. Classification, regression, and outlier identification are performed using a supervised learning model. Millions of lives might be saved if physicians used this technology to detect cardiac patients earlier and administer the appropriate medication. This could also be utilized to classify proteins, separate images, and classify text.

PROPOSED WORK

Collaborative filtering is preferred in the current paradigm of recommendation systems because it has a greater potential than other strategies to deeply stimulate a user's interest. Utilizing elements like user-profile information visited sites, and click information, collaborative filtering may identify a user's interests and then offer products that are relevant to those interests. The current techniques for collaborative filtering use both implicit and explicit characteristics and produce accurate classification or prediction results. These systems are unable to provide successful outcomes for both metrics simultaneously. In our opinion, avoiding the promotion of goods that have already been bought may help resolve the problem at hand. In order to quickly and effectively offer the best product to users, the current study suggests a Paired Annotation based Weighted Clustering Model (PAWCM) for evaluating and grouping pertinent product recommendations from a large number of online recommendations. The online product recommendation model process is shown in Figure 3.

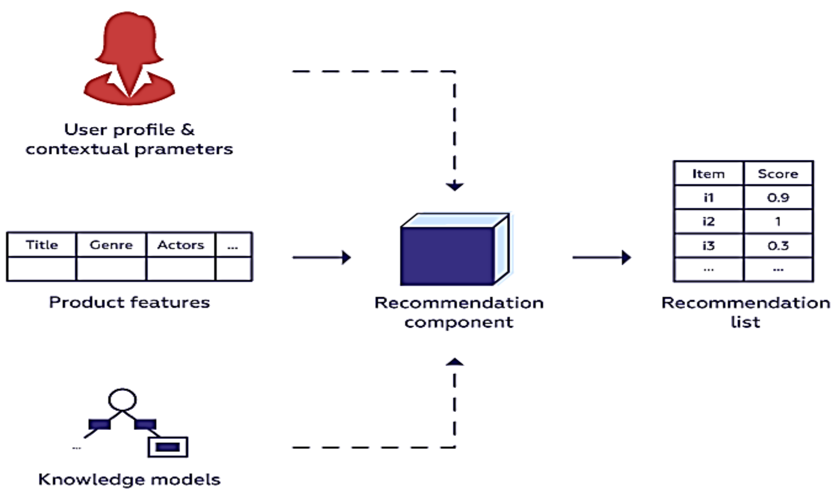

Fig 3: Recommendation Process

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Models for Machine Learning Probability, control and optimization theory are all aspects of machine learning. Computers can now progress activities based on real-world data by using a large range of machine-learning techniques. When selecting a machine-learning algorithm, training time, accuracy, and the quantity of parameters and variables are all important considerations. It is possible to examine hidden data using implicit knowledge gleaned from machine-learning algorithms' training data. Model accuracy and recall are all used to gauge how well the model performs. These machine-learning methods cover a wide range of data analysis topics. With ML-based models, visual processing, forecasting, pattern matching, robotics and expert systems are all made easier. Supervised or unsupervised learning methods of machine learning can be distinguished. For forecasting, supervised learning makes, use of a well-known dataset termed the "training dataset."
Classification aids in the division of a document to draw information from specific features of the record. Each record is made up of a tuple that contains the collection of characteristics, recommendations as well as the mark of the class. Additionally, the predictor, independent variable, and dependent variable are used to express the tuples for characterisation that recommends a product. Figure 4 depicts the basic structure of the recommended algorithm, which is a illustration of the suggested model.

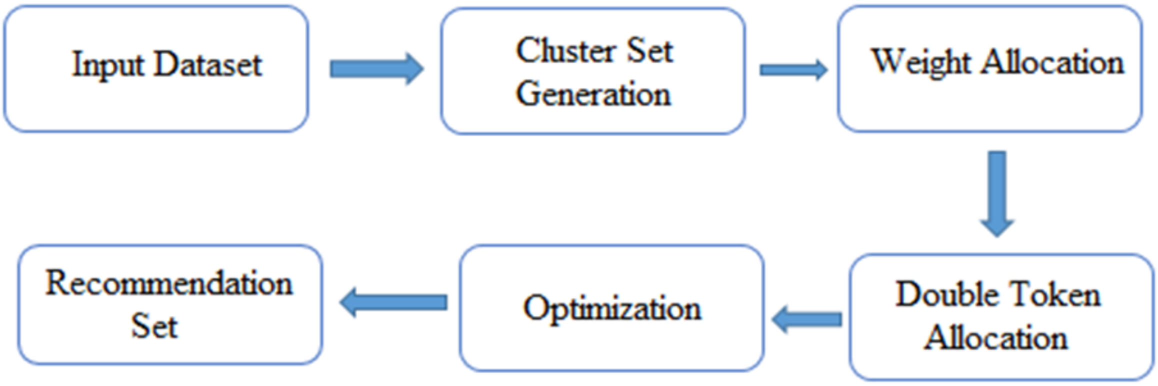

Fig 4: Proposed Framework

Paired Annotation-based Weighted Clustering Model (PAWCM) first clusters data, then extracts relevant features from the clusters. Each extracted feature is then given weights, and the weights are then used to label the extracted features at the top level for accurate product recommendation. They are then re-labelled with improved accuracy levels by using optimization techniques on the re-labelled and re-linked features depending on weight. As a result of this technique, we can understand the recommended model approach is efficient.

Algorithm PAWCM

Input: Recommender Dataset (RDS), Weights (W), Threshold Limit (TL)
Output: Recommendation Set (RS), Labelled Features (LF)

Using the dataset as a whole, perform clustering by looking for values that are comparable to each other.
For each I in RDS (N)

$$Feat(R(i)) = \sum_{i=1} \frac{\mathrm{RDS(i) + mean(RDS(i), RDS(i+1) + \omega}}{|TL|}$$

The comparison difference of the occurrences in the recommendation dataset, where, ω denotes similarity instances. Using parameters, the events are compared to all the other entries in the set before being clustered according to the equation.

$$Cluster\_Set(R(i)) = Feat(N) - \sum_{i \in RDS(i)} \frac{|RDS(N)^T|}{Feat(R(i))} + \mathrm{min(Feat(RDS(i,i+1))}$$

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Research Article

Where RDS(N) is the last record and T is the Threshold limit. The process of allocating weights to the extracts features in the recommender dataset is performed as

$$Weight(RDS(N)) = \sum_{i=1}^{N} \frac{Cluster\_Set(R(i)) + \sum_{i=1}^{N} \mathrm{Feat(i+1)}}{(\omega - i)^N}$$

Where i and i+1 indicate the neighbouring set of features in a cluster. The token calculation is done after weight allocation for the features considered. The token calculation is performed as

$$Token\_Set(Cluster\_Set(i)) = \sum_{i \in RDS(N)} Max(Weight(RDS(i+1) + \min\,(Feat(RDS(N)W_i^T$$

All cluster characteristics are linked to a Cluster Set when a token calculation is completed on the cluster features. The equation is used to join clusters as a unique set is performed as
$Here\ \ \lambda_{i,j}$ Indicates the similarity level of the neighbour pixel. The resemblance between the characteristics is computed as

$$\mathrm{resemblance}(R(i, i+1) = \sum_i \sum_j |\, Feat - Token\_Set(RDS(i)) \,| + Max(W(N)\,| + \lambda$$

The connected clusters' path is shown here by λ. The double token is used to achieve unique clustering after all cluster groups have been joined. The clustering of double tokens is carried out as follows

$$Dou\_Token(RDS(N)) = \sum_i \sum_j \frac{(Token\_Set(RDS(M-i)(i, i+1) + \max(reseblance(RDS(N))}{F(i) + \max(Weight(R(i))}$$

The cost reduction performed on the product recommendation model is performed as

$$Optimize\left(Dou_{Token(RDS(N))}\right) = \frac{Weight(resemblance\left(R(i)\right) + \lambda}{\max\,(\mathrm{Dou\_Token(RDS(i, i+1)))}}$$

RESULTS

An application that creates and offers suggestions for products or content that a specific user would like to purchase or interact with is known as product recommendation software. By using an ML method and various data on both particular items and individual customers, the system creates an increased net of complex connections between those things and those individuals. The suggested model is run in Google Colab and implemented in Python. The link provides access to the dataset. http://jmcauley.ucsd.edu/data/amazon/links.html. The proposed Paired Annotation based Weighted Clustering Model (PAWCM) is associated with the traditional Semantic Personalized Recommendation System (SPRS) Model and the results are evaluated by considering the factors such as Pre-Processing Accuracy Levels, Data Pre-processing Time Levels, Feature Extraction Accuracy Levels, Weight Allocation Time Levels, Clustering Accuracy Level, Double Token Allocation Accuracy, Product Recommendation Accuracy and Error Rate.
Recommender System (RS) is among the most prominent Artificial Intelligence applications, attracting researchers from all over the world. RSs are created using different ML algorithms. In the realm of RSs, choosing the best machine-learning algorithm to provide consumers with a service or product is the most challenging challenge. To apply data mining techniques, raw data must be transformed into well-formed data sets via the process of data preparation. The purpose of data imputation is to either manually or electronically make corrections and input missing values. Figure 5 shows the data pre-processing times for the proposed and conventional models.

Journal of Information Systems Engineering and Management
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Fig 5: Time Levels of data Pre-processing

Data pre-processing includes operations like instance selection, cleaning, one-hot encoding, normalisation, transformations, feature selection and extraction, and more. The end outcome of data preparation is the training dataset. The proposed model accurately performs pre-processing by providing a useful dataset for analysis. Figure 6 shows the pre-processing accuracy values for the proposed and conventional models.

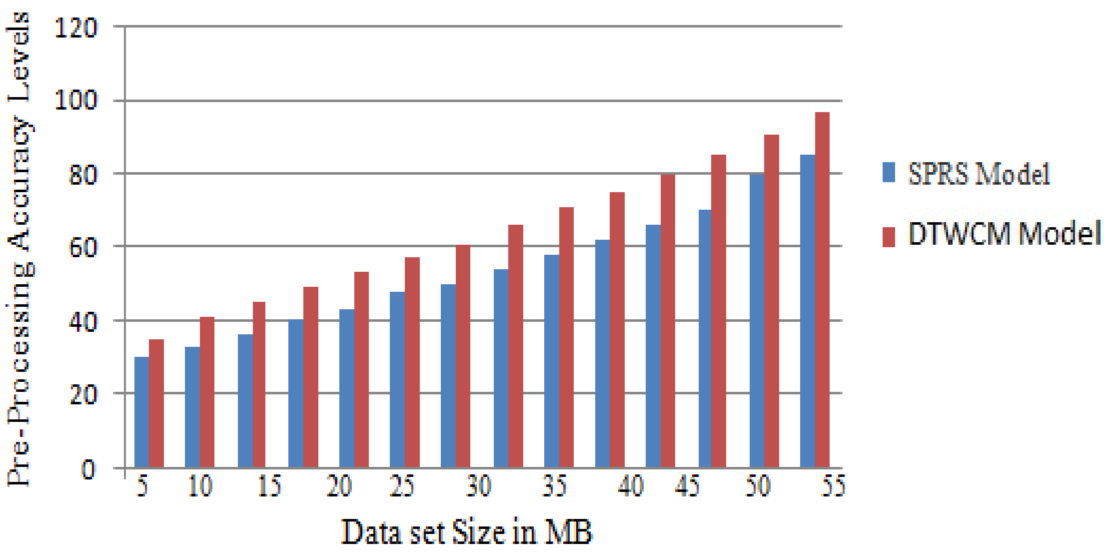

Fig 6: Pre-Processing Accuracy Levels

A clustering-based recommender system based on user feedback and rating concepts is analysed in the proposed model. Only the rating information and product quality in that cluster are used by our system to suggest an item to a customer in a certain cluster. This allows us to minimize the algorithm's running time by avoiding computations over the complete data set. The suggested model has good levels of clustering accuracy. Figure 7 illustrations the evaluation among the suggested model and the conventional model.

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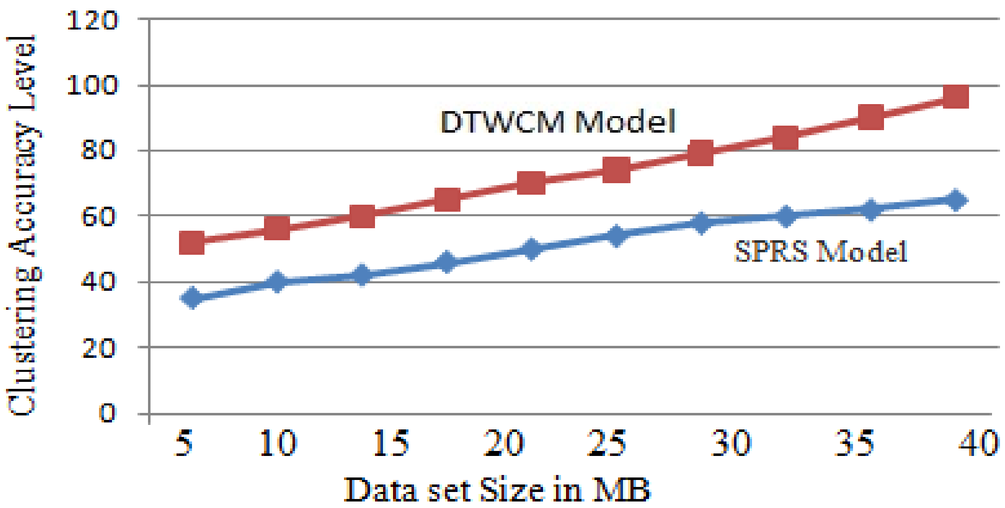

Fig 7: Clustering Accuracy Level

The proposed model allocated double tokens for the user reviews that are helpful in product recommendation. The double token features are used in the process of accurate and quality product recommendations. Figure 8 shows the suggested and conventional models' level of accuracy for double token allocation.

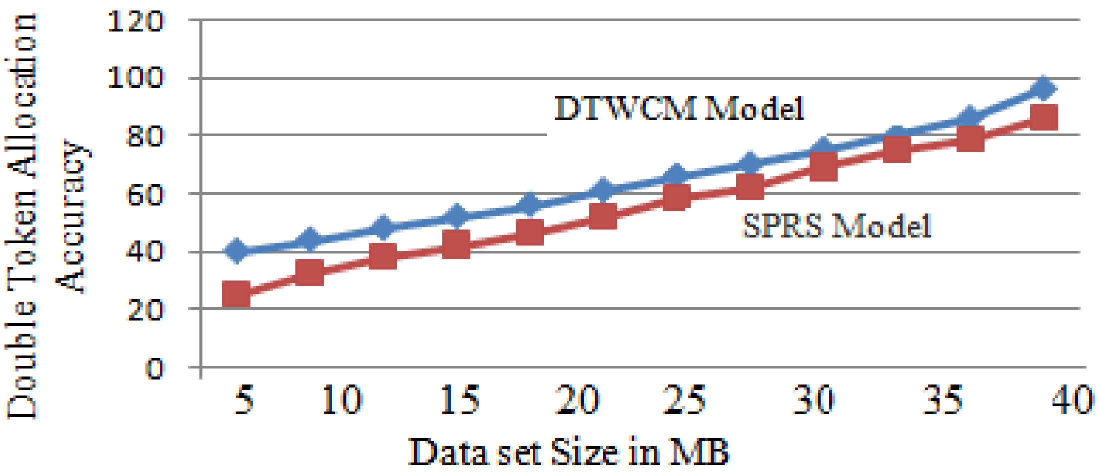

Fig 8: Double Token Allocation Accuracy

The proposed model after double token allocation, assigns weights to the most relevant features for recommending the best product. The features are considered based on the allocated weights. Figure 9 displays the weight allocation time levels for the proposed and current methods.

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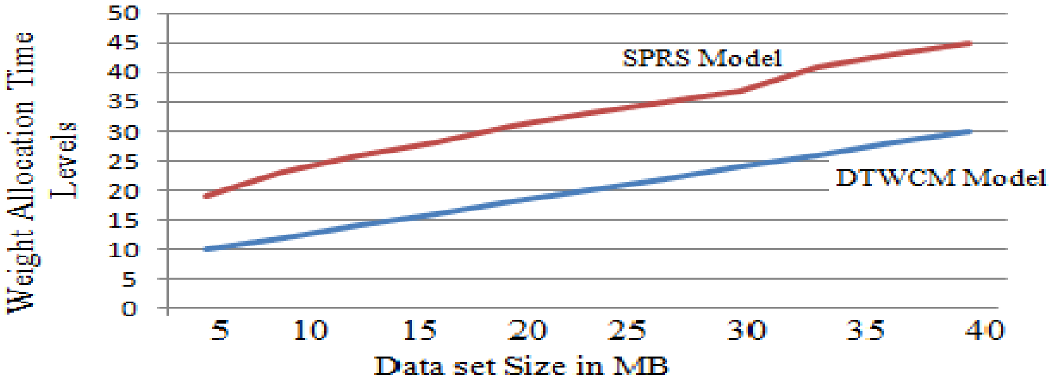

Fig 9: Weight Allocation Time Levels

Reduce the resources required to explain a large quantity of data by using feature extraction. Extraction of features is a broad word for methods of building variable combinations that prevent these problems while maintaining the data's accuracy. When compared to a standard model, the suggested model's feature extraction accuracy is higher. Figure 10 displays the proposed and conventional model feature extraction accuracy levels.

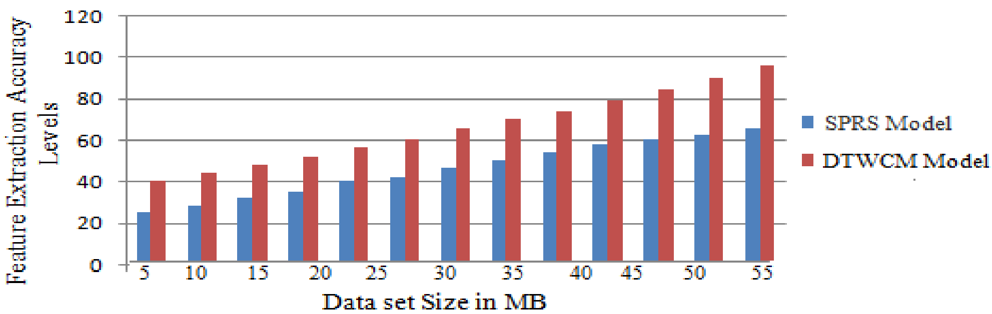

Fig 10: Feature Extraction Accuracy Levels

A product recommendation is essentially a filtering process of attempting to forecast and display the things that a user would like to buy. In essence, recommendation engines are systems for filtering data that employ algorithms and information to propose the products that will be most useful to a particular user. Figure 11 illustrates the standard and suggested models' product recommendation accuracy.

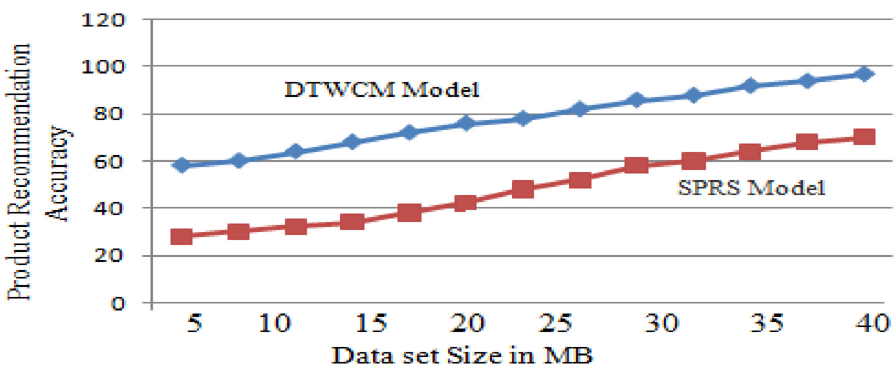

Fig 11: Product Recommendation Accuracy

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Table 1 illustrates the suggested classifier's performance levels. When compared to the current classifiers, the model's classifier performance and product recommendation accuracy are higher.

Table 1. Classifier Performance Levels

Classifiers	Accuracy (%)	Precision	Recall	F-Measure
KNN	82	72.6	69.8	76.2
SPRS	89	78.4	72.8	74.8
PAWCM	97	95.7	94.6	91.6

The proposed model assigns double tokens to the features and then allocates the weights to the features for better and more accurate analysis. The proposed model suggests the best product for the users. In comparison to the conventional approach, the suggested model makes fewer errors while offering a product to the consumer. Figure 12 shows the suggested and conventional models' error rate levels.

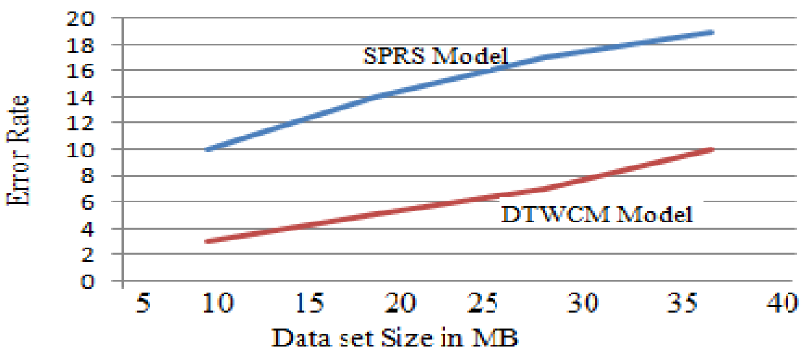

Fig 12: Error Rate

CONCLUSION

The Recommendation System is the most important aspect of life. The availability of a user-generated recommendation system has increased the appeal of online shopping. The recommender system delivers appropriate services. Therefore, recommender systems are a benefit to society by supporting users in choosing among their alternatives. To make recommendations, the recommender system employs a variety of strategies. Algorithms for making suggestions are typically built based on the most popular things. However, this should not be the only use for it. It's important to offer various products to keep customers from getting bored with the same or well-known things. Because of this, there could be greater precision utilised to recognise the best products with quality for the user's double token weighted clustering model can analyze and group pertinent product recommendations from a large number of online suggestions in this study, quickly and effectively recommending the best product to users. The proposed approach uses unstructured user evaluations and sentiment analysis to transform them into structured forms that can be combined with machine learning for better outcomes.

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