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BIG DATA FOOD MAPPING FRAMEWORK USING MAP REDUCE TECHNOLOGIES FOR EFFICIENT ONLINE FOOD MARKETING SYSTEM

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ABSTRACT

Companies with a strong customer emphasis are the primary users of data mining nowadays. Inconsistencies and redundancies are not immediately applicable for starting a data mining process since data is likely to be faulty. In data analysis, missing values are unavoidable, and cause serious problems. Faulty knowledge is retrieved and incorrect inferences are drawn when missing values are handled and replaced incorrectly, thereby leading to high computational time with high data and large iterations. Due to heterogeneous datasets, there is a lack of exact mapping technique, and while visualizing the extracted data the mild handling of data leads to inaccurate data extraction, which lowers all the efficient processes contributing towards the accuracy. Hence in this paper, to overcome the issues a novel Big Data Food Mapping framework is proposed which incorporates association rule mining, followed by a fuzzy clustering-based binning procedure followed by a score-based normalization. Map Reducing, including initial mapping based on genetic operators and entropy generation, was also performed. The reduction is done using fuzzy logic and a Graph Neural Network. After that, the data is mined using Concept analysis and Long Short –Term Memory (LSTM). The outcomes were more accurate and displayed using T-distributed stochastic neighbor embedding (t-SNE) based dual clustering.

Keywords: *Online Food Delivery, Fuzzy Clustering-based Binning Technique, Score–based Normalization, Map Reducing, T-distributed stochastic neighbor embedding (t-SNE), Dual Clustering.*

1. INTRODUCTION

Food is an important part of our lives, civilizations, and overall well-being. As more people use digital and network technologies, the methods by which food is produced, cooked, and consumed are becoming more interactive and creative [1]. The advent of information technology has made it possible to gather and analyses massive amounts of data. Because food is such a common topic in our lives, enormous volumes of food-related data are created daily all around the world [2]. The semantic web (web sites, social media, and online databases) has recently generated an increasing quantity of digital data connected to food production, processing, and consumption. People may now share their food consumption habits with others through digital channels such as social media [3-4]. Nowadays, it's not uncommon to see individuals at restaurants snapping photos of delectable food and posting them on social media to share with others. Identifying human food choices and consumption patterns has piqued the curiosity of scientists in a variety of fields [5]. Texts, pictures, and videos are all examples of digital data presentation. Text data, for example, play an important part in our lives and is examined extensively. For communication reasons, large volumes of text data are created and consumed [6-7]. Text data also contains people's knowledge, views, and tastes, and is typically rich in semantic information [8].

Big data, or enormous data sets, opens up new possibilities in service suggestions. Traditional recommendation services have efficiency and

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scalability issues when analyzing large data sets. The Map-Reduce system is used by Hadoop, a big data application [9]. This design scheme, which is built on a user behavior ontology model and integrates customized suggestions by combining explicit interest and implicit demand, can assist users in obtaining correct information about scientific and technical accomplishments that they are interested in. It is becoming increasingly important to businesses in terms of assuring profitability and ensuring long-term viability [10-11].

Big data has considerably eased decision-making processes beyond its ability to manage data storage concerns, and Big Data Analytics (BDA) demonstrated to increase businesses' profitability, operational efficiency, and marketing effectiveness in the short and long term [12]. The competence of a company's BDA has a direct and indirect impact on its success. Data is processed and evaluated in real-time with the aid of Big Data in a short amount of time. As a result, rapid action is possible, which is difficult to do with conventional technologies [13]. Big Data Analytics solutions provide innovative methods to solve some of the most important marketing issues, as well as stunning results. These findings have the potential to improve marketing department execution [14-15] which is defined by four dimensions, according to previous computer theory: volume, velocity, diversity, and veracity. Later, as a fifth dimension, "value" was introduced, which relates to the gathering and utilization of consumer data [16]. The heterogeneity in data (i.e., "Variety") develops as a result of today's data economy's cross-enterprise nature. Though data may be stored in silos (for example, social media data vs. company data), when all of this data is analyzed, new opportunities emerge [17-18]. This digital revolution has resulted in a considerable impact on business processes by enhancing the veracity, volume, and variety of information produced from unstructured data, which has given rise to an innovative era in which business performance is reliant on data-driven decision-making capabilities [19].

Customer knowledge (CK) is an important component of executing a marketing plan with data-driven decision-making. "The mix of experience, value, and insight information that is needed, generated, and absorbed throughout the transaction and exchange between the customers and the enterprise" are what CK stands for [20-22]. To successfully target customers, the segmentation – targeting – positioning (STP) enables companies to emphasize the strength of their products, the value proposition, or the needs of their customers. The STP process can be optimized using data analytics to conduct in-depth studies of customer knowledge. End-users, enterprise customers, service providers, and prosumers all benefit from these options [23-24]. In nearly all businesses, data mining has emerged as a significant method for discovering meaningful information from data most of the Techniques used for Big Data mapping resulted in inconsistency, and redundancy data leads to faulty data which necessitates the implementation of a novel big data mapping technique for better performance.

The Contribution of this paper includes,

- Association rule mining to discover null values, followed by a fuzzy clustering-based binning procedure.
- Threshold associating the probabilistic relationship with the resource required, depending on the outcomes of the binning technique.
- Score-based normalization is performed, based on which the required attribute subset is determined
- Mapping based on genetic operators and entropy generation. The reduction is then carried out using fuzzy logic and a Graph Neural Network.
- Here Concept analysis and LSTM were used. The findings are displayed using t-SNE based dual clustering.

The content of the paper is organized as follows: section 1 represents the introduction; section 2 presents the related work; the novel solutions are presented in section 3; the implementation results and its comparison are provided in section 4; finally, section 5 concludes the paper.

2. LITERATURE SURVEY

Misra et al [25], Besides sensors, big data from social media is also becoming important for the food industry. In this review, we present an overview of IoT, big data, and artificial intelligence (AI) and their disruptive role in shaping the future of Agri-food systems. Following an introduction to the fields of IoT, big data, and AI, this paper discuss the role of IoT and big data analysis in agriculture (including greenhouse monitoring, intelligent farm machines, and drone-based crop imaging), supply chain modernization, social media (for open innovation and sentiment analysis) in the food industry, food quality assessment (using spectral methods and sensor fusion), and finally,

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food safety (using gene sequencing and blockchain-based digital traceability).

Liu et al [26], To fill the knowledge gap in business-to-business (B2B) research, this paper investigated whether UGC has differential impacts on stock performance for B2B and B2C firms by using big data. They collected a large dataset of 84 million tweets from 20.3 million Twitter accounts and 8 years of stock data for 407 companies from the S&P 500 index. The results from machine learning methods are transformed into monthly panel data. Then they conducted a fixed-effects model on the panel data and found that UGC has a significant impact on firms' stock performance and that its impact on stock performance is much stronger among B2C firms than among B2B firms. While consumers' positive sentiment does not play a significant role in stock performance, consumers' negative sentiment and WOM significantly impact stock prices.

Bhat et al [27], This paper presents a novel work of implementing the MapReduce technique to analyze and retrieve data. An attempt is made to retrieve data by adopting the MapReduce technique. A task is divided into several sub-tasks, and these sub-tasks can be processed simultaneously by different processors or several commodity hardware. A novel and effective way of implementing MapReduce is represented in this paper. In other words, this work examines the method and the outcome of the MapReduce technique, which is a solution to the problem of processing a huge amount of data.

Chautan et al [28], This study focuses on tracking the sentiments of the customers through which these brands can identify the issues which lead to unsatisfactory responses or reviews on various online and social sites. Further study paves ways for innovative service recovery mechanisms to frame a sustainable business practice for gaining competitive advantage. In this study, sentiment analysis tools like IBM Watson, social mention, and tone analyzers were used to observe the reactions of customers and used disruptive technology to analyze how brands could improve their service recovery behavior to secure and reach more customers by figuring out the reasons for service failure.

Meek et al [29], Based on Dual Process Theory and Social Impact Theory, this study explores which contextual and descriptive attributes of restaurant reviews influence the reviewee to accept a review as helpful and thus, “Like” the review. Utilizing both qualitative and quantitative methodologies, a big data sample of 58,468 restaurant reviews on Zomato was analyzed. Results revealed the informational factor of positive recommendation framing and the normative factors of strong argument quality and moderate recommendation ratings, influence the generation of a reviewee “Like”. This study highlights the important filtering function a heuristic can offer prospective customers which can also result in greater social impact for the Online Opinion Platform

An overview of IoT, big data, AI, and their disruptive role in shaping the future of Agri-food systems were reviewed [25]. stock performance for B2B and B2C firms by using big data were investigated [26]. This paper presents Map Reduce Technique for analyzing and retrieving the data [27]. Used disruptive technology to improve their service in online and social sites [28]. This study highlights the important filtering function that results in greater social impact for the Online Opinion Platform [29]. Hence, to overcome the issues a novel big data mapping has to be implemented for better performance.

3. BIG DATA FOOD MAPPING FRAMEWORK

The pace with which successful organizations are evolving, as well as the massive amounts of data generated by the digital world, need the development of innovative ways for extracting meaningful information from large amounts of data. Pre-processing the data is required to perform an accurate extraction of information from a huge dataset. As a result, a novel Big Data Food Mapping framework uses association rule mining to discover null values, followed by a fuzzy clustering-based binning procedure. Unwanted information is eliminated based on the threshold associating the probabilistic relationship with the resource required, depending on the outcomes of the binning technique. Then a score-based normalization is performed, based on which the required attribute subset is determined for further processing, reducing compilation time. Map Reduce is a crucial juncture in extracting precise data from large amounts of data, including initial mapping based on genetic operators and entropy generation. The reduction is then carried out using fuzzy logic and a Graph Neural Network. After that, the data is mined using Concept analysis and LSTM.

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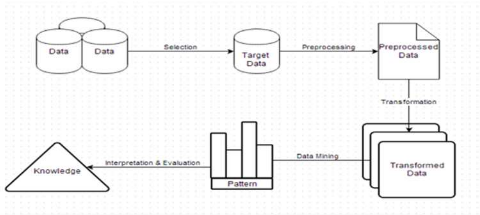

Figure 1: Block Diagram Of Big Data Food Mapping Network

The findings were displayed using t-SNE based dual clustering, which finds and visualizes the difference and similarity of the probabilistic function. Thus, the knowledge extracted much accurately from the complex big data with comparatively low computational time

3.1 Association Rule Mining Using Supremacy Algorithm

Association Rule Mining is a Data Mining approach for discovering patterns in data. Association Rule Mining patterns indicate connections between data which means they help to show the probability of relationship between the data items, within the large datasets in various types of databases. They also find out the null values and replace them with the probable value associated with the dataset. Figure 2 is the flow chart for the supremacy algorithm.

Initially, the overall data is taken into consideration, then the frequent dataset searched by the customers is generated. In the next step of the algorithm, the questions asked by the customer are analyzed so that the value is being searched for the question. If the customer requested question matches the null data or the missing data, then the association rule is set for replacing the missing data values. The key factors for the association rule are Support, Lift, and Confidence. The association rules may be created from the frequent itemsets based on two essential requirements:

- The rules fulfill the assumed minimum support threshold
- The rule has a higher confidence limit than the expected minimum confidence threshold.

Confidence is the same as that conditional probability. The confidence based on the item set support count was calculated using the conditional probability represented by equation (1).

$$Confidence\ (S => P) = \frac{Probability\ of\ S\ \&P}{Support\ S} \quad (1)$$

Where S and P is the frequent item set.

Lift is associated with an association rule's success in predicting or identifying situations as having an improved response as compared to a random choice targeting model. The lift value of an association rule is the ratio of the rule's confidence to its predicted confidence.

$$Lift\ = \frac{Confidence}{Expected\ Confidence} \quad (2)$$

Figure 2 depicts the probability of finding a relationship in large data set with a Null value.

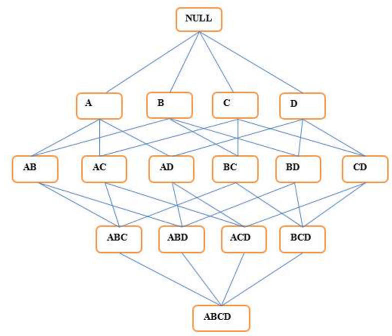

Figure 2: The Probability Of Finding A Relationship In Large Data Set With A Null Value.

To discover the null values and to reallocate the values with the new ones this association algorithm with supremacy algorithm is used. For example, if in a data set the customer-required resource is stated as null, then it finds the probable data to be replaced with the null set. Figure 3shows the probability of finding the data to replace it with the null set.

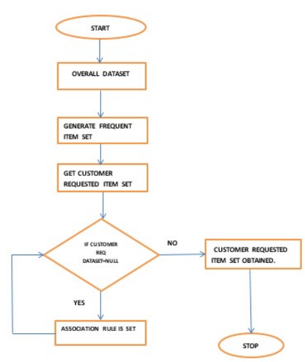

Figure 3: Flow Chart For The Supremacy Algorithm

The association rule is acting within the supremacy algorithm in which the preprocessing of the data is carried out. Initially, the overall data is taken for analysis, then the frequently used item set is derived. Then it gets the customer requested source and discovers the null values. Finally, the association rule is set in terms of min-support, min-confidence, min-lift, etc. Thus the association rule-

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based algorithm discovers the null data and replaces it with the probable data

3.2 Fuzzy Clustering based binning-procedure and Score based Normalization.

In our technique, we are taking almost 21000 datasets containing restaurant details, which include the name of the restaurant, address, rating, price list, cuisines, etc. if the customer is searching for the top rating restaurant Indian cuisine with the lowest price in Andhra Pradesh, at first, the Top rated restaurants were clustered and the remaining will be binned. Figure 4 explains the fuzzy clustering binning technique for the above-mentioned question

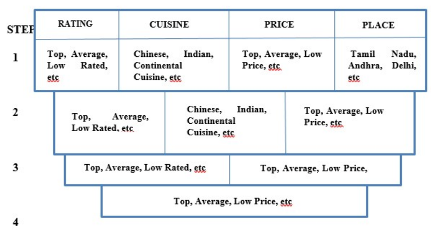

Figure 4: Fuzzy Clustering-Based Binning Technique

The Question asked by the customer is “Top Rated Indian Cuisine Restaurant with the lowest price in Andhra Pradesh”. The steps followed in the binning procedure for the above-mentioned question were given below

STEP 1: The question asked by the customer is split into categories and the binning procedure continues. Here the question is clustered into four categories as Rating, Cuisine, Price, Place. Then the unwanted data in a category is eliminated and the remaining data were stored. In the place category, Restaurants in Andhra Pradesh are stored and the remaining states were eliminated as unwanted data. The unwanted data were eliminated based on the Threshold based on the probabilistic relationship of the resource required. So that the huge data is somewhat reduced according to the need of the customer.

STEP 2: In this step, Cuisine Category is selected and only the Indian cuisine is stored. The remaining unwanted data such as the Continental Cuisine, Chinese Cuisine were eliminated as they are unwanted data as per the question asked by the customer.

STEP 3: In the next step Top Rated Restaurants were selected, other restaurants with minimum ratings were eliminated.

STEP 4: In the Final Step, the remaining category called the price is taken into consideration and the final list of the restaurants based on the need of the customer is displayed.

These were the steps followed in the Fuzzy Clustering-based binned procedure.

Score-based Normalization aggregates all data obtained in separate levels are frequently adjusted to a nominally comparable basis. It is processed by averaging and searching the particular values from the dispersed date in large data. For Example, If the customer wants to resource the list of the restaurant, then it is clustered then the list of restaurants was listed in such an order. Here score is based on the Rating, Price, Votes given by the customers. Based on that, the restaurant list as per the need of the customer is created.

Initially, mapping is carried out by a basic search mechanism which is given as the genetic operator in the proposed system. Entropy generation is nothing but the values generated to search for the required resource in the big data. It follows with the Fuzzy concept which is explained in the fuzzy clustering-based binning procedure. Then the computational information can be provided by a graph-based structure in this case by utilizing GNN. Long Short Term Memory (LSTM) is designed to avoid long-term dependency problems. While we are eliminating the unwanted data as per the need of the customer it should not get completely removed from the data set. In the short term while the data should get removed after the process gets completed then the data will get regain its original position hence it avoids another null value in the big data set. For that purpose, only the LSTM s were proposed.

4. RESULTS AND DISCUSSIONS

This segment provides a detailed description of the implementation results as well as the performance of the proposed system and a comparison section to ensure that the proposed system performs valuable.

4.1 Experimental Setup

This work has been implemented in a working platform of PYTHON with the following system specification and the simulation results are discussed below,

Platform	: Python
OS	: Windows 8
Processor	: 64-bit Intel processor
RAM	: 8GB RAM

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Dataset **:**Zomato Dataset

4.1.1 Dataset Description

Here Zomato Dataset of about nearly 212000 data was taken from different places in India. The data contains the details such as Reg ID, Name of the restaurant, Address, City, Latitude, Longitude, Zip code, Country, Cuisine, Timings, Average cost, Price range, Currency accepted, Highlights, Rating comments, Votes, Photo Count, Open table, Delivery, Takeaway, etc.

4.1.2 Results for the Proposed Methodology

The results for the proposed methodology is given below,

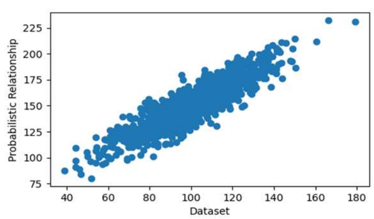

Figure 5: Probabilistic Relationship Of Data Required Using Fuzzy Concept

Figure 5 gives the probabilistic relationship of data required using the fuzzy concept of the proposed system. t-SNE is a technique for both visualization and dimensional reduction. It identifies observable groups depending on the similarity of different characteristics to detect a pattern in the information.

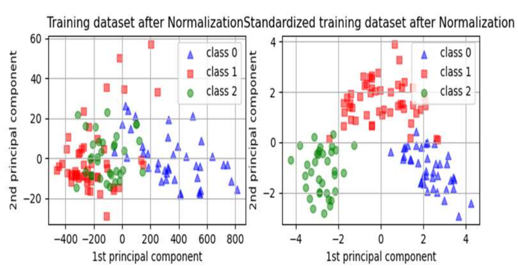

Figure 6: (A) Training Dataset After Normalization (B) Standardized Training Dataset After Normalization

Initially, the preprocessing datasets were taken for normalization. It is categorized into three classes. Then Using score-based normalization, the standardized training dataset is obtained as a result of it.

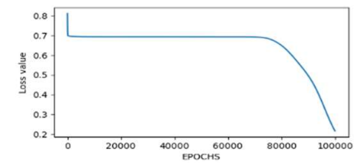

***Figure 7:** EPOCHS Vs Loss Value*

Figure 7 gives the graphical representation between EPOCHS and loss values. The number of iterations over the information is represented by the epoch. Loss is the error over the training set, often expressed as mean squared error. For 0 epoch, the loss value reduces from 0.8 to 0.7 error. Then the loss value is constantly 0.7 up to epoch 75000. Again the loss value is declining from 0.7 to 0.2 in the 100000 epoch. The loss or the error over the training set is decreasing due to the binning and mapping technique, which is proposed in this paper.

The execution time is calculated which is the product of the number of instructions to the average time per instruction using the formula,

$$Execution\ time = Number\ of\ instructions \times average\ time\ per\ instructions \quad (3)$$

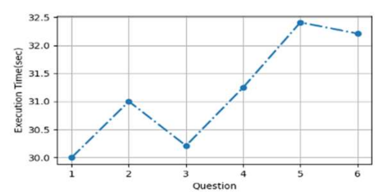

Figure 8: Execution Time Vs Questions Searched By The Customer

Every question is different from different customers also the number of categories varies concerning the customers. So based on the number of categories in the question, the execution time also gets varies. Figure 8 shows the execution time for various questions in terms of seconds. For question 1 the execution time is 30 s. For question 2,3,4,5,6 the execution time is 31 s, 30.25 s ,31.25 s,32.45 s, and 32.25 s respectively.

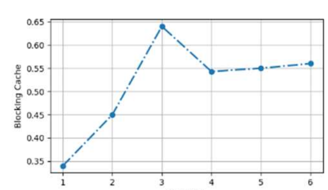

Figure 9: Graphical Representation For Blocking Cache Vs Question

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Blocking Cache represents the data retrieval reorganization method that pulls subsets of data into the cache and operates on this block to prevent having to request data from the main data set again. For question 1,2,3,4,5,6 the blocking cache is 0.34, 0.45, 0.64 ,0.545, 0.55 and 0.56 respectively.

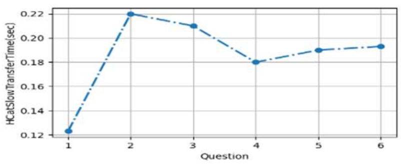

Figure 10: Graphical Representation Of HC At Slow Transfer Time Vs Questions.

Figure 10 gives the graphical representation of HC at slow transfer time for six different questions. For Question 1,2,3,4,5,6 the HC at slow transfer time is 0.125 s ,0.22 s ,0.2165 s ,0.18 s, 0.1945 s, and 0.195 s respectively.

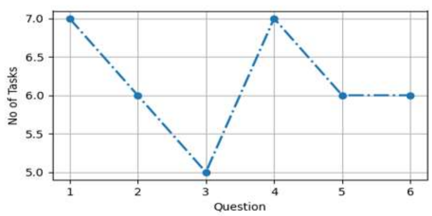

Figure11: Graphical Representation Between No. Of Tasks Vs Questions

Figure 11 shows the no of tasks required to perform the process for each question by the program. For questions, 1, 2, 3, 4, 5, 6 the no of tasks performed is 7, 6, 5, 7, 6, and 6 respectively. For the execution time, blocking cache, HC at slow transfer, and No of tasks, the graph was plotted vs questions. These six questions were taken randomly for the implementation of the program. Based on the nature of the question the parameters such as execution time, blocking cache, HC at slow transfer, and No of tasks were simulated.

In the next section, the performance parameters for sensitivity, specificity, accuracy, E-learning, OTA, and OFD in the proposed system were compared with the existing techniques.

4.2 Comparison metrics

4.2.1 Sensitivity (%)

Sensitivity is deduced using the formula [30]

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive+Fals Negative}} *100(4)$$

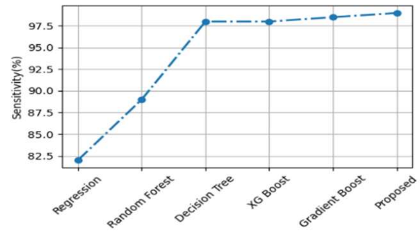

Figure 12: Sensitivity (%) Comparison

Figure 12 gives the comparison of Sensitivity (%) for the existing and the proposed techniques. For Regression, the Sensitivity is 82.4 %. For Random Forest, the Sensitivity is 87.8%. For the Decision Tree, the Sensitivity is 97.6 %. For XG Boost, the Sensitivity is 97.6%. For Gradient Boost, the Sensitivity is 97.7 %. For the proposed technique, the Sensitivity is 97.8%. Comparatively, the Sensitivity rate is higher for the proposed methodology.

4.2.2 Specificity (%)

Specificity is derived from the equation [30]

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative+False Positive}} *100 \ (5)$$

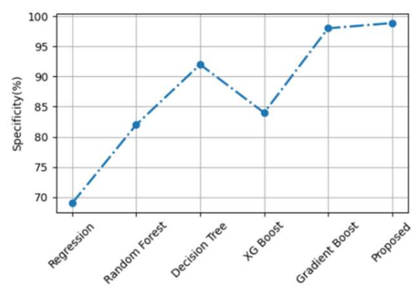

Figure 13: Specificity (%) Comparison

Figure 13 gives the comparison of Specificity (%) for the existing and the proposed techniques. For Regression, the Specificity is 69 %. For Random Forest, the Specificity is 82%. For the Decision Tree, the Specificity is 93 %. For XG Boost, the Specificity is 84%. For Gradient Boost, the Specificity is 98 %. For the proposed technique, the Specificity is 99%. Comparatively the Specificity rate is higher for the proposed methodology.

4.2.3 Accuracy (%)

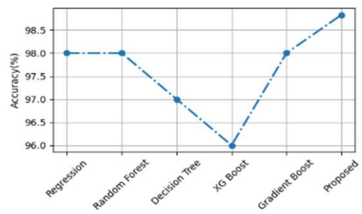

Figure 14: Accuracy (%) Comparison

Figure 14 gives the comparison of Accuracy (%) for the existing and the proposed techniques. For Regression, the Accuracy is 98 %. For Random Forest, the accuracy is 98%. For the Decision Tree, the accuracy is 97 %. For XG Boost, the accuracy is 96%. For Gradient Boost, the accuracy is 98 %. For the proposed technique, the accuracy is 98.9%. Comparatively, the Accuracy rate is higher for the proposed methodology.

4.2.4 Precision

The closeness of two or more measurements to each other is known as precision. The formula is presented as,

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

Where,
TP - True Positive
FP –False Positive

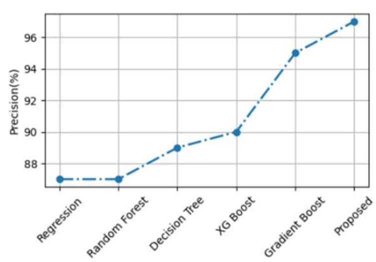

Figure 15: Precision (%) Comparison

Figure 15 gives the comparison of precision (%) for the existing and the proposed techniques. For Regression, the precision is 87 %. For Random Forest, the precision is 87%. For the Decision Tree, the precision is 89 %. For XG Boost, the precision is 90%. For Gradient Boost, the precision is 95% %. For the proposed technique, the precision is 95%. Comparatively the precision rate is higher for the proposed methodology. Thus It is observed that the sensitivity, specificity, accuracy, and precision percentage are higher for the proposed methodology.

4.2.5 Online Travel Agencies (OTA)

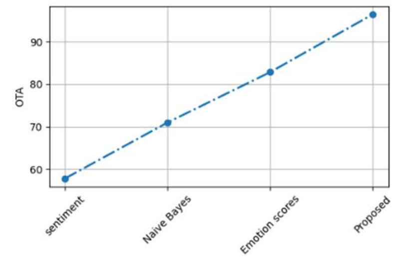

Figure 16: Online Travel Agencies (Ota) Comparison

Figure 16 provides the comparison of Online travel agencies for the existing and the proposed methodologies. For Sentiment Technique, OTA is valued is 58, For Naïve Bayes Technique OTA value is 71, For the Emotion Scores Technique OTA value, is 83. For the Proposed Methodology OTA value is about 98, which is comparatively higher than that of the existing methodologies.

4.2.6 Online Food Delivery (OFD)

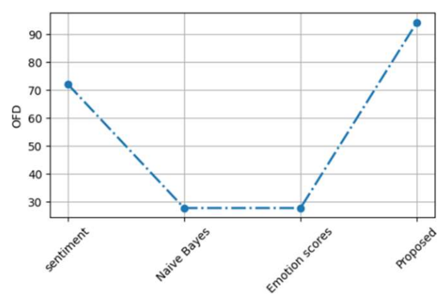

Figure 17: Online Food Delivery (Ofd) Comparison

Figure 17 provides the comparison graph of Online Food Delivery for Existing and proposed methodologies. For Sentiment Technique OFD value is 71, For Naïve Bayes Technique OFD value is 29, For the Emotion Scores Technique OFD value, is 29. For the Proposed Methodology, the OFD value is about 98, which is comparatively higher than that of the existing methodologies.

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4.2.7 E-learning

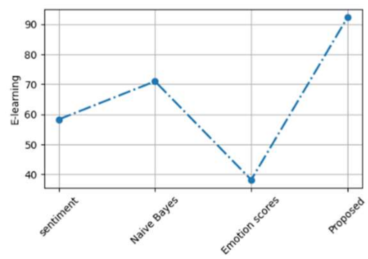

Figure 18: E-Learning Comparison

Figure 18 depicts the E-learning comparison is done for the existing and proposed methodologies. For Sentiment technique 59, Naïve Bayes technique 70, For Emotion Scores 39, and the proposed Technique E-learning value is 96. This is comparatively higher than the existing techniques.

5. CONCLUSION

The proposed Big Data Food Mapping Framework using Association rule followed by fuzzy clustering based on the binning procedure and Score-based normalization was tested effectively and the superiority over other models was determined. Also, the complexity of the basic system has been reduced by introducing the fuzzy clustering binning technique as it binned the unwanted data in each step as per the requirement of the customer. Lesser compilation time is achieved using Score based Normalization. The results of the proposed system were compared with the other existing system and the proposed Big Data Food Mapping technique framework outperforms all the existing techniques. The current strategy provides better accuracy and precision of 98.9% and 97% respectively over other modes existing techniques.

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