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Integrating Fuzzy Logic and Machine Learning for Analyzing Consumer Behavior in Digital Marketing

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***Abstract* – A dramatic change in consumer behavior has resulted from the widespread use of digital technologies including social media, electronic word of mouth, and mobile platforms. Consumers' reliance on these digital platforms for research, content creation, and relationship building with marketers has increased the demand for sophisticated analytics software to study online shoppers' actions. As a countermeasure, this research presents a hybrid clustering approach that combines PSO with Fuzzy C-means (FCM). By incorporating FCM into each generation of PSO, the suggested FCM-PSO model improves global search capabilities and overcomes FCM's drawbacks, such as sensitivity to initialization and convergence to local optima. The model is fed high-quality data by a strong data pre-processing pipeline that removes duplicates and uses semantics to choose features. The hybrid model achieves a 98.37% accuracy and an F1-score of 98.52%, which is far better than traditional and existing hybrid techniques, according to experimental assessments. These results demonstrate how well the model captures nuanced and complicated patterns in customer behavior. All things considered, intelligent clustering techniques have a lot of promise for making targeted digital marketing strategies more effective by providing more in-depth understanding of customers' changing preferences.**

Keywords— Particle Swarm Optimisation (PSO), Fuzzy Clustering Means (FCM), Search Engine Optimization (SEO), Search Engine Machine (SEM).

I. Introduction

The consumer behavior has been radically revolutionized by the incorporation of big data analytics in digital marketing. In this comprehensive analysis it looks at how big data could reveal hidden patterns in customer tastes and habits. There is a lot of evidence in the existing literature on consumer behavior and big data that it can improve marketing and the customer experience. But there are a lot of holes in the research such studies that follow customers over time to see how trust and loyalty are affected by ongoing personalization powered by big data. Academic knowledge will be advanced and practical insights for ethically optimizing marketing strategies and boosting customer experiences will be offered by addressing these gaps [1]. By taking close attention to these details it can paint a more complete picture of how digital marketers are responsibly exploiting big data. Businesses may now improve customer satisfaction and engagement by using big datasets to personalize marketing strategies for each consumer. According to recent research on consumer behavior and big data analytics powered by big data have the ability to revolutionize marketing customer service and company results. A more thorough grasp of the topic can only be achieved by conducting additional research into the significant gaps that still exist [2]. While many studies have looked at how big data may improve digital marketing and customer behavior very few have investigated how big data-driven personalization affects customers' trust and loyalty to a business over the long term. As a marketing strategy digital marketing makes use of digital assets such as the internet mobile devices and web-based applications to promote a product or service. Digital marketing encompasses a wide range of strategies some of which include social media marketing email marketing SEO, SEM and many more. Traditional marketing is the antithesis of digital marketing. Banner ads radio, newspapers and personal salespeople are all examples of traditional marketing [3].

The biggest gripe with old-school marketing was how much work went into it but how few people actually saw the results. Companies were unable to tailor their ads to meet customer needs. In analyzing the evolution of consumer behavior in the Online Space the paints a detailed picture of how digital marketing tactics interact with shifting customer habits [4]. Social media marketing content marketing influencer marketing and data analytics are some of the important parts of the digital marketing ecosystem that the paper explains in its first section. The article continues with an in-depth examination of how consumer behavior has changed throughout time in relation to the internet looking at how consumer preferences decision-making and interaction with digital marketing content has changed and are changing. Simply said digital marketing is the expansion of traditional marketing tactics methods and tools onto the internet. The rise of digital marketing has been revolutionary in allowing for the simultaneous pursuit of broad dissemination and personalization in advertising [5]. Digital marketing has evolved into something new one that is user-centered more quantifiable pervasive and interactive all because of the proliferation of devices and the tightening of technological constraints.

The subsequent structure of the paper is outlined as follows. Section 2 examines the pertinent literature, Section 3 introduces the fuzzy c-means-PSO algorithm for clustering, and Section 4 outlines the experimental results. This job is ultimately completed in section 5.

II. Literature Survey

The analysis of consumer behavior delves into the history and influence of CNN in the banking industry specifically looking at how they have helped improve consumer behavior satisfaction and enable data-driven decision-making. Because DL and CNN in particular have just emerged, digital marketing tactics have been utterly transformed. This is because can now glean deeper insights from massive diverse information. CNNs have been modified to handle various types of data in the industry such as consumer behavior social media interactions online behavior patterns transaction histories and more [6]. In order to gain a better grasp of the subject at hand it have employed a ML strategy that is fuelled by DL and makes use of supervised and unsupervised ML approaches. The offered predicted information and key performance indicators of the various ML approaches. Data mining ML encompasses both supervised and unsupervised learning [7]. The goal of DL a classification approach is to uncover rules and insights by mapping input and output layers with transformation functions. This area of ML typically makes use of a stochastic BP technique. Class labels which are the output layer's dependent variables are mapped to independent multivariate consumer behavior variables during the mapping process. In addition it evaluated our DL method's predictive power against that of other popular ML prediction methods such as DT, RF, SVM and ANN. Using the same dataset it discovered that DL performed better than ML [8].

By mining massive volumes of data for patterns and insights ML can foretell what's to come and lend a hand with decision-making. The strategic decision-making process of organizations is significantly improved by this functionality [9]. The digital marketers' attitudes towards and awareness of ML and DL tools as well as their adoption and utilization of these tools to assist strategic and operational management according to the ML research gap analysis. In order to better plan for the future these advanced analytical tools employ ML to learn from past data. There are numerous industries that can benefit from the ML and DL tools [10]. This article presents research that focuses on their usage in consumer behavior marketing analysis specifically in relation to enhancing marketing management's strategic DL and operational decisions. To address the requests of to discuss the methodological issues consumer behavior researchers face when dealing with text and to evaluate the various NLP methods used in marketing to analyze consumer review text it will undertake a review of these methods [11]. While topic modeling and other supervised ML technologies based on NN models have seen extensive use in marketing research they have only lately emerged from consumer behavior and are as prevalent in the field [12]. With this study it looks at how ML algorithms can be used to optimize consumer behavior analytics. The finally popular ML models like DT, SVM and NN with optimization techniques like GA gradient descent and bayesian optimization is something it looks into [13].

It may tackle a variety of function optimisation problems, or problems that can be changed to function optimisation problems, with ease by implementing and applying PSO, a population-based optimisation method. A variant of particle swarm optimisation, known as particle swarm optimisation for TSP, was suggested. This study proposes FCM-FPSO, a fuzzy clustering approach that combines FCM and FPSO. In comparison to the FCM and FPSO algorithms, the Fuzzy C-means-PSO method outperforms them in six real-world data sets.

III. Proposed System

In contemporary society, virtually everyone is online. Digital marketers predominantly utilise the internet as a strategy for selling products and services. This is due to its capacity to conserve considerable time, costs, and other resources. Products and services promoted through digital platforms are known as digital marketers. They intend to market the brands using a variety of digital media platforms. As an example, brands can learn which media platforms are most effective for reaching their target audience by utilising social media as a marketing strategy.

Market research and targeted advertising rely on the extensive consumer data found in the Consumer Behaviour and Shopping Habits Dataset. It details the demographic information (age and gender), the identity information (customer ID), and the transaction value (purchase amount in USD). Information such as the purchased item, category, and location can provide light on consumer tastes and patterns by area. Customers have distinct preferences, which are met by the Size, Colour, and Season data [14].

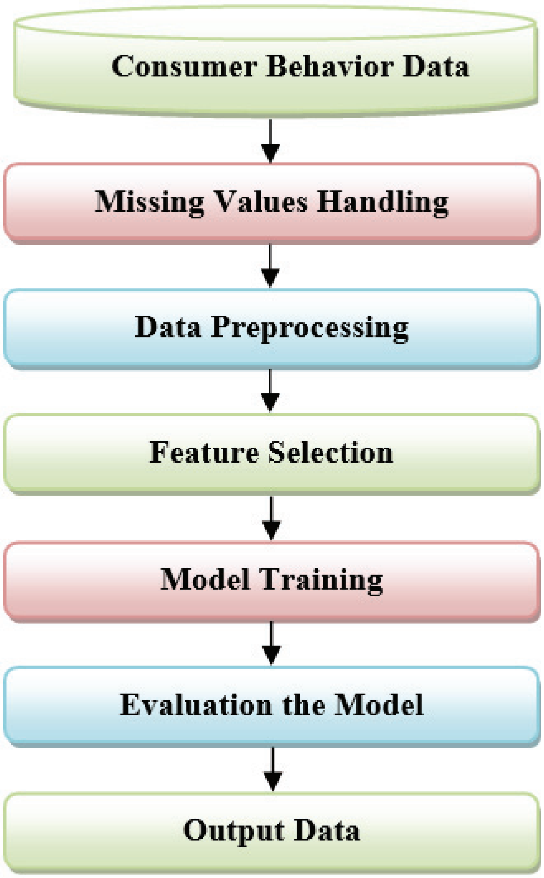

Fig. 1. Prediction Model for Customer Behavior in Digital Marketing

The proposed model utilises these attributes of customer behaviour as input variables. The method employs association analysis to extract purchasing rules derived from consumer behaviour. Figure 1 illustrates the architectural framework for forecasting consumer behaviour utilising an association rule-based methodology [15].

A. Missing Value Handlong:

Because data pre-processing increases accuracy and reliability in predictive modelling, ensuring data integrity must be the first stage in analysing consumer behaviour. To ensure accurate statistical patterns and unbiased predicted results, they will remove duplicate records. Utilising similarity measurements enables the identification of duplicate records, preservation of unique entries, and enhancement of overall data consistency. In order to keep datasets complete and avoid losing important information that could impact the quality of analysis or model performance, it is essential to manage missing values effectively [16]. To reduce biases in training for future modelling, several imputation methods are employed to estimate absent variables. Mean imputation is a common technique that uses the average of the available numbers to replace the missing value, as shown in Equation(1).

$$x_i = \frac{1}{n}\sum_{j=1}^{n} x_j , \forall x_i \in missing\ values \quad (1)$$

In employing average imputation to substitute missing values via Equation (2) the median of a dataset serves as a dependable option when the distribution is skewed.

$$x_i = \bar{x}, \forall x_i \in missing\ values \quad (2)$$

To classify variables, it employs method transfer, which is defined in Equation (3), to fill in missing values with the mode.

$$x_i = M, \forall x_i \in missing\ values \quad (3)$$

B. Data Preprocessing:

Three fields are numerical and eight are nominal in nature within the dataset. To make analysis more efficient, all data fields are translated to a standard numerical representation. In the pre-processing phase, feature selection plays a crucial role. Filter is the feature selection method that is utilised.

After the variables are uniformly represented as numerical values, the input variables will undergo a feature selection procedure to evaluate their relevance to the output. Equation (4) below shows the analysis of correlation coefficient, which is the feature selection strategy to utilise.

$$q = \frac{m(\sum U_j A) - (\sum U_j) * (\sum A)}{\sqrt{\left[m \sum U_j^2 - (\sum U_j)^2\right] * [m(\sum A^2) - (\sum A)^2]}} \quad (4)$$

Let m represent the total number of data points, q denotes the PCC, U_j signify the state value of the variable or attribute, and A indicate the consumer's target behaviour.

C. Feature Selection:

1) The Guided of Semantic Ranking:

While forward search algorithms typically have complexity that is linear to M, there are unique characteristics of digital marketing applications that can be used to improve greedy search. Consequently, the predictive performance can be preserved while the time complexity is reduced. Our selection process begins with the increasing categorisation of features into groups with clear semantic significance. Furthermore, features that are extremely unimportant are removed using generative feature quality metrics [17]. Our feature selection approach is described at a high level in Algorithm 1.

Algorithm 1: The Algorithm for Feature Selection	
1.	Let $T = \{\}$, every characteristic in the set $= E$
2.	Employ the developed semantic-based classifier to partition E into subsets, represented as $E = \{E_1, E_2, \ldots, E_l\}$, where l is the quantity of semantic categories.
3.	for $j = 1,2, \ldots l$
	a. Assess the significance of all characteristics in E_j by correlation analysis, thereafter exclude features with low relevance, and create a new subset E_j^*.
	b. Navigate forward in E_j^*:
	i. Choose the feature e^* from E_j^* such that the model φ^* constructed with $\{T, e^*\}$ achieves optimal performance compared to all models constructed with$\{T, e\} \forall e \in E_j^*$.
	ii. Evaluate whether φ^* surpasses the prior model by employing model quality metrics such as BIC:
	A. If not, cease selection within this category, increment $j = j + 1$, and go to 3.
	B. If affirmative, $T = \{T, e^*\}$, remove e^* from E_j^*, proceed to $3a$.
4.	Designate T as the collection of chosen features.

D. Model Training:

1) Algorithm for Fuzzy C-means:

The set of m objects is partitioned using fuzzy c-means. $p = \{p_1, p_2, \ldots, p_m\}$ cluster centres or $Y = \{y_1, y_2, \ldots, y_d\}$centroides in c^Qdimensional space into $d(1 < d < m)$fuzzy clusters.A fuzzy matrix τ consisting of m rows and d columns, where m represents the number of data objects and d denotes the number of clusters, characterises the fuzzy clustering of objects [18].

Integrating FCM's clustering efficiency with PSO's global optimization abilities to solve local optima and initialization sensitivity difficulties is what makes the hybrid Fuzzy C-means-PSO model in this work innovative. This model improves upon previous combinations (e.g., [18]) by using FCM iteratively within PSO generations to refine particle fitness more robustly for high-dimensional consumer behaviour data, which increases convergence and accuracy (98.37%).

The degree of association or membership function of the jth item with the ith cluster is signified by τ the element in the jth row and ith column of τ_{ji}. The values of u are given by equations $(5) - (7)$.

$$\tau_{ji} \in [0,1]\ \forall j = 1,2 \ldots m; \forall i = 1,2, \ldots d \quad (5)$$

$$\sum_{i=1}^{d} \tau_{ji} = 1 \quad \forall j = 1,2 \ldots m \quad (6)$$

$$0 < \sum_{i=1}^{d} \tau_{ji} < m \quad \forall i = 1,2 \ldots d \quad (7)$$

Fuzzy C-means algorithm's goal is to find the minimum value of the following equations $(8)-(9)$:

$$I_n = \sum_{i=1}^{d}\sum_{j=1}^{m} \tau_{ji}^{n} c_{ji} \quad (8)$$

$$c_{ji} = \|P_i - Y_i\| \quad (9)$$

where c_{ji} is the distance in Euclidean distance from object P_i to the cluster centre Y_i and n is a scalar that affects the fuzziness of the generated clusters; $n(n > 1)$ is also known as the weighting exponent. Equation (10) is used to obtain the Y_i, which is the centroid of the ith cluster.

$$Y_i = \frac{\sum_{j=1}^{m} \tau_{ji}^{n} P_j}{\sum_{j=1}^{m} \tau_{ji}^{n}} \quad (10)$$

2) Clustering Problem for Hybrid Fuzzy C-Means-PSO: While the Fuzzy C-Means method generally converges to local optima, it is more efficient than the FPSO technique since it requires less function evaluations. A hybrid clustering technique known as FCM-FPSO, which incorporates the Fuzzy C-Means and FPSO algorithms, is presented in this study. This algorithm combines the best features of both the FCM and PSO algorithms.The Fuzzy C-Means-PSO algorithm enhances the fitness value of each swarm particle by implementing FCM at each iteration or generation. Here is an expression of the Fuzzy-C-Means-PSO algorithm as it pertains to the fuzzy clustering problem shown in Algorithm 2:

Algorithm 2: The Algorithm Hybrid Fuzzy C-means-PSO	
1.	Set the values of O, d_1, d_2, x *and* n which are parameters of Fuzzy C-means-PSO.
2.	Construct a swarm consisting of O particles, where (W, *obest*, *hbest and U are* $m \times d$ *matrices*.
3.	Initialise W, U, *obest* for each particle, and *hbest* for the swarm.
4.	Algorithm for PSO:
4.1	Determine the cluster centroids for each particle.
4.2	Determine each particle's fitness level.
4.3	For every particle, determine the *obest*.
4.4	Determine the global best *hbest* for the swarm.
4.5	Recalculate the velocities of all particles
4.6	Revise the location matrix for each particle.
4.7	If the condition for PSO termination is not satisfied, proceed to step 4.
5.	Algorithm for Fuzzy C-means
5.1	Determine the locations of each particle's clusters.
5.2	Find the distance c_{ji} for each particle using the following formula: $j = 1,2 \ldots m; i = 1,2 \ldots d$
5.3	Please update the function membership τ_{ji}, , : $j = 1,2 \ldots m; i = 1,2 \ldots d$ and for every particle.
5.4	For every particle, determine the *obest*.
5.5	Determine the optimal *hbest* -swarm algorithm.
5.6	If the termination criterion for Fuzzy C-means is not satisfied, proceed to step 5.
6.	Continue to step 4 in the event that the terminating condition for Fuzzy C-means-PSO is not met.

IV. RESULT AND DISCUSSION

In order to stay up with the fast-paced world, marketing has also embraced digitalization, just like any other form of company. Digital marketing refers to the promotion of a product or service via digital channels, including the internet, mobile devices, and web-based services. Among the many subsets that make up digital marketing are SEM, social media marketing, SEO, email marketing, and social media marketing. Traditional marketing is the antithesis of digital marketing. The biggest gripe with old-school marketing was how much work went into it, but how few people actually saw the results. Companies were unable to tailor their ads to meet customer needs.

The proposed Fuzzy C-means-PSO method enhances particle fitness values by integrating FCM into each PSO generation, hence exceeding prior methodologies like FCM-FPSO. This iterative integration enhances convergence speed, more efficiently circumvents local optima, and attains superior performance, achieving an accuracy of 98.37%, compared to earlier hybrid models.

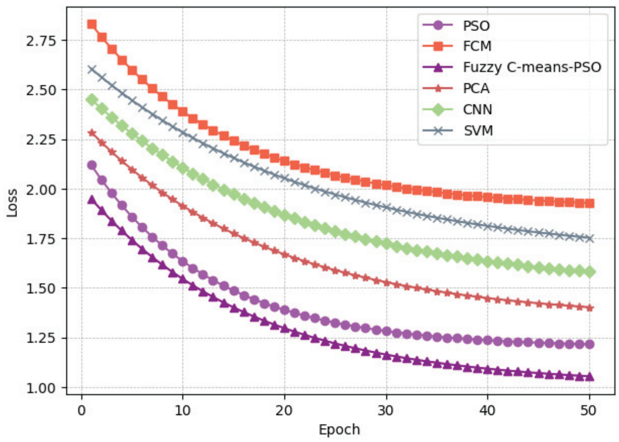

Fig. 2. Loss Curve of the Models

Figure 2 shows that Fuzzy C-means-PSO can represent complicated online behaviours at some levels, leading to less loss when making step-by-step predictions about web pages.

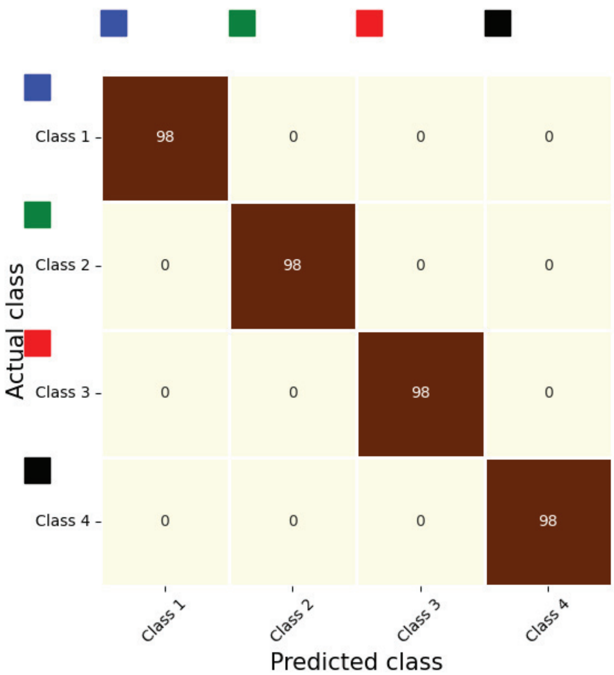

Fig. 3. Confusion Matrix

Figure 3 displays the calibration curve, which is precisely diagonal and has a scale that fits greater than 0.98. This indicates that the model was doing a good job and getting good results in terms of accuracy.

TABLE I. PERFORMANCE EVALUATION(%)

Models	Accuracy	Precision	Recall	F1-Score
PSO	90.84	89.38	88.72	90.91
FCM	93.27	92.71	91.80	93.35
Fuzzy C-means-PSO	**98.37**	**96.23**	**95.87**	**98.52**
PCA	96.78	95.34	94.63	96.72
CNN	89.64	88.17	87.48	89.77
SVM	88.48	87.26	86.34	88.57

Table 1 shows that Fuzzy C-means can detect patterns in consumer behaviour with low false negatives, with an F1-score of 98.52% and a recall of 95.87%.

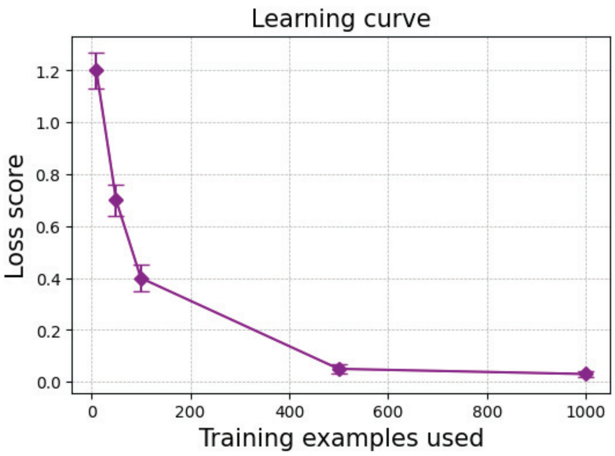

Fig. 4. Loss of the Learning Curve

In Figure 4, they can observe both the learning curve and the learning loss curve. High loss scores were still seen in early learning, according to both graphs.

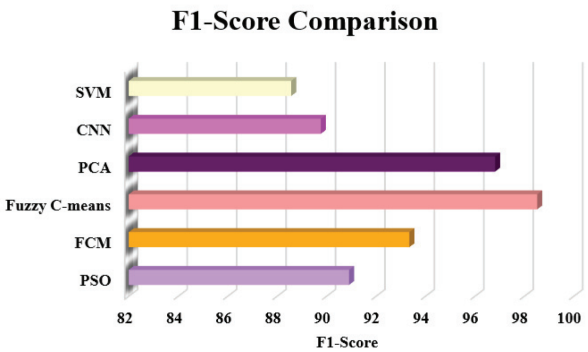

Fig. 5. Comparison F1-Score

This makes prediction very important and makes sure that marketing campaigns are based on what people actually want. As seen in Figure 5, F1-Score performance has an effect.

V. CONCLUSION

Organizations' understanding and power over consumer behaviour has been radically revolutionized by the incorporation of big data analytics in digital marketing. Organisations' approach to marketing strategy development and execution has been radically altered by the convergence of big data technology with digital marketing methodologies in the modern digital era. Beyond that, big data offers unmatched possibilities for analysing consumer behaviour and deciphering the customer's purchase process and experience. Consumer behaviour encompasses the choices and actions made by individuals when it comes to choosing, buying, and utilising goods and services. Preprocessing, feature selection, and model training are the three processes that make up the proposed model. An extensive data pre-processing pipeline is put in place to remove duplicate records and other cleaning approaches to guarantee high-quality data for model training. Because there is a lot of data and features are highly dimensional, the feature selection procedure takes a long time. This research proposes a Fuzzy C-means-PSO hybrid fuzzy clustering approach that combines the best features of the two algorithms. With a score of 98.37%, the suggested system outperforms all previous models.

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