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Entropy Weighting Fuzzy Local Information C- means (EWFLICM) Clustering Approach for Proficient Customer Behaviour Mining in Telecom Industry

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Abstract--- *The data-intensive industries such as telecommunication organisations need business intelligence technique to improve the visibility and core operations of the organization. Customer clustering will enable to reliably analyse customer composition and improve service and marketing quality. Paying attention to customer service is regarded among the most vital components of the telecom industry's profitability. Clustering algorithms are often used for major data analysis technique for evaluating telecom customers. These algorithms are implemented to analyze customer's behaviour patterns in the massive amount of telecom data. The current research, Customer Behaviour Mining (CBM) method is presented with fuzzy clustering algorithms. Considering the patterns of behaviour of customers and projecting how they can behave in the future, we develop a new methodology called Entropy weighting Fuzzy Local Information C- Means (EWFLICM) for clustering the large amount of data in telecom industries. Entropy function is introduced to EWFLICM clustering algorithm for weight updating. It optimizes the weighting parameter to control the contribution of the local factor for clustering of customers in mobile phone activity dataset. Five major activities such as received SMS, sent SMS, incoming calls, outgoing calls and internet activity have been carryout in mobile phone activity dataset. The cluster analysis is then carried out based on two factors, i.e. maximum period used by telecommunications services and the number of services used for each group of customers. Such support was committed to mining customer's future behaviour. The proposed EWFLICM system is described in terms of accuracy, Silhouette Coefficient (SC), Agglomerative Coefficient (AC), error rate and calculation time.*

Keywords---*Customer Behaviour Mining (CBM), Telecom Industry, Fuzzy C Means (FCM), Fuzzy Local Information C- Means (FLCIM), and Entropy Weighting Fuzzy Local Information C- Means (EWFLICM) Algorithm.*

I. INTRODUCTION

Industry of domestic telecommunications market competition has been more logical and fiercer through the globalization of the world economy and business internationalization. Higher standards for the Telecom industry's service quality have been set forward by fast-growing group of users, diversified operations and competition environment [1-2]. Customer gratification and desirability are the major goals in today's top-level companies in the telecom industry. It has a significant impact on the revenue and profits of companies. Customers' profitability is the

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profit in which the company makes from serving a customer or customer group throughout a given period. The customers who give more profit to the company are named high profitability customers. Therefore, recognizing the customer's profitability has been the most important aspect in the future growth of the companies. To resolve this issue, it is necessary to understand the behaviour of consumers and to identify it as per their level of use, so that the essential decisions will be taken in order to improve in providing services.

The data mining model is being used to understand the behaviour of the system effectively and make the best decisions [3]. This research work focuses Customer Behaviour Mining (CBM) method in telecom data based on different datamining clustering algorithms. Cluster analysis is a data mining methodology used to classify together of group variation in minimal and optimal with divergence function as well as its goal of finding an optimal cluster array. Clustering strategy group a telecom customer depending on the data found in the customer. It is also grouped based on the services offered with the telecom company and their relationships by the company [4]. Over the last two decades, numerous types of clustering approaches were researched, including partition clustering, hierarchical clustering, fuzzy clustering etc. Among them soft computing methods gives better clustering results. Clustering divides a variety of population into similar sub clusters or group to share some common feature in each cluster. In Telecom Company, therefore, it's more effective to use this clustering strategy to group the customers as per their services.

Fuzzy C Means (FCM) clustering algorithm offers a comprehensive and efficient way of classifying large collections of clients via enabling the same customer to exist with multiple service groups (clusters) and membership levels [5-6]. Fuzzy clustering can accommodate significant variables in the surrounding cluster, either very small or a degree higher than reasonable. This offers a versatile and reliable approach to cluster assigning of data points. Though, the FCM still have the following limitations, (1) The importance of the element impacts the other after the clustering process, (2) During the pre-processing phase, data might be lost or some features may not be in the clustering, (3) Local spatial domain data would not be well clustered, and (4) Data noise can affect the poor quality of the system. However, the FCM algorithm in variation requires clustering of image to resolve drawbacks of FCM. Suggested algorithm uses the current fuzzy way of integrating local spatial information. Thus, a proposed algorithm as Fuzzy Local Information C-Means (FLICM) improves the performance of clustering and overcome the issues of FCM algorithms. In the FLICM algorithm, weighting factor computation for varied samples still becomes unsolvable issue. Since the traditional FLICM algorithm, weighting parameter is set to predefined value. Changing the values of the weighting parameter greatly affects the value of the clustering. To overcome this issue, Entropy function is introduced to weight value computation based on the sample range. In this research, Entropy weighting Fuzzy Local Information C- Means (EWFLICM) clustering algorithm is proposed to cluster the customers in the Mobile phone activity dataset for telecommunication industry.

II. LITERATURE REVIEW

Li [7] proposed work incorporating the FCM and Subtractive Cluster Method (SCM) approaches, which could evaluate a fast-discrete algorithm that prevents initializing a new clustering centroid. Certain empirical analysis has established cross-selling opportunities for the telecommunications industry. Empirical results indicate that only a

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fast-discrete algorithm incorporating FCM and SCM will result in the differentiation of association rule index patterns improving the probability of cross-selling performance. The quantitative association rule algorithm on fuzzy clustering will overcome the fasten iterative frequency problem and define discrete self-adoption classification to help the business department in making accurate decisions.

Guo and Wang [8] proposed to model user interaction actions based on incoming/outgoing call holding time by using the FCM clustering algorithm to identify that tier in the user pyramid model. Obtain three classifications for each stage. Evaluate each classification's proportion and communication pattern to enable operators to understand their subscribers more. The method and statement could be used as the basis for precision marketing in the telecommunications industry.

Asokan and Mohanavalli [9] proposed research aims at analyzing the two key strategies of soft-clustered and hard-cluster clustering to evaluate the churn ratio as the measure to improve Customer Relation Management (CRM), which is the K means and FCM clustering on broad telecommunications data. FCM reaches the churn ratio of the K-means reliably and helps CRM more efficiently.

Gayathri and Mohanavalli [10] designed a new approach to promote soft clusters and hard clustering. In particular, the telecommunications industry performs general data created by different data mining techniques. This research focuses mainly on the implementation of a suitable clustering algorithm to classify the customer’s soft partitions, which is the FCM clustering algorithm to accurately measure the churn ratio.

Ren et al [11] presented a parallel approach to accelerate the determination of k. Implement two methods of choosing the initial centroids which will save computational iterations in clustering K-means on forwarding centroids carrying and Minimal force. All methods are designed to accelerate the computation of K-means and to recognize k.

Fathian and Azhdari [12] proposed a temporal fuzzy clustering based on Frechet distance to detect significant changes in customers' behavior for a telecom company during a 10-month period. Provided that combining the temporal clustering with trajectory analysis is an effective way to recognize customers’ behavior among the clusters, the results showed that there are seven distinct customer behavior patterns two of which lead to the customer drop or churn. These patterns can be used to reduce the risk and costs of customers churn and to design optimum services.

Arumawadu et al [13] introduced a new clustering approach for K-means in Sri Lanka to determine the competitiveness of cluster customers in the telecommunications industry. In addition, the model of Recency, Frequency and Monetary is utilized primarily while parameter of input in distortion and clustering of K-means curve define the optimum clusters initially. Given the solutions, the gain of telecommunications Sri Lankan customers has been primarily divided into three levels.

The goal of the study by Ansari and Riasi [14] is to merge FCM clustering with Genetic Algorithms (GAs) to group customers using steel. Using the Length Recency, Frequency, Monetary Value (LRFM) method, clients were classified into two clusters. Findings showed the customers according to the first group used to have a higher relationship length recency of trade, and frequency of trade, thus far less value in actual relative to the regular values

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for all customers of such categories. The combined algorithm (i.e., FCM and genetic algorithm) in this analysis was also found to have a lower Mean Squared Error (MSE) relative to FCM clustering.

Al-Shboul et al [15] proposed a framework is based on combining two heuristic approaches; Fast Fuzzy C-Means (FFCM) and Genetic Programming (GP). FFCM was first used to cluster the data set and exclude outliers, representing abnormal customers' behaviors, to reduce the GP possible sensitivity towards outliers and training resources. For the purpose of this work, a data set was provided by a major Jordanian telecommunication mobile operator.

The suggested algorithm by Krinidis and Chatzis [16] combines information with spatial locally and gray level information within creative and blurry manner. Developed methodology is known as Fuzzy Local Information C-Means (FLICM). It resolves inconveniences in proven FCM algorithms which at the same time improve the performance of clustering. Studies on synthetic and real-world images depict the FLICM algorithm are significant, supplying noisy images with robustness.

Hu et al [17] proposed method contained three steps: 1) calculate the multi scale gradients and the differences between eigenvalues of Hessian matrix. 2) In order to generate the enhanced micro vessels structures, a Feed Forward Neural Network (FFNN) was trained by 2.26 million pixels for dealing with the correlations between multi-scale gradients and the differences between eigenvalues. 3) The FLICM was used to cluster the pixel values in enhance line signals.

Praseeda and Shivakumar [21] proposed a Flexible K-Medoids algorithm which sorts and consolidates the hybrid enhancement of K-Means, K-Median and K-Medoids algorithms which gives a deep analytics on the telecom data that reflects in the outcome of the strategic consolidation of the customers' behaviour.

III. MATERIAL AND METHODS

The latest clustering methodology such as FCM and FLICM methods are discussed in this section below.

Fuzzy C Means (FCM) Clustering

A clustering method involves in minimizing some objective function, belongs to the groups objective function algorithms. When the algorithm is able to minimize an error function [18], it is often called C-Means being c the number of classes or clusters which is formed by using fuzzy technique known to be FCM. The FCM approach uses a fuzzy membership which assigns a degree of membership for every class. The importance of degree of membership [19] in fuzzy clustering is similar to the pixel probability in a mixture modelling assumption. When the membership function computed is highest between all the more options is there with the purpose of the data belongs to the current cluster. The benefit of FCM is the formation of new clusters from the data points that have close membership values to existing classes [20]. Basically, there are three basic operators in FCM method: the fuzzy membership function, partition matrix and the objective function. The major advantage of this work is convergence and learning in Unsupervised. The major limitations of this FCM clustering are 1. High time consumption for computation, 2. Speed Sensitivity and local minima sensitivity and 3. Noise Sensitivity and expectation of short membership degree on outliers.

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Fuzzy Local Information C-Means (FLICM) Clustering Algorithm

Fuzzy Local Information C-Means (FLICM) clustering algorithm will be used for data clustering. The main feature of FLICM is with a local similarity measure to ensure selfishness to noise and conservation of results. FLICM is proposed which used fuzzy local information to associate local data with entire dataset. Existing FLICM clustering algorithm, fuzzy factor is fixed which reduces the clustering results. So tuning of the fuzzy factor plays a major important role. In the proposed work, instead of fixing fuzzy factor which is tuned by Entropy function.

IV. PROPOSED ENTROPY WEIGHTING FUZZY LOCAL INFORMATION C-MEANS (EWFLICM) ALGORITHM

The Contemporary Research is concentrated for Customer Behaviour Mining (CBM) scheme in telecom industry using different clustering algorithms. In this study, clustering of large amount of data in telecom industries are done by Entropy weighting Fuzzy Local Information C- Means (EWFLICM), considering the patterns of behaviour of customers and projecting how they can behave in the future. Entropy function is introduced to EWFLICM clustering algorithm for weight updating. The CBM model helps determine the behaviour patterns of consumers and forecasts how they will be able to act in the future. Next, the clustering strategy of EWFLICM can be used to classify customers based on services. The cluster analysis is then carried out on the basis of two factors, i.e. the number of hours being used by telecommunications services and the number of services chosen by each group's customers.

FLICM [16] is characterized by the use of a fuzzy local similarity measure, which aims at guaranteeing higher clustering accuracy. In particular, a novel fuzzy factor is introduced into the objective function of FLICM to enhance the clustering performance. This fuzzy factor is defined as

$$G_{ki} = \sum_{j \in N_i, i \neq j} \frac{1}{dis_{ij} + 1} \left(1 - \mu_{kj}\right)^m \left|\left|cr_j - v_k\right|\right|^2 \qquad (1)$$

Where d_{ij} is the spatial Euclidean distance of the i^{th}Call Detail Records (CDRs) and j^{th} CDRs of SMS, Call, Internet - MI. The objective function of FLICM is given by

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{N} \left(\mu_{ki}^m \left|\left|cr_k - v_i\right|\right|^2 + G_{ki}\right) \qquad (2)$$

Fuzzy local information and $L_p$norm distance-based clustering is proposed for grouping of the customers as per their services.Firstly, consider the case of CDRs, i.e. $cr_i \in \mathbb{R}$. Let $p \in (0, 1]$.Denote the local window centred at $cr_i$by N_i. Let μ_{kj} be the degree of membership of the j^{th} CDRs in the k^{th} cluster with centre v_k. Also construct a symmetric matrix 'K' whose i, j^{th} entry measures the spatial similarity of the i^{th} CDRs and the j^{th} CDRs. The objective function of the proposed FLICM method is as follows:

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \left(\mu_{ki}^m \left|\left|cr_k - v_i\right|\right|^2 + weG_{ki}\right) \qquad (3)$$

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Where$\|\cdot\|$ denotes the Euclidean distance. Here $G_{ki}$is the $L_p$norm- based local factor introduced to incorporate the local information, which is defined as

$$G_{ki} = \sum_{j \in N_i} K_{ij} \left(1 - \mu_{kj}\right)^m \left|\left|cr_j - v_k\right|\right|^p \qquad (4)$$

In (4), we> 0 is a weighting parameter to control the contribution of the local factor. Note that $we$is fixed as 1 in FLICM. In order to improve the clustering accuracy, we is computed via the use of the Entropy function it named as EWFLICM. Shannon entropy provides a way to estimate the average minimum number of weights needed to increase the clustering results, based on the frequency of the weights.

$$H(we) = -\sum_{i=0}^{N-1} prb_i \log_2 prb_i \qquad (5)$$

$\text{prb}_\text{i}$is the probability of a given weights (we_i). At initially some random weights values are given as input to the clustering algorithm, then from those weights which one is having the higher entropy is considered for clustering. Similar to FLICM, proposed EWFLICM also compute a $\text{K}_\text{ij}$which is given as follows,

$$K_{ij} = \begin{cases} 0, i = j \\ \dfrac{1}{dis_{ij} + 1} \quad , i \neq j \end{cases} \qquad (6)$$

Wheredis_{ij} is the spatial Euclidean distance of the i^{th} data and j^{th} data. Let us give an interpretation of local factor G_{ki}. For each CDRi, assume $\mu_{ki} \simeq 1$, that is, cr_ihas a large probability of belonging to the k^{th} class. Assume CDR data$j$ has similar sample as data$i$, namely $j \in N_i$and $cr_i \simeq cr_j$. Thus $\left\|cr_j - v_k\right\|^p \simeq \left\|cr_i - v_k\right\|^p$. To minimise the energy function (3), $\left(1 - \mu_{kj}\right)^m$is forced to approach zero, such that $\mu_{kj} \simeq 1$. Hence, conclude that $\mu_{ki} \simeq \mu_{kj}$if $j \in N_i$and $cr_i \simeq cr_j$. That is, if two records have similar ranges, they tend to be in the same cluster by minimising the objective function. Moreover, by using the spatial kernel K_{ij}, the local factor G_{ki}has more flexibility to adjust the influence of neighbouring data.

V. RESULTS AND ANALYSIS

In this part, measure the presentation of suggested EWFLICM algorithm with existing methods such as FLICM and FCM. This section, Telecommunications - SMS, Call, Internet – MI dataset is used for implementation via MATLAB tool. Dataset is collected from https://dataverse.harvard.edu/dataset.xhtml?persistentId =doi:10.7910/DVN/EGZHFV. This dataset provides information about the telecommunication activity over the city of Milano. The dataset is the result of a computation over the Call Detail Records (CDRs) generated by the Telecom Italia cellular network over the city of Milano. CDRs log the user activity for billing purposes and network management. The individual file consists of the attributes such as Date time, Cell ID, country code, sms in, sms out, call in, and call out and internet. The name of the file is sms-call-internet-mi-2013-11-01.txt .Each file includes the details of the individual day. One month period of the dataset is used in this work for implementation. In order to

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measure the results of the clustering methods the following metrics such as accuracy, error, SC, AC and time comparison are evaluated in Telecommunication dataset.

Table 1: Clustering Metrics Comparison Vs. Clustering Algorithms

METRICS	FCM	FLICM	EWFLICM
ACCURACY (%)	82.19	85.65	91.72
ERROR (%)	17.81	14.35	8.28
SILHOUETTE COEFFICIENT (SC)	0.8192	0.8793	0.9418
AGGLOMERATIVE COEFFICIENT (AC)	0.7925	0.8536	0.9245
TIME COMPARISON (SECONDS)	23	19	13

Accuracy metrics indicate how much one clustering (i.e., set of clusters) is similar to another (ground-truth) clustering.

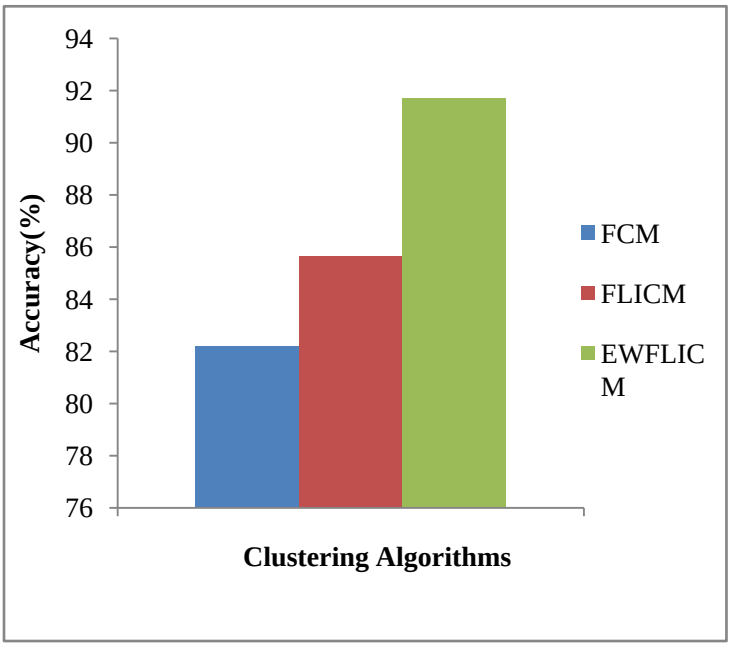

Figure 1:Accuracy Comparison Vs.Clustering Algorithms

Figure 1 shows the accuracy results of three clustering methods such as FCM, FLICM and proposed EWFLICM algorithm. This figure 1 shows how each algorithm responses to telecom dataset. From the figure 1 it shows that the proposed EWFLICM algorithm gives higher accuracy results of 91.72%, whereas FCM, and FLICM gives lesser accuracy of 82.19%and 85.65% respectively (Table 1). Accuracy results of the proposed algorithm is high since the proposed work, entropy based weighting is used to compute the weight of the FLCIM clustering (Table 1).

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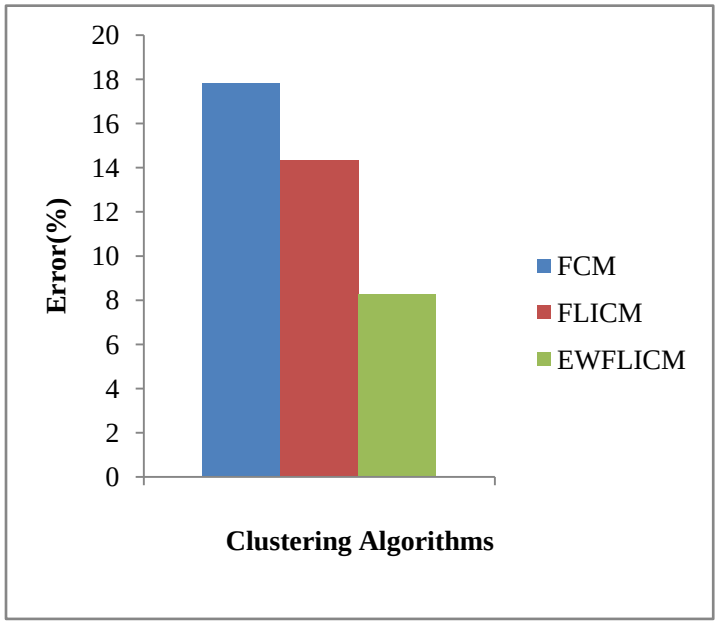

Figure 2:Error Comparison Vs. Clustering Algorithms

Figure 2 indications the error results comparison results of clustering algorithms such as FCM, FLICM and proposed EWFLICM algorithm. From the figure 2 it achieves that the proposed work gives lesser error results of 8.28% for Telecom dataset, whereas other clustering methods such as FCM, and FLICM gives higher error value of 17.81%and 14.35% respectively (Table 1).

Silhouette Coefficient (SC)

Silhouette values have been used to evaluate the quality of clusters and to define the optimum number of clusters or partitions assisted by the data. The silhouette of every data is an indicator of how close it is to the cluster assigned to it compared to the nearest neighbouring cluster. For each object i, a silhouette values (i) is obtained that is specific to a particular clustering solution and that expresses a ratio of the within-cluster dissimilarity for i and the between-cluster dissimilarity for the closest neighbour cluster to i. The Silhouette Coefficient (SC) is given by:

$$s(i) := \frac{b(i) - a(i)}{\max(a(i), b(i))} \quad (7)$$

b(i) denotes the average between-cluster dissimilarity between i and each object in the closest neighbouring cluster to i. a(i) denotes the average within-cluster dissimilarity between i and each object in the same cluster. The difference between b(i) and a(i) is divided by the largest of the two values to constrain the range to [-1,1].

Agglomerative Coefficient (AC)

Agglomerative Coefficient (AC) (cluster library) is a measure of the clustering structure of the dataset. For each observation i, denote by m(i) its dissimilarity to the first cluster it is merged with, divided by the dissimilarity of the merger in the final step of the algorithm. The AC is the average of all 1 - m(i). Agglomerative Coefficient (AC) is given by:

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$$A = 1 - m(i) \quad (8)$$

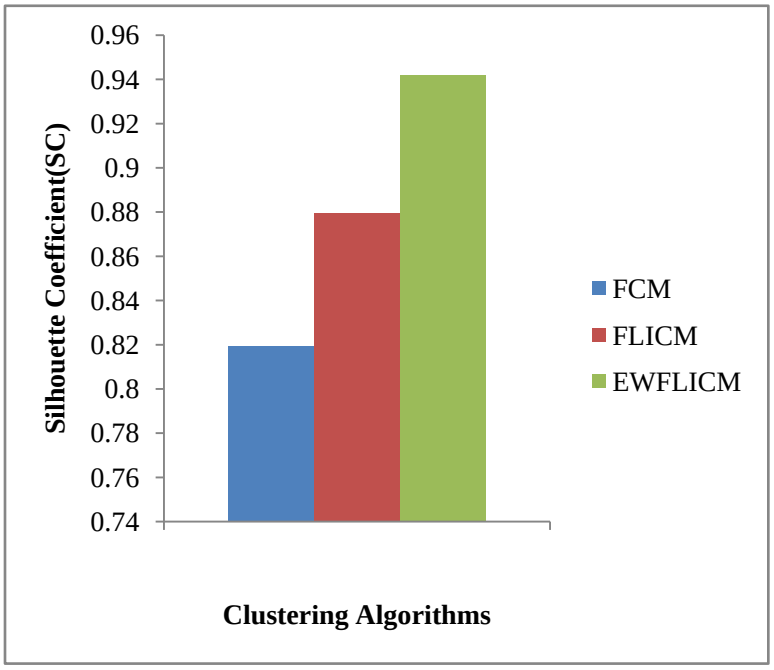

Figure 3:Silhouette Coefficient (sc) Comparison vs. Clustering Algorithms

Silhouette Coefficient (SC) results comparisons of clustering algorithms are shown in the figure 3. Figure 3 it shows the proposed work shows improved SC results of 0.9418, whereas FCM, and FLICM gives lesser SC value of 0.8192 and 0.8793 respectively(Table 1).

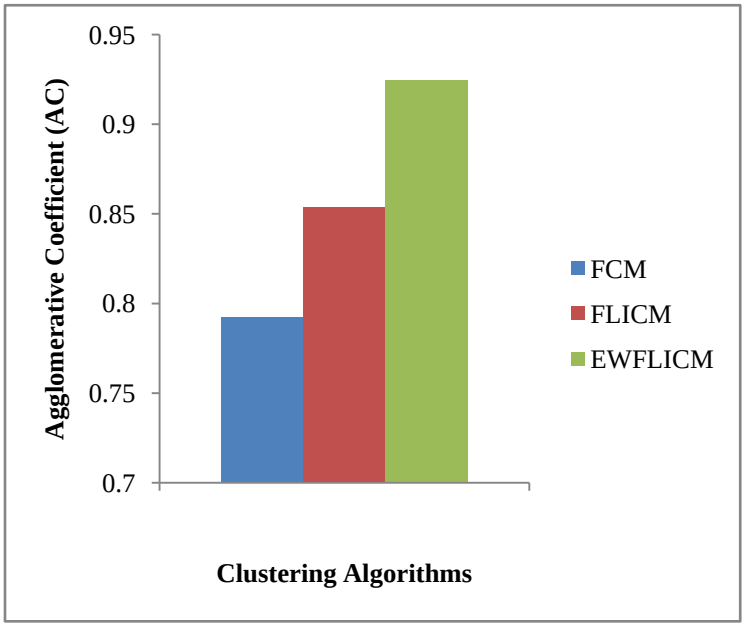

Figure 4:Agglomerative Coefficient (AC) Comparison vs. Various Clustering Algorithms

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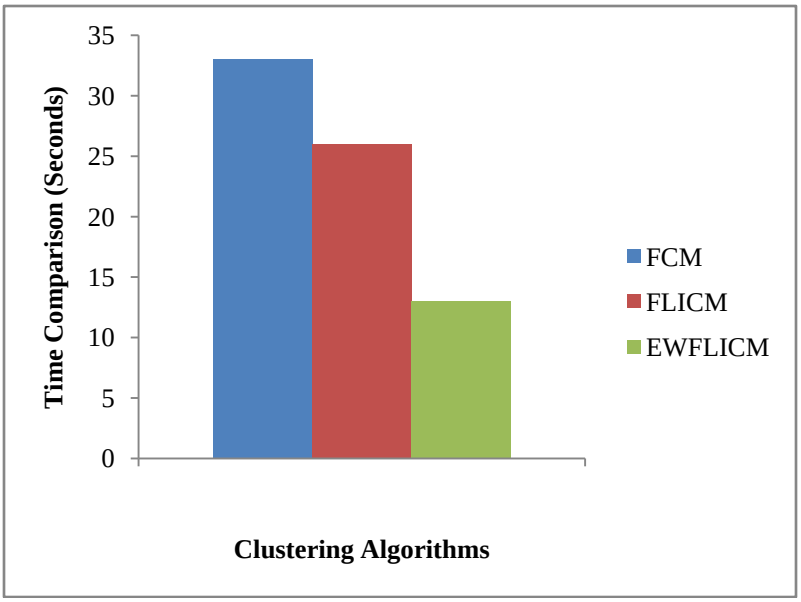

Figure 5:Time ComparisonVs. Various Clustering Algorithms

Clustering algorithms such as FCM, FLICM and proposed EWFLICM algorithm results of AC is illustrated in Figure 4. The anticipated KWFLICM system contributes greater AC results of 0.9115 for S5 in contrast with the FCM, and FLICM which provides greater error significance of 0.7835and 0.8641 respectively (Table 1). The several algorithms effects with respect to the time comparison is indicated in Table 1 and Figure 5. The result shows that the proposed EWFLICM algorithm takes time period of 13 seconds, while other clustering methods such as FCM and FLICM utilizes time period of 33 seconds and 26 seconds (Table 1) which is significantly greater value.

VI. Conclusion And Future Work

This research concentrates on Customer Behaviour Mining (CBM) technique improvement for utilizing in to telecommunications industry. Entropy weighting Fuzzy Local Information C- Means (EWFLICM) algorithm is the principle factor in implementing CBM system for the purpose of clustering huge amount of data. The clustering of customers mainly relies on services in EWFLICM.In EWFLICM clustering algorithm, Shannon entropy is introduced to estimate the average minimum number of weights to clustering results based on the frequency of the weights. EWFLICM, fuzzy local information and L_p norm distance-based clustering is used for grouping of the customers as per their services. Initially some random weights values are given as input to the clustering algorithm, and then from those weights which one is having the higher entropy is considered for clustering. Comparing all three methods including the proposed stratagem offers better accuracy and lesser time comparatively. The implementation of clustering methods is accomplished via Harvard Data verse dataset of Telecommunications - SMS, Call, Internet - MI. Proposed EWFLICM algorithm gives higher accuracy results of 91.72%, whereas FCM, and FLICM gives lesser accuracy of 82.19%and 85.65% respectively. The various parameters such as error, Silhouette Coefficient (SC), Agglomerative Coefficient (AC) and time comparison in Telecommunication dataset are estimated for Telecommunication dataset. In the future, the present work is extended to churn prediction and feature selection in Telecom industry.

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