

An Improved Fuzzy Multiple Object Clustering in Remodeling Of Roofs With Perceptron Algorithm

D. Neguja^{1*}, A. Senthilrajan²

¹Research Scholar, Department of Computational Logistics, Alagappa University, Karaikudi, India

* **Corresponding Author Email:** neguja@gmail.com- **ORCID:** 0000-0001-2408-2202

²Professor, Department of Computational Logistics, Alagappa University, Karaikudi, India

Email: agni_senthil@yahoo.com- **ORCID:** 0000-0003-4265-7097

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Abstract:

The novel way is completely discrete technique to remodel the roof of old buildings from the real value related repetition. Pointed quantities of partition for most of the developing renovation or modifications at the roof via a strategy are some parameters simplifying a fuzzy multiple object technique, where every segment is linked to all clusters with specialized matching weights of roof segments. The strategy considers multiple objects of perceptron algorithm across the in depth joints and incorporates of 3 layers: (i) every part is featured with the leading direction of a vector of exact measures of the roof densities, (ii) most required factor of evaluation is completed to review the principle changes in lowering the outcomes of the clutter, and (iii) the squared Euclidean location most of the number one retained major components is used to carry out clustering through the equal vintage fuzzy Multiple object-approach using perceptron method. A perceptron technique, multiple object is applied strategy in this research and the image parts and its neighboring segments are added to form a cluster by using the use of immediate computation of the resulting fuzzy number and overall idea of the process of the technique is to compute the mapping concept of sequentially located from equally well-defined clusters. The fuzzy number is applied to multiple objects using perceptron algorithm of the segment and compared with fuzzy technique. The outcome is to bring the nearest neighbor of the fuzzy value,.

1. Introduction

Renovation of roofs are one of the most important remodeling in any kind of building, which are uncovered to all climatic situations and disasters. The state of the roofs, whether they are aged, decrepit or modernized, outreaches the ideas about the preservation of the building. An appropriate and high-class roof is of great significance for the building because it gives safety and console to users and guards against external weather conditions and climate changes. Along with the accurate way of the stage on the roof, its preservation is also imperative. Flat roofs are focus to show off and steady loss of preserving qualities and are especially vulnerable to this kind of harm because of their shape and application as coverings for certain materials. The earliest small flaws could show up years after the remodeling process. Roof damage can be eliminated with prompt repair. Importantly, taking easy steps to

fix the roof won't increase expenses while also helping to prolong its lifespan. The age of a flat roof, the materials used in its construction, the standard of the initial installation, the amount of maintenance it has gotten, and the climate it is exposed to are just a few of the variables that determine when renovations are necessary. A flat roof's requirement for renovations is contingent upon several aspects, including the roof's age, the materials used in its construction, the caliber of the initial installation, the amount of maintenance it has gotten, and the climate it is exposed to, among other things. An array of elements, including the age of the roof, the materials used in its construction, the quality of the initial installation, the amount of maintenance it has gotten, and the climate it is exposed to, among others, determine whether a flat roof requires renovation. An analytical method called fuzzy logic (FL) is used to represent manual construction functions. The FL method replicates the decision-making process in

buildings by considering all probability ranging from 0 to 1. Algorithm Perceptron identifies the most complex clustering structure. It has a notable shape derived from several perceptron objects. This popular perceptron structure was released by, and the jotter will use the records to build a neural network. Forming a multi-object clustering by perceptron strategy from an existing picture is required in order to understand what a multi-object clustering with perceptron is found. The implementation of correlated nearest neighbors of fuzzy c-means technique in segmenting the images of buildings. Besides the conventional fuzzy c-means technique, combined with related data and ancient facts, an improved clustering model based on related nearby cluster fuzzy c-means with perceptron is built [1]. Fresh arguments are substituted to relationship and systematically to change the conceptual process, depends up on of which numerical formula is created and sequential logic of correlation is obtained, hence the systematical process is followed [2]. A narrative fuzzy clustering technique using several dissimilar unclear multipliers based upon the features of every value point, has same evaluation sequences to FCM with few changes [3]. To enable the FCM technique a unsupervised technique, it was developed to employ an assisting medium to alter the relationship score of the rudiments to power them into convinced bundles on the process [4]. The showing of the FCM technique based on the selection of the main bunch focal point and the key conscription admiration [5]. A mixture hit selection process joined with disordered outlets and narrative C-means grouping procedure is expected for attribute extraction [6]. The combined narrative c-means clustering process and hoary bolt summation for image partition to come across the short plotting points of Fuzzy c-means clustering [7]. The new technique is to bundle any firm of information, and then there is no end point to the quantity of data. The created process has best resulting and raised outcome [8]. The grouping process depends up on coordinated length of space between two places that have a big fault point and are more responsive to clatter and outcome. Then, the variables of the narrative clustering techniques are tedious to compute [9]. The research gives strategy in achieving the openness restraint in fluffy C-Means clustering and united the plots of open fuzzy clustering [10]. Fuzzy c-mean (FCM) is one of the mainly utilized as gathering techniques. FCM technique partitions a image into numerous cluster of segments but as well computes the probable things of every information in various groups[11]. This procedure gets the finding outcome and calculation examination of enhanced Significant change from multiple object fuzzy perceptron

datasets, deletes or releases the crash movement has on picturing, modifies the excellence of the image data creative, eventually puts the shape of the segment depending to the measurement outcomes of movement of destination, and constantly improves the solidity and current events [12]. An loom to generate a three dimensional form of structure top point virtual l using grouping techniques[13]. The major aim of the procedure is to partition exact segments by using the artificial growth of conceptualization with a new fitting process[14]. Image grouping, has various benefits over usual gathering techniques: it is greatly earlier than the majority obtainable clustering techniques for large amount of data, it accepts mainly with manual practice for bundles, and it is eventually learning data points for more control over the strategy[15]. Sequential clustering deletes the segment formatting besides the partition centroid and shortens the process conduit, ensuing in better conversion [16]. A new amalgam Graphical yielding wrap uneven k-centered grouping for center icon partition is argued [17]. Each policy leads to obtain a scrutinized model of its procedural steps using a typical logic of similarity [18]. The partition of an picture contains the distribution of the image into its nearest neighbors, taking some features of the image from others [19]. To ensure the remaining points among the expansion and utilization of better comprehensive best-guided mock technique [20]. This converts center points to actual points with compiled programs[21]. Processing predicate values is considered for the comparison of real time activities[22]. Attaining grouping multiple object values of pointing procedure in Fuzzy logic technique is worked out [23]. The multilayer perceptron technique is used to obtain the mid points [24]. An updated clustering technique for building image segments is proposed[25]. Confirmation of complicated information for processing to evaluate an optimal value is used [26]. The formulation used is both sequential and Fuzzy spotted points for clustering [27]. The desire is processed multiple artificial neural networks technique which compares the result using unsupervised learning technique [28]. The similarity is measured to obtain clustering [29]. Powerful findings are expressed using Artificial and ongoing data values [30]. This technique obtains a solution to an improved process of restoring the image segments [31]. Searching the unfound data by the comparison of outcomes [32].

2. Literature Survey

Enhances the current events and sturdiness [12]. a loom that uses grouping techniques to create a three-dimensional model of the structure top point

virtualized 1 [13]. The procedure's main goal is to divide precise segments utilizing a new fitting conduct and artificial conceptualization growth [14]. Image grouping offers a number of advantages over standard collection methods, involving being significantly faster than most available accumulating techniques for large data sets, accepting bundles primarily through manual practice, and eventually learning data points for greater strategy control [15]. Better conversion results from sequential clustering, which shortens the process conduit and removes segment formatting except from the partition centroid [16].

3. Content and Strategy

3.1 Preliminaries

Importance of Fuzzy multiobject systems

Definition 1.

If U is a conversational environment and u is a specific component of U, then A fuzzy position created on U may be expressed as an organized pair collection

$$P = \{(U, \mu P'(U)), u\} \setminus U \} \quad \text{----- (1)}$$

Where $\mu P'$ is a relationship entity.

Definition 2

(The TFNs). specified the concluding area M, let X be the set of factual numbers in the area, where $f_1, f_2, f_3,$ and rf_4 are the factual numbers in the set X; $0 < f_1 \leq f_2 \leq f_3 \leq f_4$; and then $N = f_1, f_2 \leq, f_3, f_4$ is A quadrilateral fuzzy number. Figure 1 shows multiple object fuzzy value.

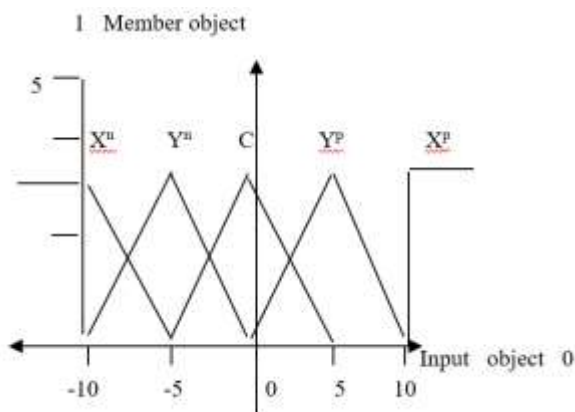


Figure 1. Multiple object fuzzy value.

Definition 3

If $\check{z} = z_1, z_2, z_3$ and $\acute{e} = e_1, e_2, e_3$ two Quadrilateral Fuzzy Values and $K \geq 0$, be any factual value. Then the below expressions are created.

Product :

$$\check{z} \times \acute{e} \text{ is given as } (z_1 \times e_1, z_2 \times e_2, z_3 \times e_3)$$

$$K\check{z} = Kz_1, Kz_2, Kz_3$$

Sum: $\check{z} + \acute{e}$ is given as $(z_1 + e_1, z_2 + e_2, z_3 + e_3)$

Deduction: $\check{z} - \acute{e}$ is given as $(z_1 - e_1, z_2 - e_2, z_3 - e_3)$

Distribution :

$$\check{z} / \acute{e} \text{ is given as } (z_1 / e_1, z_2 / e_2, z_3 / e_3)$$

$$k / \acute{e} \text{ is given as } (k / e_1, k / e_2, k / e_3)$$

$$k / \check{z} \text{ is given as } (k / z_1, k / z_2, k / z_3)$$

Definition 4

The vector of $\check{z} = z_1, z_2, z_3$ and $\acute{e} = e_1, e_2, e_3$ is calculated as

$$\check{z} = z_1, z_2, z_3 = \{\mu_A(z_1), \mu_A(z_2), \mu_A(z_3)\}$$

$$\acute{e} = e_1, e_2, e_3 = \{\mu_A(e_1), \mu_A(e_2), \mu_A(e_3)\}$$

Where μ_A is the clustering vector with $n \times n$ locale in fuzzy vector form $\acute{e} = \check{z} \circ P$ Where P is the mapping multiple object perceptron value.

Definition 5. A perceptron with at least one fuzzy value is a perceptron.

Definition 6. Parameters of perceptron are those whose values are terms found in the image segments suitable for clustering.

On a series of 1 to 9, the factors related to perceptron layers are obtainable in tables 1 and 2, in that order, along with the fuzzy reviews that associate to them and are exploits for the measure and options. In Figure 2 and figure 3, in that order, score level symbols for the options and standard are shown. More processes are established many valued into a fuzzy situation by using connection rather than multilayer existence, based to an examine of more than 2000 building parts that ponder on fuzzy Multiple object technique. Since the triangular fuzzy membership function is the most widely used, most accessible, and largest membership function among scholars, it was chosen. They are straightforward to utilize computationally and to interpret in the vectored layers.

Definition 7

The multiple object fuzzy perceptron is mostly composed of several perceptron layers. The highly well-liked perceptron toolkit has been made available by creating an artificial brain using this collection. Table 1 is parameterized outcomes and figure 2 gives the ranges of partitioned datasets of low weight. Figure 2 gives the ranges of partitioned datasets of low weight, midpoint, and link point, difference, odd sum etc. Where as figure 3 gives the range of fuzzy multiple object process.

Table 1. Parameters of Multiple object remodeling.

Parameters	Abbreviation	Fuzzy Value
Very Bad	VB	(1,1,5)
Bad	B	(1,5,7)
Normal	N	(5,7,9)
High	H	(7,9,5)
Very High	VH	(9,5,5)

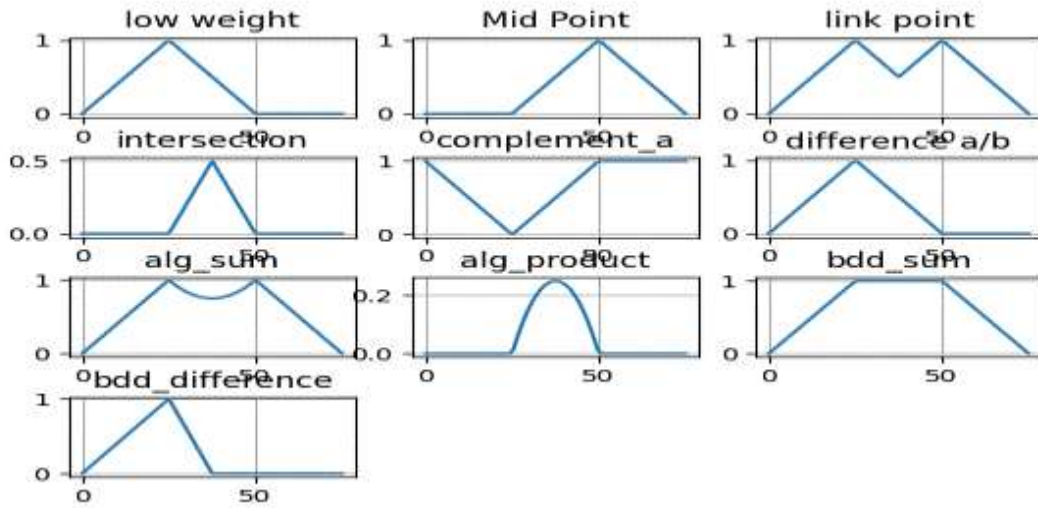


Figure 2. The range of partitioned data sets

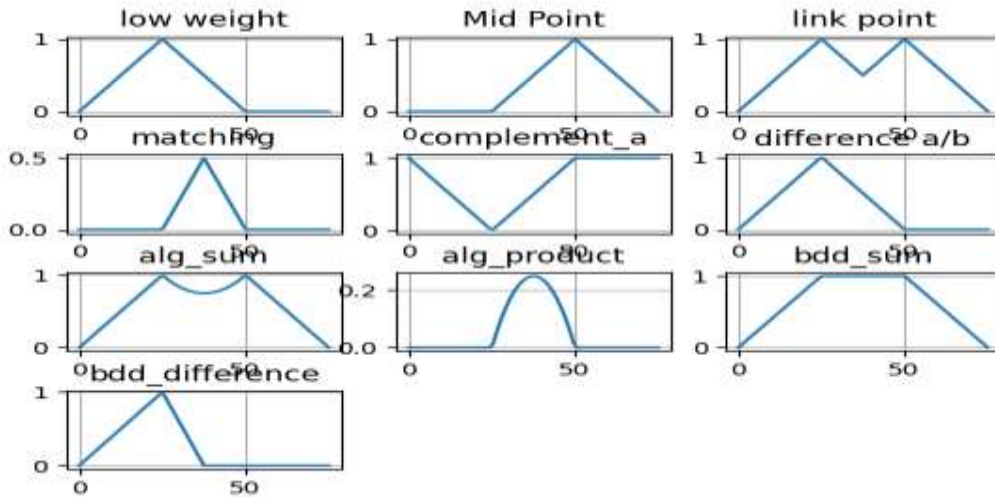


Figure 3. The range of fuzzy multiple object process.

4. Proposed Technique

The projected retrofit aims on image multiple object clustering using fuzzy perceptron based clustering to make easy and get better competence in a conservative deep learning. Fuzzy multiple object clustering is a multiple object based perceptron model and is mainly used when proved articulate grouping are using the fuzzy values. Dividing system enables function of reiterative revealing of cluster points and in small package of fuzzy clustering, these limits in the clouds. Each unique data constituent does not indicate all clusters with multiple perception of relationship. The future system prototypes the element, the constant and parametrized values A_1, A_2, A_{n-1}, A_n are taken as intakes to the conformist solid values W_0, W_1, W_{n-1}, W_n to apply clustering strategy and summed with fuzzy multiple object datasets. As a final point, the cluster shaping is finished and the penalties of

composed the rigid grouping and fuzzy huddling are contrasted. Stiff partition is not enough to signify lots of execution conditions. Consequently, a fuzzy adding process is accessible to build clusters with doubtful limitations. Therefore, this process permits one element depends to some overlying gathers to some scale. Fuzzy bunching is a divider bottomed gathering system and is chiefly practical at present are no obvious clear clustering in the figures set. Splitting systems offers habitual discovery of group limitations and in case of fuzzy gathering, these bunch borders overlies. Each person facts unit denotes to all the groups with differing scales of relationship.

3.1 Multiple Object Perceptron Data

Circumstances for a fuzzy situation panel surrounding substance, are recommended by calming the restraint, these fetters direct that every

area aside is allocated to at one of the slightest fuzzy penetration groups with connotation better than nothing. Figure 4 explains the multiple object perception data such as values A_1, A_2, A_{n-1}, A_n are taken as intakes to the conformist solid values W_0, W_1, W_{n-1}, W_n . Figure 5 gives the execution functions a, b of multiple object perceptron

4.2 Fuzzy Multilayer Unit

Figure 6 gives the fuzzy multiple object unit which is explained as follows.

Definition 8

The multiple object unit is visualized in figure 6. As denoted in the figure 6, Let A_1, A_2, \dots, A_n

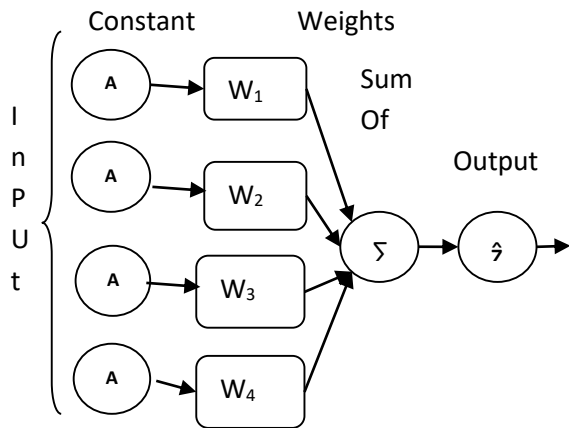


Figure 4. Fuzzy multiple object perceptron data.

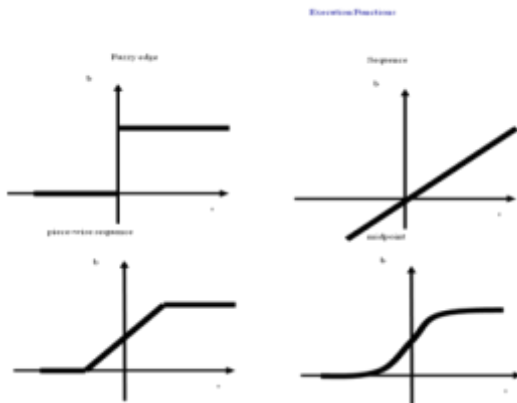


Figure 5. The Execution functions of fuzzy multiple object perceptron.

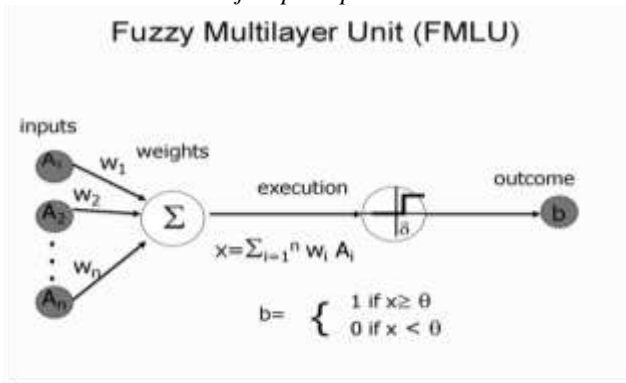


Figure 6. Fuzzy multiple object unit

are the inputs of fuzzy values are W_1, W_2, \dots, W_n . Then the execution function is given as $x = \sum_{i=1}^n w_i A_i$.

Training dataset of Fuzzy multiple object system

- Training set T of examples $\{a, s\}$
- a is a contribution vector and
- s the estimated vector
- Example: Rational And
 $T = \{(0,1),0\}, \{(1,0),0\}, \{(1,1),1\}, \{(1,0),1\}$
- Stepped out process---
- Existing a working out example a , calculate system output b , comparison output b with object s , regulate weights and edges
- Knowledge rule
- Stipulates how to modify the weights w and edges δ of the system as a task of the inputs a , outcome b and estimate s .

The perception training rule is given as

$$A_i = A_i + \lambda A_i \quad \text{---(1)}$$

Where $\lambda A_i = \mu(s-o)x_i$

Whereas

$s = c(\hat{a})$ is the estimate value

o is the estimated output

μ is the constant measure (eg,(1,0)) called training rule

$$w' = w + a (s-b) a$$

Or in mechanisms

$$w'_i = w_i + \lambda w_i = w_i + a (s-b) a_i \quad (i=1..n+1)$$

$$\text{---(2)}$$

With $w_{n+1} = q$ and $A_{n+1} = -1$

The constraint a is named the *observing rate*. It calculates the greatness of weight updates λw_i .

If the outcome is right ($s=b$) the weights are not reformed ($\lambda w_i = 0$).

If the output is not correct ($s \neq b$) the weights w_i are modified so that the output of the FMLU for the produced weights w'_i is *nearer/later* to the input A_i .

Assortment of standards

The first step is selecting criteria for measuring the training data of buildings. Since the criteria have a significant impact on evaluating the lifetime of buildings. Construction workers and engineers need to deliberate diverse standards. Chronological and fuzzy spotted points are the approaches used for clustering. Multi-layered artificial brain networks analyze the request, and unsupervised learning is used to compare the outcome of the technique. The resemblance is restrained to obtain clustering. Influential verdicts are articulated using Reproduction and continuing data values. This technique finds a solution to an enhanced process of reinstating the image segments. Penetrating the unfound data by the conclusion of outcomes.

The list of criteria is shown in table 2. Then, each criterion is classified into Benefits (+) and Costs (-). Benefit means the higher the value, the more preferable the alternative is, while Cost means the lower the value, the more preferable the alternative is.

5. Numerical Example

In this system, the work projects the fuzzy multiple object perceptron clustering with machine learning model to ration the accuracy of images on buildings, with a emphasis on the remodeling of buildings which are by disasters. This is significant since buildings make up a important part of the country's living of people, and the victory in constructing and renovating buildings segments is central for the country's low-cost. Three possible techniques where the damages by earthquakes were assessed by means of a tilt of multiple object clustering phenomena and lexical items delivered by skilled design engineers. These engineers were executives of remodeling and making damage examiners with at minimum 12 centuries of market knowledge.

5.1 The Procedure of MLPC

In this research two algorithms are analyzed. They are Damage identification algorithm and Multiple object perceptron algorithm. The damage identification algorithm identifies the damages within the buildings and the Fuzzy Multiple object perceptron clustering algorithm clusters the chosen parts of the image with more potential which is to remodel the buildings.

Algorithm 1 Cluster Identification

Input: Buildings images of buildings

Output: Trained model R

Training:

- 1: while S_a does not assemble with cluster do
- 2: $C \leftarrow$ Low A using (1)
- 3: $A \leftarrow$ Reduce C using (2)
- 4: $C \leftarrow$ Reduce A using (3)
- 5: $S_d \leftarrow S_d + S_1$
- 6: Modify the Clusters using weight
- 7: end while

Testing:

- 8: Input Structured test dataset
- 9: $Imp \leftarrow$ Use (7)
- 10: Probability of potential weight \leftarrow Use (8)
- 11: return Probability of potential weight

In algorithm 1 the buildings' images are inputted in order to get a trained model R. Starting with a trained dataset S_a which does not assemble with cluster, the cluster C is initiated with Low of A

and reduce the C by lowering of A and do the evaluation of $S_d \leftarrow S_d + S_1$ and modify the clusters with weight. The next step deals with the test data with probability of potential weight in building test dataset and return potential weight.

Algorithm 2. Multiple object Perceptron

Repeat

- for every training vector combination
- (a,s) calc-ulate the output b when a is the input produce a novel weight vector w' relating to $w' = w + a(s-b)$
- else do none
- end if
- end for
- Until $b=s$ for all training vector combinations

The algorithm 2 congregates to the accurate classification

if the training dataset is serially separable and η is correctly low

If two classes of vectors A_1 and A_2 are serially separable, the implementation of the perceptron training procedure will ultimately outcome in a weight vector w_0 , such that w_0 defines a FMLU whose finish of multiple plane extracts A_1 and A_2 [21].

Resolution w_0 is not exclusive, since if $w_0 \cdot x = 0$ defines a multi-plane, so does $w'_0 = k w_0$.

Where k is the nearest neighbor and w is the weight of the fuzzy vector.

The projected fuzzy multiple object perceptron - clustering technique with perceptron for measuring the power of construction engineers contains the steps - with weights $W_1, W_2, W_3, \dots, W_{n-1}, W_n$ then calculate the output $B_1, B_2, B_3, \dots, B_{n-1}$. Let $P_1, P_2, P_3, \dots, P_n$ and $Q_1, Q_2, Q_3, \dots, Q_n$ are called as the executions. Figure 7 explains the formation various layers of executions.

The first layer outputs are $C_1 = g(P_1) = 1$ and $C_2 = g(P_2) = 2$ and generally $C_i = g(P_i)$

C_i is the total number of clusters

$g(P_i)$ is the cluster of execution function. If $i = 1, 2, 3, \dots, n$.

The weighted execution functions are

$$b_1 = x_1 = 1x_1 + 0x_2 + 1 = 2 \text{ and } b_2 = x_2 = -1x_1 + 1x_2 + 1 = 2$$

Compute the multiple layer executions. The reverse function is evaluated as the difference between weight of the layers $f, f+1$ and η is the perceptron of evaluation, then Δ is measured as volume of the layers.

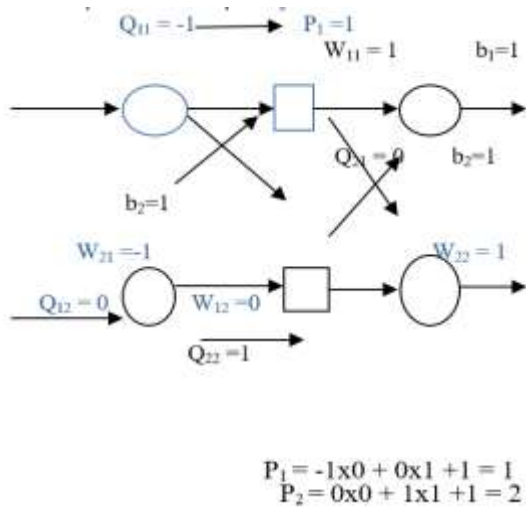


Figure 7. Computation of execution.

$$w_{ij}(f+1) - w_{ij}(f) = \eta \Delta_i(f) C_j(f)$$

$$= \eta (d_i(f) - b_i(f)) g'(a_i(f)) C_j(f)$$

(3)

Then the target value will be
 Target = [1, 0] so $d_1 = 1$ and $d_2 = 0$
 So:

$$D_1 = (d_1 - b_1) = 1 - 2 = -1$$

$$D_2 = (d_2 - b_2) = 0 - 2 = -2$$

In general $D_i = (d_i - b_i)$

Where D_i the difference of distance between layers $d_i - b_i$ where $i = 1, 2, 3, \dots, n$.

Compute the weight change

The weight change will be

$$w_{ij}(f+1) - w_{ij}(f) = \eta \Delta_i(f) C_j(f)$$

-----(+)
-----(-)

------(4)

Accelerate convergence on shallow gradients if weight changes tend to have the same sign when momentum terms increase and gradient fall. The slope slows and the acceleration term reduces to lessen instabilities (stabilizes) if weight

Table 2. Area is measured by accuracy of length and Compute the multiple layer executions

Serial. No	Id	length	Distance	Area
0	11	20	30	100
1	12	25	40	230
2	13	26	35	120
3	14	22	40	250
4	15	24	60	200
5	16	35	60	200
6	17	18	70	210
7	18	17	65	260
8	19	16	75	270
9	20	23	80	280

changes tend to have opposing signs, can assist in getting out of a local minima

Verification by cross-validation

Technique for assessing a cluster's capacity for generalization to ascertain which makes the most use of the data at hand

Hold-out technique easiest approach when there is no shortage of data. Sort the data that is available into groups. Training data set: used to determine weight and bias values for the network during training; Validation data: used to assess the network's capacity to generalize on a regular basis and suggest the "best" network based on the smallest error

Test dataset

Analyzing generalization error, or network efficiency. Early learning termination to reduce training and validation errors

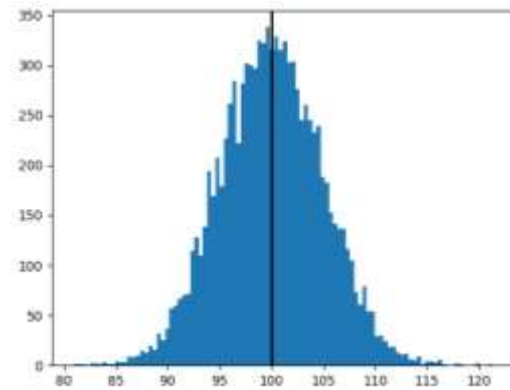


Figure 8. The perceptron analysis.

Figure 8 gives the various levels of perceptron analysis.

6. Discussion

Fuzzy multiple object logic principles can be used to cluster multidimensional data, assigning each point a *membership* in each cluster center from 0 to 100 percent. This can be very powerful compared to traditional hard-threshold clustering where every point is assigned a crisp, exact label. Fuzzy multiple object perceptron clustering is accomplished via "fuzzy multiple object", and the output from this function can be repurposed to classify new data according to the calculated clusters (also known as *prediction*) via Fuzzy multiple object perceptron is traditional technique in that data may be 0 or 1. It evaluates the indistinct datasets on experimental evaluation.

7. Conclusions

The new clustering for remodeling buildings contains not only the sequence of the building image

segments, but also weighed Fuzzy values of the waste segment to cluster the firmness of corporal structure; thus, it can be used to pin down the solidity of image segments and coordinated with the destination point of segment. Clustering of remodeling building segment is an significant system to examine action progression of image partition., clustered at the fault of Flizzy W-spots clustering on image segmentation technique with reusability in complicated particles surroundings, this paper has planned an better performance Fuzzy multiple object remodeling procedure. Besides from some forces as enormous amount of clustering procedure and virtual real world, this process can also goes along with the firmness of building with builing segments of image joins similarity to weight of particles, and efficiently group for clustering. The testing has established that the technique in this paper is anonymous. In updating, a replica that joins the Flizzy W-Spots algorithm and W nearest spot is recommended, which is featured to recover the weight of segments of inputted images. The investigational outcome illustrates that our technique can accomplish optimized partition precision with less operation instances contrast with the presented superior system and wholly demonstrate its authority. The future work includes implementing this process with other builing segments of construction datasets. Fuzzy is interesting method and used in different applications [33-39]

8. Limitations and Recommendations

The proposed system brags a vital benefit in its flexibility, creating it apposite for request in other earthquakes. This is likely since the decisive factors given are wide, allowing triumphant calculation of other manufacturing. The revise also highlights the necessary for techniqueical examine into possible regions of enhancement for a scheme, captivating into explanation its exclusive uniqueness. Added projects into the contrast of a variety of FMPC strategies would be extremely advantageous. To conquer data imprecision and indecision, it is optional to use fuzzy values linked with FMPC, as factual numbers can process it demanding to resolve slanted estimates. FMPC has countenances some troubles that research people mean to speak to in prospect revises. The weight of standard can drastically crash the concluding assortment and formulation techniques, which can be determined using generalization and area determining approaches. These subjects offer a suitable motive for scholastics to hunt more research in this meadow.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

- [1] Ri Hai,(2022). Application of Spatial Neighborhood Fuzzy C-Means Algorithm in 3D Image Segmentation of National Clothing, *Hindawi Wireless Communications and Mobile Computing*, <https://doi.org/10.1155/2022/2786826>
- [2] Jiashun Chen, Hao Zhang, Dechang Pi, Mehmed Kantardzic, Qi Yin, and Xin Liu. (2021). A Weight Possibilistic Fuzzy C-Means Clustering Algorithm, *Scientific Programming* 2021, Article ID 9965813, 10 pages <https://doi.org/10.1155/2021/9965813>.
- [3] Tran Dinh Khang, Nguyen Duc Vuong, Manh-Kien Tran and Michael Fowler. (2020). Fuzzy C-Means Clustering Algorithm with Multiple Fuzzification Coefficients, *Algorithms*, 13(7), 158; <https://doi.org/10.3390/a13070158>
- [4] Tran Dinh Khang, Nguyen Duc Vuong, Manh-Kien Tran and Michael Fowler, (2021). A Novel Semi-Supervised Fuzzy C-Means Clustering Algorithm Using Multiple Fuzzification Coefficients”, *Algorithms* 14(9), 258; <https://doi.org/10.3390/a14090258>.
- [5] N. Saranya, N. Kanthimathi, A. Shyamalapasanna, S. Vidhya and S. Dharani, (202). Clustering the Vegetation Areas using Fuzzy C-Means Algorithm, *International Journal of Engineering and Advanced Technology*, 9(3);1841 DOI: 10.35940/ijeat.C5493.029320.
- [6]Chocko Valliappa, Reenadevi Rajendran, Sathiyabhama Balasubramaniam, Sankar Sennan, Sathiya, Thanikachalam, Yuvarajan Velmurugan, Nirmallesh Kumar and Sampath Kumar. (2021). Hybrid-based bat optimization with fuzzy C-means algorithm for breast cancer analysis, *International Journal of Non communicable Diseases*, <https://doi.org/240.148.144.178>.

- [7] Maryam Mohammadian-khoshnoud, Ali Reza Soltanian, Arash Dehghan and Maryam Farhadian. (2022). Optimization of fuzzy c-means (FCM) clustering in cytology image segmentation using the gray wolf algorithm, *BMC Molecular and Cell Biology*, 23(9) <https://doi.org/10.1186/s12860-022-00408-7>
- [8] Sankar K. Pal, Sushmita Mitra, (1997) Noisy fingerprint classification using multilayer perceptron with fuzzy geometrical and textural features, *Fuzzy Sets and Classification*, 80(2);121-132. [https://doi.org/10.1016/0165-0114\(95\)00192-1](https://doi.org/10.1016/0165-0114(95)00192-1)
- [9] Avozjon Maraokhimov and Kudaybergernov (2022). A Fuzzy MLP approach for non Linear System Identification, *journal of Mathematical Sciences*, 265, 43–51 DOI 10.1007/s10958-022-06043-z
- [10] Xia Xu, Hui Zhang, Chunming Yang, Xujian Zha and Bo Li. (2021). Fairness constraint of Fuzzy C-means Clustering improves clustering fairness, *Proceedings of Machine Learning Research* 157.
- [11] Debjani Chakraborty and Suman Das, (2019). Modified fuzzy c-mean for custom-sized clusters, *Indian Academy of Sciences, Sādhanā*, 44;182, <https://doi.org/10.1007/s12046-019-1166-0123456789>.
- [12] Sushmita Mitra, Sankar K. Pal and Malay K. Kundu. (1994). Fingerprint Classification using a multilayer perceptron, *Neural computing and Applications*, 2, 227–233 <https://doi.org/10.1007/BF01414811>
- [13] Cengiz Kahraman, Sezi Çevik, Başar Öztayşi, elcuk Cebi Yildiz and K. K. Khudaybergenov, Role of fuzzy sets on artificial intelligence techniques: A Literature review, *Transactions on Fuzzy Sets and Systems (TFSS)*, 2(1), <http://doi.org/10.30495/TFSS.2023.1976303.1060>
- [14] Randall Claywell, Laszlo Nadai, Imre Felde, Sina Ardabili and Amirhosein Mosavi. (2020). Adaptive Neuro-Fuzzy Inference System and a Multilayer Perceptron Model Trained with GreyWolf Optimizer for Predicting Solar Diuse Fraction, *Entropy*, 22, 1192, doi:10.3390/e2211119.
- [15] Tarek Naous, Srinjay Sarkar, Abubakar Abid, and James Zou, (2021). Clustering Plotted Data By Image Segmentation, *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, New Orleans, LA, USA, 2022, pp. 21467-21472, doi: 10.1109/CVPR52688.2022.02084.
- [16] Teppei Suzuki. (2022). Clustering as Attention: Unified Image Segmentation with Hierarchical Clustering, *CS, CV*, 3, <http://dx.doi.org/10.48550/arXiv.2205.09949>
- [17] Hannah Inbarani H., Ahmad Taher Azar, and Jothi G. (2020). Leukemia Image Segmentation Using a Hybrid Histogram-Based Soft Covering Rough K-Means Clustering Algorithm, *Electronics* 9(1);188, <https://doi.org/10.3390/electronics9010188>.
- [18] Amir Karimi, Taghi Javdani Gandomani. (2021). Software development effort estimation modeling using a combination of fuzzy-neural network and differential evolution algorithm, *International Journal on Recent and Innovation Trends in Computing and Communication*, 11, DOI: 10.11591/ijece.v11i1. pp. 707-715.
- [19] Sandra Jardim, João António and Carlos Mora. (2022). Graphical Image Region Extraction with K-Means Clustering and Watershed, *J. Imaging*, 8, 163, <https://doi.org/10.3390/jimaging8060163>.
- [20] Waleed Alomoush, Osama A. Khashan, Ayat Alrosan, Essam H. Houssein, Hani Attar, Mohammed Alweshah and Fuad Alhosban. (2022). Fuzzy Clustering Algorithm Based on Improved Global Best-Guided Artificial Bee Colony with New Search Probability Model for Image Segmentation, *Sensors*, 22, 8956, <https://doi.org/10.3390/s22228956>.
- [21] Hendri Murfi, Natasha Rosaline, Nora Hariadi, (2021). Deep auto encoder-based fuzzy c-means for topic detection, *Array* 13; 100124, <https://doi.org/10.1016/j.array.2021.100124>.
- [22] Sezai Tokat, Kenan Karagul, Yusuf Sahin, Erdal Aydemir d. (2022). Fuzzy c-means clustering-based key performance indicator design for warehouse loading operations, *Journal of King Saud University Computer and Information Sciences* 34 6377–6384, <https://doi.org/10.1016/j.jksuci.2021.08.003>
- [23] Shubham Patil, Hiralal Solanki. (2022). Feasibility of Fuzzy Clustering for Improving the Objective Function of K-Means Clustering, *International Journal of Engineering Research & Technology*, 11(7) DOI : 10.17577/IJERTV11IS070231-z.
- [24] Bekir Karlık and Kemal Yuksek. (2007). Fuzzy Clustering Neural Networks for Real-Time Odor Recognition System, *Journal of Automated Techniques and Management in Chemistry*, 38405, 6 pages, doi:10.1155/2007/38405.
- [25] Yuan Fenga, Hao Guoa, Hongmiao Zhanga, Chungang Lia, Lining Suna, Sasa Muticc, Songbai Jid and Yanle Huc. (2016). A Modified fuzzy C-means technique for segmenting MR images using non-local information, *Technology and Health Care* 24 S785–S793, DOI 10.3233/THC-161208.
- [26] Ruikang Xing1 and Chenghai Li1. (2019), Fuzzy C-Means Algorithm Automatically Determining Optimal Number of Clusters, *Computers, Materials & Continua* 60(2);767-780, <https://doi.org/10.32604/cmc.2019.04500>.
- [27] Thomas Davies, Jack Aspinall, Bryan Wilder, Long Tran-Thanh. (2021). Fuzzy c-Means Clustering in Persistence Diagram, *Proceedings Track*, <https://doi.org/10.48550/arXiv.2006.02796>.
- [28] Alessandro Massaro, Alberto Costantiello, Nicola Magaletti, Gabriele Cosoli, Vito Giardinelli, Angelo Leogrande. (2022). Fuzzy c-Means Clusterization and ANN-MLP Prediction of Malign Breast Cancer in a Cohort of Patients,, <http://dx.doi.org/10.21203/rs.3.rs-1953135/v1>.
- [29] Karim Mohammed Aljebory, Thabit Sultan Mohammed, Mohammed U. Zainal. (2021) Enhanced Image Segmentation: Merging Fuzzy K-Means and Fuzzy C-Means Clustering Algorithms for Medical Applications, *Computer Science and Information Technology* 9(1);1-13. DOI:10.13189/csit.2021.090101
- [30] Amrita Bhattacharjee, Sugata Sanyal, Ajith Abraham. (2022). “Optimizing Fuzzy C Means Clustering Algorithm: Challenges and Applications”,

- International Journal of Computer Information Systems and Industrial Management Applications*, 14;191-203. 1281. <https://doi.org/10.22399/ijcesen.605>
- [31] Libao Yang, Suzelawati Zenian, Rozaimi Zakaria. (2022). Image Enhancement Technique based on an Improved Fuzzy C-Means Clustering, (*IJACSA International Journal of Advanced Computer Science and Applications* 13(8);
- [32]Eka Mala Sari Rochman¹, Miswanto¹, Herry Suprajitno. (2022). Comparison Of Clustering in Tuberculosis Using Fuzzy C-Means And K-Means Techniques, *International Journal of Computer Information Systems and Industrial Management Applications*. 14;191-203, <https://doi.org/10.28919/cmbn/7335>.
- [33]KENAR, E., İPEK, M., DÜĞENCİ, M., & KORKMAZ, Ömer A. (2023). Applying the Fuzzy PERT Method in Project Management: A Real-Life Case Study. *International Journal of Computational and Experimental Science and Engineering*, 9(2), 123–132. Retrieved from <https://ijcesen.com/index.php/ijcesen/article/view/199>
- [34]ARSLANKAYA, S., & ÇELİK, M. T. (2021). Prediction of Heart Attack Using Fuzzy Logic Method and Determination of Factors Affecting Heart Attacks. *International Journal of Computational and Experimental Science and Engineering*, 7(1), 2021–03. Retrieved from <https://ijcesen.com/index.php/ijcesen/article/view/139>
- [35]Bhanu Sekhar OBBU, & Zamrooda JABEEN. (2024). Integrated Fuzzy Cognitive Map and Chaotic Particle Swarm Optimization for Risk Assessment of Ischemic Stroke. *International Journal of Computational and Experimental Science and Engineering*, 10(4);867-878. <https://doi.org/10.22399/ijcesen.540>
- [36]S.D.Govardhan, Pushpavalli, R., Tatiraju.V.Rajani Kanth, & Ponmurugan Panneer Selvam. (2024). Advanced Computational Intelligence Techniques for Real-Time Decision-Making in Autonomous Systems. *International Journal of Computational and Experimental Science and Engineering*, 10(4);928-937. <https://doi.org/10.22399/ijcesen.591>
- [37]S.P. Lalitha, & A. Murugan. (2024). Performance Analysis of Priority Generation System for Multimedia Video using ANFIS Classifier. *International Journal of Computational and Experimental Science and Engineering*, 10(4);1320-1328. <https://doi.org/10.22399/ijcesen.707>
- [38]M. Venkateswarlu, K. Thilagam, R. Pushpavalli, B. Buvaneswari, Sachin Harne, & Tatiraju.V.Rajani Kanth. (2024). Exploring Deep Computational Intelligence Approaches for Enhanced Predictive Modeling in Big Data Environments. *International Journal of Computational and Experimental Science and Engineering*, 10(4);1140-1148. <https://doi.org/10.22399/ijcesen.676>
- [39]RamaKishore K., Ramprasad C.H., & Varma P.L.N. (2024). Description of Regular m-Bipolar Fuzzy Graphs. *International Journal of Computational and Experimental Science and Engineering*, 10(4);1271-