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ARTICLE

A Type-1 Linguistic Variable Intuitionistic Fuzzy Similarity Measure for Word Cognition Detection

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Abstract
Introduction: Similarity measures have been proven over time for their usefulness in solving real-time problems. Researchers modify and develop new methods to suit different areas of application relative to specific data sets. The existing similarity measures on some application domains gave ineffective results.
Objectives: This study modified existing similarity measures and converted them into intuitionistic fuzzy similarity measure for word cognition detection in dementia patients. Materials and Method: Similarity measures of bigram, Dice and Canberra were modified as Dice1, Dice2, Canberra1, Canberra2 and bigram which were extended to intuitionistic fuzzy similarity measures, and the text and pattern were classified into type-1 linguistic variable. Experiments were conducted on both existing and modified methods with stored data sets while evaluations were performed on generated results using average similarity measure, average processing time and root mean square error.
Result: Experimental results indicated that modified Dice2 gave the highest similarity value of 0.98, followed by Dice, modified Dice1, modified Canberra1, modified Canberra2, Canberra, modified bigram with the values of 0.93, 093, 0.90, 0.89, 0.84 and 0.82 respectively for 100 pairs of text and pattern matching of equal length of characters. Considering the processing time for experimental cases of 20, 50 and 100 sets of text and pattern matching of both equal and unequal length of strings, modified Dice2 computed the lowest processing time followed by modified Dice1, modified bigram, Canberra, modified Canberra1, Dice, and modified Canberra2. MD2 gave a more effective and efficient IFSM compared to existing IFSM for dementia patients. The results of root mean square error on both existing and modified methods indicated that modified Dice2 has the lowest value. Modified Dice2 classified the word entered by the user as against word generated randomly by the computer as type-1 linguistic variable of simple, moderate and high as suggested by the experts.
Conclusion: Modified Dice2 gave the highest similarity value, lowest processing time, lowest root mean square error which could be used for word cognition detection.
Significance: An enhanced IFSM for dementia patients cognition progressive monitoring was developed.

Keywords: Similarity measure; fuzzy similarity measure; intuitionistic fuzzy similarity measure; efficiency.

1.0 Introduction

Similarity measure is a scientific measure for determining the degree of similarity between two objects. Distance measure is the dual concept of similarity measure. Several approaches had been scientifically opined for evaluating similarity measure. These measures are as many as the broad significance and applicability of similarity measure whose suitability depends on the application area like pattern recognition, medical diagnosis, hierarchical cluster analysis, approximate analogical reasoning, rule matching in fuzzy control, neural networks, query processing with different fuzzy semantics (Brindaban et. al., 2021). Similarity measures are based on set operations like union, intersection, maximum difference, symmetric difference etc.

Sets represents elements or group (Laijun& Haiping, 2016) of elements that have common properties. A set is a tool that can be used to model real life problems. Set can be represented in various forms like crisp set, fuzzy set, intuitionistic fuzzy set among others. A crisp set evaluates to either 0 or 1. It doesn't depict the degree of membership. Fuzzy set is preferred to crisp set because it represents how human mind perceives and manipulate information. Human mind process hedges like weak, moderate, strong, good, very good, tall, very tall, brilliant, more brilliant to mention but few. These hedges are modelled as linguistic property, for instance type-1 linguistic fuzzy set gives overlapping partition which leads from one set to another such as small, medium and big. Fuzzy considers only membership function, to improve this it is extended to intuitionistic fuzzy set which considers membership and vagueness of a set with respect to the universal set. Intuitionistic fuzzy sets make descriptions of the objective world become more realistic, practical, accurate and promising. It has diverse application to fields like data processing, identification of functional dependency relationship between concepts in data mining systems, approximate reasoning, pattern recognition, decision making, medical diagnosis, logic programming, sale analysis and new product marketing. It can also be applied to pattern classification (XinXing et. al., 2023),other diverse applications include financial services, negotiation process, psychological investigations, machine learning, image processing, fuzzy risk analysis, fault tree analysis etc.

An area of psychology popularly known as cognition is an area that needs more attention, due to its relevance to keeping track of working memory capacity. Word cognition are not exempted in this context. It has to do with evaluating user's response to word scrabble task. Application of intuitionistic fuzzy set to this area is not common. Application of intuitionistic fuzzy similarity measure to word permutation would permit to test patient's sickness in dementia.

A number of existing similarity and distance measure had been extended to intuitionistic fuzzy similarity measure like cosine, dice, hamming, Euclidean and others (Hesamian& Chachi 2016; Thirumalai&Senthilkumar, 2017). Also based on the fact that some similarity measures are not effective in some cases, researchers developed new or modified similarity measures to suit different application areas (Hung et al, 2004). The quest for accuracy in values of intuitionistic fuzzy similarity measure to different domains had created a gap that needs to be filled in different context of intuitionistic fuzzy similarity measure application. Thus, there is need to investigate the performance of existing measures in domain of choice, and come up with measures of valid, effective and accurate intuitionistic fuzzy similarity measure in specified domain which remains the focus of this study. This research thus modified existing intuitionistic fuzzy similarity measures and Canberra. Comparative analysis was carried out on existing and modified measures with application area word cognition in dementia patients.

2.0 Materials and Methods

2.1 Related Works on Existing Intuitionistic Fuzzy Similarity Measures

Authors (Hung et. al., 2008)proposed similarity measures which were used to characterize the similarity between linguistic variables. It was proven from their research that the new similarity measure is simpler and more easily interpreted than the existing methods. The proposed similarity measures are reliable in applications with compound linguistic variables. Existing measures are not that friendly with fuzzy queries, and defining the degree of similarity between fuzzy sets. Author in (Thirumalai & Senthilkumar, 2017) reviewed distance and similarity measures of intuitionistic fuzzy set comprehensively. This shows that distance and similarity measures of IFSs are based on geometric distance model and set theoretic approach. Their reviews indicate that the most widely used tools are Hamming distance, Euclidean distance and Hausdourff distance. Two other measures were defined by combining Hausdorff metric to weight Hamming distance and weight Euclidean distance. There were non-extended methods and new proposed methods that satisfied the conditions of the metric. These methods have some good geometric properties that are not as fit as proposed ones (Hung & Yang, 2008).

Jun Ye considered the information carried by membership and non-membership degree in IFSs as a vector representation with two elements. The author proposed a cosine similarity measure and a weighted cosine similarity measure between intuitionistic fuzzy similarities based on the concept of cosine similarity measure for fuzzy sets. The proposed measures were compared with the existing measures to test for efficiency. Research revealed that cosine similarity measure is the most reasonable. This was demonstrated with application to pattern recognition and medical diagnosis. Existing similarity measures cannot carry out pattern recognition in some cases(Wen-Liang et. al., 2008).

Jun Ye developed a decision-making method with optimism, neutralism and pessimism by use of the Dice similarity measure based on the reduct IFSs of interval valued intuitionistic fuzzy set [IVIFS]. The author addressed the issue of decision-making method using the dice similarity measure between the reduct IFSs of IVIFS to treat the influences of optimism neutralism and persimism on the multicriteria decision making problem. The author also proposed Jacccard, Dice and cosine similarity measures between intutionistic trapezoidal fuzzy numbers that are treated as continuous and applied them to multicriteria group decision making problems. In fuzzy environment, information available is imprecise/uncertain, which is a torment for decision maker in the decision-making process. Dice is preferred to Jaccard and cosine because it gives better result when second vector is undefined. Result of Dice similarity measure based on expected interval of trapezoidal fuzzy numbers was compared with Zeng's single expected value method with known criteria weight. This proposed method is simple and effective in the decision-making problem with completely unknown criteria weights (Jun, 2012).

Authors (Muthuraj & Devi, 2019) applied intuitionistic fuzzy network for customer to business decision making. The method attained intuitionistic fuzzy optimization for customer to business, and resolved multi decision making problem. The method reduced the complexity of the customers to take best decision with less effort. The method minimized the decision-making criteria by means of assigning the range of sets with the contribution of similarity degree measures. The method optimized customer to business decision making, and optimize decision making problem. The application of it on customer to business has not received much attention over the internet.

A novel approach was proposed for the construction of cognitive map based on intuitionistic fuzzy logic. The new model called intuitionistic fuzzy cognitive map extends fuzzy cognitive map by considering expert hesitancy in determination of causal relation between the concept of a domain. It's advantage over fuzzy cognitive map model is that it can incorporate additional information regarding the hesitancy of the experts in the definition of the cause-effect relations between the concepts involved in a domain. Furthermore, intuitionistic fuzzy cognitive map is capable of modelling real world medical decision-making tasks closer to the way human perceive them. Existing methods lack ability to perform approximate reasoning and handle incomplete information (Lakovidis& Papageorgiou, 2011).

Boran and other authors proposed intuitionistic fuzzy TOPSIS method for evaluation of supplier's multi-criteria group decision. Intuitionistic fuzzy weighted averaging was utilized to aggregate individual opinions of decision making for rating the important criteria and alternative. The weight of each criterion was given as linguistic terms characterized by intuitionistic fuzzy numbers. Intuitionistic fuzzy operator was utilized to aggregate opinions of decision makers. Ideal solutions were calculated based on Euclidean distance. This approach created a huge success for multi-criteria decision-making problems because of vague perception of decision maker's opinions. Proposed method is more suitable in this context because criteria provided by decision makers are difficult to precisely express by crisp data in the selection of supplier problem (Brindabanet. al., 2021).

Authors (Hwang et. al., 2012) proposed a new similarity measure formula for intuitionistic fuzzy set induced by Sugeno integral. This was compared with other existing similarity measures for intuitionistic fuzzy set and Sugeno performs better than existing ones, because it provides an operation similar to expected value. The proposed similarity measure uses a robust clustering method to recognize the pattern of intuitionistic fuzzy set. There was no existing method that considered Sugeno integral technique.

Authors (Ejagwa et. al., 2014) showed a novel application of intuitionistic fuzzy set to model the uncertainty and vagueness in career determining using normalized Euclidean distance method to measure the distance between each student and each career respectively. Moreover, career was prescribed based on smallest distance between each student and each career. Existing career determination tool lacked the vagueness and hesitancy factor. Career determination using intuitionistic fuzzy set gave accurate and proper career choice based on academic performance.

Authors (Laijun Luo & Haiping, 2016) stated that Li and Chen's similarity measure takes into account the medians of two intervals only, and thus it can easily be pointed out by the counter-intuitive examples, then Liang and Shi put forward some more reasonable similarity measures through numerical comparisons with Li and Chen's similarity measures. Mitchell proposed an improved similarity from a statistical view point on the basis of Li and Chen's similarity measure. Some similarity measures have been constructed based on distance measure, Szmidt and Kacprzyk constructed similarity measures using Hamming distance measure and put them into the multi-attribute group decision making problem. Hung and yang constructed similarity measure using Hausdorff distance, subsequently he induced similarity measures using $L_p$measure. Thus, to overcome the counter intuitives that occurs in some cases in existing intuitionistic fuzzy similarity measure, a new IFSM was proposed by authors. The constructed measure was applied to pattern recognition and medical diagnosis. Based on the proposed similarity measure, a new decision-making method is put forward for the multi-attribute decision making [MADM] problem with attribute values expressed by intuitionistic fuzzy set.

Authors (Hungand Yang, 2008)] extended several popular similarity measures between fuzzy set to intuitionistic fuzzy set that is Wang1, Wang2, Pappis and Karaca-Pilidis1,2 and 3. The authors proposed two new similarity measures of Exponential-type similarity measure based on Hamming distance, and Exponential type similarity measure based on normalized Hamming distance. (Hesamian& Chachi, 2016) proposed new definitions of similarity measures for measuring the degree of similarity between sets based on axiomatic approach. (Boran et al., 2009) proposed a new intuitionistic fuzzy similarity measure between intuitionistic fuzzy sets with respect to modification of Zhang-Fu similarity measure because existing measure gave unreasonable result in some cases.

Researches had been conducted in terms of extending, improving and modifying existing similarity measure or IFSM.Also IFSM had been applied to different domain with better performance. (Song et al, 2015; Donghai et. al., 2018; Di et. al., 2018; Muthuraj & Devi, 2019; Pranamika, 2013; Eulalia & Jamsz, 2003; Peerasak, 2014; Binyamin et. al., 2011; Harish, 2018; Guiwu& Hui, 2017; Leila et. al., 2015; Jude & Arockiaram, 2018; Anshu, 2017; Ju, 2016).

2.2 Similarity as a Relation

A similarity relation on a set U is a fuzzy binary relation

$R: U \times R \rightarrow [0,1]$ holding the following properties:

Reflexive:

$$R(x,y) = 1 \; for \; any \; x \in U \qquad 1$$

Symmetric

$$R(x,y) = R(y,x) for any x, y \in U \qquad 2$$

Transitive

$$R(x,z) \geq R(x,y) \Delta R(y,z) for any x, y, z \in U \qquad 3$$

Where the operator Δ is an arbitrary t-normΔ:$[0,1] \times [0,1] \rightarrow [0,1]$

It is a binary operator which is commutative, associative, monotone in both arguments and $1\Delta x = x$. Hence it subsumes the classical two valued conjunction operator. A relation of similarity $x_1 and x_2$ is written as $x_1 \sim x_2$.

2.3 Intuitionistic Fuzzy Set

Fuzziness is a concept of human thinking and speaking [15], which deals with subjectivity and vague concept. Fuzzy sets express the imprecision of human thinking and behaviour by appropriate mathematical tools. A fuzzy set is built from a reference set called universe of discourse.

Let X be the universe of discourse

$X = \{x_1, x_2, \quad , x_n\}$

Fuzzy set A is in $X (A \subset X)$

$\{(xi, \mu(xi))\}$

Where $xi \in x \; and \; \mu \, A: x \rightarrow [0,1]$ is the membership function of A.

$VA: x \rightarrow [0,1]$ is a non-membership function of A.

Intuitionistic Fuzzy Set (IFS) is a tool in modelling real life problems like sale analysis, new product marketing, financial services, negotiation process, psychological investigation e.t.c. (Ejagwa, 2014).

2.4 Conditions for Intuitionistic Fuzzy Similarity Measure

Let S be real function S such that:

$IFS \times IFS \rightarrow R^+$.

S is called a similarity measure if it satisfies the following conditions:

$IFS \times IFS \rightarrow R^+$.

$IS1 - S(A,B) = S(B,A), \forall A, B \in IFS$

$IS2 - S(D, D^c) = 0, if \; D \; is \; a \; crispset$

$IS3 - S(E,E) = max_{A,B} \in IFSS(A,B), \forall E \in IFS$

$IS4 - \forall A, B, C \in IFS, if A \subset B \subset C, then$

$S(A) \geq S(A,C) and S(B,C) \geq S(A,C)$

(Hung &Yang, 2008)

2.4.2 Methods for the classification of IFV

Text and Patterns were converted into IFV using proposed methods for IFV (Raji-Lawal et. al., 2020).

2.4.2.1 Existing Methods for the classification of IFV

2.4.2.1.1 Intuitionistic fuzzy similarity measures for classification of intuitionistic fuzzy values of text and string:

Equations 4,5 and 6 are existing IFSM(s) from which the new methods were derived using different mathematical rules and theorem.

(i) Dice(D) Intuitionistic fuzzy similarity measure

$D_{IFS}(A, B)$

$$= \sum_{i=1}^{n} \frac{2(\mu_A(x_i) * \mu_B(x_i)) + (V_A(x_i) * V_B(x_i))}{(\mu_A^2(x_i) + \mu_B^2(x_i) + V_A^2(x_i) + V_B^2(x_i))} \qquad 4$$

(ii) Canberra Intuitionistic fuzzy distance measure:

$CA_{IFS}(A, B)$

$$= \sum_{i=1}^{n} \frac{|\mu_A(x_i) - \mu_B(x_i)| + |V_A(x_i) - V_B(x_i)|}{|\mu_A(x_i) + \mu_B(x_i)| + |V_A(x_i) + V_B(x_i)|} \qquad 5$$

$$S_{CA} = 1 - CA_{IFS}(A,B) \qquad 6$$

$S_{CA}(A, B)$ represent Canberra Intuitionistic Fuzzy Similarity Measure

2.4.2.2 Proposed Methods for the classification of IFV

2.4.2.2.1 Modified Intuitionistic fuzzy similarity measures for classification of intuitionistic fuzzy values of text and string:

(i) Modified Dice1 and 2 Intuitionistic fuzzy similarity measure

Dice method was modified into equations 7 and 8, that is MD1 and MD2 by introducing the power function and a constant to improve the growth rate:

$MD1_{IFS}(A, B)$

$$= (\sum_{i=1}^{n} \frac{(\mu_A(x_i) * \mu_B(x_i)) + (V_A(x_i) * V_B(x_i))}{\max((\mu_A^2(x_i), \mu_B^2(x_i)) + max(V_A^2(x_i), V_B^2(x_i)))})^{\frac{1}{n}} \qquad 7$$

$MD2_{IFS}(A, B)$

$$= (\sum_{i=1}^{n} \frac{2 * (\mu_A(x_i) * \mu_B(x_i)) + (V_A(x_i) * V_B(x_i))}{((\mu_A^2(x_i) + \mu_B^2(x_i)) + (V_A^2(x_i) + V_B^2(x_i)))})^{\frac{1}{n}} \qquad 8$$

MD represent Modified Dice

(ii) Modified Canberra Intuitionistic fuzzy similarity measure:

Existing method Canberra Intuitionistic fuzzy similarity measure in equation 6 was extended into two methods stated in equations 9 and 10, using information theoretic measures for IFSs and their proof of validity on monotonic and exponential function (Anshu, 2016).

- Modified Canberra1 Intuitionistic fuzzy similarity measure:

$$S_{MC1}(A,B) = \left(\frac{e^{-CA_{IFS}(A,B)} - e^{-1}}{1-e^{-1}}\right)^{\frac{1}{n}} \quad 9$$

$S_{MC1}(A,B)$ represent Modified Canberra1 Intuitionistic fuzzy similarity measure

- Modified Canberra2 Intuitionistic fuzzy similarity measure:

$$S_{MC2}(A,B) = \left(\frac{1 - CA_{IFS}(A,B)}{1 + CA_{IFS}(A,B)}\right)^{\frac{1}{n}} \quad 10$$

$S_{MC2}(A,B)$represent Modified Canberra2 Intuitionistic fuzzy similarity measure

Proof:

Let F be a monotonic decreasing function and since $0 \leq C_{IFS}(A,B) \leq 1$,

Therefore $f(1) \leq f(C_{IFS}(A,B)) \leq f(0)$

Now we have to select a useful and reasonable F for each case.

Let us assume F as f(x) = 1-x, thus the similarity measure $S_{CA}(A,B) = 1 - CA_{IFS}(A,B)$ is well defined, and also satisfies all the properties of a valid measure of similarity between IFSs.

Now we choose the exponential function $f(x) = e^{-x}$, from which we can say that the measure

$$S_{MC1}(A,B) = \frac{e^{-CA_{IFS}(A,B)} - e^{-1}}{1-e^{-1}} \text{is well defined}$$

On the other hand, if we choose the function F as $f(x) = \frac{1}{1+x}$, for which the similarity measure is:

$$S_{MC2}(A,B) = \frac{1 - CA_{IFS}(A,B)}{1 + CA_{IFS}(A,B)}$$

3.0 Result and Discussion

3.1 Equal Strings of Text and Pattern Matching

3.1.1 Experiment on conversion of text and pattern to intuitionistic fuzzy value :

There are twenty text and pattern match in table 4.4 as denoted from A1 to A20 as an example. Text and Patterns were converted into IFV using proposed methods for IFV by author in (Raji-Lawal et. al., 2020).

3.1.2 Experiment on equal length of text and pattern matching:

Data set of equal and length of text and patterns were collected on anagram dictionary of www.senseagent.com/en/anagram. The experiment was conducted with 20, 50 and 100 sets of equal length of text and pattern matching using new methods of MB_{IFS}, $MD1_{IFS}$, $MD2_{IFS}$, S_{MC1} and S_{MC2} with existing ones of Dice and Canberra. The average similarity values of each method were computed. Considering 100 sets of equal length of text and pattern matching, figure 1 shows the average similarity measure of both existing and new methods. As indicated on figure 1 $MD2_{IFS}$ has the highest similarity values of 0.975, followed by Dice, MD1, S_{MC1}, S_{MC2} , MB and CA with the values of 0.927, 0.927, 0.904, 0.887, 0.837 and 0.821 respectively. Considering the experimental cases of 20, 50 and 100 sets of text and pattern matching of equal length of strings, averagely the similarity values are in increasing order of MD2 > Dice > MD1 > S_{MC1}> S_{MC2} > MB > CA. MD2 is an enhanced intuitionistic fuzzy similarity measure for dementia patients. According to author Raji-Lawal (2020) research, Modified Euclidean IFSM was proposed, it has a less effective similarity value of 0.871.

The experiment was conducted with 20, 50 and 100 sets of text and pattern matching using new methods of MB_{IFS}, $MD1_{IFS}$, $MD2_{IFS}$, S_{MC1} and S_{MC2} with existing ones of Dice and Canberra. The average processing time were computed. Figure 2 shows the average processing time of both existing and new methods. As indicated on figure 2 $MD2_{IFS}$ has the lowest processing time of 0.855, followed by MD1, MB, CA, S_{MC1}, DICE and S_{MC2} in ascending order with the values of 0.880, 0.948, 0.971, 0.989, 0.991 and 0.992 (ms) respectively. Considering the processing time experimental cases of 20, 50 and 100 sets of text and pattern matching of equal length of strings, averagely the processing time are in increasing order of MD2 > MD1 > MB > CA > S_{MC1}> Dice > S_{MC2}. The proposed method Modified Euclidean IFSM by (Raji-Lawal et. al., 2020)gave a less efficient processing time of 1.533. Thus, MD2 is more efficient and hence an enhanced IFSM for dementia patients.

3.1.3 Classification of IFS with equal length of string into type-1 linguistic term

The classification of type -1 linguistic variable was termed as simple for B1, moderate for B2 and hard as B3. The generated IFVs as indicated in table 1 for each text and pattern matching were used to measure with respect to the set of thresholds to determine the value of hard, moderate and simple. The similarity values of all linguistic terms were compared to get the highest score which would determine the classification category of text and pattern. The similarity values of all linguistic terms were depicted in table 2 while table 3 shows the linguistic terms for each method relative to their text and pattern matching. For example, table 4.6 shows the classification of IFS data set of A1:[1,0][1,0][0.6,0.4] representing text and pattern (signer/singer) which was passed into both new and existing methods to derive intuitionistic fuzzy similarity value. The new and old methods calculated the IFS between text A1 and patterns B1 : [0.9,0.1][0.9,0.1][0.4,0.6], B2 : [0.9,0.1][0.9,0.1][0.6,0.4] and B3 : [0.9,0.1][0.9,0.1][0.8,0.2] which represent simple, moderate and hard respectively. These classifications were based on Evans calibration (Evan, 1996). The similarity values of MD2(A1, B1) is 0.991, MD2(A1, B2) is 0.997 and MD2(A1, B3) is 0.992. The other values for each method were stated in table 4.5. The text and pattern of A1 is classified into linguistic term as B2 which indicates moderate as shown in table 4.6. The same process is applicable to other methods as illustrated in table 4.6.

3.1.4 Evaluation of equal length of string using root mean square error

The root mean square error (RMSE) as indicated in equation 11 is used for the evaluation of average similarity values of text and pattern with equal length on proposed methods of MB_{IFS}, $MD1_{IFS}$, $MD2_{IFS}$, S_{MC1} and S_{MC2} with existing ones of Dice and Canberra. MD2 has the lowest root mean square error value of 0.017, followed by Dice, MD1, S_{MC1}, S_{MC2} , CA and MB with the values of 0.042, 0.054, 0.077, 0.092, 0.145 and 0.151

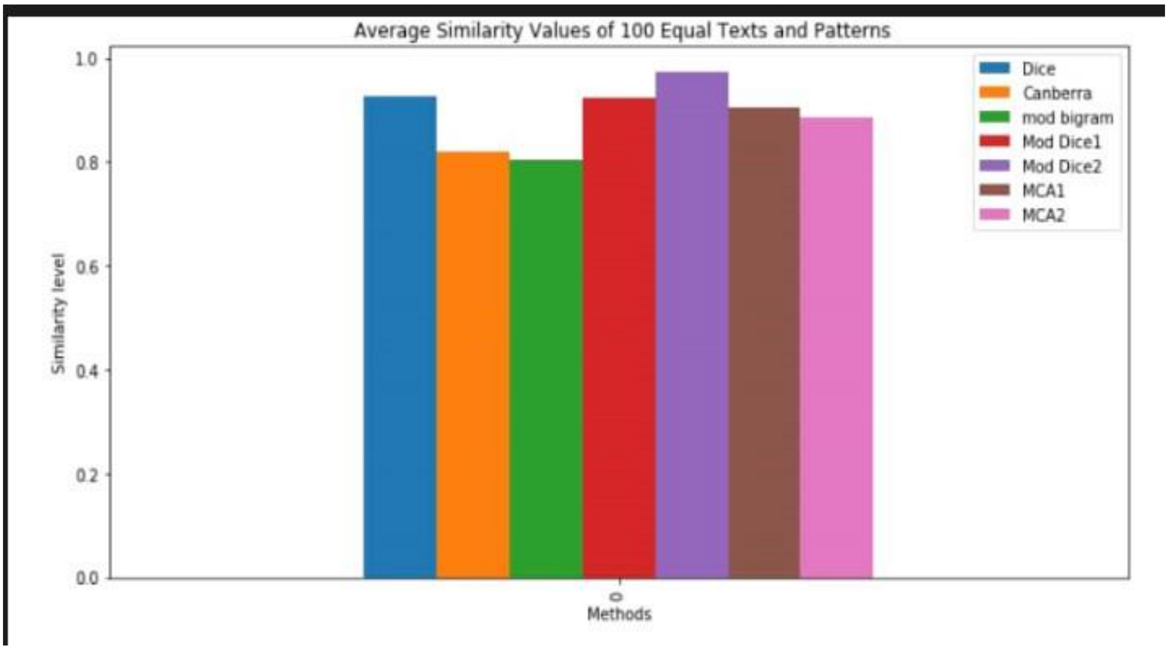


Fig.1. Average Similarity Measure of 100 Equal String Length of Text and Pattern Matching Using New and Old Methods

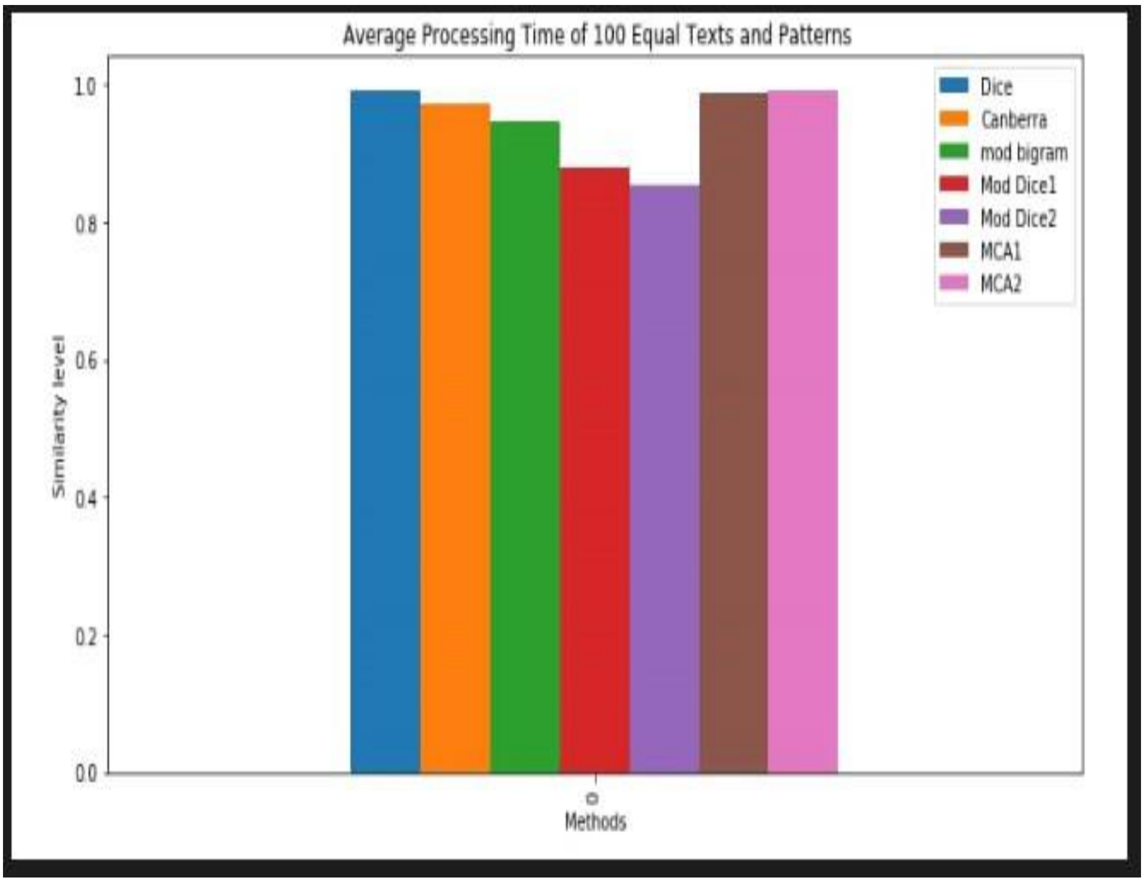


Fig. 2: Average Processing Time of 100 Sets of Equal String Length of Text and Pattern Matching Using New and Old Methods.

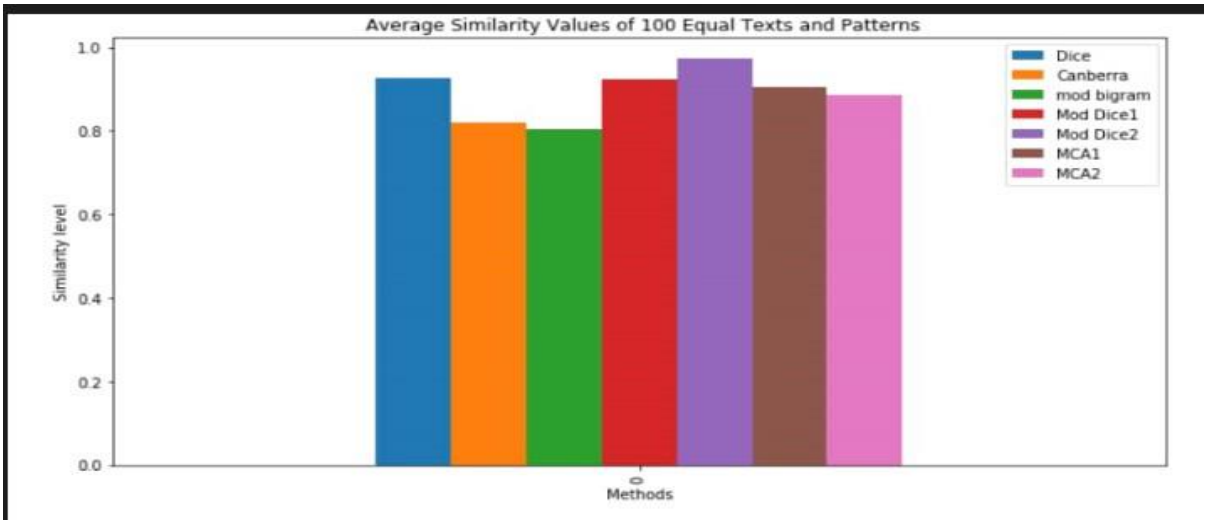


Fig. 3: Average Similarity Measure of 100 Unequal String Length of Text and Pattern Matching Using New and Old Methods

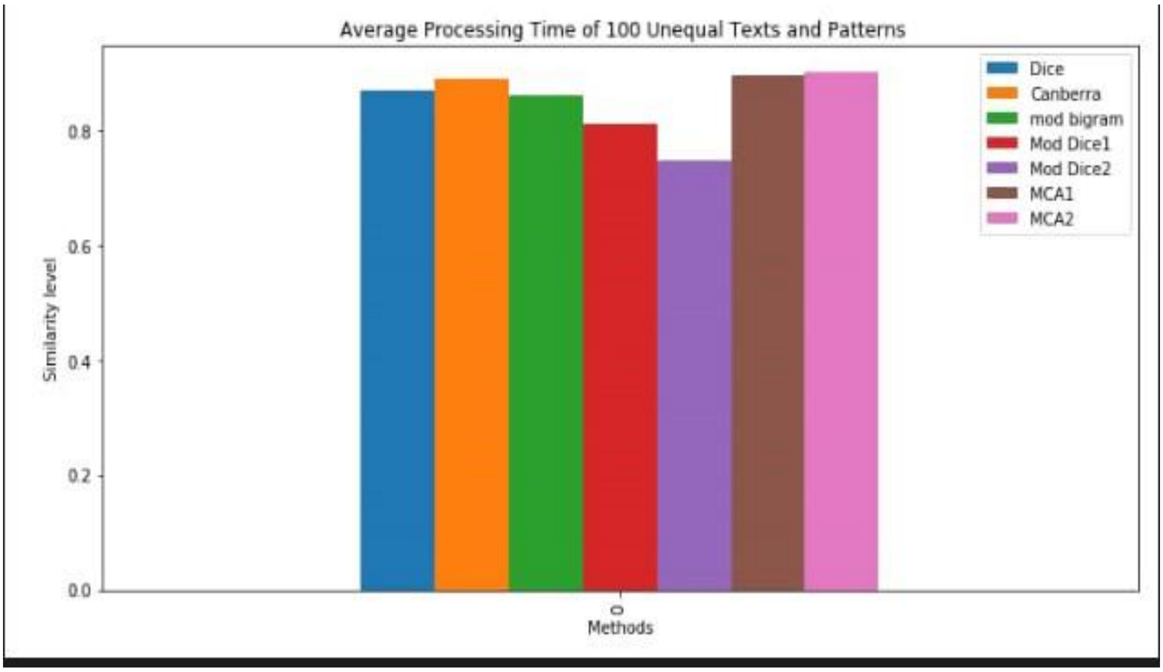


Fig. 4: Average Processing Time of 100 Sets of Unequal String Length of Text and Pattern

respectively. The lower value of root mean square error indicate better fit, hence, MD2 has the lowest RMSE of 0.017. This indicates that it has a better fit than other methods with higher RMSE.

Where x_i is predicted value and y_i is the expected value. On table 2 the last row shows the values of root mean square error (RMSQ) for each of the methods using equation 11. The predicted values for each method are the similarity values on table 4.5, while the expected value for a similarity value is the highest similarity value which is 1.

The experiment was conducted with 20, 50 and 100 sets of unequal length of text and pattern matching using new methods of MB_{IFS}, $MD1_{IFS}$, $MD2_{IFS}$, S_{MC1} and S_{MC2} with existing ones of Dice and Canberra. Considering 100 sets of unequal length of text and pattern matching

$$\text{Rootmeansquare error} = \sqrt{\sum_{i=1}^{n} \frac{(x_i - y_i)^2}{n}} \quad 11$$

3.2 Unequal Strings of Text and Pattern Matching

3.2.1 Experiment on conversion of unequal length of text and pattern to intuitionistic fuzzy value (IFV):

Text and Patterns were converted into IFV as indicated on table 4 using proposed methods for IFV by author in (Raji-Lawal et. al., 2020).

the average similarity values were computed. Figure 3 shows the average similarity measure of both existing and new methods. As indicated on figure 3 $MD2_{IFS}$ has the highest similarity values of 0.967,

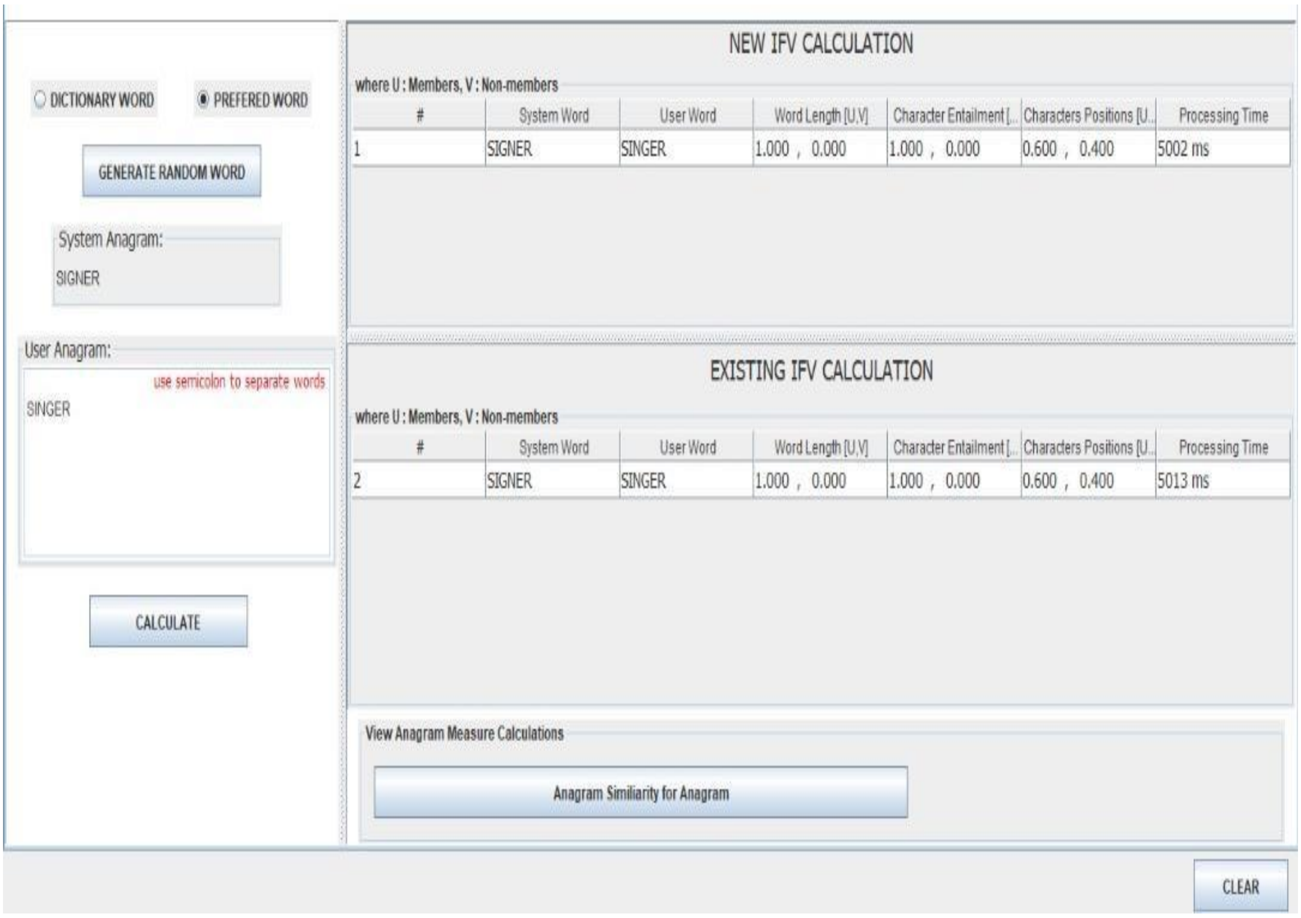


Fig. 5: Implementation of IFV of Equal Length Text and Pattern

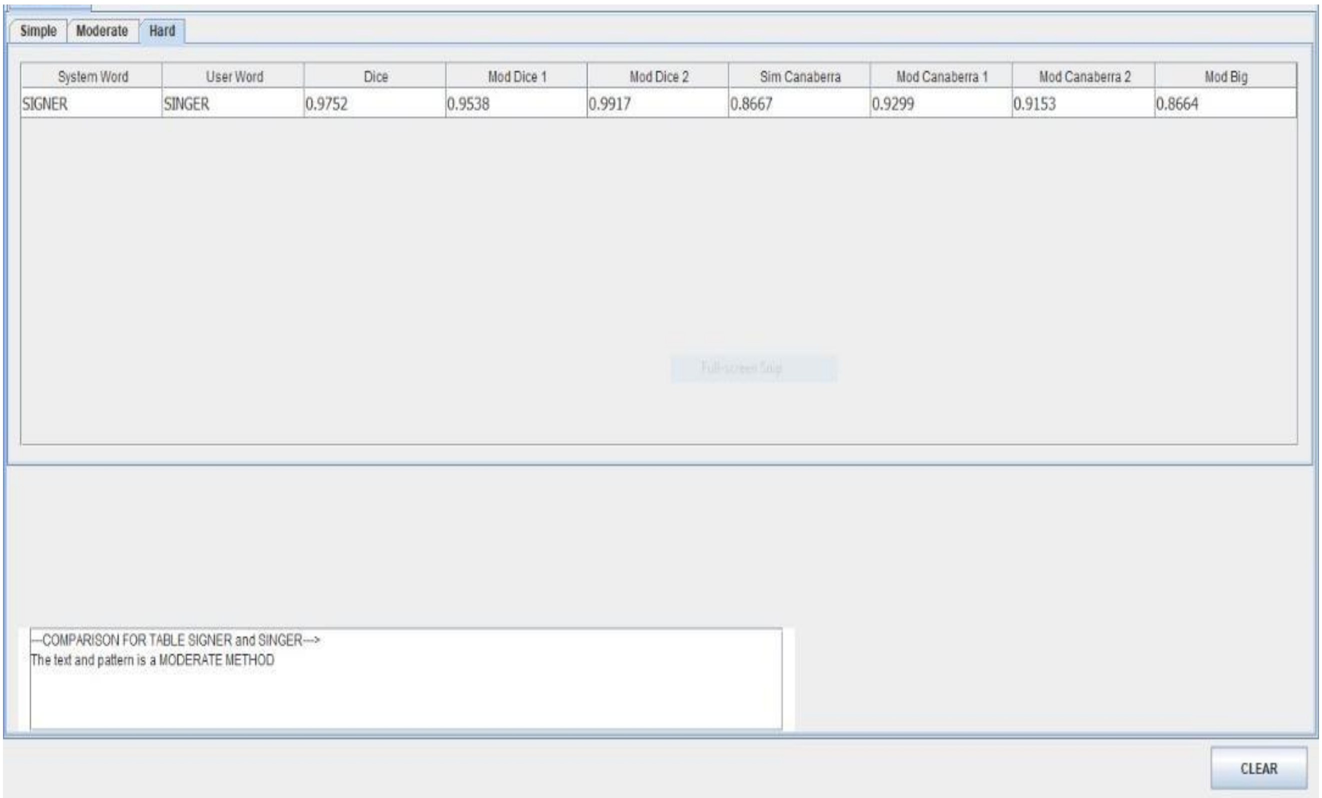
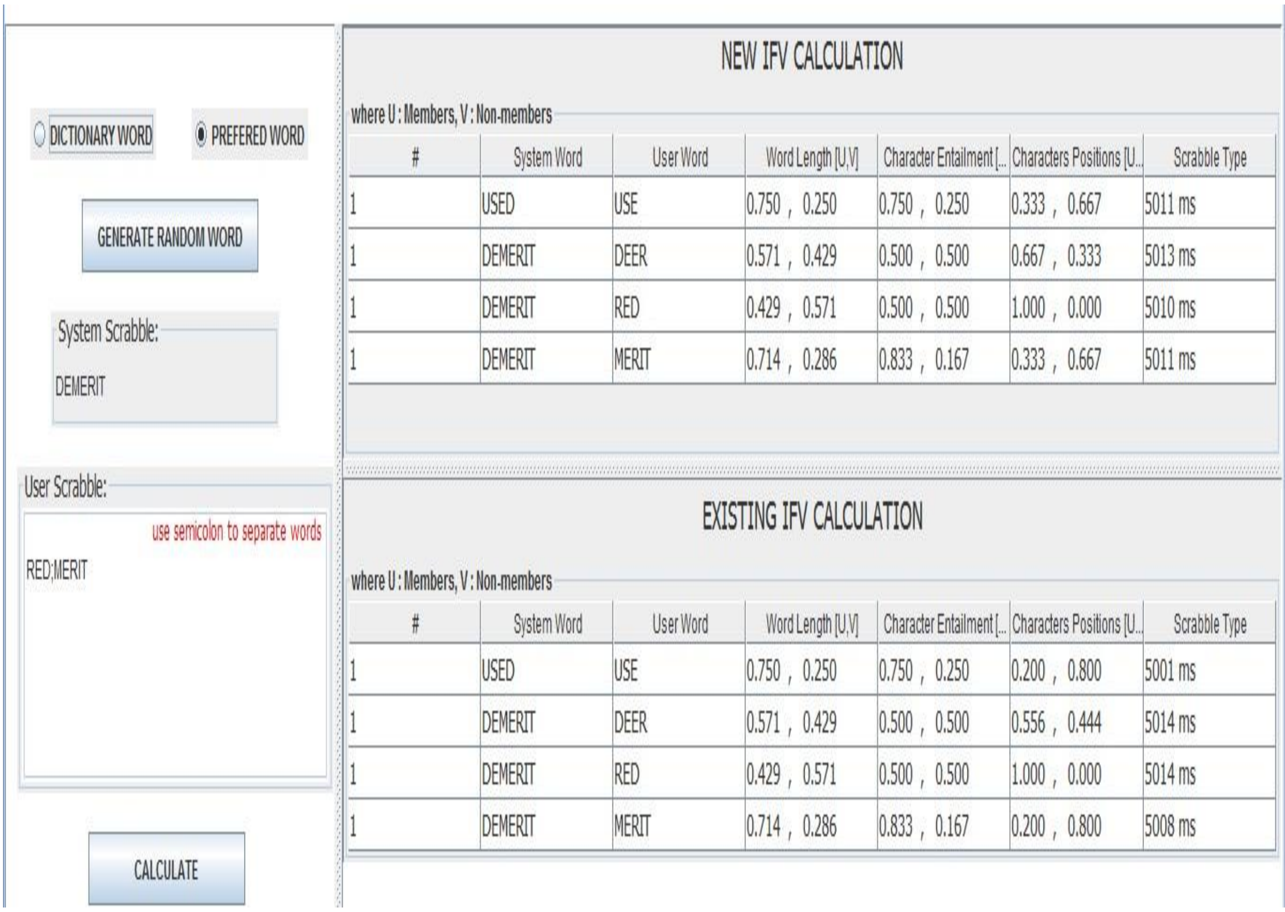


Fig. 6: Implementation of IFSM and Classification of Equal Length Text and Pattern



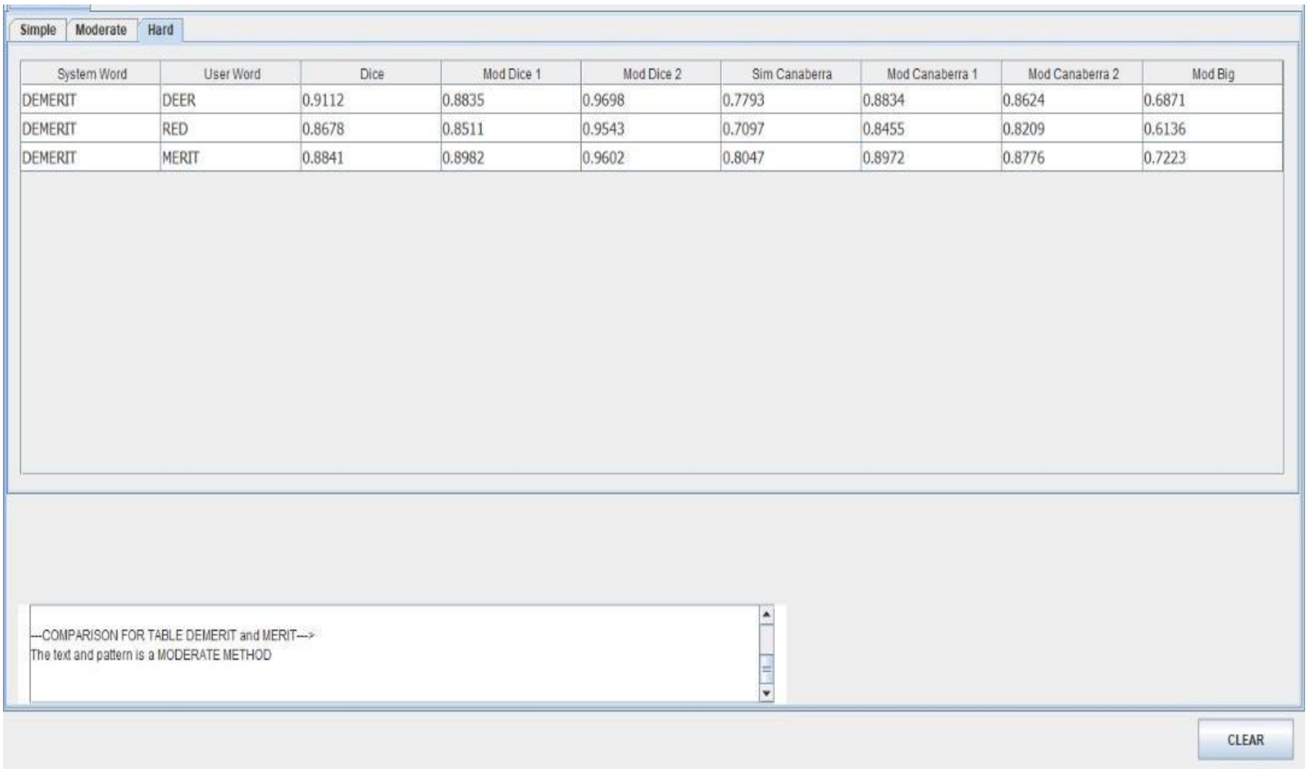
NEW IFV CALCULATION

#	System Word	User Word	Word Length [U,V]	Character Entailment [...	Characters Positions [U...	Scrabble Type
1	USED	USE	0.750 , 0.250	0.750 , 0.250	0.333 , 0.667	5011 ms
1	DEMERIT	DEER	0.571 , 0.429	0.500 , 0.500	0.667 , 0.333	5013 ms
1	DEMERIT	RED	0.429 , 0.571	0.500 , 0.500	1.000 , 0.000	5010 ms
1	DEMERIT	MERIT	0.714 , 0.286	0.833 , 0.167	0.333 , 0.667	5011 ms

EXISTING IFV CALCULATION

#	System Word	User Word	Word Length [U,V]	Character Entailment [...	Characters Positions [U...	Scrabble Type
1	USED	USE	0.750 , 0.250	0.750 , 0.250	0.200 , 0.800	5001 ms
1	DEMERIT	DEER	0.571 , 0.429	0.500 , 0.500	0.556 , 0.444	5014 ms
1	DEMERIT	RED	0.429 , 0.571	0.500 , 0.500	1.000 , 0.000	5014 ms
1	DEMERIT	MERIT	0.714 , 0.286	0.833 , 0.167	0.200 , 0.800	5008 ms

Fig. 7: Implementation of IFV of Unequal Length Text and Pattern



System Word	User Word	Dice	Mod Dice 1	Mod Dice 2	Sim Canaberra	Mod Canaberra 1	Mod Canaberra 2	Mod Big
DEMERIT	DEER	0.9112	0.8835	0.9698	0.7793	0.8834	0.8624	0.6871
DEMERIT	RED	0.8678	0.8511	0.9543	0.7097	0.8455	0.8209	0.6136
DEMERIT	MERIT	0.8841	0.8982	0.9602	0.8047	0.8972	0.8776	0.7223

Fig. 8: Implementation of IFSM and Classification of Unequal Length Text and Pattern

Table 1: Intuitionistic Fuzzy Similarity Sets for Pattern/Text(X,Y) with Equal Length

S/No.	Text/Pattern(X,Y)	IFV [jaccard, modified canbera, Dice] (Existing Method)	IFV [jaccard, modified canber Modified Bigram] (Propose Method)
A1	SIGNER/SINGER	[1.0,0.0][1.0,0.0][0.6,0.4]	[1.0,0.0][1.0,0.0][0.6,0.4]
A2	LEARNT/RENTAL	[1.0,0.0][1.0,0.0][0.8,0.2]	[1.0,0.0][1.0,0.0][0.8,0.2]
A3	GALLERY/REGALLY	[1.0,0.0][1.0,0.0][0.5,0.5]	[1.0,0.0][1.0,0.0][0.5,0.5]
A4	RESIGN/SIGNAL	[1.0,0.0][1.0,0.0][0.4,0.6]	[1.0,0.0][1.0,0.0][0.4,0.6]
A5	ANTLER/RENTAL	[1.0,0.0][1.0,0.0][0.8,0.2]	[1.0,0.0][1.0,0.0][0.8,0.2]
A6	BOARD/BROAD	[1.0,0.0][1.0,0.0][0.75,0.25]	[1.0,0.0][1.0,0.0][0.75,0.25]
A7	NAILS/SNAIL	[1.0,0.0][1.0,0.0][0.25,0.75]	[1.0,0.0][1.0,0.0][0.25,0.75]
A8	WEAN/ANEW	[1.0,0.0][1.0,0.0][0.66,0.33]	[1.0,0.0][1.0,0.0][0.66,0.33]
A9	DENTER/ RENTED	[1.0,0.0][1.0,0.0][0.4,0.6]	[1.0,0.0][1.0,0.0][0.4,0.6]
A10	DENTER/TENDER	[1.0,0.0][1.0,0.0][0.2,0.8]	[1.0,0.0][1.0,0.0][0.2,0.8]
A11	TRADERS/STARRED	[1.0,0.0][1.0,0.0][1.0,0.0]	[1.0,0.0][1.0,0.0][1.0,0.0]
A12	PLEASE/ELAPSE	[1.0,0.0][1.0,0.0][0.8,0.2]	[1.0,0.0][1.0,0.0][0.8,0.2]
A13	PLEASE/ASLEEP	[1.0,0.0][1.0,0.0][0.6,0.4]	[1.0,0.0][1.0,0.0][0.6,0.4]
A14	CASTERS/ACTRESS	[1.0,0.0][1.0,0.0][1.0,0.0]	[1.0,0.0][1.0,0.0][1.0,0.0]
A15	SUED/USED	[1.0,0.0][1.0,0.0][0.667,0.33]	[1.0,0.0][1.0,0.0][0.667,0.33]
A16	REWARD/REDRAW	[1.0,0.0][1.0,0.0][0.8,0.2]	[1.0,0.0][1.0,0.0][0.8,0.2]
A17	REWARD/DRAWER	[1.0,0.0][1.0,0.0][1.0,0.0]	[1.0,0.0][1.0,0.0][1.0,0.0]
A18	PRAISED/ASPIRED	[1.0,0.0][1.0,0.0][0.83,0.17]	[1.0,0.0][1.0,0.0][0.83,0.17]
A19	PRAISED/DESPAIRED	[1.0,0.0][1.0,0.0][0.83,0.17]	[1.0,0.0][1.0,0.0][0.83,0.17]
A20	WARDER/WARRED	[1.0,0.0][1.0,0.0][0.6,0.4]	[1.0,0.0][1.0,0.0][0.6,0.4]

Considering the experimental cases of 20, 50 and 100 sets of text and pattern matching of equal length of strings, averagely the similarity values are in decreasing order of MD2 > MD1 > S_{MC1}> S_{MC2} > Dice> MB > CA. MD2

3.2.2 Experiment on equal length of text and pattern matching for processing time:

The experiment was conducted with 100 sets of text and pattern matching using new methods of MB_{IFS}, $MD1_{IFS}$, $MD2_{IFS}$, S_{MC1} and S_{MC2} with existing ones of Dice and Canberra. The average processing times were computed. Figure 4 shows the average processing times of both existing and new methods for 100 sets of unequal string length of text and pattern matching. As indicated on figure 4 $MD2_{IFS}$ has the lowest processing time of 0.749ms, followed by MD1, MB, DICE, CA, S_{MC1} and S_{MC2} in ascending order with values 0.811ms, 0.861ms, 0.869ms, 0.889ms, 0.895ms and 0.902ms respectively. Considering the processing time experimental cases of 20, 50 and 100 sets of text and pattern matching of equal length of strings, averagely the processing time are in increasing order of MD2 > MD1 > MB > DICE > CA > S_{MC1}> S_{MC2}. The proposed method Modified Euclidean IFSM by authors in [13] research gave a less efficient processing time of 1.8754. Thus, MD2 is more efficient and hence an enhanced IFSM for dementia patients.

3.2.4 Classification of IFS with unequal length of string into type-1 linguistic term

The classification of type-1 linguistic term is done for simple as B1, moderate as B2 and hard as B3. The generated IFV as indicated in table 4 for each unequal length text and pattern matching is used to measure with respect to the set of thresholds to determine the value of hard, moderate and simple. The similarity values of all linguistic terms were compared to get the highest score which would determine the classification

is an enhanced intuitionistic fuzzy similarity measure for dementia patients. According to (Raji-Lawal et. al., 2020), Modified Euclidean IFSM was proposed, it has a less effective similarity value of 0.844.

category of text and pattern. The similarity values of all linguistic terms were depicted in table 5 while 6 shows the linguistic terms for each method in relative to their text and pattern matching. For example, table 6 shows the classification of IFS data set of A1: [0.57,0.43] [0.67,0.33] [0.67,0.33] representing text and pattern (largely/gear) which was passed into both new and existing methods to derive intuitionistic fuzzy similarity value. The new and old methods calculated the IFS between text A1 and patterns B1:[0.4,0.6][0.4,0.6][0.4,0. 6], B2:[0.6,0.4][0.6,0.4][0.6,0.4] and B3:[0.8,0.2][0.8,0.2] [0.8,0.2] which represent simple, moderate and hard respectively. The similarity values of MD2(A1,B1) is 0.997756, MD2(A1,B2) is 0.983976 and MD2(A1,B3) is 0.932634,. The other values for each method were stated in table 5. The text and pattern of A1 is classified into linguistic term as B2 which indicates moderate as shown in table 6. The same process is applicable to other methods as illustrated in table 6.

3.2.6 Evaluation of methods with unequal length of string using root mean square error

The root means square error (RMSE) of average similarity values of text and pattern with unequal length for proposed methods MB_{IFS}, $MD1_{IFS}$, $MD2_{IFS}$, S_{MC1} and S_{MC2} with existing ones of Dice and Canberra were evaluated using equation 11. MD2 has the lowest root mean square error value of 0.04, followed by Dice, MD1, S_{MC1}, S_{MC2}, CA and MB with the values of 0.1, 0.1, 0.1, 0.1, 0.2 and 0.3 respectively. The lower value of root mean square error indicates a better fit. MD2 has the lowest RMSQ of 0.04 which indicates that it has a better fit than other methods with higher RMSQ

Table 2: IFSM Values of Equal Words X,Y IFSs with Respect to B1, B2 and B3

			Equal Strings(Anagram)				
	EXISTING METHODS		PROPOSED METHODS				
S/NO.	Dice	Canbera	MD1	MD2	Mod. CA1	Mod. CA2	MB
(A1,B1)	0.974359	0.866667	0.957657	0.991379	0.929294	0.91446	0.878274
(A1,B2)	0.991453	0.933333	0.982794	0.997143	0.964764	0.956466	0.949264
(A1,B3)	0.975207	0.866667	0.953312	0.991666	0.929294	0.91446	0.866373
(A2,B1)	0.92562	0.8	0.920068	0.974565	0.893466	0.873581	0.77886
(A2,B2)	0.975207	0.866667	0.953312	0.991666	0.929294	0.91446	0.866373
(A2,B3)	0.992	0.933333	0.975937	0.997326	0.964764	0.956466	0.929535
(A3,B1)	0.987125	0.9	0.974411	0.99569	0.947066	0.935298	0.925181
(A3,B2)	0.987125	0.9	0.971941	0.99569	0.947066	0.935298	0.918164
(A3,B3)	0.954357	0.833333	0.938212	0.984548	0.911433	0.893904	0.825853
(A4,B1)	0.991453	0.933333	0.989313	0.997143	0.964764	0.956466	0.968281
(A4,B2)	0.974359	0.866667	0.957657	0.991379	0.929294	0.91446	0.878274
(A4,B3)	0.92562	0.8	0.920068	0.974565	0.893466	0.873581	0.77886
(A5,B1)	0.92562	0.8	0.920068	0.974565	0.893466	0.873581	0.77886
(A5,B2)	0.975207	0.866667	0.953312	0.991666	0.929294	0.91446	0.866373
(A5,B3)	0.992	0.933333	0.975937	0.997326	0.964764	0.956466	0.929535
(A6,B1)	0.940439	0.816667	0.929863	0.979739	0.902464	0.883716	0.804002
(A6,B2)	0.982236	0.883333	0.961167	0.994043	0.93819	0.924841	0.887965
(A6,B3)	0.9909	0.916667	0.971062	0.996957	0.955923	0.945837	0.915674
(A7,B1)	0.982236	0.883333	0.966631	0.994043	0.93819	0.924841	0.903195
(A7,B2)	0.940439	0.816667	0.92949	0.979739	0.902464	0.883716	0.803034
(A7,B3)	0.869565	0.75	0.8869	0.954481	0.866269	0.843433	0.697627
(A8,B1)	0.961633	0.844741	0.946035	0.987044	0.917557	0.90091	0.846684
(A8,B2)	0.989691	0.911519	0.973981	0.996552	0.953189	0.942573	0.923956
(A8,B3)	0.984274	0.888147	0.96118	0.99473	0.940756	0.927853	0.888003
(A9,B1)	0.991453	0.933333	0.989313	0.996425	0.964764	0.956466	0.968281
(A9,B2)	0.974359	0.866667	0.957657	0.985682	0.929294	0.91446	0.878274
(A9,B3)	0.92562	0.8	0.920068	0.972613	0.893466	0.873581	0.77886
(A10,B1)	0.975207	0.866667	0.957074	0.985482	0.929294	0.91446	0.876672
(A10,B2)	0.92562	0.8	0.918368	0.972013	0.893466	0.873581	0.774551
(A10,B3)	0.848	0.733333	0.874314	0.956216	0.857128	0.83345	0.668348
(A11,B1)	0.852713	0.733333	0.879302	0.958031	0.857128	0.83345	0.679852
(A11,B2)	0.930233	0.8	0.919812	0.972523	0.893466	0.873581	0.77821
(A11,B3)	0.977444	0.866667	0.950472	0.98321	0.929294	0.91446	0.858653
(A12,B1)	0.92562	0.8	0.920068	0.972613	0.893466	0.873581	0.77886
(A12,B2)	0.975207	0.866667	0.953312	0.984189	0.929294	0.91446	0.866373
(A12,B3)	0.992	0.933333	0.975937	0.991914	0.964764	0.956466	0.929535
(A13,B1)	0.974359	0.866667	0.957657	0.985682	0.929294	0.91446	0.878274
(A13,B2)	0.991453	0.933333	0.982794	0.994231	0.964764	0.956466	0.949264
(A13,B3)	0.975207	0.866667	0.953312	0.984189	0.929294	0.91446	0.866373
(A14,B1)	0.852713	0.733333	0.879302	0.958031	0.857128	0.83345	0.679852
(A14,B2)	0.930233	0.8	0.919812	0.972523	0.893466	0.873581	0.77821
(A14,B3)	0.977444	0.866667	0.950472	0.98321	0.929294	0.91446	0.858653

(A15,B1)	0.961284	0.844333	0.945581	0.981521	0.917338	0.900659	0.845466
(A15,B2)	0.989614	0.911	0.973539	0.991101	0.952914	0.942244	0.922698
(A15,B3)	0.98454	0.889	0.961892	0.987132	0.94121	0.928387	0.889976
(A16,B1)	0.92562	0.8	0.920068	0.972613	0.893466	0.873581	0.77886
(A16,B2)	0.975207	0.866667	0.953312	0.984189	0.929294	0.91446	0.866373
(A16,B3)	0.992	0.933333	0.975937	0.991914	0.964764	0.956466	0.929535
(A17,B1)	0.852713	0.733333	0.879302	0.958031	0.857128	0.83345	0.679852
(A17,B2)	0.930233	0.8	0.919812	0.972523	0.893466	0.873581	0.77821
(A17,B3)	0.977444	0.866667	0.950472	0.98321	0.929294	0.91446	0.858653
(A18,B1)	0.914995	0.789	0.913493	0.97029	0.887509	0.866917	0.762281
(A18,B2)	0.969565	0.855667	0.947989	0.982353	0.923411	0.907648	0.851942
(A18,B3)	0.991634	0.922333	0.972027	0.990587	0.958931	0.949441	0.918406
(A19,B1)	0.914995	0.789	0.913493	0.97029	0.887509	0.866917	0.762281
(A19,B2)	0.969565	0.855667	0.947989	0.982353	0.923411	0.907648	0.851942
(A19,B3)	0.991634	0.922333	0.972027	0.990587	0.958931	0.949441	0.918406
(A20,B1)	0.974359	0.866667	0.957657	0.985682	0.929294	0.91446	0.878274
(A20,B2)	0.991453	0.933333	0.982794	0.994231	0.964764	0.956466	0.949264
(A20,B3)	0.975207	0.866667	0.953312	0.984189	0.929294	0.91446	0.866373
AVG	0.957751	0.855379	0.946167	0.98342	0.923108	0.907845	0.849401
RMSQ	0.042	0.145	0.054	0.017	0.077	0.092	0.151

Table 3: Classification of Equal Word IFS into B1: Simple or B2: Moderate or B3: Hard

	Existing Methods		Proposed Methods				
	Dice	CA	MD1	MD2	S_{MCA1}	S_{MCA2}	MB
A1	B2	B2	B2	B2	B2	B2	B2
A2	B3	B3	B3	B3	B3	B3	B3
A3	B1	B1	B1	B1	B1	B1	B1
A4	B3	B3	B3	B3	B3	B3	B3
A5	B2	B2	B2	B2	B2	B2	B2
A6	B2	B2	B2	B2	B2	B2	B2
A7	B1	B1	B1	B1	B1	B1	B1
A8	B2	B2	B2	B2	B2	B2	B2
A9	B1	B1	B1	B1	B1	B1	B1
A10	B1	B1	B1	B1	B1	B1	B1
A11	B3	B3	B3	B3	B3	B3	B3
A12	B3	B3	B3	B3	B3	B3	B3
A13	B2	B2	B2	B2	B2	B2	B2
A14	B3	B3	B3	B3	B3	B3	B3
A15	B2	B2	B2	B2	B2	B2	B2
A16	B3	B3	B3	B3	B3	B3	B3
A17	B3	B3	B3	B3	B3	B3	B3
A18	B3	B3	B3	B3	B3	B3	B3
A19	B3	B3	B3	B3	B3	B3	B3
A20	B2	B2	B2	B2	B2	B2	B2

Table 4: Evaluation of IFSs from Given and Patients Unequal Words X and Y

S/No	Pattern/Text	IFV [jaccard, modified canbera, modified bigram] (Proposed Method)	IFV [jaccard, modified canbera, dice] (Existing Method)
A1	LARGELY/GEAR	[0.57,0.43][0.67,0.33][0.67,0.33]	[0.57,0.43][0.67,0.33][0.56,0.44]
A 2	GALLERY/REAL	[0.57,0.43][0.667,0.333][0.833,0.167]	[0.57,0.43][0.667,0.333][0.78,0.22]
A 3	ANTLER/LATER	[0.83,0.167][0.83,0.167][0.8,0.2]	[0.83,0.167][0.83,0.167][0.78,0.22]
A 4	ANTLER/RENT	[0.667,0.333][0.667,0.333][0.8,0.2]	[0.667,0.333][0.667,0.333][0.75,0.25]
A 5	RENTAL/TEN	[0.5,0.5][0.5,0.5][0.8,0.2]	[0.5,0.5][0.5,0.5][0.714,0.286]
A 6	RENTAL/NET	[0.5,0.5][0.5,0.5][1.0,0.0]	[0.5,0.5][0.5,0.5][1.0,0.0]
A 7	RENTAL/RENT	[0.67,0.33][0.67,0.33][0.4,0.6]	[0.67,0.33][0.67,0.33][0.25,0.75]
A 8	GALLERY/GALL	[0.57,0.43][0.5,0.5][0.5,0.5]	[0.57,0.43][0.5,0.5][0.33,0.67]
A 9	GALLERY/ALL	[0.43,0.57][0.33,0.67][0.67,0.33]	[0.43,0.57][0.33,0.67][0.50,0.50]
A 10	BROAD/ROAD	[0.80,0.20][0.80,0.20][0.25,0.75]	[0.80,0.20][0.80,0.20][0.75,0.25]
A 11	LARGELY/LAY	[0.43,0.57][0.50,0.50][0.83,0.17]	[0.43,0.57][0.50,0.50][0.75,0.25]
A 12	NAILS/NAIL	[0.8,0.2][0.8,0.2][0.25,0.75]	[0.8,0.2][0.8,0.2][0.14,0.86]
A 13	ACRE/ACE	[0.75,0.25][0.75,0.25][0.67,0.33]	[0.75,0.25][0.75,0.25][0.60,0.40]
A 14	ALTER/TAR	[0.6,0.4][0.6,0.4][1.0,0.0]	[0.6,0.4][0.6,0.4][1.0,0.0]
A15	DARTERS/RATER	[0.71,0.29][0.67,0.33][0.67,0.33]	[0.71,0.29][0.67,0.33][0.6,0.4]
A16	LAMENT/L AME	[0.67,0.33][0.67,0.33][0.4,0.6]	[0.67,0.33][0.67,0.33][0.25,0.75]
A17	DESPAIR/PAID	[0.57,0.43][0.57,0.43][0.67,0.33]	[0.57,0.43][0.57,0.43][0.56,0.44]
A18	SHEAR/SHARE	[1.0,0.00][1.00,0.0][0.5,0.5]	[1.0,0.00][1.00,0.0][0.5,0.5]
A19	TRADERS/DEAR	[0.57,0.43][0.67,0.33][0.83,0.17]	[0.57,0.43][0.67,0.33][0.78,0.22]
A20	TRADERS/REAR	[0.57,0.43][0.50,0.50][1.0,0.0]	[0.57,0.43][0.50,0.50][1.0,0.0]

Table 5: IFSM Values of IFSs with Respect to B1, B2, B3 for Unequal Strings

S/No.	Existing Methods		Proposed Methods				
	Dice	CA	MD1	MD2	MCA1	MCA2	MB
(A1,B1)	0.993282	0.943333	0.982765	0.997756	0.970062	0.962888	0.949181
(A1,B2)	0.952693	0.836667	0.918976	0.983976	0.913224	0.895948	0.776091
(A1,B3)	0.811212	0.676667	0.816453	0.932634	0.825703	0.799654	0.544245
(A2,B1)	0.828116	0.71	0.832792	0.939068	0.844256	0.819514	0.577577
(A2,B2)	0.964343	0.89	0.9458	0.98797	0.941743	0.929014	0.846055
(A2,B3)	0.962544	0.868	0.931678	0.987356	0.930007	0.915288	0.808718
(A3,B1)	0.710152	0.578579	0.761512	0.892176	0.769689	0.741105	0.441601
(A3,B2)	0.919866	0.778779	0.88937	0.972542	0.881962	0.860743	0.703472
(A3,B3)	0.999042	0.978979	0.995069	0.999681	0.988908	0.986082	0.985279
(A4,B1)	0.81944	0.688667	0.822735	0.935777	0.832406	0.806799	0.556903
(A4,B2)	0.970773	0.888667	0.947285	0.990161	0.941032	0.928179	0.850046
(A4,B3)	0.981533	0.911333	0.956354	0.993806	0.953091	0.942455	0.874695
(A5,B1)	0.888889	0.8	0.885207	0.9615	0.893466	0.87358	0.693642
(A5,B2)	0.962963	0.866667	0.932481	0.987499	0.929294	0.91446	0.810811
(A5,B3)	0.903226	0.8	0.884478	0.966642	0.893466	0.87358	0.691928
(A6,B1)	0.786517	0.733333	0.831413	0.923073	0.857128	0.83345	0.574713
(A6,B2)	0.898876	0.8	0.888126	0.965087	0.893466	0.87358	0.700525
(A6,B3)	0.891089	0.733333	0.864291	0.962292	0.857128	0.83345	0.645624
(A7,B1)	0.90875	0.82	0.899694	0.968608	0.90426	0.885749	0.728258
(A7,B2)	0.968832	0.886667	0.952063	0.989501	0.939967	0.926926	0.862972
(A7,B3)	0.894548	0.78	0.887246	0.963536	0.882625	0.861479	0.698445
(A8,B1)	0.968141	0.876667	0.944992	0.989266	0.934634	0.92068	0.843887
(A8,B2)	0.986383	0.923333	0.973725	0.99544	0.959461	0.950078	0.923227
(A8,B3)	0.868781	0.723333	0.853526	0.954194	0.851622	0.827473	0.621799
(A9,B1)	0.950587	0.876667	0.940708	0.98325	0.934634	0.92068	0.832463
(A9,B2)	0.933007	0.83	0.904716	0.977151	0.909642	0.891861	0.740519

(A9,B3)	0.795548	0.676667	0.811357	0.926592	0.825703	0.799654	0.534117
(A10,B1)	0.80677	0.683333	0.821234	0.930929	0.82943	0.803623	0.553861
(A10,B2)	0.885755	0.75	0.870282	0.960368	0.866269	0.843433	0.659145
(A10,B3)	0.849689	0.816667	0.890461	0.947153	0.902464	0.883716	0.706065
(A11,B1)	0.880886	0.813333	0.889163	0.958605	0.900667	0.881685	0.702981
(A11,B2)	0.944154	0.833333	0.911734	0.981027	0.911433	0.893904	0.757887
(A11,B3)	0.879074	0.766667	0.865774	0.957948	0.875371	0.853445	0.648954
(A12,B1)	0.890312	0.763333	0.869283	0.962013	0.873554	0.85144	0.656877
(A12,B2)	0.80677	0.683333	0.821234	0.930929	0.82943	0.803623	0.553861
(A12,B3)	0.885755	0.75	0.870282	0.960368	0.866269	0.843433	0.659145
(A13,B1)	0.849689	0.816667	0.890461	0.947153	0.902464	0.883716	0.706065
(A13,B2)	0.970366	0.876667	0.9415	0.990023	0.934634	0.92068	0.834568
(A13,B3)	0.988617	0.923333	0.970474	0.996191	0.959461	0.950078	0.914011
(A14,B1)	0.755556	0.666667	0.800025	0.910798	0.820095	0.793701	0.512048
(A14,B2)	0.911111	0.866667	0.920307	0.969446	0.929294	0.91446	0.779468
(A14,B3)	0.941176	0.8	0.902952	0.979995	0.893466	0.87358	0.736196
(A15,B1)	0.852183	0.717333	0.841231	0.948079	0.848311	0.82389	0.595314
(A15,B2)	0.986532	0.921444	0.966367	0.99549	0.958459	0.948875	0.902458
(A15,B3)	0.977145	0.887161	0.94755	0.992323	0.94023	0.927236	0.850759
(A16,B1)	0.910653	0.79595	0.901152	0.969284	0.891274	0.871125	0.731804
(A16,B2)	0.969308	0.872373	0.95324	0.989663	0.932342	0.918006	0.866177
(A16,B3)	0.893572	0.74551	0.886099	0.963185	0.863811	0.840741	0.69574
(A17,B1)	0.917236	0.787731	0.891038	0.971614	0.886821	0.86615	0.707438
(A17,B2)	0.996064	0.956431	0.992604	0.998686	0.976993	0.971354	0.977976
(A17,B3)	0.932205	0.794005	0.89831	0.976871	0.890221	0.869946	0.724901
(A18,B1)	0.640394	0.595583	0.741707	0.861951	0.779577	0.751303	0.408035
(A18,B2)	0.837438	0.720019	0.846263	0.942579	0.849794	0.825493	0.606061
(A18,B3)	0.92511	0.782237	0.903745	0.974386	0.88384	0.86283	0.738137
(A19,B1)	0.827927	0.656478	0.83262	0.938997	0.81436	0.787635	0.57722
(A19,B2)	0.964381	0.870243	0.945981	0.987983	0.931205	0.916681	0.846541
(A19,B3)	0.962787	0.844212	0.931896	0.987439	0.917273	0.900585	0.809287
(A20,B1)	0.776341	0.656478	0.820146	0.919075	0.81436	0.787635	0.551663
(A20,B2)	0.904293	0.791363	0.899489	0.967022	0.88879	0.868347	0.727759
(A20,B3)	0.909908	0.712483	0.878036	0.969019	0.84563	0.820995	0.676919
AVG	0.899138	0.796556	0.892791	0.964385	0.891103	0.872128	0.719868
RMSQ	0.1	0.2	0.1	0.04	0.1	0.1	0.3

character entailment and character permutation using both existing and new methods.
Figure 5 shows the computation of randomly generated text with user input using both new and existing methods. Figure 6 illustrates how randomly generated text with user input using both new and existing methods. Figure 6 illustrates how randomly generated text and user's pattern are transformed into type-1 linguistic variable of hard, moderate and simple. For example, signer was generated by the system and the user formed singer. The type-1 linguistic variable of signer/singer was classified as moderate, which is displayed on figure 6.

Figures 7 and 8 illustrate how randomly generated text and user's pattern of unequal string length are transformed into linguistic term of hard, moderate and simple. For example, the randomly generated word is DEMERIT while user's pattern is RED and the linguistic term is moderate as indicated in figure 6. The implementation code for the developed system is under the appendix. This could be applied to cognition measure in dementia patients. The practical implication

Table 6: Classification of Unequal Word IFS into B1: Simple or B2: Moderate or B3: Hard

	Existing Methods		Proposed Methods				
	Dice	CA	MD1	MD2	S_{MCA1}	S_{MCA2}	MB
A1	B2	B2	B2	B2	B2	B2	B2
A2	B2	B2	B2	B2	B2	B2	B2
A3	B3	B3	B3	B3	B3	B3	B3
A4	B3	B3	B3	B3	B3	B3	B3
A5	B2	B2	B2	B2	B2	B2	B2
A6	B2	B2	B2	B2	B2	B2	B2
A7	B2	B2	B2	B2	B2	B2	B2
A8	B2	B2	B2	B2	B2	B2	B2
A9	B1	B1	B1	B1	B1	B1	B1
A10	B2	B2	B2	B2	B2	B2	B2
A11	B2	B2	B2	B2	B2	B2	B2
A12	B2	B3	B3	B2	B3	B3	B3
A13	B3	B3	B3	B3	B3	B3	B3
A14	B3	B2	B2	B3	B2	B2	B2
A15	B2	B2	B2	B2	B2	B2	B2
A16	B2	B2	B2	B2	B2	B2	B2
A17	B2	B2	B2	B2	B2	B2	B2
A18	B3	B3	B3	B3	B3	B3	B3
A19	B2	B2	B2	B2	B2	B2	B2
A20	B3	B2	B2	B2	B2	B2	B2

of this is that the methods will be able to measure and detect patients' cognition level. This will hence specify if the patient is not demented, mildly, moderately or strongly dement. The conditions will be specified by using the adopted linguistic variables. In case the result of text randomly generated by the computer and pattern supplied by the patient / user is simple which means the patient is responding to treatment. The classification of the results into moderate or high of randomly generated text and patient pattern implies that the patient is recovering or alright.

4.0 Conclusion

This research explored several IFSM in terms of their application areas, strength and weaknesses. Research shows that there are many intuitionistic fuzzy similarity measures, but there is still quest for more effective ones. Applications of IFSM to psychology domain are in phases. The first phase converts text and pattern of strings from given and patient's word to intuitionistic fuzzy set using the proposed similarity measures. The deduced set is classified with type-1 intuitionistic fuzzy set using Evans's calibration. This classification is done using intuitionistic fuzzy similarity measures. Five methods of modified Dice1, modified Dice2, modified Canberra1, modified Canberra2 and modified bigram were derived from existing methods. Experiments were performed on these modified methods and the result showed that modified Dice2 is the most effective by generating the highest similarity value, most efficient by generating the lowest processing time and best fit by generating the lowest root mean square error. The method was used for classification of text and pattern matching into type-1 lingustic variable of low, moderate and high.

This research is constrained to type-1 linguistic variable due to time frame, also the only fuzzy and intuitionistic fuzzy similarity measures were explored. Other measures like neutrosophic, inter-value similarity measures and others can be explored for more efficient cognition detection in dement patients.The study reveals interesting features of various types of set, characteristic features and linguistic variable properties. Suggestions for further research works are to modify other existing similarity measures and convert them into intuitionistic fuzzy similarity measures.

Also, a type-1 linguistic variable could be extended into type-2 or 3 for more intensive results.

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6.0 Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

7.0 Authors Contribution

Raji-Lawal H.Y. developed the concept, designed and implemented the research. Akinwale A.T. supervised the execution of the research, Ishola P.E, Oloyede A and Ajagbe T reviewed some literatures

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