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Mapping Love: A Heptapartitioned Neutrosophic Machine Learning Study of University Students' Romantic Sensations

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Abstract. This paper introduces the novel concept of single valued heptapartitioned neutrosophic sets (SVHNSs) which is the generalized version of the neutrosophic sets. This set consists of seven membership functions which are more sensitive to real-world problems. Membership functions are defined as an absolute true, relative true, absolute false, relative false, contradiction, unknown (undefined) and ignorance respectively. This scenario of indeterminacy provides a better accuracy. Moreover, several properties of this set are also addressed. This study focuses on the romantic sensations experienced by young boys and girls in a variety of contexts. The data set supporting this study comprises individuals aged 18-25, with data collected from the Psychology Department at Peshawar University, Pakistan. This data was critically analyzed using the Single-Valued Heptapartitioned Neutrosophic Set (SVHNS). For a real-world application involving the romantic feelings of young individuals across various dimensions, machine learning and graphical algorithms such as Encrypted K-Means Clustering, Encrypted K-Means Clustering Heat Map, Encrypted Elbow Method, Decrypted K-Means Clustering, Encrypted Correlation Matrix, and Decrypted Correlation Matrix were applied and visualized. These algorithms assist in examining and developing relationships among various factors that influence the romantic feelings of young men and women. The proposed techniques offer new dimensions not only for psychological studies in general but also specifically for understanding emotional disorders and breakups in romantic relationships among university students.

2020 Mathematics Subject Classifications: 68T05, 03E72, 62H30, 91F20

Key Words and Phrases: Neutrosophic Set, Single Valued Heptapartitioned Neutrosophic Set (SVHNS), Distance Measures, K-Means Algorithm, Machine Learning Techniques, Applications of SVHNS

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1. Introduction

Fuzzy set theory (FST) was for the first time established by computer scientist Zadeh in the year of 1965 in [1]. After that, an ample of theoretical achievement in a related topic was explored. Sine FST has flexible boundaries so it can be installed in a number of real-world problems that has got uncertainty. When the domain of study is wide then in that case FST can be applied but very carefully because chances of errors swelled up. To control such pieces of errors interval valued FST was initiated in [2]. The extension of FST was made in [3] by introducing a novel concept of intuitionistic fuzzy set theory (IFST). The beauty of IFST lies in fact that it governs the incomplete information by its truth and false candidature-ship values. This theory has one serious drawback which is that it cannot afford the existence of indeterminate data. This gap was unbridged for a piece of time but finally a strong researcher Smarandache [4] filled in this gap by introducing extremely a new theory which is known as neutrosophic set theory (NST).One effective mathematical paradigm for handling partial, ambiguous, uncertain, or confusing data is (NST). The generalization of IFST was made to NST in [5] and the authors developed number of examples for better understanding the situation. Single valued NST was addressed in [6] and in continuation, complex NST was studied in [7]. Soft set theory (SST) was initiated for the first time by polished researcher Molodtsov in [8]. This theory is actually generalization of FST. This is used to reduce the error that exists in the mathematical problems that can be handled by FST and IFST. This theory uses the concept of decision variables and these variables can be connected with the power set of the CST. The key point of this theory is that it does not demand grade of membership as in FST while studying the data in between the lines. Since the inception of this theory up to date, number of attempts is made. The combination of FST with SST was made in [9] and a new theory was given birth and is known as fuzzy soft set theory (FSST). The authors presented examples for clear understanding the notion. The study was stretched and the notion of vague soft set theory (VSST) in [10] was explored with the explanation of examples. For clear understanding the notion of IVVSST was installed in [11-13]. The notion of SEST was studied in [14]. The idea of SMST was reflected in [15]. It was noted and studied that FSST was lacking of false and impermanency possible state of problems and so this gap was bridged in [16] and new theory sprung off with the name NSST. The authors defined the basic operations, operators and established the basic results. Examples were also generated for almost all results for clear understanding. Since the inception to date NSST has got big attention of the researchers because it is used in every walk of life keeping in view this the authors made further study on NSST in [17-24]. SST was engaged with other theories in [25,26]. All the basic operations and operators are also defined and addressed on the behest of these said theories. The n-valued refined NSST was studied in [27] and complex NSEST was studied in [28.29]. The time-NSS was installed in [30]. The authors provided examples for explanation of this new idea. Much more study was made in [31-36] on NSST and its engagements with number of operators namely aggregation and dombi weighted etc. These operators are effective techniques to handle NSST. The Q- FSST and multi Q-FSST were addressed in [37,38]. The notion of Q-IFSST and its basic were given in [39]. Finally, the notion of Q-NSST was studied in [40]. The similarity measures etc. were discussed in [41-46].

1.1. Literature review

The more generalization and refinement of NST was addressed in [47] while introducing extremely a new theory which is known as quadripartitioned NST. On the basis of this concept, basic operations were introduced and better examples were installed to understand it. The authors, actually divided the indeterminacy that happened in [4] into two parts which are named as contradiction and ignorance. The authors also proposed the definitions of distance, similarity measure (SM) and entropy. Finally, applications of the proposed situation are used in problems concerning pattern recognition etc. quadripartitioned NST was further generliased excellently into pentapartitioned NST, in this case the indeterminacy was stretched in [48] into three possibilities i.e. contradiction, unknown and ignorance. Then on the basis of this novel idea, basic operations and related results were studied and examples were established for almost all results. In continuation, further it was stretched in to heptapartitioned NST in [49]. The authors also discussed the basic results and properties. Since polarity makes big contribution in the field of science and since the inception of refined NST no touch had been given so in this direction the first attempt was made in [50] and introduced the notion of QSVBNST. The authors addressed some practical problems that are used in day to day life while using the notion of distance approach. The study of imaginative play in children was beautifully addressed in [51] and since imaginative play involves a lot of imaginary elements, the research of imaginative pretend play in children aged 1 to 10 years was chosen for SVRNS analysis. When compared to other neutrosophic sets, SVRNS will be a better fit for describing these facts. For a practical use involving child psychology, machine learning algorithms like K-means, parallel axes coordinate, etc., were implemented and visualized. The suggested algorithms assist in analyzing a child's mental capacity based on creative play. These algorithms facilitate the establishment of a relationship between a number of factors influencing imaginative play and a child's cognitive capacities, allowing for the derivation of logical conclusions. There is also a quick comparison of the various algorithms that were employed. These two distinct indeterminate values characterize the Double-Valued Neutrosophic Set (DVNS), a modified version of a neutrosophic set introduced by the authors [52]. This excellent work defines and illustrates its associated properties and axioms. In a number of scientific domains, including data mining, machine learning, and pattern recognition, clustering is crucial. FSs and IFSs cannot handle ambiguous and inconsistent data as accurately as DVNS can. This is in contrast to SVNS. A clustering approach is built upon the definition of a generalized distance measure between DVNSs and the associated distance matrix. In order to cluster the data represented by DVNI, this article suggests using the double-valued neutrosophic minimum spanning tree (DVN-MST) clustering technique. The uses and efficiency of this clustering technique are illustrated with illustrative cases. The DVN-MST clustering algorithm is compared to various clustering algorithms, such as fuzzy minimum spanning tree, intuitionistic fuzzy minimum spanning tree, and single valued neutrosophic minimum spanning Tree. In a multicriteria decision-making situation where the criteria values for alternatives are taken into account in a DRINS environment, this suggested cross entropy is employed [53]. Likewise, a cross entropy based on indeterminacy and employing DRINS is suggested. The DRINW cross entropy and the indeterminacy based cross entropy between the ideal alternative and an alternative are derived in order to rank the alternatives corresponding to the cross entropy values. During the process of making decisions, the choice or options that are most desired are selected. A practical example is given to show how the suggested approach can be used. A quick comparison between the suggested approach and the current approaches is done. This paper introduces the triple refined indeterminate neutrosophic set (TRINS), a case of the refined neutrosophic set [54]. It offers the added ability to sensitively and accurately depict the ambiguous, imprecise, inconsistent, and partial information that exists in the real world. Further study can be seen in [55-57]. New research on fuzzy set and soft set theory has also been made by new models of decision-making and new algebra structures based on interval-valued and neutrosophic sets. The trigonometric $\wp$-rung and neutrosophic interval-valued approaches were used by Hatamleh et al. to propose weighted and geometric operators and, further on, to propose the concept of interaction operators to Pythagorean neutrosophic sets [59, 61, 62]. In Mahase and Shihadeh [60], the authors studied (α, β)-intuitionistic fuzzy ideals of ordered ternary semigroups. AI-assisted fuzzy soft relations were also used in health monitoring through wearable devices [63]. El-Sheikh and Abd El-Latif [64] introduced fundamental research on soft topological structures, and these were further developed in research on supra compactness and separation axioms [65, 66]. The authors addressed number of examples for better understanding the results and their applications. Neutrosophic cognitive maps (NCMs), a model based on neutrosophic logic, are used in this study to examine young children's imaginative play [58]. In order to create connections between the various ideas associated with children's imaginative play in the age range of 1 to 10 years old, who come from socially, economically, and educationally disadvantaged backgrounds, NCMs are built with the assistance of expert advice. The NCMs play a crucial role in removing the obstacle caused by the intricate and frequently imprecise nature of social or psychological data. Expert interpretations and video recordings of kids playing were used to gather data. Experts said that 15 characteristics / concepts associated with kids using the same toy were seen, and while some of the relationships between the concepts were unclear, it was permissible to apply NCMs. These NCMs were constructed based on the opinions of five experts, and one of their concealed patterns turned out to be a fixed point. This section reviews some important concepts pertaining to the theory of SVNSs.

2. Preliminaries

In this section, some basic definitions are reviewed pertaining to the theory of single valued neutrosophic set (SVNS) which are necessary for the upcoming sections.

Definition 1. *[59] A neutrosophic set (NS) A on the universe of discourse X is categorized by truth membership function MF- $T_A(x)$, an indeterminacy MF- $I_A(x)$, and a false MF-$F_A(x)$. The functions $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or non-standard subsets of $]-_0,+_1[$; that is $T_A(x) : X \longrightarrow]-_0,+_1[$, $I_A(x) : X \longrightarrow]-_0,+_1[$ and $F_A(x) : X \longrightarrow]-_0,+_1[$ with the condition $-_0 \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3^+$.*
It was challenging to use this definition of a neutrosophic set in practical scientific and technical domains. As a result, [6] established the idea of a single valued neutrosophic set.

Definition 2. *[6] A single valued neutrosophic set (SVNS) A on the universe of discourse X is characterize by truth MF- $T_A(x)$, an indeterminacy MF- $I_A(x)$, and a false MF-$F_A(x)$. The functions $T_A(x)$, $I_A(x)$ and $F_A(x)$ are subsets of $]0,1[$; that is $T_A(x) : X \longrightarrow]0,1[$, $I_A(x) : X \longrightarrow]0,1[$ and $F_A(x) : X \longrightarrow]0,1[$ with the condition $0 \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3$. So SVNS can be written as*

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\}$$

Definition 3. *[6] A SVNS A is contained in the other SVNS B, if $T_A(x) \leq T_A(x), I_A(x) \geq I_A(x), F_A(x) \geq F_A(x)$ for each $x \in X$, $B \Leftrightarrow A \subseteq B \& B \subseteq A. A^c = \{\langle x, T_A(x), 1 - I_A(x), F_A(x)\rangle : x \in X\}$*

Definition 4. *[6] Let A and B be two SVNSs on the universe of discourse X then*

(i) . $A \cup B = \{x, \langle max(T_A, T_B), min(I_A, I_B), max(F_A, F_B)\rangle; x \in X\}$

(ii) . $A \cap B = \{x, \langle min(T_A, T_B), max(I_A, I_B), min(F_A, F_B)\rangle; x \in X\}$

3. Single Valued Heptapartitioned Neutrosophic Sets

Neutrosophic set theory (NST) is one of the most excellent and interesting theory which is used fully in pure and applied mathematics as well. This theory considers three possible membership values and these are true, false and indeterminacy membership values respectively. The two values are clear crystal. The third one is extremely interesting because it deals with uncertainty that happened everywhere in our daily life. The indeterminacy has got infinite number of refinement. The accuracy can be improved and uncertainty can be possibly reduced into certainty and the error can be griped that may happened in the calculation due to purely using the indeterminacy value as it as. The research can be made more realistic and sensible if the refinement of the indeterminacy is done. In the real applications the indeterminacy can be divided into seven possible values as absolute true, relative true, absolute false, relative false, contradiction, unknown (undefined) and ignorance. This scenario of indeterminacy provides a better accuracy.

Definition 5. *A single valued heptapartitioned neutrosophic set (SVHNS) A on the universe of discourse X is characterize by absolute true MF- $T_A(x)$, relative true MF- $RT_A(x)$,an unknown $U_A(x)$, a contradiction $C_A(x)$, an ignorance $G_A(x)$, an absolute false MF-$F_A(x)$ and relative false $RF_A(x)$. The functions $T_A(x)$,$RT_A(x)$, $U_A(x)$, $C_A(x)$, $G_A(x)$, $F_A(x)$ and $RF_A(x)$ are subsets of $]0,1[$; that is $T_A(x) : X \longrightarrow]0,1[$, $RT_A(x) : X \longrightarrow]0,1[$, $U_A(x) : X \longrightarrow]0,1[$, $C_A(x) : X \longrightarrow]0,1[$, $G_A(x) : X \longrightarrow]0,1[$, $F_A(x) : X \longrightarrow]0,1[$ and $RF_A(x) : X \longrightarrow]0,1[$ with the condition $0 \leq supT_A(x) + supRT_A(x) + supU_A(x) + supC_A(x) + supG_A(x) + supF_A(x) + supRF_A(x) \leq 7$. So SVHNS can be written as*

$$A = \{\langle x, T_A(x), RT_A(x), U_A(x), C_A(x), G_A(x), F_A(x), RF_A(x)\rangle : x \in X\}$$

Definition 6. *A SVHNS A is contained in the other SVHNS B, if $T_A(x) \leq T_A(x), RT_A(x) \leq RT_A(x), U_A(x) \leq U_A(x), C_A(x) \geq C_A(x), G_A(x) \geq G_A(x), F_A(x) \geq F_A(x), RF_A(x) \geq RF_A(x)$ for each $x \in X$, $A = B \Leftrightarrow A \subseteq B \& B \subseteq A$.*

$$A^c = \{\langle x, F_A(x), RF_A(x), G_A(x), 1 - U_A(x), C_A(x), T_A(x), RT_A(x)\rangle : x \in X\}$$

Definition 7. *Let A and B be two SVHNSs on the universe of discourse X then*

(i) . $A \cup B = \{x, [\begin{matrix} max(T_A, T_B), max(RT_A, RT_B), min(C_A, C_B), min(U_A, U_B), \\ max(G_A, G_B), min(F_A, F_B), min(RF_A, RF_B) \end{matrix}]; x \in X\}$

(ii) . $A \cap B = \{x, [\begin{matrix} min(T_A, T_B), min(RT_A, RT_B), max(C_A, C_B), max(U_A, U_B), \\ min(G_A, G_B), max(F_A, F_B), max(RF_A, RF_B) \end{matrix}]; x \in X\}$

4. Characterization of Single Valued Heptapartitioned Neutrosophic Sets in terms of Distance Measures

In this section, the concept of general distance is defined between two SVHNSs and the different types of distance measures are discussed and these are weighted Hamming distance and weighted Euclidean distance. In addition to this, algorithms are designed and the flowcharts are also picture out for clear understanding the situation.

Definition 8. *Let us consider two SVHNSs A and B on the universe of discourse on $X = x_1, x_2, ...x_n$ which are represented by*
$A = \{\langle x_i, T_A(x_i), RT_A(x_i), C_A(x_i), U_A(x_i), G_A(x_i), RF_A(x_i), F_A(x_i)\rangle : x_i \in X\}$ *and*
$B = \{\langle x_i, T_B(x_i), RT_B(x_i), C_B(x_i), U_B(x_i), G_B(x_i), RF_B(x_i), F_B(x_i)\rangle : x_i \in X\}$ *such that* $T_A(x_i)$, $RT_A(x_i), C_A(x_i), U_A(x_i), G_A(x_i), RF_A(x_i), F_A(x_i) \in [0,1]$ *and* $T_B(x_i), RT_B(x_i), C_B(x_i), U_B(x_i), G_B(x_i)$, $RF_B(x_i), F_B(x_i) \in [0,1]$ *for every $x_i \in X$. Let $w_i(i = 1, 2, ...n)$ is weight of elements $\xi_i(i = 1, 2, ...n)$, $w_i \geq 0(i = 1, 2, ...n)$ and $\sum_{i=1}^n w_i = 1$. Then, the generalized heptapartitioned neutrosophic soft set weighted distance is defined as*

$d_\lambda(A, B) = [\frac{1}{7}\sum_{i=1}^n w_i\{|T_A(x_i) - T_B(x_i)|^\lambda + |RTC_A(x_i) - RTC_B(x_i)|^\lambda + |C_A(x_i) - C_B(x_i)|^\lambda + |U_A(x_i) - U_B(x_i)|^\lambda + |G_A(x_i) - G_B(x_i)|^\lambda + |RF_A(x_i) - RF_B(x_i)|^\lambda + |F_A(x_i) - F_B(x_i)|^\lambda\}]^{\frac{1}{\lambda}}$
with, $\lambda > 0$.

The above equation reduces to the SVHNS weighted Hamming distance and the SVHNS weighted Euclidean distance, by replacing $\lambda = 1, 2$ respectively. The SVHNS weighted Hamming *distance is given as:*

$$d_\lambda(A,B) = [\tfrac{1}{7}\sum_{i=1}^{n} w_i\{|T_A(x_i) - T_B(x_i)| + |RTC_A(x_i) - RTC_B(x_i)| + |C_A(x_i) - C_B(x_i)| + |U_A(x_i) - U_B(x_i)| + |G_A(x_i) - G_B(x_i)| + |RF_A(x_i) - RF_B(x_i)| + |F_A(x_i) - F_B(x_i)|\}]$$

where, $\lambda = 1$.

The following is the SVHNS weighted Euclidean distance:

$$d_\lambda(A,B) = [\tfrac{1}{7}\sum_{i=1}^{n} w_i\{|T_A(x_i) - T_B(x_i)|^2 + |RTC_A(x_i) - RTC_B(x_i)|^2 + |C_A(x_i) - C_B(x_i)|^2 + |U_A(x_i) - U_B(x_i)|^2 + |G_A(x_i) - G_B(x_i)|^2 + |RF_A(x_i) - RF_B(x_i)|^2 + |F_A(x_i) - F_B(x_i)|^2\}]^{\frac{1}{2}}$$

where, $\lambda = 2$.

The algorithm to obtain the generalized SVHNS weighted distance $d_\lambda(A,B)$ between two SVHNS A and B is given in Algorithm 1.

Generalized SVHNS Algorithm:

$|1.ProcedureGeneralizedSVHNSDistance(a, b, weights, \lambda)|$

$|2.distance \longrightarrow 0|$

$|3.For(i \in \langle a \rangle)|$

$|4.distance \longrightarrow distance + weights[i] * (|$

$|5.(a[i].truth - b[i].truth) + |$

$|6.(a[i].true_tending_complex - b[i].true_tending_complex) + |$

$|7.... +$

$||8.(a[i].indeterminacy - Confusion - b[i].indeterminacy - Confusion)|$

$|9.)^\lambda|$

$|10.Returndistance/7|$

The related flowchart is given in Figure 1.

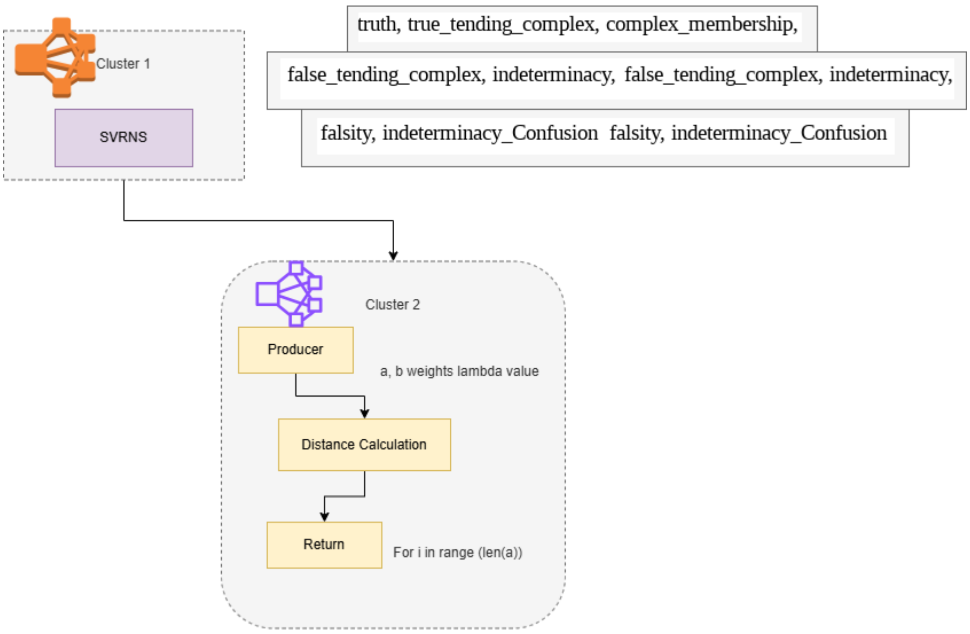

Figure 1: Flow Chart for SVHNS

5. Characterization of K-Means algorithm in Terms of Single Valued Heptapartitioned Neutrosophic Sets

Algorithm 2. K-mean algorithm using SVHNS data set is given as

1. Initialize SVHNS instances a and b with respective truth values, complex memberships, etc.
2. Create a 2D array of SVHNS values with the attributes of a and b.

3. Initialize K (number of clusters) and max iterations.
4. Randomly initialize centroids using SVHNS values.
5. Initialize empty arrays beta and nj for centroid updates.
6. Create an empty array prev clusters to track previous clusters.
7. Loop for max iterations:
a. Create empty clusters for each iteration.
b. Assign data points to the closest clusters.
c. Update beta and nj values for centroid calculations.
d. Update centroids based on beta and nj.
e. Check for convergence by comparing current clusters with previous clusters.
f. If convergence is reached, exit the loop.
g. Update previous clusters.
8. Print the final clusters and centroids.
Example Usage:
a. Create SVHNS instances a and b.
b. Define SVHNS values using the attributes of a and b.
c. Create an instance of the SVHNS class with initialized values.
d. Run k-means SVHNS with SVHNS values, $K = 2$, and print the final clusters and centroids.
The related flow chart is given in Figure 2

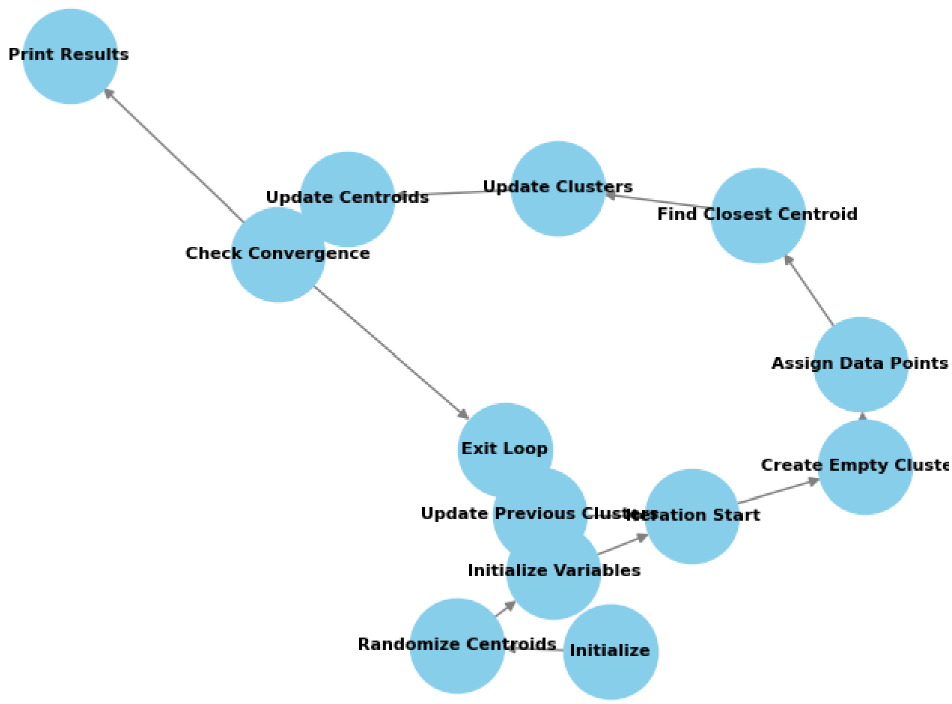

Figure 2: Flow Chart for K-Mean Clustering of SVHNS Data Set

After gathering and processing the data, we employed the following machine learning approaches in this research.

6. Characterization of Machine Learning Techniques in Terms of Single Valued Heptapartitioned Neutrosophic Sets

Encrypted K-Mean Clustering method is a novel method for K-mean clustering on a data which is encrypted and this method has the ability to preserve the confidential data of sensitive information. Heat map is supposed to be very informative structure and as we know that heat maps helps us in understanding the correlation in data (the graphical illustration of data where values are represented by colors) and in particular here encrypted correlation heat map has been reflected for the given data in future section. A method for determining the proper value of K (number of clusters) in K-means clustering is the elbow method. The Elbow method is a strategy for determining the appropriate value of K (number of clusters). It creates consistency in the cluster analysis design. The Elbow Method is used to determine the optimal number of clusters within the dataset. This helps reveal natural groupings of individuals with similar data patterns, contributing to a better understanding of the diversity in experiences represented in the data. Implementing the Elbow Method on the encrypted SVHNS dataset enhances the robustness and reliability of our analysis. Decrypted K-Mean clustering is very useful in the field of security measures. When K-Means clustering is applied to decrypted datasets, the data becomes accessible not only to the intended recipient but also potentially to others along the transmission path, raising security concerns. Encrypted and decrypted correlation matrices are used to analyze inter-component relationships while maintaining data security, with the encrypted version ensuring a secure environment during analysis.

7. Data set Visualization and Structural Characterization

Researchers conducted sessions with young adults of varying backgrounds to explore romantic emotions in young adults. During the sessions, held in educational institutions and community settings, participants explored romantic feelings and experiences. A professional psychologist facilitated each session, fostering a comfortable environment for open communication. In the course of collecting data, participants discussed their favorite romantic themes, relationships, and everyday experiences. Participants were treated with small gestures like sharing their favorite sharing-gifts snacks or chocolates to create a relaxed atmosphere. Subsequently, participants were prompted to engage in simulated romantic conversations, simulating phone calls with their imagination. A total of 10 sessions were conducted in educational institutions, and 2 in community settings, ensuring a varied dataset. To enhance diversity, an additional 7 videos were sourced from online platforms, showcasing young adults engaging in similar romantic scenarios. The recorded descriptions from these sessions and videos were crucial in assigning values to seven membership functions, forming the basis for constructing the romantic sentiment analysis system (RSAS).
Table 1 outlines the parameters employed in analyzing romantic feelings, with the first 11 parameters drawn from existing literature and an additional 5 parameters introduced by the expert to capture the nuances of romantic emotions among young adults.

Table 1: Parameter Description for Romantic Feelings

S.No	**Parameter Name**	**Description**
1.	Shared Dreams (SD)	The shared dreams and aspirations within the context of romantic feelings, whether based on real or imaginative situations or settings.
2.	Expressive Dance (ED)	Movements expressing romantic feelings, indicating cognitive patterns and emotional involvement.
3.	Non-verbal Communication (NVC)	Non-verbal expressions using body parts (hands, head) to convey romantic ideas or emotions.
4.	Emotional Expression (EE)	Movement of facial muscles for non-verbal communication, reflecting romantic emotions.
		Continued from previous page

Table 1 – continued from previous page

S.No	Parameter Name	Description
5.	Quality Time Together (QTT)	Duration and nature of social interactions during romantic moments, influence the depth of emotional connection.
6.	Play Materials Used(PMU)	Objects or symbols representing romantic elements in the context of romantic feelings.
7.	Collaborative Creativity (CC)	Partner's approach to using provided elements, offering insights into shared imaginative experiences in romantic feelings.
8.	Expressing Feelings (EF)	Vocal or non-vocal expression of romantic feelings and emotions by both partners.
9.	Emotional Tone (ET)	Tone reflecting the mood and state of mind of both partners during romantic interactions.
10.	Mutual Roles (MR)	The roles both partners assume and assign to each other within the context of romantic feelings.
11.	Shared Enthusiasm (SE)	Extent of the partners' involvement and shared excitement during romantic activities.
12.	Emotional Gaze (EG)	Movement of the eyes expressing emotions and connection during romantic moments.
13.	Associative Thinking (AT)	Mental process by which both partners form associations and create shared romantic experiences.
14.	Grammaticality Correct Expressions (GCE)	Ability to construct grammatically correct sentences expressing romantic feelings with proper structure and syntax.
15.	Connected Conversations (CC)	Whether sentences formed during romantic interactions are related to each other, enhances the depth of connection.
16.	Gift Sharing (GS)	The act of sharing symbolic or imaginary gifts within the context of romantic feelings.

8. Method of Romantic Feeling Assessment

The expert views on the evaluation parameters for romantic feelings are provided below:

1. Shared Dreams (SD): An imaginative theme based on real situations increases the truth membership function. Degrees of complexity and indeterminacy are considered within the $[0, 1]$ range.

2. Expressive Dance (ED): Truth membership increases with physical movements expressing romantic feelings. Complex and indeterminate values from $[0, 1]$ if movements are challenging to interpret.

3. Non-verbal Communication (NVC): Truth membership increases with non-verbal expressions. Body parts conveying romantic ideas contribute. Complex and indeterminate values are assigned within $[0, 1]$.

4. Emotional Expression (EE): Facial movements reflecting romantic emotions increase truth membership. Complex and indeterminacy values are assigned within $[0, 1]$ for difficult interpretations.

5. Quality Time Together (QTT): Truth membership increases with social interactions during romantic moments. Indeterminate and complex values from $[0, 1]$ for challenging interpretations.

6. Play Materials Used (PMU): No specific expert views provided. The dataset represents objects or symbols representing romantic elements.
7. Collaborative Creativity (CC): Truth membership increases with a partner's imaginative use of elements. Indeterminate and complex values from $[0,1]$ for difficult interpretations.
8. Expressing Feelings (EF): Truth membership increases with vocal/non-vocal expressions. Indeterminate and complex values from $[0,1]$ for difficult interpretations.
9. Emotional Tone (ET): Truth membership increases with the tone reflecting the mood. Indeterminate and complex values from $[0,1]$ for challenging interpretations.
10. Mutual Roles (MR): Truth membership increases with realistic role identification. Indeterminate and complex values from $[0,1]$ for difficult interpretations.
11. Shared Enthusiasm (SE): Truth membership increases with partners' involvement and excitement. No specific views on indeterminacy or complexity.
12. Emotional Gaze (EG): Truth membership increases with eye movements expressing emotions. Complex and indeterminacy values are assigned within $[0,1]$ for difficult interpretations.
13. Associative Thinking (AT): Truth membership increases with the mental process of forming associations. Indeterminate and complex values from $[0,1]$ for challenging interpretations.
14. Grammatically Correct Expressions (GCE): Truth membership increases with grammatically correct expressions. Indeterminate and complex values from $[0,1]$ for challenging linguistics.
15. Connected Conversations (CC): Truth membership increases with related sentences during romantic interactions. Indeterminate and complex values from $[0,1]$ for challenging coherence.
16. Gift sharing (GS): No specific expert views provided. The dataset represents the act of sharing symbolic or imaginary gifts within romantic feelings.
These expert views guide the evaluation process, incorporating truth, indeterminacy, and complexity considerations for each romantic parameter.

9. Characterization of 16 feeling in Term of Example

This section is devoted to an example based on young couple of 19-years-old and the following observations and interview about their romantic relationship were made by the physicalists while moving in domain of 16 decision variables. The developed Table 2 is given below.

Table 2: Discription of 16 Feelings

Feeling	**T**	**RT**	**U**	**C**	**G**	**RF**	**F**
Shared Dreams	0.4	0.2	0.15	0	0.25	0	0
Expressive Dance	0.3	0.3	0	0	0.25	0.15	0
Non-verbal Communication	0	0	0	0	0.25	0.75	0
Emotional Expression	0	0.75	0.25	0	0	0	0
Quality Time Together	0.2	0.2	0.2	0.3	0.1	0	0
Play Materials Used	0.15	0	0.3	0	0.25	0	0.3
Collaborative Creativity	0.15	0.3	0	0	0.25	0	0.3
Expressing Feeling	0.4	0.2	0.2	0.1	0.1	0	0
Emotional Tone	0.2	0.25	0.25	0	0.2	0	0.1
Mutual Roles	0.5	0	0.25	0	0.25	0	0
Shared Enthusiasm	0.5	0.25	0.25	0	0	0	0
Emotional Gaze	0	0	0.5	0	0.5	0	0
Associative Thinking	0.75	0	0	0	0.25	0	0

Continued on next page

Table2 – continued from previous page

	T	RT	U	C	G	RF	F
Feeling							
Grammatically Correct Expressions	0.75	0	0.25	0	0	0	0
Connected Conversations	0.15	0	0.3	0.25	0	0	0.3
Gift sharing	0.15	0	0.3	0.25	0	0.2	0.1

Table 2 explains the description of the discussed parameters. The provided information presents a set of parameters for evaluating romantic feelings, each associated with a description and a corresponding dataset represented as SVHNS. Below is a concise summary in Table 3

Table 3: SVHNS for Example

S.No	Parameter Name	Description	SVHNS
1.	Shared Dreams (SD)	Dreams and aspirations shared within romantic feelings, real or imaginative	[0.4,0.2,0.15, 0,0.25,0,0]
2.	Expressive Dance (ED)	Movements expressing romantic feeling, indicating cognitive patterns and emotional involvement	[0.3,0.3,0, 0,0.25,0.15,0]
3.	Non-verbal Communication (NVC)	Non-verbal expressions using body parts to convey romantic ideas or emotions	[0,0,0, 0,0.25,0.75,0]
4.	Emotional Expression (EE)	Movements of facial muscles for non- verbal communication, reflecting romantic emotions.	[0,0.75, 0.25,0,0,0,0]
5.	Quality Time Together (QTT)	Duration and nature of social interactions during romantic moments	[0.2,0.20,0.20,0.3,0.1,0,0]
6.	Play Materials Used (PMU)	Objects or symbols representing romantic elements	[0.15,0,0.3, 0,0.25,0 .0.3]
7.	Collaborative Creativity (CC)	Partner's approach to using provided elements, offering insights into shared imaginative experiences	[0.15,0.3, 0,0,0.25,0 .0.3]
8.	Expressing Feeling (EF)	Vocal or non-vocal expression of romantic feelings and emotions	[0.4,0.20, 0.20,0.1,0.1,0 ,0]
9.	Emotional Tone (ET)	Tone reflects the mood and state of mind during romantic interactions	[0.2,0.25, 0.25,0,0.2,0 .0.1]
10.	Mutual Roles (MR)	Roles both partners assume within romantic feelings	[0.5,0, 0.25, 0,0.25,0,0]
11.	Shared Enthusiasm (SE)	Extent of partners involvement and shared excitement during romantic activities	[0.5,0.25, 0.25,0,0 ,0,0]
12.	Emotional Gaze (EG)	Movement of the eyes expressing emotions and connection during	romantic moments [0,0.0.5, 0,0,0.5 ,0,0]
13.	Associative Thinking (AT)	Mental process by which both partners from associations and create shared romantic experiences	[0.75,0, 0,0 ,0.25,0,0]
14.	Grammatically Correct Expressions(GCE)	Ability to construct grammatically correct sentences expressing romantic feelings	[0.75,0, 0.25,0,0 ,0,0]

continued on next page

Table3 – continued from previous page

S.No	Parameter Name	Description	SVHNS
15.	Connected Conversations (CC)	Whether sentences formed during romantic interactions are related	[0.15,0, 0.3,0.25,0 ,0,0.3]
16.	Gift Sharing	The data set represents the act of sharing symbolic or imaginary gifts within romantic feelings.	[0.15, 0, 0.3, 0.25, 0, 0.2, 0.1]

Likewise the SVHNS tuples for the other data sets was done with the help of the expert. Then these SVHNS sets are used for analysis using machine learning algorithms.

10. Results and Discussions

Many Python libraries, including pandas, numpy, matplotlib, sklearn, seaborn, and pylab, were utilized for the purpose of graphical representation and data visualization. Python programming was used to visualize the previously stated techniques, and K-means clustering was performed based on the elbow curve result. These graphics have led to logical conclusions, and it has also been addressed how sixteen different aspects contribute to young boys' and girls' romantic feelings. A heat map's color scale, which clearly displays the correlation and associativity aspects, shows blue correlation for darker shades and reddish correlation for lighter shades. When two variables show a correlation with each other, it means they are connected. Reddish correlation is the term used to describe the relationship between an increase in one attribute and an increase in another. Blue connection occurs when one quality increases while another decreases. The heat map clearly shows the correlation and associativity aspects with a color scale where darker shades indicate a blue correlation and lighter ones indicate a reddish link. The Elbow Method is strategically applied to determine optimal clusters, significantly contributing to a richer understanding of diversity in romantic feelings. This nuanced methodology aims to; comprehend 16 distinct feelings by considering absolute true, relative true, absolute false, relative false, contradiction, unknown (undefined) and ignorance. The application of K-means clustering on the data set revealed intriguing patterns in romantic feelings. Distinct clusters emerged, each characterized by individuals with similar romantic preferences. The correlation analysis provided deeper insights into the emotional landscape, particularly highlighting the relationships between dimensions such as "quality time together" and "expressing feelings." These findings underscore the complexity and interconnectedness inherent in romantic experiences. The Elbow Method, strategically employed, determined optimal clusters, contributing significantly to our understanding of the diverse nature of romantic feelings. The results affirm the effectiveness of advanced machine-learning techniques in unravelling the complexities of human emotions, especially in the context of romantic experiences.

Figure 3, while testing Encrypted K-Mean clustering method on feature T for the parameters "shared dreams" on the $y - axis$ against "expressive dance" on the $x - axis$, it was found that higher concentration of points lies near $x = 0.2$ and $y = 0.3$. Initial centroid $c_1 atx = 0.00 andy = 0.0$ and an Initial centroid $c_1 atx = 0.00 andy = 0.0$, second centroid $c_2 atx = 0.00 andy = 0.19$ and third centroid $c_3 atx = 0.05 andy = 0.9$ After bring in action K-mean clustering we got closed to c_3 as shown in the Figure 3.

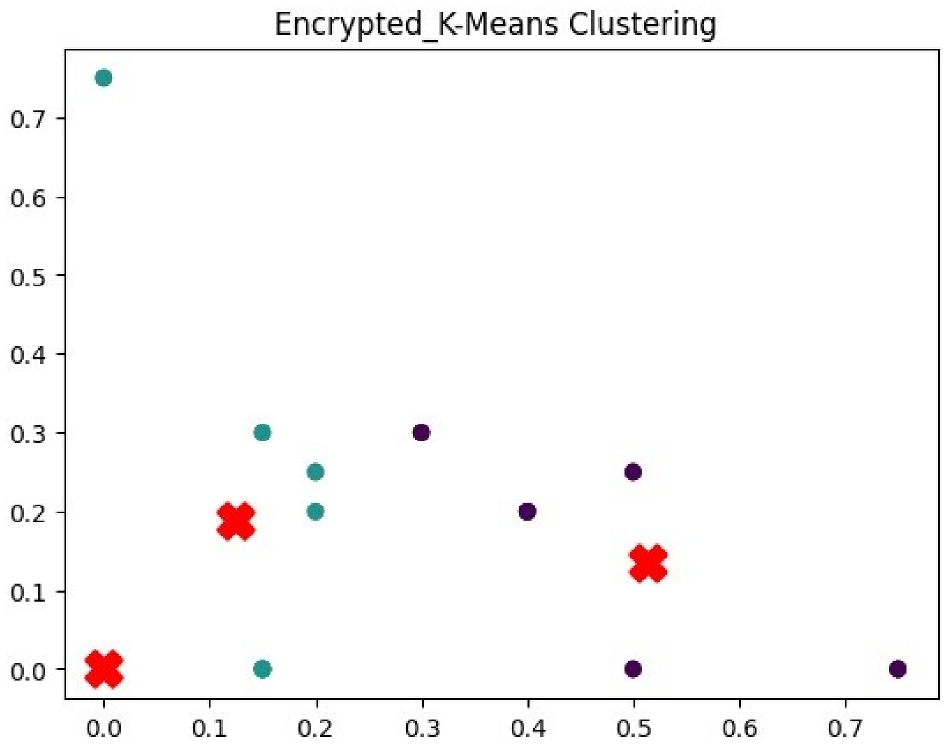

Figure 3: Encrypted K-Mean Clustering Method

The Figure 4 has been devoted to heat map and as we know that heat maps helps us in understanding the correlation in data (the graphical illustration of data where values are represented by colors) and in particular here encrypted correlation heat map has been reflected for the given data. The picture represents 32 combined feeling of male and female. Here we see that the dominant colour is dark blue and also at second number the influential colour is sky colour. Encrypted correlation heat map offering a visual representation of correlations while keeping the security of the data.

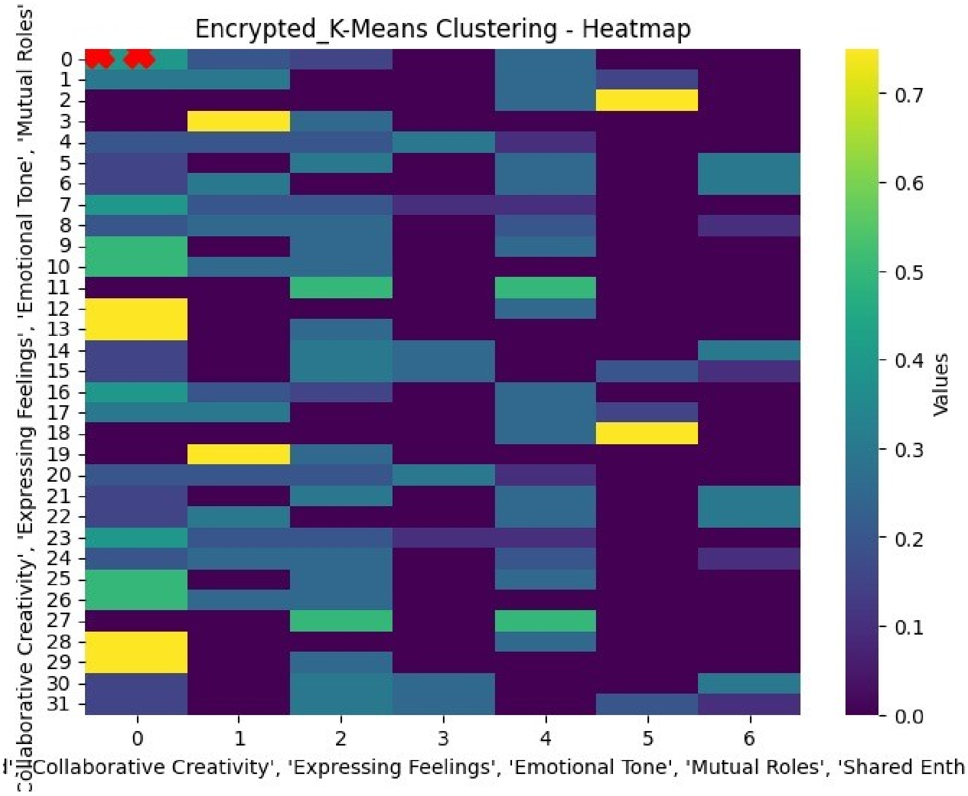

Figure 4: Encrypted K-Mean Clustering Heat Map

Figure 5 reflects encrypted Elbow method (this method is used to decide how many clusters it should consider and this method is actually the graph between K and distortion WCSS). Here the K-values are taken along x-axis and the distortion (WCSS) is taken along y-axis. We see that there are number of K-values but we encounter the business value of K which is at 4 that is at $k = 4$ the optimal value is 4 because here we see that the drastic change in y-axis value occurred at $k = 4$ the value of $y = 2.4$ as shown in the Figure 5.

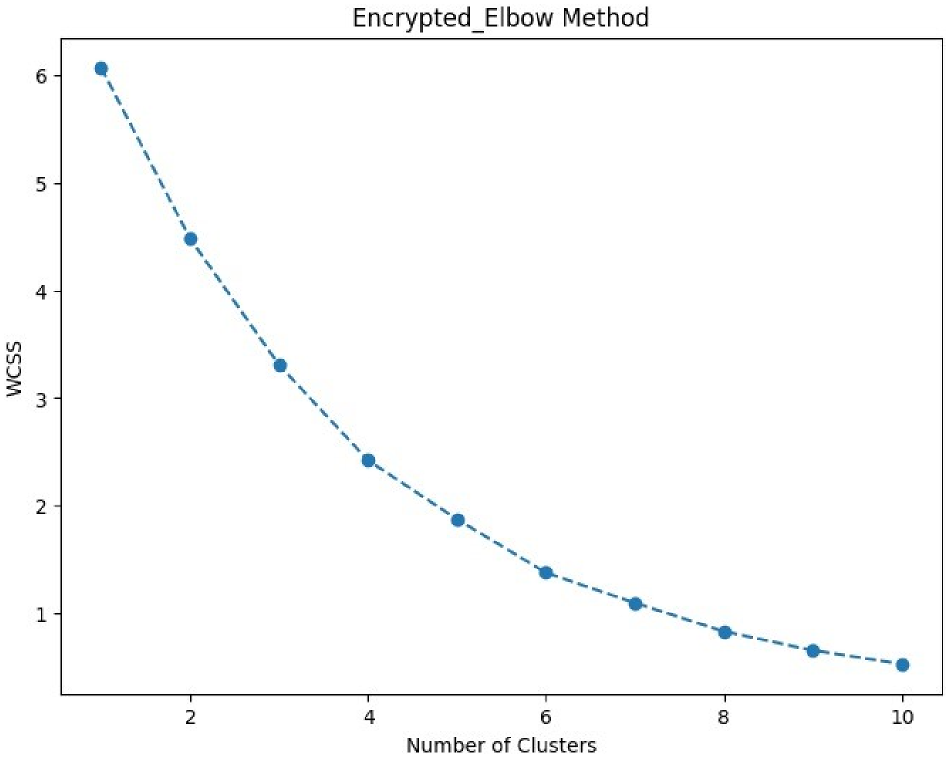

Figure 5: Encrypted Elbow Method

Figure 6 , decrypted K-Mean clustering on feature T(where the data is already decrypted) for the parameters "Shared dreams" on the $y-axis$ against "Gift sharing" on the $x-axis$, it was found that higher concentration of points lies near $x = 0.15andy = 0.18$. Initial centroid $c_1atx = 0.00andy = 0.0$ and an Initial centroid $c_1atx = 0.00andy = 0.0$ and second centroid $c_2atx = 0.00andy = 0.8$. After bring in action K-mean clustering we got closed to centroid $c_3atx = 0.25andy = 0.18$ as shown in the figure. The decrypted showcasing the versatility and security of the data.

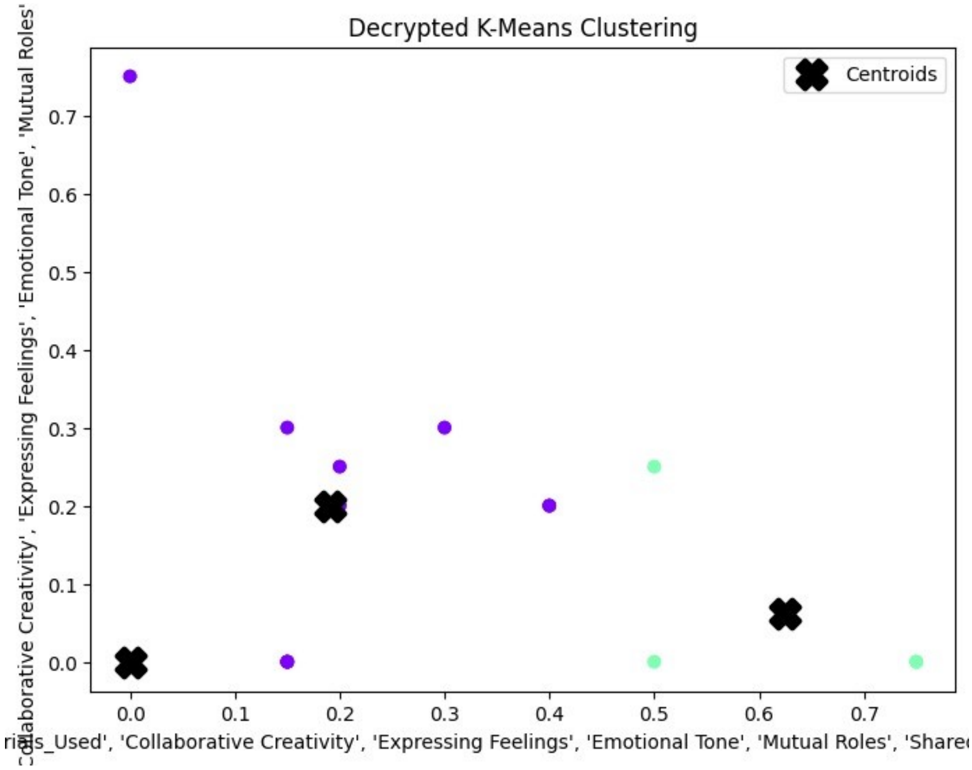

Figure 6: Decrypted K-Mean Clustering

In Figure 7 Encrypted correlation matrix for feature T(where the data is already encrypted) is developed and we see that the off diagonal is filled with single element one and moreover we see that dark green shows positive correlation and the midnight blow shows negative correlation. The positive and negative correlations are symmetric about the off diagonal which is reflected by dark red colour. Here we notice that the highest positive value is 0.89 so this means that there is strong relationship between gift sharing and emotional tone and similarly the others. We notice that there are alsonegative values and the most negative value is -0.69 which indicates that there is strong negative relationship between emotional gaze and consummate love and associative thinking similarly the others. The correlation of variables to itself can be seen on the diagonal from bottom right to left. The correlation matrices highlighting the interior-component relationships in a secure environment.

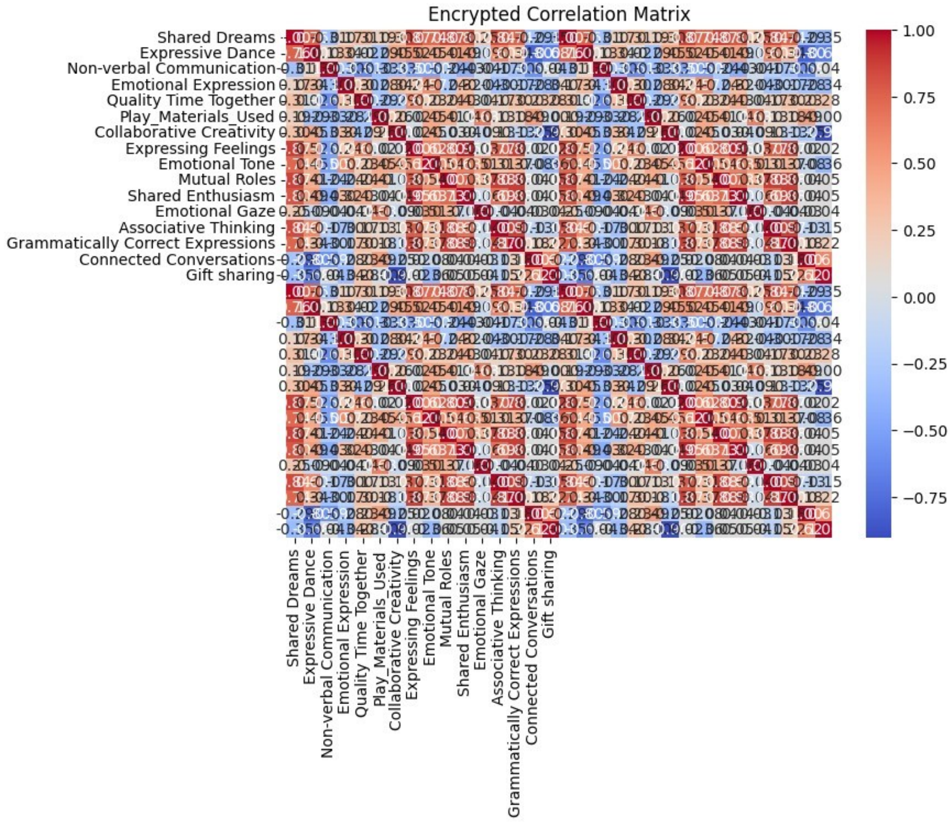

Figure 7: Encrypted Correlation Matrix

Figure 8 decrypted correlation matrix has been plotted against the data.

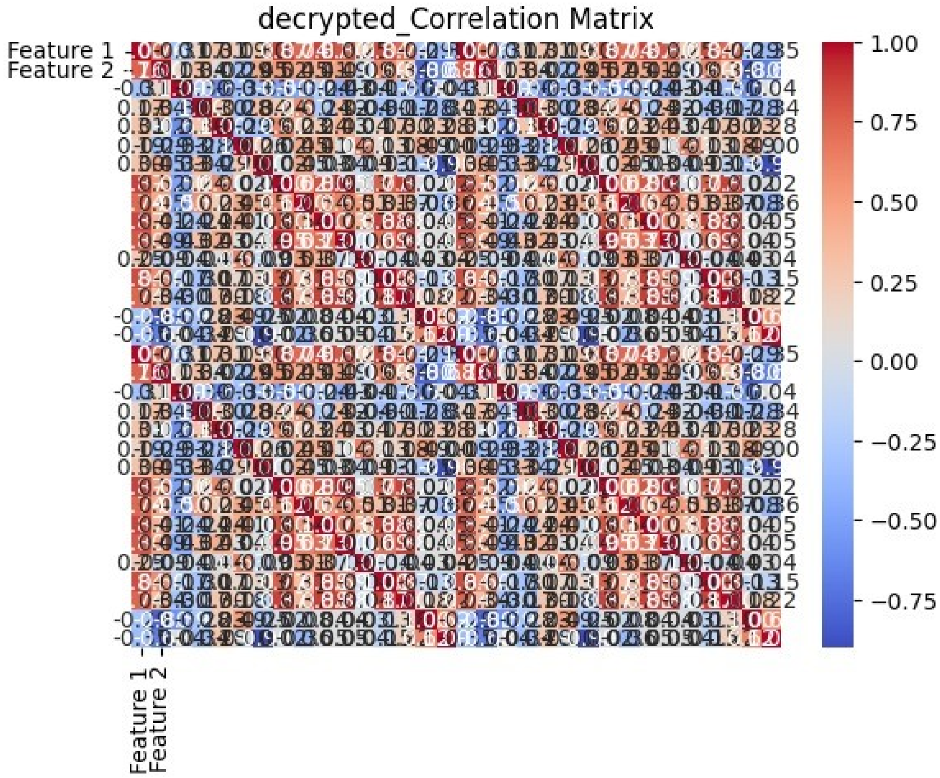

Figure 8: Decrypted Correlation Matrix

11. The Comparative Analysis in Table 4

The application of K-means clustering on the data set reveals intriguing patterns in romantic feelings. Distinct clusters emerge, each characterized by individuals with similar romantic preferences. Correlation analysis provides deeper insights into the emotional landscape, highlighting relationships between dimensions such as "Quality time together" and "Expressing feelings."
Visibility: The Elbow Method determines optimal clusters, contributing significantly to our understanding of the diverse nature of romantic feelings.
Associativity: The results affirm the effectiveness of advanced machine-learning techniques in unravelling the complexities of human emotions, especially in the context of romantic experiences. The multidimensional analysis provides a holistic view, emphasizing the need for a nuanced approach to exploring and understanding intricate emotional states.
Dynamicity: Medium Dynamicity: The data set exhibits a moderate level of dynamicity, indicating some variability or changes in patterns over the observed dimensions or features.
Strong Dynamicity Analysis: Through a robust analysis, it is evident that the data set showcases a strong level of dynamicity. This suggests significant variations and complexities in the relationships within the data.
Scalability: Medium Scalability: The data set demonstrates a moderate level of scalability, indicating a reasonable ability to handle an increase in size or complexity without a significant decrease in performance.
Strong Scalability Analysis: A thorough scalability analysis indicates that the data set possesses strong scalability. This suggests the data set's capability to efficiently handle increased volume or complexity, making it versatile for diverse analytical tasks.

Table 4: Comparative Analysis

Factors	**Heat Map**	**K-Means**
Correlation	Strong correlation visualization.	Weak correlation analysis dynamicity.
Visibility	Weak Visibility in terms of factor	Medium visibility in terms of factor.
Associativity	Strong associativity representation.	Strong associativity analysis.
Dynamacity	Medium dynamicity.	Strong dynamicity analysis.
Scalability	Medium scalability.	Strong scalability analysis.

Graphical Representation of Table 4, in terms of Factors and Methods are given in Figure 9

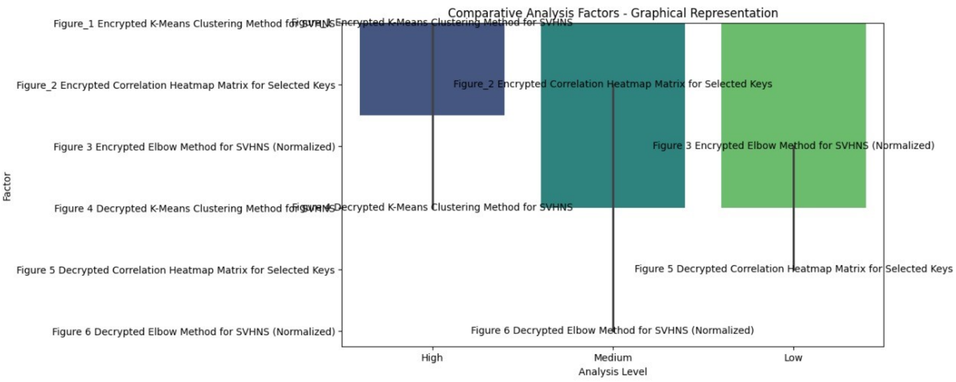

Figure 9: Analysis Level

12. Conclusion

In conclusion, this study presents a comprehensive exploration of romantic feelings, leveraging advanced machine-learning techniques. The application of K-means clustering, correlation analysis, and innovative visualization methods has deepened our understanding of the emotional landscape. The results underscore the intricate nature of romantic experiences and the interconnectedness of various emotional dimensions.

The dual-layered approach, combining machine-learning techniques with the single valued heptapartitioned neutrosophic set (SVHNS), has proven effective in providing a nuanced understanding of 16 distinct feelings. Expert evaluations further enriched our exploration, shedding light on the interplay between physical expressions and emotional authenticity.

On behalf of single valued heptapartitioned neutrosophic set (SVHNS) which is the generalized version of the neutrosophic set is utilized to make this study successful and this set consists of seven membership functions which are more sensitive to real-world problems. Membership functions are defined as an absolute true, relative true, absolute false, relative false, contradiction, unknown (undefined) and ignorance respectively. Moreover, several properties of this set were addressed.

This study focuses on the romantic sensations experienced by young boys and girls in a variety of contexts. The data set supporting this research includes individuals aged 18-25, with data collected from the Psychology Department at Peshawar University, Pakistan. This data set was

critically analyzed using the Single-Valued Heptapartitioned Neutrosophic Set (SVHNS).For real-world application, the study examines romantic feelings across various dimensions using machine learning and graphical algorithms. These include Encrypted K-Means Clustering, Encrypted K-Means Clustering Heat Map, Encrypted Elbow Method, Decrypted K-Means Clustering, Encrypted Correlation Matrix, and Decrypted Correlation Matrix. These algorithms are applied and visualized to uncover patterns and groupings within the data.The proposed methods help examine and establish relationships among several factors that influence romantic feelings among young men and women. These techniques offer new dimensions not only for psychological studies in general but also specifically for understanding emotional disorders and relationship breakups among young university couples.
Future research endeavors should focus on expanding emotional data sets to enhance the robustness of emotion analysis methodologies. Refining SVHNS parameters and integrating sentiment analysis would further contribute to a more nuanced understanding of human feelings. Exploring demographic factors is essential to uncover variations in emotional experiences across diverse populations. Advanced emotion detection methods and clustering techniques should be explored to provide a more holistic understanding of human emotional experiences. Additionally, incorporating real-time data and dynamic factors could capture the evolving nature of emotions, ensuring the relevance and applicability of emotion analysis methodologies in dynamic social contexts. This study lays the foundation for future investigations into the intricate fabric of human emotions, opening promising avenues for continued research and exploration.

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