An Integrated Rough Set on Intuitionistic Fuzzy Approximation Space and Soft Set for Decision Making

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ABSTRACT

Data analysis and decision-making skills need to advance in the current computing era. The majority of our tools are exact, deterministic, and incisive. However, there are uncertainties in most real-life circumstances. Numerous theories, including fuzzy sets, rough sets and its variations, have been instituted to address such ambiguities. However, each of these hypotheses has drawbacks of its own. The idea of a soft set is presented in order to get around the restrictions. However, if the information system's properties are nearly same rather than exactly the same, the soft set also fails. In order to extract decisions, we propose a model in this study that comprises two processes, namely pre-process and post-process to make appropriate decisions. Rough set on intuitionistic fuzzy approximation spaces are used in pre-processing to obtain nearly equivalent classes, whereas soft sets are used in post-processing for decision-making. The results of testing the suggested model on an institutional dataset demonstrate the research's practicality.

Introduction

In the current era of the internet, a vast amount of data is accessible in many different fields. Because of this, it is extremely difficult to glean meaningful information from the vast amount of data that exists in the universe. Thus, among the most prominent fields of study in recent years have been decision making, knowledge representation, and information retrieval. Particularly, one key elements of an information database is knowledge acquisition and information retrieval. Additionally, using information at the appropriate time and location gives you a competitive edge. As a result, data analysis tools for knowledge acquisition and decision making require improvement. The majority of our conventional tools are exact, deterministic, and incisive. However, a lot of real-world issues that arise from engineering, economics, and social science are not necessarily clear-cut with an abundance of uncertainties. Consequently, the existence of uncertainty precludes the application of classical approaches. Numerous mathematical modeling methods are being developed to address uncertainty in real-world tasks. The notion of probability, fuzzy sets[1], intuitionistic fuzzy sets[2], rough sets[3], fuzzy rough sets, and rough fuzzy sets[4], as well as rough sets on fuzzy approximation spaces and intuitionistic fuzzy approximation spaces[5], are some of the key theories that address uncertainty. Further, discovery of the influencing elements that affects the decisions and helps in knowledge mining are studied[6]. Besides, rough computing is used to develop a novel capacity maturity decision making model that identifies critical process areas for the development of high-quality education[7]. In order to predict missing associations, a prediction model utilizing Bayesian classification and rough computing is developed[8]. Likewise, information entropy and rough computing are used to analyze the performance of educational institutions[9]. Similarly using rough computing, several methods of information extraction from knowledge discovery databases are also examined[5]. However, each of these hypotheses has drawbacks of its own. Molodstov introduced the conception of soft set as a mathematical procedure for administering uncertainty in order to get around these limitations[10].

Soft Set is a data mining technique facilitates decision-making. However, it has some constraints. Besides, in the literature, a soft set application to a decision-making problem was proposed[11]. An information database (Z,A), where A is a set of characteristics of the objects Z, is considered in this application. According to their reasoning, an item can only be a part of a parameter if it completely satisfies it. On the other side, the object does not belong to the parameter if it does not satisfy it. As a result, the parameter value can only be between 0 and 1. However, it is commonly observed that, an information system is quantitative in nature as opposed to qualitative in real-world scenarios[12]. For a given parameter, objects are hence almost identical rather than exactly the same. It suggests that an object may only partially satisfy a parameter rather than completely. However, they did not account for this feature in their study[11]. We suggest a decision-making paradigm with two phases, for instance pre-phase and post-phase, to get over this constraint. In pre-phase, we find the nearly equivalence of objects given a parameter using Rough Sets on Intuitionistic Fuzzy Approximation Spaces (RSIFAS). To get decisions in post-phase, we employ soft set approaches. The foremost advantage of the suggested paradigm is its capability to function well with qualitative and quantitative data.

The remainder of the article is structured as follows: The rough set on intuitionistic fuzzy approximation space that determines the nearly equivalence of entities for a characteristic is covered following the introduction. Further, the principles of soft set approaches are clarified. Furthermore, the suggested decision-making model is presented. An empirical investigation using proposed decision making algorithms to rank the organizations is then presented. Finally, the last section concludes the article.

Foundations of Rough Set on Intuitionistic Fuzzy Approximation Space

In this section of the article, we delineate the definitions, concepts, and findings concerning rough sets within the context of intuitionistic fuzzy approximation spaces. For non-membership and membership functions related to an intuitionistic fuzzy set, we use the conventional notation $\nu(z)$ and $\mu(z)$, respectively.

Let Z be the universe of a finite collection of items that are not empty. A subset of $(Z \times Z)$ that is intuitionistic fuzzy is called an Intuitionistic Fuzzy Relation (IFR) on Z. An IFR R on Z is an Intuitionistic Fuzzy Proximity Relation (IFPR) that satisfies the condition $\nu_R(z,z) = 0$; $\mu_R(z,z) = 1$ for all $z \in Z$ and $\nu_R(z_1,z_2) = \nu_R(z_2,z_1)$; $\mu_R(z_1,z_2) = \mu_R(z_2,z_1)$ for all $z_1, z_2 \in Z$[13].

Let $J = \{(\beta,\alpha) \mid \beta,\alpha \in [0,1] \text{ and } 0 \leq \beta+\alpha \leq 1\}$. Then the (β,α)-cut of R is given as $R_{\beta,\alpha}$, and is defined as $R_{\beta,\alpha} = \{(z_1,z_2) \mid \mu_R(z_1,z_2) \geq \beta,\ \nu_R(z_1,z_2) \leq \alpha\}$. Two objects z_1, z_2 are termed as (β,α)-similar concerning R if $(z_1,z_2) \in R_{\beta,\alpha}$ and is denoted as $z_1 R_{\beta,\alpha} z_2$. Likewise, two objects z_1, z_2 are said to be (β,α)-identical concerning R if $z_1 R_{\beta,\alpha} z_2$ or z_1 is transitively (β,α) - similar to z_2 and we write $z_1 R(\beta,\alpha) z_2$. Thus, $R(\beta,\alpha)$ generates an equivalence relation $R^*_{\beta,\alpha}$. Hence, $R_{\beta,\alpha}$ generates an approximation space, $(Z, R(\beta,\alpha))$, known as intuitionistic fuzzy approximation space. Given a target entity, $Y \subseteq Z$, the lower and upper approximation is elucidated as $\underline{Y}_{\beta,\alpha}$ and $\overline{Y}_{\beta,\alpha}$ respectively, where

$$\underline{Y}_{\beta,\alpha} = \cup\{X \mid X \in R^*_{\beta,\alpha} \text{ and } X \subseteq Y\} \tag{1}$$

$$\overline{Y}_{\beta,\alpha} = \cup\{X \mid X \in R^*_{\beta,\alpha} \text{ and } (X \cap Y) \neq \phi\} \tag{2}$$

If $\underline{Y}_{\beta,\alpha} = \overline{Y}_{\beta,\alpha}$, then the target entity Y is called (β,α)-crisp, otherwise it is termed as (β,α)-rough. If Y is (β,α)-rough, then the boundary region is elucidated as $BR_{\beta,\alpha}(Y) = \overline{Y}_{\beta,\alpha} - \underline{Y}_{\beta,\alpha}$.

Almost Indiscernibility

The universe can be thought of as an enormous number of entities. Each entity has specific parameters, and the values of those parameters reveal some facts about that specific entity. Entities in the same facts category cannot be distinguished from one another. This is the key concept of rough set theory and is referred to as indiscernibility relation. An indiscernibility relation regards all identical things in a collection as elementary. However, it has been noted in numerous real-world applications using data gathered from multiple sources that two distinct objects, z_i and z_j, may have parameter values that are almost equal but not precisely the same. For instance, considering the objects as patients, the characteristics of the illnesses are nearly equal as opposed to exactly equal. In light of this, the intuitionistic fuzzy proximity relation is introduced, generalizing the indiscernibility relation of rough set theory to an almost indiscernibility relation.

Information Database

One way to think of an information database is as a two dimensional table. While every column of the information database is regarded as a parameter, every row is regarded as an object or entity. The primary goal of data mining is to categorize the items in an information database and extract knowledge from them. However, some of the facts in the elementary information database is not clear and distinct in a normal real-world setting. In recent years, rough sets have emerged as the most effective technique for dealing with data ambiguity. The definition of an information database is a quadruple $I = (Z, A, V, f)$, where A is the set of parameters that define the finite set of entities Z, $V = \cup_{a \in A} V_a$ and f is the mapping that maps entity to parameters.

For instance, consider a sample information database of smart phones presented in Table 1. In the given Table 1, $Z = \{z_1, z_2, z_3, z_4, z_5\}$, $A = \{\text{Brand, Color, Storage, Price}\}$, and $V_{Color} = \{\text{Grey, White, Blue, Black}\}$. The smart phone z_2 is characterized by Brand: Apple, Color: White, Storage: 256 and Price: 65000.

Smart phones	Parameters			
	Brand	Color	Storage (GB)	Price (INR)
z_1	Samsung	Grey	128	30000
z_2	Apple	White	256	65000
z_3	Samsung	Grey	128	30100
z_4	Motorola	Blue	256	32000
z_5	Apple	Black	128	68000

Table 1. Sample information database

Rudiments of Soft Set

For several decades, the theory of soft sets[10] has been continuously developed, and a rapidly expanding number of academics are showing interest in this approach. The approach is a analytical tool for handling ambiguous, imprecise, and unclear objects. In this section, we furnish an outline of the paper's background by outlining the basic ideas, symbols, and findings on soft sets[10,11], all of which serve as the foundation for our suggested decision-making model.

Consider a set of parameters A to characterize a set of entities Z. Assume, $P(Z)$ refers to the power set of Z and $E \subseteq A$. A tuple (F,E) is termed as a soft set over Z, in which $F : E \to P(Z)$ is a function. Stated differently, the soft set is a parameterized subset family of entities Z. The set of a-approximate entities of the soft set (F,E) can be regarded as $F(a)$ for $a \in E$. Below, we provide an example for reference.

Consider a collection of smartphones $Z = \{z_1, z_2, z_3, z_4, z_5, z_6\}$ characterized by parameters $A = \{$Android, Cheap, Camera, Handy, Expensi
Assume that $F(\text{Android}) = \{z_2, z_5\}$; $F(\text{Cheap}) = \{z_1, z_2\}$; $F(\text{Camera}) = \{z_2, z_4, z_5\}$; $F(\text{handy}) = \{z_1, z_3, z_6\}$; and $F(\text{Expensive}) = \{z_3, z_4\}$. Table 2 illustrates how this can be represented as an information database.

Smart phones	Parameters				
	Android	Cheap	Camera	Handy	Expensive
z_1	0	1	0	1	0
z_2	1	1	1	0	0
z_3	0	0	0	1	1
z_4	0	0	1	0	1
z_5	1	0	1	0	0
z_6	0	0	0	1	0

Table 2. Illustration of soft set example

In this instance, defining a soft set entails identifying expensive smartphone, handy smartphone, camera smartphone, cheap smartphone, and android smartphone. It is important to remember that for some $a \in A$, the sets $F(a)$ might be void. In traditional mathematics, an object is represented mathematically, and its exact solution is then determined. Generally speaking, mathematical models are too complex and unable to pinpoint the precise answer. As a result, we present the idea of an approximate answer and compute it as discussed in the section .

We approach this problem in the opposite way in soft set theory. Since the original description of the entity is approximate in nature, it is not required introducing the concept of an exact solution. Soft set theory is very practical and easy to apply because it does not impose any limitations on the approximate description. But, it does have some restrictions. Consider the information database depicted in Table 2 as an example.

It is evident from Table 2 that a smartphone either belonging to a feature or doesn't. However, based on parameter values, an object in real life belongs to a parameter. For instance, one needs to be aware of the prices of smartphones in order to determine whether they are expensive or not. Let the pricing of the smartphones $\{z_1, z_2, z_3, z_4, z_5, z_6\}$ be Rs. 25,875, Rs. 22,570, Rs. 43,775, Rs. 43,775, Rs. 43,675, and Rs. 43,690. The aforementioned data makes it evident that the z_3 and z_4 smartphones are expensive. However, it is impossible to argue that the z_5, and z_6 smartphones are not expensive. Therefore, when making decisions, the parameter values must be taken into account in order to determine whether an object belongs to a parameter. This serves as the rationale for the suggested decision-making paradigm that will be discussed in the following section.

Hypothetical Design of Decision Making

This section presents a hypothetical research design of the proposed model for making decisions. An abstract representation of the suggested paradigm, which includes pre-process and post-process is outlined in Figure 1. An information database's data is typically in a hybrid format. Either qualitative or quantitative data values are indicated. Consequently, it is necessary to transform the quantitative data into qualitative data. In pre-process, we use a RSIFAS to process the quantitative data after it has been cleaned. Besides, employing rough set reduction approach, the superfluous features are removed from the information database. Using the classification obtained in the pre-process, the soft set technique is used to mine decisions from the information database. This model's primary benefit is that it can be applied to both discrete and continuous data. Furthermore, it assigns appropriate weight to data values rather than 0 and 1.

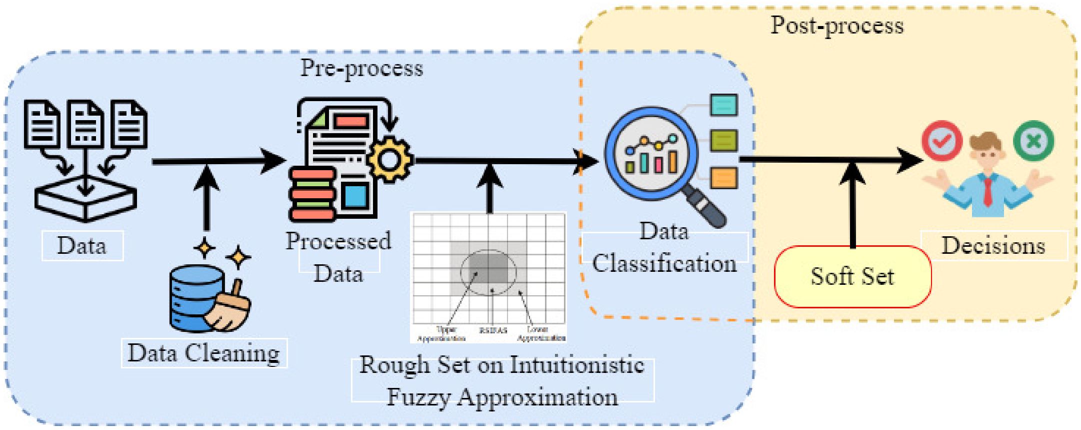

Figure 1. Hypothetical research design of decision making

Any model starts with choosing the right problem. The problem definition is constantly linked to the incorporation of existing knowledge. However, the possible reliability or usefulness of pattern of data elements or a single data element may differ greatly from enterprise to enterprise due to the reasoning and knowledge acquisition that may be connected with incompleteness and vagueness. Consequently, obtaining good conclusions from the multivariate data is the topmost significant difficulty. In order to mine appropriate classification, we employ RSIFAS reduction. Furthermore, we extract decisions using soft set techniques based on the pre-process classification.

Pre-process of Hypothetical Research Design

Figure 2 illustrates the pre-process architectural design in this area, which includes problem comprehension, cleaning of data, target data, IFPR, and data categorization. The foundational steps of every model include problem definition along with existing knowledge. A target dataset is then generated by organizing the goals and related factors, which will be used for decision-making. To start, a series of data cleaning procedures are accomplished to make sure the data are as accurate as feasible. These procedures include noise removal, consistency checks, and data completeness. As explained in Section II, intuitionistic fuzzy proximity relations are used to calculate equivalence classes for each parameter. To determine the almost indiscernibility of the objects z_i and z_j, we define an IFPR $R(z_i, z_j)$ concerning the membership and non-membership mapping as defined below.

$$\mu_R(z_i, z_j) = 1 - \frac{|V_{z_i} - V_{z_j}|}{\text{Max range}} \tag{3}$$

$$\nu_R(z_i, z_j) = \frac{|V_{z_i} - V_{z_j}|}{2(V_{z_i} + V_{z_j})} \tag{4}$$

In addition to becoming symmetric, the non-membership and membership functions have been defined so that their values fall between 1 and 0. Further, (β, α)-equivalence classes are induced and the almost indiscernible items are identified by the IFPR. Additionally, the information system is used for parameter reduction, which is a crucial component of the rough set. By doing this, the number of parameters may be reduced and the object categorization can meet all of the requirements. Reduction parameters have been shown to be able to eliminate unnecessary parameters and provide the decision maker with clear, concise information. If the set of parameters is dependent, we can use the dependency qualities of parameters to find all minimal subsets of parameters with the same number of elementary sets without compromising the reduced information system's classification power[14].

Parameter reduction is a crucial component of rough computing. Reduction can reduce the number of features and ensure that the entity classification meets all of the requirements. It has been noted in real-world applications that reduct parameters can eliminate unnecessary parameters in relation to a particular categorization produced by parameters and facilitate straightforward decision-making. Let $E \subseteq A$ and $a \in E$. If $Z/E = Z/(E-a)$, then the feature a is dispensable, else $a \in E$ is indispensable in E.

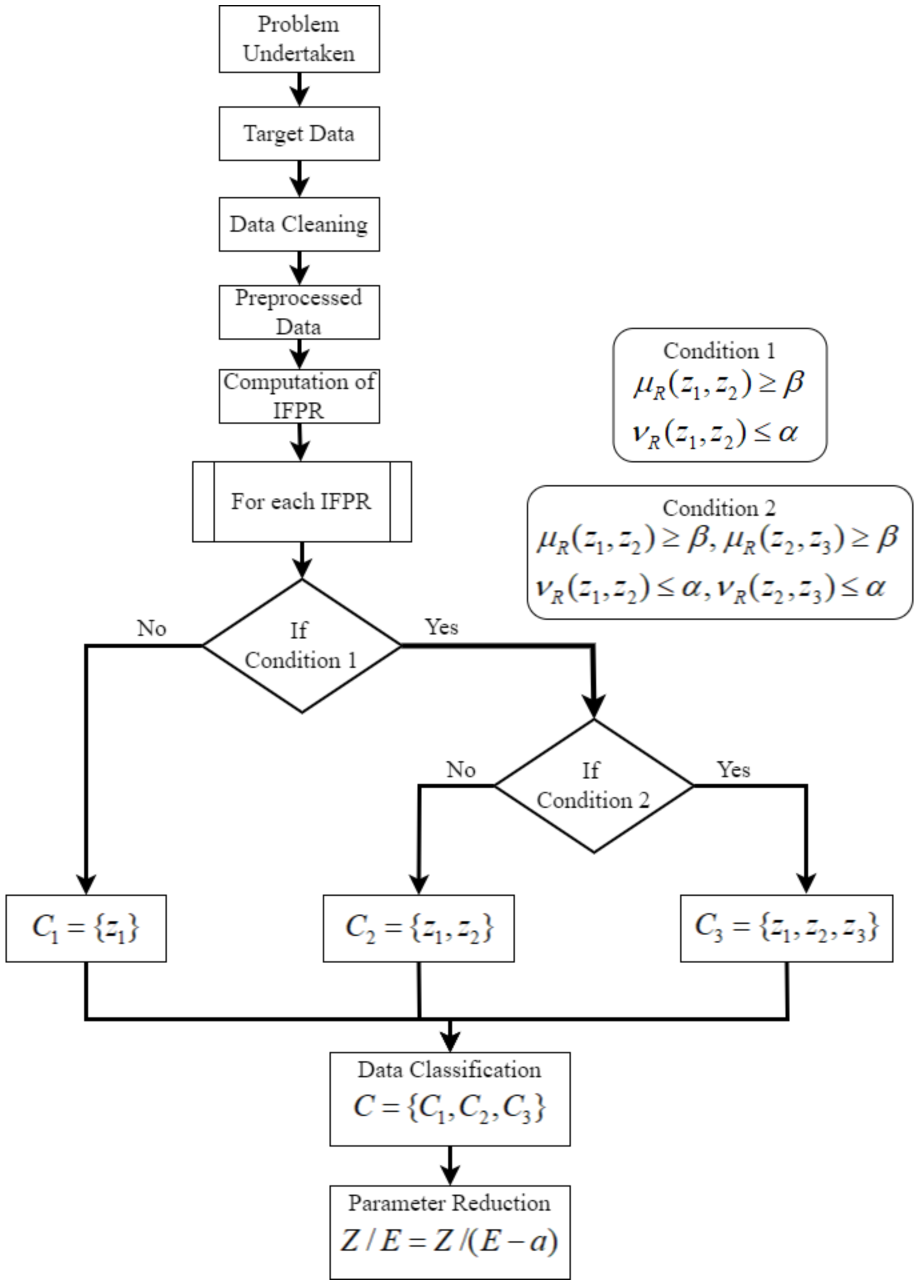

Figure 2. Pre-process of hypothetical research design

Post-process of Hypothetical Research Design

The application of soft set approaches for making decisions is covered in this section. The preprocessed classification serves as the post-process's input. Let Z be the conversation universe. Let $Z/R^{a_i}_{\beta,\alpha}$ be the categorization that the parameter a_i yields. Assume that there are q-number of (β, α) indiscernibility classes $C_j; 1 \leq j \leq q$ in the categorization $Z/R^{a_i}_{\beta,\alpha}$. Thus, we have $Z/R^{a_i}_{\beta,\alpha} = \{C_1, C_2, C_3, \cdots, C_q\}$.

Moreover to represent a soft set in a tabular form, we must compute the table's entries. Assume $|C_j| = m$. It means there are m-objects in the categorization C_j. Calculate U^{a_i} for every indiscernible class $C_j \in Z/R^{a_i}_{\beta,\alpha}$ to fill the i^{th} parameter cells of the table, where

$$U^{a_i} = \frac{\sum V_{z_t}}{m \times \text{Max range of feature } \ a_i}; \ \ z_t \in C_j \tag{5}$$

Calculate U^{a_i} for each $a_i \in A$. Further, decisions can be extracted from the soft set's tabular form depending on the choice value. The choice value of an object $z_k \in Z$ is defined as CV_k, where $U^{a_i}_k$ are the cell values of the soft set table, and

$$CV_k = \sum_{a_i \in A} U^{a_i}_k \tag{6}$$

To retrieve decisions from the information database, we now suggest a straightforward and weighted procedure. To get decisions, the following algorithm can be used.

Algorithm 1 *(Straight forward decision making algorithm)*
Input: Maximum range of $a_i \in A$ and $Z/R^{a_i}_{\beta,\alpha}$
Output: Inferred recommendations
1. Start
2. For every $a_i \in A$, do
3.   For every $C_j \in Z/R^{a_i}_{\beta,\alpha}$, do
4.   Calculate U^{a_i} using Eqn. 5
5.   End for
6. End for
7. For every $z_k \in Z$, do
8.   Calculate Cv_k using Eqn. 6
9. End for
10.Compute $Cv_i = Max\ Cv_k$ and determine the value of i
11.Write $\{z_i\}$
12.End

It is well known that choices regarding an information database's specifications may alter. As a result, the factors considered when making decisions might not be equally significant. It implies that while some criteria might be regarded as low priority, others might be regarded as high priority. We apply weights to the selected parameters in order to get around this restriction. Assume the weights of parameter $a_i \in A$ be w_i, where $w_i \in (0, 1]$. Accordingly, we define below the stacked decision making algorithm for making decisions.

Algorithm 2 *(Stacked decision making algorithm)*
Input: Maximum range of $a_i \in A$ and $Z/R^{a_i}_{\beta,\alpha}$
Output: Inferred recommendations
1. Start
2. For every $a_i \in A$, do
3.   For every $C_j \in Z/R^{a_i}_{\beta,\alpha}$, do
4.   Calculate U^{a_i} using Eqn. 5
5.   End for
6. End for
7. For every $z_k \in Z$, do
8.   Calculate $Cv_k = \sum_{a_j \in A}(w_i \times U^{a_i}_k)$
9. End for
10.Compute $Cv_i = Max\ Cv_k$ and determine the value of i
11.Write $\{z_i\}$
12.End

Experimental Study on Organization Ranking

To illustrate the model, a real-world application is suggested in this section. To demonstrate our suggested paradigm, we look at an information database, which is a group of institutions, and attempt to rank them. In Table 3, we outline the feature narration, the inscriptions to be used, along with its range. Institutions might not meet all the requirements to be at the top. Nevertheless, some of these characteristics might affect the score more than others. These parameters may vary for a range of values. As the value of decreases and increases, an increasing number of factors will become essential. Furthermore, some parameters influence other parameters; hence, for each parameter, almost indistinguishable institutions are found using an intuitionistic fuzzy proximity relation. The results that are generated can be used to evaluate institutions.

The placement performance of any institution serves as an attribute for the quality of the output and it is obtained from 385 which is roughly 24% of the overall weight. A high-quality input is necessary for any institution to provide high-quality output. Any institution's primary resources for providing high-quality education are its infrastructure and intellectual capital. As a result, the infrastructure and intellectual capital scores were set at 250 and 200, correspondingly, representing 15% and 12% of the aggregate weight. Following deployment, the students meet the organization's expectations which make the recruiter happy. It has a score of 200, or about 12%, and is an essential component of every institution. Extracurricular activities receive a score of 80 with a weight of 6% and often boost students' confidence levels. At the same time, prospective students place a high value on student satisfaction, which is assigned a score of 60 with a weight of 4%. But a lot of other factors that don't affect how the institutions are ranked aren't taken into account in this study.

The information database considered here is taken from India Today. However, all the data are not taken into account because to make the analysis simple and understandable. But, it can be ported to any size of data and is ideal for parallel processing. Besides, we have kept secret the institution names.

Feature	Representation	Collective range
Intellectual capital	IC	[1-250]
Infrastructure	IF	[1-200]
Performance in placement	PP	[1-385]
Satisfaction of recruiter	SR	[1-200]
Satisfaction of students	SS	[1-60]
Curricular activities	CA	[1-80]

Table 3. Outline of features and range details

Pre-process result analysis of experimental study

The following components of the pre-process design for the experimental study undertaken are covered in detail in this section. Data from 10 institutions are taken into consideration in order to illustrate pre-process of our suggested decision making model. The notation used for representing institutions are z_i, $i = 1, 2, 3, \cdots, 10$. The information database used for analysis is produced in Table 4. Each parameter's intuitionistic fuzzy proximity relations are joined together to form (β, α)- indiscernible categories. The IFP relations that correlate to the features IC, IF, PP, SR, SS, and CA are calculated. For the parameter IC, we display the intuitionistic fuzzy proximity relation in Table 5.

Organizations	IC	IF	PP	SR	SS	CA
z_1	92	48	100	137	32	2
z_2	88	58	121	143	40	34
z_3	124	61	130	142	38	9
z_4	131	78	138	145	46	25
z_5	148	102	180	147	43	27
z_6	179	117	247	160	53	53
z_7	191	110	316	163	41	64
z_8	226	145	266	167	54	63
z_9	227	143	298	169	53	79
z_{10}	229	151	304	169	56	49

Table 4. Sample database of organizations

Likewise, Table 6, Tables 7, Tables 8, Tables 9, and Tables 10 compute the intuitionistic fuzzy proximity relation for the parameters IF, PP, SR, SS, and CA, respectively. Further, the (β, α)-indiscernibility relation classification is obtained considering the membership value greater than 92% (0.92) and non-membership value less than or equal to 6% (0.06).

The (β, α) equivalence classes obtained for various parameters is presented below and it becomes the input to the post-process of the hypothetical research design. From the analysis, it is clear that $Z/R^{SR}_{\beta,\alpha}$ contains only one class and hence we have

R^{IC}	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8	z_9	z_{10}
z_1	1.0, 0.0	0.984, 0.011	0.872, 0.074	0.844, 0.087	0.776, 0.117	0.652, 0.161	0.604, 0.175	0.464, 0.211	0.460, 0.212	0.452, 0.213
z_2	0.984, 0.011	1.0, 0.0	0.856, 0.085	0.828, 0.098	0.760, 0.127	0.636, 0.170	0.588, 0.185	0.448, 0.220	0.444, 0.221	0.436 0.222
z_3	0.872, 0.074	0.856, 0.085	1.0, 0.0	0.972, 0.014	0.904, 0.044	0.780, 0.091	0.732, 0.106	0.592, 0.146	0.588, 0.147	0.580, 0.149
z_4	0.844, 0.087	0.828, 0.098	0.972, 0.014	1.0, 0.0	0.932, 0.030	0.808, 0.077	0.760, 0.093	0.620, 0.133	0.616, 0.134	0.608, 0.136
z_5	0.776, 0.117	0.760, 0.127	0.904, 0.044	0.932, 0.030	1.0, 0.0	0.876, 0.047	0.828, 0.063	0.688, 0.104	0.684, 0.105	0.676, 0.107
z_6	0.652, 0.161	0.636, 0.170	0.780, 0.091	0.808, 0.077	0.876, 0.047	1.0, 0.0	0.952, 0.016	0.812, 0.058	0.808, 0.059	0.800, 0.061
z_7	0.604, 0.175	0.588, 0.185	0.732, 0.106	0.760, 0.093	0.828, 0.063	0.952, 0.016	1.0, 0.0	0.860, 0.042	0.856, 0.043	0.848, 0.045
z_8	0.464, 0.211	0.448, 0.220	0.592, 0.146	0.620, 0.133	0.688, 0.104	0.812, 0.058	0.860, 0.042	1.0, 0.0	0.996, 0.001	0.988, 0.003
z_9	0.460 0.212	0.444, 0.221	0.588, 0.147	0.616, 0.134	0.684, 0.105	0.808, 0.059	0.856, 0.043	0.996, 0.001	1.0, 0.0	0.992, 0.002
z_{10}	0.452 0.213	0.436, 0.222	0.580 0.149	0.608, 0.136	0.676, 0.107	0.800 0.061	0.848, 0.045	0.988, 0.003	0.992, 0.002	1.0, 0.0

Table 5. IFPR of the future IC

R^{IF}	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8	z_9	z_{10}
z_1	1.0, 0.0,	0.950, 0.047	0.935, 0.060	0.850, 0.119	0.730, 0.180	0.655, 0.209	0.690, 0.196	0.515, 0.251	0.525, 0.249	0.485, 0.259
z_2	0.950, 0.047	1.0, 0.0	0.985, 0.013	0.900, 0.074	0.780, 0.138	0.705, 0.169	0.740, 0.155	0.565, 0.214	0.575, 0.211	0.535 0.222
z_3	0.935, 0.060	0.985, 0.013	1.0, 0.0	0.915, 0.061	0.795, 0.126	0.720, 0.157	0.755, 0.143	0.580, 0.204	0.590, 0.201	0.550 0.212
z_4	0.850, 0.119	0.900 0.074	0.915, 0.061	1.0, 0.0	0.330, 0.067	0.805, 0.1	0.340, 0.085	0.665, 0.150	0.675, 0.147	0.635 0.159
z_5	0.730, 0.180	0.780, 0.138	0.795, 0.126	0.830, 0.067	1.0, 0.0	0.925, 0.034	0.960, 0.019	0.785, 0.087	0.795, 0.084	0.755, 0.097
z_6	0.655, 0.209	0.705, 0.169	0.720, 0.157	0.805, 0.100	0.925, 0.034	1.0, 0.0	0.965, 0.015	0.860, 0.053	0.870, 0.050	0.830, 0.063
z_7	0.690, 0.196	0.740, 0.155	0.755, 0.143	0.840, 0.085	0.960, 0.019	0.965, 0.015	1.0, 0.0	0.825, 0.069	0.835, 0.065	0.795 0.079
z_8	0.515, 0.251	0.565, 0.214	0.580, 0.204	0.665, 0.150	0.785, 0.087	0.560, 0.053	0.525, 0.069	1.0 0.0	0.990 0.003	0.970, 0.010
z_9	0.525, 0.249	0.575, 0.211	0.590, 0.201	0.675, 0.147	0.795, 0.084	0.870, 0.050	0.835, 0.065	0.990, 0.003	1.0, 0.0	0.960, 0.014
z_{10}	0.485, 0.259	0.535, 0.222	0.550, 0.212	0.635, 0.159	0.755, 0.097	0.830, 0.063	0.795, 0.079	0.970, 0.010	0.960, 0.014	1.0, 0.0

Table 6. IFPR of the future IF

$Z/A = Z/(A-SR)$. It implies that the feature SR is a superfluous feature and may be eliminated from the information database.

$$\begin{aligned}
Z/R^{IC}_{\beta,\alpha} &= \{\{z_8,z_9,z_{10}\},\{z_6,z_7\},\{z_3,z_4,z_5\},\{z_1,z_2\}\} \\
Z/R^{IF}_{\beta,\alpha} &= \{\{z_8,z_9,z_{10}\},\{z_5,z_6,z_7\},\{z_4\},\{z_1,z_2,z_3\}\} \\
Z/R^{PP}_{\beta,\alpha} &= \{\{z_7,z_9,z_{10}\},\{z_6,z_8\},\{z_5\},\{z_1,z_2,z_3,z_4\}\} \\
Z/R^{SR}_{\beta,\alpha} &= \{z_{10},z_9,z_8,z_7,z_6,z_5,z_4,z_3,z_2,z_1\} \\
Z/R^{SS}_{\beta,\alpha} &= \{\{z_6,z_8,z_9,z_{10}\},\{z_2,z_3,z_4,z_5,z_7\},\{z_1\}\} \\
Z/R^{CA}_{\beta,\alpha} &= \{\{z_6,z_{10}\},\{z_9\},\{z_7,z_8\},\{z_4,z_5\},\{z_3\},\{z_2\},\{z_1\}\}
\end{aligned}$$

R^{PP}	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8	z_9	z_{10}
z_1	1.0, 0.0	0.918, 0.054	0.944, 0.036	0.966, 0.021	0.915, 0.045	0.727, 0.122	0.532, 0.178	0.673, 0.139	0.583, 0.165	0.566, 0.170
z_2	0.918, 0.054	1.0, 0.0	0.975, 0.018	0.952, 0.033	0.834, 0.098	0.645, 0.171	0.451, 0.223	0.592, 0.187	0.501, 0.211	0.485, 0.215
z_3	0.944, 0.036	0.975, 0.018	1.0, 0.0	0.977, 0.015	0.859, 0.081	0.670, 0.155	0.476, 0.209	0.617, 0.172	0.527, 0.196	0.510, 0.200
z_4	0.966, 0.021	0.952, 0.033	0.977, 0.015	1.0, 0.0	0.882, 0.066	0.693, 0.142	0.499, 0.196	0.639, 0.158	0.549, 0.183	0.532, 0.188
z_5	0.915, 0.045	0.834, 0.098	0.859, 0.081	0.882, 0.066	1.0, 0.0	0.811, 0.078	0.617, 0.137	0.758, 0.096	0.668, 0.123	0.651, 0.128
z_6	0.727, 0.122	0.645, 0.171	0.670, 0.155	0.693, 0.142	0.811, 0.078	1.0, 0.0	0.806, 0.061	0.946, 0.019	0.856, 0.047	0.839, 0.052
z_7	0.532, 0.178	0.451, 0.223	0.476, 0.209	0.499, 0.196	0.617, 0.137	0.806, 0.061	1.0, 0.0	0.859, 0.043	0.949, 0.015	0.966, 0.010
z_8	0.673, 0.139	0.592, 0.187	0.617, 0.172	0.639, 0.158	0.758, 0.096	0.946, 0.019	0.859, 0.043	1.0, 0.0	0.910, 0.028	0.893, 0.033
z_9	0.583, 0.165	0.501, 0.211	0.527, 0.196	0.549, 0.183	0.668, 0.123	0.856, 0.047	0.949, 0.015	0.910, 0.028	1.0, 0.0	0.983, 0.005
z_{10}	0.566, 0.170	0.485, 0.215	0.510, 0.200	0.532, 0.188	0.651, 0.128	0.839, 0.052	0.966, 0.010	0.893, 0.033	0.983, 0.005	1.0, 0.0

Table 7. IFPR of the future PP

R^{SR}	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8	z_9	z_{10}
z_1	1.0, 0.0	0.970, 0.011	0.975, 0.009	0.960, 0.014	0.950, 0.018	0.885, 0.039	0.870, 0.043	0.850, 0.049	0.840, 0.052	0.840, 0.052
z_2	0.970, 0.011	1.0, 0.0	0.995, 0.002	0.990, 0.003	0.980, 0.007	0.915, 0.028	0.900, 0.033	0.880, 0.039	0.870, 0.042	0.870, 0.042
z_3	0.975, 0.009	0.995, 0.002	1.0, 0.0	0.985, 0.005	0.975, 0.009	0.910, 0.030	0.895, 0.034	0.875, 0.040	0.865, 0.043	0.865, 0.043
z_4	0.960, 0.014	0.990, 0.003	0.985, 0.005	1.0, 0.0	0.990, 0.003	0.925, 0.025	0.910, 0.029	0.890, 0.035	0.880, 0.038	0.880, 0.038
z_5	0.950, 0.018	0.980, 0.007	0.975, 0.009	0.990, 0.003	1.0, 0.0	0.935, 0.021	0.920, 0.026	0.900, 0.032	0.890, 0.035	0.890, 0.035
z_6	0.885, 0.039	0.915, 0.028	0.910, 0.030	0.925, 0.025	0.935, 0.021	1.0, 0.0	0.985, 0.005	0.965, 0.011	0.955, 0.014	0.955, 0.014
z_7	0.870, 0.043	0.900, 0.033	0.895, 0.034	0.910, 0.029	0.920, 0.026	0.985, 0.005	1.0, 0.0	0.980, 0.006	0.970, 0.009	0.970, 0.009
z_8	0.850, 0.049	0.880, 0.039	0.875, 0.040	0.890, 0.035	0.900, 0.032	0.965, 0.011	0.980, 0.006	1.0, 0.0	0.990, 0.003	0.990, 0.003
z_9	0.840, 0.052	0.870, 0.042	0.865, 0.043	0.880, 0.038	0.890, 0.035	0.955, 0.014	0.970, 0.009	0.990, 0.003	1.0, 0.0	1.0, 0.0
z_{10}	0.840, 0.052	0.870, 0.042	0.865, 0.043	0.880, 0.038	0.890, 0.035	0.955, 0.014	0.970, 0.009	0.990, 0.003	1.0, 0.0	1.0, 0.0

Table 8. IFPR of the future SR

Post-process result analysis of experimental study

Data classification can be done with soft set analysis. However, pre-processing has already classed the data. Using soft set strategies to produce effective decisions is the aim of this process. We take into consideration the classification obtained for parameter IC in order to demonstrate post-process computation. According to the above computation it is understood that $Z/R^{IC}_{\beta,\alpha}$ contains four classes. Assume that, these four classes be $C_1 = \{z_1, z_2\}$, $C_2 = \{z_3, z_4, z_5\}$, $C_3 = \{z_6, z_7\}$, $C_4 = \{z_8, z_9, z_{10}\}$.

R^{SS}	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8	z_9	z_{10}
z_1	1.0, 0.0	0.867, 0.056	0.900, 0.043	0.767, 0.090	0.817, 0.073	0.650, 0.124	0.850, 0.062	0.633, 0.128	0.650, 0.124	0.600, 0.136
z_2	0.867, 0.056	1.0, 0.0	0.967, 0.013	0.900, 0.035	0.950, 0.018	0.783, 0.070	0.983, 0.006	0.767, 0.074	0.783, 0.070	0.733, 0.083
z_3	0.900, 0.043	0.967, 0.013	1.0, 0.0	0.867, 0.048	0.917, 0.031	0.750, 0.082	0.950, 0.019	0.733, 0.087	0.750, 0.082	0.700, 0.096
z_4	0.767, 0.090	0.900, 0.035	0.867, 0.048	1.0, 0.0	0.950, 0.017	0.883, 0.035	0.917, 0.029	0.867, 0.040	0.883, 0.035	0.833, 0.049
z_5	0.817, 0.073	0.950, 0.018	0.917, 0.031	0.950, 0.017	1.0, 0.0	0.833, 0.052	0.967, 0.012	0.817, 0.057	0.833, 0.052	0.783, 0.066
z_6	0.650, 0.124	0.783, 0.070	0.750, 0.082	0.883, 0.035	0.833, 0.052	1.0, 0.0	0.800, 0.064	0.983, 0.005	1.0, 0.0	0.950, 0.014
z_7	0.850, 0.062	0.983, 0.006	0.950, 0.019	0.917, 0.029	0.967, 0.012	0.800, 0.064	1.0, 0.0	0.783, 0.068	0.800, 0.064	0.750, 0.077
z_8	0.633, 0.128	0.767, 0.074	0.733, 0.087	0.867, 0.040	0.817, 0.057	0.983, 0.005	0.783, 0.068	1.0, 0.0	0.983, 0.005	0.967, 0.009
z_9	0.650, 0.124	0.783, 0.070	0.750, 0.082	0.883, 0.035	0.833, 0.052	1.0, 0.0	0.800, 0.064	0.983, 0.005	1.0, 0.0	0.950, 0.014
z_{10}	0.600, 0.136	0.733, 0.083	0.700, 0.096	0.833, 0.049	0.783, 0.066	0.950, 0.014	0.750, 0.077	0.967, 0.009	0.950, 0.014	1.0, 0.0

Table 9. IFPR of the future SS

R^{CA}	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8	z_9	z_{10}
z_1	1.0, 0.0	0.600, 0.444	0.912, 0.318	0.712, 0.426	0.688, 0.431	0.363, 0.464	0.225, 0.470	0.238, 0.469	0.037, 0.475	0.412, 0.461
z_2	0.600, 0.444	1.0, 0.0	0.688, 0.291	0.888, 0.076	0.912, 0.057	0.762, 0.109	0.625, 0.153	0.638, 0.149	0.438, 0.199	0.812, 0.090
z_3	0.912, 0.318	0.688, 0.291	1.0, 0.0	0.800, 0.235	0.775, 0.250	0.450, 0.355	0.312, 0.377	0.325, 0.375	0.125, 0.398	0.500, 0.345
z_4	0.712, 0.426	0.888, 0.076	0.800, 0.235	1.0, 0.0	0.975, 0.019	0.650, 0.179	0.512, 0.219	0.525, 0.216	0.325, 0.260	0.700, 0.162
z_5	0.688, 0.431	0.912, 0.057	0.775, 0.250	0.975, 0.019	1.0, 0.0	0.675, 0.162	0.538, 0.203	0.550, 0.200	0.350, 0.245	0.725, 0.145
z_6	0.363, 0.464	0.762, 0.109	0.450, 0.355	0.650, 0.179	0.675, 0.162	1.0, 0.0	0.862, 0.047	0.875, 0.043	0.675, 0.098	0.950, 0.020
z_7	0.225, 0.470	0.625, 0.153	0.312, 0.377	0.512, 0.219	0.538, 0.203	0.862, 0.047	1.0, 0.0	0.988, 0.004	0.812, 0.052	0.812, 0.066
z_8	0.238, 0.469	0.638, 0.149	0.325, 0.375	0.525, 0.216	0.550, 0.200	0.875, 0.043	0.988, 0.004	1.0, 0.0	0.800 0.056	0.825, 0.062
z_9	0.037, 0.475	0.438, 0.199	0.125, 0.398	0.325, 0.260	0.350, 0.245	0.675, 0.098	0.812, 0.052	0.800 0.056	1.0, 0.0	0.625, 0.117
z_{10}	0.412, 0.461	0.812, 0.090	0.500, 0.345	0.700, 0.162	0.725, 0.145	0.950, 0.020	0.812, 0.066	0.825, 0.062	0.625, 0.117	1.0, 0.0

Table 10. IFPR of the future CA

The value of U^{IC} for class C_1 is calculated below.

$$U^{IC} = \frac{V_{z_1} + V_{z_2}}{m \times 250} = \frac{92+88}{2 \times 250} = 0.36$$

Likewise, the values of U^{IC} for classes C_2, C_3 and C_4 are computed as 0.54, 0.74, and 0.91 respectively. The computation is repeated for the entire parameters infrastructure (IF), performance in placement (PP), satisfaction of student (SS), and

Organizations	IC	IF	PP	SS	CA
z_1	0.36	0.28	0.32	0.53	0.02
z_2	0.36	0.28	0.32	0.69	0.42
z_3	0.54	0.28	0.32	0.69	0.11
z_4	0.54	0.39	0.32	0.69	0.32
z_5	0.54	0.55	0.47	0.69	0.32
z_6	0.74	0.55	0.67	0.90	0.64
z_7	0.74	0.55	0.79	0.69	0.79
z_8	0.91	0.73	0.67	0.90	0.79
z_9	0.91	0.73	0.79	0.90	0.99
z_{10}	0.91	0.73	0.79	0.90	0.64

Table 11. Soft set tabular presentation

Organizations	IC	IF	PP	SS	CA	Aggregate value	Rank
z_1	0.36	0.28	0.32	0.53	0.02	1.51	10
z_2	0.36	0.28	0.32	0.69	0.42	2.07	8
z_3	0.54	0.28	0.32	0.69	0.11	1.94	9
z_4	0.54	0.39	0.32	0.69	0.32	2.26	7
z_5	0.54	0.55	0.47	0.69	0.32	2.57	6
z_6	0.74	0.55	0.67	0.90	0.64	3.50	5
z_7	0.74	0.55	0.79	0.69	0.79	3.56	4
z_8	0.91	0.73	0.67	0.90	0.79	4.00	2
z_9	0.91	0.73	0.79	0.90	0.99	4.32	1
z_{10}	0.91	0.73	0.79	0.90	0.64	3.97	3

Table 12. Ranking of organizations according to straight forward decision making algorithm

curricular activities (CA) and is presented in Table 11. It is considered as a tabular representation of soft set. It is clearly seen that the objects are partially belonging to the parameters and takes value between 0 and 1.

Further, to rank the organizations relating to the features $A = \{IC, IF, PP, SS, CA\}$, the aggregate values of the organizations are obtained as discussed in the straight forward Algorithm 1. The aggregate values of all the organizations are presented in Table 12. According to the computation, the first rank belongs to the institution z_9. Similarly, the second and third rank goes to the organization z_8, and z_{10} respectively. Likewise, the ranking of other organizations can be obtained from Table 12.

Further, we carry out the result analysis relating to Algorithm 2. As mentioned in earlier section, we now use Algorithm 2 to analyze the identical instance. Assume that the features $A = IC, IF, PP, SS, CA$ are given the following weights. Assume that the weights be 30%, 40%, 60%, 10%, and 20%, respectively, correspond to the parameters IC, IF, PP, SS, and CA. Table 13 displays the weighted choice value for each object based on the weights.

Organizations	IC	IF	PP	SS	CA	Aggregate value	Rank
	$w_1 = 0.3$	$w_2 = 0.4$	$w_3 = 0.6$	$w_4 = 0.1$	$w_5 = 0.2$		
z_1	0.36	0.28	0.32	0.53	0.02	0.469	10
z_2	0.36	0.28	0.32	0.69	0.42	0.685	9
z_3	0.54	0.28	0.32	0.69	0.11	0.898	8
z_4	0.54	0.39	0.32	0.69	0.32	1.015	7
z_5	0.54	0.55	0.47	0.69	0.32	1.235	6
z_6	0.74	0.55	0.67	0.90	0.64	1.843	5
z_7	0.74	0.55	0.79	0.69	0.79	2.506	4
z_8	0.91	0.73	0.67	0.90	0.79	2.849	3
z_9	0.91	0.73	0.79	0.90	0.99	3.482	1
z_{10}	0.91	0.73	0.79	0.90	0.64	3.429	2

Table 13. Ranking of organizations according to stacked decision making algorithm

According to the computation, the first rank belongs to the organization z_9 whereas the second rank belongs to the organization z_{10}. Likewise the third rank goes to the organization z_8. Similarly, the ranking of the other organizations man be referred from Table 13 relating to stacked decision making algorithm. The aforementioned ranking choice of organization complies with the selection criteria. As a result, the algorithm performs better while making decisions under a variety of conditions.

Conclusions

A soft set is a generic mathematical technique used to solve a variety of real-world issues including ambiguous or fuzzy objects and uncertainties. According to the literature, Maji and Roy[15] combined the rough-set and soft-set techniques for decision making. However, an object in each of these models has the option of belonging to or not belonging to a parameter. As a result, the parameter values can only be 0 or 1. However, it is frequently observed in real-world problems that an entity may only partially correspond to a feature. The reason for this is because parameter values in an information database are almost identical. This restriction is removed by the suggested decision-making approach. Furthermore, the suggested model reduces to the current model if almost indiscernibility becomes indiscernibility. As a result, it works better at solving real-world problems in a variety of scenarios. In order to make decisions about ten organizations based on several criteria, we have used a real-world scenario. We have demonstrated the use of RSIFAS to make decisions by taking into account soft sets.

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Author contributions statement

Author, Madhusmita Mishra has conceptualized the problem, and methodology based on her research work. Hybridization of rough computing with bio-inspired computing is a challenging task and it has been carried out by Madhusmita Mishra. The implementation and analysis are being carried out by Madhusmita under the supervision of D. P. Acharjya. Besides, Author D. P. Acharjya has thoroughly reviewed the paper since its drafting stage by Madhusmita. The figures, tables, and their presentation are carried out by author D. P. Acharjya. In addition, D. P. Acharjya has thrown light to expand the comparative study using various other techniques.

Data Availability

The supporting data used to demonstrate the model is presented in the article. The model can be evaluated over

Competing Interests

The authors of this research certify that they have no affiliation with or involvement in any organization or entity with financial interest such as project grants; educational grants; consultancies; stock ownership, or other equity interest. The authors also have no conflict of interest in terms of non-financial interest (such as personal or professional relationships, affiliations, knowledge, or beliefs) in the subject matter or materials discussed in this manuscript.