Analysis of Teaching-Learning Efficiency Using Attribute Based Double Bounded Rough Neutrosophic Set Driven Random Forests

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Abstract
Face-on-Face interaction constitutes an integral part of the classroom atmosphere as it provides teachers with an opportunity to understand their students intimately. Hence, this study deals with attribute based double bounded rough neutrosophic set driven random forests using Gini Impurity based split to arrive at a decision regarding the teaching-learning efficiency. A mathematical model is constructed using double bounded rough neutrosophic set which is utilised to evaluate the expression of the students with the help of a real-time data by capturing the images of the students against different subjects. The decisions made are then used to fit a random forest model to establish inferences regarding the teaching-learning efficiency for different subjects. The constructed model is then validated using newly added test objects.

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Keywords: Image processing, Neutrosophic image processing, Image segmentation, DICOM image**:** ouble Bounded Rough Sets, Rough Sets, Neutrosophic Sets, Fuzzy Sets, Face Expressions, Student expression detection, Facial key points, Random forests, Decision Trees, Gini Index Impurity s.

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1. Introduction

"Actions speak louder than words"

The notion that facial expressions make-up the roads leading to several significant observations, both psychological and physical trace back to the pioneer of facial expression detection, Paul Ekman [1]. Ekman, a contemporary psychologist is known well to have established the concept of facial expressions as a universal phenomenon. In 1973, he along with Tomkins [2], Gellhorn [3], Izard [4] popularised the facial feedback theory [5] put forward by James [6], almost a century back before the theory revolutionised psychology.

The idea was further shaped and bettered by Buck [7] to pave the stepping stones towards providing much serious considerations towards facial expression detection models. The facial feedback theory suggests that an individual's experience of emotions is often influenced by feedback from their facial movements. With increasing developments in the study of the facial feedback hypothesis, researchers suggest that observations play a pivotal role in contributing towards target affective judgements and expression manipulation [8]. Hence, it can be said that the excitement behind face recognition and expression analysis has successfully initiated a crossover between facial feedback theory in psychology and expression recognition [11,12,13,14].

Drawing on these conclusions, the authors have utilised the same concepts to construct a model that'd help derive decisions from the observations a student makes while listening to a subject and making judgements to manipulate their expressions and evaluate the purity of each decision made. The proposed model would be an extension of the attribute based double-bounded rough neutrosophic set [9] system for decision making wherein a random forest [10] is utilised to establish the purity/count of every attribute against the subject for which the image was taken.

1. Double Bounded Rough Neutrosophic Set Driven Random Forest in Deriving Inferences

In this section, a mathematical model is developed by combining the Double Bounded Rough Neutrosophic Set Theory [9] and random forest techniques to arrive at the conclusion and draw inferences from the decisions made for the objects present in the approximation space.

1.1. The Double Bounded Rough Neutrosophic Set For an N-information System

Throughout this section, there is consideration of a covering-based N-information system given by $I = (U, A, F, N)$ where U defines the universe and is a non-empty finite set of objects. A signifies the non-empty finite set of fuzzy attributes defined by the mapping

$$\mu_{\mathrm{a}}: U \to [0,1]\ \forall a \in A$$

while F is a function defined by the mapping $F: A \to \rho(U)\ \forall\ a \in A$ such that $F(a) \subseteq U$ would contain those elements of U that possess the attribute a with the assumption that $U\ F(a) = U, a \in A$.

Equation 2.1.1: For every $a \in A$ and $x \in X$, the evaluation of F is carried out by the equation given by

$$\alpha_{\mathrm{i}} = \frac{(\sum_{i=1}^{n}(w(a_j) * \mu_p(x_i))}{\sum_{j=1}^{k} w(a_j)}$$

$$F(a) = \{x \in X | \alpha_{\mathrm{i}} \leq \delta\}$$

Here, n denotes the number of elements in U, k denotes the number of attributes in the universe, $w(a_{\mathrm{j}})$ signifies the weights assigned to the attributes that lies in the range [0,1], $\mu(pi)$ denotes the mean of the feature points that describe the dataset, and δ signifies the threshold to group the attributes by making the choice of an appropriate interval spacing.

Algorithm 2.1.1: Consider a set X defined by $X \subseteq U$. For any $x \in X$, the neighbourhood function $N(x)$ could be defined by $U\ N(x)$ and is computed using the shortest distance by computing the mean algorithm [9] given by

1. Let s denote the object chosen and S be the set of all objects in U
2. This object is identified by the value it possesses against every parameter Pi that can be represented by t.
3. Taking the absolute difference between the t for every s against the mean of every parameter Pi will be represented by b.
4. The absolute difference between the t' for every $s' \in S$ against the mean of every parameter Pi will be represented by c.
5. Whenever the absolute difference between b and c is greater than a threshold, the count variable for every object would be incremented for every iteration.
6. The objects in s' whose count is greater than a chosen threshold given by δ' would be declared as the neighbours of the chosen object s

Both the functions F and N would be constructed from the scenario or systems under consideration with expert knowledge and interference. Sometimes, the neighbourhood function could also be devised using any relation that has been observed while studying the data in hand amongst the elements of U.

For any set P' given by $P' \subseteq A$ and fuzzy membership function μ_a, a double bounded rough set that has three distinct elements in the set namely the lower approximation, the right upper approximation and the left upper approximation can be constructed. Here, the lower approximation set would be composed of the elements in P' that have an I-relationship defined with both x and y while the right and the left upper approximations would deal with the elements in P that have an I-relationship with either x or y [19].

The subset X of U defines the double bounded rough set $DRS(a{\sim}X)$ as the collection of the lower approximation $DR\_(a{\sim}X)$, right upper approximation $DR^{-}(a{\sim}X)$ and left upper approximation $^{-}DR\ (a{\sim}X)$ of X with respect to the attribute a. Here, the lower, left upper, and right upper approximations are defined by

$$DR\_(a{\sim}X) = N(F(a) \cap N(x))$$

$$^{-}DR(a{\sim}X) = N(X) \cup (N(F(a)) \cap N(X))$$

$$DR^{-}(a{\sim}X) = N(F(a)) \cup \left(N(F(a)) \cap N(X)\right)$$

Conclusively, the double bounded rough set $DRS(a{\sim}X)$ is given by

$$DRS(a{\sim}X) = (DR\_(a{\sim}X),\ ^{-}DR\ (a{\sim}X), DR^{-}(a{\sim}X))$$

The double bounded rough set provides the definite, possible, plausible, unascertainable elements of X that possess the attribute a. It must be noted that for every $a \in A, DRS(a{\sim}X)$ can be achieved.

For the set P', assuming $\forall\ p\ \in P'$, define a fuzzy set μ_P given by the mapping $\mu_P: U \to [0,1]$ that provides the degree of membership of a parameter on the elements of U. Developing on the knowledge of indeterminacy, one can define a neutrosophic set for every double bounded rough set by

$$DR = \{DRS(a{\sim}X) |\ X \subseteq U, a \in A\}$$

$$DR\_ = \{DR\_(a{\sim}X| \subseteq U, a\ \in A\}$$

$$DR^{-} = \{DR^{-}(a{\sim}X| \subseteq U, a\ \in A\}$$

$$^{-}DR = \{\ ^{-}DR(a{\sim}X| \subseteq U, a\ \in A\}$$

With the definitions of the DBRS established, a fuzzy set $\mu_{\infty}: DR\_ \to [0,1]$ can be defined for the lower approximation, right upper approximation, and left upper approximation as

$$\mu\_(DR(a{\sim}X)) = \max\{\min(\mu_{\mathrm{p}}(x))\}\ \ x \in DR\_(a{\sim}X)$$

$$\mu^{-}(DR(a{\sim}X)) = \max\{\min(\mu_{\mathrm{p}}(x))\}\ \ x \in DR^{-}(a{\sim}X)$$

$$^{-}\mu(DR(a{\sim}X)) = \max\{\min(\mu_{\mathrm{p}}(x))\}\ \ x \in\ ^{-}DR(a{\sim}X)$$

Definition 2.1.1: To construct a double bounded rough neutrosophic set, one needs to handle the three fundamental functions that define any neutrosophic set namely the truth membership, the indeterminacy and the non-membership which are almost always independently related.

A neutrosophic set takes the form

$$N = \{(x, \alpha N(x), \beta N(x), \gamma N(x) | x \in X\}$$

where $\alpha N, \beta N\ and\ \gamma N$ represent the three membership functions identified by the mapping $X \to]0-, 1+[$ which possess a sum that falls in the range defined by $\to]0- \leq \alpha N(x) + \beta N(x) + \gamma N(x) \leq 3+[$.

A neutrosophic fuzzy set defined in the N information space over the relation $\bar{\mu}: DR \to [0,1]\ X\ [0,1]\ X\ [0,1]$ can be given by

$$\bar{\mu}(DRS(a\sim X)) = (\mu\_(DR(a\sim X)), \mu^{-}(DR(a\sim X)), {}^{-}\mu(DR(a\sim X)))$$

Hence, the double bounded rough neutrosophic set $\overline{\mu}(DRS(a\sim X))$ in an N-information system identified by $I = (U, A, F, N)$ can be utilised to evaluate any attribute $a \in A$ defined for any dataset with no requirement of a training dataset to fit the model for validation and testing and can be given by

Equation 2.1.2:

$$V(a) = 2(max\left(\left(\frac{Ta + Ia}{2}\right), \left(\frac{1 + Ia - Fa}{2}\right)\right) - min\left(\left(\frac{Ta + Ia}{2}\right), \left(\frac{1 + Ia - Fa}{2}\right)\right))$$

where $T_a\ represents\ \ \mu\_(DR(a\sim X))$

$I_a\ representes\ \ \mu^{-}\big(DR(a\sim X)\big)$

$F_a\ represents\ {}^{-}\mu(DR(a\sim X)))$

Here, $V(a)$ is computed for every $a \in A$ and the values of all the attributes for a single object constitute a list given by V. The final decision corresponding to the object would be the maximum of all the elements present in V given by:

$$V = [V(a1), V(a2), \dots , V(ak)]$$

$$decision(x) = \max(V)\ \forall x \in X$$

Here, V is a fuzzy set obtained using the attribute based double bounded rough neutrosophic set method defined by the function $\mu_{v} : V \rightarrow [0,1]$.

In a similar fashion, the decision is evaluated for every object in the universe U and the collection of decisions are defined by the set D given by

$$D = \{\max(v1)\,, \max(v2)\,, \dots, \max(vn)\}$$

which is then appended to a relational universe U' that has the same number of objects as in U and shares a link with the set U that was utilised to compute the attribute values. The relational universe U' would then be fit into a random forest for evaluating newly added objects and draw inferences

1.2.Attribute Driven Random Forest in an N-Information System

In this section, a random forest is constructed for the N-information system defined by $I' = (U\ , A')$. Here, A' denotes the set of attributes that would describe the decisions made using the double bounded rough neutrosophic set model to generate inferences regarding the decisions made and evaluate a new object being added to the information system.

Moving forward, the set of unique decisions from the set of decisions D that was constructed using the double bounded neutrosophic set model would constitute the set S that defines the state any element $x \in X$ is in at any given time t where $X \subseteq U$.

$$S = \{S_1, S_2, \ldots, S_m\}$$

where m denotes the number of unique decisions in D.

The objective of this section is to predict the state of each object and evaluate any new object added in the given N-information system using Random Forest Technique [18]. The construction of the individual decision trees that would be bagged and aggregated would be performed using Gini Impurity Indexing.

Equation 2.2.1: For any $a' \in A'$ and $s \in S$, the Gini Impurity is given by the expression

$$G(a''_i) = \sum_{j=1}^{n}((n_j/n) * (1 - P(a''_i|s)^2); \; i = 1,2, \ldots, k$$

where n denotes the number of elements in U.

Here, $P(a_i|s)$ denotes the probability of the number of objects in U possessing the attribute a'_i with respect to the decision d. The root nodes and subsequent nodes with the best split would then be given by:

$$G_{\text{bestSplit}} = \min\big(G(f1), G(f2), \ldots, G(fl)\big)$$

With respect to the information system, the process to identify the best node from the set of attributes in U by estimating the best split using Gini impurity indexing takes the form:

```
def gini_impurity (val):
    n = val.sum()
    p_sum = 0
    for key in val.keys():
        p_sum = p_sum  +  (val[key] / n ) * (val[key] / n )
        gini = 1 - p_sum
return gini
```

Finally, the leaf node present at the maximum depth of the tree would contain the number of states an attribute a' is in.

In a similar fashion, several decision trees may be constructed which are then bagged i.e., bootstrapped and aggregated to give rise to a random forest. This attribute based neutrosophic rough set driven random forest model can now be utilised to validate the decision of any newly added object in the relational universe U'.

2. Application of The ADBRS Driven Random Forest Model to Draw Inferences Regarding the Teaching-Learning Efficiency Using Student Expressions

Objective: To implement the attribute based double bounded rough neutrosophic set driven random forest model to analyse the facial expressions of students while in class with reference to different subjects and infer the efficiency of the teaching-learning process by evaluating the various expressions displayed by the object against the different subjects for which the images were taken and validate the decision for a newly added object.

Data: The paper utilises real-time data for analysis by capturing the photographs of students while in class against four subject periods. There were 100 images in the dataset chosen with explicit age variation present between the different images chosen so as to increase the diversity in establishing the efficiency of the teaching learning process.

***Facial Key Points*:** An online face detector and key point marker titled makesense.ai [20] was employed to evaluate the feature points for determining the attributes. Since the dataset is relatively smaller when compared against a dataset with 1000 entries, but large enough to train, validate, test, and make satisfactory predictions, manual marking of the 15 essential facial key points was employed.

The fifteen feature points were marked on the pivotal points of the face. These fifteen features were divided into their respective x and y coordinates to get 30 parameter values and would constitute the parameter set P.

fig1: A sample to indicate how the facial points were chosen

The fifteen facial feature points thus constructed are as follows:

Table1: Facial Feature Points

Point	Co-ordinates	Parameters
0	(left_eye_center_x, left_eye_center_y)	(P1,P2)
1	(right_eye_center_x, right_eye_center_y)	(P3,P4)

2	(right_eye_inner_corner_x, right_eye_inner_corner_y)	(P5,P6)
3	(right_eye_outer_corner_x,right_eye_outer_corner_y	(P7,P8)
4	(left_eye_inner_corner_x, left_eye_inner_corner_y)	(P9,P10)
5	(left_eye_outer_corner_x, left_eye_outer_corner_y)	(P11,P12)
6	(right_eyebrow_inner_x, right_eyebrow_inner_y)	(P13,P14)
7	(right_eyebrow_outer_x,right_eyebrow_outer_y)	(P15,P16)
8	(left_eyebrow_inner_x, left_eyebrow_inner_y)	(P17,P18)
9	(left_eyebrow_outer_x, left_eyebrow_outer_y)	(P19,P20)
10	(nose_tip_x,nose_tip_y)	(P21,P22)
11	(mouth_left_corner_x, mouth_left_corner_y)	(P23,P24)
12	(mouth_right_corner_x, mouth_right_corner_y)	(P25,P26)
13	(mouth_center_top_lip_x, mouth_center_top_lip_y)	(P27,P28)
14	(mouth_center_bottomlip_x, mouth_center_bottomlip_y)	(P29,P30)

The diversity of the dataset with respect to the ages of the individuals chosen could be presented through the following chart

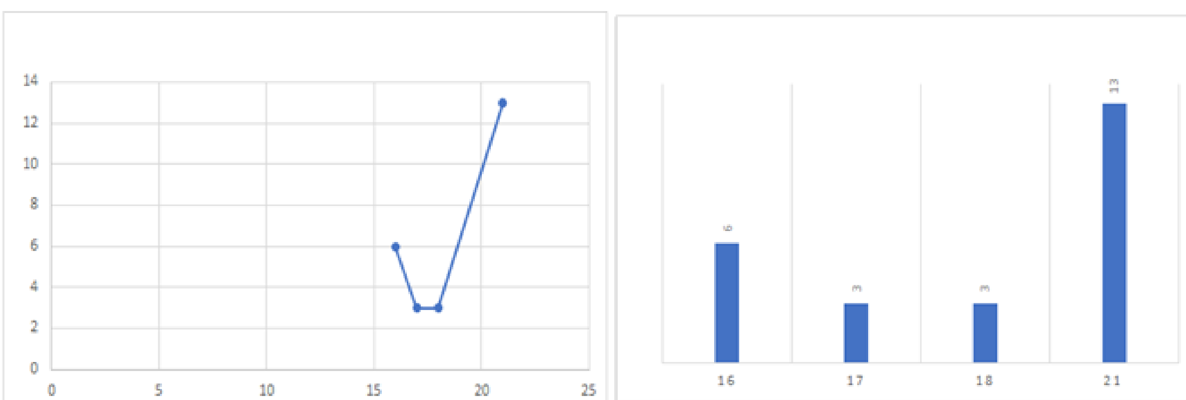


fig2: Age of the students vs. count: Linear and Bar Graph Representation

Throughout this section, there is consideration of a covering based N-information system I defined by $I = (U, A, F, N)$ where U describes the universe and is a collection of the 100 images in the dataset given by

$$U = \{0,1, \dots, 100\}$$

A is the collection of the attributes given by

$$A = \{C, B, E, S, U\}$$

where: C denotes concentrating

B denotes bored

E denotes excited

S denotes sleepy

U denotes uncertainty

The fuzzy set for A, A_{fuzzy} is given by:

$\{(\text{concentrating}, \mu_{\text{concentrating}}), (\text{bored}, \mu_{\text{bored}}), (\text{excited}, \mu_{\text{excited}}), (\text{sleepy}, \mu_{\text{sleepy}}), (\text{uncertainty}, \mu_{\text{uncertainty}})\}$

$$A_{\text{fuzzy}} = \{(C, 0.45), (B, 0.22), (E, 0.36), (S, 0.54), (U, 0.53)\}$$

Where:

$\mu_{\text{concentrating}}$ = w(concentrating) = 0.45

μ_{bored} = w(bored) = 0.22

μ_{excited} = w(excited) = 0.36

μ_{sleepy} = w(sleepy) = 0.54

$\mu_{\text{uncertainty}}$ = w(uncertainty) = 0.53

F is a function defined by the mapping $F: A \to \rho(U)\ \forall\ a \in A$ such that $F(a) \subseteq U$ would contain those elements of U that possess the attribute a with the assumption that $U\ F(a) = U, a \in A$. To estimate $F(a)$, the mean of each of the objects were evaluated following which the individual means were multiplied against the individual weights of the attributes.

The sum of the product of the object-mean and attribute weights were divided against the sum of the attribute weights. The result was compared against the threshold which is the median of the dataset chosen. To give an idea regarding the process followed in **equation 2.1.1**, an example has been provided with respect to the first object in the dataset.

Table2: Computation of F using αi for the first attribute

$\boldsymbol{\mu_p(x_1)}$	$\boldsymbol{\mu_p(x_1)}$ * **w(a$_1$)**	$\boldsymbol{\mu_p(x_1)}$ * **w(a$_2$)**	$\boldsymbol{\mu_p(x_1)}$ * **w(a$_3$)**	$\boldsymbol{\mu_p(x_1)}$ * **w(a$_4$)**	$\boldsymbol{\mu_p(x_1)}$ * **w(a$_1$)**	$\sum_{j=1}^{k}(w((a_j)) * \mu_p(x_1)))$	$\sum_{j=1}^{k} w(a_j)$	$\boldsymbol{\alpha i}$
158.82	71.475	34.94333	57.18	85.77	84.18167	333.5397	2.1	155.23

Similarly, the object-mean and attribute weight product was computed and its ratio against the sum of the attribute weights was compared against the threshold. The threshold for αi has been chosen to be the median of the dataset by dividing it into appropriate partitions according to the attribute weights.

With these definitions, the categorisation of the 100 images in the dataset has been done into the five attributes chosen namely C(concentrating), B(bored), S(sleepy), E(excited), and U(uncertainty).

Table3: F(a) vs A

a	F(a)
C	[0, 2, 3, 6, 13, 14, 15, 16, 17, 18, 20, 27, 39, 42, 43, 45, 46, 47, 48, 50, 54, 56, 57, 58, 59, 60, 62, 64, 67, 68, 70, 73, 75, 77, 80, 82, 89, 92, 96, 98, 99]
B	[7, 9]
E	[10, 11, 12, 23, 25, 38, 65, 72, 74, 78, 84, 87, 88]
S	[4, 5, 8, 26, 29, 30, 31, 32, 33, 35, 49, 51, 52, 53, 61, 63, 69, 76, 79, 81, 83, 85, 86, 90, 91, 93, 94, 95, 97]
U	[1, 19, 21, 22, 24, 28, 34, 36, 37, 40, 41, 44, 55, 66, 71]

N denotes the neighbourhood function and is more than often defined by the mapping $N: U \rightarrow \rho(U)$ which associates every $x \in U$ to a subset $N(x)$ and would contain the neighbours of the object x.

The neighbours of x are then evaluated using the **algorithm 2.1.1**. The value of the threshold to declare an xm as a neighbour of xn has been calculated through thorough experimentation and has been decided upon as 25. The neighbours of xn are defined by $N(x)$ which is a subset of the universal set U.

Depending on the system under study, the value of the threshold can suitably vary. To give an idea about the computation followed, there is consideration of the first ten images in the dataset.

Table4: Neighbours of xn

Object (xi)	**N(xi)**
x0	[0, 1, 6, 13, 14, 15, 16, 17, 18, 20, 27, 32, 42, 43, 48, 52, 54, 56, 57, 59, 61, 62, 63, 64, 67, 68, 69, 70, 73, 75, 93, 94, 98, 99]
x1	[0, 1, 2, 3, 5, 6, 14, 15, 16, 17, 18, 20, 21, 22, 24, 27, 28, 32, 35, 42, 43, 48, 49, 50, 51, 52, 56, 57, 59, 60, 61, 62, 64, 66, 68, 69, 70, 71, 77, 93, 94, 95, 97, 98, 99]
x2	[1, 2, 6, 14, 15, 16, 17, 18, 27, 42, 43, 48, 54, 56, 57, 58, 59, 60, 63, 64, 67, 68, 70, 75, 77, 85, 86, 90, 91, 95
x3	[1, 3, 10, 11, 12, 14, 16, 18, 21, 22, 24, 27, 28, 32, 35, 48, 49, 51, 52, 53, 56, 57, 61, 62, 64, 69, 70, 72, 93, 94, 97, 99]
x4	[4, 53, 96]
x5	[1, 5, 10, 11, 12, 19, 21, 22, 24, 28, 32, 33, 35, 36, 40, 44, 46, 49, 50, 51, 53, 60, 66, 71, 72, 77, 80, 82, 93, 94, 97, 99]
x6	[0, 1, 2, 6, 13, 14, 15, 16, 17, 18, 20, 27, 42, 43, 48, 52, 54, 56, 57, 58, 59, 60, 61, 62, 63, 64, 67, 68, 69, 70, 73, 75, 77, 85, 86, 90, 91, 93, 95, 98]
x7	[7]
x8	[8, 15, 17, 21, 22, 24, 28, 31, 45, 48, 56, 57, 60, 63, 77, 99]
x9	[9, 38, 65]
x10	[3, 5, 10, 11, 12, 19, 21, 22, 24, 28, 32, 33, 35, 49, 51, 53, 71, 72, 93, 94, 97]

Next, there is construction of the double bounded neutrosophic rough set to estimate the decisions for every $x \in U$. As the computation of 100 images may crowd the region here, an image is chosen to give an illustration of the procedure.

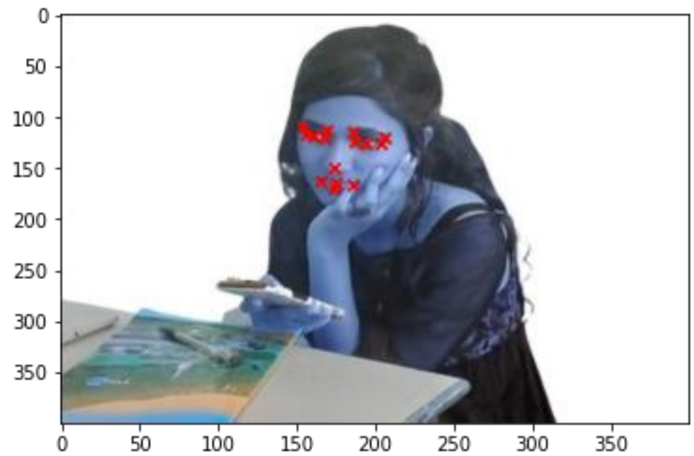


figure3: Image Considered For Evaluation

The index of the image chosen is 20. The neighbours of the chosen image, $N(20)$ are given by

$$\{0, 1, 6, 13, 14, 15, 16, 17, 18, 20, 27, 32, 35, 42, 43, 48, 51, 52,$$

$$54, 56, 57, 59, 61, 62, 64, 67, 68, 69, 70, 73,75, 93, 94, 98, 99\}$$

After construction of the double bounded rough set using the equations given in section 3.1, the neutrosophic values of the image chosen are computed using the **equation 2.1.2**.

$$V(concentrating) = 0.525$$

$$V(bored) = 0.54$$

$$V(sleepy) = 0.525$$

$$V(excited) = 0.459$$

$$V(uncertainty) = 0.495$$

Hence, the expression detected in the face is given by

$$decision(20) = \max(V(concetrating), V(bored), V(sleepy), V(excited), V(uncertainty))$$

Therefore, the expression detected is **bored.**

In a similar fashion, the expressions are detected for all the images in the dataset and the decisions made are appended to the dataset containing the scores for the subject IDs and image IDs for which the images were captured. This dataset, also known as the relational dataset, was taken from Kaggle [21].

By utilising the subject IDs, essential parameters like gender and age of the student, and the decisions made using attribute based DBRS, the following data frame was constructed.

Table5: Constructed data frame for the first ten entries

StudentId	SubjectId	Gender	Age	Marks	SubjectExpression
0	A	Female	16	72	excited
1	A	Male	16	69	excited
2	B	Female	16	72	excited
3	C	Female	16	74	bored
4	D	Female	16	97	attentive
5	A	Female	21	90	bored
6	A	Female	21	47	excited
7	B	Female	21	95	attentive
8	A	Female	21	76	uncertain
9	A	Male	16	71	attentive

The Gini Index was computed for the attributes $a' \in A'$ given by the list ['SubjectId', 'Gender', 'Age', 'Marks'] against the individual student expression that was evaluated using the formula $V(a)$ and by computing the formula $decision(x) = \min(V)\ \forall x \in X$ using the **equation 2.2.1**.

The Gini values to estimate the root node that were obtained are as follows:

$$Gini\ for\ SubjectId = 0.759$$

$$Gini\ for\ Gender = 0.745$$

$$Gini\ for\ Age = 0.709$$

$$Gini\ for\ Marks = 0.341$$

Even though the Gini for the feature 'Marks' is minimum, the choice was made to construct a random forest using individual decision trees with the root as the feature 'Age' which has the next minimum in the list. The reason for dropping the feature 'Marks' and proceeding to construct a decision tree with the other feature lay in the lack of distinction the corresponding feature provided. Constructing a decision tree with a feature that has minimal distinction might not be the suitable solution in a system where we seek to use as many minimum decision trees as possible to draw the inferences.

So, the root of the decision tree chosen would be the feature **'Age'** with an impurity index of **0.709** and a maximum entropy of **0.291**. The evaluation of the subsequent nodes was performed in reference to the root node against the decision made. In the next depth, division was carried out with the Gini for **Gender** as **0.542** and for **SubjectID** as **0.531**. In this fashion, several decision trees were aggregated and boosted i.e., bagged to give rise to a random forest. The tree in the forest with the most likely interference was chosen for three cases: The overall dataset, the 16-18 age group, and the 20-21 age group.

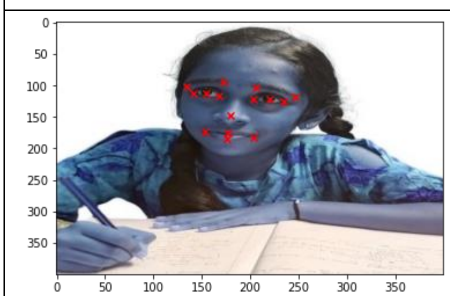
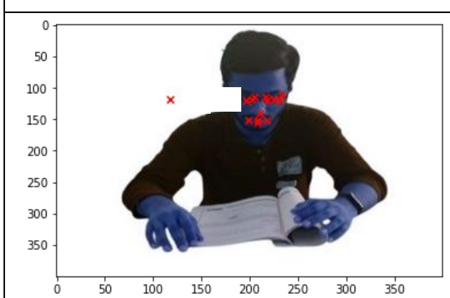
The results and inferences drawn from the construction of the ADBRS driven random forest are presented in detail in Section 4 with an illustration of applying a new object to validate its decision utilising the model constructed.

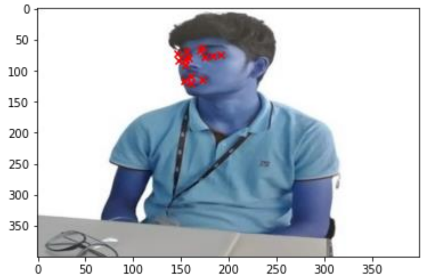
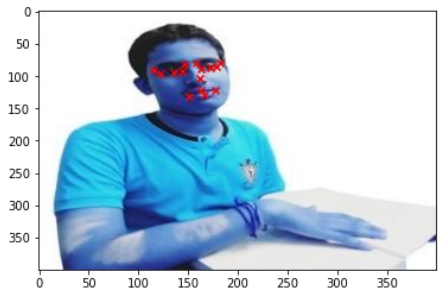
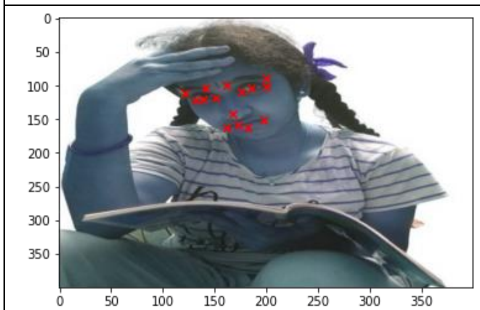
The greatest advantage of the model proposed comes down to its ability to make decisions without any prior knowledge of the decisions with respect to the object involved and to validate a newly added observation using the already existing model without the need to handle the photographs of the newly added object against the existing DBRNS.

3. Results

3.1. Data was taken from the images and the expressions of the students against different subject durations for which the photos were taken were computed

Table6-1: Images and The Corresponding decisions made

Image	Values evaluated	Maximum Value	Expression Detected
	$V(A) = 0.525$ $V(B) = 0.525$ $V(E) = 0.540$ $V(S) = 0.459$ $V(C) = 0.495$	$V(E)$	The person is ***excited*** to be in class
	$V(A) = 0.525$ $V(B) = 0.525$ $V(E) = 0.495$ $V(S) = 0.540$ $V(C) = 0.459$	$V(S)$	The person is feeling ***sleepy*** in class

	$V(A) = 0.679$ $V(B) = 0.555$ $V(E) = 0.545$ $V(S) = 0.540$ $V(C) = 0.525$	$V(A)$	The person is ***attentive*** in class
	$V(A) = 0.525$ $V(B) = 0.615$ $V(E) = 0.495$ $V(S) = 0.585$ $V(C) = 0.525$	$V(B)$	The person is ***bored*** in the class
	$V(A) = 0.540$ $V(B) = 0.492$ $V(E) = 0.540$ $V(S) = 0.525$ $V(C) = 0.615$	$V(C)$	The person is ***uncertain*** of the things being taught in the class

Due to the relatively larger size of the dataset, few images have been utilised in the table illustrated above to give an idea about the process executed

3.2. Construction of the individual decision trees to be bagged to draw inferences regarding the teaching-learning process efficiency.

Gini Index Impurity based split was employed to construct the individual decision trees that constitute the random forest. The visualization of the individual decision tree has been done by considering the following three cases.

Case 1: Individual decision tree for the dataset as a whole

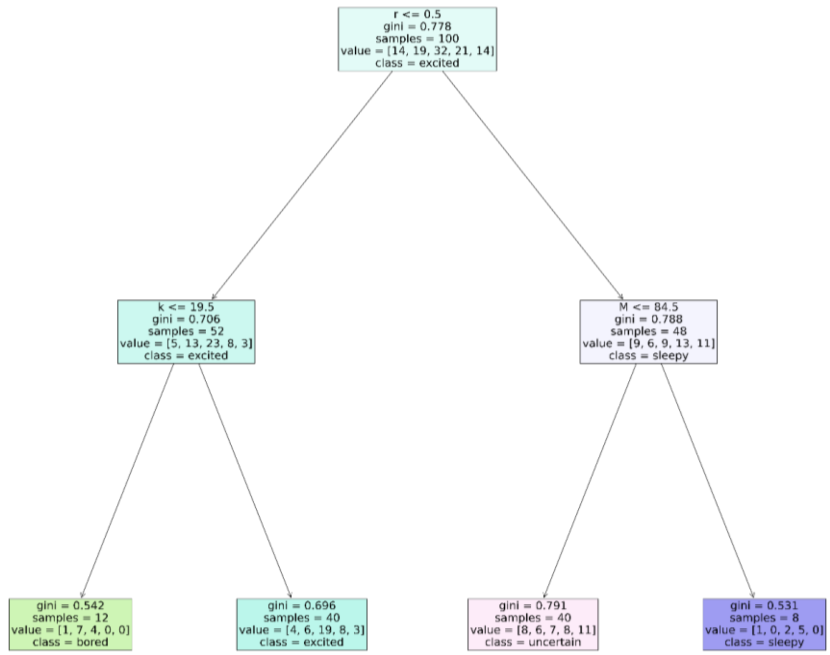


fig4-1: Individual Decision Tree From The Random Forest: Without Age Distinction

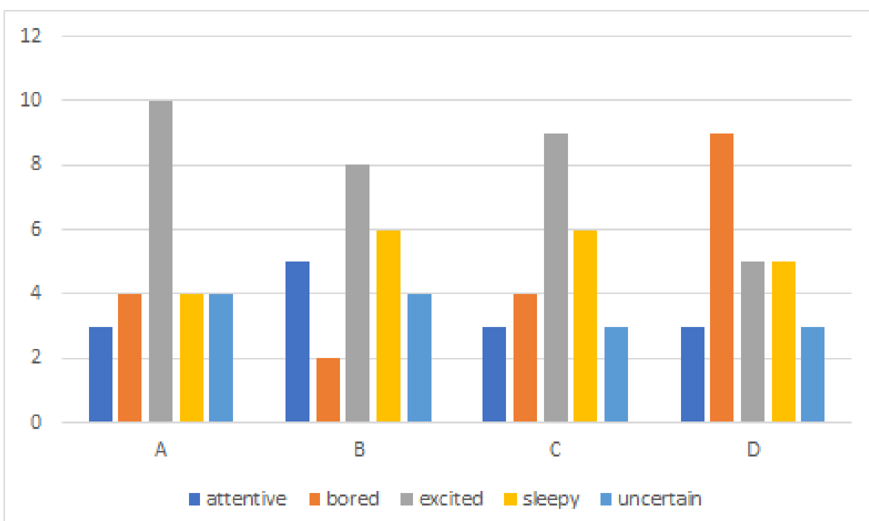


fig4-2: Distribution of the various expressions observed across the dataset against the subject for which the expressions were computed.

There is construction of individual decision tree for the dataset as a whole without age distinction and the inferences can be visualized using the following tree from the random forest which has been evaluated to be the most likely estimation.

Inference: Across the age groups, subject A has the highest excitement levels. Subject B and C have comparable excitement levels and almost equal number of students who fell asleep in class hours. Hence, it can be concurred that special measures from the teacher's side can improve the reception for both the subjects mentioned. Subject D indicates high boredom levels and it can be concluded that either the subject is too dry or the learning process isn't efficient.

Case 2: Individual Decision Tree for the age group 16-18

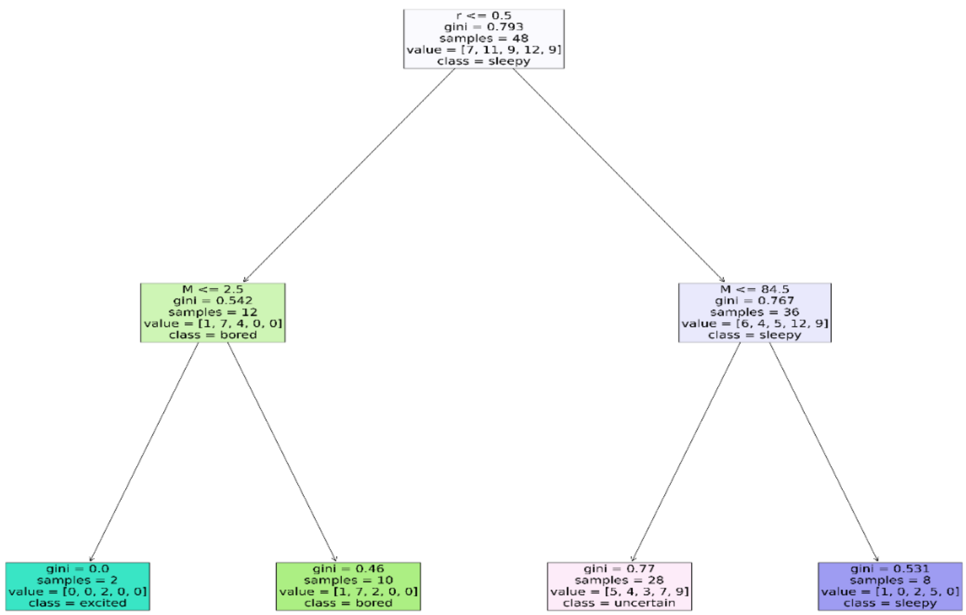


fig5-3: Individual Decision Tree from the Random Forest for the age group 16-18

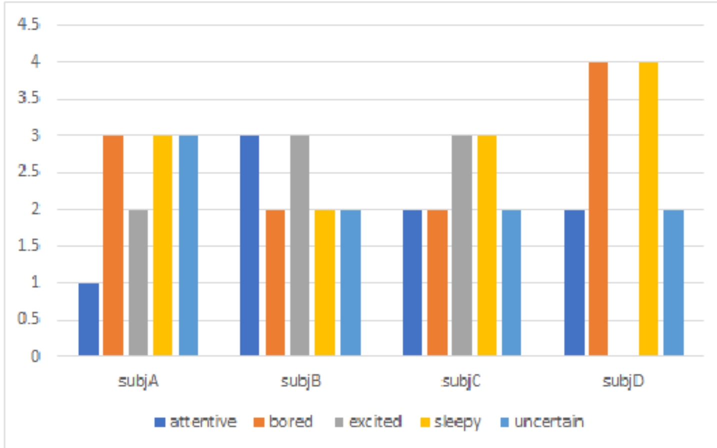


fig5-2: Distribution of the various expressions observed for the age group [16-18] against the subject for which the expressions were computed.

Inference: For High Schoolers, Subjects A and D seem to have the highest count of people who were either bored or uncertain. Hence, it can be concurred that either the subject is too dry or the teaching-learning flow was inefficient. Subjects B and C, on the other, have higher counts of people who are attentive or bored and excited or sleepy respectively. This could mean that if the teacher looks into the matter, they can try and engage more people to like the subject.

Case 3: Individual Decision Tree for the age group 20-21

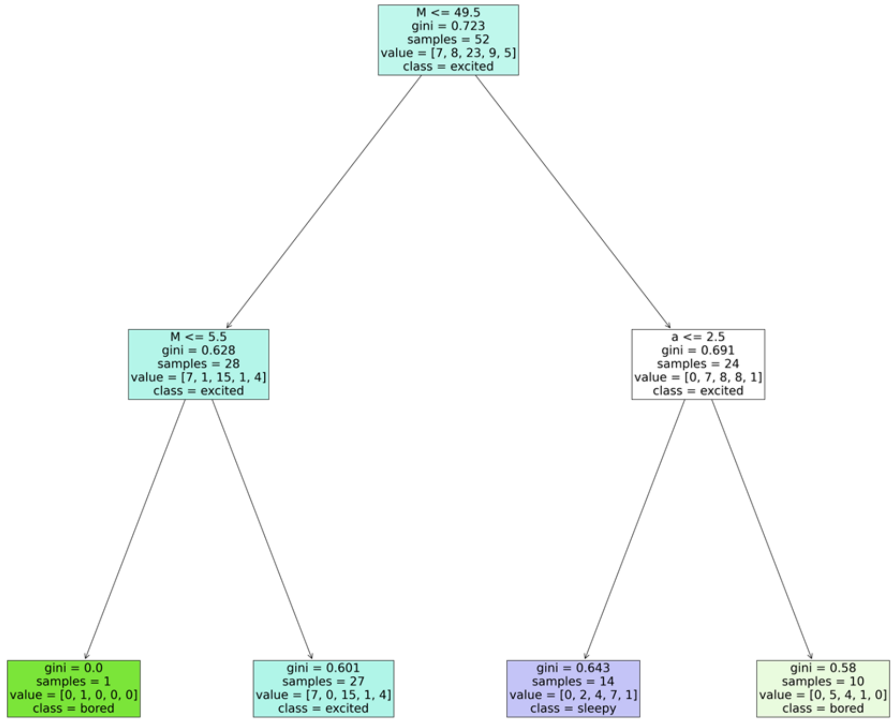


fig6-1: Individual Decision Tree from the Random Forest for the age group 20-21

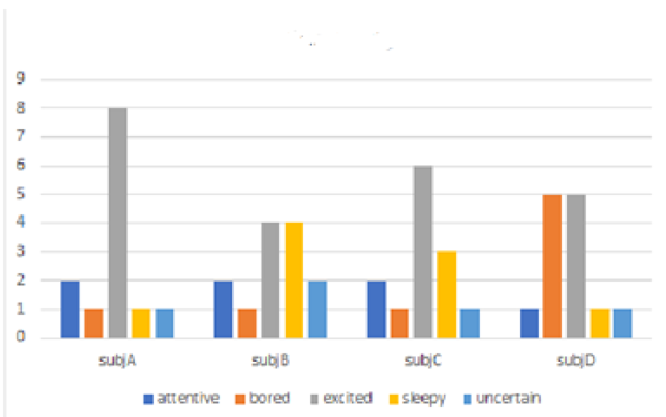


fig6-2: Distribution of the various expressions observed for the age group [20-21] against the subject for which the expressions were computed.

Inferences: For University Sophomores, Subjects A and C have a minimum distribution with respect to the uncertainty, boredom, and sleepy faces of the student. This means that the teaching-learning process is efficient. Subjects B and D, on the other, have equal distributions of boredom, excitement, and sleepiness with respect to the student. This could mean that if the teacher looks into the matter, they can improve the engageability and interactivity of the classroom atmosphere.

Case 4: Evaluation of a new object using the ADBNS-driven-random forest model

Let there be addition of a new object a given by [2,1,17,76]. The list a is encoded, meaning the first index indicates that the subjectID is B (as there are four subject IDs, A, B, C and D, encoding them would give values of 0,1,2,3,4), the second indicates that the person is male (as there is presence of two sexes, male and female, encoding would give values of 1 and 0), the third indicates that the new object's age is 17 and the fourth index indicates that the person has scored 76 marks in subject B

Decision Evaluated: The person is ***uncertain*** about the subject studied.

Inference: The person has scored higher marks, but hasn't had an excellent grasp of the subject due to his expressions of uncertainty during that period. There is a need to establish better learning efficiency for the student mentioned.

4. Applications

The model constructed is extremely advantageous in the sense that it doesn't require prior information with respect to the decisions made for the dataset. With existing features, ADBRNS can help determine the decision and the decisions made can be utilised to both evaluate the impurity and draw inferences as well as fit into a classifier for training any similar models for future use.

Combined with frequency estimation algorithms like Apriori, FP Growth, and ECLAT, the model can help teachers and schools make early estimates on students who suffer from attention deficiency, belong to the spectrum, or display signs of ADHD and provide them with the adequate help they need.

The constructed model may also be used to approximately narrow down convicts who are guilty of committing a crime by simply utilising their mugshots, thereby saving the task of having to investigate a bigger crowd.

5. Results

The facial expressions of various students were detected using attribute based double-bounded rough neutrosophic set method. The decisions made were used against the scores of every student to evaluate the decision impurity and draw inferences regarding the teaching-learning efficiency.

6. Acknowledgement

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