

Identification of Learners' Emotions in a Learning Environment Using Naïve Bayes Algorithm and Evaluation of Academic Achivement with Random Forest AI

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ABSTRACT

Emotions have undergone unusual stages all through the pandemic situation creating a trauma in the minds of learners that extirpate the growth of a learner. The main objective of the work is to identify the face emotions of learners in the learning environment that helps to estimate the attention of learners during lectures in the learning environment. The identification of facial emotions is performed using naïve bayes algorithm. Based on the emotional records, the academic achievement is analyzed with random forest algorithm. The findings of the research are that the attention of the learners in the learning environment with positive emotions produces good academic results.

KEYWORDS

Academic Performance, Emotional Intelligence, Emotions, Learning Environment, Naïve Bayes, Random Forest

1. INTRODUCTION

Recent progress in visual sensors and computer vision methods facilitated computerized monitoring of behavior and emotional states of learners at different levels (Dinesh et al. 2016). Learners emotional states such as tired, interested and confused are mechanically resolved from facial expressions (Whitehill et al. 2014, Calvo and Mello 2010), and attention state is calculated from different visual cues such as face look, head movement, and body postures (Won et al. 2014). Emotional Intelligence is a precondition for developing a good rapport with a group of learners, which subsequently can

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be the basis for producing learners having more rendezvous, a speediness to work together, a larger eagerness to seize menaces in their learning, a more positive approach, better inspiration, more resourcefulness and more stubbornness.

The essential things to be done while using EI in teaching are competent to distinguish and react to own emotions and those of the learners in the learning environment so as to formulate more effectual in each one's individual roles and also to persuade an emotional state in the learners which is favorable to learning. Emotions are instinctive one to human being and it plays a foremost part in the educational sector. Each and every learner arrives out with diverse emotions within the learning environment which is varied consistent with the circumstances faced by the learner in and out of the learning environment. The emotions are grouped under three categories such as positive, negative or neutral. The most intricate emotion is categorized as negative emotion that spotlights on consciousness. Although too many negative emotions can make experience overwhelmed, troubled, exhausted, or tense out. When negative emotions are beyond balance, predicaments may emerge too vast to handle.

In this paper, section 1 is the introduction part followed by the related work in section 2. The third section explains about the proposed work, Naïve Bayes algorithm and Random Forest. Then the implementation section discusses the results along with the metrics followed by conclusions and future work.

2. LITERATURE REVIEW

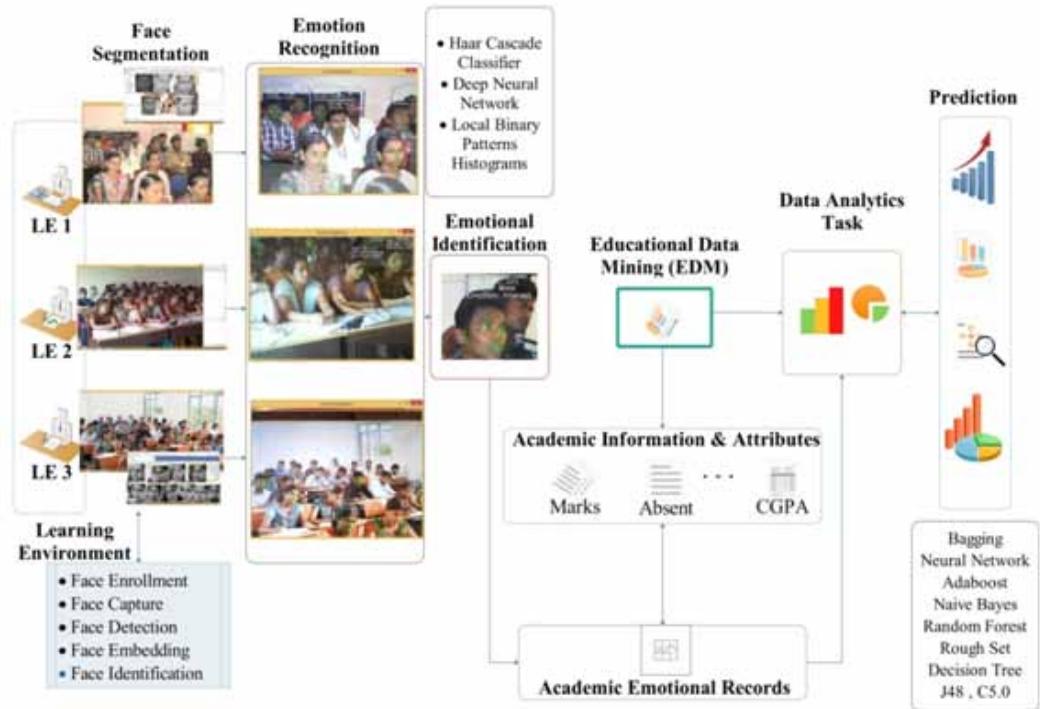
In the field of education, assessment of an enduring learner commitment in the learning process is required with the intention of assess courses and improve learning outcomes (Fredricks et al. 2004, Fredricks et al. 2011) that can be done through questionnaires. However with the propagation of current e-learning, it became probable to gather implied usage data to approximate action and engagement of learners within learning activities (Martinez et al. 2015). A review of research on measurement of learner commitment in technology-mediated learning (Henrie et al. 2015) have offered a review of quantitative and qualitative observational measures to measure behavioral, cognitive, and emotional indicators of learner commitment. Attention was classified as one of the factors of cognitive commitment, while interest, anxiety, and boredom contributed to emotional commitment. In the sphere of learning, the prolonged attention is used to illustrate the capability to sustain attentiveness over extended periods of time, such as during lectures in the learning environment. Educational research is frequently spotlighted on preserving learner attention during lectures (Young et al. 2009), because prolonged attention is distinguished as an imperative aspect of the learning achievement (Risko et al 2012). Though, tracking of individual learners' conscientious state in the learning environment by using self reports is intricate and impedes with the learning process (Chen et al. 2015). In the work presented by Bahel (2021), architecture for analysis of student's engagement in video-based online classroom systems was discussed that starts with the detection of the faces of the student from their incoming video feed.

3. PROPOSED WORK

Figure 1 illustrates the process of identifying emotions in the learning environment. Originally, the practice is executed in two stages: training and testing phase. The weight value of each image is spawned during training phase and the testing image is used to make out the emotion of the learner in testing phase. The video input is detained in the learning environment. From the detained video, the face detection is achieved with Haar Cascade Classifier, which a face detector model to perceive face locations.

Subsequently skin segmentation aids in distinguishing the potential regions enclosing the frontal faces and codes every frame relating to 21 emotions: gratitude, contentment, happy, enthusiasm, interest, inspiration, self control, imaginative, pleasure, hope, anger, detached, irritated, depression,

Figure 1. Emotion recognition in the learning environment



frightened, dependent, antagonistic, anxiety, discouraged, bored and irresponsible. The facial features from the video source is hauled out and mapped with the essential emotions and the yield will be the emotion detection. The population of the investigation is 10,648 and it is accomplished with 120 learners for the period of four years with different subjects. The dataset were devised with Emotional Based Learning Environment (EBLE) and Multi Assessment Method (MAM) where dissimilar learning practices were exploited to haul out the concluding upshots. The inspected factors like models of Emotional Based- Learning (EBL) and EI are grouped under two kinds: positive and negative. Dissimilar emotions of the learner in the three special learning environments are attained to scrutinize the upshot of a learner. Furthermore, MAM is exploited to assess the performance of the learners. MAM encompasses of assignments, problem scenario, oral examination, written exam, presentations, holistic demonstration, team play, projects, teamwork, discussion, creative empowerment approach and feedback. The alteration in the emotions of learners is as well viewed that facilitates to endow with learning consequently.

To recognize the emotion of a face, Naive Bayes algorithm is utilized. From the perceived emotions, the learners with negative emotions are recognized and learning is done equally.

From the recognized face, the emotions of the learners are sorted out by their facial expressions like eye brow, lip movement and so on. The emotions of the learners are recognized from the input image using Eigen spaces technique. If the input image is alike to a few expressions training set, the renovated image will have less deformation than the image renovated from other eigenvectors of training expressions. The eigenvectors of the covariance matrix ought to be recognized in an attempt to disembark at an elucidation. The paces realized in this technique are

Appraise the elements of input image beside the chosen k Eigen vectors.

Reform the image from the elements.

If the distance amid the transformed image and the original image is further than a threshold ϵ , the input image is not a face image.

Determine the distance of the input image from the training images.

Diminish emblematic error in lesser dimensional subspace of input.

Choose eigenvectors in proportion to m largest Eigen values of total scatter.

The histogram of skin pixels and non-skin pixels of the existing frame of and skin area and non-skin area worked out in the image by means of skin tone algorithm. After recognizing the emotions of every learner, the learning is afforded to the learners with positive approach. The positive learning environment creates learning openings that support examination and edifice of acquaintance and adroitness. It is noteworthy that the learning environment proffers the finest occasion for learners to be vibrant learners, aggravated to learn more, tackled to take risk, sensitively sustained and feeling usually esteemed.

The benefits of distinguishing emotions are to endow with a positive learning that agrees to the learners to intellect tranquil, confined and engaged. In so doing, the learners will be more open to energetically take part in the activities of the learning environment. Several of the constraints employed in the positive learning environment are spotlighting on each learner, inspiration to be present at learning environment, a probability to learn from and regarding them, keep track of growth of the learner etc.,.

3.1 Ennobling Education Using EI

The positive emotions augment upcoming growth and success changing brains in ways that increase consciousness, concentration, and reminiscence which support to take in added information, grab plentiful deliberations in mind at one time and comprehend how dissimilar notions are associated to each other. The self-confidence in oneself facilitates to enlarge the positive emotions. The deliberations and deeds are prolonged using positive emotions that throw in to upcoming accomplishment. It is extremely indispensable to balance both positive and negative emotions. Therefore the effect of a learner can be enhanced with the Emotional-Based learning within the learning environment.

As learners learn in an extensive assortment of backgrounds, such as outside locations and open-air environments, the phrase is frequently employed as a more precise or favored option to classroom, which has more inadequate and conventional implications - a space with rows of desks and a chalkboard, for instance. Instructor disputes that learning environments have both a straight and not direct persuade on learners learning, together with their commitment in what is being educated, their inspiration to learn, and their intelligence of comfort, belonging, and individual protection. For case in point, learning environments packed with light and inspiring educational materials would probably be well thought-out more favorable for learning than dreary spaces devoid of panes or adornment.

3.2 Evaluation of Emotional intelligence by Facial Emotion Recognition

Appearance of emotion is an act of social distribution, though emotional recognition is whether others get the message. This capability to comprehend the emotions of others becomes predominantly significant to synchronize activities and work autonomously, grow interpersonal groups and formulate relationships more conventional and simple to handle (Schellwies 2015).

Emotion recognition is measured as an essential trait of emotional competency (Banziger et al. 2009). An individual learner who is sensitively capable reveals finest performance of the emotion means in two key fields, emotion production and emotion perception (Scherer 2007). Regardless of there has been considerable study of the competence of individuals to distinguish emotions from facial and vocal expressions (Ekman et al. 2005, Scherer 2003), there has been a lack of distress with regards to the expansion of psychometrically sound and erect authenticated test mechanisms competent of analyzing individual disparities in this significant capability. Shaping whether there is

one universal aspect underlying emotion compassion and appreciation capability or whether separate modality-specific capabilities subsist is important in terms of research in addition to exposed realistic insinuations in terms of consequences and design of tests (Banziger et al. 2009).

3.3 Naïve Bayes Algorithm for Face Identification Using Face Embeddings

The stages of classifier and extraction process are given in figure 2. In initialization stage, the feature extraction and feature selection is performed using Data Base (DB). Then the data present in the DB entered into the training stage. After that, the output is predicted using various predictive models by applying test data.

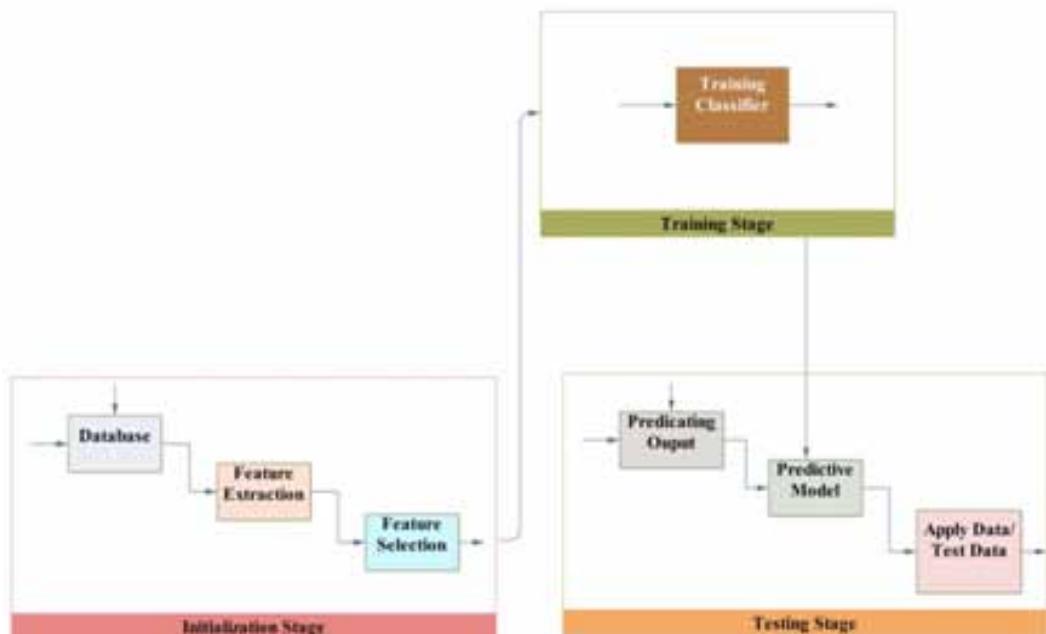
3.4 Bayes' Theorem for Naive Bayes Algorithm

In a machine learning categorization problem, there are multiple features and classes, say, C_1, C_2, \dots, C_k . The major intend in the Naive Bayes algorithm is to compute the conditional probability of an object with a feature vector x_1, x_2, \dots, x_n belongs to a particular class C_i ,

$$P(C_i | x_1, x_2, \dots, x_n) = \frac{P(x_1, x_2, \dots, x_n | C_i) \cdot P(C_i)}{P(x_1, x_2, \dots, x_n)} \text{ for } 1 \leq i \leq k \quad (1)$$

$$P(x_1, x_2, \dots, x_n | C_i) = P(x_1, x_2, \dots, x_n, C_i) \quad (2)$$

Figure 2. Stages of Classifier and Extraction



The conditional probability term, $P(x_j | x_{j+1}, \dots, x_n C_i)$ becomes $P(x_j | C_j)$ as of the supposition that features are independent. From the calculation above and the independence assumption, the Bayes theorem boils down to the following easy expression:

$$P(C_i | x_1, x_2, \dots, x_n) = \left(\prod_{j=1}^{j=n} P(x_j | C_i) \right) \cdot \frac{P(C_i)}{P(x_1, x_2, \dots, x_n)} \text{ for } 1 \leq i \leq k \quad (3)$$

The expression $P(x_1, x_2, \dots, x_n)$ is constant for all the classes, we can simply say that $P(C_i | x_1, x_2, \dots, x_n) \propto \left(\prod_j = 1_j = n P(x_j | C_i) \right) P(C_i)$ for $1 \leq i \leq k$

$$P(C_i | x_1, x_2, \dots, x_n) \propto \left(\prod_{j=1}^{j=n} P(x_j | C_i) \right) \cdot P(C_i) \text{ for } 1 \leq i \leq k \quad (4)$$

The steps in Naive Bayes are

Change the data set into a frequency table

Generate probability table by verdict the probabilities

Exploit Naive Bayesian equation to compute the posterior probability for every class. The class with the maximum posterior probability is the result of prediction.

Naive Bayes is a categorization algorithm for binary or two-class and multi-class categorization crisis. The method is simple to comprehend while illustrated by means of binary or categorical input values.

3.5 Representation for Naive Bayes Models

The representation for naive Bayes is probabilities. For a learned naive Bayes model, a catalog of probabilities is stored to file comprises Class Probabilities which is the probabilities of every class in the training dataset and Conditional Probabilities which is the conditional probabilities of every input value agreed every class value.

A naive Bayes classifier models a joint distribution over a label Y and a set of observed random variables, or features, (F1, F2..., Fn) by means of the supposition that the full joint distribution can be factored as follows:

$$P(F_1, \dots, F_n, Y) = P(Y) \prod_i P(F_i | Y) \quad (5)$$

To categorize a datum, unearth the most feasible label agreed the feature values for every pixel, using Bayes theorem:

$$P(y | f_1, \dots, f_m) = \frac{P(f_1, \dots, f_m | y) P(y)}{P(f_1, \dots, f_m)} \quad (6)$$

$$= \frac{P(y) \prod_{i=1}^m P(f_i | y)}{P(f_1, \dots, f_m)} \quad (7)$$

$$\arg \max_y P(y | f_1, \dots, f_m) = \arg \max_y \frac{P(y) \prod_{i=1}^m P(f_i | y)}{P(f_1, \dots, f_m)} \quad (8)$$

$$= \arg \max_y P(y) \prod_{i=1}^m P(f_i | y) \quad (9)$$

Multiplying various probabilities together frequently upshots in underflow, as an alternative calculate log probabilities which have the same argmax:

$$\arg \max_y P(y | f_1, \dots, f_m) = \arg \max_y \log P(y, f_1, \dots, f_m) \quad (10)$$

$$= \arg \max_y \left\{ \log P(y) + \sum_{i=1}^m \log P(f_i | y) \right\} \quad (11)$$

To calculate logarithms, use `math.log()`, a built-in Python function.

3.6 Random Forest

Random Forest (RF) is a supervised classification algorithm that is utilized for classification and the regression sort of problems. RF creates the forest with a number of trees. In common, the more trees in the forest the more tough the forest looks like. Similarly, in the RF classifier, the higher the number of trees in the forest provides the high accuracy consequences. RF classifier will handle the missing values. The steps of Random forest are as follows:

- Choose k features by chance from total m features where $k \ll m$.
- Among the k features, compute the node d using the best split point.
- Split the node into daughter nodes using the best split.
- Repeat 1 to 3 steps until l number of nodes has been reached.
- Construct forest by repeating steps 1 to 4 for n number times to create n number of trees forming the RF.

3.7 Neural Network (NN)

A neural network is a series of algorithms that efforts to distinguish underlying associations in a set of data through a procedure that imitates the way the human brain operates. Neural networks can acclimatize to changing input. As a result the network produces the best probable outcome without requiring revamping the output criterion. A neural network encloses layers of interconnected nodes.

Each node is a perceptron and is like a multiple linear regression. The dataset consists of 10,648 instances and the parameters are set as follows learning rate is 0.3, momentum is 0.2 and number of epochs is 500 with 10 hidden layers given in figure 3.

3.7.1 Back Propagation Algorithm

1. Form a network with input layer, hidden layer and output layer.
2. Initialize weights to small random number
3. for each example in training set perform
 - 3.1 Forward Pass

$$y_h = \sigma\left(\sum_i w_{hi} x_i\right)$$

$$\delta_h = y_h (1 - y_h) \sum_k w_{hk} \delta_k$$

3.2 Backward Pass

$$y_k = \sigma\left(\sum_h w_{kh} x_h\right)$$

$$\delta_k = y_k (1 - y_k) (t_k - y_k)$$

3.3 Update each network weights W_{ij}

$$w_{ij} \leftarrow w_{ij} + \Delta w_{ij}$$

with

$$\Delta w_{ij} = \eta \delta_j x_{ij}$$

end

4. Do until stopping criteria is attained

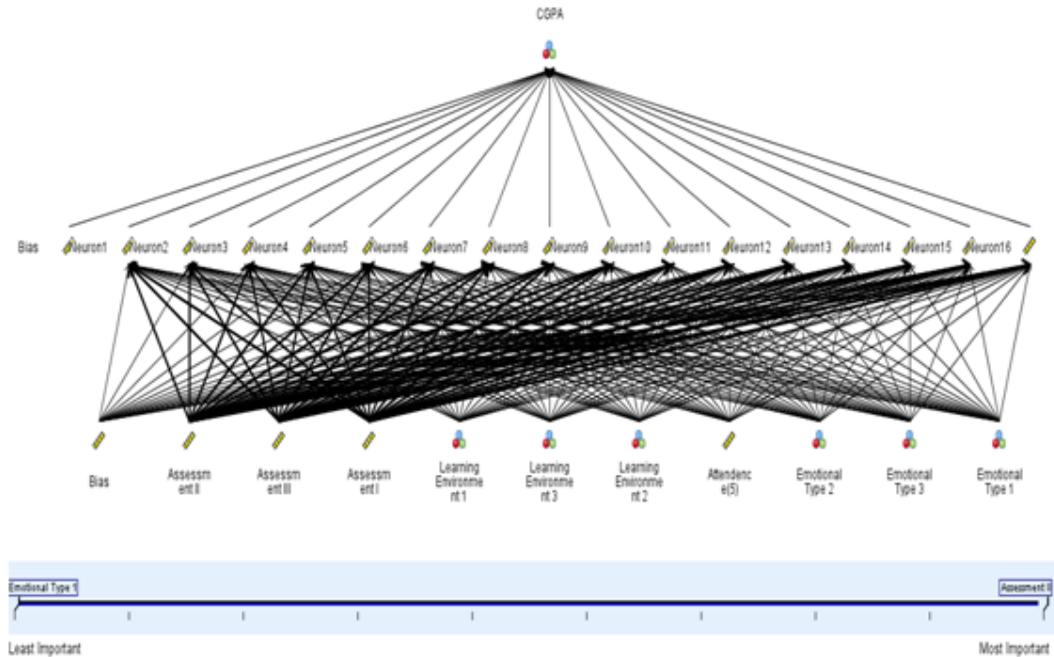
4. IMPLEMENTATION RESULTS AND DISCUSSION

The emotions of 120 learners with a population of 10,648 are retrieved and the implementation is done using python.

4.1 Face Emotion Estimator Models For Foretelling Facial Expression

The scaffold of the mechanical emotional state detection system is described in figure 4. The inputs are the video frames detained from the camera. The face of the learners under different learning environment is captured through web camera. The captured images are segmented to recognize the face. Feel Trace was utilized to detain the videos and extract the training datasets. LBP features

Figure 3. Neural Network Training with MLP



were extracted from the captured videos and k-NN algorithm was used for regression (Goutami and Pushpalatha 2017, Saeed et al. 2018)). For training, the LBP features were extracted from 10 video image sequences. Video captures from the FPGA connected camera were processed, and the LBP features were utilized for the k-NN regression with dimensional emotion labels.

The selection of a dataset is conducted with an eye to the set of target emotions for classification. As mentioned previously, some emotional expressions resemble each other. As well, restrained expressions, such as disdain, can be tremendously rigid to pick up on. Consequently, some datasets will surpass others for convinced emotional sets. NNs trained on a restricted set of emotions usually are apt to upshot in higher rates of precise categorizations. To offer the most severe instance, training on a dataset enclosing examples of various emotions is liable to generate very high accurateness. Naïve Bayes algorithm is utilized to extract the features from the face image using Naïve Bayes classifier. Then the image is tested to ensure the accurate identification of a facial emotion from the face. Figure 5 depicts the identification of face emotion.

4.2 Evaluation of Emotional Intelligence Diagnostic Performance Using Random Forest

Table 1 shows the confusion matrix of the implementation. In the confusion matrix, the diagonals correspond to instances classified correctly in line with allusion data and the off-diagonals were misclassified. The metrics used to measure the performance are Confusion Matrix, Specificity, Precision, Accuracy, Kappa Statistics, Sensitivity and Recall and F-measure given in table 2. The overall accuracy of the model is 84.24%. In the work by Bahel (2021), the reliable validation accuracy is found to be 77.5%. The kappa statistics is 0.789 which is good agreement. The performance metrics such as True Positive (TP), False Positive (FP), Accuracy, Recall, Precision, F-measure, specificity are computed.

Figure 4. LBP features in Face Emotion estimator models

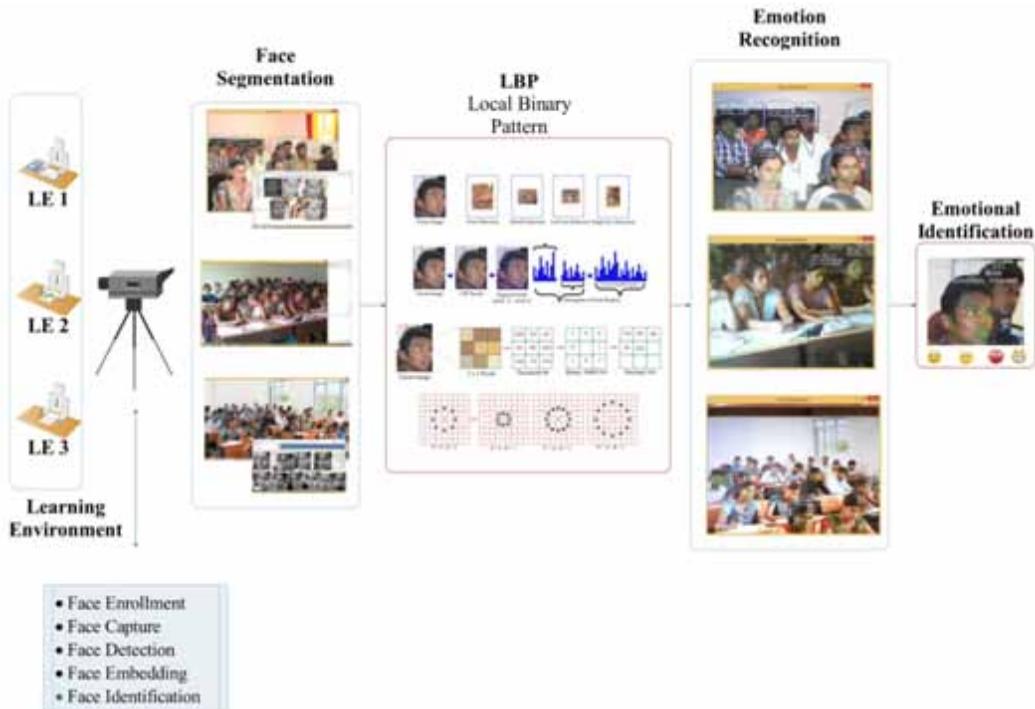


Figure 5. Face Emotion Identification



Figure 6 and figure 7 represents the gain chart and lift chart with the RF algorithm. With the EBLE, the specified RF algorithm behaves well obtaining good outcomes in increasing number. Figure 8 represents the decision tree outcome of Random Forest algorithm. The number of trees in the RF decision tree is 200.

5. CONCLUSION

The research attempted to scrutinize the responsibility of an instructor-learner rapport using an instructor’s level of EI and the learners’ reflections upon the examined instructors. The results of the

Table 1 Confusion Matrix for Random Forest

Predicted	Predicted							Classified as	Classification Overall
	CGPA	E	C	B	A	F	D		
	E	2168	0	0	0	188	174	a = E	2811
	C	1	415	2	0	0	177	b = C	661
	B	0	19	252	4	0	0	c = B	306
	A	0	0	4	857	0	0	d = A	957
	F	462	0	0	0	3054	0	e = F	3906
	D	424	54	1	0	0	1328	f = D	2007
Truth Over call		2841	652	295	960	3889	2011	10648	

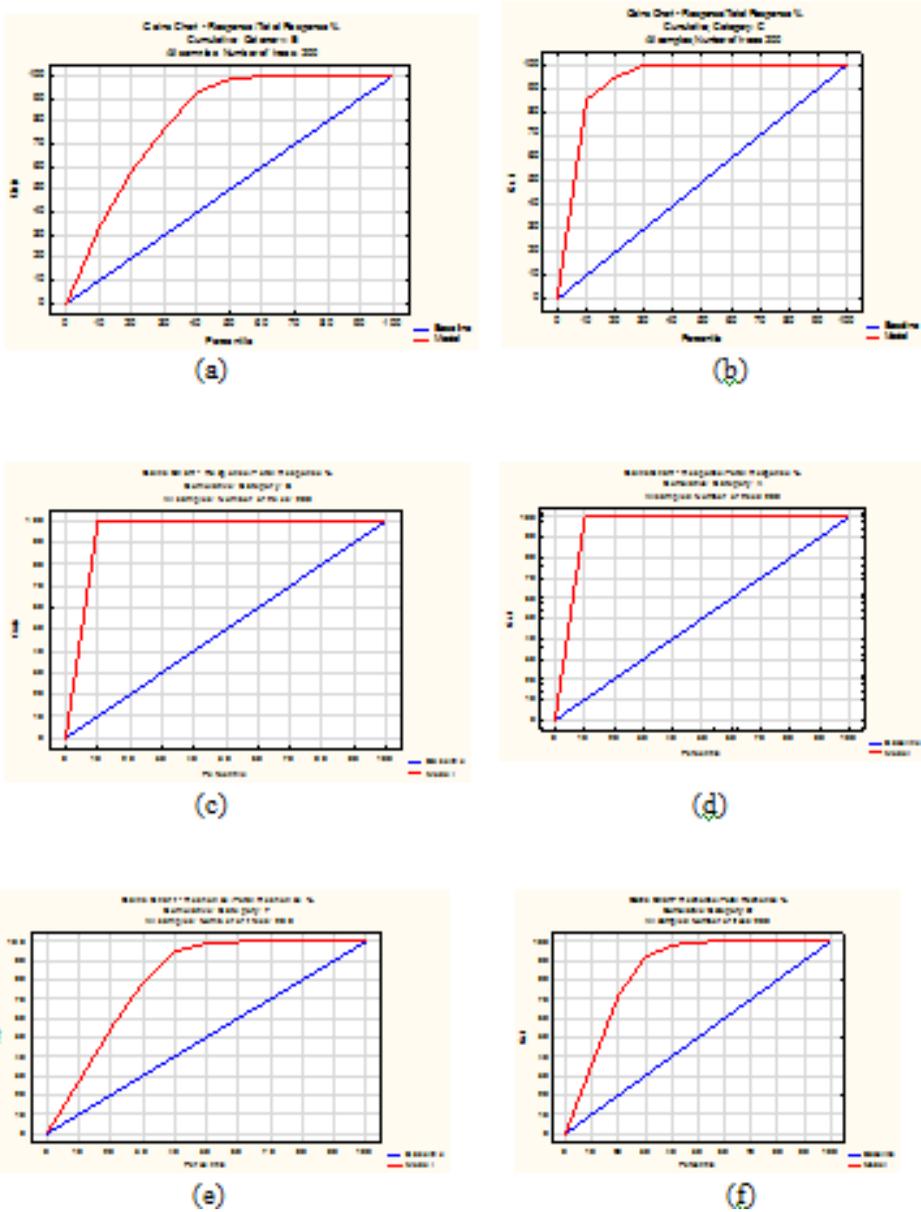
Table 2 Metrics with Random Forest algorithm

CGPA	TP	FP	TN	FN	Recall	Precision	Sensitivity	Specificity	F-measure
E	2168	887	6167	362	0.856917	0.709656	0.856917	0.874256	0.776365
C	415	73	8916	180	0.697479	0.85041	0.697479	0.991879	0.76639
B	252	7	9302	23	0.916364	0.972973	0.916364	0.999248	0.94382
A	857	4	8719	4	0.995354	0.995354	0.995354	0.999541	0.995354
F	3054	188	5880	462	0.868601	0.942011	0.868601	0.969018	0.903818
D	1328	351	7426	479	0.73492	0.790947	0.73492	0.954867	0.761905
Overall Accuracy: 0.842446									
Cohen's kappa: 0.789004									

research portray the association amid the learners' positive attitude inside the learning environment. The outcomes designate a rapport amid instructors' level of EI and the way they are evaluated by their learners. The positive association amid the instructors' level of EI and the way they are assessed by their learners designates that learners' success. A major positive association amid EI and academic achievement designates that academic achievement does not only depend on cognitive and theoretical facets of intellect but it is too exaggerated by emotional capabilities of a learner. The consequences of this study designate the significance of EI in academic achievement is associated. So, it can be stated that there is a significant relationship between EI and academic achievement. This research work achieved 84.24% accuracy compared to 77.5% in previous works.

In the investigation of the upshots, it is recognized the learners attention in learning the subject with intricate troubles also made simple and dissimilar solving techniques were pioneered by each learner for a single problem. Also, studied rationality in subgroups to attain more information about the conditions in which the subjects are the most irrational. The hypothesis states that the positive emotions generated from the learning environment enhance the attention of the learners towards the lectures. Even though, the learners' undergone pandemic situations like covid'19, the academic performance get increased when learners' connected with positive emotions. Therefore, the emotions and the attention in the learning environment are imperative factors that induce good academic achievement in any educational sector.

Figure 6. Gain Chart of CGPA with Random Forest



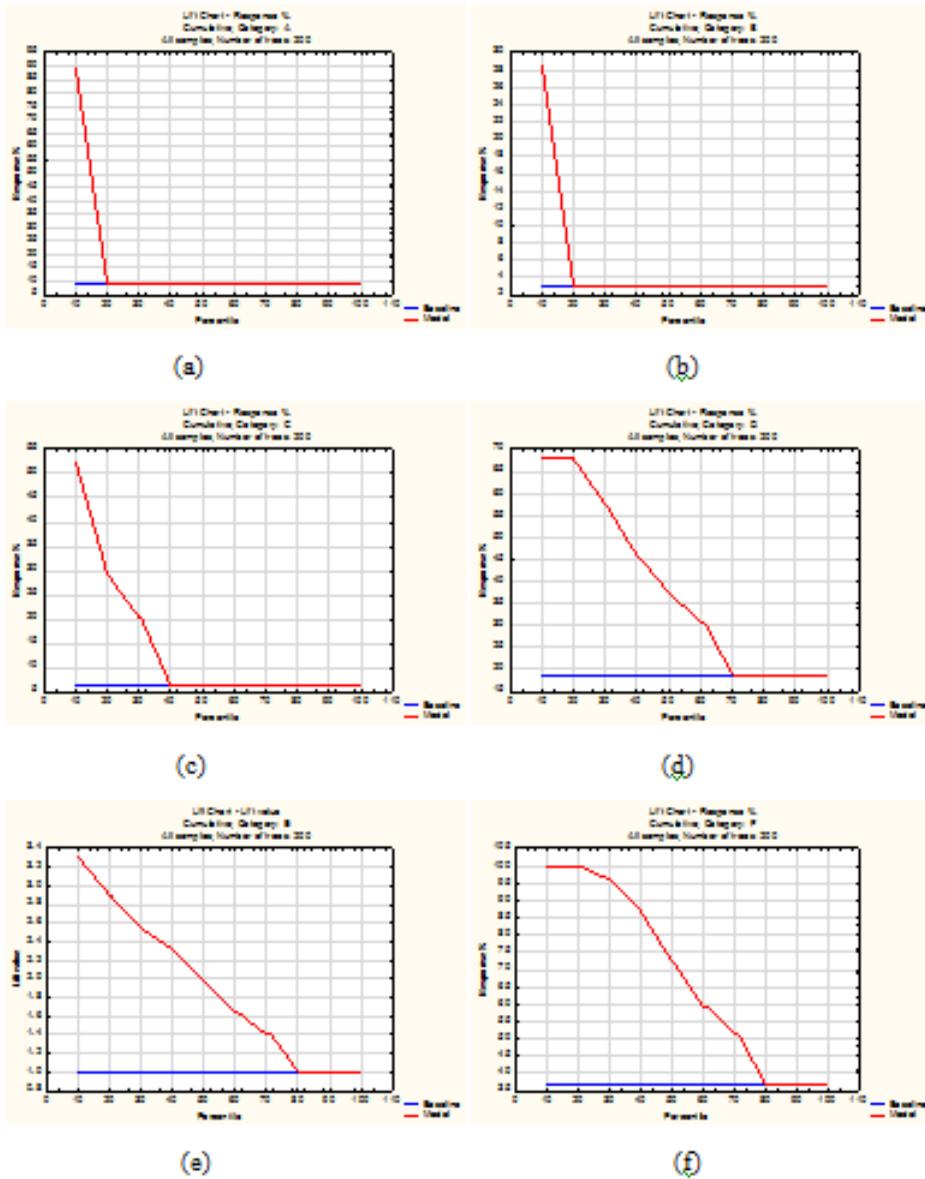
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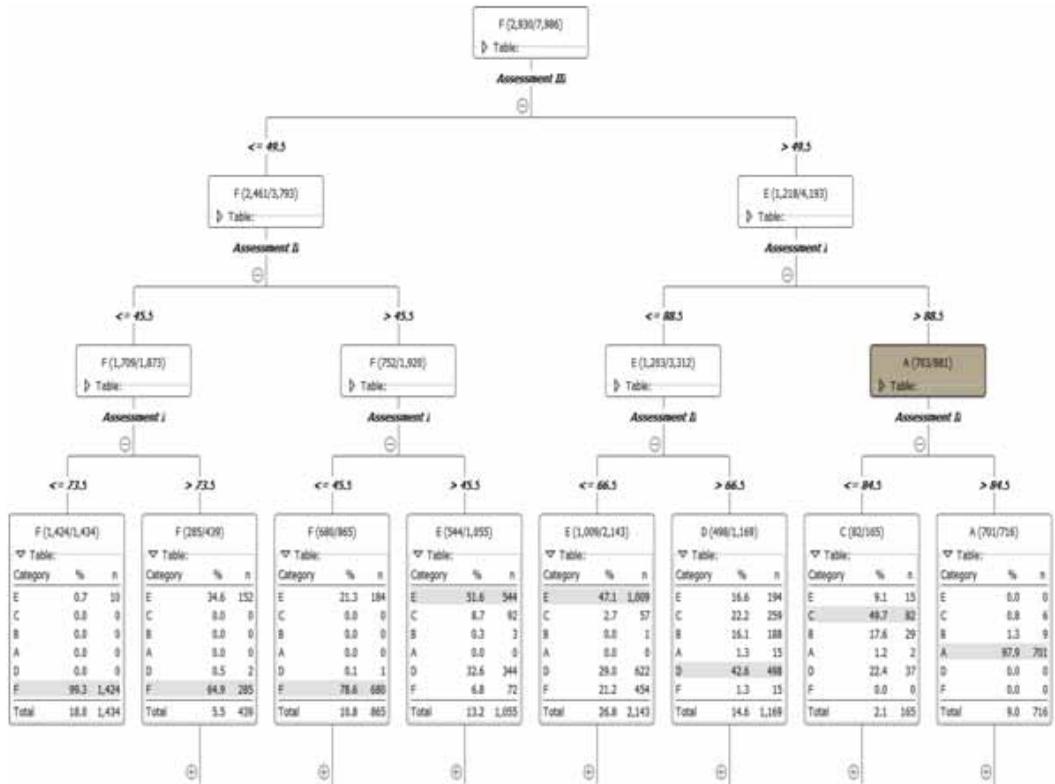
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Figure 7. Lift Chart of CGPA with Random Forest



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Figure 8. Decision Tree generated from Random forest



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