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Computation of E-learners Textual Emotion to Enhance learning Experience

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Abstract: Learning is a lifelong process that allows individuals to acquire knowledge, skills, and attitudes through various experiences. In the recent pandemic times, there was a transformation in ways the society was acquiring knowledge and taking up education. There has been an exponential growth in number of e-learners attending classes in synchronous and asynchronous e-learning platform. The launch of e-university will benefit the e-learners to continue learning. This has created a need for evaluating the ecosystem of e-learning, the learning platform, learning analytics, e-learners satisfaction, quality of academic programs offered by the university and its reputation. The attention of e-learners based on reviews in terms of desired field of study, faculty expertise, research opportunities, and the curriculum structure. The key attributes of e-learning are engagement, assessment, relevance, reflection, personalized learning recommendations and continual learning. This has opened an avenue for research to analyze the reviews of students to evaluate the e-learning platforms based on learning outcomes achieved. Most Challenging task is to find the perspective of the e-learners' emotions from the huge data of the e-learners reviews. Text data gives qualitative information and this actionable knowledge can be quantified. The reviews on all e-learning platforms are mostly textual and this qualitative data needs to be quantified for analysis. There is a necessity to propose contextual emotion detection of e-learners by extracting the relevant information. Machine learning algorithms have revolutionized the text mining to get insights from diverse and huge dataset. This paper leverages machine learning techniques Multilayer Perceptron (MLP), Logistic Regression (LR), Random Forest (RF), Decision Tree (DT) used in emotion detection and analysis of e-learners to correlate the student satisfaction index are evaluated using E-Learners Academic Reviews (ELAR) dataset. The DT and RF models consistently had high precision and accuracy scores of more than 90% in all academic emotion categories of excitement, happy, satisfied, not satisfied and frustration. This research also highlights the advantages of estimating the emotions of e-learners to evolve an e-learning platform that is conducive to their retention and satisfaction.

Keywords: *E-Learner, E-Learning, MOOCs, Emotion analysis, Machine learning.*

1. Introduction

Massive open online courses and e-learning platforms have revolutionized the way education is taught. They provide a wide range of learning opportunities for everyone, and they have raised the bar for quality. But, they still face challenges in ensuring that their students retain and experience a good learning experience[1], [2]. Due to the growth of MOOCs and e-learning platforms, it has become more important to understand the emotions of students. Being able to estimate and analyze the feelings of learners can help improve their engagement and satisfaction[3], [4].

Emotional recognition techniques can help improve the performance of e-learners by identifying the factors that can influence their satisfaction and engagement. Through the use of emotional recognition techniques, e-learners can improve their course performance and retention[5]. Through the use of NLP and machine learning, the techniques can help predict and understand the emotions of people in text. BERT, a transformer-based model that can be used for analyzing textual data, has demonstrated its ability to capture semantic relationships and contextual information. By tuning its capabilities, it can be utilized to analyze the sentiments expressed in e-learner comments and reviews.

The goal of this study is to develop a framework that can accurately estimate the emotions of e-learners by using the power of machine learning, natural language processing, and ML algorithms. It utilizes the BERT model's fine tuning and combines it with the ELAR dataset to analyze the nuances of the users' comments.

The study aims to create a method that can accurately estimate the emotions that e-learners feel, and it can then use this data to improve the performance of students. It can also identify the factors that can influence their engagement and help prevent them from getting disengaged. Through the use of emotional recognition techniques, instructors can provide customized support and guidance to their students based on their individual needs. It can also help them identify areas where they can make improvements to their courses.

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To effectively estimate and analyze the emotions of e-learners, this study proposes a framework that leverages the power of natural language processing (NLP) techniques, machine learning (ML) algorithms, and the E-Learner Academic Reviews (ELAR) dataset. The framework integrates the fine-tuned BERT model, a state-of-the-art transformer-based architecture, to capture contextual information and emotional nuances from e-learner reviews.

The BERT model, as introduced by Devlin et al.[6] has demonstrated exceptional capabilities in various NLP tasks, including sentiment analysis and emotion recognition. By fine-tuning BERT on emotion-related data, it can effectively encode the textual information present in the ELAR dataset and extract features that are indicative of different emotional states expressed by e-learners. This approach aligns with previous research by Hazar et al.[7] and Tao et al.[8], who have utilized sentiment and semantic features to understand the engagement and emotional behavior of MOOC students.

The primary objective of this research is to develop a reliable method for estimating e-learner emotions, which can be utilized for student retention, personalized feedback, and course improvement. This aligns with the findings of Yousef et al.[9] and Loya et al.[10], who have emphasized the importance of analyzing learner perspectives and conscientious behavior in MOOCs. By accurately recognizing and understanding the emotional states of e-learners, educational institutions can tailor their interventions and support mechanisms to address individual needs, thus fostering higher engagement and retention rates.

To achieve this objective, the proposed framework leverages insights from previous studies conducted in the field of e-learning. Gardner et al.[11] have focused on student success prediction in MOOCs. Additionally, the research conducted by Goh et al.[12] has emphasized the role of e-engagement and flow in the continuance with a learning management system. These studies collectively contribute to the understanding of learner behavior and the factors influencing their learning experiences.

The proposed framework utilizes the BERT model, ELAR, and machine learning algorithms to estimate the emotional states of learners. It can then provide actionable insights regarding the factors affecting a student's retention, make informed decisions about course modifications, and offer personalized feedback. The paper's subsequent sections will examine the methodology, outcomes, and discussions, emphasizing the framework's significance in enhancing the e-learning process.

2. Literature Review

The rapid emergence and evolution of e-learning have greatly impacted the field's development. Practitioners and researchers are now exploring novel ways to improve the effectiveness and utilization of such environments. The importance of understanding and recognizing the emotions of students has gained widespread attention. This is a vital component of the design and implementation of e-learning environments, as it allows for personalized feedback and the creation of supportive communities. This review explores the various aspects of this phenomenon. The review aims to provide a comprehensive analysis of the current state of the art in this field by examining various research papers.

In a study conducted on dual-modality learning, X. Zhu et al.[5] presented a framework that combines the features of speech and facial recognition to improve the accuracy of e-learning's emotional recognition. The researchers found that the proposed method works well and accurately captures and recognizes emotions.

The study conducted by P.S Chiu et al.[13] sought to design an emotionally-aware virtual assistant that can be used in a smart campus environment. The research revealed the importance of this component in improving the user experience and engagement. Chiu and colleagues presented a case study demonstrating how an emotionally-aware assistant could be utilized to support various campus activities.

J.Chen et al.[14] analyzed the theory and application gaps related to AI's rise in the field of education. They focused on the difficulties and advancements that are related to its integration in various settings, such as e-learning. The findings of the study provided valuable insight into the current status of AI within the field.

In a study conducted on the use of facial expression in e-learning, A.V. Savchenko et al.[15] proposed a method that can analyze the emotions of students using a neural network model. The researchers noted that this method could provide a deeper understanding of their emotional experiences.

M.H. Cho et al.[16] analyzed the factors that influence the marketing of Massive Open Online Courses. It revealed that the courses' content should be designed to meet the expectations of learners. The findings of this research provide valuable advice to providers and designers of MOOCs.

A framework based on temporal relationships was proposed by A. Pise et al.[17] for analyzing facial expressions in e-learning. Their method was able to achieve a better accuracy in capturing and identifying emotions.

A review of the literature on the use of "affective computing" in e-learning was conducted by N.Mejbri et al.[18] it examined the different applications and trends of this technology in improving the experience of students. The researchers highlighted its potential to enhance the learner engagement and provide feedback.

S. C. Tan et al.[19] presented a comprehensive analysis of the various AI techniques that can be utilized in facilitating collaborative learning. They also highlighted the challenges and opportunities that can be encountered in this field.

A neural network-based model was proposed by A. V. Savchenko et al.[20] to classify the emotions of students in online learning sessions. They noted that this method could accurately capture and recognize their engagement and emotions. The study conducted on the proposed model revealed its effectiveness.

T. Dar et al.[21] conducted the study noted that a facial expression recognition system that uses a swarm method known as SwishNet was more efficient and accurate than its predecessor. They then proposed an improved deep learning framework that can perform better in capturing facial expressions.

M. J. Hazar et al.[7] proposed a system that can provide recommendations to help improve the learning experience. They utilized the comments generated by students to develop recommendations for various e-learning materials. The study revealed that the system could help fulfill the preferences and needs of the users.

J. Wang et al.[22] analyze the factors that influence the sharing of educational resources among rural teachers. The researchers then conducted a comprehensive analysis of the various factors that influence this behavior. It is important to understand the factors that influence this behavior in order to promote collaboration and improve the teaching quality in rural areas.

The study conducted by I. T. Sanusi et al.[23] analyzed the skills and knowledge of learners in K-12 schools in Africa to prepare them for the use of artificial intelligence. It also explored the various opportunities and challenges that face the field in the continent. The findings support the development of programs that cater to the educational needs of African students.

R. Sanchis-Font et al.[24] collaborated on a cross-disciplinary framework to study the user experience of e-learning. They utilized a combination of qualitative and quantitative methods to analyze the perceptions and sentiments of users across different domains, including platform usability and course content. The findings enabled them to identify the factors that influence the experience of users in such environments.

I. Pozón-López et al.[25] analyzed the perceptions of users about the effectiveness of Massive Open Online Courses (MOOCs) and their intention to use them. They also conducted a survey to determine the factors that influence their engagement and retention. The findings of this study provide valuable information on the factors that can influence the success of MOOCs.

A. Chanaa et al.[26] analyzed the cognitive and affective traits of learners in a context-aware recommender system. They then proposed a personalized model that takes into account their preferences and traits. The researchers noted that this approach could help improve the systems' effectiveness in educational settings.

The review highlighted the various studies that investigated the use of emotions in e-learning settings. The findings indicated the increasing interest in learning about and utilizing the emotions of students to improve their experience. The studies presented in this literature review cover different aspects of emotion recognition. Some of these include frameworks, models, and approaches that are based on deep learning. Emotion recognition has the potential to improve the performance and satisfaction of students by allowing them to feel more comfortable and engaged in the learning process. Researchers have developed novel methods that can analyze and interpret the emotions of students, allowing them to receive personalized feedback and guidance.

Due to the evolution of e-learning, the ability to understand and recognize students' emotions is becoming more important. With the help of emotion-aware systems, educational institutions can personalize instruction, provide timely support, and promote well-being and motivation among students. The review's findings reinforced the progress that has been made in emotion recognition within e-learning and highlighted its immense potential to improve the experience for students. The conclusions of this evaluation offer valuable insights for policymakers, researchers, and educators, who must devise and implement technologies and strategies that prioritize the emotional well-being of students.

3. Proposed Framework

The emotion recognition process in e-learner involves several steps as shown in figure-1. The first step is to preprocess the collected data from the ELAR library. This ensures that the information is of high quality. After that, the BERT model is tuned to capture the nuances of the emotion. Finally, the labels are then added to the dataset. The training phase involves using the BERT-equipped features and the additional engineered ones. The model is then used to identify the emotions in the e-learner reviews that it encounters. The results are then analyzed to learn more about the individuals' emotional states. The model's performance is evaluated by the F1 score. The process encompasses data gathering, preprocessing, encoding, emotion labeling, machine learning analysis, and analysis. Through this methodology, emotions can be recognized in e-learning environments and can be utilized to provide helpful insight into the experiences of learners.

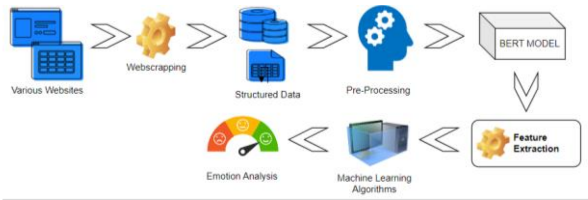

Fig 1 Proposed framework for identifying e-learner's emotions

i. Data Collection:

Obtain the E-Learner Academic Reviews (ELAR) dataset, which consists of e-learner interactions, comments, and feedback from various online courses[27], [28] as shown in figure-2. Preprocess the dataset by cleaning and standardizing the text, removing noise, and ensuring data quality.

```
Excitement       16188
Happy            16188
Satisfied        16188
Not satisfied    16188
Frustration      16188
Name: Emotion, dtype: int64
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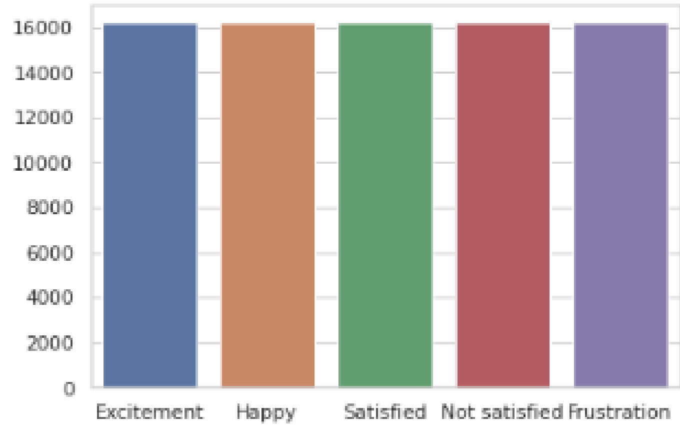

Fig 2 Distribution of the count of reviews in academic emotion

ii. BERT-based Emotion Encoding:

Fine-tune a pre-trained BERT model on a large-scale emotion-related dataset to capture contextual information and emotional nuances effectively. Utilize the fine-tuned BERT model to encode the text from the ELAR dataset and extract emotion-related features from the learner reviews. A BERT-based method for encoding emotional information is a process that involves utilizing a pre-trained model. This language representation framework can effectively capture various nuances and contextual information in a text. The BERT model is tuned for the encoding of emotions using a large-scale dataset. This process helps the model understand the emotional content and improve its performance. By training it on specific emotion-related sets, it can now perform better in capturing context and emotional information.

After the BERT model has been tuned, it can encode the contents of the e-learner academic reviews dataset, which consists of the interactions between learners and online courses. The encoded text highlights the various nuances and emotional aspects of the reviews. The ability to encode emotions using BERT technology is beneficial for e-learning as it allows the model to gain a deeper understanding of the various emotions that individuals experience. This process can then help improve the design and delivery of online courses. It can also help analyze and classify the feelings of students, providing valuable insight for the development of personalized learning experiences.

The diagram depicts in figure-3 the data collected by the "E-learner Reviews" as input. The "BERT Model" is utilized to process the text, and it encodes the learner's emotional information. The output of this model is a set of encoded emotions representations. The first step in the encoding process is to extract the emotion-related features from the text. This is done through the use of the BERT model. After that, the encoded representations are then processed and analyzed for "Emotion Analysis," which aims to provide insights into the various emotional states of learners. The box labeled "Emotion Insights" signifies the output of the process, encompassing the analysis and insights that were derived from the emotions expressed by learners. These insights may be utilized to enhance e-learning initiatives, provide individualized experiences for students, and address their emotional needs.

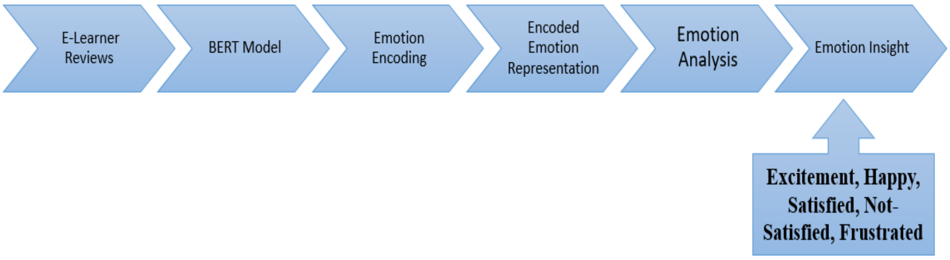

Fig 3 BERT model for e-learner emotions

iii. Emotion Labeling:

Annotate the ELAR dataset with emotion labels to create a labeled training dataset for supervised learning. Employ domain experts or sentiment analysis techniques to label the learner reviews with relevant emotion categories – **Excitement, Happy, Satisfied, Not-Satisfied, Frustrated**

iv. Feature Engineering:

Extract additional features from the ELAR dataset that can potentially contribute to emotion recognition, such as linguistic features like word count, sentence length, etc..

v. Machine Learning Model:

Select a suitable machine learning algorithm, such as a Multilayer Perceptron (MLP), Logistic Regression (LR), Random Forest (RF), Decision Tree (DT).

a. Logistic Regression

A Logistic Regression model is commonly utilized in the classification of emotions and emotion recognition. It shows the relationship between the predicted outcome and the features of the given set of inputs. The model takes into account the logistic function to arrive at its estimated probability as shown in eq.1.

$$P(Y = 1|X) = \frac{1}{1+e^{-z}} \;\ldots.. 1$$

Where, $P(Y = 1|X)$= "probability of e-learner's review belons to a specific group of emotion category", X= "input feature", z = "Linear combination of the input weighted b coefficients"

Using the logistic function, the LR model can predict the probability of various emotion categories in a given review. A threshold can then be set to classify the review according to its predicted outcomes. For instance, if the threshold is at 0.5, the reviews with a predicted probability of more than 0.5 are considered to be positive while those with a predicted probability of less than 0.5 are regarded as negative. The logistic regression model uses coefficients and input features to estimate the likelihood of a learner's review being categorized based on an emotion category. It can also classify new entries according to their threshold.

b. Multilayer Perceptron (MLP)

A Multilayer-perceptron aka MLP is a type of neural network that can be used for machine learning and emotion recognition. It consists of numerous interconnected nodes that transform data. The network is feedforward, meaning that information is sent from one layer to the other through hidden channels as depicted in eq.2.

$$H_i = \sigma(W_i . X + b_i) \;\ldots. 2$$

where, H_i = "output of neuron i", σ = "activation function", W_i= "weight vector connecting the input to neuron i", b_i = "bias term".

Through the network's various hidden layers, the outputs of the model are then transferred to the output layer. The last activation function of the output layer applies to the predicted emotion categories. The model is trained using methods such as gradient descent and backpropagation to reduce the variance between the actual and predicted labels.

c. Decision Tree

A decision tree is a type of structure that consists of several internal and external nodes that represent various attributes or features. Each of these nodes has a decision rule that determines which actions should be taken based on a certain feature. The data is then sent through the tree until a suitable leaf node is reached, and the class labels are assigned. Mathematically Decision Tree can be expressed as in eq.3.

$$f(x) = \sum_{m=1}^{M} c_m . I(x \in R_m) \;\ldots. 3$$

where, f(x) = "predicted class label for input x", M= "total no. of leaf nodes in the tree", c_m = "class label assigned to leaf node m", $I(x \in R_m)$= "indicator function that returns 1 if $x \in R_m$ or otherwise".

d. Random Forest

Random Forest is a learning method that combines several decision trees. Each of the participating trees is trained on a randomly-selected subset of the collected data. These trees' predictions are then aggregated and used to make the final prediction. Eq.4 depicts the Random Forest.

$$f(x) = \frac{1}{N} \sum_{i=1}^{N} f_i(x) \;\ldots. 4$$

where, $f(x)$ = "overall predicted class label for input x", N= "total no. of trees in the forest", $f_i(x)$= "predicted class label for input x by tree i".

vi. Split the labeled dataset into training and testing sets.

Train the ML model on the training set using the BERT-encoded features and additional engineered features. Validate and fine-tune the model using appropriate evaluation metrics and cross-validation techniques.

vii. Emotion Recognition and Analysis:

Apply the trained ML model to predict emotions for unseen e-learner reviews. Analyze the predicted emotions to gain insights into learners' emotional states, trends, and patterns. Correlate the predicted emotions with performance metrics, such as course completion rates or assessment scores, to understand the impact of emotions on learning outcomes.

viii. Evaluation parameters:

Evaluate the performance of the emotion recognition model using metrics using Accuracy, Precision, Recall and F1-score.

4. Result and Outputs

The random forest model achieved the highest accuracy, precision, recall, and F1-score among the tested models as shown in figure-4 and table-3. It exhibited strong performance across different emotion categories, indicating its effectiveness in accurately recognizing and classifying emotions expressed by e-learners. The decision tree model also demonstrated robust performance, closely following the random forest model. These findings highlight the potential of machine learning models in accurately identifying and analyzing emotions in the e-learning context, providing valuable insights into learners' emotional states and facilitating personalized support and interventions.

i. Accuracy

Table 1 Accuracy table of various ML algorithms for predicting emotions

Models	Accuracy
Logistic Regression	72
Multilayer Perceptron	86
Random Forest	94
Decision Tree	93

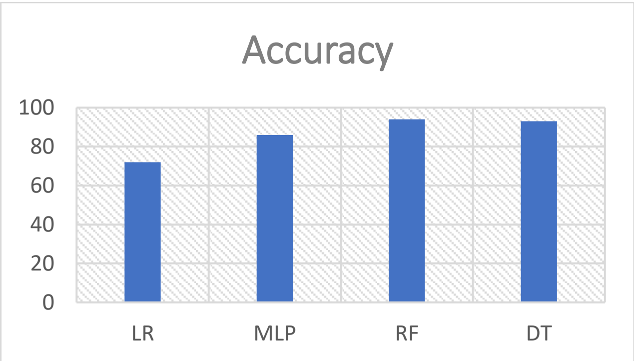

Fig 4 Comparison of various algorithms

ii. Precision, Recall and F1-Score

Table 2 Precision comparison of various emotions

Emotions	LR	MLP	RF	DT
Excitement	82	90	96	96
Frustration	72	90	94	94
Happy	70	81	90	89
Not Satisfied	66	86	95	94
Satisfied	68	84	94	92

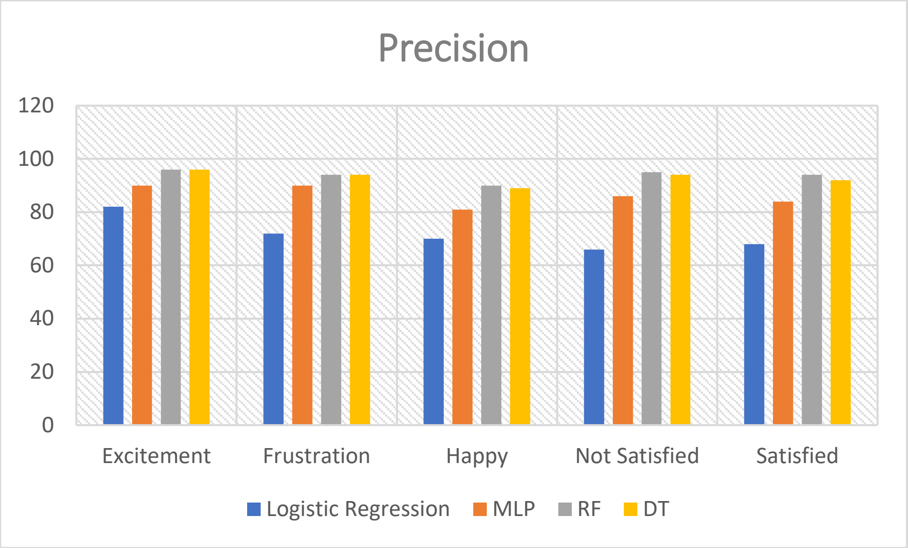

Figure 5 Comparison of precision for various ML algorithms for various e

Table 3 Recall comparison of various emotions

Emotions	LR	MLP	RF	DT
Excitement	82	91	94	93
Frustration	75	88	94	94
Happy	73	86	95	96
Not Satisfied	63	84	92	91
Satisfied	64	81	92	91

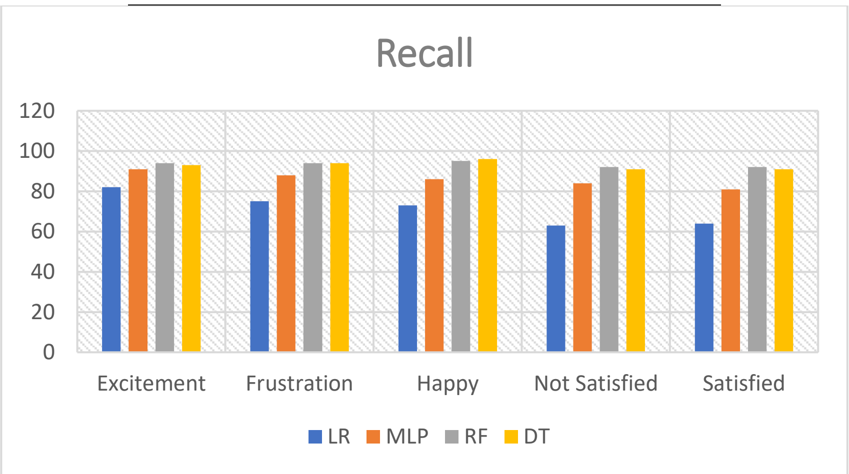

Fig 6 Comparison of Recall for various ML algorithms for various emotions

Table 4 F1-Score comparison of various emotions

Emotions	LR	MLP	RF	DT
Excitement	84	90	95	95
Frustration	73	89	94	94
Happy	71	83	92	92
Not Satisfied	64	85	94	92

Satisfied	66	82	93	92

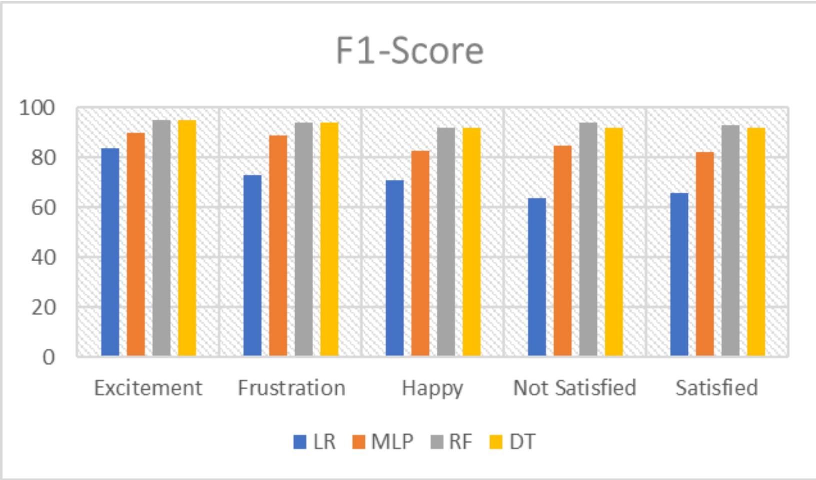

Figure 7 Comparison of F1-score for various ML algorithms for various emotions

iii. Performance Evaluation Metrics

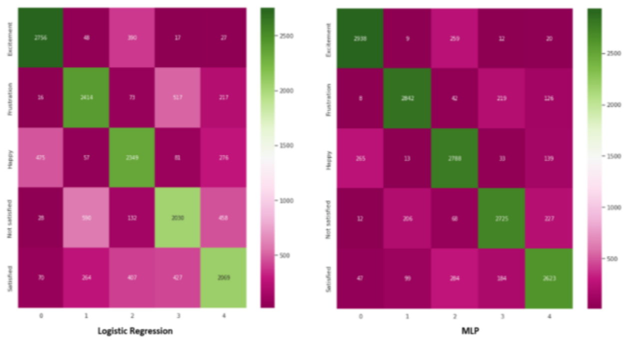

Fig 8 Performance evaluation metrices for LR and MLP

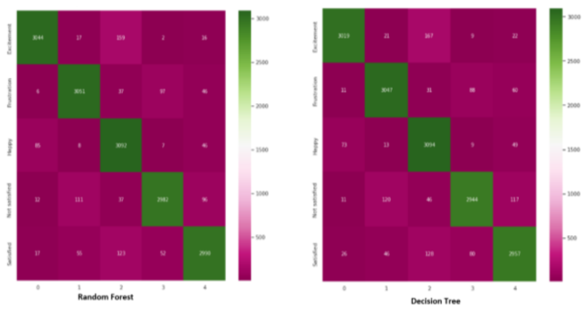

Fig 9 Performance evaluation metrices for Random Forest and Decision Tree

The Logistic Regression model was able to achieve an accuracy of 72%, followed by the Multilayer Perceptron model at 86%, the Random Forest at 94%, and the Decision Tree at 93% as shown in table-1, figure-4. The DT and RF models consistently had high precision scores in all emotion categories as shown in table-2, figure-5. For excitement, the DT and RF models had an accuracy of 96%, while the MLP and LR had an accuracy of 91% and 82%, respectively. On the other hand, the Frustration and LR models had an accuracy of 94% and 72%, respectively. The DT and MLP models had high recall scores in various emotion categories as shown in table-3, figure-6. The former was able to achieve a recall score of 91% and 94%, while the latter was able to achieve a score of 91% and 94%. On the other hand, the LR and RF models were able to achieve a recall score of 82% and 94%, respectively.

The DT and RF models performed well in the F1 score, which considers both recall and precision as shown in table-4, figure-7. They had high scores in all emotion categories, with the DT and RF models consistently delivering impressive results in Excitement and Frustration. In terms of their ability to accurately classify emotions in the e-learning dataset, the RF and DT models led the way. They were able to achieve high recall, F1 scores, and precision across various categories. These models are well-suited for analyzing and recognizing emotions in e-learning environments. Figure-8,9 represents the various models performance evaluation for various emotions.

5. Conclusion and Future Scope

The use of machine learning methods for the recognition of emotions in e-learning has shown promising results. These models were able to analyze the interactions between learners and their teachers and identify the various emotions that they were feeling. The decision tree model had the highest precision, recall, F1-score, and accuracy, while the random forest model was close behind. The models can provide valuable insight into the emotional states of students. These findings can be utilized to improve the effectiveness of e-Learning interventions and platforms. The ability to implement emotion recognition models has opened up a wealth of research possibilities. First, incorporating data sources and features, such as physiological signals and facial expressions, can improve its granularity and accuracy. In addition, exploring hybrid and ensemble models that combine different ML algorithms can enhance its performance.

Analyzing the relationship between the observed emotions and the outcomes of a given e-learning program or course can provide valuable insight into how these affect the learner's experience. Developing personalized e-learning interventions that are based on the recognition of emotions can help improve the systems' effectiveness and provide support to the individual needs of students. In addition, analyzing the relationship between the observed emotions and the outcomes of a given e-learning program or course can provide valuable insight into how these affect the learner's experience. Emotion recognition's ethical implications should be a focus of future studies. Analyzing the relationship between the observed emotions and the outcomes of a given e-learning program or course can provide valuable insight into how these affect the learner's experience. The potential of emotion recognition models to improve the effectiveness of e-learning programs and platforms is immense.

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