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IoT-based Emulated Performance Evaluation NLP Model for Advanced Learners in Academia 4.0 and Industries 4.0

Lisha Yugal[1], Suresh Kaswan[2], B. S. Bhatia[3], Aditi Sharma[4*,5]

[1] Department of Computer Science and Engineering, RIMT University, Gobindgarh, Punjab, India
[2] Department of Computer Science and Engineering, Sharda University, Andijan, Uzbekistan
[3]Department of Computer Science and Engineering, RIMT University, Gobindgarh, Punjab, India
[4]Department of Computer Science and Engineering, Symbiosis Institute of Technology, Symbiosis International University, Pune, India
[5]IEEE Senior Member, Symbiosis Institute of Technology, Pune, India

Emails: lishayugal26@gmail.com; sureshkaswan@gmail.com; bsbhatia29@hotmail.com; aditi.sharma@ieee.org
*Corresponding Author: aditi.sharma@ieee.org

Abstract

In recent years, most of the research exhibits in the field of Education 4.0 Training Systems (ETS) and Industry 4.0 Training Systems (ITS) that has the ability to learn the behavior of the learners, interns, or trainees. Understanding the feelings and emotions of learners toward learning is essential for creating a practical and exciting learning experience. Patience-emotions detection and sentiments analysis have emerged as an integral part of the understanding of the behaviors of learners, thus there is a need to expand the overall educational or training process in academics and industries. This model enables teachers, trainers and instruction designers to obtain valuable information, which can be used to optimize teaching strategies to improve learning outcomes. To achieve this goal with IoT-enabled objects, an Academician can create a more personalized and effective learning environment for students, trainees and interns. A novel emulated framework is designed and implemented with IoT and machine learning techniques to analyze the performance of learners. The model receives feedback from 1000 learners using IoT devices and analysis the missing information in the learning systems, that missing information lacked effective learning. This emulated framework analyzes the performance of the model. A novel and innovative early warning system is also created to send the warning on WhatsApp or email to several users in a single shot, when achieving certain goals such as file's size limits and so on. In this research SVM, MCC, NLP and CNN machine learning algorithms are applied to detect students' feelings and emotions to track the feedback via IoT enabled system.

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1. Introduction:

In the academies, it is vital to comprehend the patience, emotions and sentiments expressed by learners in order to design effective and captivating learning experiences. Patience, Emotion and sentiment detection have emerged as invaluable tools to analyze the performance of the learners that can offer profound insights into learner feedback, thereby enhancing the overall educational process. The objective of developing an affective model is to construct a model that can accurately identify patience, emotions and sentiments conveyed in learner feedback pertaining to learning materials. By achieving this, educators and instructional designers can access valuable information to customize their teaching strategies and improve learning outcomes [18,19]. There are some influencing factors that play an important role in the implementation strategies such as patience, emotions and sentiment analysis in academics. Emotions hold a fundamental role in the process of learning, as they greatly influence learners' motivation to keep more patience to learn the things, engagement, and overall performance.

Through the detection and understanding of these emotions, educators can adapt their teaching methods to better cater to learners' needs. Emotion detection allows for the identification of emotions such as frustration, confusion, boredom, or excitement, enabling educators to intervene appropriately by providing assistance or challenges. Additionally, it contributes to the creation of a positive and supportive learning environment that fosters a sense of belonging and reduces stress and anxiety, Soleymani (2017). Likewise, sentiment analysis provides insights into learners' overall attitudes, satisfaction levels, and perceptions of learning materials. By analyzing sentiments expressed in feedback, educators can identify areas where learners exhibit high levels of satisfaction or dissatisfaction, enabling them to make data-driven decisions to enhance their instructional practices. Sentiment analysis is also instrumental in identifying common issues or challenges faced by learners, facilitating targeted interventions and efficient allocation of resources. By incorporating emotion detection and sentiment analysis into the educational process, educators can gain a comprehensive understanding of learners' experiences and emotions, thereby fostering more effective and learner-centric instructional design [7,9].

This research aims to develop an affective model for emotion detection and sentiment analysis in learner feedback, to automate the process of comprehending and categorizing the emotions and sentiments expressed by learners. This model focuses to uplevel the techniques through NLP (natural language processing) including ML (machine learning) [10] to analyze the textual feedback generated by learners on learning materials.

By accurately detecting emotions, the effective model enables educators to identify learners' emotional states throughout their learning journey. This information can be utilized to personalize the learning experience, provide timely interventions, and create supportive learning environments. Additionally, sentiment analysis empowers educators to assess overall learner satisfaction and identify areas that required to improvement in learning materials or instructional strategies [8,12]. Ultimately, the development of an affective model seeks to provide educators and instructional designers with valuable insights that can inform decision-making processes, enhance instructional design, and elevate the overall learning experience for learners. Through the creation of a reliable and effective affective model, educators can gain a better understanding of learners' emotions and sentiments, leading to more customized and impactful educational interventions. The structure of the research include following sections First Section include some introduction about the proposed research and Second Section recent work the literature-related work The third section related to some results analysis in the experiments, by conferring the research methodology and dataset. Further we trained the model in section Fifth, optimize the model in Section Sixth and Performance analysis in Section Seven, Finally, we conclude the research including limitations and further future research.

2. Related Work

Ahmad Z,and et. al. (2020) focuses on the application of transfer learning techniques for the task of emotion detection in text data [1]. Main Contributions of this research is a novel approach to emotion detection that utilizes transfer learning. It leverages cross-lingual word embeddings to bridge the gap between languages, making it possible to apply models trained on one language to another. The authors demonstrate the effectiveness of their approach on multiple datasets and languages, highlighting its potential for cross-lingual emotion detection.

The work proposed in Ahuja R and et. al. (2019), influenced the various feature extraction techniques on the performance of sentiment analysis [2]. The results and findings of the paper are the results of experiments that compare the performance of sentiment analysis using different feature extraction techniques. They include discussions of which techniques are more effective for specific tasks or datasets.

The paper titled with "Role of sentiment analysis in education sector in the era of big data: a survey" by Archana and et al. 2017 focus on Deep Learning Models for Sentiment Analysis focused on Deep learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or Transformer-based models like BERT or GPT, have demonstrated promising results in sentiment analysis tasks. These models have the ability to automatically learn hierarchical representations of text and capture intricate contextual relationships [3]. CNNs are effective at capturing local dependencies within text, while RNNs excel in modeling sequential dependencies.

Transformer-based models leverage attention mechanisms to consider the entire input text simultaneously, capturing global contextual relationships. Deep learning models for sentiment analysis typically require substantial amounts of labeled training data and significant computational resources for training. However, they have the potential to achieve state-of-the-art performance in sentiment classification tasks. The choice of sentiment classification technique depends on factors such as the availability of labeled training data, the need for interpretability, the diversity of the text data, and the computational resources available for training and inference.

The paper titled with " Hybrid approach for emotion classification of audio conversation based on text and speech mining" by bhaskar2015 and et al. focus on Rule-based Methods and Machine Learning Algorithms [13] Both rule-based methods and machine learning algorithms are widely employed in sentiment analysis. Rule-based methods rely on predefined rules that capture sentiment-related patterns, such as the presence of positive or negative words, negation, or intensifiers. These rules are applied to the text to determine its sentiment. On the other hand, machine learning algorithms utilize labeled sentiment data for training, learning patterns, and features that distinguish between different sentiment categories. Once trained, these algorithms can classify new, unlabeled text based on the learned patterns. Each approach, whether rule-based or machine learning-based, has its own advantages and disadvantages. Rule-based methods offer interpretability and allow for the incorporation of explicit domain knowledge. However, they may struggle to generalize well to diverse texts. Machine learning algorithms, on the other hand, can handle a wide range of texts and capture complex patterns but may lack interpretability.

3. Proposed Methodological Framework for IOT-based NLP model

In this research, important information is collected from learners by establishing connections among servers and storing the information locally. Then the data is preprocessed before implementing the machine learning algorithms, then the results are stored after applying the algorithm to analyze the things. An early warning IOT-based decision system is designed in Python to train a model to perform smoothly. It will resist the failure of the system due to the file size limit. That warning messages are sent via email and WhatsApp. This model has a novel approach to reaching several WhatsApp users or email users in a single shot to warn them at an instance. The data is further uploaded over the cloud for further processing. The implementation of feedback conceptualization is presented in Figure 1.

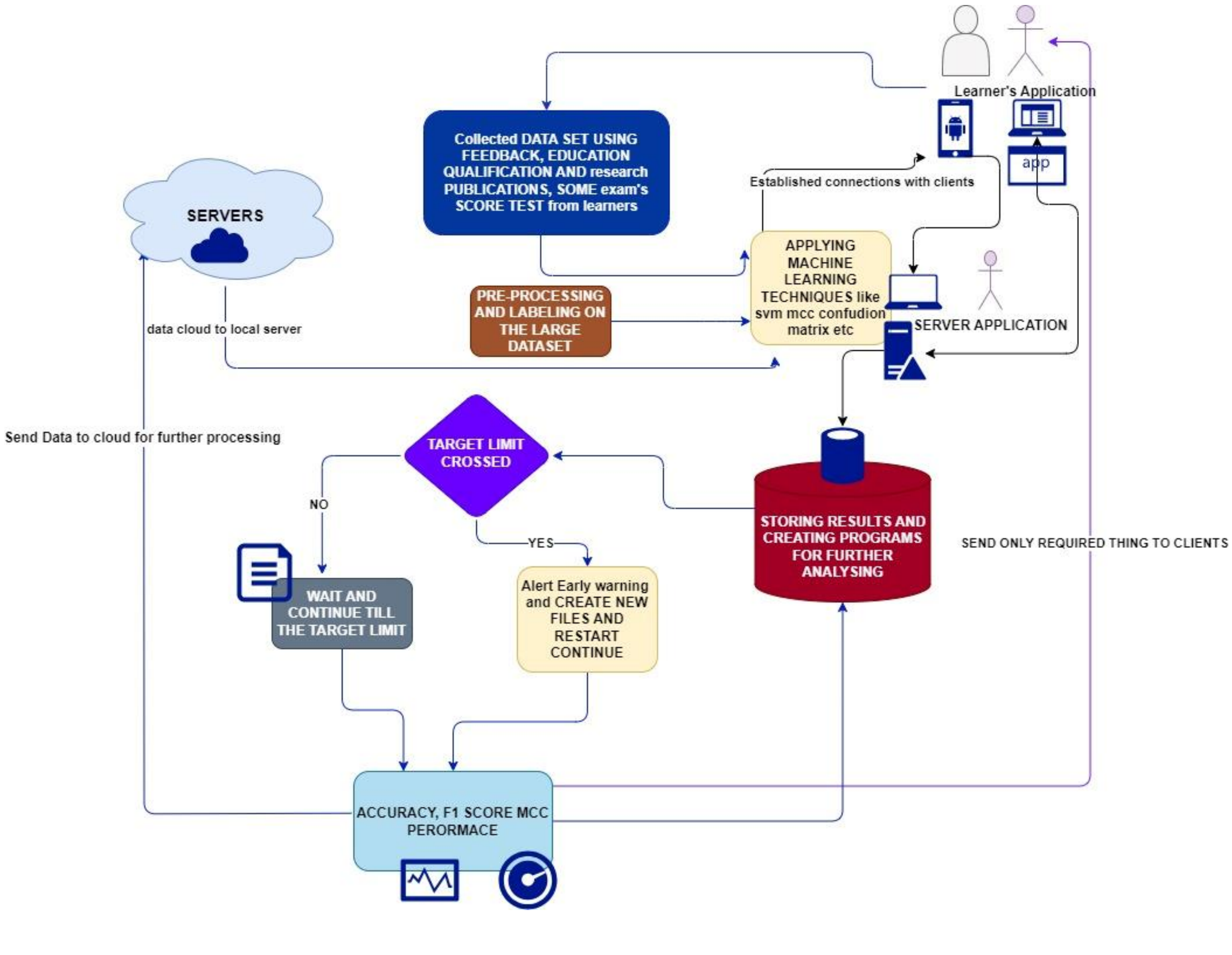


Figure 1: Conceptualization of feedback framework for Academia and

In this framework, in the first phase, feature extraction is employed. The following terminologies have been worked upon in this model implementation for feature extraction-

a. **Bag-of-Words (BoW) representation**: In sentiment analysis, a common method for feature extraction is BoW representation. This approach treats text as a collection of words, disregarding grammar and word order. Each word in the text is counted, and these frequencies are used as features for sentiment classification. The resulting feature vector represents the presence or absence of words in the text, capturing the overall distribution of words.

b. **Term Frequency-Inverse Document Frequency (TF-IDF):** Another widely employed technique for feature extraction is TF-IDF. This method considers the importance of words in a document compared to their frequency across the entire dataset. Term Frequency (TF) measures the frequency of a word in a specific document, while Inverse Document Frequency (IDF) calculates the importance of a word in the dataset by inversely weighting frequently occurring words. The TF-IDF score, obtained by multiplying TF and IDF, indicates the relevance of a word to a particular document.

c. **Word Embeddings and Contextualized Representations:** Word embeddings are dense vector representations that capture the semantic meaning of words. Generated through unsupervised learning techniques like Word2Vec, GloVe, or fastText, word embeddings can capture word similarities and relationships, enabling sentiment analysis models to grasp the contextual meaning of words. Rocha L. (2020), Contextualized representations, such as ELMo, GPT, or BERT, take word embeddings a step further by considering the context in which words appear. These models generate representations that are contextualized based on the entire input text. Contextualized representations capture the varying meanings of words based on their surrounding context, enhancing the accuracy and performance of sentiment analysis models [2]. By employing these feature extraction techniques, sentiment analysis models can convert raw text data into numerical representations that capture crucial linguistic and semantic information. These features serve as inputs for machine learning algorithms or deep learning models to accurately classify sentiments. The choice of feature extraction technique relies on the specific requirements of the sentiment analysis task and the available resources for training and inference [5,6].

The next step is to train the model either to choose Machine Learning or Deep Learning techniques for emotion detection and sentiment analysis. This decision depends on factors such as data complexity, availability of labeled training data, and computational resources. Machine learning models, such as Naive Bayes, Support Vector Machines (SVM), or Random Forest, are suitable for simpler datasets and limited labeled training data [14,17]. They can perform well when the features are well-defined and the relationships between features and emotions are relatively straightforward. Deep learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or Transformer-based models (e.g., BERT, GPT), are better suited for complex datasets and when ample labeled training data is available. These models automatically learn hierarchical representations and capture intricate patterns, leading to improved performance.

The third phase is for data collection, Figure 2 which will be gathering learner feedback on learning materials. Data collection is done through Surveys, Online Platforms, Interviews or Focus Groups, Social Media, and Discussion Forums. The surveys are designed and distributed to learners, soliciting their feedback on their experiences with the learning materials. Also, they incorporate open-ended questions that allow learners to articulate their thoughts, emotions, and sentiments. Online Platforms are the utilization of online learning platforms or learning management systems equipped with feedback features.

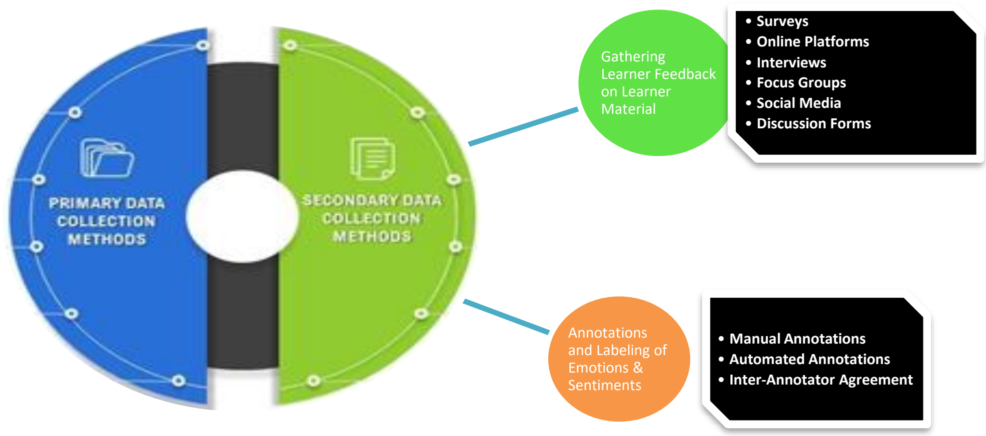


Figure 2: Data Collection Methods

Encourage learners to provide feedback on specific learning materials, lessons, or modules. Interviews or Focus Groups are mainly concerned with conducting interviews or organizing focus groups with learners to obtain more detailed feedback. Pose questions that delve into their emotional responses and sentiments regarding the learning materials. Social Media and Discussion Forums are the platforms for monitoring purposes where learners might share their experiences and opinions about the learning materials [11]. Once the learner feedback data has been amassed, the subsequent stage involves annotating and labeling the emotions and sentiments expressed within the feedback. This labeling process is crucial for training the affective model. Manual Annotation is used to enlist trained annotators or experts to manually review each feedback entry and assign appropriate labels to indicate the emotions and sentiments present. Then a set of predefined emotion categories (e.g., happiness, sadness, anger, fear, surprise) and sentiment categories (positive, negative, neutral) are designed to ensure consistent annotation. After this existing sentiment analysis tools or emotion detection algorithms are utilized to automatically assign initial labels to the feedback data. However, manual verification and adjustments should still be undertaken to ensure accuracy and reliability. If multiple annotators are involved, the inter-annotator agreement is calculated to assess the consistency and reliability of the assigned labels. Methods such as Cohen's kappa coefficient can be employed for this purpose. It is imperative to conduct the annotation and labeling process meticulously and consistently to generate high-quality training data for the affective model.

The next phase is preprocessing illustrated in Figure 3. This phase comprises three modules. First is text cleaning and standardization in which cleaning and standardization of the textual data is done, the text is obtained from learner feedback on learning materials to develop an effective model for emotion detection and sentiment analysis.

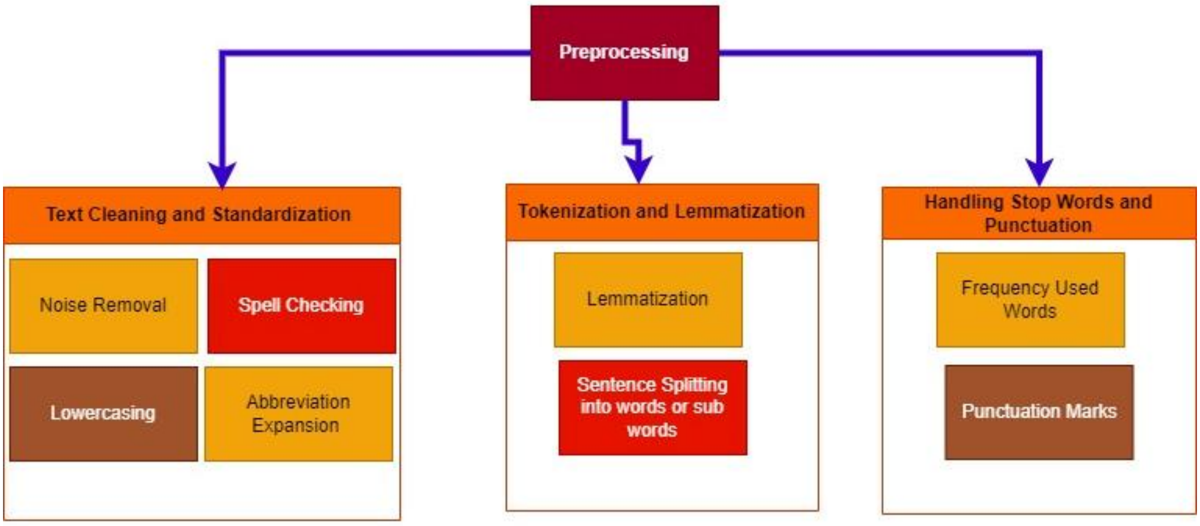


Figure 3: Pre-processing in Sentiment Analysis

This involves noise removal, lowercasing, spell checking, and abbreviation expansion. Noise removal comprises eliminating irrelevant characters, symbols, or special characters that do not contribute to the text's meaning, such as HTML tags or URLs. In lowercasing, all text is converted to lowercase to ensure consistency and avoid treating the same word with different cases as separate entities.

Spell Checking utilizes spell checking algorithms or libraries to correct common spelling errors in the text data. Expand abbreviations and acronyms is done to their full forms to enhance uniformity and clarity in the text.
Second module is tokenization and lemmatization. Tokenization is the process of dividing the text into individual units, known as tokens. In this module, sentences are split into words or sub-word units [25]. Additionally, lemmatization is applied to transform words into their base or dictionary form, known as lemmas. These techniques aid in standardizing the text representation and reducing vocabulary size.

Third is Handling Stop Words and Punctuation. Stop words refer to frequently used words, such as ["a", "an", "the," or ","d"] that do not carry significant meaning in sentiment analysis or emotion detection. Removing stop words helps reduce noise and enables a focus on more informative words. Punctuation marks, such as commas, periods, or exclamation marks, can also be eliminated to avoid unnecessary interference during analysis [24]. However, it is important to note that certain punctuation marks may convey sentiment or emotional significance and should be retained accordingly. By implementing text cleaning, standardization, tokenization, lemmatization, and handling of stop words and punctuation, the textual data is preprocessed to facilitate subsequent processing and feature extraction. This enhances the accuracy and meaningfulness of the analysis conducted on the emotions and sentiments expressed in learner feedback [20, 21].

In this preprocessing emotion labeling is done by utilizing existing emotion classification models. In the development of an affective model for emotion detection, it is beneficial to explore pre-existing emotion classification models. These models have undergone training on extensive datasets and are designed to categorize text into different emotion categories. By leveraging these models, researchers and practitioners can take advantage of established frameworks and methodologies. Another approach to emotion labeling involves the manual annotation and labeling of learner feedback data. Trained annotators or experts carefully review each feedback entry and assign suitable emotion labels based on the expressed emotions. This process typically entails defining a predetermined set of emotion categories (such as happiness, sadness, anger, fear, surprise) and associating each feedback entry with the most relevant emotion label. Manual annotation and labeling provide greater control over the emotion categories and ensure alignment with the specific context of the learning materials and the expressions of the learners. Although this approach can be time-consuming and resource-intensive, it allows for a more customized and context-specific emotion labeling process.

Both the utilization of existing emotion classification models and manual annotation approaches have their advantages. Existing models offer efficiency and convenience, while manual annotation allows for customization and alignment with specific learning contexts. The choice between these approaches depends on the available resources, the desired level of customization, and the specific requirements of the affective model development process [1, 29].

4. Experimental Sentiment Analysis

Within the field of sentiment analysis, there are various techniques available for classifying sentiment [4, 28] in text. These techniques aim to categorize text into different sentiment categories, such as positive, negative, or neutral. Some commonly used techniques for sentiment classification include lexicon-based approaches and machine learning algorithms, they have been implemented in this work as follows-

a. Lexicon-based Approaches:

These approaches rely on sentiment lexicons or dictionaries that contain pre-defined sentiment scores for words. The sentiment of a text is determined by aggregating the sentiment scores of the words present in the text.

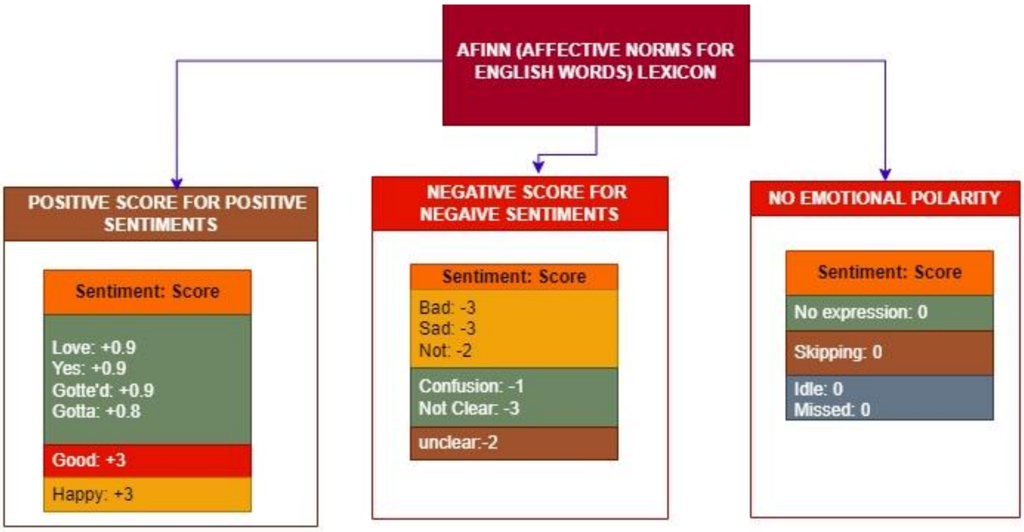


Figure 4: Lexicon-based Approaches

b. Machine Learning Algorithms:

Machine learning algorithms, such as Naive Bayes, Support Vector Machines (SVM), or Random Forest, can be utilized for sentiment classification. These algorithms are trained on labeled sentiment data and learn to classify text based on patterns and features extracted from the data. In this research, SVM has been implemented.

Algorithm 1:

Feedback Collector at Backend through NLP:

Create a *list l(i)* for *feedback f(i)*
    feedback f(i) is collected from *learners l(i)*
Repeat the process:
    Implement NLP and Label *words w(i)* and *sentences s(i)*
    Calculate polarity score
    Initialize Sentiment Counter
Store results in CSV files

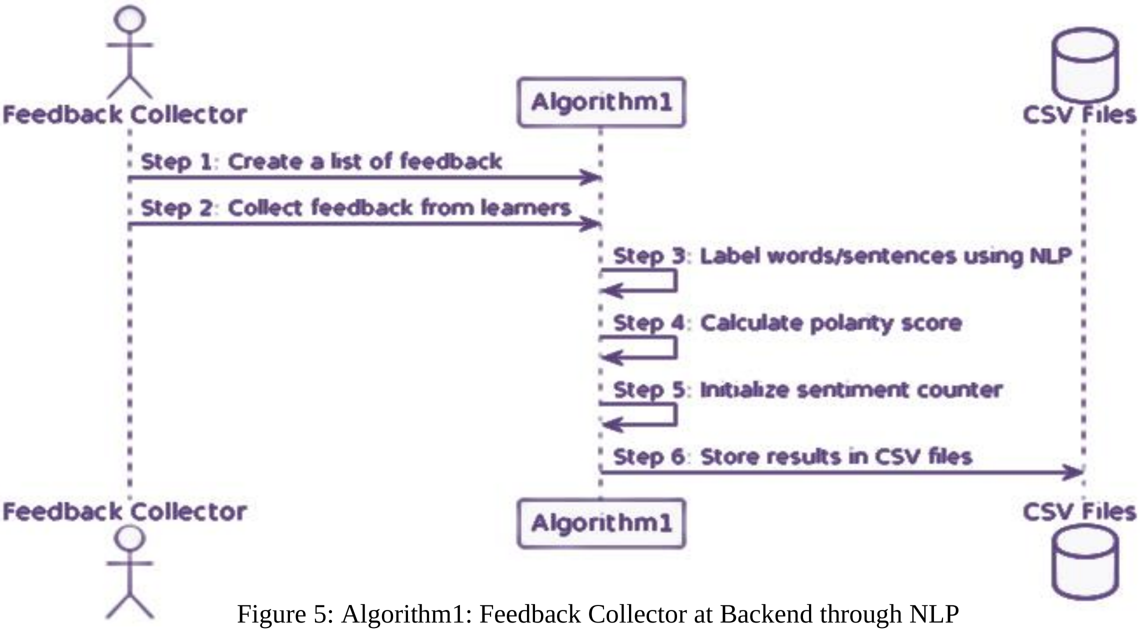


Figure 5: Algorithm1: Feedback Collector at Backend through NLP

Algorithm 2:

Model monitoring and early alert messaging:

Create a CSV weblink (URL) file for email and WhatsApp

Create a List *l(j)* of emails and WhatsApp numbers

Send messages:

Open Python IDE

Create a Script

Set a variable for decision making

Check conditions and monitor the model

Set a timer to re-execute the program.

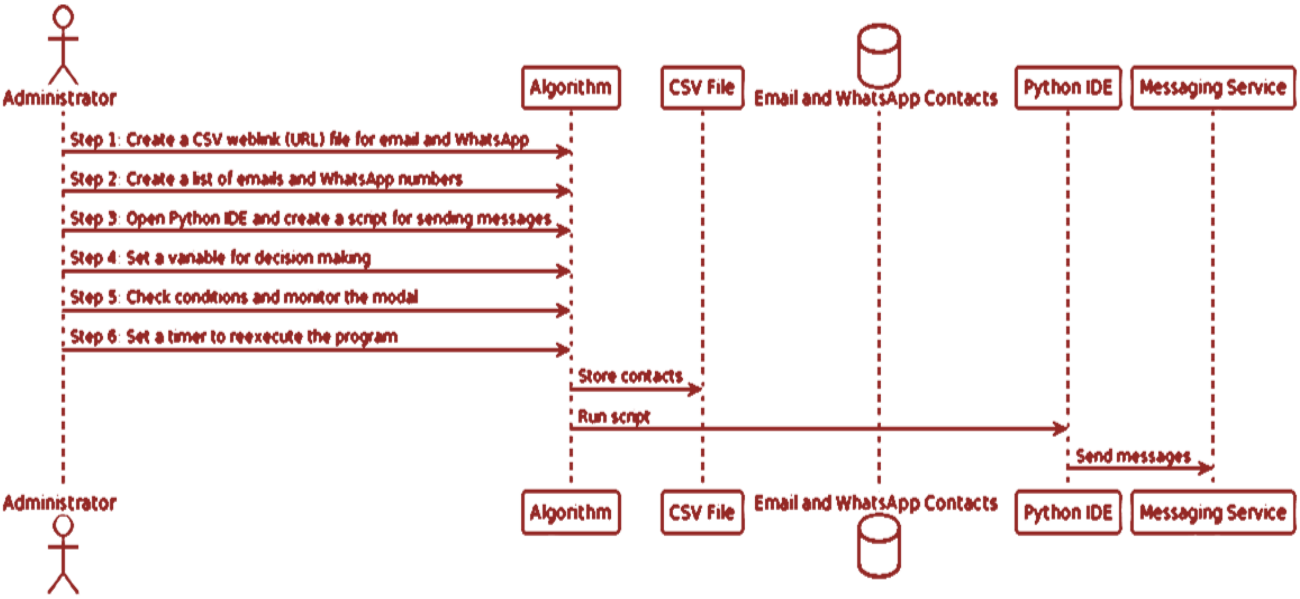


Figure 6: Algorithm2: Model monitoring and early alert messaging

5. Result analytics and Evaluation Metrics for Emotion Detection and Sentiment Analysis

In NLP implementation TextBlob an open-source python library for processing textual data is used due to its offering of simple API to access its methods and perform basic NLP tasks.

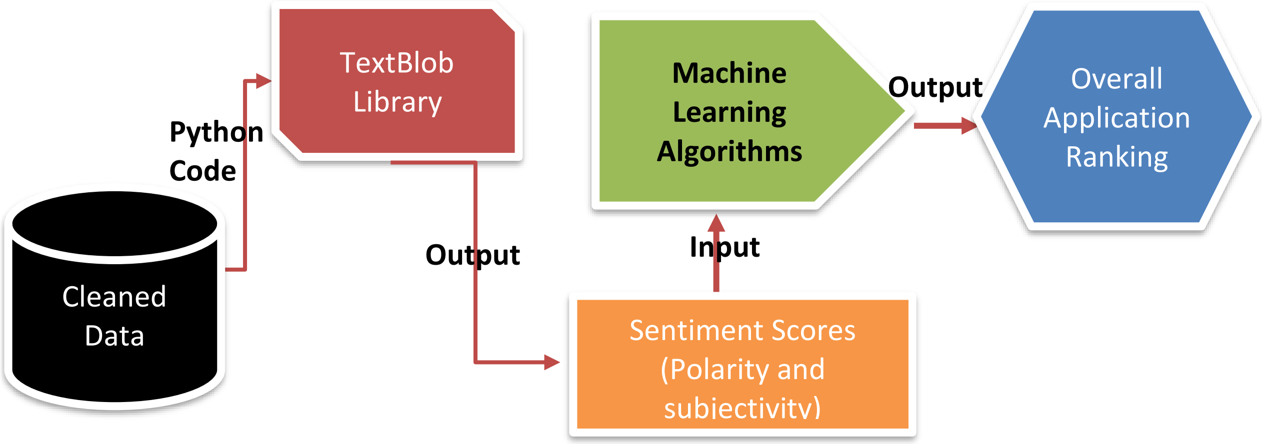


Figure 7: TextBlob Library for Sentiment Scores

Once the model choice is made, the affective model can be trained using the labeled training data. The data is divided into training and validation sets, and the model is trained on the training set while monitoring its performance on the validation set. The training process involves optimizing the model's parameters using techniques like backpropagation and gradient descent to minimize loss or maximize accuracy.The affective model is trained iteratively by feeding the training data to the model, updating its parameters, and fine-tuning its performance. Training continues until the model achieves satisfactory performance on the validation set, balancing accuracy and generalization.

To evaluate the performance of the affective model in emotion detection and sentiment analysis, it is crucial to divide the dataset into training and testing sets. The training set is utilized to train the model, while the testing set is used to assess the model's ability to generalize to unseen data. [15],[16]. The dataset is typically split randomly, ensuring that both the training and testing sets have a representative distribution of emotions and sentiments present in the data. The common practice is to allocate around 70% of the data for training and the remaining 30% for testing. However, the specific split ratio can vary based on the dataset size and characteristics.

Rule-based methods (Figure 8) involve the creation of manually crafted rules [30,31] that identify sentiment based on specific linguistic patterns or features present in the text. These rules are often derived from linguistic knowledge or domain-specific expertise. Various evaluation metrics can be employed to assess the performance of the affective model, depending on the specific task of emotion detection or sentiment analysis.

a. Sentiment Intensity Analyzer from the learner's feedback

```
Response: 'I am enjoying this course a lot!'
Predicted Sentiment: negative

Response: 'I find fog computing fascinating because it brings technology closer to the real world, making it more tangible.'
Predicted Sentiment: negative

Response: 'Understanding fog computing can be challenging, but I'm motivated to learn because it's a critical concept in modern technology.'
Predicted Sentiment: negative

Response: 'As a learner, I appreciate when instructors break down complex topics like fog computing into manageable parts.'
Predicted Sentiment: negative

Response: 'I feel more confident in my understanding of fog computing after discussing it with my peers during group study sessions.'
Predicted Sentiment: negative

Response: 'Sometimes, I get overwhelmed with the technical details of fog computing, but I know that persistence pays off.'
Predicted Sentiment: negative

Response: 'Exploring fog computing makes me realize how rapidly technology is evolving, and it excites me to be a part of this era.'
Predicted Sentiment: negative

Response: 'I value real-world applications of fog computing, as it helps me see its relevance beyond the classroom.'
Predicted Sentiment: negative

Response: 'It's essential for educators to gauge our comprehension of fog computing through quizzes and assessments.'
Predicted Sentiment: negative

Response: 'When instructors encourage questions and discussions, it enhances my learning experience regarding fog computing.'
Predicted Sentiment: negative

Response: 'I'm curious about the future developments in fog computing and how it will impact various industries.'
Predicted Sentiment: negative
```

Figure 8.: Rule-based Performance Evaluation

In this work, the sentiments of the learner are analyzed with NLP. Sentiment model [32,33] is trained using machine learning, by using tools nltk and vader (Valency Aware Dictionary and Sentiment Reasoner) for the task of predicting the sentiments of the learner in the learning field of education and training system. Once the affective model for emotion detection and sentiment analysis is developed and optimized, it is deployed in a real-time system for continuous analysis of learner feedback.

In figure 9 through the Python script feedback responses through IoT sensors [34,35] from the given nos. of users are recorded and there is an alarm set message to the sender after reaching to the limit that is defined as early warning message. We have set an alert by using two case scenarios first using email and second using WhatsApp application. This enables educators and instructional designers to gain timely insights and make data-driven decisions to enhance the learning experience. Real-time analysis involves integrating the affective model into the learning platform or system where learner feedback is collected. As new feedback is generated, it is processed through the affective model for emotion detection and sentiment analysis. The model's predictions and analysis results are then available for educators and instructional designers to review and act upon. By analyzing learner feedback in real time, educators can quickly identify emotional states, sentiments, and trends among learners. This enables them to address challenges, provide personalized support, and adapt instructional strategies to better meet the needs of individual learners or groups of learners.

Figure 9: IoT based emulation through Python Script for Prediction of Sentiment analysis countn and Early warning message on WhatsApp

Figure 10 and Figure 11 illustrates the sentimental analysis count results for predicting positive, negative and neutral count for the learners, here result shows that positive count is very high, negative sentiment prediction is low whereas neutral is an average shift behavior from learners side. This allows for early detection of any performance degradation or shifts in learner behaviors that may impact the model's effectiveness.

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\gkwithsk\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
'I am frustrated with this topic.' is Negative
'I'm struggling to understand the material.' is Negative
'I am enjoying this course a lot!' is Positive
'I find fog computing fascinating because it brings technology closer to the real world, making it more tangible.' is Positive
'Understanding fog computing can be challenging, but I'm motivated to learn because it's a critical concept in modern technology.' is Positive
'As a learner, I appreciate when instructors break down complex topics like fog computing into manageable parts.' is Positive
'I feel more confident in my understanding of fog computing after discussing it with my peers during group study sessions.' is Positive
'Sometimes, I get overwhelmed with the technical details of fog computing, but I know that persistence pays off.' is Neutral
'Exploring fog computing makes me realize how rapidly technology is evolving, and it excites me to be a part of this era.' is Positive
'I value real-world applications of fog computing, as it helps me see its relevance beyond the classroom.' is Positive
'It's essential for educators to gauge our comprehension of fog computing through quizzes and assessments.' is Neutral
'When instructors encourage questions and discussions, it enhances my learning experience regarding fog computing.' is Positive
'I'm curious about the future developments in fog computing and how it will impact various industries.' is Positive
Number of Positive Sentences: 9
Number of Negative Sentences: 2
Number of Neutral Sentences: 2
```

Figure 10: Sentimental Analysis Count: Python Code

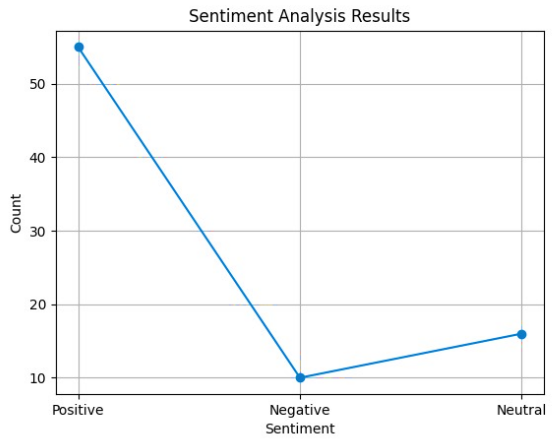


Figure 11: Prediction of Sentiment analysis count

b. Performance Analysis of the Affective Model:

The performance of the affective model is analyzed by computing the Precision, Recall, confusion matrix and F1 Score evaluation metrics. These metrics are particularly useful when dealing with imbalanced datasets. These results provide insights into the model's performance in accurately detecting emotions or sentiments in unseen testing data. These metrics help to identify the strengths and weaknesses of the affective model in distinguishing between different emotion or sentiment categories. Measurement of the accuracy is the proportion of correctly classified instances[36,37] out of the total number of instances, providing an overall measure of the model's ability to predict the correct emotion or sentiment category. The implemented framework achieved an accuracy 78% → 83% (Figure 11) when CNN was used with transfer learning.

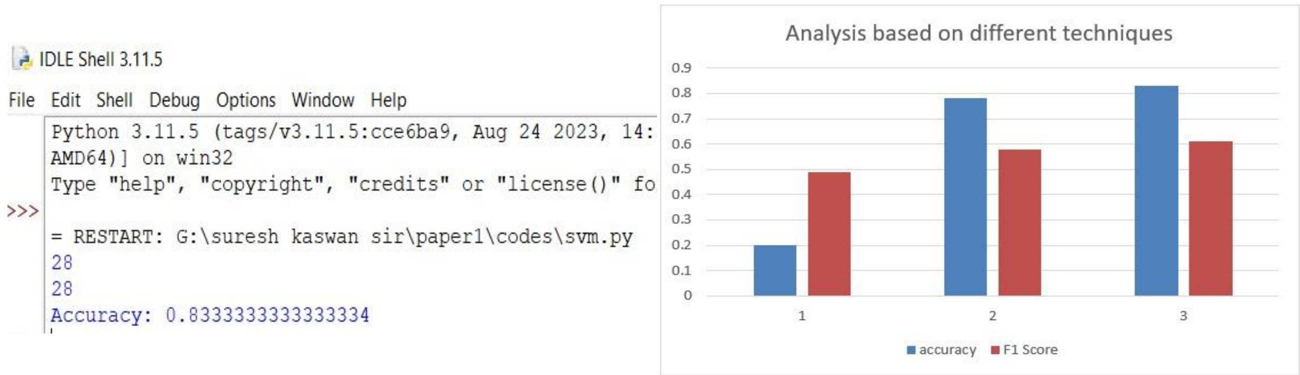
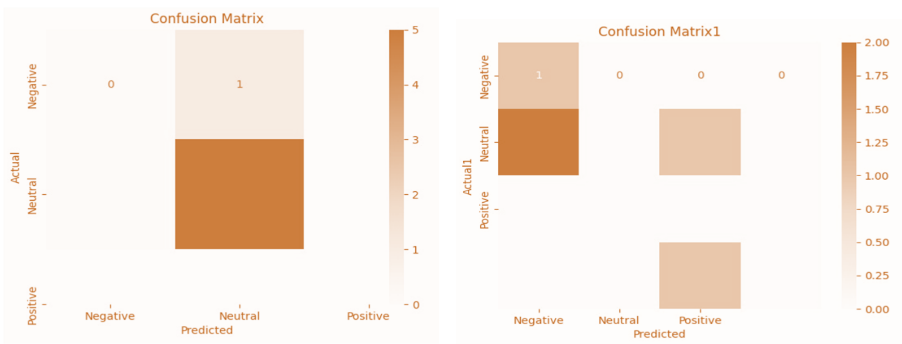


Figure 12: Illustration of Accuracy

Precision represents the proportion of correctly predicted positive instances out of all predicted positive instances, while recall measures the proportion of correctly predicted positive instances out of all actual positive instances. The F1 score is the harmonic mean of precision and recall, offering a balanced measure of the model's performance. We achieved an improvement from 0.49 to 0.61, as shown in figure 12, when transfer learning was used for this purpose.



(a) (b)

Figure 13.: Confusion Matrix: Result (a)- Result (b)

The confusion matrix displays the counts of true positive, true negative, false positive, and false negative predictions. It offers a comprehensive view of the model's performance across different emotion or sentiment categories.

Furthermore, it is crucial to consider the context and domain of the affective model's application. The evaluation results are interpreted in relation to the specific requirements and objectives of the educational setting or application. This analysis enables refinement of the affective model, making necessary adjustments, and iterating the training process to enhance its performance. By conducting a comprehensive performance analysis of the affective model, educators and instructional designers can gain valuable insights into the model's accuracy and effectiveness in emotion detection and sentiment analysis. This analysis facilitates further improvements in instructional design and personalized interventions, leading to enhanced learning experiences.

Model maintenance includes periodic retraining of the affective model using updated or additional labeled data. As the educational context evolves and new patterns or emotions emerge, retraining the model helps it adapt and capture the latest trends in learner feedback. This may also involve revisiting the model's hyperparameters, architecture adjustments, or ensemble techniques to ensure sustained optimal performance. Additionally, model maintenance may involve addressing concept drift, which refers to changes in the distribution or characteristics of learner feedback over time. Regular monitoring and model maintenance help identify and mitigate any concept drift, ensuring the affective model remains accurate and reliable in analyzing learner emotions and sentiments.

By establishing a system for regular monitoring and model maintenance, educators and instructional designers can ensure the affective model remains up to date and continues to provide valuable insights for enhancing the learning experience. It enables continuous improvement and adaptation to meet the evolving needs of learners.

6. Conclusion and Future Scope

The development of an affective model for emotion detection and sentiment analysis in learner feedback brings numerous benefits to enhancing educational experiences. By accurately detecting and analyzing emotions and sentiments expressed by learners, the affective model provides valuable insights to educators and instructional designers. These insights enable them to personalize instruction, address learner challenges, and create a supportive and engaging learning environment. One significant benefit is the ability to tailor teaching strategies to meet the specific needs of learners. By understanding learners' emotional states, educators can adapt their instruction to provide appropriate support, motivation, and challenges. This personalized approach helps improve learner engagement, motivation, and overall performance. This research enables educators to identify areas of learner satisfaction or dissatisfaction with learning materials and to analyze sentiments expressed in feedback to help identify strengths and weaknesses in instructional design, allowing for targeted improvements. By addressing areas of dissatisfaction, educators can enhance the quality of learning materials and create a positive learning experience for learners. Furthermore, the effective model fosters a supportive and inclusive learning environment. By detecting emotions such as frustration, confusion, or stress, educators can intervene and provide timely assistance to learners also can be able to reduce negative emotions and promote a sense of belonging and well-being among learners. The development of effective models for emotion detection and sentiment analysis in education can opens up promising avenues for future research and applications. This Intelligent Tutoring System is designed with unique approach to send feedback responses and warning alarm to learners in a single run, that helps to create more interactive and responsive learning experiences. In future work, Augmented reality and Virtual reality experiences will be adding on in the present work for a classified interaction from learners' feedback.

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