

Developing Multilingual Capabilities for All- Inclusive Learner Feedback

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Abstract—Initially Feedback is collected either quantitatively or qualitatively but failed to satisfy users who desire to provide feedback verbally .Many users prefer expressing opinions verbally, especially in multilingual settings, which can present challenges for traditional text-based sentiment analysis systems. To address this, our project integrates Gradio, a user-friendly interface tool, to allow users to record their audio feedback from both Telugu and English to English text directly on the webpage. This audio spoken input converted into text, making it ready for further analysis. In order to perform further analysis we have developed several models for the analysis of the feedback's sentiment. They include BERT with BERT tokens, BERT combined with Logistic Regression, and BERT with LSTM and multinomial Navie Bayes. We measured all the above models' performances in terms of accuracy and reliability. From all tested models, the model BERT with Multinomial Naive Bayes (Multinomial NB) achieved the highest accuracy rate, 98%. This model yielded the best performance in sentiment analysis , making it our most reliable option for the task.

Index Terms—Gradio, NLP, Sentiment Analysis, Multinomial Naïve Bayes , Php.

I. INTRODUCTION

In today's fast-paced and diverse educational landscape, the ability to collect and analyze student feedback is essential for institutions striving to improve learning experiences and instructional methodologies. Feedback serves as a vital tool for evaluating faculty performance, course content effectiveness, institutional facilities, and overall student satisfaction. However, conventional feedback collection methods often rely on text-based surveys and forms, which may not fully capture the emotions and nuanced responses of students. Moreover, many students prefer to express their opinions verbally rather than through written text, making traditional feedback systems inadequate in multilingual and diverse classroom settings. To address these limitations, this project introduces a multilingual and audio-based feedback system that enhances accessibility and inclusivity using advanced technologies such as Gradio, Natural Language Processing (NLP), and Machine Learning (ML)-driven sentiment analysis.

II. LITERATURE SURVEY

Zainab Mutlaq Ibrahim, Mohamed Bader-El-Den, Mihaela Cocea[1]: This study aims to develop a data mining based framework for analyzing students' assessment feedback that will be obtained from social media sites and/or text feedback. The study consists of three stages: The first stage is to build a model that automatically

detect the polarity of student feedback using sentiment analysis methods. The second stage is to build a model that automatically classify issues of assessment. And finally, test the correlation between issue(s) and students' performance. The research uses different popular algorithms for text classification to analyze students' feedback of assessment to enhance learning process.

Edisutoyo, Ahmed alharef, Riyadi Yanto[2]: In this paper, evaluating the substance of the courses taught in the lecture process is to use Lecturer Evaluation Effectiveness by Students (EDOM). The EDOM is a feedback questionnaire that can be used by educators to assess and evaluate pedagogical competencies that they have and aims to make continuous improvements to various matters related to the teaching process in the classroom. In addition to questions in the form of a Likert scale, EDOM also accommodates open-ended questions. However, this type of question tends not to be considered in the feedback assessment and is not explored more deeply to gain insight. Therefore, in this study text mining was carried out to find out the sentiments given by students, whether positive or negative sentiments using Convolutional Neural Network (CNN). The experimental results showed that CNN was able to achieve accuracy, precision, recall, and F1-Score of 87.95%, 87%, 78%, and 81%, respectively.

Imad Zyout1,2, Mo'ath Zyout[3]: In this paper re-researchers put forward a sentiment analysis system that leverages three distinct embedding techniques: automatic, global vectors (GloVe) for word representation, and bidirectional encoder representations from transformers (BERT). This system LBRCE, AI&DS Department 5 Developing multilingual capabilities of All-Inclusive learner feedback features an attention layer, with the best model chosen through rigorous comparisons. In developing the sentiment analysis model, we employed a hybrid dataset comprising students' feedback and comments. This dataset comprises 3,820 comments, including 2,773 from formal evaluations and 1,047 generated by ChatGPT and prompting engineering. Our main motivation for integrating generative AI was to balance both positive and negative comments. We also explored recurrent neural network (RNN), gated recurrent unit (GRU), long short-term memory (LSTM), and bidirectional long short-term memory (Bi-LSTM), with and without pre-trained GloVe embedding

Faizi, ENSIAS[4]: In this paper, is to propose a lexical-based approach that can predict the underlying sentiments of each student review, thus, enabling teachers to assess to what extent students are satisfied with the online learning resources and teaching practices. To enhance the performance of the proposed approach, a new education sentiment lexicon was built and incorporated into the model. After its implementation on a dataset that was extracted from the Web, this sentiment analysis lexical approach has proven to correctly predict the sentiment polarities of the great majority (i.e. 86.45%) of student.

Irfan Ali Kandhro1 , Shaukat Wasi2 , Kamlesh Kumar1 , Malook Rind1 and Muhammad Ameen[5]: In this paper, : Long Short-Term Memory Model (LSTM) is used for analyzing the sentiments expressed by students through textual feedback. For this purpose, dataset has been built through student's feedback and then divided into 70% and 30% for training and testing. The proposed model has been trained using softmax and adam along with drop out values 0.1 and 0.2. Obtained results showed that our model provides 99%, and 90% accuracy over training and validation with 0.2 and 0.5 losses respectively

Mohammad aman[6]: This paper addresses those problems and uncovers the best model for analyzing LBRCE, AI&DS Department 6 Developing multilingual capabilities of All-Inclusive learner feedback those feedbacks with the use of machine learning techniques such as Support Vector Machines (SVM), Maximum Entropy (ME), Naive Bayes (NB), and Complement Naive Bayes (CNB) and applying neutral class. And, found SVM as the highest performer with an accuracy of 97% by applying different preprocessing and feature extraction techniques and avoiding neutral class, which outperform state-of-art work by 2%.

Prabhira Kumar Shety, Nalini Kanta Barpanda[7]: In this paper, The implementation of sentiment analysis helps understand learners' appreciation of lessons, which they prefer to express in long texts with little or no restriction. Such expressions depict the learner's emotions and mood during class engagements. This research deployed four classifiers, including Naïve Bayes (NB), Support Vector Machine (SVM), J48 Decision Tree (DT), and Random Forest (RF), on a qualitative feedback text after a semester-based course session at the University of Education, Winneba. After enough training and testing using the k-fold cross-validation technique, the SVM classification algorithm performed with a superior accuracy of 63.79%.

III. METHODOLOGY

A. Data Collection

A PHP-based web interface is used as the core platform for gathering student feedback in both text and audio formats. The interface is designed to be user-friendly and intuitive, allowing students to easily submit feedback on a variety of academic topics. These topics include teacher performance, course content, examination patterns,

and facilities such as the library, sports, and co-curricular activities. In addition to text feedback, students can also submit audio feedback. This option offers a more personal and expressive way for students to communicate their opinions, allowing them to convey emotions, tone, and nuances that might be lost in text-based responses. The audio files can be recorded and uploaded directly through the interface, with support for languages like Telugu, catering to a diverse student population.

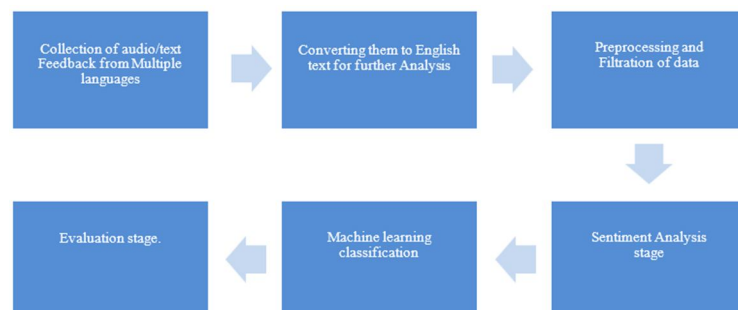


Fig. 1 Model Representation



Fig.2 The Overview of our Data Collection Interface

B. Converting Audio Feedback to Text for Further Analysis

The conversion of audio feedback into text enables the use of various machine learning models and sentiment analysis tools to assess the feedback more accurately.

Audio Feedback Upload

The process begins when students submit their audio feedback through the PHP-based web interface. The feedback may be in various languages, such as Telugu, and is recorded and uploaded to the system. This step allows the system to capture the diversity of student opinions in both text and audio formats.

Speech Recognition and Transcription

Once the audio is uploaded, speech recognition tools are employed to transcribe the spoken words into written text. These tools analyze the audio files, identify the words, and convert them into text. The accuracy of this transcription is crucial for ensuring that the feedback is captured accurately, regardless of the language or accent.

Language Detection and Translation

In cases where the audio is in a language other than English, such as Telugu, the system detects the language and translates the transcribed text into English. The translation tools ensure that the meaning of the original feedback is preserved and made consistent with the other feedback data collected in English. This translation process helps eliminate language barriers and allows for a comprehensive analysis of all feedback.

Ensuring Text Consistency

After translation, the system performs additional checks to maintain the accuracy and clarity of the transcribed text. This includes refining translations to ensure that the meaning behind the feedback is accurately conveyed. Advanced language models may be used at this stage to ensure that the text maintains its context and integrity.

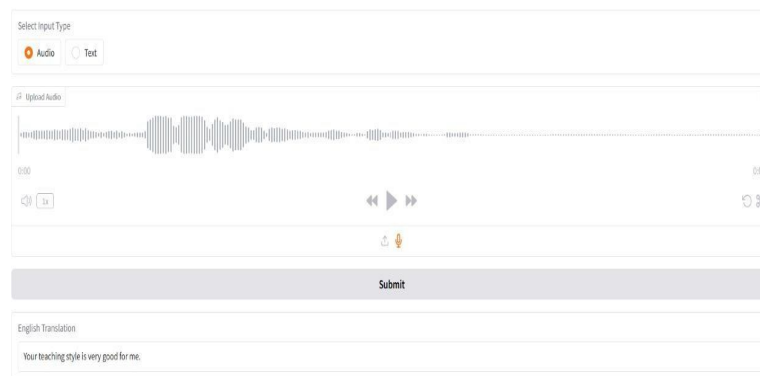


Fig.3 Converting Audio Feedback to Text

C. Data Preprocessing

One of the first steps in text preprocessing is converting all feedback text to lowercase. This is necessary because text data can contain variations in letter case (e.g., "Good" vs. "good"). One of the first steps in text preprocessing is converting all feedback text to lowercase. This is necessary because text data can contain variations in letter case (e.g., "Good" vs. "good"). Stopwords are common words in a language, such as "the", "and", "is", "in", and "it", that carry little to no meaningful information when it comes to sentiment analysis. Since these words occur frequently in text, they can skew the results of sentiment analysis by diluting the significance of more important words. The process of removing affixes from a word so that we are left with the stem of that word is called stemming. For instance, words like "running", "runner", and "ran" are reduced to the base word "run". This process helps to unify different variations of a word. For audio feedback, the preprocessing steps are adapted to handle the nuances of speech and convert spoken content into a usable text format for analysis. Since audio feedback can vary in quality, language, and speech patterns. The first step in audio feedback preprocessing is converting the recorded audio into text. This is done using speech recognition tools or APIs, which process the audio signal and transcribe it into a readable text format.

Audio feedback may be recorded in various languages, such as Telugu, Hindi, or other regional languages. To ensure uniformity in the analysis, the transcribed feedback, if not in English, is translated into English using translation tools or machine translation models.

D. Sentiment Analysis

The Sentiment Analysis stage is a critical part of the feedback processing system, where Natural Language Processing (NLP) techniques and machine learning models are applied to analyze feedback and determine the sentiment (positive, neutral, or negative) across various categories. The primary focus of this stage is to gain actionable insights from student feedback by categorizing and quantifying sentiments effectively.

Typically, sentiment is categorized into three classes:

- Positive Sentiment: Reflects favorable feedback.
- Negative Sentiment: Indicates unfavorable feedback.
- Neutral Sentiment: Represents neutral or unbiased feedback.

Label mapping is an essential step in sentiment analysis that plays a key role in maintaining consistency and clarity when interpreting sentiment categories. This process involves assigning specific numerical values to different sentiment categories, such as positive, neutral, and negative, to simplify the classification process and enhance the overall understanding of the results.

In sentiment analysis, feedback is typically classified into three main categories: positive, neutral, and negative. Positive sentiment reflects favorable opinion so attitudes, neutral sentiment indicates unbiased or indifferent feedback, and negative sentiment highlights unfavorable opinions. To ensure uniformity, each of these categories is associated with a numerical label. For example, the label 1 is commonly used for positive sentiment, 0 for neutral, and -1 for negative. This standardized labeling helps in processing and interpreting data effectively.

Corpus creation is a vital step in sentiment analysis, where a structured dataset is prepared to train and test sentiment analysis models. A corpus is a collection of text data that reflects the specific context, domain, or language relevant to the analysis. The quality and relevance of the corpus play a significant role in determining the performance of the sentiment analysis system.

The process begins with collecting text data from various sources such as social media posts, customer reviews,

feedback forms, or survey responses. The data should align with the objectives of the sentiment analysis, whether it's analyzing customer satisfaction, product reviews, or general public opinions.

E. Machine Learning Classification

We used multinomial naïve bayes model as our machine learning model because When working with text data, such as feedback from students or faculty, the primary challenge lies in converting the unstructured text into a form that can be analyzed numerically. One effective approach to tackle this challenge is by using the Multinomial Naive Bayes (MNB) algorithm, especially when the goal is to classify text into categories such as positive, neutral, or negative sentiment. MNB is particularly suited for this task due to its simplicity, effectiveness, and the nature of text data.

The MNB algorithm is widely used for text classification tasks because it works well with discrete data, such as word counts.

In the case of sentiment analysis, where we need to classify feedback text into specific sentiment categories, MNB can leverage the word counts generated by tools like Count Vectorizer to classify text effectively.

Count Vectorizer transforms the raw text into a document-term matrix where each row represents an individual document (feedback entry) and each column represents a unique word from the entire corpus. The value in each cell of this matrix indicates the frequency of a word in a particular document. This numerical representation of text is crucial because machine learning algorithms like MNB can only work with numbers, not raw text.

Feature extraction is a crucial step in sentiment analysis, transforming raw textual data into a structured format that machine learning models can understand and process effectively. It involves representing text as numerical vectors while preserving essential information that can be used to detect sentiments like positive, negative, or neutral.

Count Vectorizer looks at all the documents in the corpus (set of text data) and creates a vocabulary — a set of unique words found in all documents.

Count Vectorizer assigns an index to each unique word in the vocabulary. Each word in the vocabulary becomes a column in the resulting feature matrix.

For each document, Count Vectorizer counts the occurrences of each word from the vocabulary. These counts are placed in the corresponding column for that word.

F. Probability Calculation and Sentiment Prediction

The foundation of MNB is the Bayes Theorem, which determines the posterior probability of a class based on the available data (text). Finding the probability of each potential class c given a document d , which is represented as a collection of words $w_1, w_2, \dots, w_n$, is the aim. The fundamental equation for Bayes' Theorem is:

$P(c|d) = P(d|c) \cdot P(c)$ Where:

- $P(c|d)$ is the posterior probability of class c given the document d ,
- $P(d|c)$ is the likelihood of the document given the class c ,
- $P(c)$ is the prior probability of class c ,
- $P(d)$ is the probability of observing the document across all classes.
- In the Multinomial Naive Bayes model, we assume that each word in the document is conditionally independent given the class, simplifying the likelihood term:
- $P(d|c) = \prod_{i=1}^n P(w_i|c) = \prod_{i=1}^n \frac{count(w_i, c) + 1}{\sum_{w \in V} count(w, c) + 1} P(w_i|c)$
- Where w_i represents individual words in the document.

The likelihood $P(w_i|c)$ is estimated from the training data and is based on the multinomial distribution of word occurrences. To classify a new document, we compute the posterior probability for each class and select the class with the highest probability.

$$\hat{c} = \arg \max_c \left(\log(P(c)) + \sum_{i=1}^n count(w_i) \cdot \log(P(w_i|c)) \right)$$

IV. RESULTS

we present the outcomes from each stage of our Gradio-integrated feedback system, which collects Telugu feedback, translates it into English. The following results showcase the accuracy and efficiency of transcription, translation, and sentiment analysis.

Select Input Type

☐ Audio ☒ Text

Enter Text

“మీ బోధన స్పష్టంగా ఉంది మరియు అనుసరించడం సులభం, కానీ కోర్సు ప్రగతి కొన్నిసార్లు నెమ్మదిగా అనిపిస్తుంది.”

Submit

English Translation

"Your teaching is clear and easy to follow, but course progress seems slow at times."

Fig.4 Translation of Telugu Text to English text

Upon receiving audio feedback, the system begins by transcribing spoken Telugu directly into text, accurately capturing the user's input. This text is then translated into English, allowing all feedback to be uniformly processed and analyzed. This two-step input feature enhances accessibility, making it convenient for users who find it easier to communicate by speaking rather than typing. By offering both transcription and translation, the system can accommodate a multilingual user base, ensuring feedback is recorded in a way that facilitates consistent analysis. This approach makes the feedback process inclusive and adaptable to diverse user preferences.

Select Input Type

☒ Audio ☐ Text

Upload Audio

0:00

Submit

English Translation

Your teaching style is very good for me.

Fig.5 Translation of Telugu & English audio to English Text

we experimented with several models to analyze feedback sentiment, including BERT with BERT tokens, BERT combined with Logistic Regression, and BERT with LSTM. Each model was evaluated for its performance in terms of accuracy and reliability. Among all the models tested, the BERT with Multinomial Naive Bayes (Multinomial NB) consistently outperformed the others, achieving an accuracy rate of 98%. This model demonstrated superior performance in classifying sentiment accurately and efficiently, making it the most reliable choice for our sentiment analysis task. While other models, such as BERT with Logistic Regression and BERT with LSTM, also showed decent results, Multinomial NB stood out for its high accuracy and robustness in handling the feedback data

A high accuracy rate of 0.98, as reflected in the matrix, confirms the reliability of the Multinomial Naive Bayes model in capturing sentiment patterns accurately. The results indicate that the model performs well in real-world feedback analysis, with minimal error in predicting the correct sentiment class. This effectiveness suggests that the preprocessing and model selection choices were well-suited for the dataset and purpose of the analysis.

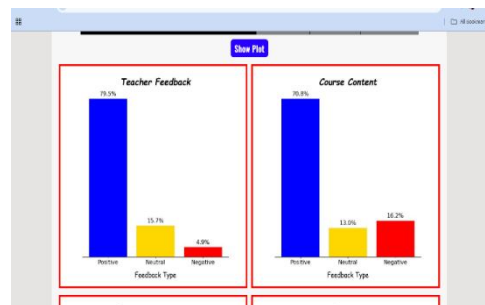


Fig. 6 Plottings After The Analysis Of Data

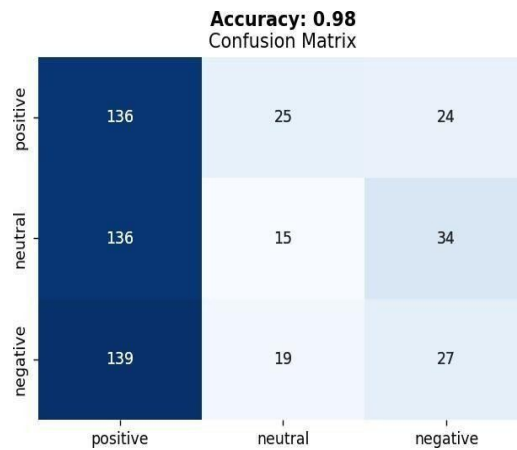


Fig. 7 accuracy and Confusion matrix of out Model

V. CONCLUSION

The system successfully combines various technologies to offer an efficient solution for analyzing student feedback. It utilizes Gradio, SpeechRecognition, and Google Translator to process Telugu audio and text inputs, translating them into English for sentiment analysis. The feedback data undergoes preprocessing with NLP techniques such as stopword removal, stemming, and lemmatization, ensuring that the input is in a standardized form for further analysis. By employing the Multinomial Naive Bayes model, the system classifies feedback into positive, neutral, and negative categories, providing a clear understanding of student sentiment. This integration of speech recognition, translation, and sentiment analysis demonstrates how advanced technologies can be effectively utilized to process multilingual feedback in real-time. Overall, the system offers a seamless, automated approach for gathering and analyzing student feedback, making it a valuable tool for educational institutions to gain insights into students' experiences and improve academic offerings.

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