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Social Media Content Analyzer

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Abstract: In an era dominated by online interactions, the potential of social media as a communication medium is immense. As a pivotal channel for disseminating information across various sectors, social media has redefined connectivity, sharing, and communication. However, a significant gap exists in addressing student complaints and opinions, often leading to dissatisfaction and hindrance in their educational experience. This research aims to bridge this gap by developing the Social Media Content Analyzer System. Leveraging Natural Language Processing (NLP) techniques, the system is designed to extract, analyze, and interpret textual information from social media platforms, providing actionable insights to prioritize and enhance students' lifestyle and learning conditions. The implementation of this system promises a transformative impact on the educational sector. By automating the process of monitoring and addressing student complaints, it ensures a more responsive and conducive learning environment, ultimately contributing to an improved student experience as well as a solution driven institution.

Keywords*: Social media, Content Analyzer, Natural Language Processing, Sentiment Analysis, Artificial Intelligence*

1. Introduction

In this digital age, social media platforms and online forums have become essential channels for communication and expression. The enormous use of social media has necessitated numerous researchers to be analyzing inherent data to produce meaningful or useful outcomes [1]. Educational institutions, such as schools and universities, can greatly benefit from leveraging these platforms to gather valuable feedback and insights from their students. By analyzing the sentiments expressed by students on social media and other forums, schools can gain a comprehensive understanding of students' opinions, concerns, and suggestions, giving the oppotunity to focus on a wide-level feedback and improvement process.

Sentiment Analysis, a combination of Natural Language Processing (NLP) and machine learning, is a technique used to analyze large volumes of text to determine whether it expresses positive, negative, or neutral sentiment [2]. It helps organizations make informed decisions, enhance customer experiences, and manage brand reputation [3]. Sentiment Analysis is applied across various fields, including business, marketing, customer service, financial markets, healthcare, education, and politics. Sentiment analysis has helped in gauging public opinion in many areas [4]. The growing availability of unstructured or semi-structured data has made Sentiment analysis famous but potent research area [5]. In the education sector, student attitudes significantly influence the educational process. Advancements in sentiment annotation techniques and Artificial Intelligence methodologies enable the labelling of student comments with their sentiment orientation. This study aims to address the challenges of providing efficient attention to pertinent matters in the education sector, enabling institutions to understand and analyze the complex range of student attitudes to enhance learning-teaching practices. Many students utilize platforms like Twitter to voice their concerns and emotions, with social media emerging as a vital tool for empowerment. Approximately 96% of internet-connected students engage in at least one social network [6], highlighting the significant role social media plays in their lives. As social media becomes increasingly integrated into education, it offers a practical avenue for addressing student welfare and promoting educational reform [7]. However, students' opinions on crucial aspects of their educational life, such as accommodation, interactions with peers and staff, often go

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unattended to. Without a proper channel for communication, these expressions fail to reach the authorities who can initiate positive changes.

To address this gap, the Sentiment Analyzer Application is proposed. This system aims to provide a platform for harvesting and gathering students' opinions from social media and other forums. By prioritizing the importance and urgency of their complaints and sentiments, the application can alert educational institutions to issues requiring timely intervention. Moreover, the identification of positive sentiments can serve as recommendations for improving the school system, enhancing its acceptance among students. By providing a data-driven approach to gathering and analyzing student feedback, the Social Media Analyzer Application empowers schools to make informed decisions and take proactive measures to enhance the educational experience for the students. The insights gained from the application can help schools prioritize resources, address student concerns, and foster a more engaging and supportive learning environment. This study aims to develop a Social Media Analyzer Application that utilizes advanced Natural Language Processing (NLP) techniques to analyze sentiments expressed by school students on social media platforms. The specific objectives are to collect and preprocess a comprehensive dataset of student social media interactions, ensuring data quality and relevance to the local educational context, to select and apply suitable machine learning algorithm in classifying sentiments into positive, negative, or neutral categories, using the insights to inform educational strategies and to develop a comprehensive framework for student opinion analysis. The study would contribute to the field of educational technology by providing a practical application of sentiment analysis, ultimately yielding a more responsive and student-centric educational system.

2. Literature Review

Sentiment analysis, also called opinion mining, has its roots in the late 20th century when researchers began exploring computational methods to analyze and extract subjective information from textual data [8]. Early research on sentiment and opinion began earlier, with Bo Pang and colleagues pioneering the use of machine learning algorithms to automatically categorize text documents based on emotional tone [9]. Early implementations focused on classifying movie reviews and product reviews into positive, negative, or neutral sentiments. However, their accuracy and scalability were limited, prompting researchers to explore more advanced techniques.

The advent of machine learning algorithms, such as Support Vector Machines (SVM), Naive Bayes classifiers, and deep learning architectures, revolutionized sentiment analysis by improving accuracy and scalability [10]. Social media platforms like Twitter and Facebook have become fertile grounds for sentiment analysis, providing vast amounts of user-generated content for analysis [11], [12], [13]. This has led to profound impact on decision-making, enabling businesses and policymakers to make data-driven decisions informed by public opinion. Sentiment analysis continues to evolve rapidly, driven by advances in machine learning, deep learning, and natural language processing.

2.1 Review of Related Works

Sentiment Analysis methodologies and technology have progressed dramatically over time, moving from traditional rule-based systems to cutting-edge deep learning architectures. Traditional sentiment analysis methods depend on rule-based approaches and manually crafted lexicons to identify sentiment-bearing words and phrases within text. Rule-based sentiment analysis has been widely used due to its simplicity and interpretability. However, these methods often struggle with ambiguity, context dependence, and limited scalability. The modern sentiment analysis methods leverage machine learning and deep learning techniques to automatically learn patterns and relationships from labeled data. However, sentiment analysis technology experiences difficulty in handling linguistic subtleties, sarcasm, and context-dependent sentiment expressions. Also, lack of interpretability and explainability in deep learning models poses challenges for understanding and trusting the decisions made by sentiment analysis systems.

Praveenkumar et al. [14] worked on the significance of student feedback in the context of the higher education system, particularly focusing on its role in assessing teaching quality. The objectives outlined were to recognize students' feelings and emotions towards online teaching, to measure sentimental word association, to express results and generate sentiment visualization. Of necessity here is the gap identified in sentiment analysis, particularly in real-time classroom feedback using machine learning techniques.

Zhang [15] investigated sentiment analysis and satisfaction evaluation concerning online teaching in universities during the COVID-19 pandemic. The study probed lack of emotional communication between teachers and students in online education which could negatively affect teaching quality. Based on the survey data, the study constructs a multi-index system for evaluating online teaching satisfaction. It utilizes fuzzy Bayesian network models to calculate probability values of top-level indices accurately, providing insights into the strengths and weaknesses of online teaching during the epidemic period.

Zhou et al. [16] compared Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformer models. Their findings highlight that while CNNs are effective in capturing local features, they lack the ability to understand long-term dependencies, which LSTMs address more effectively. However, the study emphasizes that Transformer-based models, particularly BERT, excel in both accuracy and efficiency due to their attention mechanisms, which considers the entire context of a sentence. Despite their superior performance, Transformer models require substantial computational resources, presenting a trade-off between accuracy and scalability. These insights are crucial for this study in selecting the most appropriate model, balancing performance with computational feasibility.

Grimalt-Álvaro and Usart [17] investigated how sentiment analysis can help to characterize interactions between students and teachers and improve learning through timely, personalized feedback. The research is driven by three primary goals. Firstly, it seeks to identify and analyze the Sentiment Analysis techniques employed in formative assessment within higher education settings. Secondly, it aims to explore the development and implementation of frontend software designed for visually representing Sentiment Analysis results. Lastly, it endeavours to assess the general contributions of Sentiment Analysis as a tool for assessing students in higher education. The findings of the review shed light on several key aspects. Firstly, there is a discernible evolution in Sentiment Analysis techniques, with a notable shift towards automatization and the integration of natural language processing (NLP) and machine learning (ML) approaches. However, challenges persist, particularly in terms of data collection and ethical considerations.

Chandra and Sudhanshu [18] explored the potential of leveraging sentiment analysis on Twitter to forecast trends. The study worked on challenges in social media sentiments analysis and developed a text and visual sentiment on twitter data for sentiment analysis by using NLP-based opinion clustering, textual mining, emotion API and some machine learning techniques for visual ontology. The authors also discussed the challenges of real-time data processing and the need for robust sentiment classification models.

2.2 Gap Analysis

The incorporation of emojis into textual data presents a significant challenge in the domain of sentiment analysis. This challenge arises from the inherent ambiguity of emojis, which lack clear definitions and are subject to varied interpretations based on cultural context and individual perception. Consequently, this variability can lead to potential misclassifications within sentiment analysis models. Emojis derive their meaning not only from their standalone representation but also from the surrounding text and contextual cues. Failure to comprehend these subtleties may cause sentiment analysis models to overlook the nuanced emotional intent conveyed by emojis, resulting in inaccuracies in analysis. Secondly, remarkable concerns in Sentiment Analysis include language ambiguity, cultural nuances, and the diverse expressions of sentiment across different languages. These present significant barriers when analyzing text to draw meaningful insights. To address this gap effectively, there is a need to investigate cross-lingual embeddings capable of capturing semantic similarities across languages. Moreover, existing sentiment analysis methods are primarily based on English texts, and there is scarcity of studies on languages with the limited corpus resources. Each sentiment analysis task in different languages requires separate feature engineering. With the increasing volume of data, real-time sentiment analysis is challenging. Analysing these data in real-time requires highly efficient algorithms and computational resources and these can be cost-intensive among other things. Integrating multimodal data for sentiment analysis involves combing information from different sources, such as text, images, and videos, to understand and analyze information more accurately. Different modalities represent data in various forms and structures, making it challenging to combine them into a cohesive analysis framework.

Sentiment analysis models commonly find it challenging to adapt to different domains or industries due to varying language use and context. This gap highlights the need for developing adaptable sentiment analysis models that can be fine-tuned for specific domains.

3. Methodology

The study adopted qualitative and quantitative methods for the development of the Social Media Analyzer Application. Exhaustive review on sentiment analysis and NLP were done while collection of diverse datasets of student-authored content from social media platforms and forums were carried out so as to ensure representativeness of the student population. Data pre-processing activities carried out included cleaning and preparing the collected data for analysis, including tokenization, normalization, and removal of extraneous information. Model development was done by constructing an NLP-based sentiment analysis model using machine learning algorithms to classify sentiments accurately. Model evaluation was done by assessing the model's performance through metrics such as accuracy, precision, recall, and F1 score. Finally, a user-friendly Social Media Analyzer Application was built which enables real-time sentiment analysis and reporting.

Furthermore, data were collected from social media platforms where local students are active through *web scraping* (i.e. utilizing automated scripts to extract relevant student posts and comments from social media platforms), *surveys* (deploying online surveys to gather supplementary data on student sentiments and experiences) and *interviews* (conducting semi-structured interviews with students to gain deeper insights into their educational experiences and sentiments).

Data analysis techniques include sentiment classification (utilizing algorithms such as Support Vector Machines (SVM), Naïve Bayes, and deep learning models like

Bidirectional Encoder Representations from Transforms (BERT)), text analytics (analyzing text data to identify patterns, trends, and correlations between sentiments and educational outcomes) and statistical analysis (applying statistical methods to validate the findings and ensuring the reliability of the results).

Development tools include python programming language (which is rich in extensive libraries that support various aspects of sentiment analysis, data collection, preprocessing, model training, and evaluation), Keras (high-level neural networks API running on TensorFlow used for developing the Deep Neural Network (DNN) model for sentiment classification), Pandas (used for handling and preprocessing the social media data), scikit-learn (for data mining and data analysis), Streamlit (used to develop a user-friendly web interface for the sentiment analysis system) and Matplotlib and Seaborn (for data visualization).

3.1 System Requirements for the Sentiment Analysis Application

The following Table 1 represent the Sentiment Analysis system requirements using the MoSCoW method (i.e. Must have, should have, could have and won't have) to identify what is key, important, not so important and can be ignored respectively. The Rs are the requirement identification tags.

Table 1. Sentiment Analysis functional and non-functional system requirements

Req. Id.	Requirement	Category	MoSCoW Analysis
R1	The system must implement Text Preprocessing for Data Cleaning and Analysis.	Functional	Must-have
R2	The system must collect students' complaints from social media platforms and forums.	Functional	Must-have
R3	The system must employ TF-IDF to convert text into numerical features.	Functional	Must-have
R4	The system must classify the preprocessed text into sentiment categories (e.g., positive, negative, neutral) using machine learning or deep learning models	Functional	Must-have
R5	The system must provide real-time sentiment predictions through the Streamlit app	Functional	Must-have
R6	The system must display the predicted category and confidence level to the user	Functional	Must-have
R7	Train and Evaluate Bernoulli Naive Bayes Model	Functional	Must-have
R8	Train and Evaluate Linear SVC Model	Functional	Must-have
R9	Train and Evaluate Logistic Regression Model	Functional	Must-have
R10	Save Trained Models for Future Use	Functional	Should-have
R11	Load Trained Models for Sentiment Prediction	Functional	Should-have
R12	The system could provide options for domain-specific sentiment analysis (e.g., healthcare, finance) to enhance accuracy in specialized contexts	Functional	Could-have
R13	Explore and Display New Data Predictions	Functional	Could-have
R14	The system could incorporate a feedback means for users to provide suggestions for improvement	Functional	Could-have
R15	The system should be compatible with other data analytics tools and platforms for seamless integration	Non Functional	Could-have
R16	The system should have a user-friendly interface for ease of use	Non-Functional	Should-have
R17	The system should be scalable to handle increasing data volume	Non-Functional	Should-have
R18	The system should provide accurate sentiment predictions with high precision and recall	Non-Functional	Should-have
R19	The system should be reliable and provide consistent results over time	Non-Functional	Should-have
R20	Optimize and Fine-Tune Model Parameters	Non-Functional	Should-have
R21	Ensure Compatibility with Python 3.7 and Above	Non-Functional	Must-have
R22	Achieve Response Time < 5 second for Prediction	Non-Functional	Should-have
R23	Provide Adequate Documentation for the Codebase	Non-Functional	Must-have

3.2 System Architecture for the Sentiment Analysis System

The software development process employed in this study is the CRISP-DM (CRoss Industry Standard Process for Data

Mining) Process Model. Its focus on understanding data and extracting actionable insights makes it particularly relevant for the Social Media Analyzer. The CRISP-DM process is inherently iterative, allowing for continuous refinement and adaptation. The processes involved run in the order of business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

Figure 1 presents the system architecture of the machine learning workflow for the sentiment analysis system. Social media data is pre-processed and split into training and test sets. An algorithm is used to train a model with the training set, which is then evaluated using the test set. Feedback from the model's performance is used to refine and improve the algorithm and model iteratively.

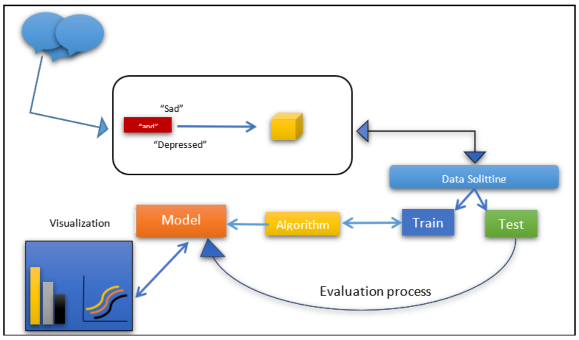


Fig 1. The system model diagram of the sentiment analysis system

3.3 Use Case Diagram for the Sentiment Analysis System

Figure 2 represents the use case diagram illustrating the various interactions between users and the Sentiment Analysis system. It highlights the central actions that the actors –Students, Data Analyst, School Administrator, and Teacher can perform.

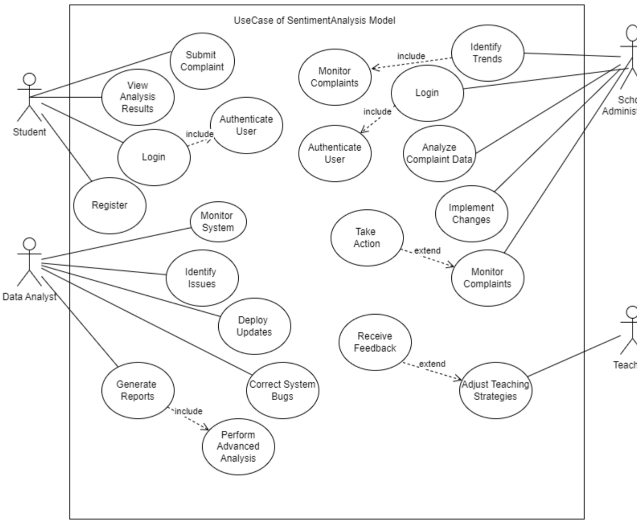


Fig 2. Use Case diagram showing interaction between actors and Sentiment Analysis system

3.4 Sequence Diagram for the Sentiment Analysis System

Figure 3 represents the sequence diagram which highlights and extensively explains the sequence of steps taken by the actors (e.g. Student and Administrator) of this system. The student is expected to log in to the system, submit complaints while the system processes the complaints and gives feedback. Also, the Administrator's behavioural interactions are also demonstrated.

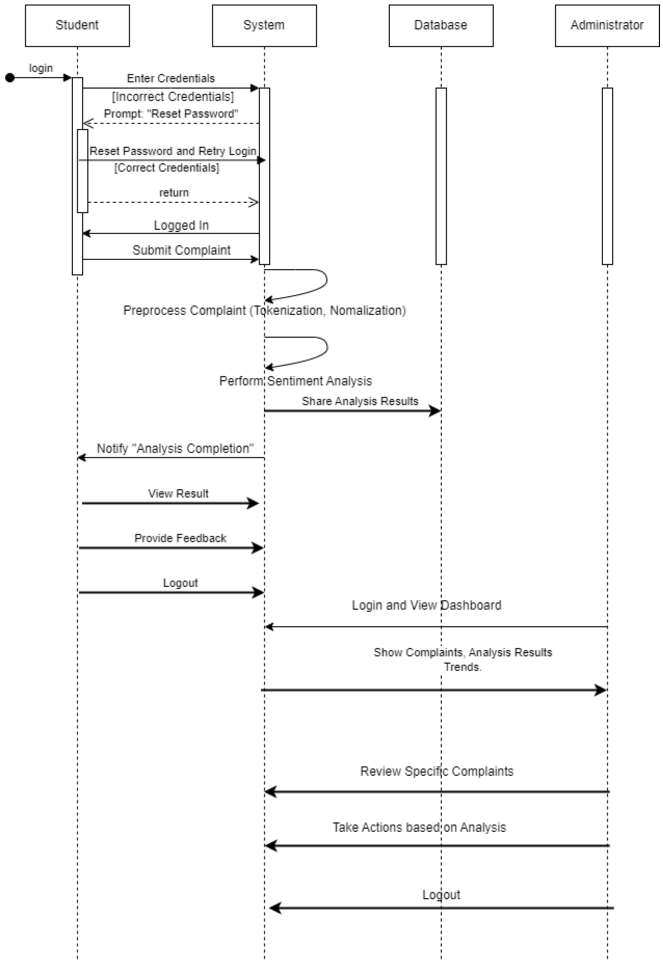


Fig 3. Sentiment Analysis System Sequence Diagram

3.5 Process Flowchart for student using the Sentiment Analysis System

Figure 4 shows a simplified process flowchart outlining the step-by-step ordering of actions taken by the Student when using the Sentiment Analysis system.

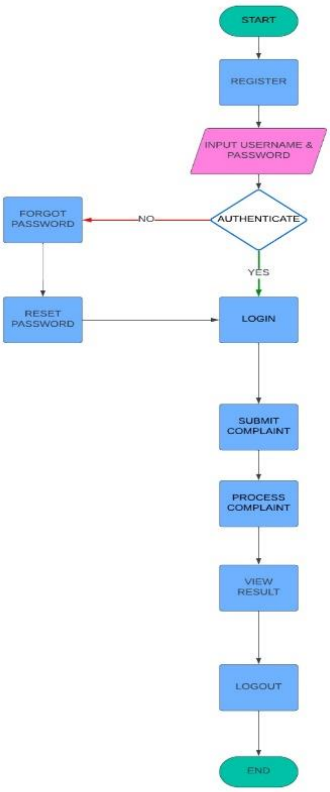


Fig 4. Flowchart of the Sentiment Analysis system usage.

4. Implementation and Outputs

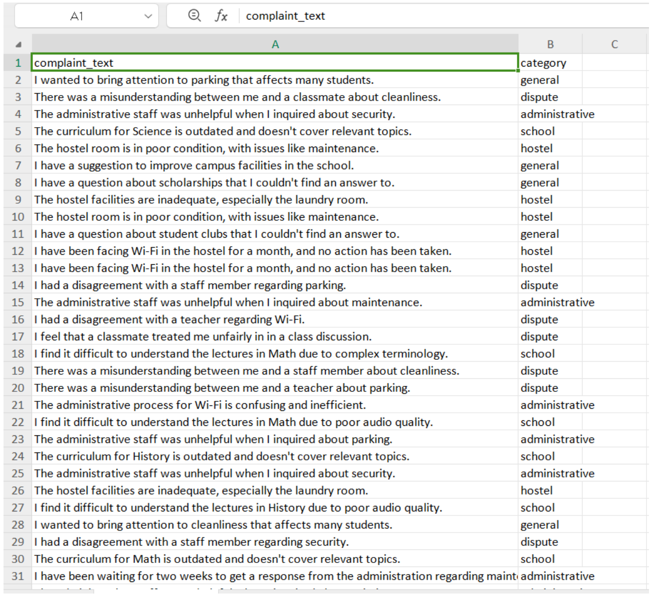
The development of the Social Media Analyzer Application employed the Cross-Industry Standard Process for Data Mining (CRISP-DM) approach. The process is systematic and iterative leading to structured approach to planning, executing, and evaluating the data mining application. The following phases are the implementations involved in the development of the Sentiment Analysis system:

4.1 Business Understanding

The CRISP-DM process starts with Business Understanding, where project objectives are defined and aligned with the school's goals. Stakeholder interviews and workshops are conducted to understand feedback processes, pain points, and desired outcomes. Clear project objectives and success criteria are defined, including improving student engagement and enhancing the educational experience. The project scope is established, and resources and constraints are assessed, including data infrastructure, privacy, and budget. This helps plan the subsequent phases of the CRISP-DM process effectively.

4.2 Data Understanding

Figure 5 depicts a generated synthetic dataset containing student complaints and their corresponding categories, which is a starting point for analysis. The complaints datasets are unstructured data with their respective categorisations e.g. administrative, dispute, and general. Exploratory data analysis (EDA) helps in gaining deeper insights into the data which helps in prioritising area of urgent attention. The extract feature's function applies the TF-IDF vectorizer to the pre-processed complaint text, transforming it into a matrix of numerical features. Each row in the matrix represents a complaint, and each column represents a unique word or term in the vocabulary. The resulting feature matrix is then ready to be used as input to the sentiment analysis model.



A1 | fx complaint_text

	A	B	C
1	complaint_text	category	
2	I wanted to bring attention to parking that affects many students.	general	
3	There was a misunderstanding between me and a classmate about cleanliness.	dispute	
4	The administrative staff was unhelpful when I inquired about security.	administrative	
5	The curriculum for Science is outdated and doesn't cover relevant topics.	school	
6	The hostel room is in poor condition, with issues like maintenance.	hostel	
7	I have a suggestion to improve campus facilities in the school.	general	
8	I have a question about scholarships that I couldn't find an answer to.	general	
9	The hostel facilities are inadequate, especially the laundry room.	hostel	
10	The hostel room is in poor condition, with issues like maintenance.	hostel	
11	I have a question about student clubs that I couldn't find an answer to.	general	
12	I have been facing Wi-Fi in the hostel for a month, and no action has been taken.	hostel	
13	I have been facing Wi-Fi in the hostel for a month, and no action has been taken.	hostel	
14	I had a disagreement with a staff member regarding parking.	dispute	
15	The administrative staff was unhelpful when I inquired about maintenance.	administrative	
16	I had a disagreement with a teacher regarding Wi-Fi.	dispute	
17	I feel that a classmate treated me unfairly in in a class discussion.	dispute	
18	I find it difficult to understand the lectures in Math due to complex terminology.	school	
19	There was a misunderstanding between me and a staff member about cleanliness.	dispute	
20	There was a misunderstanding between me and a teacher about parking.	dispute	
21	The administrative process for Wi-Fi is confusing and inefficient.	administrative	
22	I find it difficult to understand the lectures in Math due to poor audio quality.	school	
23	The administrative staff was unhelpful when I inquired about parking.	administrative	
24	The curriculum for History is outdated and doesn't cover relevant topics.	school	
25	The administrative staff was unhelpful when I inquired about security.	administrative	
26	The hostel facilities are inadequate, especially the laundry room.	hostel	
27	I find it difficult to understand the lectures in History due to poor audio quality.	school	
28	I wanted to bring attention to cleanliness that affects many students.	general	
29	I had a disagreement with a staff member regarding security.	dispute	
30	The curriculum for Math is outdated and doesn't cover relevant topics.	school	
31	I have been waiting for two weeks to get a response from the administration regarding maint	administrative	

Fig 5. Synthetic dataset containing student complaints and categorisation for Data Understanding

4.3 Data Preparations

The Data Preparation phase is a crucial step in the development of the Social Media Analyzer Application, which involves transforming raw data into a format suitable for sentiment analysis. This phase includes data loading, preprocessing, and feature extraction. The data is loaded into a pandas DataFrame, which contains two columns: 'complaint_text' and 'category'. The preprocessing process includes tokenization, lowercase conversion, removal of stop words, lemmatization, and feature extraction. The Term Frequency-Inverse Document Frequency (TF-IDF) technique is used to assign weights to each word in the complaint text, identifying the most informative and discriminative words for sentiment analysis. The resulting feature matrix is then used as input for the sentiment analysis model. Finally, label encoding is performed on the complaint categories using the LabelEncoder from scikit-learn. The resulting data is suitable for training and evaluating the sentiment analysis model, ensuring high-quality and relevant input for learning patterns and making accurate predictions.

```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.optimizers import Adam
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

# Download required NLTK data
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')

# 1. Data Preprocessing
def preprocess_data(data):
    # Tokenization
    data = data.apply(nltk.word_tokenize)

    # Convert to lowercase
    data = data.apply(lambda x: [word.lower() for word in x])

    # Remove stop words
    stop_words = set(stopwords.words('english'))
    data = data.apply(lambda x: [word for word in x if word not in stop_words])

    # Lemmatization
    lemmatizer = WordNetLemmatizer()
    data = data.apply(lambda x: [lemmatizer.lemmatize(word) for word in x])

    # Join tokens back into strings
    data = data.apply(lambda x: ' '.join(x))
```

Fig 6. Data Preparation Implementation

4.4 Data modelling and Data splitting

The Social Media Analyzer Application focuses on building and training a sentiment analysis model using prepared data to accurately classify student complaints based on the sentiment expressed in the complaint text. A Deep Neural Network (DNN) model is implemented using the Keras library, which can learn complex patterns and representations from text data. The model architecture consists of several layers, including a dense layer with 128 units and a ReLU activation function, dropout layers to prevent overfitting, a second dense layer with 64 units and a softmax activation function, and an output layer with a probability distribution over categories. The model is compiled using the Adam optimizer and sparse categorical cross-entropy loss function. The model is trained using the train_model function, fitting it to the training data and adjusting internal parameters to improve accuracy. The model's performance is evaluated using the evaluate_model function, which measures test loss and test accuracy metrics. By the end of the Modeling phase, the model can predict the sentiment category of student complaints based on the complaint text.

```python
# 3. Label Encoding
def encode_labels(labels):
    encoder = LabelEncoder()
    encoded_labels = encoder.fit_transform(labels)
    return encoded_labels

# 4. Model Architecture
def create_model(input_shape, num_classes):
    model = Sequential()
    model.add(Dense(128, activation='relu', input_shape=input_shape))
    model.add(Dropout(0.5))
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(num_classes, activation='softmax'))

    optimizer = Adam(learning_rate=0.001)
    model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy', metrics=['accuracy'])

    return model
```

Fig 7. Data modelling and Data splitting Implementation

4.5 Evaluation

The evaluation phase of a trained sentiment analysis model is crucial to assessing its performance. The model's accuracy and loss metrics show remarkable performance across 10 epochs of training. The model consistently improves in accuracy, with a high accuracy of 0.9991, indicating it can correctly classify most complaints. Loss, on the other hand, represents the discrepancy between predicted and actual values. The model's performance on the test set is further validated, with a low test loss of 0.0016 and a perfect accuracy of 1.0000, indicating its ability to predict unseen complaints and make accurate predictions. These evaluation metrics demonstrate the model's robustness and effectiveness.

```
Epoch 1/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 12s 12ms/step - accuracy: 0.3206 - loss: 1.5612
Epoch 2/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7807 - loss: 1.3428
Epoch 3/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8872 - loss: 0.9896
Epoch 4/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9713 - loss: 0.5340
Epoch 5/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9936 - loss: 0.2364
Epoch 6/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9925 - loss: 0.1130
Epoch 7/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9935 - loss: 0.0657
Epoch 8/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9985 - loss: 0.0516
Epoch 9/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9987 - loss: 0.0396
Epoch 10/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9991 - loss: 0.0260
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We rec
ommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
Test Loss: 0.0016
Test Accuracy: 1.0000
```

Fig 8. System evaluation and classification results

4.6 Deployment

The Streamlit app is a Python library that simplifies the creation of web applications for machine learning and data science projects. It provides an intuitive platform for users to input complaints and receive real-time predictions of the complaint category and corresponding confidence level. The app's user interface is designed to be simple and accessible, allowing easy input of users' complaints. The preprocessing phase involves tokenization, lowercase conversion, stop word removal, and lemmatization to prepare the complaint text for feature extraction and prediction. The TF-IDF vectorizer extracts relevant features from the text, which are then used by the trained sentiment analysis model to predict the complaint's category based on learned patterns and relationships. The app calculates the confidence level associated with the prediction, providing users with valuable insights into the model's reliability and sentiment strength. The app can be run locally by executing the Streamlit script.

```python
# Streamlit app
def main():
    st.title('Student Complaint Sentiment Analysis')

    # Get user input
    complaint_text = st.text_area('Enter your complaint:', height=200)

    if st.button('Submit'):
        # Preprocess the complaint text
        preprocessed_text = preprocess_text(complaint_text)

        # Extract features
        features = vectorizer.transform([preprocessed_text]).toarray()

        # Make predictions
        predictions = model.predict(features)
        predicted_category = label_encoder.inverse_transform(np.argmax(predictions, axis=1))[0]
        confidence = np.max(predictions) * 100

        # Display the results
        st.subheader('Complaint Category:')
        st.write(predicted_category)
        st.subheader('Confidence Level:')
        st.write(f'{confidence:.2f}%')

if __name__ == '__main__':
    main()
```

Figure 9. *System deployment*

5. System Evaluation and Testing

System evaluation and testing are important toward ensuring the reliability, performance, and effectiveness of the Student Complaint Sentiment Analysis application. This includes testing various scenarios, such as submitting complaints with different lengths, categories, and sentiments. Findings revealed that the application correctly preprocesses the complaint text, applies the trained sentiment analysis model, and displays the predicted category and confidence level accurately. The performance and accuracy of the sentiment analysis model within the Streamlit app were evaluated. The evaluation measures the model's accuracy, precision, recall, and F1 score, provides insights into its real-world performance. To assess the model's robustness and generalization ability, the app was tested with complaints having spelling errors, grammatical mistakes, or colloquial language to ensure that the preprocessing steps effectively handle these variations. The output of this study provides a valuable tool for analyzing and understanding student sentiments. The insight is towards supporting data-driven, decision-making system that enhances the student experience.

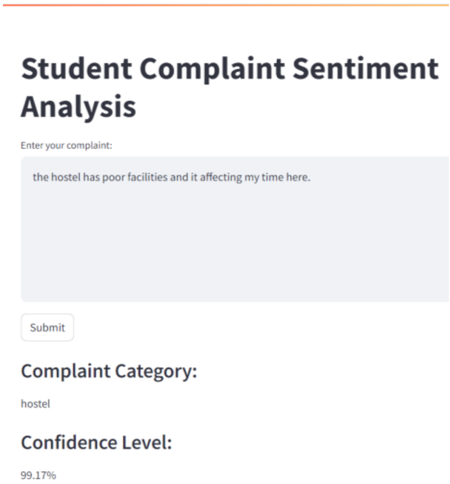


Fig 10. Screenshot showing the interface of the Sentiment Analysis System

6. Conclusion and Recommendation

This study developed a sentiment analysis system for student complaints using machine learning techniques. The research was conducted in a structured manner, following the CRISP-DM methodology. The data preparation process included data cleaning, preprocessing, and feature extraction. The development of the Deep Neural Network (DNN) model was described, along with the training and evaluation procedures. A Streamlit app was developed to achieve a user-friendly sentiment analysis system. The evaluation of the developed system demonstrated high accuracy and performance in classifying student complaints into their respective categories. The sentiment analysis system offers a powerful tool for schools to gain valuable insights into student sentiments, enabling data-driven decision-making and targeted interventions to address students' concerns effectively. By leveraging the power of machine learning, the system automates the analysis of student complaints, saving time and resources while providing objective and quantifiable insights. The developed system has the potential to revolutionize the way educational institutions approach student feedback management. It promotes a proactive and responsive approach to addressing student concerns, ultimately leading to improved student satisfaction and overall better educational outcomes.

The system can be further enhanced and adapted to different educational contexts, making it a valuable asset for schools and universities worldwide. It is recommended that educational institutions integrate the sentiment analysis system into their existing feedback mechanisms. By incorporating the system into the school's official complaint filing process, students can submit their complaints through a centralized platform and can be attended systematically. The integration should also include provisions for data privacy and security, ensuring that sensitive student information is protected.

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