Project Description:

Title: Automated Robust Feedback Analysis System for Departments and Teachers

Name: Marina Reda Abdullah Mekhael. **program: AIS** **ID : 221101235**

paper	Sentimental Analysis on Student Feedback using NLP & POS Tagging	Sentiment analysis of students feedback: A study towards optimal tools	Sentimental Analysis of Student Feedback using Machine Learning Techniques	Students feedback analysis model using deep learning-based method and linguistic knowledge for intelligent educational systems	Student Feedback Sentiment Analysis Model Using Various Machine Learning Schemes A Review
abstract	The paper focuses on using sentiment analysis in the educational domain, specifically for analyzing student feedback. The authors propose a method utilizing Natural Language Processing (NLP) and Part-of-Speech (POS) Tagging to automatically analyze text feedback	The study focuses on sentiment analysis of students' feedback to understand their sentiments towards courses and instructors. It aims to enhance instructors' performance by analyzing feedback collected typically at the end of the semester using survey forms. The paper explores the	The paper discusses the significance of feedback in education, emphasizing its role in helping organizations evaluate and improve their working environment and teaching methods. It focuses on understanding the true sentiment of students through textual feedback, which is essential for academic	The study introduces DTLP (Deep Learning and Teaching Process), a new deep learning-based method for analyzing student feedback. It employs convolutional neural networks (CNNs), bidirectional LSTM (BiLSTM), and attention mechanisms. The DTLP addresses challenges	The study presents a sentiment analysis model to improve teaching quality in universities. It explores various machine learning techniques for analyzing student feedback collected via Google Survey Forms. Multinomial Naive Bayes, Stochastic Gradient Decent, Support Vector Machine, Random Forest, and Multilayer Perceptron Classifiers were used, with the performance of Multinomial Naive Bayes and Multilayer Perceptron found to be most effective.

	from students and conclude the extent of teaching effectiveness based on sentiment polarity.	use of machine learning techniques, such as Support Vector Machines (SVM), Maximum Entropy (ME), Naive Bayes (NB), and Complement Naive Bayes (CNB), for this purpose, finding SVM as the most accurate.	administration and instructors to address issues	like contextual polarity, sentence types, word coverage limits, and word sense variations, showing significant performance improvements over existing systems	
Introduction	The introduction discusses the significance of sentiment analysis in education, emphasizing its utility in understanding students' attitudes and opinions. It highlights the challenge of manual sentiment analysis due to the large volume of data and the need for automatic processing using NLP.	It highlights sentiment analysis (SA) as a key computational tool for interpreting student opinions on platforms like Facebook or Twitter. The research aims to identify the best tools for sentiment analysis in educational settings, focusing on preprocessing, feature extraction, and machine learning techniques to enhance	The paper discusses the significance of feedback in education, emphasizing its role in helping organizations evaluate and improve their working environment and teaching methods. It focuses on understanding the true sentiment of students through textual feedback, which is essential for academic administratio	The paper discusses how technological advancements have dramatically innovated education. It highlights the use of technology by educational institutions to gather information about student experiences and to assess and adjust teaching approaches	This section discusses the importance of sentiment analysis, especially in the context of natural language processing and machine learning. It highlights the relevance of student feedback in evaluating teaching performance and the utility of sentiment analysis in this context.

		teaching methods.	n and instructors to address issues		
Methodology	The methodology involves creating a real-time dataset of student feedback, preprocessing the data to reduce noise, and applying machine learning algorithms for sentiment classification. The paper describes using POS tagging and feature extraction processes to classify feedback into positive, negative, or neutral categories.	The methodology includes corpus collection, data preprocessing, feature extraction, sentiment classification, polarity detection, and performance analysis. The research process is detailed in steps, starting from data collection to the final analysis	The paper outlines different approaches to sentiment analysis, including lexicon-based, machine learning, and hybrid approaches. It specifically focuses on machine learning techniques utilizing supervised and unsupervised learning	The DTLP system, for classifying student feedback into positive and negative categories, includes modules for input, pre-processing, feature extraction, feedback analysis, and visualization	Various machine learning techniques like Multinomial Naive Bayes, Stochastic Gradient Descent, Support Vector Machine, Random Forest, and Multilayer Perceptron are detailed. Their implementation and specific application in the context of sentiment analysis of student feedback are discussed.
Data Collection & Features	The study collected 2200 student feedback responses through an online survey. The dataset comprised comments labeled with positive, negative, and neutral	The research used a data set from the University of Portsmouth, comprising Facebook messages of students expressing their opinions about lectures. The data set	Students are provided with a set of questions to answer in sentences. This textual feedback format is used to capture the exact sentiment of the students,	Features necessary for classification focus on aspects like word embeddings, sentiment knowledge, linguistic and statistical knowledge, and are used to determine	Student feedback was collected from public and private universities in Karachi at the end of the semester Fall-2018. The feedback was gathered via Google Survey Forms, and the dataset included information about teaching quality and learning experience.

	sentiment polarities.	includes positive, negative, and neutrally categorized data, determined by the intensity of expression. The amount of data for analysis was fixed using a trial and error method, and the data were labeled into different classes based on sentiment intensity.	which is crucial for effective sentiment analysis	the sentiment of sentences as positive or negative	
Models Used	The paper employs machine learning techniques, specifically NLP algorithms, to analyze and classify the sentiments of student feedback.	The paper experimente d with Support Vector Machines (SVM), Naive Bayes (NB), Complement Naive Bayes (CNB), and Maximum Entropy (ME) for sentiment classification	The paper employs various machine learning algorithms for the classification problem, such as Support Vector Machine (SVM), Naive Bayes, and Random Forest	The paper utilizes deep learning models, specifically CNN, BiLSTM, and attention mechanisms for analyzing student feedback. These models process word-level features and generate hidden states to classify the feedback effectively.	The models used in this study are Multinomial Naive Bayes, Stochastic Gradient Decent, Support Vector Machine, Random Forest, and Multilayer Perceptron Classifiers. Each model's functionality and suitability for the analysis are elaborated upon.
Evaluation Techniques	The evaluation involved analyzing the polarity of	The study conducted performance analysis based on a	Sentiment polarity in the textual content is detected	the study involves assessing the classification accuracy and	The study employed various evaluation metrics such as Confusion Matrix, Precision, Recall, and

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<td>the feedback using the collected dataset. The performance of the model was assessed based on its ability to accurately classify the sentiments.</td>
<td>combination of preprocessin g features and machine learning algorithms. The evaluation involved comparing various models using metrics such as accuracy, recall, precision, and F-score</td>
<td>using a lexicon, which is then used to develop the machine learning model. The testing data is evaluated using this model</td>
<td>performance of the DTLP model in different feedback scenarios.</td>
<td>F-score to analyze the results of the models.</td>
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<tr>
<td>Results</td>
<td>The results showed that 60% of the feedback was positive and 40% negative. The analysis was visualized and presented through graphs, demonstratin g the distribution of sentiments among the feedback.</td>
<td>The results showed that almost all models performed better after preprocessin g. The study found that SVM outperforme d other models in terms of accuracy and recall in both state-of-the-art research and their study. However, NB and ME showed improved accuracy in their work compared to previous research. The optimal</td>
<td>The paper presents a comparative analysis of different machine learning algorithms, focusing on their accuracy and F-score, in the "Performance Analysis" section, Analysis shows that accuracy of MNBC is 0.77%-1.27% better than RF, and SVM performs 0.78%-0.81% better than MNBC ,and NB 80%</td>
<td>the performance improvement of DTLP over existing systems and its effectiveness in classifying student feedback with high accuracy. DTLP Full (WEF/WLF) obtained the highest accuracy (88.78%)</td>
<td>The results indicated that Multinomial Naive Bayes and Multilayer Perceptron performed more effectively compared to other approaches. The performance of each model is assessed and compared in detail.
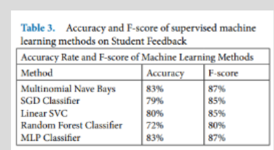
Table 3. Accuracy and F-score of supervised machine learning methods on Student Feedback
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<tr><th colspan="3">Accuracy Rate and F-score of Machine Learning Methods</th></tr>
<tr><th>Method</th><th>Accuracy</th><th>F-score</th></tr>
<tr><td>Multinomial Nave Bays</td><td>83%</td><td>87%</td></tr>
<tr><td>SGD Classifier</td><td>79%</td><td>85%</td></tr>
<tr><td>Linear SVC</td><td>80%</td><td>85%</td></tr>
<tr><td>Random Forest Classifier</td><td>72%</td><td>80%</td></tr>
<tr><td>MLP Classifier</td><td>83%</td><td>87%</td></tr>
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		model was SVM, followed by ME, based on the analysis of preprocessing features and machine learning techniques.			
Contributions	The main contribution of the paper is the development of an automated system for sentiment analysis of student feedback in the educational sector. The system aims to enhance the understanding of students' opinions and improve the educational process based on their feedback.	The paper contributed by investigating different levels of preprocessing in combination with various feature extraction methods and machine learning algorithms on student feedback data. The study suggests SVM and ME as the best models for this type of analysis	The paper contributes to the field of sentiment analysis in educational settings by exploring various machine learning techniques and providing a comparative analysis of their effectiveness in analyzing student feedback	The study contributes a new deep learning-based method for analyzing student feedback, employing a unified feature set and various strategies to solve challenges in sentiment analysis. It also includes extensive experiments for performance evaluation and confirms the effectiveness of the DTLP model in improving the quality of teaching and understanding student feedback.	The study contributes to improving teaching quality by providing insights from sentiment analysis of student feedback. It also offers guidance for future researchers in text and sentence classification, emphasizing the significance of choosing appropriate machine learning models.

AIE241 => Assignments => Project Preparation

Name: Aly Maher Abdelfattah Abdelrahman **ID:** 221101789 **Program:** AIS

Aspect	Sentiment Analysis of Student Textual Feedback to Improve Teaching Judith Goodness Khanyisa Mabunda, Ashwini Jadhav, Ritesh Ajoodha	Sentimental Analysis for Students' Feedback using Machine Learning Approach Kousalya. L1, Subhashini. R2	Student Feedback Sentiment Analysis Model using Various Machine Learning Schemes: A Review Irfan Ali Kandhro1*, Muhammad Ameen Chhajro1, Kamlesh Kumar1, Haque Nawaz Lashari1 and Usman Khan2
Abstract/Introduction	Focuses on developing a sentiment analysis model to assess the effectiveness of teaching and learning based on student feedback. Uses machine learning models like SVM, MNB, Random Forest, K-NN, and Neural Networks.	Focuses on classifying student feedback based on sentiment polarity (positive, negative, neutral) using machine learning and lexicon-based approach. Employs Random Forest classifier for performance evaluation.	Aims to present a sentiment analysis model to improve teaching quality in universities. Explores various machine learning techniques for classifying student feedback collected through Google Survey Forms.
Methodology	Utilizes feature engineering, re-sampling techniques, and various machine learning models to classify feedback into three sentiment classes.	Implements a sentiment analyzer using machine learning algorithms and a lexicon-based approach. Incorporates the Random Forest classifier and SVM for analysis.	Uses Multinomial Naive Bayes, Stochastic Gradient Descent, SVM, Random Forest, and Multilayer Perceptron Classifier. Analyzes the results using Confusion Matrix, Precision, Recall, and F-score.
Data Collection & Features	Employs student feedback data from Kaggle. Uses features like CountVectorizer, TFIDF, and SMOTE for feature engineering and class balance.	Collects real-time student feedback through an online portal. Utilizes features extracted from feedback, such as positive and negative sentiment words identified by SentiWordNet.	Collects student feedback from public and private sector universities using Google Survey Forms. The dataset contains information on the quality of teaching and learning.
Models Used	Support Vector Machines, Multinomial Naïve Bayes, Random Forests, K-Nearest Neighbours, and Neural Networks.	Random Forest and Support Vector Machines.	Multinomial Naive Bayes, Stochastic Gradient Descent, Support Vector Machine, Random Forest, Multilayer Perceptron Classifier.

Evaluation Techniques	Uses a confusion matrix for evaluation and 5-fold cross-validation to assess classifier accuracy. Emphasizes the importance of large datasets for significant learning in sentiment analysis.	Emphasizes the use of three-fold cross-validation for tuning hyperparameters in Random Forest and SVM. Focuses on feature impact analysis to refine feature sets.	Uses confusion matrix, precision, recall, and F-score for evaluation. Emphasizes the importance of balanced data samples in the dataset.
Results	Neural Networks performed best after re-sampling with an accuracy of 84%. K-NN model was efficient in predicting student sentiment towards teaching practices with an accuracy of 81% before re-sampling.	Achieved a high accuracy of 90% using the Random Forest classification technique.	Found that Multinomial Naive Bayes and Multilayer Perceptron were more effective than other approaches, with accuracies of 83% for both MNB and MLP classifiers.
Contributions	Developed a predictive model for classifying student responses using sentiment analysis. Suggested possible strategies to use model outputs for improving teaching. Highlights the impact of class distribution on model accuracy and the need for large datasets in sentiment analysis.	Highlighted the efficacy of combining machine learning with a sentiment lexicon for analyzing student feedback. Showed the effectiveness of Random Forest in classifying sentiments in student feedback. Suggested future applications of the technique in various domains of opinion mining like product reviews and political discussion forums.	Presents a sentiment analysis model for improving teaching quality. Demonstrates the effective use of machine learning techniques for sentiment classification in an educational context. Highlights the importance of MNB and MLP for future research in sentence and text classification.
Key Insights	Emphasized the importance of balancing class distribution in datasets for accurate sentiment analysis and the potential of neural networks in analyzing student feedback in real-time.	Demonstrated the utility of feature impact analysis in sentiment analysis and the potential of applying NLP techniques for better prediction of polarity results. Suggested the need for exploring the best classification techniques for higher accuracy.	Recommends using MNB and MLP for future sentiment classification research. Emphasizes the need for more preprocessing and feature extraction from datasets and suggests extending the work to multilingual implementations.

Project Preparation

Name: Hamza Nashaat Abdelbaki (AIS) Id:221100328

Aspect	Sentiment Analysis of Student Evaluations of Teaching Using Deep Learning Approach.	A Sentiment Analysis Model to Analyze Students Reviews of Teacher Performance Using Support Vector Machines	Aspect-Based Opinion Mining on Student's Feedback for Faculty Teaching Performance Evaluation
Abstract/Introduction	Problem: Open-ended questions in lecturer evaluation forms (EDOM) are often not analyzed in depth, leading to missed insights. Solution: Text mining using CNNs is proposed to analyze these questions and identify positive and negative sentiments.	Problem: Difficulty in efficiently analyzing and utilizing qualitative student feedback for teacher evaluation. Solution: Application of Support Vector Machines (SVM) algorithm with three kernels: linear, radial, and polynomial to predict sentiment (positive, negative, or neutral) of comments.	Problem: Traditional methods struggle to efficiently analyze and utilize qualitative student feedback. Solution: This study proposes a supervised aspect-based opinion mining system based on a two-layered LSTM model.
Methodology	This approach uses a multi-channel CNN for text classification. It first converts words to vectors, then uses convolutions with multiple filter sizes to extract features. Max-pooling reduces dimensionality, and dropout prevents overfitting. Finally, fully connected and softmax layers classify the text.	We calculated sensibility, specificity and predictive values as evaluation measures. The results of this work may help other experiments to improve the classification process of comments and suggest teacher improvement courses for teachers.	demonstrate the creation of academic domain data, followed by preprocessing step; afterward, we describe skip gram model for generating domain word embedding; lastly, we explain the working mechanism of our two layer LSTM neural network for aspect extraction and aspect sentiment classification.
Data Collection & Features	The dataset used in this study was sourced from student feedback comments on the EDOM application at Department of Information Systems, Telkom University.	The dataset used in this work comprises 1040 comments in Spanish of three groups of systems engineering students at Polytechnic University of Aguascalientes. They evaluated 21 teachers in the first school grade (2016).	manually tagged data set constructed from the last five years students' comments from Sukkur IBA University as well as on a standard SemEval-2014 data set.
Models Used	Convolutional Neural Network (CNN).	Term frequency-inverse document frequency(TF-IDF), Support vector machine(SVM), Naïve Bayes.	Natural Language Toolkit(NLTK) corpus, Skip Gram Model, LSTM model.

Evaluation Techniques	To evaluate performance, accuracy, recall, precision, and F1-Score is calculated and the evaluation has shown positive results.	three kernels in SVMs: ROC, Sensibility, Specificity.	Precision, Recall, F1 Score and Accuracy.
Results	he experimental results showed that CNN was able to achieve accuracy, precision, recall, and F1-Score of 87.95%, 87%, 78%, and 81%, respectively.	Linear kernel achieved a balanced accuracy above 0.80. Sensitivity values were significantly higher than Specificity for all kernels. Polynomial kernel (SVM Poly) had the lowest performance in all metrics except Sensitivity.	Found that Multinomial Naive Bayes andMultilayer Perceptron were more effective than other approaches, withaccuracies of 83% for both MNB and MLP classifiers.
Contributions	by leveraging advanced technology to unlock valuable insights from student feedback, ultimately leading to improved lecturer performance and enhanced student learning outcomes.	By evaluating the performance of teachers through constructing a model called SocialMining to benefit students in their education.	by developing a novel and efficient system for analyzing student feedback, providing deeper insights into faculty performance and offering valuable guidance for improvement.

Name :Sohila Ahmed Zakria

ID :221101149

Program :AIS

Paper Title	Abstract/ Introduction	Methodology	Data Collection & Features	Models Used	Evaluation Techniques	Results	Contributions	Key Insights
Aspect Sentiment Analysis of Student Textual Feedback to Improve Teaching by Judith Goodness Khanyisa	Investigates the development of a sentiment analysis model to classify student feedback and enhance teaching practices based on sentiment analysis.	Employs a combination of feature engineering, re-sampling techniques, and machine learning models to classify student feedback.	Utilizes student feedback data from Kaggle.	Support Vector Machines, Multinomial Naïve Bayes, Random Forests, K-Nearest Neighbours, and Neural Networks.	Confusion matrix and 5-fold cross-validation.	Neural Networks demonstrated superior performance with an accuracy of 84%. K-NN also exhibited promising results with an accuracy of 81%.	Introduces a sentiment analysis model for classifying student feedback.	Emphasizes the importance of balanced class distribution and large datasets in sentiment analysis.
Sentimental Analysis for Students' Feedback using Machine Learning Approach by Kousalya. L1 and Subhashini. R2	Proposes a sentiment analysis approach utilizing machine learning to classify student feedback.	Implements a sentiment analyzer employing machine learning algorithms and a lexicon-based approach.	Gathers real-time student feedback through an online portal.	Random Forest and Support Vector Machines.	Three-fold cross-validation.	Achieved a remarkable accuracy of 90% using Random Forest.	Highlights the efficacy of combining machine learning with a sentiment lexicon.	Demonstrates the effectiveness of Random Forest in classifying sentiments in student feedback.

Paper Title	Abstract/ Introduction	Methodology	Data Collection & Features	Models Used	Evaluation Techniques	Results	Contributions	Key Insights
Student Feedback Sentiment Analysis Model using Various Machine Learning Schemes: A Review by Irfan Ali Kandhro et al.	Provides an in-depth review of various machine learning techniques for sentiment classification in student feedback.	Utilizes Multinomial Naive Bayes, Stochastic Gradient Descent, Support Vector Machine, Random Forest, and Multilayer Perceptron Classifier.	Collects student feedback from public and private sector universities using Google Survey Forms.	Multinomial Naive Bayes, Stochastic Gradient Descent, Support Vector Machine, Random Forest, Multilayer Perceptron Classifier.	Confusion matrix, precision, recall, and F-score.	Multinomial Naive Bayes and Multilayer Perceptron were found to outperform other approaches.	Presents a sentiment analysis model for improving teaching quality.	Suggests potential future applications of the technique in various domains of opinion mining.
Sentiment Analysis of Student Feedback for Course Evaluation by Ahmad Abdollahi et al.	Evaluates the effectiveness of machine learning algorithms for sentiment analysis of student feedback.	Employs various machine learning algorithms, including Support Vector Machines, Random Forest, Linear Regression, and Logistic Regression	Collects student feedback from online courses through course evaluation surveys.	Support Vector Machines, Random Forest, Linear Regression, and Logistic Regression.	Confusion matrix, accuracy, precision, recall, and F-score.	SVM and Random Forest demonstrated the best performance with an accuracy of 87%.	Explores the potential of machine learning for sentiment analysis in course evaluation.	Emphasizes the importance of selecting appropriate machine learning algorithms for specific tasks.

Paper Title	Abstract/ Introduction	Methodology	Data Collection & Features	Models Used	Evaluation Techniques	Results	Contributions	Key Insights
Aspect-based Sentiment Analysis of Student Feedback for Teaching Effectiveness Evaluation by Jianwen Zhang et al.	Proposes an aspect-based sentiment analysis approach to evaluate teaching effectiveness.	Employs a hierarchical attention mechanism to identify aspects of student feedback and a sentiment analysis model to classify sentiment.	Collects student feedback from online courses.	Hierarchical attention mechanism and sentiment analysis model.	Accuracy, precision, recall, and F-score.	Achieved an accuracy of 89% in sentiment analysis and effectively identified aspects of student feedback.	Introduces an aspect-based sentiment analysis method for teaching effectiveness evaluation.	Demonstrates the effectiveness of the hierarchical attention mechanism for aspect identification.

Name: Omar Adly Mahmoud Nasr

ID: 221101398

Program: AIS

Aspect	Sentiment analysis of Students' feedback before and after COVID-19 pandemic	**Sentiment Analysis and Opinion Mining on Educational Data**	**Sentiment Analysis in the Education Domain: A Systematic Mapping Study**
Abstract/Introduction	Explores the impact of the COVID-19 pandemic on education, with a shift to online teaching. The study presents a hybrid approach of student sentiment analysis based on feedback collected through Google survey forms and WhatsApp social media platforms before and during the pandemic, using SVM and Naïve Bayes algorithms for classification and comparative analysis.	Examines the role of sentiment analysis, also known as opinion mining, in education. It focuses on emotional analysis at various levels (document, sentence, entity, aspect) and explores sentiment annotation techniques and AI methodologies like machine learning, deep learning, and transformers. Discusses the impact of sentiment analysis on educational procedures and challenges such as multi-polarity and polysemous words.	Presents a systematic mapping study on the application of NLP, deep learning, and machine learning solutions for sentiment analysis in the education domain, covering studies from 2015 to 2020. Highlights the growing application of deep learning in this field and identifies various aspects that need consideration for research maturity.
Methodology	Used machine learning techniques for sentiment analysis of student feedback. Data was collected through online platforms, and SVM and Naïve Bayes algorithms were applied for classification. Also utilized TextBlob and VADER for sentiment analysis,	Explores various levels and techniques of sentiment analysis in education, including aspect-based sentiment analysis, entity-level extraction, and sentiment annotation. Discusses the use of machine learning and deep learning methods in sentiment analysis and	Conducted a systematic mapping study using the PRISMA framework, reviewing 92 relevant studies out of an initial 612 found on sentiment analysis of students' feedback in learning platform environments. Focused on research trends, models, approaches, evaluation metrics, data sources,

	integrated with NLTK Python library.	their applications in the education sector.	and challenges in sentiment analysis in education.
Models and Techniques Used	SVM and Naïve Bayes algorithms were the primary machine learning techniques used. The study also employed TextBlob and VADER for sentiment analysis, highlighting the differences in their annotation methods.	Discussed sentiment analysis tools like IBM Watson, Microsoft Azure Text Analytics API, OpinionFinder 2.0, Repustate, Sentistrength, and educational domain-specific tools. Compared performance using SVM and k-fold cross-validation techniques. Also mentioned techniques like topic modeling and similarity analysis using LDA and LIWC.	Reviewed various machine learning, deep learning, and natural language processing techniques applied in sentiment analysis, such as NLTK, Random Forest, Multilayer Perceptron, and sentiment lexicons. Identified the most commonly used tools, frameworks, and libraries in sentiment analysis research.
Results	Achieved an average accuracy of 85.62% using SVM with K-fold cross-validation. Found that there were more negative instances of feedback during fully online classes as compared to blended teaching mode.	The study reported that educational-domain tools outperformed commercial tools in sentiment analysis. Various studies were mentioned, with methodologies and results, such as an accuracy of 80.67% for aspect-based sentiment classification and the use of reinforcement learning for conversational agents.	Identified the most investigated aspects in education regarding sentiment analysis, the most widely used approaches and models, and common evaluation metrics. Highlighted the challenges in sentiment analysis research in education, including fine-grained analysis, figurative language, generalization, and complex language constructs.
Contributions	Proposed a methodology for sentiment analysis of student feedback in different teaching modes (face-to-face vs. online) due to the COVID-19	Provided insights into the role of sentiment analysis in enhancing educational procedures, different levels of sentiment analysis, and annotation	Offered a structured overview of sentiment analysis in the education domain, identifying research trends, commonly used

	pandemic. Highlighted the importance of this analysis for understanding students' perspectives and improving teaching methodologies.	techniques. Discussed challenges in adapting sentiment analysis in education and proposed future directions for research in this area.	approaches and models, challenges, and future directions. Emphasized the need for structured datasets, standardized solutions, and increased focus on emotional expression and detection in sentiment analysis research.
Key Insights	Identified the effectiveness of SVM in sentiment analysis of student feedback, especially in online learning contexts, and underscored the shift in student sentiment before and during the pandemic.	Highlighted the importance of sentiment analysis tools and methodologies for understanding student engagement, pedagogy, and educational policies. Explored challenges like negation handling, multi-polarity, and polysemous words in sentiment analysis in education.	Stressed the importance of deep learning in sentiment analysis research in education and identified a variety of challenges and potential future research directions, including fine-grained analysis, handling of figurative language, and scarcity of datasets.

NLP phase 1
Name :Abdelrahman Mohamed Mahmoud (AIS)
ID:221101107

Aspect	Paper 1: Aspect-Based Sentiment Analysis in Serbian Higher Education	Paper 2: Sentiment Analysis of Vietnamese University Students' Feedback	Paper 3: Sentiment Analysis in MOOCs
Abstract/Introduction	Explores ABSA of student opinion surveys in Serbian, focusing on identifying sentiments and aspects in free text reviews.	Introduces a system for automatic categorization of student feedback in Vietnamese, focusing on sentiment analysis using Naïve Bayes, Maximum Entropy, and SVM.	Reviews sentiment analysis in MOOCs, focusing on evaluating students' feedback and identifying research trends.
Methodology	Utilizes NLP, machine learning models, rules, and dictionaries for ABSA at the sentence segment level.	Collects student feedback and annotates it into positive, negative, and neutral categories. Employs three classifiers for sentiment analysis.	Conducts a systematic literature review using the PRISMA framework to analyze sentiment analysis in MOOCs.
Models and Techniques Used	Applies multiple machine learning models for aspect tagging and sentiment polarity assignment.	Uses Naïve Bayes, Maximum Entropy, and SVM classifiers for sentiment categorization.	Reviews various techniques like supervised, unsupervised, lexicon-based approaches, and statistical analysis in sentiment analysis.
Results	Achieves F-measures of 0.83 for positive sentiment and 0.94 for negative sentiment. Aspect F-measures range between 0.49 and 0.89.	Finds Maximum Entropy algorithm to be the most effective with an accuracy of 91.36%.	Identifies six key research areas in MOOC sentiment analysis, highlighting the growing application of deep learning.
Contributions	Presents the first study of ABSA at the sentence segment level for the Serbian language, particularly in the	Develops a Vietnamese sentiment dataset and an automated system for categorizing student feedback.	Provides a comprehensive overview of sentiment analysis applications in MOOCs and suggests areas for future research.

	context of student reviews in higher education.		
Key Insights	Highlights the quality of ABSA depends on the source of reviews (official surveys vs review websites).	Demonstrates the effectiveness of traditional algorithms in sentiment analysis with appropriate feature selection.	Stresses the importance of deep learning in sentiment analysis in MOOCs and the need for advanced word representation and NLU techniques.

Mohamed Ahmed Fathi(AIS) ID : 221101699

Aspect	Paper 1: Aspect-Based Sentiment Analysis in Serbian Higher Education	Paper 2: Sentiment Analysis of Vietnamese University Students' Feedback	Paper 3: Sentiment Analysis in MOOCs
Abstract/Introduction	Explores ABSA of student opinion surveys in Serbian, focusing on identifying sentiments and aspects in free text reviews.	Introduces a system for automatic categorization of student feedback in Vietnamese, focusing on sentiment analysis using Naïve Bayes, Maximum Entropy, and SVM.	Reviews sentiment analysis in MOOCs, focusing on evaluating students' feedback and identifying research trends.
Methodology	Utilizes NLP, machine learning models, rules, and dictionaries for ABSA at the sentence segment level.	Collects student feedback and annotates it into positive, negative, and neutral categories. Employs three classifiers for sentiment analysis.	Conducts a systematic literature review using the PRISMA framework to analyze sentiment analysis in MOOCs.
Models and Techniques Used	Applies multiple machine learning models for aspect tagging and sentiment polarity assignment.	Uses Naïve Bayes, Maximum Entropy, and SVM classifiers for sentiment categorization.	Reviews various techniques like supervised, unsupervised, lexicon-based approaches, and statistical analysis in sentiment analysis.
Results	Achieves F-measures of 0.83 for positive sentiment and 0.94 for negative sentiment. Aspect F-measures range between 0.49 and 0.89.	Finds Maximum Entropy algorithm to be the most effective with an accuracy of 91.36%.	Identifies six key research areas in MOOC sentiment analysis, highlighting the growing application of deep learning.
Contributions	Presents the first study of ABSA at the sentence segment level for	Develops a Vietnamese sentiment dataset and an automated system	Provides a comprehensive overview of sentiment analysis applications

	the Serbian language, particularly in the context of student reviews in higher education.	for categorizing student feedback.	in MOOCs and suggests areas for future research.
Key Insights	Highlights the quality of ABSA depends on the source of reviews (official surveys vs review websites).	Demonstrates the effectiveness of traditional algorithms in sentiment analysis with appropriate feature selection.	Stresses the importance of deep learning in sentiment analysis in MOOCs and the need for advanced word representation and NLU techniques.