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Smart Learning Paths: Enhancing Education with Machine Learning Sentiment Analysis

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Abstract: The post-COVID surge in E-learning led to the need for a robust recommendation system due to the overwhelming number of online courses. Our proposed solution integrates Smart learning paths with advanced web scraping, machine learning, and sentiment analysis to extract comprehensive information from diverse platforms. Smart Learning paths adapts to the dynamic E-learning landscape, offering nuanced insights through quantitative metrics and qualitative sentiment analysis. Rigorous real-world experiments validate its effectiveness, making it a beacon of innovation in reshaping how users navigate and select personalized pathways in online education. The integration of web scraping, machine learning, and sentiment analysis ensures adaptability to evolving needs, transcending traditional metrics and prioritizing user experience.

Keywords: *Academic Courses, Machine learning, Sentimental Analysis*

1. Introduction

In the dynamic landscape of online learning, where a plethora of courses beckon learners, the challenge of discerning the most suitable educational path persists. The conventional model often lacks the personalized touch necessary for effective decision-making. This paper unfolds a groundbreaking methodology aimed at resolving this quandary by integrating sentiment analysis, machine learning, and web scraping techniques to furnish users with precisely tailored course recommendations. Our innovative approach commences with web scraping, a technique that serves as the backbone of our comprehensive dataset. By delving into various online platforms, we extract pivotal information ranging from course titles and descriptions to instructor details. Crucially, we spotlight user reviews, a goldmine of insights reflecting the sentiments and real-world experiences of past learners. The application of sentiment analysis becomes the linchpin of our methodology. As a formidable component of machine learning, sentiment analysis enables the system to discern the nuances embedded within user reviews. This analysis goes beyond more quantitative metrics, providing a qualitative understanding of the sentiments expressed. Learners, thus, gain profound insights into the perceived quality, relevance, and overall satisfaction associated with specific courses. Our approach promotes an informed decision-making process rather than just offering course recommendations. By deciphering sentiments, our system goes beyond the surface-level characteristics of courses, providing

users with a holistic view that resonates with their individual learning preferences. This personalized touch ensures that learners embark on educational journeys that align seamlessly with their goals and expectations. As the digital realm continues to evolve, our innovative approach stands as a beacon in the sea of online learning options. It's not merely about revolutionizing accessibility but also about redefining the selection process. In a world inundated with choices, our methodology becomes a guiding compass, navigating learners through the vast ocean of online courses with precision and purpose. In essence, this paper heralds a new era in personalized learning, where sentiment analysis becomes the compass, and web scraping and machine learning converge to offer users an educational experience that is not just vast but uniquely their own. In the era of E-learning, the uses of machine learning algorithms stands as a pivotal advancement in refining the course recommendation process. These algorithms, deployed to train models on the amassed dataset, synergize course attributes and sentiment scores as features. A noteworthy feature of these models is their adaptability to predict sentiment even for courses with limited user reviews. This amalgamation of sentiment analysis with other critical course attributes, encompassing popularity, duration, pricing, and skill level, culminates in the creation of a holistic recommendation system. This system, grounded in machine learning, comprehensively evaluates multiple factors to suggest courses that align with individual preferences and learning goals. The essence of our proposed recommendation system lies in its commitment to alleviating the challenges faced by learners

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when confronted with the daunting task of selecting competitive courses. By offering personalized recommendations rooted in individual preferences and learning goals, the system becomes a beacon of guidance in the vast landscape of E-learning. The integration of sentiment analysis and machine learning equips learners with the requisite information to make informed decisions, thereby enhancing their overall E-learning journey.

2. Previous work

This article examines, via a case study, the application of sentiment analysis in Massive Open Online Courses. It explores how sentiment analysis can provide insights into learners' experiences and engagement levels in online educational environments. The paper highlights the significance of MOOCs in online education and the challenges of monitoring and enhancing learner engagement. It discusses the different types of methodology used in the paper work, including data collection and sentiment analysis techniques. The findings reveal patterns of positive, negative, and neutral sentiments expressed by participants and discuss how these sentiments correlate with different course phases and topics. The study also looks at how sentiment analysis affects educators and instructional designers, suggesting it can guide interventions to improve engagement and enhance the overall learning experience in MOOCs.[1] This research paper explores using sentiment analysis to enhance e-learning by evaluating users' opinions. It discusses how sentiment analysis can improve the quality and effectiveness of online education by gauging user satisfaction and engagement. The methodology involves collecting and analyzing user-generated content, such as feedback and comments, to extract sentiments expressed by e-learners. The findings categorize sentiments as positive, negative, or neutral, providing insights into user experiences across different courses or features of e-learning platforms. The paper suggests that these insights can help tailor instructional design, identify areas for improvement, and address user concerns, ultimately creating a more engaging and effective learning experience.[2] The goal of this research study is to employ the Feature Ensemble Model to improve sentiment analysis for tweets that contain fuzzy sentiments. It addresses the challenges of analyzing ambiguous and nuanced sentiments in tweets, proposing a model that combines various features to enhance accuracy. In particular, Twitter sentiment analysis is shown in the article to be highly relevant in social media spaces, and the difficulties in effectively analyzing fuzzy sentiments. To create a model that can accurately represent the nuances of fuzzy sentiments, a wide range of elements, such as lexical, syntactic, and semantic aspects, are used in the process. The findings demonstrate that the Feature Ensemble Model significantly improves sentiment analysis accuracy for tweets with fuzzy sentiments, providing a more nuanced understanding of sentiment expressions. The paper discusses the practical implications of the improved model, suggesting applications in social media monitoring, brand perception analysis, and public opinion tracking, due to its effectiveness in handling fuzzy sentiments and extracting meaningful insights from Twitter data.[3] This research paper explores sentiment analysis applied to tweets concerning social events, aiming to understand the sentiments expressed on Twitter during such occasions. It recognizes Twitter's role as a platform for expressing opinions and emotions, seeking to analyze these sentiments to gain insights into public reactions and perceptions during social events. The introduction highlights the increasing usage of Twitter during social gatherings and the potential of sentiment analysis to glean insightful information from this stream of data. The methodology consists of classifying tweets into positive, negative, and neutral feelings using natural language processing techniques. It may also include ways for managing language that is relevant to a given context and event-related subtleties. The findings reveal patterns and trends in sentiments expressed on Twitter during various social events, providing insights into public reactions and emotional responses. The paper discusses the implications of sentiment analysis on social event-related tweets, highlighting its potential applications in gauging public opinion, understanding event impacts, and informing event organizers, marketers, and policymakers.[4] This research paper explores sentiment embeddings and their role in enhancing sentiment analysis algorithms. It emphasizes the significance of sentiment analysis in understanding user opinions and emotions in text data. The paper argues that traditional methods may struggle with the nuanced and contextual nature of sentiments, leading to the exploration of sentiment embeddings. The methodology involves using natural language processing to convert sentiments into continuous vector representations for more nuanced analysis. Findings suggest that sentiment embeddings aid in capturing the semantic links between sentiments, enhancing the model's capacity to comprehend subtleties and context. The paper also discusses practical applications, such as improving sentiment classification accuracy and handling ambiguous or mixed sentiments in text data.[5] This research study investigates the joint use of topic recognition and sentiment analysis in the examination of video transcriptions. It aims to enhance natural language processing techniques to understand sentiments and identify topics in transcribed video content. The introduction emphasizes the importance of analyzing multimedia data, particularly videos, and argues that combining sentiment analysis and topic recognition can provide a more thorough understanding of video content. The methodology involves using natural language processing algorithms to process transcriptions, identify sentiments, and recognize key topics. Findings suggest that this approach can offer a more holistic understanding of video content, allowing for the extraction of emotional tones and thematic elements. The paper discusses practical implications, such as improved content indexing, personalized recommendations, and a better understanding of audience reactions to videos.[6] In this study, the use of (DCNNs) for sentiment analysis on Twitter is examined. By utilizing deep learning techniques, particularly DCNNs, it seeks to increase sentiment analysis's accuracy and efficiency. The introduction highlights the challenges posed by Twitter data, such as brevity, informal language, and context dependence, and proposes deep learning as a solution to effectively capture the intricate patterns within tweets for sentiment analysis. The methodology involves designing and implementing DCNNs for sentiment analysis on Twitter, utilizing the network's using convolutional layers for automated extraction relevant features from tweet data and discern sentiment patterns. The findings demonstrate the effectiveness of DCNNs in capturing complex patterns within Twitter data, outperforming traditional methods by automatically learning hierarchical representations of text. The paper discusses the practical implications of employing DCNNs for Twitter sentiment analysis, including improved sentiment classification accuracy and scalability in handling large volumes of tweet data.[7] This study looks at how machine learning techniques can be used to analyze twitter sentiment, focusing on their effectiveness in classifying tweet sentiments. It emphasizes the significance of automated sentiment analysis on Twitter, given the platform's dynamic and diverse nature. To train machine learning algorithms, like SVM, Random Forest, or Naive Bayes for sentiment classification, the process entails taking a labeled dataset of tweets and extracting information from the text. The findings show the results of using these methods, which may include a comparison of several machine learning algorithms and performance metrics such as precision, recall, accuracy, recall, or F1-score. The paper also discusses practical implications, such as applications in brand monitoring, public opinion analysis, and real-time response systems, highlighting the potential of machine learning in enhancing sentiment analysis on Twitter [8] The performance evaluation of machine learning classifiers for sentiment analysis is the main objective of this research article. It investigates the use of different classifiers, including Decision Trees, Naive Bayes, and Support Vector Machines, to evaluate how well they categorize feelings in text data. The introduction highlights the importance of sentiment analysis in understanding opinions and emotions in text and emphasizes the need for reliable machine learning classifiers for automation. The methodology involves using labeled datasets and extracting features from the text to train and evaluate multiple classifiers. Performance is measured using different types of layers such as F1-score, recall, accuracy, and precision. The findings offer a comparative analysis of classifier performance, discussing their strengths and weaknesses and providing insights for selecting appropriate classifiers for sentiment analysis tasks. The paper also explores practical implications, such as guiding classifier selection based on dataset characteristics and model parameters.[9] This research paper introduces "SentiView," a tool for sentiment analysis and visualization of sentiment trends related to internet popular topics. It explores how SentiView can analyze sentiments associated with trending subjects on the internet. The paper highlights the growing importance of sentiment analysis in understanding internet trends and the need for tools that can assess and visually represent sentiment trends. SentiView is described as offering a thorough approach to sentiment analysis and visualization. sentiment analysis using natural language processing and graphical representations, such as graphs or charts, for visualization. The findings discuss how SentiView captures and visualizes sentiment dynamics, providing insights into public opinions, emotions, and trends associated with internet popular topics. Practical applications include monitoring public sentiment and understanding the evolving sentiments surrounding internet popular topics.[10] This research paper explores sentiment analysis as a complex issue, acknowledging the complexities in understanding sentiments expressed in textual data. The introduction emphasizes the increasing relevance of sentiment analysis in various domains and the challenges posed by nuanced, context-dependent sentiments influenced by diverse factors. The methodology may outline challenges like sarcasm, irony, or cultural nuances, and discuss the use of diverse data sources, such as social media or product reviews, to capture sentiment diversity. The findings likely delve into challenges in accurately classifying sentiments across contexts, addressing sentiment shift over time, and adapting to the dynamic nature of language. The paper may also explore potential solutions, such as advanced natural language processing techniques or hybrid systems, to tackle the multi-faceted aspects of sentiment analysis.[11] In this study, the use of (BiLSTM) networks for sentiment analysis of comment messages is investigated. It highlights the value of sentiment analysis in interpreting user thoughts from comments and recommends that BiLSTM be used for this purpose because of its capacity to identify sequential patterns and contextual dependencies. The methodology likely involves preprocessing comment texts, converting them into numerical representations, and training the BiLSTM model to learn temporal dependencies and contextual information. The findings discuss how BiLSTM's bidirectional nature helps capture both past and future context, leading to a more comprehensive understanding of sentiment expressions.

The paper may also explore BiLSTM's advantages in handling challenges like long-range dependencies and subtle nuances in sentiment expression, demonstrating its effectiveness in analyzing sentiments in various comment datasets.[12] This study highlights the expanding significance and wide range of applications of sentiment analysis by providing an extensive overview of sentiment analysis techniques and methodologies. It emphasizes the need for a systematic understanding of these methods to address the evolving challenges in sentiment analysis effectively. The survey encompasses a wide array of methodologies, including traditional machine learning techniques, natural language processing algorithms, and recent advances in deep learning. It also examines several strategies, including hybrid models, machine learning-based strategies, and lexicon-based strategies. The findings synthesize the current sentiment analysis landscape, categorizing and discussing the strengths and limitations of various methods, and may also highlight emerging trends and future directions in sentiment analysis research.[13] This paper uses (RNNs), more precisely (LSTM) networks, for text sentiment analysis. It shows the importance of sentiment analysis in understanding opinions and emotions in text and suggests LSTM networks as effective for capturing temporal dynamics and contextual nuances in sentiment expression. The methodology likely includes preprocessing text data, converting it into numerical form, and training the LSTM model to learn sequential patterns in sentiment. The findings discuss how LSTM's architecture, with memory cells and gates, helps capture long-term dependencies for a more nuanced comprehension of sentiment dynamics. The paper may also explore practical implications like improved accuracy and the ability to capture subtle sentiment nuances, applicable in social media, customer reviews, and opinion mining.[14] This research paper focuses on aspect-level sentiment analysis tailored for e-commerce data, aiming to analyze sentiments at a detailed level by considering specific aspects or features of products, services, or user experiences. The introduction emphasizes the importance of this analysis in e-commerce, highlighting the need for a thorough understanding of customer opinions about different attributes. The approach most usually entails extracting and analyzing sentiments associated with particular elements from customer evaluations or comments using machine learning models and NLP techniques. The findings offer insights into sentiment analysis results at the aspect level, providing a nuanced understanding of customer satisfaction or dissatisfaction with various e-commerce features. Practical applications include informing product development, refining marketing strategies, and making targeted improvements based on specific customer feedback.[15] It emphasizes the need for advanced techniques like deep learning to handle sentiment complexities in non-English languages. Neural networks and RNNs, which are deep learning techniques, along with specially designed data preprocessing and Urdu-specific model training, are probably part of the methodology. The findings discuss the effectiveness of these techniques in capturing Urdu sentiment nuances, potentially comparing them to traditional methods and exploring broader applications in public opinion understanding and social media monitoring.[16] This paper mainly focuses on sentiment analysis and classification of movie reviews, aiming to systematically analyze sentiments in textual reviews. The introduction highlights the need for automated methods to assess sentiments in the vast amount of textual data from moviegoers. The process of classifying reviews into positive, negative, and neutral feelings probably involves machine learning algorithms and NLP. The findings present insights into sentiment dynamics within movie reviews, discussing the accuracy of sentiment classification models and challenges in handling subjective language. Additionally, the paper explores practical implications, such as applications in movie recommendation systems and understanding audience preferences, benefiting filmmakers and studios in gauging the reception of their productions.[17]

This research paper presents a sentiment analysis poll using data from social media, aiming to provide a comprehensive overview of methods, techniques, and trends. The introduction emphasizes sentiment analysis' growing significance in social media and the need for understanding diverse approaches. It is expected that the survey will address deep learning, machine learning, and natural language processing techniques, such as emotion detection and lexicon-based methods. Findings offer insights into methods' strengths, limitations, and applicability across platforms. Additionally, the survey may discuss emerging trends and future directions, acknowledging the dynamic nature of online communication and sentiment analysis methodologies.[18] This study describes a Direction DSRP for healthcare data in networks that are not totally predictable. It addresses secure and efficient routing challenges in environments where network conditions are not entirely predictable. The protocol relies on directional information and density metrics to guide routing and incorporates encryption for security. The study emphasizes the sensitivity of healthcare data and the need for secure routing. The findings likely discuss the protocol's effectiveness in ensuring secure and efficient data transfer, considering routing accuracy and encryption strength. The protocol has practical implications for enhancing patient data confidentiality and integrity, particularly in unpredictable network environments.[19] This study use Naïve Bayes and sentiment dictionary-based techniques to analyze the sentiment of Danmaku videos. It aims to categorize sentiments expressed in the interactive context of these videos. The introduction emphasizes the unique nature of Danmaku videos, highlighting the need for specialized sentiment analysis techniques. The methodology likely involves Naïve Bayes for classification and sentiment dictionaries for nuanced sentiment understanding. The findings discuss the outcomes of sentiment analysis, including method strengths and limitations. The study may suggest practical applications such as understanding audience reactions and informing content creators.[20] This research paper mainly analyze sentiment in distance education course materials. By employing various machine learning techniques, the study seeks to understand the sentiments of students toward the content of their courses. The ultimate goal is to provide valuable insights that can enhance the effectiveness and quality of distance education programs. Through sentiment analysis, educators and course designers can gain a deeper understanding of how students perceive and engage with the course materials, allowing them to make informed decisions to improve the overall learning experience. This approach not only benefits students by tailoring course materials to their preferences but also helps institutions refine their distance education offerings to better meet the needs and expectations of their learners.[21] The research investigates the application of sentiment analysis to the development of a product recommendation system based on user reviews. It aims to improve user experience by providing personalized recommendations that align with their preferences. The study focuses on analyzing the opinions and emotions expressed in user reviews to identify positive and negative sentiments associated with products. This analysis helps in making more informed recommendations to users. Overall, the findings emphasize the importance of sentiment analysis in improving recommendation systems and, ultimately, consumer satisfaction. [22] The paper delves into sentiment analysis applied to English texts, aiming to discern the emotional context and tone of the content. It explores many ways for classifying text sentiments as good, negative, or neutral, including both basic keyword-based approaches and more sophisticated machine learning techniques. The study underscores the significance of sentiment analysis in deciphering public sentiment and opinions regarding various subjects or products. By elucidating these methods, the paper offers valuable insights into the practical application of sentiment analysis in English text analysis.[23] The research looks at how machine learning techniques can be used to analyze the sentiment of scientific texts. It focuses on using these methods to understand the emotional tone and sentiment expressed in scientific literature. The study discusses various machine learning approaches for analyzing sentiment, including the use of labeled datasets to train models for sentiment classification. The research aims to provide insights into how machine learning can be leveraged to enhance sentiment analysis in scientific texts, potentially aiding researchers in understanding the broader sentiment within their field. Overall, this paper specifically shows the importance of sentiment analysis in scientific literature and demonstrates the potential of machine learning techniques in this domain.[24] The paper delves into sentiment analysis as applied to YouTube videos, with a focus on discerning the emotional context and tone of the content. It explores a range of methodologies, including NLP techniques, to extract and analyze sentiment from numerous elements such as video comments, titles, and descriptions. The study aims to offer valuable insights into the sentiments of viewers towards video content, which can be particularly useful for content creators and marketers in understanding audience reactions. By employing sentiment analysis, the research seeks to deepen the understanding of the emotional impact and reception of YouTube videos. Overall, this research contributes to the improvement of sentiment analysis in multimedia content by tackling the particular issues presented by video-based platforms such as YouTube.[25]

3. Classifiers

For this we used different types of classifiers

I. Naive Bayes:

Description: Utilizes Bayes' theorem with the assumption of feature independence.

Equation: None. Decision boundary is determined by conditional probabilities.

II.Decision Tree:

Description: Hierarchical structure using if-else conditions to partition feature space.

Equation: None. Decision boundary represented by a series of if-else conditions.

III. Support Vector Machine (SVM):

Description: Seeks optimal hyperplane maximizing margin between classes.

Equation: w \cdot x + b = 0$w \cdot x + b = 0$, where ww =weight vector, xx = input feature vector, and bb = bias term.

IV.Random Forest:

Description: Ensemble of decision trees with aggregated predictions.

Equation: None. Decision boundary not represented by a single equation; predictions combined from multiple decision trees.

4.Comparison Table of Classifier

The performance evaluation of various classifiers shows clear distinctions in their strengths across precision, recall, F1-Score, and accuracy metrics. Notably, both the Decision Tree and Random Forest classifiers display superior overall performance, achieving high accuracy rates of 91.28% and 93.0%, respectively. This high accuracy is attributed to a balanced combination of precision, recall, and F1-Score. The Naive Bayes classifier also demonstrates competitive results. Meanwhile, the Support Vector Machine exhibits a balanced performance, maintaining a solid accuracy of 87.45%. These insights offer valuable guidance for selecting the most suitable classifier based on specific task requirements and priorities.

5.Methodology

The dataset is preprocessed, generating scores and divides the data into training set and testing sets. A model is then constructed and evaluated using metrics. Finally, the results are analyzed to gauge the model's performance and effectiveness in handling the given dataset as shown in Fig.1.

I. Web scraping:

Classifier	Precision	Recall	F1-Score	Accuracy %
Naive Bayes	**0.84**	**0.79**	**0.81**	**81.83**
Decision tree	**0.87**	**0.97**	**0.92**	**91.28**
Support vector machine	**0.87**	**0.88**	**0.88**	**87.45**
Random forest	**0.93**	**0.93**	**0.93**	**93.0**

Web scraping can be used to extract comments from different web pages. This process involves automating the extraction of comments from the HTML code of the web pages using a web scraping tool. It includes scraping comments from web pages to

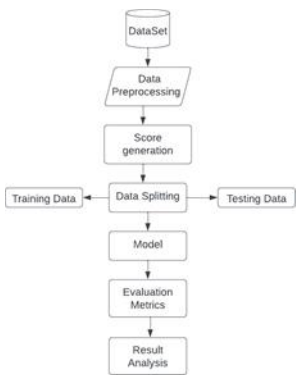


Fig.1: Model of proposed system

identify the target website or web pages that contain the comments you want to extract. Once you have identified the target web pages, you can use a web scraping tool like Beautiful Soup, Scrapy, or Selenium to extract the comments, as shown in Fig.2.

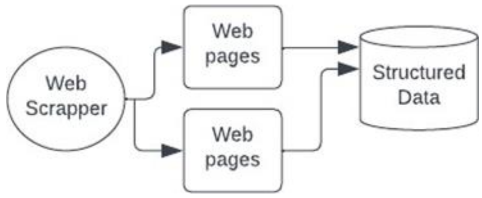


Fig. 2: Web Scraping

II. Data collection

The information has been gathered from diverse educational platforms such as Coursera, Udemy, Internshala, among others. Reviews and comments found on these platforms have been extracted using web scraping tools like Beautiful Soup. The collected data has been consolidated into a single file, which encompasses details about courses, customer reviews, and ratings.

III. Data Preprocessing

The gathered data undergoes preprocessing through a series of operations that involve tasks such as data cleaning, text preprocessing to address data leaks and unstructured content, as well as data integration, reduction, and normalization. These operations are carried out using different types of Python libraries such as pandas, scikit-learn, and NumPy etc.

IV. Text preprocessing

1)Tokenization:

The collected textual data, including customer reviews and course descriptions, is tokenized by breaking it down into seperate words or tokens. This involves splitting the text based on whitespace or punctuation marks, resulting in a list of distinct units for subsequent processing. This tokenization step facilitates further analysis and manipulation of the text data.

2)Removing Punctuation:

Following tokenization, the next step involves eliminating punctuation marks, such as periods, commas, question marks, and quotation marks, from the text. This process aids in reducing noise and allows for a more focused analysis on the essential words or tokens within the textual data.

3)Stopword Removal:

After eliminating punctuation marks, the next preprocessing step involves removing common words that contribute little to the sentiment or overall meaning of the text. These consist of prepositions (like "in," "on"), conjunctions (like "and," "or"), and articles (like "the," "a"). By concentrating on more important and instructive words, this technique is known as stopword removal it is an essential for Reduce the dimensionality of text data while enhancing sentiment analysis accuracy.

4)Lowercasing:

Subsequent to stopword removal, the text data undergoes a transformation where all characters are converted to lowercase letters. This step ensures consistency in word representations by treating words with different cases (e.g., "good" and "Good") as identical during sentiment analysis. Lowercasing helps maintain uniformity in the textual data and contributes to a more accurate analysis of sentiment by treating variations in letter case uniformly.

V. Data Splitting

The preprocessed dataset is divided into two separate subsets: namely training and testing. 70% of the overall dataset is set aside for training purposes. This subset of data is used to train machine learning models. In contrast, the testing set accounts for 30% of the overall dataset. This subset is designated for assessing the performance of trained models. The split of training and testing sets makes it easier to evaluate model generalization and efficacy on previously unseen data. The training of the model involves utilizing the Random Forest algorithm, which takes the training data as input. Random Forest is employed to train the model by utilizing the provided training dataset. Through this training process, the algorithm learns patterns and relationships within the data. Once the model is trained, It gains the ability to make predictions based on newly acquired or previously unknown data. The trained Random Forest model is then used to predict results, offering insights or classifications for instances not previously encountered during the training phase. This predictive capability is a key aspect of leveraging machine learning algorithms like Random Forest for various applications.

I. Evaluation Metrics

Based on the model's predictions, several performance metrics are computed, including accuracy, precision, recall. These metrics give a thorough evaluation of how well the model handles various data characteristics and produces accurate predictions.

Accuracy: This indicator, which shows the percentage of correctly identified occurrences out of all instances, assesses how accurate the model's predictions are overall.

Precision: Precision measures how well the model predicts positive outcomes; it is expressed as the ratio of accurately predicted positive cases to all instances projected to be positive.

Recall: Recall measures the model's capacity to accurately identify all pertinent events; it is sometimes referred to as sensitivity. It is the proportion of all real positive instances to all correctly projected positive instances.

Collectively, these measures contribute to evaluating the model's performance, helping in the determination of its effectiveness in different aspects. By comparing these results, a rating can be assigned to the model, and the accuracy rate provides an overall measure of the model's success in making correct predictions.

6.Proposed System

The development of our educational recommendation system involves a seamless integration of frontend and backend technologies. The frontend is crafted using Jinja, a Python-based web template engine, providing a dynamic and interactive user interface. Flask serves as the backend framework, facilitating the processing and communication between the user interface and the underlying functionalities. To gather crucial information about online courses, such as title, video length, video tutor, and user comments, we employ web scraping techniques leveraging the Beautiful Soup library. This allows us to extract pertinent data from various platforms, including YouTube, Coursera, and others. The core of our recommendation system lies in the training algorithm, where we utilize the Random Forest algorithm. This machine learning approach allows the model to learn and generate informed predictions using the features gathered from the courses. Users play an integral role in the recommendation process by entering the URL of the course they are interested in. The system then dynamically fetches data through web scraping, learning from reviews and comments associated with the course.Subsequently, the model classifies each course into three categories: class 1 for courses with ratings greater than 3, class 0 for courses with ratings equal to 3, and class -1 for the rest. The assigned classes are pivotal in sorting and arranging the courses in descending order, providing users with a clear and organized view of the available options. This prioritization allows users to differentiate between courses based on their preferences and the community's feedback. In summary, our recommendation system, built on Jinja for the frontend, Flask for the backend, Beautiful Soup for web scraping, and powered by the Random Forest algorithm, ensures a user-friendly experience. By dynamically analyzing course data and incorporating user feedback, our system empowers users to make informed decisions when navigating through the multitude of online learning options.

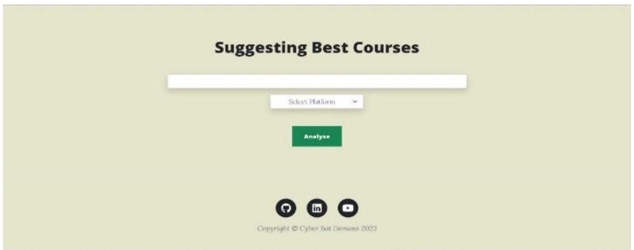


Fig.3: Dashboard of proposed model

The provided information describes a dashboard where users are required to input links to courses they wish to analyze for sentiment and recommendations. In this context, users are expected to paste the URLs or links of the specific courses they want to assess. The dashboard likely processes this input to generate sentiment analysis and recommendations for the mentioned courses.as shown in Fig.3.This functionality could be part of an online platform, educational tool, or similar service that aims to help users understand the sentiments and receive recommendations related to specific course content.

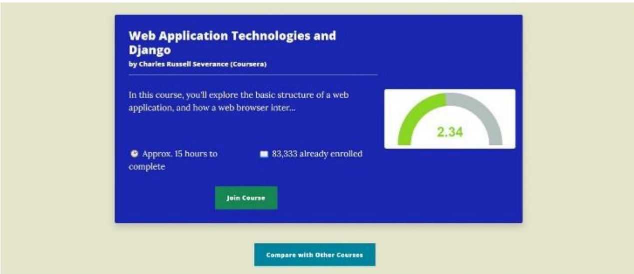


Fig. 4: Course Rating propsed model

The information provided indicates that there is a screenshot displaying the predicted rating of a course generated by a model. Shown in Fig.4This suggests that the model is capable of predicting or assigning a rating to a given course. The screenshot likely showcases the outcome of the model's analysis, presenting users with a predicted rating for the course in question. This feature could be valuable for users seeking insights into the perceived quality or effectiveness of a particular course based on the model's predictions.

Fig.5: Comparative Analysis of the Courses

The additional information suggests that the screenshot presents a comparative analysis of courses across various platforms, along with their respective ratings. Fig.5 indicates that the model not only predicts ratings for individual courses but also allows users to compare and contrast courses from different platforms. The comparative analysis likely provides users with a side-by-side view of how courses are rated on various platforms, offering valuable insights for making informed decisions about which courses to pursue based on their ratings across different educational platforms.

7.Results

The course that the model predicts to have a high rating is identified as the best course among all the compared courses. Following this determination, adjustments are made to the recommendation algorithm. This may involve fine-tuning the system's parameters or incorporating new features to enhance its performance. Fine-tuning the algorithm involves optimizing its parameters to achieve better results or adapt to specific characteristics of the data. Additionally, the inclusion of new features can provide the model with more information, potentially improving its ability to make accurate predictions. This iterative process of refining the recommendation system aims to continuously enhance its effectiveness in suggesting courses that are likely to receive high ratings, thereby increasing the overall user experience and happiness with the educational platform.

The figures discussed below show the rating classification diagram of different courses assigns a class label of 1 to courses with ratings greater than 3, a class label of 0 to courses with ratings equal to 3, and a class label of -1 to all other courses.

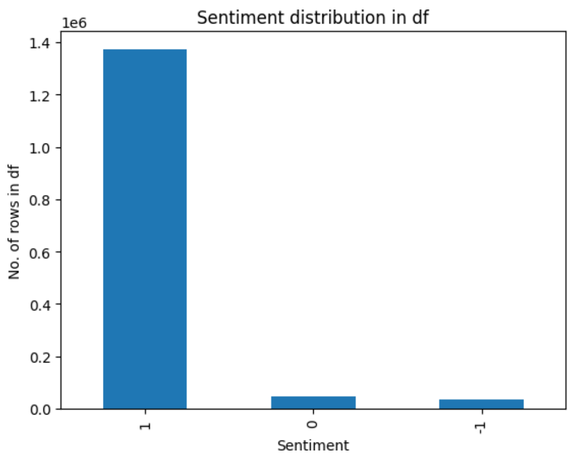
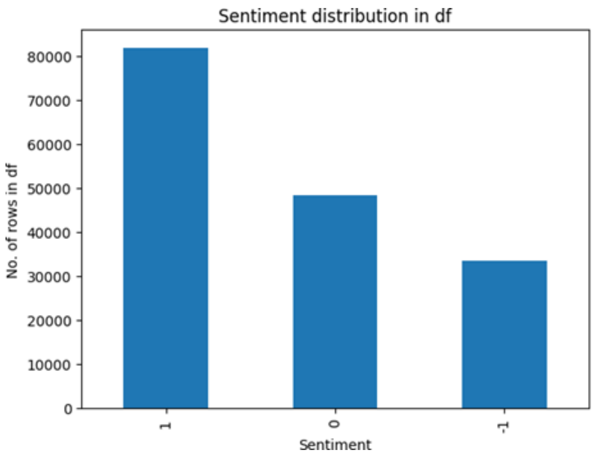


Fig.6: Result of proposed system

8. Comparative Analysis of the Courses



	Precision	Recall	F1-Score	Support
-1	0.9	0.96	0.93	9487
0	0.91	0.9	0.9	14793
1	0.96	0.94	0.95	24822
Accuracy			0.93	49102
Macro avg	0.92	0.93	0.93	49102
Weighted avg	0.93	0.93	0.93	49102

The classification model demonstrates strong performance metrics across various evaluation measures. With an overall precision of 0.92, it correctly identifies 92% of positive events. The recall score of 0.93 indicates that the model accurately detects 93% of actual positive events. The F1-Score, at 0.93, signifies a balanced performance between precision and recall. The model achieves an accuracy of 93% across all classes, representing the proportion of correctly classified examples in the dataset. Examining individual class performance, class -1 exhibits a precision of 0.90, recall of 0.96, and F1-Score of 0.93, based on 9487 occurrences. For class 0, precision is 0.91, recall is 0.90, and F1-Score is 0.90, derived from 14793 occurrences. Class 1 displays the highest precision at 0.96, recall at 0.94, and F1-Score at 0.95, with 24822 instances.

9. Conclusion

In this paper, a comprehensive approach to suggesting the best courses is presented, utilizing sentiment analysis through machine learning and web scraping techniques. The proposed methodology involves web scraping to collect course information from online learning platforms, sentiment analysis to assess user sentiments expressed in reviews, and machine learning algorithms to construct a recommendation system. However, this research is not without its limitations. While sentiment analysis offers valuable insights, it may not capture the nuances of every user's preferences and experiences. Addressing these limitations could involve incorporating more advanced sentiment analysis techniques and exploring hybrid recommendation approaches, thereby further Increasing the accuracy and customisation of course recommendations. In summary, the paper contributes to the field of course recommendation systems by leveraging sentiment analysis through machine learning and web scraping. It provides learners with a valuable tool for selecting the best courses, enhancing their online learning experience, and ultimately empowering them to achieve their learning goals.

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