1. INTRODUCTION

Educational technology has been notably shaped by the growing prevalence of Massive Online Open Courses (MOOCs). These courses aim to make education accessible worldwide and provide access to online resources (Zhenghao, Alcorn, Christensen, Eriksson, Koller, & Emanuel, 2015). The influence of MOOCs can be seen in the numbers: More than 58 million users worldwide have enrolled in a MOOC. Currently, more than 220 million learners are participating in MOOCs worldwide (A Decade of MOOCs, 2021). The widespread popularity of MOOCs is also evident from the fact that more than 700 prestigious universities participate in them and offer a variety of courses accessible through platforms such as Coursera, edX, and Udacity. The wide availability of MOOCs signifies a shift in educational approaches that emphasizes the democratization of knowledge and promotes a culture of continuous, lifelong learning (Shah, 2016). Individuals can use these courses to learn new skills, enhance their understanding, and foster professional development according to their preferences (Zhenghao et al., 2015).

A key aspect of MOOCs is the inclusion of communication platforms, particularly discussion forums. These forums facilitate interaction between learners and instructors, as well as peer-to-peer exchanges (Zhang, Chen, & Phang, 2018). These forums play an important role in supporting different learning approaches that shape the educational experiences of MOOC participants. Moreover, these forums serve as a valuable channel for students to articulate their questions and urgent concerns (Feng, Chen, Zhao, Chen, & Xi, 2015). However, considering the substantial quantity of MOOC participants and the limited number of instructors, it poses a challenge to effectively track and respond to students' posts and questions. Quick responses to important posts are often necessary to help students overcome obstacles during their learning journey. Failure to provide timely feedback can lead to learner frustration and increase dropout rates (Hone & El Said, 2016). Therefore, it is necessary to develop mechanisms that differentiate urgent posts and ensure that they receive immediate attention and response from instructors (Almatrafi, Johri, & Rangwala, 2018). Implementing an effective system for monitoring and handling urgent posts would allow instructors to give precedence to their responses and effectively handle the overwhelming volume of submissions. This system would not only optimize instructors time and attention, but also empower them to devote more energy to promote community engagement and provide valuable support (Almatrafi et al., 2018).

On the other hand, model generalization, which denoting the ability of a machine learning model to respond accurately to unseen data, is a critical aspect of model development (Birjali, Kasri, & Beni-Hssane, 2021). However, the presence of a generalization constraint, characterized by a significant performance difference between training data and new, unseen data, poses a significant challenge when applying machine learning models, especially in subdomains or specific contexts where training data may be limited or unavailable. In the education domain, effective model generalization is of immense importance. Educational data are inherently diverse, encompassing different subjects, learning styles, and student demographics. Therefore, models must have the ability to adapt and perform reliably in different subdomains of the education domain (Birjali et al., 2021).

By effectively closing the generalization gap, machine learning models can provide more accurate and reliable insights, recommendations, and support for learners, educators, and educational institutions. Closing this limitation contributes to the creation of personalized and tailored learning experiences, improved learning outcomes, and more effective educational interventions (Birjali et al., 2021).

Extensive research has focused on classifying MOOC forum posts into urgent and non-urgent categories. Various word representation techniques and classification approaches have been explored to develop effective models. The goal is to prioritize posts according to their urgency. In (Almatrafi et al., 2018, Agrawal, Venkatraman, Leonard, & Paepcke, 2015, Chang, Lee, Wu, Liu, & Liu, 2021), statistical techniques like term frequency (TF), inverse document frequency (IDF), and term frequency-inverse document frequency (TF-IDF) were employed to represent words. However, they neglected the meaning of word order (Xue, & Chen, 2022), which led to a limitation in capturing the document context. These studies used conventional classification algorithms like SVM and Nearest Centroid, which require low computational effort but have poor performance because they often rely heavily on manual feature selection (El-Rashidy, Farouk, El-Fishawy, Aslan, & Khodeir, 2023).

Studies (El-Rashidy et al., 2023; Sun, Guo, Gao, Zhang, Xiao, & Feng, 2019; Guo, Sun, Wang, Gao, & Feng, 2019; Khodeir, 2021) have used pre-trained models like Google News and Glove to represent words with dense vectors that capture their contextual meaning within the document (Almeida, & Xexéo, 2019). These studies used different architectures including multiple CNNs, CNN aggregation, GRU, and attention layers to develop their models. They emphasized on including additional representational features, choosing effective features, and assigning higher weight to the most important features. However, none of these studies addressed the problem of imbalanced datasets, which can affect classification performance and lead to bias toward larger classes (Wei, & Zou, 2019; Guo, Yin, Dong, Yang, & Zhou, 2008).

Improvements in the classification of imbalanced datasets have been classified into five categories: Data, Algorithms, Cost-Sensitive, Feature Selection, and Ensemble Approaches (Ramyachitra, & Manikandan, 2014). In this study, we specifically address the data level by focusing on techniques for balancing text datasets. Common data-level methods include re-sampling to adjust the number of samples in the dataset. Oversampling involves adding samples, usually by copying samples, while under-sampling involves removing samples, often by random selection. While these methods have shown some effectiveness in data matching, they are not sufficient to completely solve the problem at hand (Branco, Torgo, & Ribeiro, 2016).

We employed BERT -based data augmentation (DA) to solve the data balancing problem (Kumar, Choudhary, & Cho, 2020). Data augmentation stands as a commonly employed method for increasing the scale of training data. This approach significantly contributes in mitigating overfitting and improving the robustness of machine learning models, especially for tasks with limited data availability (Kumar et al., 2020). Moreover, we employed BERT model as the embedding layer, fine-tuned by a novel hybrid deep learning approach, combining Convolutional Neural Network (CNN) and Bidirectional Long Short-Term

Memory (BiLSTM) layers. We named this hybrid model Convolutional BiLSTM (CBiLSTM), which enables an effective and precise classification of urgent posts. In CBiLSTM, the CNN layers effectively handle the high dimensionality of input texts, and BiLSTM layers explore feature context bidirectionally. The outcomes illustrate that CBiLSTM outperforms conventional deep learning models commonly utilized for urgent post classification using widely recognized Stanford MOOCPost Corpus defined in (Almatrafi et al., 2018). Key contributions of this paper include:

1. To tackle with data imbalance, we employ BERT-based data augmentation technique to balance the training dataset. This technique significantly enhances the model's performance and generalization, crucial for accurate classification in imbalanced scenarios. Our study is the first to employ BERT-based data augmentation for dataset balancing purpose in MOOC context.
2. To leverage the power of contextualized embeddings, we adopt the BERT pre-trained model as an embedding layer. By utilizing BERT's language understanding capabilities, our model gains deeper insight into the context and semantic meaning of the input text, resulting in more accurate and context-aware representations.
3. Proposing CBiLSTM, a hybrid model that integrates the power of CNN and BiLSTM. This fusion enables our model to extract local features with CNN by analyzing spatial relationships within the data, while effectively capturing long-term dependencies with BiLSTM. The combination of these two architectures allows our model to produce more accurate and robust predictions.
4. Our approach achieves better results for the classification of urgent posts in MOOCs using the Stanford MOOC Posts dataset, surpassing existing methods.

2. RELATED WORK

In the field of online education, MOOCs have become the most popular choice as they provide students from all walks of life with a flexible and accessible learning experience. With the ever-growing number of participants in MOOCs, discussion forums have become important centers for communication, knowledge sharing, and collaborative learning (Liyanagunawardena, Adams, & Williams, 2013). Nevertheless, the abundance of student contributions in these forums poses a significant challenge for instructors to respond on time, especially when urgent questions or concerns arise.

Consequently, researchers have focused to the classification of urgent posts within MOOC discussion forums to enhance the effectiveness and efficiency of instructor-learner interactions. Here we aim to review existing research in this area and examine various methods and approaches for classifying and prioritizing urgent posts in MOOC environments. MOOC post classification employs both traditional machine learning and deep learning algorithms (Guo et al., 2019).

In their study, (Almatrafi et al., 2018) employed metadata, linguistic features, and traditional machine learning algorithms to identify urgent posts in MOOCs. AdaBoost classification algorithm provided the better results. (Bakharia, 2016) developed a comprehensive classification model considering the dimensions of urgency, sentiment, and confusion in different domains. However, this work is still in its early stages and is not sufficiently generalizable in classifying urgent posts because it gives good results within specific courses or domains but is difficult to generalize across different domains. (Feng, Liu, Luo, & Liu, 2017) performed an analysis of over 100,000 discussion posts on Coursera. They used linear regression in combination with a Gradient Lifting Decision Tree (GBDT) to classify MOOC discussion posts. In particular, this model uses features that are independent of course content and achieved an impressive overall accuracy of 85%. (Wei, Lin, Yang, & Yu, 2017) employed a convolutional LSTM-based deep neural network to classify confusion, urgency, and sentiment in MOOC discussion forums. They learned word-level feature representations through convolutional operations, followed by learning post-level representations through an LSTM model that captures long-term temporal semantic relations. Their approach achieved an impressive 86.6% accuracy in classifying urgent and non-urgent posts.

(Guo et al., 2019) employed a hybrid deep neural network to detect urgent posts in MOOCs using pre-trained embeddings from Google News. To handle spelling errors and emoticons, they introduced a hybrid model using CNN, GRU, and Char-CNN for semantic and structural extraction. In their study, (Agrawal et al., 2015) developed a classification model to detect confusion and suggests optimal start times for video clips. The model utilized features such as bag-of-words, post metadata, and predictions for question, answer, opinion, sentiment, and urgency labels. Training was performed using standard logistic regression and for confusion label the model achieved F1-score of 77%. In other study, (Cui, & Wise, 2015) employed a binary support vector machine (SVM) to determine the relevance of question posts to course content.

Khodeir (Khodeir, 2021) utilized BERT for embedding and Bi-GRU for classification task. This model obtained 91.9% weighted F1 value. However, the proposed solution showed limited improvement, with an accuracy of 81.2% for the urgent message class, suggesting that the model is not able to effectively identify urgent messages. In a recent study, (El-Rashidy et al., 2023) introduced a four-stage model that includes coding and vectorization using pre-trained BERT, a feature aggregation method to capture data-based relationships, a CNN-based model for improved text understanding, and classification of post text using composite features. Although this approach yielded a slight improvement of 0.8% over the previous results, further improvements are needed to enhance the accuracy of the urgent class.

Article 2:

INTRODUCTION

In the realm of education, the value of student feedback has long been recognized as a vital tool for assessing the quality of instructional processes and improving overall learning experiences. Traditional educational institutions often rely on periodic surveys to gather student perspectives, seeking insights into the effectiveness of course delivery, instructor performance, and the achievement of learning objectives (Paufler, & Sloat, 2020). These surveys, typically conducted at mid-term or end-term intervals, provide quantitative data that can be analyzed statistically and can contribute to the ongoing improvements in educational practices. Over the years, the rise of online learning, particularly through Massive Open Online Courses (MOOCs), has brought a transformative shift in the dynamics of student feedback. The scalability and accessibility inherent in MOOCs attract a diverse global audience which result a need for innovative approaches to feedback collection and analysis (Chaturvedi, Goldwasser, & Daumé, 2014). While the traditional model of surveys remains applicable, the sheer volume of participants in MOOCs, often with high student-to-teacher ratios, demands more efficient and real-time feedback mechanisms. Within the MOOC ecosystem, discussion forums serve as dynamic spaces where learners engage in meaningful interactions, share experiences, and seek assistance (Stephens-Martinez, Hearst, & Fox, 2014). These forums, embedded in the MOOC infrastructure, play a pivotal role in shaping the learning environment. However, the decentralized nature of these interactions presents a challenge in harnessing the wealth of unstructured data generated by student posts, limiting the ability to extract meaningful insights (Zhang, Chen, & Phang, 2018). While these forums offer a rich source of information, a significant challenge involves efficiently extracting and classifying urgent student questions, a crucial aspect that has been overlooked in prior researches.

The need for effective MOOC feedback analysis becomes paramount in the face of reported attrition rates and the challenges posed by questionnaire biases (Pena, & Melgar, 2015). Real-time monitoring and comprehension of student feedback are crucial for reducing disengagement and providing instructors and course designers with actionable insights for course improvement (Kizilcec, Piech, & Schneider, 2013). Prior research has explored the analysis of MOOC feedback, revealing shortcomings in traditional methods like surveys and closed-ended questions, which struggle to capture the depth of student sentiments (McDonald, Moskal, Goodchild, Stein, & Terry, 2020). However, the potential lies in the unstructured data within discussion forums, where students freely express their thoughts, opinions, and, significantly, urgent questions that demand immediate attention.

In the existing literature, the specific task of urgent question extraction within MOOC feedback analysis remains notably absent. While previous studies have classified posts into urgent and non-urgent categories, none have focused specific on identifying urgent student questions. It's noteworthy to emphasize that within the broader category of urgent posts, there is a substantial amount that includes not only immediate inquiries but also valuable student answers, opinions and suggestions. Recognizing this, the efficient extraction of urgent questions becomes even more critical, ensuring prompt responses to address learners' immediate concerns (Almatrafi, Johri, & Rangwala, 2018). The need of urgent question extraction is paramount in MOOCs due to the huge number of participants and limited instructor resources. Timely identification and response to urgent questions are crucial for student engagement, satisfaction, and ultimately, course completion rates. Moreover, previous studies often face limitations in capturing the contextual meaning of words and addressing imbalanced datasets, hindering their effectiveness in distinguishing urgent posts that demand immediate attention.

Recently, the dropout rate has become a significant concern in the MOOC context (Talebi, Torabi, & Daneshpour, 2024). Previous studies highlighted the correlation between active forum participation, successful question answering, and reduced dropout rates (Alario-Hoyos, Pérez-Sanagustín, Delgado-Kloos, & Munoz-Organero, 2014; Breslow, Pritchard, DeBoer, Stump, Ho, & Seaton, 2013; Rosé, Carlson, Yang, Wen, Resnick, Goldman, & Sherer, 2014). This underscores the importance of extracting urgent questions and providing timely answers to student queries which can boost retention, engagement, and, importantly, help decrease the dropout rates. We propose BERT-based hybrid multi-output deep learning model named CBiGRU, explicitly designed to extract and classify urgent student questions within MOOC discussion forums. The proposed model is the combination of Convolutional Neural Network (CNN) and Bidirectional Gated Recurrent Unit (Bi-GRU) layers. In CBiGRU model, the CNN layers effectively handle the high dimensionality of the input texts, and Bi-GRU layers explore feature context bidirectionally. CBiGRU not only distinguishes questions from non-questions but also provides a nuanced classification based on urgency, ensuring timely and targeted support for learners. The key contributions of our paper include:

1. We propose CBiGRU, a BERT-based multi-output hybrid deep learning model to extract urgent student questions from MOOC discussion forums.
2. The first research paper in the education domain, particularly within the context of MOOCs, to extract and classify urgent student questions.
3. Implementation of BERT-based data augmentation technique to address dataset imbalance and enhance the model's ability to generalize across diverse educational contexts.
4. Employing BERT for contextualized embedding which capture the contextual meaning of words within the MOOC forum discussions.
5. Helping instructors, course designers, and policymakers to enhance decisions on course participation, and improvement, with a focus on urgent student concerns.

RELATED WORK

In the realm of MOOCs and their discussion forums, substantial research has been conducted to extract valuable insights from user-generated content. The focus of these studies ranges from student sentiment analysis to urgent post classification and to the more nuanced aspect of opinion and suggestion mining. While existing literature has made significant strides in understanding and categorizing user contributions, a notable gap exists in the specific context of urgent question extraction within MOOC discussion forums. Several studies have focused into urgent post classification within MOOCs, each contributing unique insights. Almatrafi and his co-authors (Almatrafi et al., 2018) addressed this challenge by utilizing metadata, linguistic features, and traditional machine learning algorithms, with AdaBoost produced a better result. (Bakharia, 2016) proposed a model to classify posts by urgency, sentiment, and confusion in different domains. However, this model is not very general and works well only for specific courses or domains. (Feng, Liu, Luo, & Liu, 2017) conducted an extensive analysis of discussion posts on Coursera. They used linear regression and Gradient Lifting Decision Tree (GBDT) to classify MOOC discussion posts. The proposed model is independent of course content and achieved an impressive overall 85% accuracy. Wei and his colleagues (Wei, Lin, Yang, & Yu, 2017) employed a convolutional LSTM-based deep neural network to classify confusion, urgency, and sentiment in MOOC discussion forums. They learned word-level features with convolutions operations and captured long-term semantic relations in posts through LSTM layers. The proposed model obtained 86.6% accuracy in classifying urgent and non-urgent posts and showed the potential of deep learning models. Guo et al. (Guo, Sun, Wang, Gao, & Feng, 2019) introduced a hybrid deep neural network using pre-trained embeddings from Google News to detect urgent posts in MOOCs. The model handled spelling errors and emoticons, and emphasized semantic and structural extraction. Agrawal and his co-authors (Agrawal, Venkatraman, Leonard, & Paepcke, 2015) proposed a classification model to identify confusion and recommend optimal start times for video clips. The paper leveraged features like bag-of-words, post metadata, and made predictions across various labels. Furthermore, (Khodeir, 2021) utilized BERT for embedding and Bi-GRU as classification algorithm and obtained 91.9% weighted F1 score. The paper demonstrated the effectiveness of advanced embedding techniques but highlighted the need for further improvement in accurately identifying urgent posts. In a recent study, El-Rashidy and his co-authors (El-Rashidy, Farouk, El-Fishawy, Aslan, & Khodeir, 2023) presented a four-stage model which incorporated pre-trained BERT model as an embedding layer, a feature aggregation method, a CNN-based model, and classification of urgent posts using composite features. The model enhanced text understanding and classification accuracy.

In the realm of opinion and suggestion mining, Almatrafi & Johri (Almatrafi, & Johri, 2022) analyzed MOOC discussion forum posts to summarize participants' opinions and identify suggestions for improvement. The study utilized sentiment analysis and rule-based techniques. This study marked a significant step forward in understanding participant opinions and extracting aspect-based suggestions, particularly in the educational context. Macina and her co-authors (Macina, Srba, Williams & Bielikova, 2017) suggested routing questions to willing and knowledgeable participants. They noted that certain MOOC questions necessitate instructor responses. Cui and Wise (Cui, & Wise, 2015) employed a binary support vector machine (SVM) to determine the relevance of question posts to course content. The paper obtained that only a small proportion (28%) of the learners' questions were content-related.

Despite these notable contributions, the literature reveals a substantial gap concerning the extraction and classification of urgent questions within MOOC discussion forums. Urgent questions are a unique subset of forum interactions and require immediate responses to address learners' immediate concerns. This paper introduces a BERT-based CBiGRU multi-output hybrid deep learning model. Unlike previous studies that primarily focused on general urgent post classification, our model is explicitly designed to extract and classify urgent student questions within MOOC discussion forums.

Article 3:

INTRODUCTION

In recent years, online learning has gained more popularity among students and educators worldwide, particularly with the rise of Massive Open Online Courses (MOOCs). MOOCs are designed to offer extensive access to open online resources on a global scale. MOOCs enroll a large number of students, and this capacity for scalable instruction is a fundamental benefit they offer (Chaturvedi, Goldwasser, & Daumé, 2014).

The collection and analysis of students' feedback regarding their learning experiences represent a foundational strategy for assessing the quality of educational processes. In the context of traditional educational institutions, the practice of mandating mid-term or end-term surveys for students is prevalent. These surveys serve the purpose of soliciting students' perspectives on various aspects, including the attainment of course learning objectives and outcomes, assessments of course organization and delivery, and evaluations of instructors' teaching styles and effectiveness. This evaluative approach empowers both educators and institutional leaders to incorporate students' viewpoints into the ongoing monitoring and enhancement of educational and learning process (Paufler, & Sloat, 2020).

Academic institutions prioritize quantitative feedback that can be easily summarized and analyzed using statistical methods. Surveys usually contain closed-ended questions, often in the form of Likert-scale items with different rating scales, in order to capture students' opinions. While free-text comments are routinely collected, they are frequently underutilized, despite their potential to offer valuable and insightful perspectives on various aspects (McDonald, Moskal, Goodchild, Stein, & Terry, 2020). Incorporating open-ended questions enables the capture of spontaneous expressions of personal feelings and perceptions, granting students a platform to voice their opinions and fostering a sense of value in their contributions. Due to high student-to-teacher ratios in MOOCs, traditional feedback methods are inefficient (Topali, Ortega-Arranz, Martínez-Monés, & Villagrá-Sobrino, 2021; Kizilcec, Piech, & Schneider, 2013). An innovative approach is needed for effective course management, including real-time monitoring of student progress and feedback analysis. Detecting and comprehending student feedback is critical, given the reported attrition rates. Real-time feedback and adjustments are valuable for reducing disengagement. Low MOOC completion rates mean final evaluations may lack representativeness, and the voices of dropouts may be overlooked. Additionally, questionnaire wording can introduce bias (Pena, & Melgar, 2015), making natural discourse or interaction is more effective for gathering student opinions.

The discussion forum within a MOOC has emerged as a promising aspect for gaining insights into course dynamics and tracking student progress (Stephens-Martinez, Hearst, & Fox, 2014). These forums enable learner-instructor interactions as well as peer-to-peer communication (Zhang, Chen, & Phang, 2018). They play a vital role in supporting diverse learning processes driven by the cognitive variances among MOOC participants. Additionally, these forums provide an essential platform for students to voice their questions and immediate concerns (Feng, Chen, Zhao, Chen & Xi, 2015). However, discussion forums have limitations due to their high volume of unstructured posts, which hinder instructors from effectively tracking and utilizing shared information to enhance learner retention and course quality. An efficient alternative is to employ computational models for analyzing and summarizing participant opinions and suggestions within these forums, enabling ongoing evaluation of course-related aspects.

Examinations of user-generated content within MOOC discussion forums reveal a multifaceted engagement: participants not only share their course experiences but also provide valuable opinions and suggestions for course enhancement. While the practice of suggestion mining has traditionally been explored within reviews and Twitter data for commercial purposes (Ramanand, Bhavsar & Pedanekar, 2010), the fundamental objective remains constant, which includes extracting and utilizing participant insights. This process not only aids brand owners in refining product iterations but also empowers consumers to make more informed purchase decisions. Furthermore, the principles of this business analytics task can be seamlessly applied to the realm of learning analytics. It serves both instructors and course designers in improving course offerings and provides actionable insights for learners and policymakers, enhancing decision-making regarding course participation and promotion. The main purpose of this study is to develop a BERT-based hybrid multi-output deep learning model named CBiLSTM tailored for the extraction of urgent student opinions and suggestions from MOOC discussion forums. The model's primary goal is to identify and classify opinions expressed by students as either urgent or not urgent. To the best of our knowledge, in education domain, particularly within the context of MOOCs, this paper is the first to introduce and implement a machine learning-based model explicitly designed for the systematic extraction and classification of student opinions and suggestions from MOOC discussion forums. The primary contribution of this paper is as follow:

1. Introducing a BERT-based hybrid multi-output deep learning model to extract urgent student opinions and suggestions from MOOC discussion forums.
2. Developing method for identifying and prioritizing student feedback within MOOC forums, particularly focusing on opinions and suggestions.
3. Creating the potential to enhance decision-making processes for instructors, course designers, learners, and policymakers regarding course participation, promotion, and improvement.
4. Bridging the gap between suggestion mining in commercial contexts (reviews and Twitter data) and its application in the educational domain.
5. Pioneering effort in the field, as the first known paper to introduce and implement a deep learning model explicitly designed for this purpose within the context of MOOCs.

RELATED WORK

In this section, we provide an overview of previous studies related to the field. Given the extensive body of work on MOOCs and MOOC forums over the past three years, our review focuses on empirical studies most pertinent to our research problem.

A fundamental component of MOOC learning support is the communication platform provided by discussion forums, facilitating interaction among teachers, learners, and peers (Zhang et al., 2018). Research on user-generated content within MOOC discussion forums reveals that participants not only share their course experiences but also express their opinions and offer suggestions for course improvement. Extracting student opinions and suggestion can help instructors, course designers and policy makers to enhance various aspects of the course and streamline the decision-making process. It can also help to find and extract the exact student's problem which causes their dropout rates, a critical concern in the field (Talebi, Torabi, & Daneshpour, 2024). The challenge of suggestion mining has primarily been examined in the context of reviews and Twitter data, with a predominant focus on commercial applications (Ramanand et al., 2010).

Ramanand et al. (Ramanand et al., 2010) addressed two challenges in opinion and intention mining: identifying 'wishes' for product improvements and for making purchases. The proposed approaches using English-language patterns are the first attempts at solving these problems. The wish detection method is most effective for texts with explicit wishes, like customer surveys, and moderately effective for electronic product reviews, but less so for banking service reviews. The approaches are effective in specific contexts but require improved datasets. Negi et al. (Negi, Asooja, Mehrotra, & Buitelaar, 2016) defined suggestion mining as identifying text that directly proposes or recommends an action or entity. They introduced the use of forum posts for suggestion mining, and their analysis showed that deep neural network algorithms outperformed SVM and rule association methods for both in-domain and cross-domain evaluations. Alotaibi et al. (Alotaibi, Malik, Khan, Batool, Alsufyani, & Alghamdi, 2021) extracted suggestions from opinionated text, utilizing the XGBoost classifier and word-embedding techniques. Their methodology achieved over 80% accuracy when evaluated on hotel reviews and Microsoft Windows App Studio discussion data. The study emphasized the importance of suggestion-related keywords and affirmed XGBoost's effectiveness in suggestion extraction.

Brun & Hagege (Brun, & Hagege, 2013) extracted suggestions for improvement from user comments. The system utilizes NLP (Natural Language Processing) techniques, including a deep syntactic parser and syntactico-semantic patterns, to analyze customer reviews and identify valuable suggestions. The system achieved F1-score of 73% on a corpus of printer reviews from the website 'Epinion'. In recent study, Laskari & Sanampudi (Laskari, & Sanampudi, 2023) proposed a novel hybrid model for fine-grained analysis of suggestions with aspect orientation for commercial purpose. They utilized two different datasets and evaluated the performance of their approach using various machine learning, neural network, and transfer learning models. The transfer learning approach outperformed others.

Almatrafi & Johri (Almatrafi, & Johri, 2022) proposed an approach that analyzes MOOC discussion forum posts to summarize participants' opinions towards different aspects of a course and identify suggestions for improvement. This is the first study which discussed suggestion mining in educational context. The study used sentiment analysis to detect participants' attitudes and rule-based techniques to identify suggestions. The results show that the approach is able to accurately identify aspect-based sentiments and suggestions related to course design elements.

The studies (Ramanand et al., 2010; Negi et al., 2016; Alotaibi et al., 2021; Brun, & Hagege, 2013; Laskari, & Sanampudi, 2023) have employed Natural Language Processing (NLP) techniques and machine learning models to extract valuable suggestions for improvement from user comments. While these studies have made significant contributions in their respective domains, there remains a noticeable gap in the research when it comes to the education domain, specifically within the context of MOOCs. However, while Almatrafi & Johri's (Almatrafi, & Johri, 2022) work represents a significant step forward in the education domain, there is still room for further exploration. One notable aspect to consider is the application of advanced machine learning techniques, such as deep learning models and transfer learning, which have shown promise in other domains. Additionally, a more fine-grained analysis of student opinions and the urgency of their suggestions can provide deeper insights into the dynamics of MOOC discussion forums. This paper presents a novel approach for opinion and suggestion mining within MOOC discussion forums. The primary advancement is the creation of a BERT-based hybrid CBiLSTM multi-output deep learning model designed to identify and classify urgent student opinions and suggestions.