Anticipating Tutoring Demands Based on Students' Difficulties in Online Learning

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Abstract. Anticipating the tutoring needs in online learning is essential to provide adequate support to students. Feedback and even silence are valuable clues to reveal the level of engagement. Approaches based on Artificial Intelligence (AI) can process this information and alleviate the workload of human tutors. In this study, Natural Language Processing (NLP) techniques were used to assess the performance of classifying students' difficulties in an Educational Social Network. Difficulties were classified into categories such as "personal", "technical", and "others". The model's performance allows you to anticipate and direct tutoring.

Keywords: Human Tutors · Students · Natural Language Processing (NLP) · Interactions · E-Learning

1 Introduction

Student engagement in online learning can be affected by various difficulties [1, 2], highlighting the importance of identifying these challenges early to better direct tutoring activities. In this context, one of the responsibilities of human tutors is to establish contact to gather information that helps understand the difficulties students face [3]. By analyzing responses, it's possible to find reasons behind student disengagement in the teaching-learning process. However, it's challenging for human tutors to scale their tutoring efforts, especially in educational contexts with many students. The absence of an instructor and the feeling of being alone can create difficulties for students in online learning [4].

To efficiently and broadly handle student demands, it's necessary to adopt approaches that allow for individualized attention. A promising approach is the application of Natural Language Processing (NLP) techniques in the field of Artificial Intelligence in Education (AIEd) [5, 6]. In this study, these techniques can be used to classify different types

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of difficulties reported by students in virtual learning environments mediated by Educational Social Networks (ESN). Additionally, incorporating Intelligent Tutoring Systems (ITS) features can assist human tutors in handling a large volume of information about student engagement. Therefore, this article emerges in response to these challenges, motivated by the need to cooperate with tutors to promote more effective tutoring, and is guided by the following question: 'How can the difficulties faced by students in online learning, with interactions mediated in an Educational Social Network environment, be supervised and classified?

In the context of this article, a Natural Language Processing (NLP) component was developed to supervise and classify the difficulties faced by students in online learning, with interactions in a virtual Educational Social Network (ESN) environment. Through data analysis, a model was trained to identify patterns in student responses regarding difficulties, mainly in "personal", "technical", and "others" situations. Proper identification and classification of student difficulties is a crucial step in providing personalized and relevant tutoring, assisting in the learning process, and individual student monitoring.

The article is structured into four additional sections: Sect. 2 discusses related works, Sect. 3 describes the methodology used, including techniques and procedures, Sect. 4 presents the results, and Sect. 5 concludes with final considerations.

2 Related Works

Natural Language Processing (NLP) approaches are being used to create content and personalize instructional materials [7]. In Intelligent Tutoring Systems (ITS), they are applied in conversational dialogues [8] to understand student needs. In the context of online learning (e-learning), NLP allows for conversation analysis, identifying patterns in various situations. By analyzing phonology, grammar, semantics, and context, dialogue formation models can generate content, personalize instructional materials [7], identify sentiments in social network contexts [9], and classify comments, responses, and discussions to monitor student engagement. Liu et al. [10] explore student engagement through discussions on how they learn and understand content, as well as self-regulation strategies and perseverance in learning. The authors used mapping of student interest in subjects, satisfaction, and seriousness in following didactic activities. Although NLP is promising for deciphering collected textual information and highlighting the subjectivity of student difficulties, approaches that contribute to human tutoring are necessary, as learning difficulties may present in a social dimension where only interaction and the desire to communicate can reveal them.

3 Method

To identify and classify the difficulties that discourage students in online learning, monitoring was conducted during periods of school activities mediated by virtual environments. Understanding how human tutors identify student difficulties was key to proposing strategies using NLP techniques intertwined with the interdependent network of interactions between tutors and students in the virtual environment. It was investigated whether human tutors used specific approaches to understand student difficulties, and whether these approaches left recurrent clues in interactions that could be used for classification. This classification was crucial to identify factors that demotivate students in virtual environment interactions. Initially, understanding the instructional design of human tutors' interactions with students was necessary.

3.1 Study Context

The role of tutors in the design of online instructional content can create an interaction framework that directly impacts the identification of student difficulties. The interaction between human tutors and students can offer insights and patterns that assist in classifying these difficulties. This study focused on online learning for micro and small businesses, particularly in the metropolitan area of Recife, Pernambuco, Brazil, covering various thematic courses: The course "*Trilha: Como posso inovar?*" had 588 students, 3 tutors, and 1 teacher, focusing on how current innovation strategies can benefit businesses. "*Canvas You: Meu Modelo de Negócio Pessoal*" with 69 students, 2 tutors, and 1 teacher, outlined ways to reinvent careers, overcome obstacles, find new opportunities, and deliver value to clients. "*Como a Disrupção Pode Afetar o seu Negócio - Minicurso Online*" (132 students, 2 tutors, 1 teacher) explored strategies for dealing with technological innovations, consumer trends, and breaking market conventions and paradigms. "*Novos Comportamentos de Consumo - Minicurso Online*" (702 students, 3 tutors, 1 teacher) focused on understanding current consumption patterns, connecting with consumers, and ensuring the survival of micro or small businesses. "*Strategic Planning for Entrepreneurs*" (1105 students, 6 tutors, 2 teachers) focused on developing business strategies, vision, mission, objectives, and competitor analysis. "Digital Marketing for the Entrepreneur" (1340 students, 5 tutors, 2 teachers) aimed at reaching new customers in increasingly digital consumer markets. "*How to Develop High-Performance Teams*" (257 students, 2 tutors, 1 teacher) emphasized individual skills and innovative approaches to employee performance. "*Financial Strategy for Growth*" (897 students, 3 tutors, 1 teacher) concentrated on building a future vision for micro-businesses.

3.2 Data Collection and Analysis

The courses encompassed a diverse audience, but primarily women entrepreneurs with elementary and high school education levels. They helped build skills in leadership, communication, entrepreneurship, understanding consumer behavior, business models, customer understanding, finance, digital positioning and presence, business purpose, marketing, product validation, networking, digital-era finance, and advertising on Facebook and Instagram, among others. In this context, human tutors, among other activities, analyzed student completion percentages and collected responses to standardized messages in "*Active Search*" efforts by students, recording them in a spreadsheet (Fig. 1, screenshot of the tutor's spreadsheet template), during the monitoring period from December 2022 to May 2023, to understand the difficulties that were disengaging the students.

On a monthly basis, verification and qualification of reasons were conducted. The collection of module completion percentages allowed for weekly interactions every Monday, sending targeted messages to students whose module completion performance was below 75%. In addition to this message collection phase, steps were also taken to

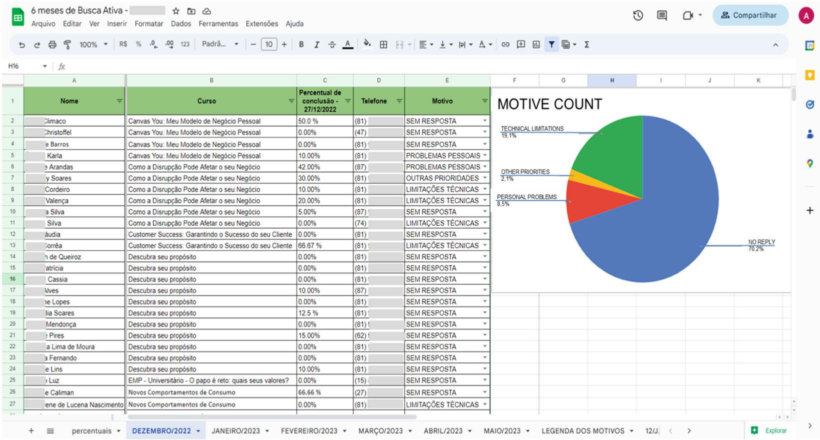

Fig. 1. Spreadsheet - Student "Active Search" Cycle.

analyze and define the NLP model (Fig. 2). The message collections corresponded to the responses of students to the messages sent by human tutors, which served as a data source for the analyses. Each message was labeled based on the joint perceptions of the human tutors and served as a source for the systematic analysis approach using NLP techniques. Section 4 presents the classification resulting from this stage of the study.

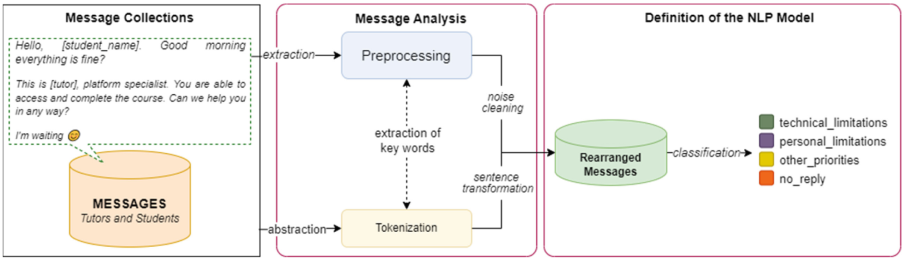

Fig. 2. Flowchart of data collection, analysis, and model definition for the analysis of tutoring messages and classification based on different types of difficulties.

The message analysis flow (Fig. 3), with the application of NLP techniques, involved text preprocessing through fundamental steps to prepare the data for analysis. These steps included removing unwanted information such as special characters, emoticons, excessive punctuation, and stop-words. After preprocessing, the text was tokenized using the Tokenizer library[1]. This step involved transforming sentences into sequences of tokens, which could be words or parts of words, limited by a vocabulary defined by the parameter num_words = 500. To feed the data into a Neural Network model, it was necessary to ensure that all token sequences had the same length. To achieve this, the

[1] https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/text/tokenizer

pad_sequences function was used, which adjusted the length of sequences by filling them with zeros when necessary.

3.3 Definition of the NLP Model

The model choice took into consideration current approaches used in Natural Language Processing (NLP). Some of these approaches include: Convolutional Neural Network (CNN), used for the discovery and recognition of patterns in textual elements [11]; Recurrent Neural Network (RNN), with feedback mechanisms that enable the retention of previous information when processing subsequent inputs; and Feedforward Multi-Layer Perceptron (MLP), with the capability to work with multiple layers for classification problems, considering the Long Short-Term Memory (LSTM) technique, which allows for the processing of input sequences and the recall of relevant information at different time steps [12].

In an experimental approach, a classification model based on word sequences (Keras Sequential) was used, with parameter variations, to find the best configuration for classifying students' difficulties based on the messages received from human tutors. Parameter variations involved tests on: Three different sizes (embedding_size = [64, 128, 256]) for the word representation vector (embedding). Three different quantities (lstm_units = [64, 128, 256]) of LSTM units, to capture context information in word sequences. Three dropout rates (dropouts = [0.2, 0.3, 0.4]) for regularization to help prevent overfitting by randomly deactivating a fraction of units during training. Three different optimizers (optimizers = ['adam', 'rmsprop', 'sgd']) to define how the model's weights would be updated during training in the quest to minimize the loss function.

Ultimately, the Dense layer had 3 neurons with sigmoid activation, indicating classification into three classes (representative of the types of difficulties: technical, personal, and others). During the execution of parameter variations, the model was built, trained, and evaluated using training data (80%) and test data (20%) with the Scikit-learn train_test_split function. The resulting accuracy in each iteration was compared to the best accuracy obtained previously, and if it was higher, the current parameters were updated as the new best-identified configuration. In the end, the best parameter configuration found was adopted for the subsequent analyses in this study, serving as the combination that maximizes the NLP model's performance in classifying students' difficulties. Section 4 presents the results of the analyses.

4 Results

In this section, the main results are presented regarding how human tutors actively sought interactions with students, mapped and classified the types of difficulties, providing information about the strategies and the overall performance of the NLP model.

4.1 "Active Search" by Students

The "active search" involved direct contact between tutors and students, allowing for individualized tutoring. Over a six-month observation period, tutors contacted 206 students from different courses. Among these, 101 students did not respond to the contact and were classified as “unresponsive” while a total of 105 students responded to the tutors’ outreach. The difficulties faced by students who responded to the tutors’ contact were classified into categories: “technical”, “personal”, and “others”. The quantities and trends of these difficulties occurred as follows (Fig. 3).

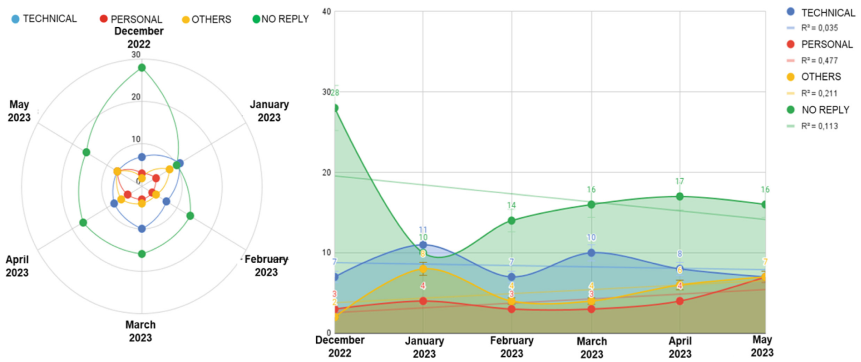

Fig. 3. Frequencies by types of difficulties classified over the course of the six-month monitoring period of human tutor activities.

When extracting messages from the students, there were responses that allowed human tutors to make inductive classifications of “technical”, “personal” and “others” difficulties. Table 1 presents a selection of messages (verbatim as received), highlighting words or phrases used to classify students’ difficulties.

Explored visually, word frequencies were obtained for each type of difficulty (Fig. 4). This allowed for the identification of specific words in the textual content of messages classified as “technical” difficulties which included words related to the platform, challenges in accessing it, availability of resources, and the level of familiarity with technologies, as well as perceptions regarding platform usage. In messages classified as “personal” difficulties, the presence of words related to the course itself and the use of personal pronouns was observed, which is essential for understanding the subjective dimension of students’ engagement regularly and without the need for assistance. On the other hand, in messages classified as “others” difficulties, there was a frequency of words related to what students would like, including elements related to other interests, courses, and individual priorities.

In this sense, conceptually (Fig. 5), it is understood that technical difficulties may be related to digital literacy, with issues related to the use of tools and technological resources in the learning environment. Personal difficulties are related to autonomy and well-being, involving emotional aspects, motivation, organization, and autonomy. Difficulties classified as “other” refer to prioritization, encompassing difficulties that do not fit into the previous categories, such as prioritizing other activities, courses, and individual preferences. In cases of “no response”, it is not possible to explicitly identify the difficulties.

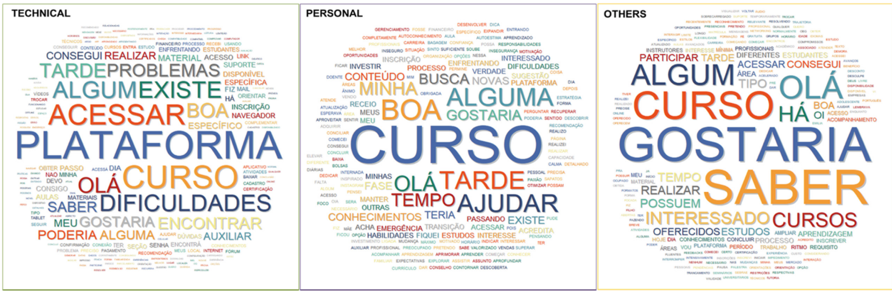

Fig. 4. Most frequent words in each type of difficulty.

Table 1. Selection of messages returned by the students.

#	Mensagens dos estudantes	Classe
1	***Estou sem computador***. *No celular tá bem ruim de navegar. Poderias me auxiliar* ***com passo a passo***?	technical
2	*Oi, [tutora]. Estou fazendo alguns seminários do [ambiente] já,* ***por isso não acessei****, mas vou.*	other
3	*Boa tarde! Tudo bem! Consegui sim, como ele é bem detalhado* ***fiquei sem tempo*** *de assistir com calma sabe. Mas pretendo concluir*	personal
4	*Sim.* ***Só não tive tempo*** *para concluir o curso*	other
5	*Sim consegui acessar normalmente. Porém,* ***sem tempo***.	other
6	*Oi [tutora]. Sim, consegui acessar! Por enquanto, tudo certo. Mas estou tendo* ***other*** *demandas*	other
7	*Eu me inscrevi em 4 cursos.* ***Consegui realizar só 2***.	other
8	***Ainda não***. ***Me passa o link para entrar***. ***E o passo a passo***	technical
9	*Oia boa tarde. Qual será o horário da aula por que* ***estou na emergênciafea***	personal
10	*Olá!* ***Consegui*** *visualizar sim.*	other
11	***Consegui ainda não***. *Mas quero conseguir.* ***Não sou familiarizada com tecnologia***	technical
12	***Não consegui acessar***	technical
13	*Eu* ***não consigo acessar*** *a página do [ambiente] Pois a confirmação do* ***e-mail*** *Pra trocar a* ***senha*** *não chega*	technical
14	*Bom dia!* ***Querida como faço***?	technical

(*continued*)

Table 1. (*continued*)

15	*Bom dia [tutora], quando eu tiver eu com **tempo livre eu acesso** sim ,obg*	other
16	*Bom dia! **Estou começando hoje o curso**. Com fé em Deus*	other
17	*Oi [tutora]! Vou bem e você? Bom [tutora] estava resolvendo algumas **pendências personal** antes de começar, acredito que ainda hoje eu entre.*	personal
18	*Boa tarde, eu **não consegui acessar a plataforma** Não sei como entra.*	technical
19	*Oi Foi sim, **não lembrava mais** Como faço?*	other
20	*Ola boa tarde Eu **não consigo fazer o acesso***	technical
21	*Sim realizei. Nenhum impedimento além do **tempo mesmo pra poder acessar**.*	other
22	*Não consegui acessar nao. **Nao entendo como mexe** Bom dia*	technical
23	*Bom dia! Ainda não realizei o acesso na plataforma, pois **fiquei doente** Como realizo*	personal
24	*Tem uma plataforma específica do [ambiente]? **Como entra**?*	technical
25	*Bom dia E porque o **imel** que cadastrei **perdi e não conseguir recupera** lo*	technical
26	*Bom dia. **Não consegui acessar**. Pode sim me **ajudar** 🙏*	technical
27	*Fiz para me inscrever em uma palestra, ja vi ela. Mas **não tive mais interesse**.*	other
28	*Olá [tutora], boa tarde! Tudo bem, obrigada por perguntar. Eu fiz a inscrição e na verdade não soube bem o que era. Permine não entrando mas. Eu tenho uma página no Instagram que vendo bolsas e sapatos, **pensei** que fosse alguma coisa ligada a vendas. Deixei de lado estou se **concentrado no meu trabalho**.*	personal
29	*Olá [tutora], estou tendo **dificuldades para acessar a plataforma**. Parece que minha senha não está funcionando. Você poderia me ajudar a redefinir?*	technical
30	***Não consigo acessar** a plataforma desde que mudei meu endereço de e-mail. Pode atualizar meus detalhes?*	technical
31	*Eu tentei **baixar** o **aplicativo** no meu tablet, mas não consegui. Existe uma versão para tablet?*	technical
32	*[tutora], eu comecei um **novo trabalho** recentemente e estou um pouco **sobrecarregado**. Mas quero muito voltar em breve, posso?*	other

(*continued*)

Table 1. (*continued*)

33	*Olá, [tutora]. A **conexão** com a **internet** no meu local é muito fraca, e isso torna difícil acessar a plataforma. Tem app?*	technical
34	*Tive uma **emergência familiar** e não pude acessar a plataforma, **minha mãe ficou internada** esse tempo todo e tive que ficar com ela.*	personal
35	*Na verdade, eu comecei a acessar o curso, mas o conteúdo **não era o que eu esperava**. Você tem other opções que possam me interessar?*	personal
36	***Não** to **conseguindo acessar** com minha **senha** do **email**, oq faço?*	technical
37	*Estou focada em **outros** estudos no **momento**, mas pretendo acessar a plataforma assim que possível.*	other
…	…	…

Note: # - message enumeration; class - type of difficulty assigned by human tutors; ... - continuation; bold - main words or phrases observed by human tutors in the classification.

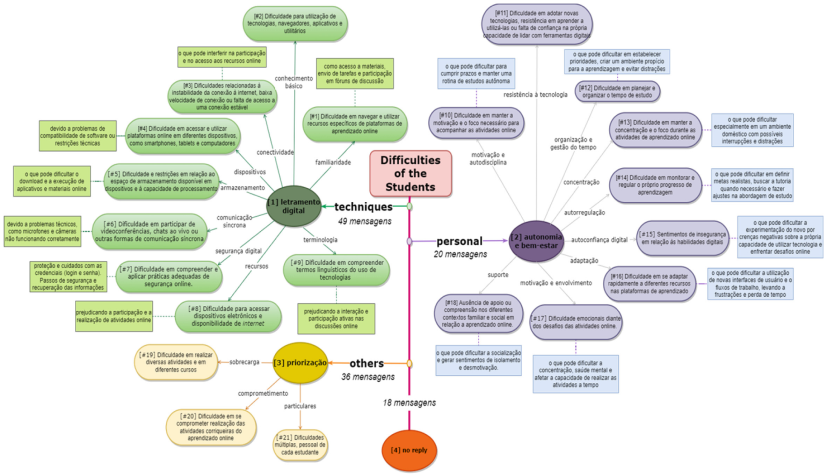

Fig. 5. Conceptualization of the types of student difficulties identified from interactions with human tutors in online learning.

The messages returned by the students and the categorization of types of difficulties carried out by human tutors allowed for the adoption of supervised NLP learning approaches. The following section presents the results of the application of the NLP model, where students' responses are input elements and types of difficulties are classes (Sect. 4.2).

4.2 Classification of Difficulties

The subsequent analyses were conducted based on the best parameter configuration for the NLP model (Fig. 6). A sequential approach was adopted, wherein the parameters of the best-tested configuration were assigned as follows: an embedding layer with 5000 units, a vector of size 256, and an input length equal to the number of columns in X; an LSTM layer with 256 units, a dropout rate, and recurrent dropout of 0.3; a dense layer

```
# Algorithm for message analysis
# Defining the model - Sequential
# Assignment of the best identified parameter configurations:
model = Sequential()
embedding_size=256
lstm_units=256
dropout= 0.3
optimizer='adam'

# EEmbedding with 5000 units, vector size of 256, and input equal to
the number of columns of X:
model.add(Embedding(5000, embedding_size, input_length=X.shape[1]))

# LSTM with 256 units, dropout rate, and recurrent dropout of 0.3:
model.add(LSTM(lstm_unit, dropout=dropout, recurrent_dropout=drop-
out))

# CDense layer with 3 units and sigmoid activation:
model.add(Dense(3, activation='sigmoid'))

# Compile the model with binary_crossentropy loss function, Adam
optimizer, and accuracy metrics:
model.compile(loss='binary_crossentropy', optimizer='adam', met-
rics=['accuracy'])

# Splitting into training and testing data:
Y = pd.get_dummies(df['classe']).values
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.2, random_state=80)

# Training the model:
model.fit(X_train, Y_train, epochs=10, batch_size=80)

# Evaluating the model - accuracy:
print('Model Accuracy - for tutoring style:')
print(model.evaluate(X_test, Y_test)[1])
```

Nota: X - representa o vetor do conjunto de mensagens retornadas pelos estudantes; Y - representa o vetor do conjunto de tipos de dificuldades classificadas pelos tutores humanos.

Fig. 6. Resulting Best Parameter Configuration for the Model.

with 3 units and 'sigmoid' activation; compiling the model with binary_crossentropy loss function, 'adam' optimizer, and accuracy metrics; converting the class variable into one-hot encoding format and assigning it to Y; splitting X and Y into training and testing sets using the train_test_split function with a 20% test size and an 80 random state; and training the model with training data X_train and Y_train, using 10 epochs and a batch size of 80.

From the model evaluation, it can be highlighted that it performs well, with a steady decline throughout the training and validation phases (Fig. 7).

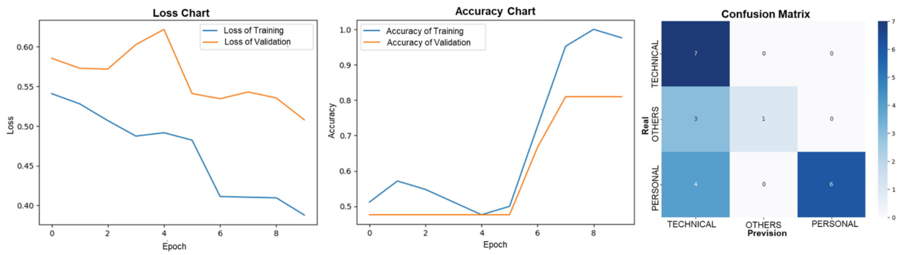

Fig. 7. Loss, accuracy, and confusion matrix of the model.

The model achieves accuracy levels (Acc) in the testing phase of approximately Acc ≈ 0.97 and in the validation phase of approximately Acc ≈ 0.81. However, it is still insufficiently capable of learning in a way that resembles the classifications made by human tutors. This becomes evident when analyzing the confusion matrix (Fig. 7), which shows the overall performance of the model in classifying students' difficulties. The approach was able to correctly classify in the validation phase (in the 20% data set, 21 messages): 7 instances as "technical", 6 instances as "personal" and 1 instance as "other". However, it made mistakes by classifying 3 instances of "other" difficulties as "technical" and 4 instances of "personal" difficulties as "technical" (Fig. 7). Therefore, it requires abstractions beyond the understanding of human tutors for accurate classification of difficulties.

5 Final Considerations

In this study, interactions between human tutors and students in the context of online learning mediated by a Learning Management System (LMS) were analyzed. The data collected through "active searching" allowed tutors to classify difficulties and served as input for the Natural Language Processing (NLP) approach analysis. The highlighted difficulties align with "technical", "personal", and "other" limitations, which suggest opportunities to enhance digital literacy, student satisfaction, and engagement with learning. Despite the overall performance of the model, it was found that the NLP approach can collaborate with the work of human tutors, enabling identification and classification of student difficulties based on messages requesting help, comments, and discussions in virtual environments. It is believed that identifying and classifying types of difficulties can help appropriately direct students to specialized tutors, recommend specific materials, or suggest peers for collaboration. However, considering that the classifications made by tutors are specific to a particular tutoring context, it is important to expand the dataset available for training and testing the classification model using data from various other online learning contexts in future work.

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References

1. Muilenburg, L.Y., Berge, Z.L.: Student barriers to online learning: a factor analytic study. Distance Educ. **26**(1), 29–48 (2005). https://doi.org/10.1080/01587910500081269
2. Panackal, N., Rautela, S., Sharma, A.: Modeling the enablers and barriers to effective E-learning: a TISM approach. Int. J. Interact. Mob. Technol. (iJIM) **16**(3), 138–164 (2022). https://doi.org/10.3991/ijim.v16i08.29455
3. Veloso, B., Daniel, M.I.L.L.: Tutoria no sistema Universidade Aberta do Brasil (UAB): uma análise dos tutores presenciais e virtuais. Revista de Educação Pública **29**, 1–17 (2020). https://doi.org/10.1111/bjet.12016
4. Pereira, A.J., Gomes, A.S., Primo, T.T., Rodrigues, R.L., Júnior, R.P.M., Moreira, F.: Learning mediated by social network for education in K-12: levels of interaction, strategies, and difficulties. Educ. Sci. **13**(2), 100 (2023). https://doi.org/10.3390/educsci13020100
5. Chen, X., Xie, H., Hwang, G.J.: A multi-perspective study on artificial intelligence in education: grants, conferences, journals, software tools, institutions, and researchers. Comput. Educ. Artif. Intell. **1**, 100005 (2020). https://doi.org/10.1016/j.caeai.2020.100005
6. Chiu, T.K., Xia, Q., Zhou, X., Chai, C.S., Cheng, M.: Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. Comput. Educ. Artif. Intell. **4**, 100118 (2023). https://doi.org/10.1016/j.caeai.2022.100118
7. Litman, D.: Natural language processing for enhancing teaching and learning. In: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 30, no. 1 (2016). https://doi.org/10.1609/aaai.v30i1.9879
8. Wang, Y., Sun, Y., Chen, Y.: Design and research of intelligent tutor system based on natural language processing. In: 2019 IEEE International Conference on Computer Science and Educational Informatization (CSEI), pp. 33–36. IEEE. (2019). https://doi.org/10.1109/CSEI47661.2019.8939031
9. Ortigosa, A., Martín, J.M., Carro, R.M.: Sentiment analysis in Facebook and its application to e-learning. Comput. Hum. Behav. **31**, 527–541 (2014). https://doi.org/10.1016/j.chb.2013.05.024
10. Liu, Z., et al.: Dual-feature-embeddings-based semi-supervised learning for cognitive engagement classification in online course discussions. Knowl.-Based Syst. **259**, 110053 (2023). https://doi.org/10.1016/j.knosys.2022.110053
11. Alrajhi, L., Alharbi, K., Cristea, A.I.: A multidimensional deep learner model of urgent instructor intervention need in MOOC forum posts. In: Kumar, V., Troussas, C. (eds.) Intelligent Tutoring Systems. ITS 2020. Lecture Notes in Computer Science, vol. 12149, pp. 226–236. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-49663-0_27
12. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Comput. **9**(8), 1735–1780 (1997)