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New data about library service quality and convolution prediction

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ABSTRACT

Library service quality, one of the key performance indicators of service qualities in universities, has been considered deeply in management strategies as part of the Fourth Industrial Revolution, especially, after the Covid-19 pandemic. We undertook a survey around universities in Ho Chi Minh City and Tien Giang University, Viet Nam focused on freshmen and sophomores to assess library service quality for improving the learning service quality. Machine learning has been deployed for predicting the library service, quality, and has been adopted successfully in depicting the assessment results. To perform the effectiveness of data, the Convolution Bidirectional Long-Short Term Memory (Conv-BiLSTM), and Convolution Bidirectional Gated Recurrent Unit (ConvBiGRU) were used. The models have illustrated appropriate performances when providing sufficient accuracy and extracting the prediction of the output.

1. INTRODUCTION

Library service quality has become of paramount importance in contributing to university quality in the digital age, especially after the COVID-19 pandemic (Ahmad & Abawajy, 2014a). Therefore, the level of service quality needs to be examined for digital service providers in demand from library service users (Ahmad & Abawajy, 2014b), (Berman, 2015). Libraries have the potential functions that could maintain the plethora of documents that serve as the key success indicators in students' educational progress and engagement (Jantti, 2016). The demand of searching for information through the COVID-19 outbreak, and service quality is needed to update the information system (IS) model and Stimulus-Organism-Response (S–O-R) model to measure the service quality (Chan et al., 2022). The personal service level is a member of quality service construed in supplying infrastructure in building management for users (Chen, 2018). There has been increasing use of libraries from abroad readers on network platforms after and through the pandemic (Chisita et al., 2022). The readers have also suggested ways to expand online services. New self-services are the things that academic services have to be equipped with criteria of electronic services to support the learning and research program in the universities (Einasto, 2014). Managers in the library are concerned about the main points: the need for access to manual services and collections, the safety of employees and patrons, new-fangled ways of working, and the library's role through the pandemic. In some cases, library leaders made new provisions individually based on the lack of time and information (Lembinen, 2023). They were determining the needs of service quality in using reader waiting time and the practical uses. Whist, many service qualities in the library, such as a connecting control system machine, self-service loan following self-return system, information desk, and even documents can be used as service facilities in a broad sense (Lyu et al., 2021).

The findings of the study about service management allowed the scholars to evaluate the geographical distribution of respondent-driven sampling of research data services including academic size centers, and activities were divided into three clusters consisting of compliance, stewardship, and transformation. The study results could be considered for the other countries and make a comparision of the suitable solutions (Nahotko et al., 2023). The Library and Information Science major is considered a new trend for digital scholarship and has been noted across the Library and Information Science (LIS) profession, especially in the academic and special research council libraries (Sibiya & Ngulube, 2023).

Machine learning has become popular in predicting the output of a model using some specific structures such as support vector machine (SVM), new robust SVM (RSVM), support vector machine with the rescaled hinge loss (RHELM), and extreme learning machine- maximum mixture correntropy criterion (ELMMMCC). A proposed method is to eliminate the correlation coefficient of less than 0.1 before applying the training model (Zhou et al., 2022). With the support of generation computer systems, data are increasing using synchronization algorithms namely Spsync (Zhang et al., 2023). The Transformer model has performed great performance in clinical image analysis, but each of them has inevitable obstacles for the convolution operation hard to evaluate the relationship between members at a certain sate and elements which is far away from the initial state in the feature route. Morevover, Transformer seems to ignore the role of current information when construing the correlation among overall elements. The suggested model comprises Encoder and Decoder. The Encoder is including of Convolutional Neural Network Layers, Feature Layers, and Transformer Encoder (Xu et al., 2023).

Big data plays an important role in prediction and contributes to the research of history, for example, the sea-level data show the changes and propensities of sea-level movement, the last records that reference the relative sea level at the present and the existing models (Shennan et al., 1995); New data collection comprising the earthworm fauna from the Sardo-Corsican system harbor including 400 specimens collected from different 19 new local regions. The new data showed the quantity of species in the region that confirms the density of the system of fauna that could be the explantion for the light of historical and ecological factors (Rota, 1992). Other data on the evolution and structure of back-arc spreading basins are established for the investigation of the mechanical interaction of the mantle wedge with the down going slab (Rodkin & Rodnikov, 1996). As we mentioned above, the scholars have been focusing on using the transformer models.

Machine learning has been adapted populously in a lot of fields of recognition and prediction, for example, using the Scikitlearn library for covid cases prediction (Maliyaem et al., 2022), and using the PySpark library for covid fatality prediction (Maliyaem & Tuan, 2022). The deep machine-learning library has been fully supported for analyzing and prediction such as LSTM, GRU, BiLSTM, BiGRU, and SimpleRNN (Tuan, 2022). Natural Language Processing (NLP) developed for connecting machines and humans deployed using deep machine learning by understanding the meaning of language has set a big step in the new technology of AI and Computer Science (Tuan & Meesad, 2021). Machine learning is deployed to understand the Vietnamese language and predict library service quality based on the data conducted the first-year and second-year students around Ho Chi Minh City after the Covid pandemic shown in Table 1. The authors have successfully applied deep machine learning in analyzing natural language in English-Vietnamese translation interconnected bilingual languages (Tuan & Meesad, 2020). The work has been expanded to deploy more models in machine learning to perform the efficiency of translation between the English language and the Vietnamese language (Minh et al., 2021; Tuan et al., 2021).

In this paper, the assessment of students about the library service quality has been used and updated every year. The main idea is to analyze the evaluation based on Vietnamese language collected from the survey (Table 2). Two models have been used to show the effectiveness of the data in the role of analysis. We establish LSTM and GRU models to perform the experimental outputs of the prediction.

2. LITERATURE REVIEWS

2.1. Machine learning

Machine learning (ML) (Tuan & Meesad, 2021) has been successfully applied and contributed to numerous areas of technology, such as natural language processing (NLP) prediction and artificial intelligence (AI). Machine learning is studied and implemented for using techniques to propose learning medical science procedures or to develop covid prediction models, for example, support vector machines (SVM), Decision Trees (DT), Boosting, Naïve Bayes (NB), and Random Forest (RF), Artificial Neural Net (ANN) and K-Nearest Neighbor (KNN) (Saleem et al., 2022). Another extension of machine learning is deep learning. Deep learning is a kind of machine learning library based on recurrent neural networks. Deep learning could be represented by specific models such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Attention Mechanism, and Pre-training of Deep Bidirectional Transformers (BERT) (Tuan et al., 2021).

2.2. Long short-term memory

Introduced by Hochreiter and Schmidhuber, LSTM is one of the kinds of RNN, that could transfer cells capable of remembering learning long-term variables (Calin, 2020). The building definition creates gates allowing information to overcome through a sigmoid function and a pointwise product.

The main functions of LSTM are related to three gates: forget, update, and output. Moreover, LSTM evolves RNN with a cell state, C_t, and connects an inside loop for its own cell. The forget gate is represented as a sigmoid function that may apply to forget irrelevant history information on Equation 1.

$$f_t = \sigma\, (W_f\, h_{t-1} {}^{+} U_f\, X_t{}^{+} b_f) \quad (1)$$

where W_f, U_f denote the matrices of the transform, b_f is a translated vector, σ represents a sigmoid function, and $f_t \in (0,1)$. The function manifests the past state that is forgotten repeated to the last state h_{t-1} consistent to the input, X_t.

2.3. Bidirectional long short-term memory

BiLSTM is also a type of recurrent neural network usually used in natural language processing. BiLSTM structure is an extension of standard LSTM, the input flows in both directions and is capable of transferring information from both sides. BiLSTM looks more powerful tool for designing models with sequential dependencies conversely between words and phrases based on directions of the sequence. In general, BiLSTM repeats one more LSTM layer, which passes reversely the direction of the information flow. BiLSTM is designed the same way as the LSTM model, but the input sequence runs backward in the additional LSTM layer.

2.4. Convolution bidirectional long short-term memory

Conv-BiLSTM (shown in Figure 3) is one of the recurrent neural networks designed for Spatiotemporal analysis and prediction where the convolution structures are established on both transitions. The Conv-BiLSTM will predict the future state by setting a grid based on the past state and local neighbor states using convolution operators shown as equations followed (Shi et al., 2015). The structures have been designed using the inputs $X_1,\ldots,X_t$, to get cell outputs $C_1,\ldots,C_t$, combining hidden states $H_1,\ldots,H_t$,, and gates i_t, f_t, o_t of the Conv-LSTM expressed in Equation 2-6.

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \odot C_{t-1} + b_i) \quad (2)$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \odot C_{t-1} + b_f\,) \quad (3)$$

$$f_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \quad (4)$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \odot C_t + b_o) \quad (5)$$

$$H_t = o_t \odot \tanh(C_t) \quad (6)$$

where ∗ represents the convolution operator, and ⊙ denotes the Hadamard product.

A combination of convolution and Bidirectional Long Short-Term Memory is patterned by a latten layer and turned into 1D output. The parameters of the Conv-BiLSTM model are represented by filters, kernel_size, padding, data_format, and activation. In this work, we used Conv1D to create a convolution kernel related to convolving the layer input to pass over a single spatial dimension and produce a form of tensor outputs. In case of choosing use_bias is True, a bias vector will be created and updated to the outputs. For choosing activation is None, the outputs will be utilized. Using this layer for making the first layer in the model, it supplies an input-shape argument transferred to the sequences of dimensional vectors.

2.5. Convolution bidirectional gated recurrent unit

In this work, we construct the model combining Convolution 1D and Gated recurrent units (shown Figure 2). The Gated recurrent units (GRUs) are performed by the reset gate r_t and update gates z_t shown by Equation (7), and Equation (8) respectively. Self-renewal states are transferred into hidden states after a sequence of linear accumulation, designed lower parameters specifically produce higher algorithm efficiency.

The GRU structure based on the information processing workflow is expressed starting from the input layer x_x^T includes input at a specific time t and length of the sequence time T. (S. Xu et al., 2019; Rahman & Adjeroh, 2019):

$$r_t = \sigma(x_t W_{xr} + h_{t-1} U_{hr} + b_r) \quad (7)$$

$$z_t = \sigma(x_t W_{xz} + h_{t-1} U_{hz} + b_z) \quad (8)$$

where W_{xr}, W_{xz}, U_{hr}, U_{hz} represent weighting parameters, b_r, b_z represent deviation parameters, and $\sigma \in [0, 1]$ is sigmoid function.

3. RESEARCH METHODOLOGY

3.1. Data preparation

This survey was construed to understand the role of the libraries for students after the COVID-19 pandemic. In 2021, the universities undertook onsite learning and the service quality needs to be prepared to serve students' requirements. Questionnaires were composed on Google form and handed out to the students around the universities, and include 3,367 responses (Table 1). Library service quality is interested in managing the scenario of numerous universities seeking a way to attract new students. The instances of the survey are also updated, and this paper derived from the data extracted on April 1st, 2023. The main attributes of the data comprised of birthday, region of residence, gender, evaluation of the library service quality (with three labels of good, neutral, and not good), the assessing explanation or detail reasons students evaluated in Vietnamese language, and other twenty-five attributes consisting of the behaviors when having a sudden luck (Thái độ của bạn khi có việc may mắn), behaviors when getting a funny event (Thái độ của bạn khi có việc đáng cười), behaviors when meeting a sudden slander (Thái độ của bạn khi bị vu khống), behaviors when having trouble (Thái độ của bạn khi gặp khó khăn), behaviors when out of money (Thái độ của bạn khi túng thiếu), behaviors when being told wicked (Thái độ của bạn khi bị mắng nhiếc), behaviors when getting advice (Thái độ của bạn khi được khuyên bảo) , behaviors about the past (Thái độ của bạn về quá khứ), religions (Tôn giáo), behaviors when cannot answer in the exam (Thái độ của bạn khi không làm được bài thi), do things good for yourself but harm someone (Thái độ của bạn khi làm việc có lợi mình hại người), do things harm yourself but good for everyone (Thái độ của bạn khi có hại mình lợi người), do things harm for oneself and someone else but good for one's family (Thái độ của bạn khi làm việc lợi gia đình có hại cho mọi người), do things good for oneself and someone but difficult (Thái độ của bạn khi có lợi cho người nhưng khó khăn), do things when meeting a beggar (Thái độ của bạn khi gặp người ăn xin), evaluate one's honesty (Tự đánh giá tính trung thực), evaluate one's morale (Tự đánh giá đạo đức), evaluate one's living condition (Tự đánh giá điều kiện sống), evaluate canteen quality (Tự đánh giá chất lượng canteen), evaluate the quality of teachers and officers (Tự đánh giá chất lượng giáo viên và nhân viên), behaviors of your major (Bạn có thích ngành học của mình không), behaviors of your university (Bạn có thích trường đại học của mình không), feeling when coming to university (Thái độ của bạn thế nào khi đi học), one's present financial situation (Tình hình tài chính hiện tại của bạn).

In this paper, the role of assessing library service quality in the situation of technology development is investigated and then improve the learning and teaching service quality. The evaluation target is chosen for prediction embracing three labels, and students' explanation in Vietnamese language where students shown the reasons for assessing service quality. The comments have been informed to students at least 15 words for the comments. The data needs to be cleaned to omit the empty instances, and 2,138 instances have been deployed for prediction. We use the tokenizer to simplify the text by deleting special characters. Some useful libraries have been used consisting of fit_on_texts, texts_to_sequences, and pad_sequences. The data has been divided into three sections with 50% for the training set, 25% for validation, and 25% for testing.

3.2. Model settings

3.2.1. Long short-term memory

LSTM has been built with 4 layers consisting of Embedding, SpatialDropout1D, LSTM, and Dense. The input value, 250, is chosen to cover the length of the text, and the output value, 64, is compatible with the values. The total parameters construed for this model is 127,630 shown in Table 3.

3.2.2. Bidirectional long short-term memory

BiLSTM is constructed with 4 layers including Embedding, SpatialDropout1D, LSTM, and Dense. The input value, 250, is chosen appropriately to the length of the comments, and the output value, 64, is chosen compatibly with the values. The total parameters increasingly construed for this model is 164,480 (see in Table 3).

3.2.3. Convolution bidirectional long short-term memory

Conv-BiLSTM is the aggregate expanded from the Long Short-Term Memory model including 6 layers. The model is built in the ordering of the Input layer, Convolution 1D, Max pooling operation for 1D temporal data, Spatial 1D version of Dropout, Bidirectional LSTM, and Dense. The values are chosen consistent with the Input value, 250, and the Output value, 32. The parameters have been apparently reduced to 82,304 (Table 3).

3.2.4. Convolutional Bidirectional Gated Recurrent Unit

Conv-BiGRU (Figure 7) has been provided as the combination extended from the LSTM model by replacing the function. The layers consisting of Conv1D, MaxPooling1D, SpatialDropout1D, Bidirectional GRU, and Dense have been deployed. The model has optimized the parameters by reducing them to 76,288 (Table 3).

3.3. Model Evaluation

In this paper, we construe the new model using accuracy and loss metrics. Accuracy is calculated by the quantity of correctly predictions calculated in the total quantity of evaluation cases. The form of accuracy is performed by Equation (9).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (9)$$

where TP denotes positive samples, FP shows mistake specimen positive, TN represents negative specimen, and FN represents mistake specimen negative. The loss of the prediction based on the metric categorical cross-entropy to evaluate the difference of the classified algorithm, and the output probability is between 0 and 1. The standard metric loss is performed by Equation (10).

$$Lcce = \frac{-1}{M}\sum_{k=1}^{K}\sum_{m=1}^{M} y_m^K \log\left(h_\theta\left(x_m, k\right)\right) \qquad (10)$$

where M is the quantity of training samples, K is the quantity of classes, y_k^m is the target label of training samples m for the set k, x is the input of training sample m, and h_θ is the model with evaluated weights.

4. EXPERIMENTAL RESULTS

In this application, LSTM has been constructed for the prediction and gained an accuracy of 0.755 and a loss of 0.581 in 16 seconds for 50 epochs. The upgraded model used is BiLSTM getting improves the accuracy by 0.824 and the loss is reduced to 0.412. We extend the model by using the combination namely Conv-BiLSTM, and Conv-BiGRU, and collect an accuracy of 0.896 and 0.904 respectively. The loss for both models is reduced optimized to 0.261 and 0.222 in 7, and 5 seconds respectively shown in Table 3.

4.1. Tables and figures

Table 1. Demographical description of the data

Sections	Content
Tổng (Sum)	3,367
Năm sinh (Birthday)	18-33: 2,881 *<18: 431* *>33: 41*
Giới tính (Gender)	Female:1,833 Male: 1,458 Other:60
Khu vực (Region)	City:2,992 Countryside:360
Giải thích (Comments)	CSVC tốt miễn bàn Rất bình thường Cảm thấy chưa tốt
Đánh giá (Evaluation)	Good:1,737 Neutral:1,015 Not Good: 310

Table 2. Shortlist evaluation of the data

Students‘ Comments	Students‘ Evaluation
Chất lượng dịch vụ cũng tạm tạm, nói chung có	Neutral
Chất lượng dạy học khá tốt, nhưng còn nhiều hạ	Neutral
Phòng học khang trang, cantin nhiều đồ ăn. Giá	Good
Trường đem lại trải nghiệm học tập tốt, có	Good
Khá tốt và mang lại cho ta cảm giác an toàn	Good
Phòng học còn nhiều hạn chế vì ở nông thôn,	Not good
Học phí không xứng đáng	Not good
Môi trường học tốt, giảng viên thân thiện	Good
Môi trường thân thiện, cơ sở vật chất tốt,	Good
Môi trường học tập năng động, cơ sở vật chất đầy đủ	Good

Table 3. Model setting

Models	Type	Layers, Cells	Parameters
LSTM	LSTM Classic	4, (250,64)	127,360
BiLSTM	Bidirectional LSTM	4, (250,64)	164,480
Conv-LSTM	Combination	6, (None, 250, 32)	82,304
Conv-GRU	Combination	6, (None, 250, 32)	76,288

Table 4. Model result

Enzyme preparation	LSTM	Bi LSTM	Conv Bi LSTM	Conv Bi GRU
Loss	0.581	0.412	0.261	0.222
Accuracy	0.755	0.824	0.896	0.904
Val-loss	0.191	0.138	0.110	0.183
Val-accuracy	0.513	0.569	0.696	0.556
Time	16	33	7	5

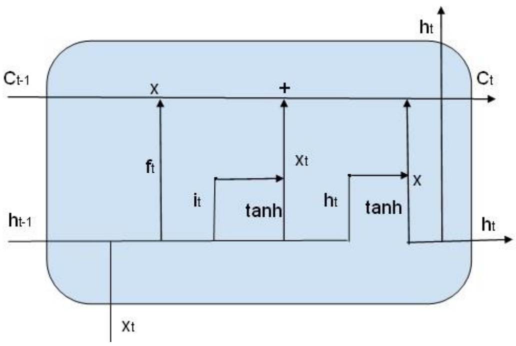

Figure 1. LSTM performance

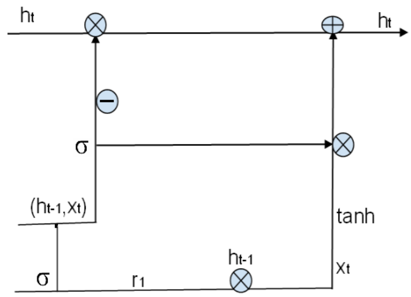

Figure 2. GRU performance

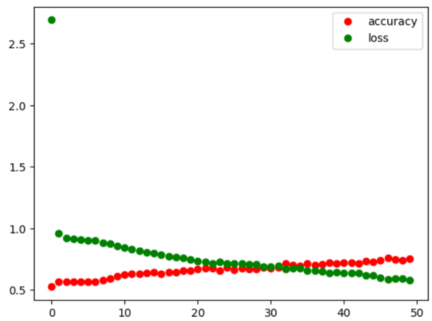

Figure 3. LSTM accuracy and loss

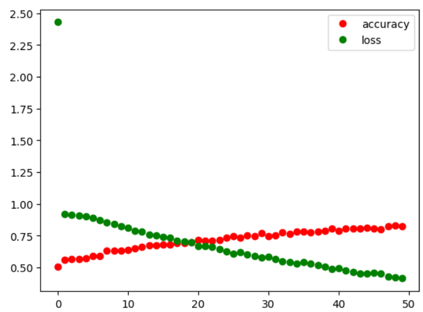

Figure 4. BiLSTM accuracy and loss

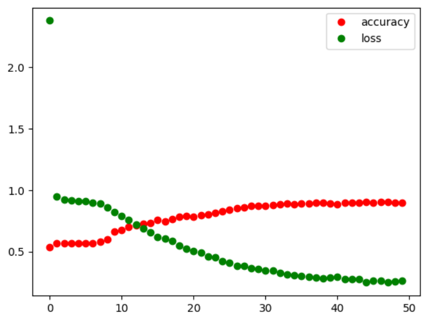

Figure 5. ConvBiLSTM accuracy and loss

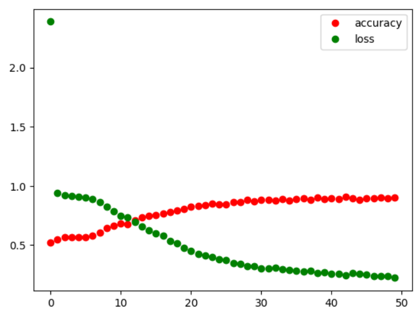

Figure 6. ConvBiGRU accuracy and loss

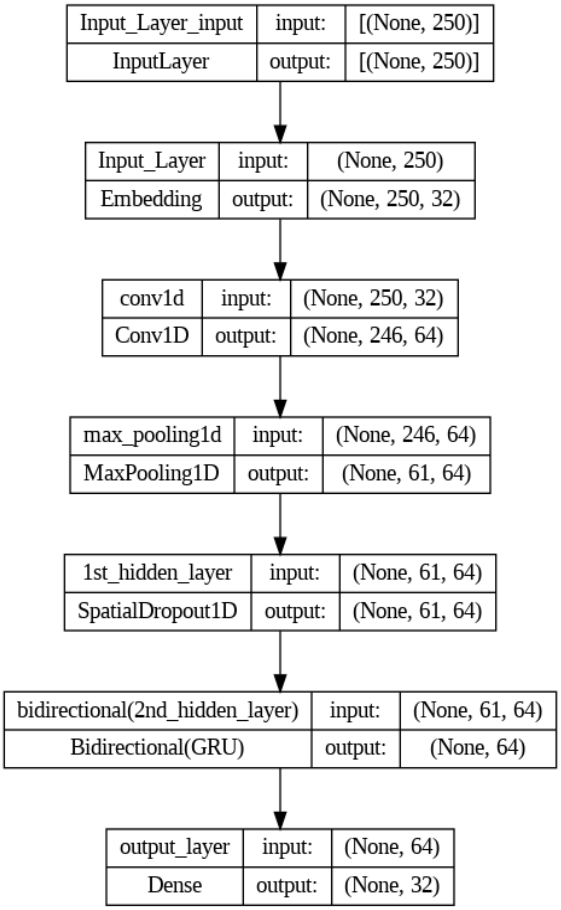

Figure 7. Convolutional GRU model building

5. DISCUSSION

The paper's pupose is to introduce the new data conducted to understand the role of library service and perform effective algorithms of machine learning in predicting. The limitation of this paper is conducted based on the data surveyed after the COVID-19 pandemic in case the response is not fully balanced. However, the data is updated every year by assessing the students that could solve the predicted outliers . The results of the survey show that the role of library service is presently important to teaching and learning after the outbreak of the epidemic. The students highly appreciated for library service quality (Good: 51.58%, Neutral: 30.15%, Not Good: 18.27%). Machine learning has significantly performed sentiment analysis settings for the evaluation of students' comments about the library service quality. The Conv-BiGRU has been proposed and predicted better than other classical models such as LSTM, GRU, and Bidirectional LSTM.

The metrics for evaluating is loss and val-loss had been used.

6. CONCLUSION

The paper has illustrated the need the library service quality to be considered in the age of running between the universities to show universities' importance. Students, especially freshmen, and sophomores, are also interested in supporting library service quality for their learning. The role of libraries could be considered for them in the kinds of online materials and hard copy books. The data has been built for the assessment of library service quality. The Conv-BiGRU has successfully predicted for assessing library service quality when reducing the parameters and then reducing the memory in a short time. The main function of the model is to analyze Vietnamese sentiment based on the comments about the library service quality after the Covid-19 pandemic. The Convolution function has been well-established and wonderfully attained when improving accuracy compared to other models. This work is the base for the university's management could consider to improving the library service quality and predicting the students' desire to satisfy the need for learning and teaching in the new state of running and development.

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The authors state that there is no conflict of Interest for this article. The images and experimental data are with the permission of the parties involved, there is no dispute or conflict of interest.

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