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Article

Analysis of Remote Learning Challenges During COVID-19 Pandemic on Pakistan's Education Sector

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Abstract: The COVID-19 pandemic spread across the world in several days. This disease has badly affected corporations, industries, and educational institutions worldwide. The education sector suffered several crises, around 77 million students were affected and absent from class during the pandemic. Using remote learning during the pandemic was beneficial, but it was difficult to find comfort and dependability. The present study examines the challenges faced by Pakistani students and teachers in remote learning, academic performance, and satisfaction levels of students and teachers who have participated in remote learning during the COVID-19 pandemic. Based on the respondents' comments, analyzed the demographic data and remote learning data using statistical calculations in the R language, and displayed the results in graphs. It used machine-learning models to calculate sentiment analysis results using the R language. According to the calculation results, the proposed study performs well using a support vector machine (SVM) and neural network (NNET), which give an accuracy of 83.5, while the accuracy of the k-nearest neighbor (KNN) is 69.9. The proposed study formulates suggestions for future work that are useful for improving the outcomes of remote learning.

1. Introduction

1.1. Background and Motivation

The COVID-19 pandemic has affected the whole world and all fields of life, such as business, industries, and education. The COVID-19 pandemic has created social distancing that increased the use of personal protective equipment for people all around the world. In the education field, we faced several emergencies for students; they did not attend any physical classes for a long period of 18 months. To compensate for this loss, remote learning is the most useful option in the COVID-19 pandemic. Students and teachers who had not used it before the pandemic took free courses on various platforms and improved their remote skills. Students and teachers used remote communication methods such as working from home (WFH), learning from home (LFH), and socializing from home (SFH) during the COVID-19 pandemic. During the COVID-19 pandemic, remote learning has faced significant challenges in Pakistan's education system. The lack of technology and internet connectivity in rural areas continues to hinder students from taking online classes. Additionally, the absence of physical classes affected students' social and emotional well-being. Addressing these challenges requires the government to invest in infrastructure, provide training for educators, and prioritize equal access to education for all

students. In the present study, we have collected responses from 386 participants across Pakistan, including students and teachers. We have analyzed participants' behaviors, comfort, confidence levels, and meeting locations when using remote tools.

2. Literature Review

Since December 2019, the world has had to fight the COVID-19 pandemic [1]. The COVID-19 pandemic has affected human health to an unprecedented extent. The pandemic has affected our lives, society, businesses, and education around the world [2]. People use remote tools for their daily communications, business, and socializing with friends [3]. More than 569 million cases were recorded by July 2022 and 14.9 million deaths were recorded in May 2022 [4]. People are working from home and students are taking classes from home [5]. During the COVID-19 pandemic, the number of platforms around the world has increased [6, 7]. In education, COVID-19 has forced students to adopt remote learning from home in a short period [8]. Everyone started using webcams and microphones, thus their usage increased day by day [9]. As a result, their market prices increased significantly within a few weeks, and webcam sales increased by 179% [10-12]. The usage of remote communication tools is growing by 200% [10]. The use of microphones and webcams is not secure, on the other hand, as evidenced by

the numerousreports that have been made [11]. It has been claimed that hackers take control of user devices on their premisesand corrupt their data [13].

The act of passing knowledge from one person to another is known as communication, and the word " communication" is derived from the Latin word "communis," which means "common" [14]. Remote communication is considered to be a non-traditional but successful communication which means the exchange of knowledge [13]. Remote learning is a modern form of education that increases the access to educational opportunities for students and teachers [15]. The COVID-19 pandemic, which has affected 94% of students worldwide in more than 190 countries [16]. According to the assessment of UNESCO educational institutions, 890 million students in 114 different countries havebeen affected by the COVID-19 pandemic [17]. Governments around the world have temporarily shut down institutions to prevent the spread of the virus [18]. During the COVID-19 pandemic, many countries imposed curfews, and lockdowns and closed educational institutions for physical education [19]. All academic activities started to be conducted remotely even in universities that were not in online mode earlier [20]. Due to the difference between face-to-face and remote communication difficulties were encountered during this transition [21]. The difficulties include a lack of internet connectivity, insufficient devices for meetings, lack of access to applications, and difficulty in accessing the learning resources [20-22]. The number of people using video conferencing increased rapidly because of the COVID-19 pandemic [19]. According to a study, more than 62 million people downloaded video conferencing platforms in March 2020.

3. Methodology

We have studied various remote learning tools and designed our survey questionnaire. We have shared this survey using social media platforms (Facebook, WhatsApp, Twitter, Instagram) with university and college teachers and students. Our study is based on only those students or teachers who have taken remote meetings during the COVID-19 pandemic. There was a limited no of users because our study did not cover the whole population of Pakistan. The dataset will be built from the input of user's responses. After filtering and removing duplicate reviews, we have 386 reviews that were used as input to our system. After that, we perform pre-processing [27], which eliminates noisy data from the dataset. An example of student and teacher feedback is displayed in Figure 1.

3.1. Proposed Framework

The framework of this study contains the five phases that are described in Figure 2. Phase one of remote learning deployment has created a dataset for statistical and sentiment analysis. In the second phase, the pre-processing includes tokenization, lowercase conversion, removal of

Figure 1. Sample of respondents' feedback before pre-processing.
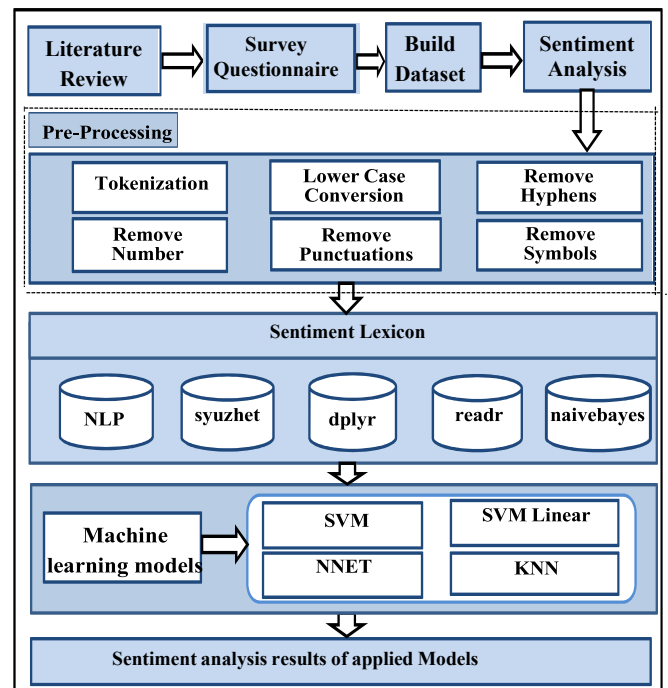
Figure 2. Dataset and sentiment analysis workflow framework.

hyphens, stemming, removal of numbers, removal of punctuation, removal of symbols, and stop word filtering that is used for sentiment analysis. In phase three, we used the R language packages NLP, dplyr, syuzhet, readr, and naivebayes to perform the sentiment lexicon. In phase four, implement the machine learning models. The last phase displays the results obtained from the applied machine learning models. The main process of sentiment analysis is pre-processing which is briefly explained in the next section.

3.1.1. Pre-processing

In this phase, the data is for pre-processing. For sentiment analysis, we used the R packages 'Quantida', 'Carat', 'Rilling', and 'e1071' for classification and clustering. The following steps are performed in pre-processing [12, 23].

Word tokenization: In word tokenization, we divide our feedback into distinct words or chunks [24]. For this step, we divided the sentence into words or tokens using a word tokenizer. Example: In his explanations, he exhibits excellent communication abilities. He "has" special "communication," "skills," "in," "his," and "descriptions," and " [25].

Lowercase conversion: In this step, we performed case conversion after the tokenization step. This process increased the value of textual data [26].

Remove hyphens: Using this technique, hyphens are removed from the text and replaced with spaces. For instance, "pre-processing" would become "pre-processing" and "long-term" would become "long-term" [27].

Remove numbers: The following stage in data pre-processing is to eliminate any digits from the text, including "12" and "555" [28].

3.2. Models Used for Sentiment Analysis

We demonstrated a sentiment analysis technique by using machine learning. The method of determining whether a piece of writing is positive, negative, or neutral is called sentiment analysis [25, 29, 30]. This helps us to understand user experiences. We used a machine learning model approach in which we applied support vector machine (SVM) linear and non-linear models to find the best hyperplane to partition the two distinct classes of data. K-Nearest Neighbor (KNN) model, is a non-parametric supervised learning classifier used to classify or predict how a given data point will be grouped [7, 31]. The neural network (NNET) model is a group of algorithms that seeks to find underlying links in a set of data by using a method that is similar to how the human brain functions.

4. Results

All results and analyses are based on the responses to an online survey. As our research is exploratory, we have performed analysis using R Studio 4.2.1 on our survey results.

4.1. Participants Analysis Results

The survey was initially distributed among 620 people. However, some respondents either did not respond or did not complete the entire survey. A total of 386 samples were filtered for the final data analysis, yielding a response rate of approximately 62.2%. All statistical analysis was performed using the R language. In our dataset, 55% of women and 45% of men submitted their responses. Participants ranged in age from 18 to 40 years with an average age of 21 years. As shown in Figure 3 shows that 84% of participants relied on remote learning tools and 16% of participants learned but did not rely on remote learning tools.
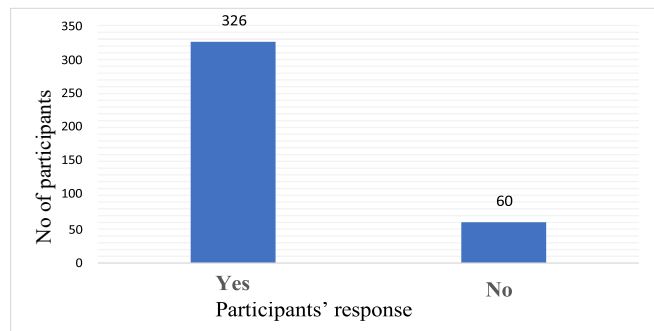

Figure 3. Participants that rely on remote learning.

From the total of our dataset, 90% of participants used remote learning tools and learned, whereas 10% of participants did not learn during the COVID-19 pandemic are shown in Figure 4. From the collected dataset of 386 participants, 70% of respondents were students, 10% of respondents were teachers, 7% of respondents were working as interns and 13% of respondents used remote learning as a teacher and also a student. The respondents contain different degree levels in which 32% of participants had a Bachler's degree, 27% of participants had a Master's degree, 24% had a higher school degree, 10% had a High school degree, 4% had a Ph.D. degree, and 8.3% respondents prefer not to say anything about remote communication. Figure 5 describes the response of the participants' concerned district and their meeting place. In the data set, 44% of the participants belong to Rahimyar Khan, 21% of the participants belong to Bahawalpur, 19% of participants belong to Multan, 7% of the participants belong to Bahawalnagar, 5% of the participants belong to Muzaffargarh and 4% of participants belong to Lahore.
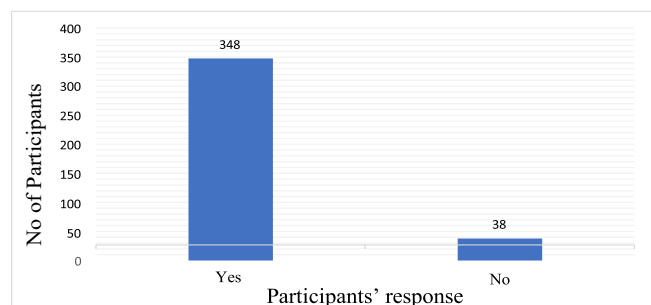

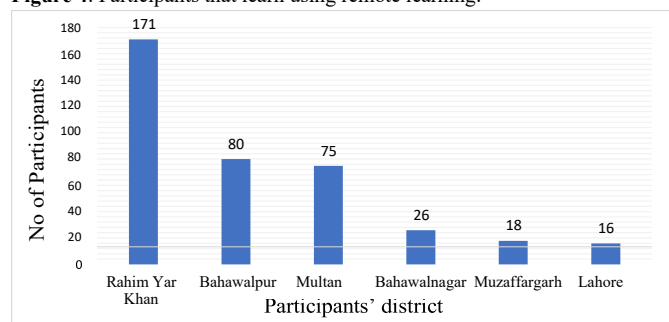**Figure 4**. Participants that learn using remote learning.

Figure 5. Participants' district-wise response

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4.1.1. Participants Remote Meeting Analysis

Our visualization in Figure 6 shows the respondent's issues in remote learning, in which 31% of participants have no issue, 20% of participants have a technical issue, 16% of participants have a financial issue, 14% of participants have management issue, 10% participants have network issue and 9% participants have all the above-mentioned issue in different time and situation.
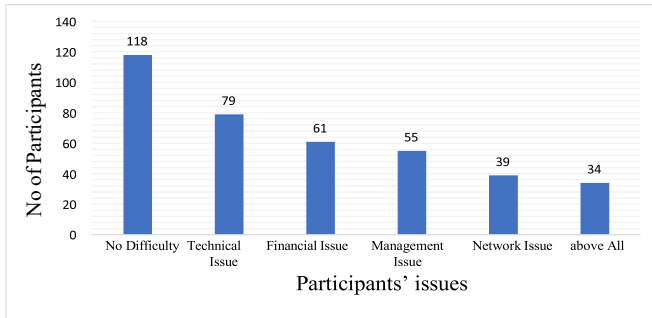

Figure 6. Participants' issues during remote learning.

As shown in
Figure 7 indicates the participants' comfortability analysis, in which 36% of participants felt comfortable, 21% of participants felt somewhat comfortable, 19% of participants were neutral, 19% of participants felt uncomfortable and 4% of participants felt somewhat uncomfortable using remote learning during COVID-19 pandemic. As shown in Figure 8, an analysis of participants' used devices in a remote meeting, in which 46% of participants used Mobile phones, 19% of participants used laptops, 15% of participants used computers, 8% of participants used laptops, and computer, 5% of participants were using a Tablet, 4% of participants were used mobile and sometimes laptop, whereas 3% participants were used mobile and sometimes computer for the remote meeting during COVID-19 pandemic.
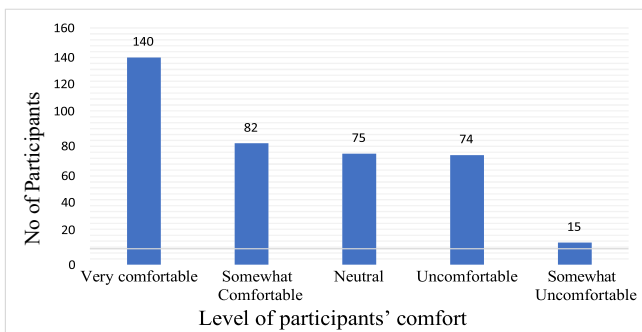

Figure 7. The comfort level of remote learning participants.

4.2. Applied Machine Learning Model Results of Sentiment Analysis

The sentiment analysis of user reviews is described in this section. We describe the machine-learning model with its statistical value and statistics by class results.
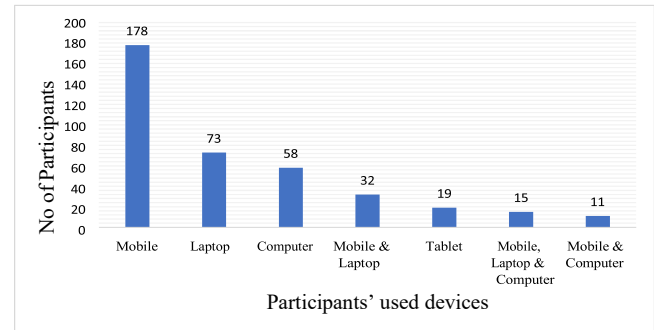

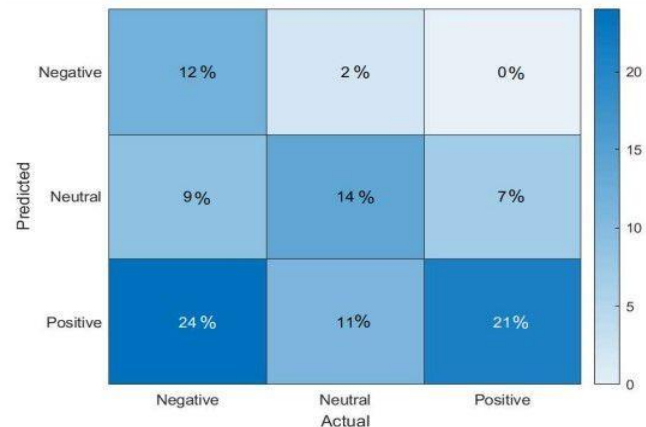**Figure 8**. Participants' used devices in remote learning.

Figure 9.Support vector machine model.

4.2.1. Support Vector Machine (SVM)

Figure 9 indicates the distribution confusion matrix of the support vector machine. The confusion matrix consists of the comfort level of audiences or users, in which the graph represents the variance between the reference of positive response, negative response, and neutral response of users. 63% of remote users consider that remote communication is better and positive as compared to other communication means. These remarkable results make the performance of remote communication higher. The overall statistics of the support vector machine model give us 84% accuracy. The dataset analysis of the model gives the result for each class that is indicated in Table 1.

4.2.2. Support Vector Machine as A Linear Model

Figure 10 indicates the confusion matrix result of the support vector machine as a linear model. The graph of the confusion matrix represents the variance between the reference states in which 55% of remote users say that remote communication is better and more positive as compared to other communication devices. 6% of users considered remote communication to be neutral, and 4% said it was negative. The support vector machine linear model accuracy of the model is 83.5%, other attributes result of their classes are indicated in Table 1.
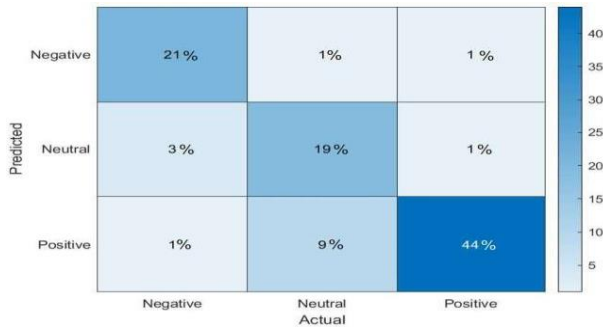
Figure 10.Support vector machine as a linear model

4.2.3. Neural Network Model (NNET)

Figure 11 indicates the confusion matrix and statistics about the neural network model. As the graph represents the confusion matrix consists of three main states such as negative, neutral, and positive. According to the given dataset, remote communication devices' neural network confusion matrix is much better than other models and gives 83.5% accuracy. Table 1 indicates the statistics of the neural network model.

4.2.4. K-nearest Neighbors Model (KNN)

Figure 12 indicates the confusion matrix of the k-nearest neighbor model. A graph represents the confusion matrix consisting of three negative, neutral, and positive states. According to the dataset results using this model, it is clear that the comfortable matrix of remote communication devices is much lower than others and gives 69.9% accuracy which is also lower than other implemented models of machine learning.
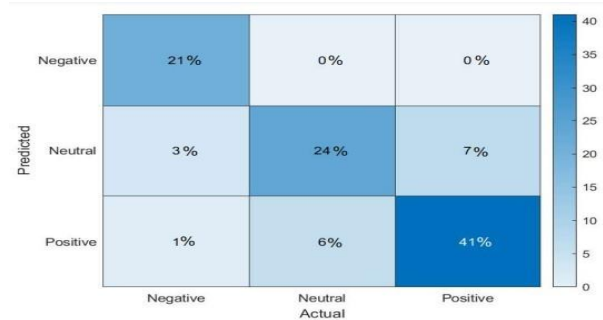

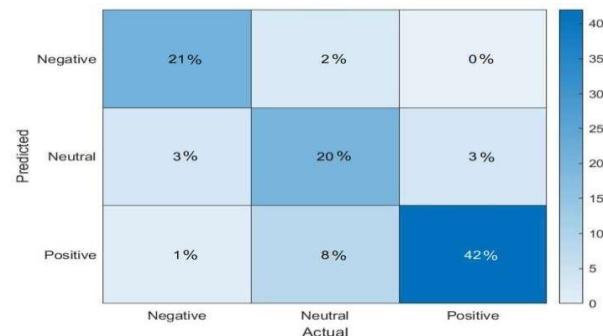
Figure 11. Neural network model.

Figure 12. K-Nearest neighbor model.

4.3. Comparative Results

Table 1 indicates the comparative results of implemented models in which the accuracy of the support vector machine, neural network, and support vector machine as linear models are the same as that is 83.5%, whereas the k-k-nearest neighbor model gives lower accuracy which is 69.9%. SVM can be valuable for understanding the key factors contributing to remote learning challenges. With proper tuning and kernel selection, SVM can be computationally efficient and provide fast predictions, which is advantageous for large-scale applications and real-time analysis. SVM is a powerful classification algorithm that effectively handles binary and multi-class classification problems. It works well even with relatively small to medium-sized datasets. The kernel trick in SVM allows it to handle non-linear relationships by transforming the input features into higher-dimensional space where a linear separation is possible. Overall, using SVM in analyzing remote learning challenges during the COVID-19 pandemic in Pakistan's education sector can provide robust, flexible, and reliable results, making it a valuable tool for educational researchers and policymakers aiming to understand and address these challenges effectively [32].

Overall, the support vector machine (SVM) and support vector machine as a linear model give better results than others in which the support vector machine accuracy is 83.5% with kappa values that are 74.1%, and support vector machine model accuracy is 83.5% with kappa value 73.72%. As shown in Figure 13 indicates the overall accuracy of implemented machine learning models in which the k-nearest neighbor gives less accuracy, whereas support vector machine, support vector machine as a linear and neural network that gives the same results.
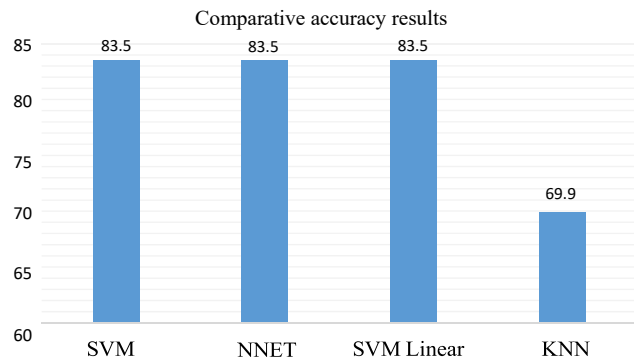
Figure 13. Comparative accuracy result of used models.

Table 1. Comparative accuracy results of applied models.

Attributes	SVM	SVM as Linear	NNET	KNN
Accuracy	0.835	0.835	0.835	0.699
95% CI	(0.7489,0.9008)	(0.7489, 0.9008)	(0.7489, 0.9008)	(0.6008, 0.7855)
No Information Rate	0.466	0.466	0.466	0.466
P Value [ACC> NIR]	9.796e-15	9.796e-15	9.796e-15	1.469e-06
Kappa	0.741	0.7372	0.7359	0.5182
MCNEMAR 'S Test P-Value	0.2533	0.3243	0.0858	0.06172

5. Discussion

We have concluded that 10% of the participants had not used any remote learning tool and 90% of the participants had used a remote learning tool but 16% of the participants were not fully relying on remote learning, while 84% of participants rely entirely and safely on using remote learning and remote communication tools. We have concluded from our results that 40.5% of users faced financial issues when all activities were closed, 20.3 % of users faced technical issues and did not use remote communication before that, 16.7% of users faced network issues during the remote meeting due to keeping at a home that is located in rural areas or those areas that did not have the facility of high-speed internet, 14.7% users have faced management issues during the remote meeting and other 7.8% users faced issues that were not specific at all. We have concluded from our survey results, that 57% of participants felt comfortable using remote learning tools because COVID-19 cases have increased day by day, therefore, it is a comfortable platform for learning at home, 23% of participants are feeling uncomfortable while using remote learning tools because many people could not afford the expenses of remote devices or they have not arranged the highly paid internet to regularly maintain the internet packages or other devices that are need for a remote meeting, and 21% participants were neutral in using remote learning because in the dangerous situation of COVID-19 when whole worlds affected, remote learning has been the best option for continuous learning in a typical situation.

6. Conclusion

The present study aims to investigate the challenges of remote meetings that Pakistan's students and teachers have faced during the COVID-19 pandemic in the educational sector. This study has explored the academic performance and satisfaction levels of students and teachers when they joined remote meetings using remote tools. After conducting respondents' reviews, we displayed their results with statistical calculations and implemented machine-learning models in which we performed sentimental analysis. According to the simulation results, the suggested study has performed well in terms of the recall, precision, f-score, and accuracy of remote communication devices. In the future, to ensure that the originality and integrity of data communication are stronger and safer, we propose to use a variety of remote communication applications. Due to a lack of communication equipment employed by schools and higher-level education, it is also possible to add the effectiveness of communication as a fact.

The proposed study includes sentiment analysis and statistical analysis. Furthermore, this proposed system could include the following: take a detailed look at the current technological infrastructure in schools and universities across Pakistan. Identify areas where improvement is needed, such as providing reliable internet connectivity and ensuring access to essential equipment for both students and teachers. Explore strategies to bridge the digital divide, especially in rural and underserved areas. This may include collaborating with telecommunications companies to expand Internet coverage, establishing community technology centers, or using innovative solutions such as satellite-based Internet access. By implementing these future initiatives, Pakistan's education sector can strive to build a more resilient and inclusive education system, capable of adapting to unexpected disruptions while ensuring quality-learning opportunities for all students.

References

[1] A. Alammary, M. Alshaikh, and A. Alhogail, "The impact of the COVID-19 pandemic on the adoption of e-learning among academics in Saudi Arabia," *Behaviour & Information Technology*, pp. 1-23, 2021.

[2] S. Hussain, M. Ayoub, Y. Yu, J. Abdul Wahid, A. Khan, D. P. F. Moller, *et al.*, "Ensemble Deep Learning Framework for Situational Aspects-Based Annotation and Classification of International Student's Tweets during COVID-19," *Computers, Materials & Continua*, vol. 75, pp. 5355-5377, 2023.

[3] K. Resch, G. Alnahdi, and S. Schwab, "Exploring the effects of the COVID-19 emergency remote education on students' social and academic integration in higher education in Austria," *Higher Education Research & Development*, pp. 1-15, 2022.

[4] A. Dedeilia, M. Papapanou, A. N. Papadopoulos, N.-R. Karela, A. Androutsou, D. Mitsopoulou, *et al.*, "Health worker education during the COVID-19 pandemic: global disruption, responses and lessons for the future—a systematic review and meta-analysis," *Human Resources for Health*, vol. 21, pp. 1-35, 2023.

[5] M. Alawamleh, L. M. Al-Twait, and G. R. Al-Saht, "The effect of online learning on communication between instructors and students during Covid-19 pandemic," *Asian Education and Development Studies*, 2020.

[6] S. Astroza, A. Tirachini, R. Hurtubia, J. A. Carrasco, A. Guevara, M. Munizaga, *et al.*, "Mobility changes, teleworking, and remote communication during the COVID-19 pandemic in Chile," *Findings*, p. 13489, 2020.

[7] S. Hussain, J. A. Wahid, M. Ayoub, H. Tong, and R. Rehman, "Automated Segmentation of Coronary Arteries using Attention-Gated UNet for Precise Diagnosis," *Pakistan Journal of Scientific Research*, vol. 3, pp. 124-129, 2023.

[8] K. Resch, G. Alnahdi, and S. Schwab, "Exploring the effects of the COVID-19 emergency remote education on students' social and academic integration in higher education in Austria," *Higher Education Research & Development*, vol. 42, pp. 215-229, 2023.

[9] E. Zarzycka, J. Krasodomska, A. Mazurczak-Mąka, and M. Turek-Radwan, "Distance learning during the COVID-19 pandemic: students' communication and collaboration and the role of social media," *Cogent Arts & Humanities*, vol. 8, p. 1953228, 2021.

[10] N. Sultana and M. Tamanna, "Evaluating the Potential and Challenges of IoT in Education and Other Sectors during the COVID-19 Pandemic: The Case of Bangladesh," *Technology in Society*, vol. 68, p. 101857, 2022.

[11] N. Fujita, "Transforming online teaching and learning: towards learning design informed by information science and learning sciences," *Information and Learning Sciences*, 2020.

[12] S. Hussain, Y. Yu, M. Ayoub, A. Khan, R. Rehman, J. A. Wahid, *et al.*, "IoT and deep learning based approach for rapid screening and face mask detection for infection spread control of COVID-19," *Applied Sciences*, vol. 11, p. 3495, 2021.

[13] P. Emami-Naeini, T. Francisco, T. Kohno, and F. Roesner, "Understanding Privacy Attitudes and Concerns Towards Remote Communications During the {COVID-19} Pandemic," in *Seventeenth*

Symposium on Usable Privacy and Security (SOUPS 2021), 2021, pp. 695-714.

[14] L. Irfan, S. Hussain, M. Ayoub, Y. Yu, and A. Khan, "A comparative analysis of social communication applications using aspect based sentiment analysis," *Pakistan Journal of Engineering and Technology,* vol. 5, pp. 44-50, 2022.

[15] O. B. Azubuike, O. Adegboye, and H. Quadri, "Who gets to learn in a pandemic? Exploring the digital divide in remote learning during the COVID-19 pandemic in Nigeria," *International Journal of Educational Research Open,* vol. 2, p. 100022, 2021.

[16] J. Lewis, *Video Conferencing Technology and Risk*: JSTOR, 2020.

[17] E. A. E. Etway, "E-Learning: Problems and Strategies of Improvements from the Faculty Students Points of View," *The Malaysian Journal of Nursing (MJN),* vol. 12, pp. 127-137, 2021.

[18] F. J. García-Peñalvo, R. R.-O. Rector, M. J. Rodríguez-Conde, and N. Rodríguez-García, "The institutional decisions to support remote learning and teaching during the COVID-19 pandemic," in *2020 X International Conference on Virtual Campus (JICV)*, 2020, pp. 1-5.

[19] K. A. Karl, J. V. Peluchette, and N. Aghakhani, "Virtual work meetings during the COVID-19 pandemic: The good, bad, and ugly," *Small Group Research,* vol. 53, pp. 343-365, 2022.

[20] G. Refaat El Said, "How Did the COVID-19 Pandemic Affect Higher Education Learning Experience? An Empirical Investigation of Learners' Academic Performance at a University in a Developing Country," 2021.

[21] B. Wang, Y. Liu, J. Qian, and S. K. Parker, "Achieving effective remote working during the COVID-19 pandemic: A work design perspective," *Applied psychology,* vol. 70, pp. 16-59, 2021.

[22] W. Ḡan, M. S. Dao, K. Zettsu, and Y. Sun, "IoT-based Multimodal Analysis for Smart Education: Current Status, Challenges and Opportunities," in *Proceedings of the 3rd ACM Workshop on Intelligent Cross-Data Analysis and Retrieval*, 2022, pp. 32-40.

[23] Y. Yu, X. Qin, S. Hussain, W. Hou, and T. Weis, "Pedestrian counting based on piezoelectric vibration sensor," *Applied Sciences,* vol. 12, p. 1920, 2022.

[24] N. Diewald, M. Kupietz, and H. Lüngen, "Tokenizing on scale. Preprocessing large text corpora on the lexical and sentence level," in *Dictionaries and Society. Book of Abstracts of the XX EURALEX International Congress, 12-16 July 2022, Mannheim, Germany*, 2022, pp. 76-76.

[25] S. Hussain, M. Ayoub, G. Jilani, Y. Yu, A. Khan, J. A. Wahid, *et al.*, "Aspect2Labels: A novelistic decision support system for higher educational institutions by using multi-layer topic modelling approach," *Expert Systems with Applications,* vol. 209, p. 118119, 2022.

[26] A. Sahar, M. Ayoub, S. Hussain, Y. Yu, and A. Khan, "Transfer learning-based framework for sentiment classification of cosmetics products reviews," *Pakistan Journal of Engineering and Technology,* vol. 5, pp. 38-43, 2022.

[27] H. Morgan, "Best practices for implementing remote learning during a pandemic," *The clearing house: A journal of educational strategies, issues and ideas,* vol. 93, pp. 135-141, 2020.

[28] M. A. Qureshi, M. Asif, M. F. Hassan, G. Mustafa, M. K. Ehsan, A. Ali, *et al.*, "A novel auto-annotation technique for aspect level sentiment analysis," *Comput Mater Contin,* vol. 70, pp. 4987-5004, 2022.

[29] M. Ayoub, S. Hussain, A. Khan, M. Zahid, J. A. Wahid, L. Zhifang, *et al.*, "A predictive machine learning and deep learning approach on agriculture datasets for new moringa oleifera varieties prediction," *Pakistan Journal of Engineering and Technology,* vol. 5, pp. 68-77, 2022.

[30] N. Bukhari, S. Hussain, M. Ayoub, Y. Yu, and A. Khan, "Deep learning based framework for emotion recognition using facial expression," *Pakistan Journal of Engineering and Technology,* vol. 5, pp. 51-57, 2022.

[31] S. Tan, "Neighbor-weighted k-nearest neighbor for unbalanced text corpus," *Expert Systems with Applications,* vol. 28, pp. 667-671, 2005.

[32] B. J. Ganesh, P. Vijayan, V. Vaidehi, S. Murugan, R. Meenakshi, and M. Rajmohan, "SVM-based Predictive Modeling of Drowsiness in Hospital Staff for Occupational Safety Solution via IoT Infrastructure," in *2024 2nd International Conference on Computer, Communication and Control (IC4)*, 2024, pp. 1-5.