Improving Online Engineering Education: Predicting Technological Awareness with Neural Net and Deep Learning Techniques

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ABSTRACT

Due to lockdowns, all educational institutions throughout the world have been shuttered, and students are unable to meet their instructors in person. Online education is the most effective method for retaining students and providing access to learning. However, it should be noted that the online education system is technologically reliant, making it difficult to administer and inaccessible to some students. Faculty and students, especially in developing countries, are both unprepared for online education, and they lack the necessary technological awareness and resources, such as internet availability, mobile or android devices, desktop/laptop computers, etc. So, this study involves the prediction of technological awareness among the faculty and students of engineering technologies when moving from a conventional education system to online education at the higher education level using Neural Net and Deep Learning techniques. The data collected through the survey consisted overall 2219 students and 257 faculty responses of seven engineering technologies. Accuracy, Kappa, and Correlation are the performance metrics for these techniques. The study results concluded that both the students and faculty of Telecommunication Engineering, students of Software Engineering, and Faculty of Computer Engineering are more aware of technology and ready for online education.

Keywords: *Online; Engineering; Education; Students; Faculty; Neural Net; Deep Learning*

INTRODUCTION

In today's world, a strong and dynamic engineering education plays an important role. As a result, this practice of imparting information benefits and enhances a country's economic situation. One may be wondering why and how getting an engineering education might be beneficial for society. Engineering graduates as compared to graduates of non-engineering backgrounds, on the other hand, learn and generate income that can alleviate societal issues. Furthermore, engineering graduates will gain valuable skills that will aid in future study and development (Turns et al., 2014). So, academic institutions and the government are searching for a new education structure that could offer access to knowledge and learning with a degree of respect comparable to the conventional education system to resolve the challenges of access and opportunity in higher engineering education (Ajmal et al., 2019; Muthuprasad et al., 2021). However, the outbreak of the COVID-19 pandemic has changed the world and contributed to the high death toll around the world and global fear and panic. Countries around the world are working to close the distance and reduce the number of students missing due to the current pandemic (M. Alau, 2020; Mäkelä et al., 2020).

The educational sector encountered an unprecedented challenge in response to the COVID-19 pandemic worldwide. However, switching seamlessly from a conventional classroom environment to an online and virtual learning environment is not easy. At this time, the gradual transformation is connected to a range of issues and challenges. However, since no one knows when the pandemic will be fully eradicated, educational institutions worldwide have chosen to use the currently available technological resources to create online learning materials for students in all academic fields (Adnan & Anwar, 2020).

Nevertheless, the worldwide closing of educational institutions has posed a great challenge for coping with a pandemic using advanced technologies, such as hardware and software, to facilitate effective online learning. Despite this, some advanced countries have become more responsive in providing course material online, educating students, and conducting examinations online (Devia & Doraisamy, 2021). However, the situation seemed different in Pakistan from other countries concerning switching to online education. Pakistan is a developing country with a lack of technological resources and awareness among the people. So, owing to the reasons such as inadequate internet access and power failures, online courses cannot be considered a better replacement for conventional classroom teaching. That is why online education in Pakistan is not readily accessible or affordable to all (Rehman, 2020).

The global outbreak of the COVID-19 pandemic caused an unparalleled upheaval in multiple facets of society, with education being one of the most severely affected areas. This profound change presented a plethora of difficulties for educators as well as students, highlighting the necessity for a thorough grasp of the worldwide effects of lockdowns on learning. The difficulties were complex and included problems with learners' socioeconomic differences, pedagogical adaptation, and technological readiness. In order to shed light on the challenges faced by teachers and students navigating the unfamiliar waters of online learning, this study aims to delve into the complex dynamics of this pivotal period in education. The importance of technological awareness in assuring the success of online education is one of the main focuses of this research. Disparities in technology access, digital literacy, and the availability of dependable internet connectivity were made evident by the abrupt move to remote learning. The study aims to illustrate the significance of bridging the technological divide and promoting a more equitable learning environment by thoroughly examining these issues. It also looks for ways to improve teachers' and students' ability to use technology in the classroom, allowing for a smoother transition to online learning environments.

There have been a variety of applications in higher education due to the introduction of information and communication technology (ICT) in the modern era. Furthermore, as technology advances, the relevance of engineering education has increased. Engineers and engineering institutes are rapidly evolving at the same time. As artificial intelligence (AI) progresses, new techniques such as deep learning and artificial neural networks are developed to enhance the efficacy of machine learning and expand the spectrum of AI implementations. Neural Net and Deep Learning are algorithms that predict possible outcomes based on user data, allowing a computer to view observed patterns rather than human experiences. It helps algorithms learn from data and make decisions and predictions, enabling automation. The neural net and deep learning model get more intuitive with each new piece of information it receives. This research outlines the implications of neural net and deep learning on predicting technological awareness amidst faculty and students and explores how it can affect online engineering education at present and in the future (Muniasamy & Alasiry, 2020).

Issues and Challenges

Like those in other nations, all educational institutions in Pakistan have been completely shut down where social distance is a problem. To ensure that students receive uninterrupted education, the HEC, Pakistan has urged educational institutes to switch to an online learning management system, and besides, the concerned authority has begun telecasting distance learning programs for students in universities. Online education has mostly been centered on the country's higher education levels (M. Alau, 2020; Rehman, 2020).

It was challenging for the students and the higher education institutional management to adopt an online learning management system because of the COVID-19 pandemic for many reasons. Owing to economic or technological limitations, there is a lack of accessibility and affordability. Some persons cannot afford a smartphone or a laptop with appropriate hardware and software requirements (M. Alau, 2020; Devia & Doraisamy, 2021). Due to technological and financial issues, many students are unable to afford or access the internet for online learning. Students struggle with online education because they do not have access to high-speed or secure internet connections (Devia & Doraisamy, 2021; Khati & Bhatta, 2020).

Students and their families are not the only ones who have issues with online classes. Many teachers and faculty at higher education institutions are still irked and indeterminate by the decision. The majority of universities administrator have convened a meeting of teachers and asked them to instruct their students via the internet. Many teachers have been wondering about this uncertain situation and unsure about how to teach students online. Then, there are the same issues with the faculties that the students and their parents have. University students will only benefit from online courses if they have access to computers or smartphones with basic internet facilities at home. It would be unfair to them if a number of them would not have such a facility (Kebritchi et al., 2017).

LITERATURE AND BACKGROUND

With today's technological advances, an online learning management system can be designed in various ways. To make the learning management system effective and efficient, it is critical to understand the needs and awareness of the faculty and students when planning online courses. The learner's preference is linked to his or her preparation or ability to engage in interactive learning and the variables that influence readiness for online learning and predicting technological awareness amongst faculty and students by applying neural net and deep learning techniques. The learnings from the study of similar literature are summarized in this section that follows:

Related Works on Online Education System:

While online education faces several challenges from two key stakeholders: students and teachers, the study by (M. Alau, 2020) found that carefully addressing issues, has the potential to create a positive environment in the field of education as an alternative teaching-learning method, resulting in positive outcomes in all areas. In Bangladesh, it is the first time connecting with an online class, so they are having difficulty adapting to this trend, as transitioning from a conventional classroom to computer-based training in a virtual classroom completely changes their learning and teaching experience. During the shutdown, most students remain at home in various parts of the country. Students use mobile internet, which disrupts online access due to weak internet signals. There are some technical difficulties, such as a lack of literacy when using a computer. Without a doubt, holding online classes is a commendable step taken by the current administration to reduce the loss of students' academic activities.

Despite having a large no of benefits of shifting to an online education system, there are different challenges that the Pakistani education system will face in transforming its educational system to an online learning environment presented (Rehman, 2020). The biggest challenge is to provide training to faculty to perform efficiently in an online framework, and it is also seen that the training rate is not advancing in the way it is expected to make online learning the best platform. Another challenge to be faced is to have a secure and strong internet infrastructure; also, not all students have the facility of notebook computers or tablets to take online classes. Managing institutional expenditures in an online framework is another challenging factor. The awareness of technology among the students and faculty also leads to a big challenge to equity among all. Online learning requires focus and concentration, and, in this era, parental support and the violent home atmosphere is a challenge for students to achieve their learning goals through an online platform. Strengthening the infrastructure and providing facilities of technology and computers even to the poorest population is a way forward in making the online platform a success.

The teacher understands the COVID-19 pandemic, their perceptions of their school's readiness, and their responses to the challenges of conducting distance learning education in the Philippines (Alea et al., 2020). Training, attitude, technical competence, time constraints, pedagogy, and methodology were the main distance learning education components. In a survey of 205 online faculty from higher education institutions in the United States, most responses were ranked high in terms of preparation, attitude, and ability to teach online in terms of course design, course communication, time management, and technical aspects. Teachers were aware that the Philippines had announced an ECQ (Enhanced Community Quarantine) response to the pandemic. Teachers' readiness for distance learning differed significantly depending on their gender, length of teaching experience, and geographic location. Overall, the teaching population in the Philippines is psychologically ready to adapt to new and creative ways of imparting wisdom, assuming that their institutions have adequate support.

An international partnership by (Naylor & Gibbs, 2018) between college students and pre-service teachers in Norway and the UK enabled pre-service teachers to use mobile technology to enhance their professional learning. The data indicated that this improved their emergent conceptions of teaching and learning. The study looks at two questions: the first is how the process of creating eBooks with iPads affected pre-service students' views of teaching and learning, and the second is what related skills and competencies pre-service teachers thought they learned from creating eBooks with iPads. The first analysis is the collaboration between pre-service teachers and college students which was described as a way for the former to expand their practice and improve strategies for learning outside the classroom using mobile technology, as per the participants. The pre-service teachers used their subject knowledge and pedagogical knowledge, and technology to engage college students in engaging learning experiences. Pre-service teachers and college students could share information and expertise and learn together, which allowed rich connections mediated by a mobile device. The second analysis is the trainees' evolving use of the iPad in their respective subject areas, the trainees' expanding perceptions of the role of technology in their teaching, and the project's effect on the trainees' perception of learning and teaching. The pre-service teacher discovered that using iPads for English work was much more convenient than using paper-based materials.

Quantitative and qualitative methods were used to assess the factors influencing student understanding of online learning among undergraduates at Sri Lanka's South Eastern University (SEUSL) (Nafrees et al., 2020). During the COVID-19 lockdown, it was found that the students had internet connection problems (i.e., 40%). Most students reported that this online learning system had increased their monthly spending (69%) and internet bill (48%). During the lockdown, more than half of the students were satisfied with their online education. Only 19% chose to learn in a classroom setting. While most students (51%) had prior experience with Zoom, they opted to use WebEx for their online education due to WebEx's user-friendliness. Most students (nearly 84%) used smartphones for their education. It shows that every undergraduate has a device that allows them to access online education. The internet speed was slower during the lockdown than before COVID-19, indicating that the number of users and usage increased. Despite their limited experience, many students prefer online education to continue their academic work while remaining secure.

This study focused on the advantages, challenges, and solutions for the online learning environment in the current situation of the COVID-19 pandemic (Farrah & Al-Bakry, 2020). The study gathered data through google forms opened to students at Palestinian Universities from 5 July 2020 to 14 July 2020. The data was gathered from 191 EFL (English as Foreign Language) students from six reputed Palestinian Universities, which were categorized according to gender (M/F), level of studies (1st year,2nd year, 3rd year, 4th year, and MA), and evaluation systems, calculated statistical analysis using mean and standard deviation and concluded that highest rating for advantage having mean=3.85 (means most students are not proficient enough to deal with technology and agreed that e-learning enhances their technological skills.). Highest rating for challenges having mean=4.13 (which means students face assignment submission problems with online courses). Highest rating for a solution having a mean=4.21(means students agreed on training instructors to minimize problems faced during e-learning). In the study, students agreed that the advantages of an online learning environment are that they become good researchers, make them confident and self-reliant, offer valuable experience, and improve their technological skills. During this environment, the challenges they faced were a lack of technical support from authorities, unreliable evaluation systems, and poor technological infrastructure. The solutions they agreed on were training teachers and students to be organized, improving attendance systems and policies, and strengthening the internet infrastructure.

The study's objective by (Kukreja et al., 2021) was to identify factors affecting students' satisfaction in online classes during the COVID-19 pandemic. For this, a survey was conducted from June 2020 to September 2020 from different universities in India. A total of 690 students participated in the survey, and after investigation, 673 participants' surveys were considered complete in all aspects. Four hypotheses are used as important factors affecting the student's satisfaction with online classes. Structural Equation Modeling (SEM) has been used for doing path analysis. The first hypothesis factor was instructor quality, and the findings of the analysis show that instructor quality positively impacts students' satisfaction in online classes during a pandemic.

The second hypothesis factor was course design. The study presented a positive impact between course design and students' satisfaction with online classes. The third hypothesis factor was ICT orientation, and the findings of the analysis showed a positive and significant impact of ICT orientation on the students' satisfaction during online classes. Finally, this research treated the student's traits under five personality dimensions (extraversion, agreeability, conscientiousness, negative emotionality, and open-mindedness) and findings show that personality plays an important role in affecting student satisfaction. Extrovert types of students harm satisfaction levels. Whereas conscientiousness, open-mindedness, and agreeableness personality type have a positive relation to students' satisfaction in online classes.

Related Works on Predictive Techniques Applications:

The study by (Muniasamy & Alasiry, 2020) describes what impact deep learning provides on eLearning resource management and how eLearning will be shaped in the future. Deep learning models (RNN, CNN, DBN, and DNN) are used to handle information in eLearning, which will develop the contents of eLearning. It was concluded that the framework would apply user-centered design principles to create content of acquired knowledge and information for targeted learners. Different deep learning tools allow eLearning developers to choose platforms according to their strengths and weaknesses and their technical skills. This exponentially improves the learning skills of the learner using eLearning platforms in which the deep learning approach is embedded. Future enhancement includes making the system more responsible for the active decision-making process; it will focus on adaptive and personalized learning that will improve learners' outcomes (learning and performance).

The study by (Shearer et al., 2015) proposes in higher education, especially in asynchronous online distance education, to analyze what is going on in courses to enable learners to progress from surface to deep learning. Implemented an iterative design-based research analysis of a completely online graduate course in which discussion forums play an important role in student work during the semester. Iteratively changing the design of a graduate adult education course using a design-based analysis methodology to see how it influenced deep learning through dialogue and learning activities (Beaudoin, 2016). The original course design, teacher activities, discussion forum participation, and instructor viewpoints were all examined during the initial process. The second and third phases included implementing and evaluating strategies to increase cognitive presence and deep learning in course discussion forums and other learning activities. Deep learning vs surface learning focused on observable attributes. It is important to understand how these design changes would affect the course's teacher; it is recognized that the design-based improvements integrated as learning experiences placed a greater demand on the faculty member's time.

Due to the COVID-19 pandemic, face-to-face teaching in schools and universities got a complete shutdown (Dias et al., 2020). A DeepLMS was designed to predict the Quality of Interaction (QoI) with LMS of HEIs (Higher-Educational Institutions). The Long Short-Term Memory (LSTM) networks were used. The LMS (Moodle), having three different databases from three different countries (Portugal, United Arab Emirates, and Greece), was used to predict the performance of DeepLMS evaluated by two users (professors and students). The DB1 contains 75 professors and 1037 students, which contains data for two academic semesters (358 days) for the academic year 2009/2010 from which (day1 till day 323) is used in training and (day 324 till day 358) is used for testing. The DB2 contains three professors and 180 students, which contains data for the spring semester of 2020 (76 days) from which (day 1 to day 68) is used in training and (day 69 to day 76) is used for testing. The DB3 contains one professor and 52 students, which contains data for a single course taught during the spring semester/fall exams 2020 (181 days), from which (day1 till day 163) is used in training and (day 164 till day 181) is used for testing. DeepLMS predicts average testing Root Mean Square Error (RMSE) < 0.009 and average correlation coefficient between ground truth and predicted QoI values r _ 0.97 (p < 0.05). The authors wish to perform a fusion on other user's quality measures on both HEI (Higher-Educational Institution) and SEI (Secondary Education Institutions) levels to predict the quality of collaboration (QoC) and Quality of Affective Engagement (QoE) as their future work.

RESEARCH OBJECTIVE AND QUESTIONS

The COVID-19 pandemic has compelled higher education to adapt face-to-face to online learning, providing new experiences and awareness for many students and faculty. In this context, the main objective of this study is to investigate students and faculty members' perceptions concerning the use of technological devices for educational purposes, specifically in terms of features used in this research (Uppal et al., 2020). Also, this academic research articulates the domain of artificial intelligence (AI) using deep learning and neural net focusing on predicting technological knowledge among students and faculty and how it may affect future online engineering education (Shearer et al., 2015; Offir et al., 2008; Villegas-Ch et al., 2020). In particular, the following research questions will be addressed in this study:

Q.1 Is it possible to predict the technological awareness among faculty and students affecting online engineering education?

Q.2 Which of the proposed features used in this research positively correlates with the technological awareness affecting online engineering education?

NEURAL NET AND DEEP LEARNING PREDICTIVE TECHNIQUES

Neural Net and Deep learning can provide many benefits to future online learners and organizations that invest in current learning management systems with intuitive algorithms and automated distribution of e-Learning content. Both techniques predict outcomes based on historical performance and individual learning goals to customize relevant e-Learning information, resulting in more personalized e-Learning material. In this research, neural net and deep learning predictive techniques have been employed to predict the technological awareness among engineering students and faculty to determine the features affecting online engineering education (Muniasamy & Alasiry, 2020; Dias et al., 2020).

i. **Neural Net:** This model utilizes a backpropagation approach to train a feed-forward neural network to learn a model (multilayer perceptron). An artificial neural network (ANN), generally known as a neural network (NN), is a mathematical or computational model based on the structure and functions of biological neural networks. A neural network comprises a network of artificial neurons that work together to process data in a connectionist way. During the learning phase, an ANN is typically an adaptable system that changes its structure based on external or internal information flowing through the network. Modern neural networks are frequently used to represent complex input-output relationships or identify data patterns (Muniasamy & Alasiry, 2020; GmbH RM. Neural Net, 2023).

A feed-forward neural network is an ANN with connections that do not create a directed cycle between the units. The information in this network flows solely in one way, forward, from the input nodes to the output nodes, passing via any hidden nodes (if any). The network has no loops or cycles. The backpropagation algorithm is a supervised learning technique that comprises two phases: propagation and weight updating. The two phases are recurring until the network's performance is satisfactory. The output values are compared against the correct solution in backpropagation algorithms to determine the value of a specified error function. The network will generally converge to a state where the computation error is minimized after repeating this method for enough training cycles (Dias et al., 2020; GmbH RM. Neural net, 2021).

A multilayer perceptron (MLP) is a feed-forward ANN model that transfers input data sets to suitable output data sets. An MLP comprises numerous layers of nodes in a directed graph, each wholly linked to the next. Multiple layers of processing units are interconnected in a feed-forward manner in this type of network. The units of these networks use a sigmoid function as an activation function in many applications. The activation function in this model is the standard sigmoid function. As a result, the attribute value ranges should be scaled to -1 and +1. The normalized parameter can be used to do this. If the learning data reflects a classification task, the output node will be sigmoid, and if the learning data reflects a numerical regression task, the output node will be linear (GmbH RM. Neural Net, 2023).

ii. **Deep Learning:** Deep Learning is arranged on a multi-layer feed-forward ANN that is trained via stochastic gradient descent by back-propagation. The network can have several hidden layers of neurons with tanh, rectifier, and maxout activation functions. High prediction accuracy is enabled by advanced features such as annealing, dropout, adaptive learning rate, momentum training, and L1 or L2 regularization. Using multithreading (asynchronously), each computed node trains a replicate of the global model parameters on its local data and regularly contributes to the global model via network model averaging (Muniasamy & Alasiry, 2020; Dias et al., 2020; GmbH RM. Deep learning, 2023).

DATA PRE-PROCESSING AND METHODOLOGY

Data pre-processing is an approach that transforms raw data into a format that can be implicit. Pre-processing converts data into a format that is suitable for efficient information extraction and accurate findings. Data in the real world is typically incomplete, inconsistent, or noisy. One of the most challenging issues is the removal of noise occurrences. Another issue that frequently arises throughout the data preparation process is missing data handling. Both symbolic and numerical features are present in real-world issues. As a result, discretizing numerical (continuous) features is a significant concern. The technique of grouping the values of symbolic features is also proper (Jayaprakash & E., 2015; Kotsiantis & Kanellopoulos, 2006).

Furthermore, in real-world data, data representation frequently employs an overwhelming range of features, only a few of which may be linked to the desired idea. There possibly will be redundancy too, where some features are correlated, and it is not required to include all of them in modeling; and interdependence, where two or more features communicate essential information that would be lost if any of them were included alone (Kotsiantis & Kanellopoulos, 2006). Data cleaning is an integral part of data pre-processing, and various attributes are taken into account to eliminate incorrect and inconsistent information.

For the current research, data has been collected encompassing seven engineering technologies of the Sir Syed University of Engineering and Technology, Karachi (a renowned private sector university of the city) using a survey approach (Zydney et al., 2020). The data of undergraduate, graduate, postgraduate, and Ph.D. students and faculty were included in the study's target population. The study comprises the following engineering disciplines data:

i. Biomedical Engineering
ii. Civil Engineering.
iii. Computer Engineering.
iv. Electrical Engineering.
v. Electronic Engineering.
vi. Software Engineering.
vii. Telecommunication Engineering.

The data was collected based on the questionnaires designed for students and faculty of the technologies as mentioned earlier separately consisting of information about the technological facilities available at their home like personal computers information and configuration, internet availability, operating system, internet bandwidth, etc. to determine the technological awareness amidst faculty and students to get prepared for online classes in the perspective of COVID-19 pandemic situation. The description of attributes used in this research is mentioned in Table 1 for faculty and Table 2 for students.

Table 1 List of Faculty data attributes with description

Attributes	Description	Values
PDT	Primary Device Type	Desktop, Laptop, Mobile Phone, Tablet, Other
SDT	Secondary Device Type	Laptop, Mobile Phone, Tablet, Other, None
PDRS	Primary Device RAM Space	2 GB, 4 GB, 6 GB, 8 GB or greater, Less than 2 GB
PDHDS	Primary Device Hard Disk Space	1 TB or greater, 40 GB, 160 GB, 250 GB, 500 GB, Less than 40GB
PDPT	Primary Device Processor Type	Core i3, Core i5, Core i7, Core i9, Other
PDOS	Primary Device Operating System	Android, Windows, macOS, Linux, Other
ICT	Internet Connection Type	Broadband, Cable, DSL, Fiber Optic, Mobile, Other
IBW	Internet Bandwidth	1-3 Mbps, 4-6 Mbps, 7-10 Mbps, 16-25 Mbps, 26-50 Mbps, 51-100 Mbps, Greater than 100 Mbps
IA	Internet Availability	1hrs – 24 hrs
TA (Class or Label)	Technological Awareness	Strongly Aware, Aware, Unsure, Unaware, Strongly Unaware

Table 2 List of Students' data attributes with description

Attributes	Description	Values
DP	Degree Program	Graduate, Postgraduate, Undergraduate, Ph.D.
PDT	Primary Device Type	Desktop, Laptop, Mobile Phone, Tablet, Other
SDT	Secondary Device Type	Laptop, Mobile Phone, Tablet, Other, None
ICT	Internet Connection Type	Broadband, Cable, DSL, Fiber Optic, Other
IBW	Internet Bandwidth	1-3 Mbps, 4-6 Mbps, 7-10 Mbps, 11-15 Mbps, 16-25 Mbps, 26-50 Mbps, 51-100 Mbps, Less than 1 Mbps, Greater than 100 Mbps
IA	Internet Availability	1hrs – 24 hrs
BTI	Best Time Interval	Afternoon, Evening, Morning, Night
TA (Class or Label)	Technological Awareness	Strongly Aware, Aware, Unsure, Unaware, Strongly Unaware

Mostly, the nature of the data gathered is categorical or nominal. The normalization of attributes, as well as dimensionality reduction, were used to accomplish data pre-processing. The data is then cleaned and validated by eliminating missing values in a dataset to maintain data quality. Fourteen datasets have been used in this study according to seven engineering technologies both for faculty and students. The RapidMiner tool is used to perform the research and analysis (RapidMiner, 2021). The flow of the process to conduct the research is depicted in Figure 1.

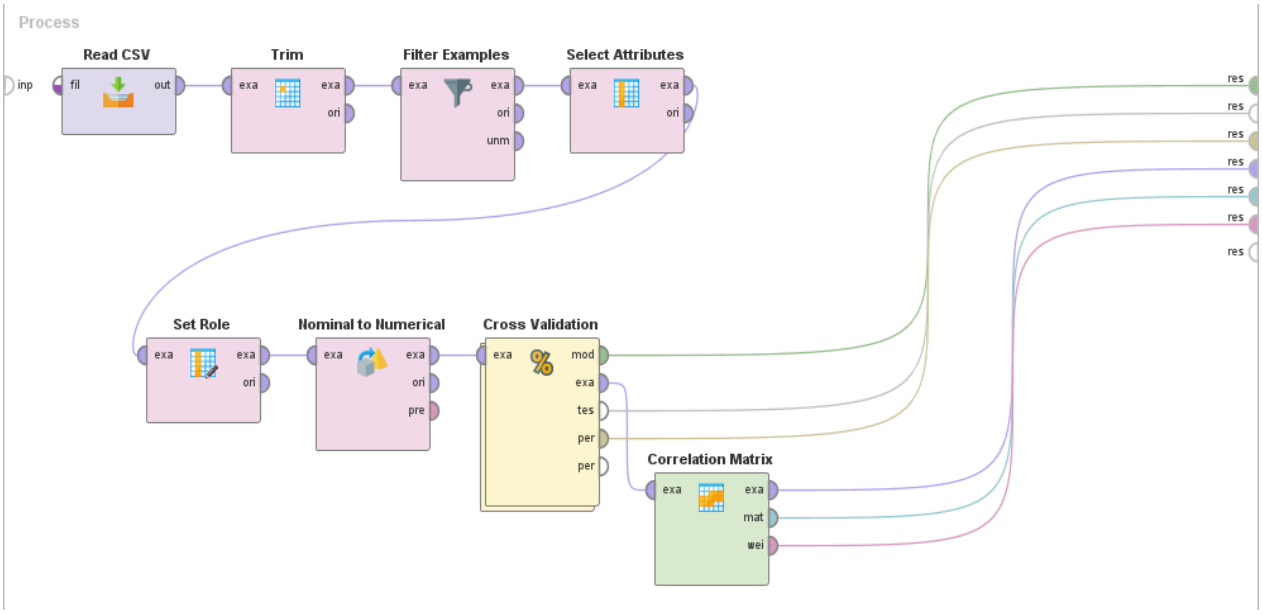

Figure 1 Flow of process

The dataset file is input to the Read CSV operator. After reading the desired dataset sheet, the Trim operator is applied to eliminate leading and succeeding spaces from the nominal values, and it produces new attributes from the specified nominal attributes. Parameters can be used to choose the needed attributes. Then, the Filter Examples operator is used to retrieve all the examples that meet the provided criteria. Next, the Select Attributes operator picks a subset of an ExampleSet's attributes and eliminates the rest. To make attribute selection more manageable, the operator provides many filter options.

A Set Role operator is applied to define the target variable or class, which was TA in this case. The Nominal to Numerical operator is implemented to convert non-numeric attributes to numeric types. This operator is used only to modify the type of the chosen attributes, but it also converts all their values to numeric values. This operator is specifically used to execute the Neural Net model because it does not support polynomial attributes. So, this was essentially implemented in a pre-processing step before executing a model.

A Cross-Validation operator is operated with stratified sampling to execute the models of NN (Neural Net) most importantly and DL (Deep Learning). It is mainly used to predict how well a model (trained by a particular learning Operator) would perform in practice. A nested Operator is the Cross-Validation Operator. It contains two sub-processes: one for training and the other for testing. A model is trained using the Training sub-process. In the Testing sub-process, the trained model is used. During the Testing phase, the model's performance is evaluated. The ten folds performed in this study mean the supplied ExampleSet is divided into ten equal-sized subgroups. A single subset of the ten subsets is selected as the test data set (i.e., the input of the Testing sub-process). The remaining nine subsets serve as training data (i.e., the input of the Training sub-process). The cross-validation process is reiterated ten times, with each of the ten subsets being utilized as test data precisely once. The ten outcomes from the ten iterations are averaged (or otherwise integrated) to get a single estimation. The sub-process flow under the cross-validation operation for both Neural Net and Deep Learning modeling with training and testing are depicted in Figures 2 and 3, respectively.

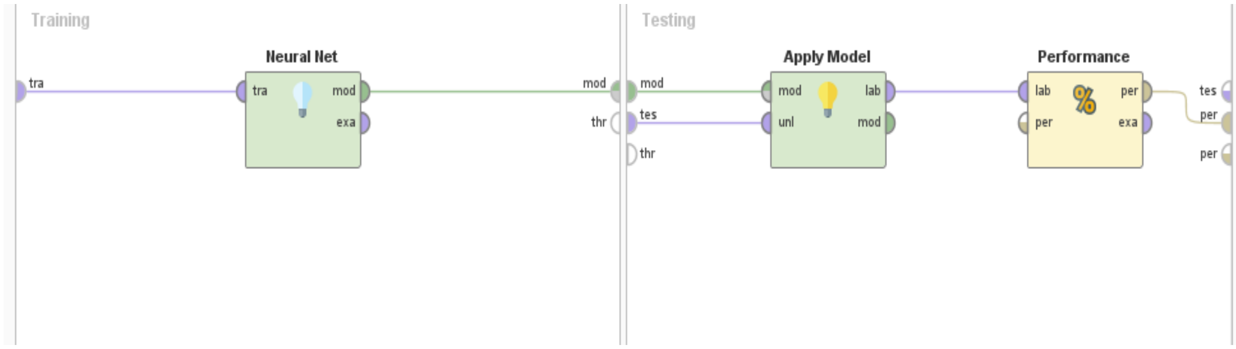

Figure 2 Flow of sub-process for Neural Net approach

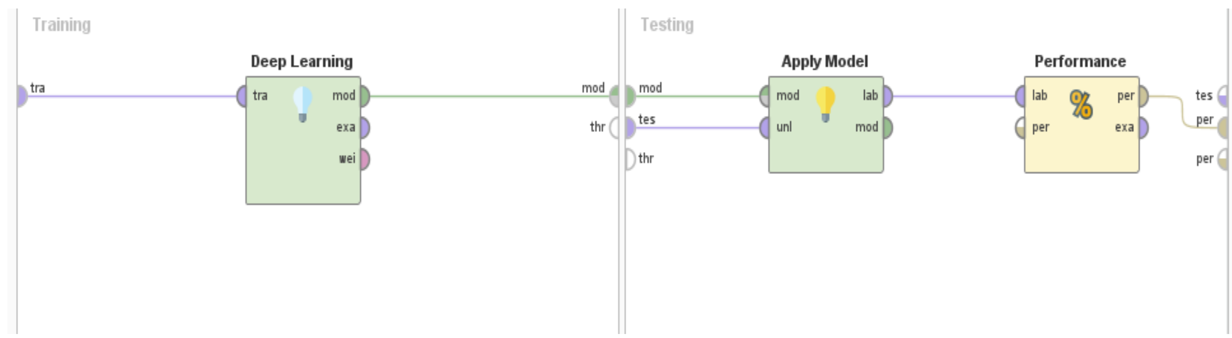

Figure 3 Flow of sub-process for Deep Learning approach

As shown in figures 2 and 3 in a training phase, Neural Net and Deep Learning techniques have already been discussed in Section V in detail. In a testing phase, the Apply Model operator is usually a learning algorithm that first trains a model on an ExampleSet. This model may then be applied to another ExampleSet. The objective is usually to predict based on anonymous data or to modify data using a preprocessing model.

A Performance operator in a sub-process is used to evaluate performance. It generates a list of values for performance criteria. These performance requirements are established automatically based on the learning task type. A Correlation Matrix operator depicted in Figure 1 is used to establish a correlation between all attributes and generate a weights vector based on those correlations. Correlation is a statistical approach for determining whether or not two attributes are linked and how strongly they are correlated.

RESULTS AND DISCUSSION:

This section explains the results using a model performance metric, analyses and compares the model's performance, and focuses on research issues related to predicting the technological awareness affecting online engineering education amidst faculty and students, as stated in section IV. As mentioned earlier, Rapidminer is used in this research to conduct data analysis. The results of this study are presented for faculty and students separated into two sub-sections.

i. Faculty Technological Awareness and Readiness to Online Education:

The data must be correctly processed before creating the models to learn more about the patterns successfully. In a previous section, the dataset description of attributes used in this research was mentioned. It might be challenging to assess a model's quality without examining its performance outcomes during training and testing. This is generally accomplished by using a performance metric, whether it measures the type of error, the accuracy of model fit, or some other approach.

Faculty datasets consist of 15 instances of Biomedical Engineering, 33 instances of Civil Engineering, 50 instances of Computer Engineering, 30 instances of Electrical Engineering, 54 instances of Electronic Engineering, 38 instances of Software Engineering, and 37 instances of Telecommunication Engineering. Accuracy, Kappa, and Correlation are selected as performance metrics produced from both Neural Net and Deep Learning techniques and computed to measure the model's performance is mentioned in; Table 3 for predicting technological awareness among faculty of different technologies.

Table 3 Summary of NN and DL performance metric

Technologies	**Neural Net**			**Deep Learning**		
	Accuracy	Kappa	Correlation	Accuracy	Kappa	Correlation
Biomedical Engineering	70%	0.258	0.316	70%	0.222	0.350
Civil Engineering	58%	0.079	0.445	80%	0.144	0.382
Computer Engineering	64%	0.048	0.210	84%	0.232	0.426
Electrical Engineering	73%	0.098	0.160	80%	0.150	0.244
Electronic Engineering	48%	0.070	0.122	56.66%	0.005	0.075
Software Engineering	78.34%	0.192	0.285	78.34%	0.106	0.083
Telecommunication Engineering	81.08%	0.177	0.449	81.08%	0.211	0.204

The percentage of accurate predictions or the relative number of correctly classified instances is referred to as accuracy. Table 3 and Figure 4 shows that the NN gives the highest accuracy on the Telecommunication Engineering faculty dataset, i.e., 81.08%. In comparison, the DL gives the highest accuracy on the Computer Engineering faculty dataset, i.e., 84%. It has been predicted from the results of the accuracy that the Telecommunication Engineering and Computer Engineering faculty are more aware and ready for online education according to NN and DL, respectively, in the perspective of the COVID-19 pandemic situation.

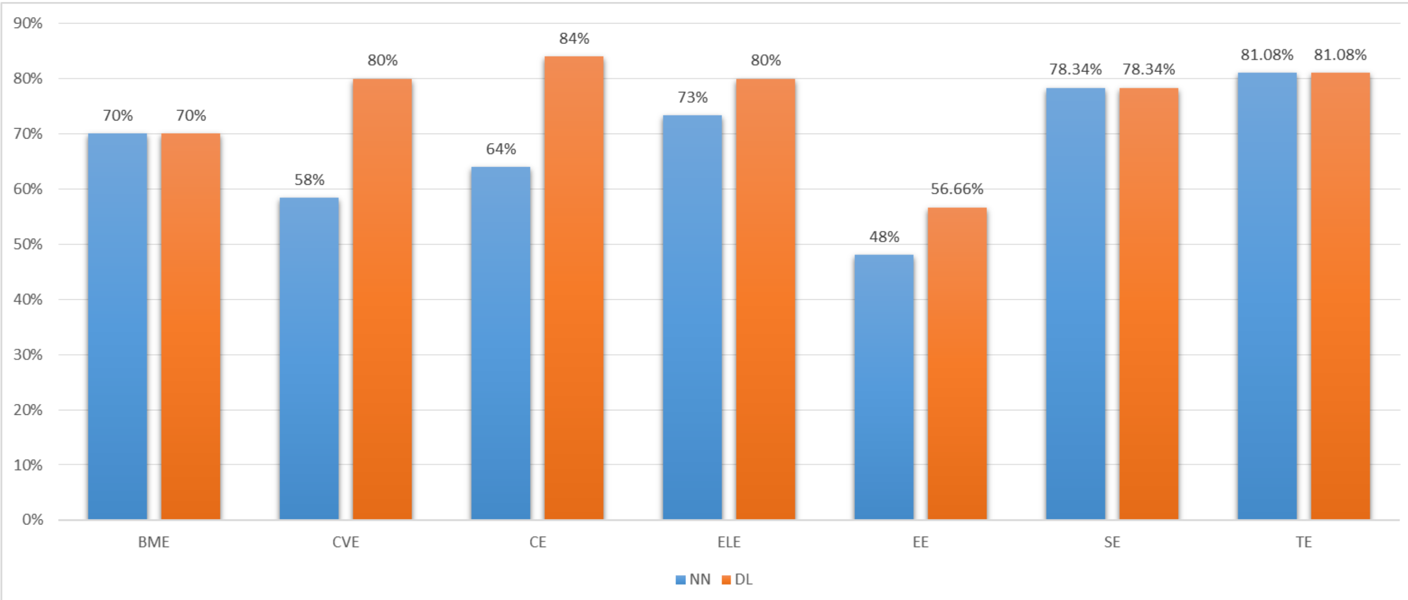

Figure 4 NN and DL Accuracies comparison in a computational representation

The kappa statistics is typically considered a more reliable metric than a simple % correct prediction computation since it accounts for correct predictions made by chance. The Correlation Coefficient, which returns between the prediction and label (or class) attributes, predicted the same results as accuracy. The experiments using both techniques have been applied repeatedly on all seven datasets belonging to different technologies.

Only the results are being presented here that have achieved the highest accuracy using both NN and DL. The Neural Net technique is executed with 500 training cycles, 0.4 learning rate, 0.9 momentum, and two hidden layers (with size ten each) on each engineering technology dataset, but the maximum accuracy is achieved on the **Telecommunication Engineering** dataset. The NN model visualization is depicted in Figure 5.

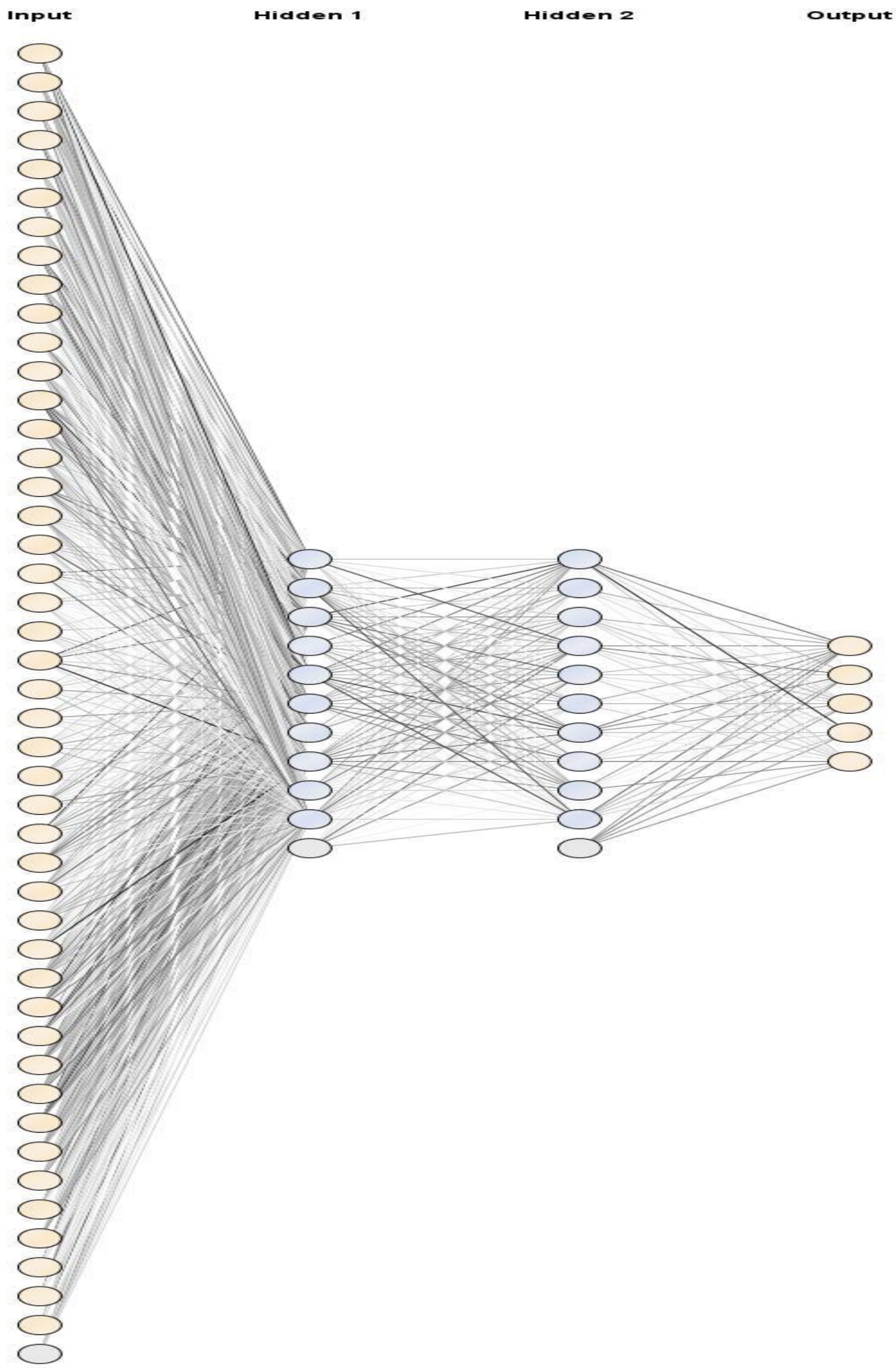

Figure 5 Neural Net model visualization

The input layer provides the attribute values mentioned in Table 1 through various input nodes. The last node of the input layer is the threshold node. The value of bias is automatically added in each hidden layer. Bias is a parameter in the Neural Network that, together with the weighted total of the neuron's inputs, is used to alter the output. Furthermore, using the bias value, the activation function can be shifted to the left or right. The output nodes are used to predict the label or class attributes related to classes Strongly Aware, Aware, Unsure, Unaware, and Strongly Unaware.

The Deep Learning technique is executed with 20 epochs and by setting the activation as a rectifier on each engineering technology dataset, but the maximum accuracy is achieved on the **Computer Engineering** dataset. The model gives 0.0019045066 MSE (Mean Square Error), 0.043640655 RMSE (Root Mean Square Error), 0.99928766 R^2, and 0.035188008 logloss.

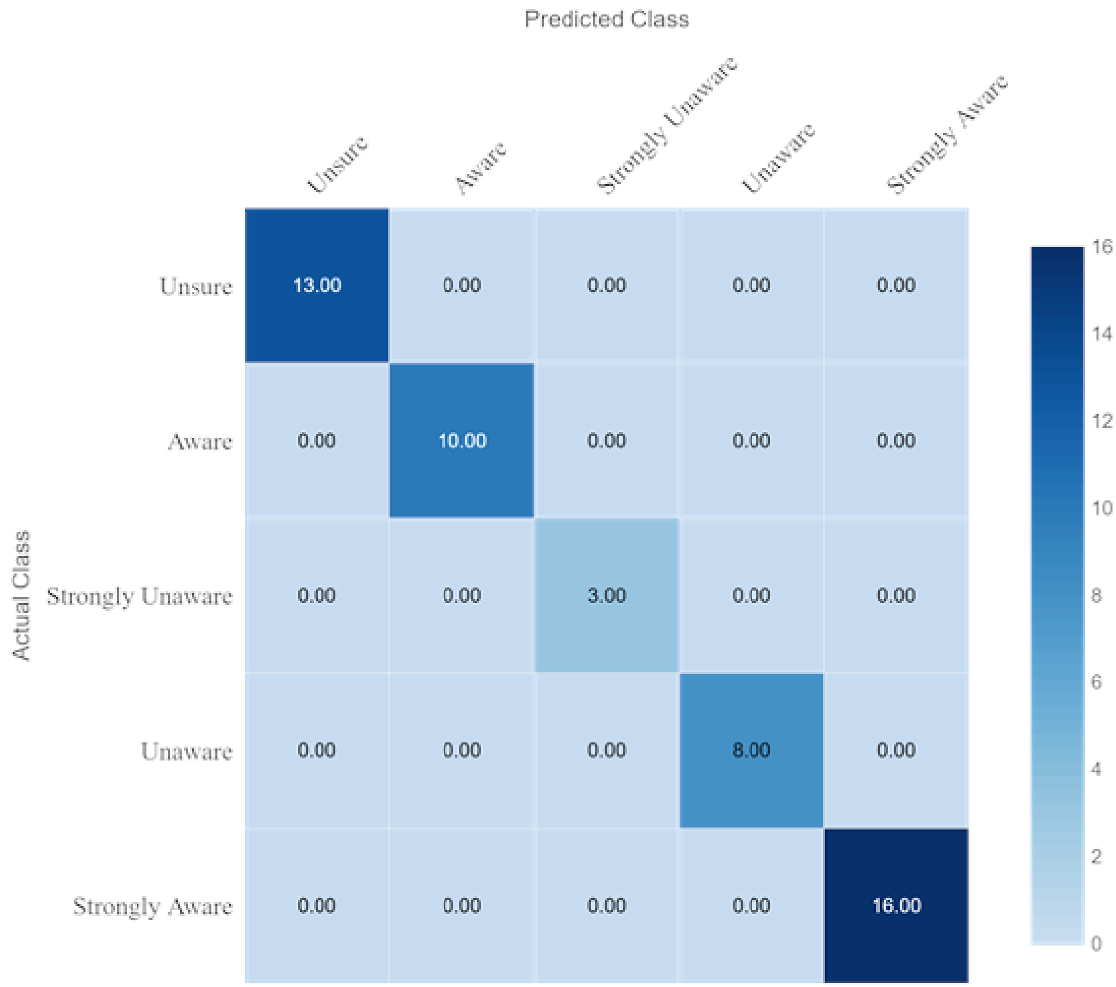

Figure 6 Confusion Matrix obtained from DL Technique

A confusion matrix that summarizes the classification problem's prediction outcomes obtained from the DL technique is demonstrated in Figure 6, showing all correct predictions highlighted with dark color and the diagonals for all five classes of Technological Awareness. The figure shows that the 13 instances are correctly predicted as a class 'Unsure,' 10 instances as a class 'Aware,' 3 instances as a class 'Strongly Unaware,' 8 instances as a class 'Unaware,' and 16 instances as a class 'Strongly Aware' for the Computer Engineering faculty dataset.

The correlation matrix obtained on Telecommunication and Computer Engineering data are shown in Figures 7 and 8, respectively showing one-to-one correspondence between the values of the attributes. The red boxes illustrate the highest correlation between the attributes whereas, the blue boxes depict the most negligible correlation between the attributes.

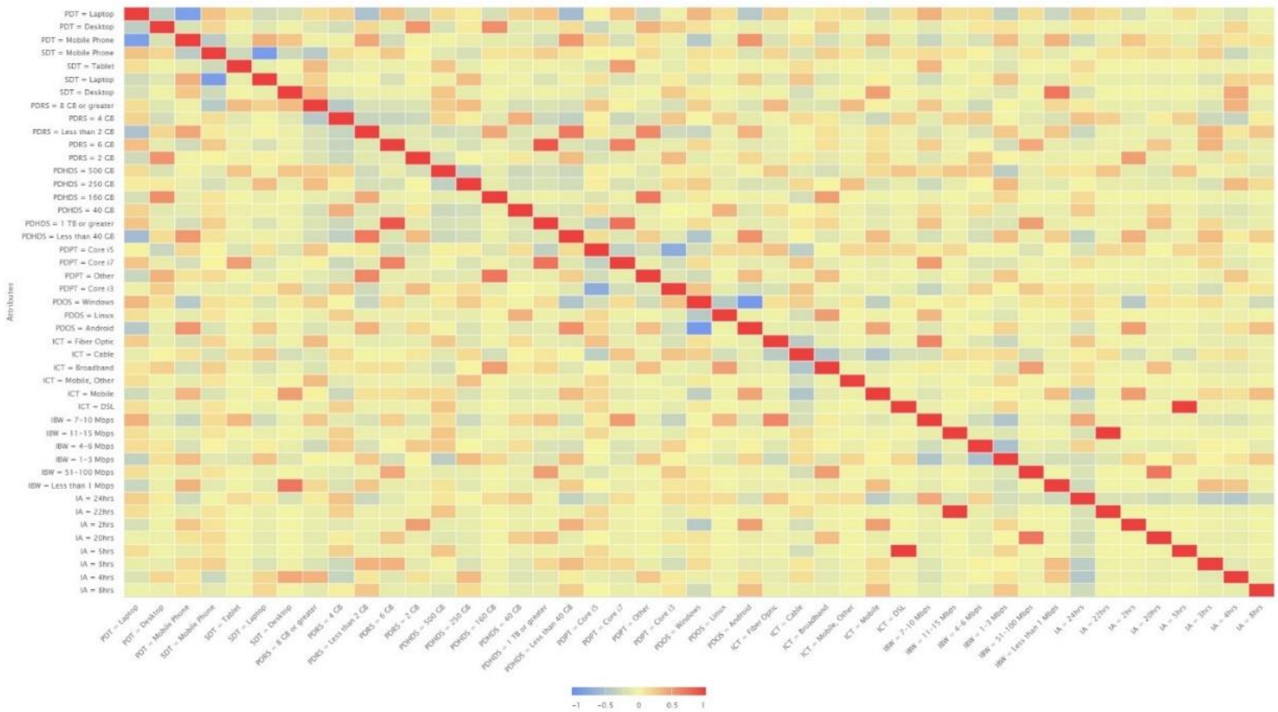

Figure 7 Correlation Matrix of Telecommunication Engineering instances

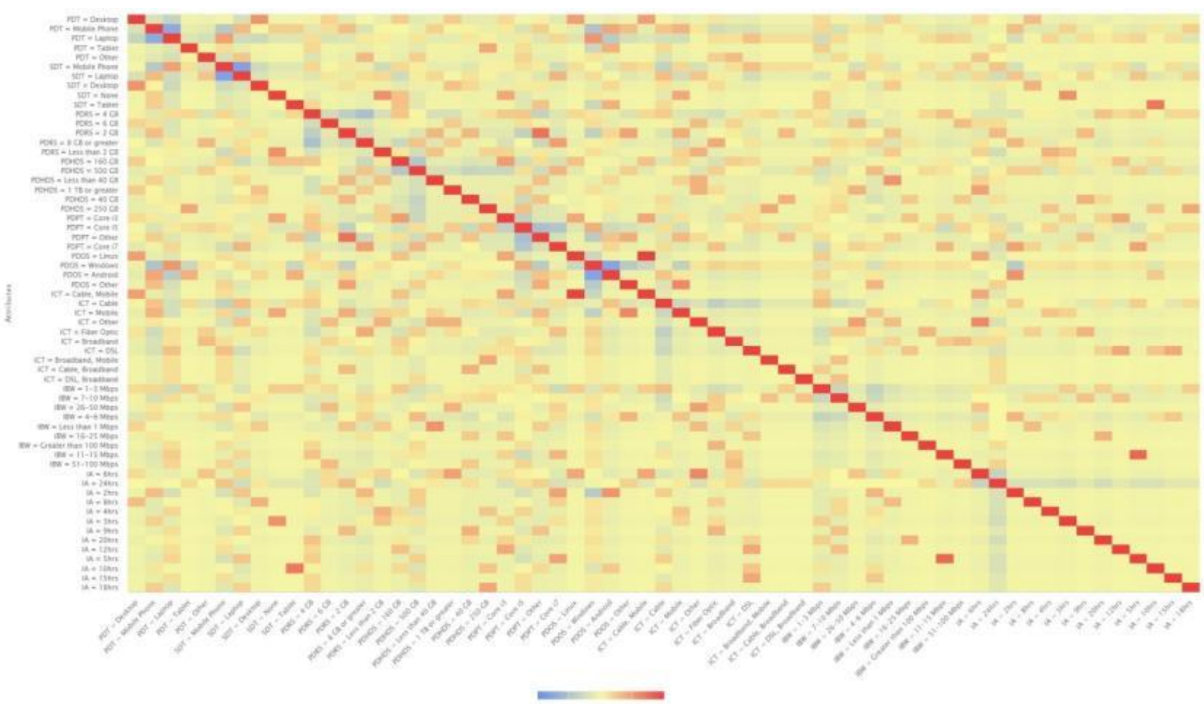

Figure 8 Correlation Matrix of Computer Engineering instances

The bar charts for each attribute value are shown in Figures 9 and 10 for Telecommunication and Computer Engineering Technologies. From the analysis of figures 7 and 9, the attribute ICT (Internet Connection Type) with the value of *'Mobile, Other'* is found the most prominent feature concerning the perception and readiness of the faculty of Telecommunication Engineering towards online learning. On the other hand, the attribute PDT (Primary Device Type) with the value of *'Laptop'* is found the least important feature. This means that faculty with mobile or other wireless internet connections are predicted to be more aware and ready for online education (Mashile & Pretorius, 2003).

Similarly, for the Computer Engineering analysis of figures 8 and 10, the attribute ICT (Internet Connection Type) with the value of *'DSL, Broadband, Other'* is found the most prominent feature whereas, the attribute PDT (Primary Device Type) with the value of the *'Mobile phone'* is found the least essential feature concerning perception and readiness of faculty. This means that the faculty who own a DSL, broadband, and other internet connection type is expected to be more aware of and prepared for online education (Mashile & Pretorius, 2003).

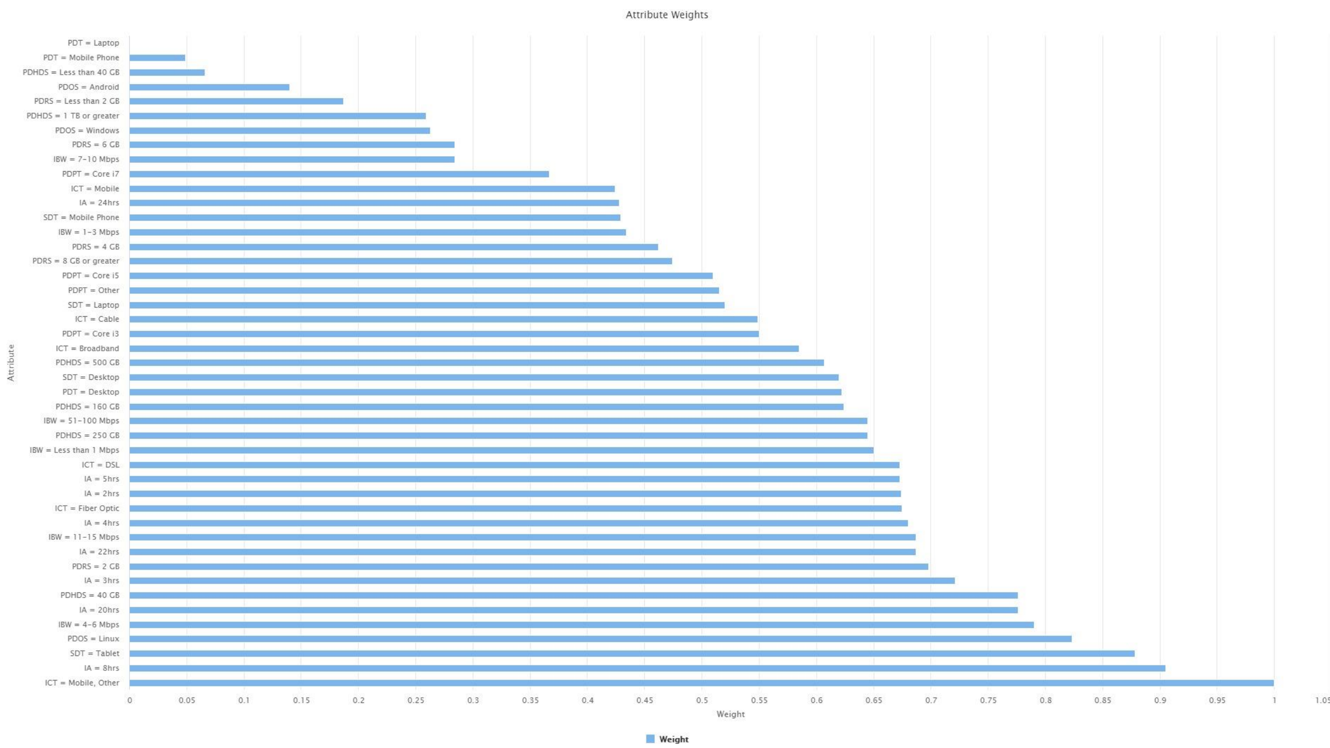

Figure 9 Representation of the Telecommunication Engineering attributes values

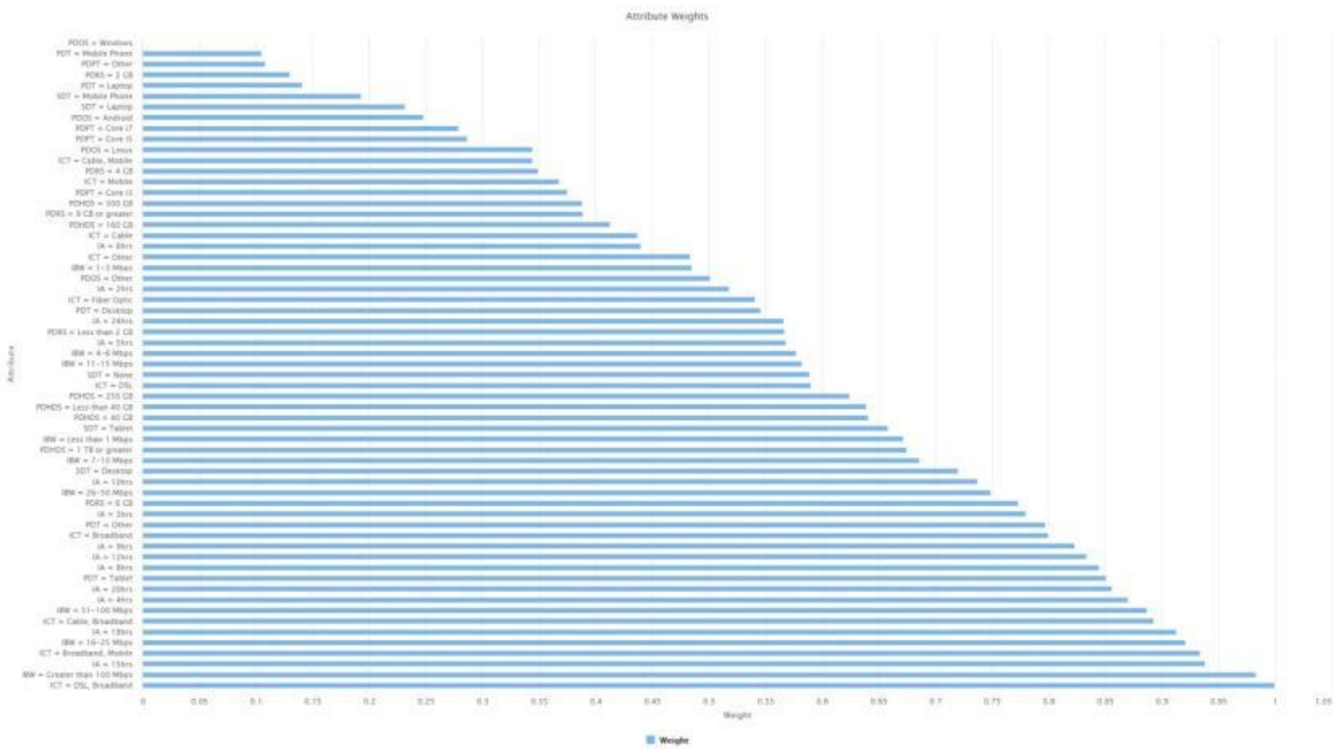

Figure 10 Representation of the Computer Engineering attributes values

ii. Students’ Technological Awareness and Readiness to Online Education:

Students' datasets include 297 Biomedical Engineering instances, 372 Civil Engineering instances, 295 Computer Engineering instances, 365 Electrical Engineering instances, 282 Electronic Engineering instances, 545 Software Engineering instances, and 63 Telecommunication Engineering instances. Table 4 lists the performance metrics such as Accuracy, Kappa, and Correlation provided by Neural Net and Deep Learning methods and calculated to assess the model's performance for predicting technological awareness among students of various technologies.

Table 4 Summary of NN and DL performance metric

Technologies	**Neural Net**			**Deep Learning**		
	Accuracy	Kappa	Correlation	Accuracy	Kappa	Correlation
Biomedical Engineering	52.48%	0.028	0.053	93.06%	0.310	0.248

Civil Engineering	55.98%	0.009	0.055	74.74%	0.182	0.213
Computer Engineering	51.42%	0.017	0.068	87.40%	0.274	0.354
Electrical Engineering	48.82%	0.018	0.025	80.52%	0.230	0.294
Electronic Engineering	55.36%	0.005	0.017	93.66%	0.225	0.270
Software Engineering	50.64%	0.014	0.002	94.28%	0.186	0.124
Telecommunication Engineering	70.96%	0.061	0.046	84.54%	0.220	0.128

On the Telecommunication Engineering student dataset, the NN has the most remarkable accuracy of 70.96%. On the other hand, the DL has the highest accuracy, 94.28%, on the Software Engineering student dataset, as shown in Table 4 and Figure 11. According to the predictions of NN and DL accuracies, in the context of the COVID-19 pandemic situation, Telecommunication Engineering and Software Engineering students are more aware and ready for online education.

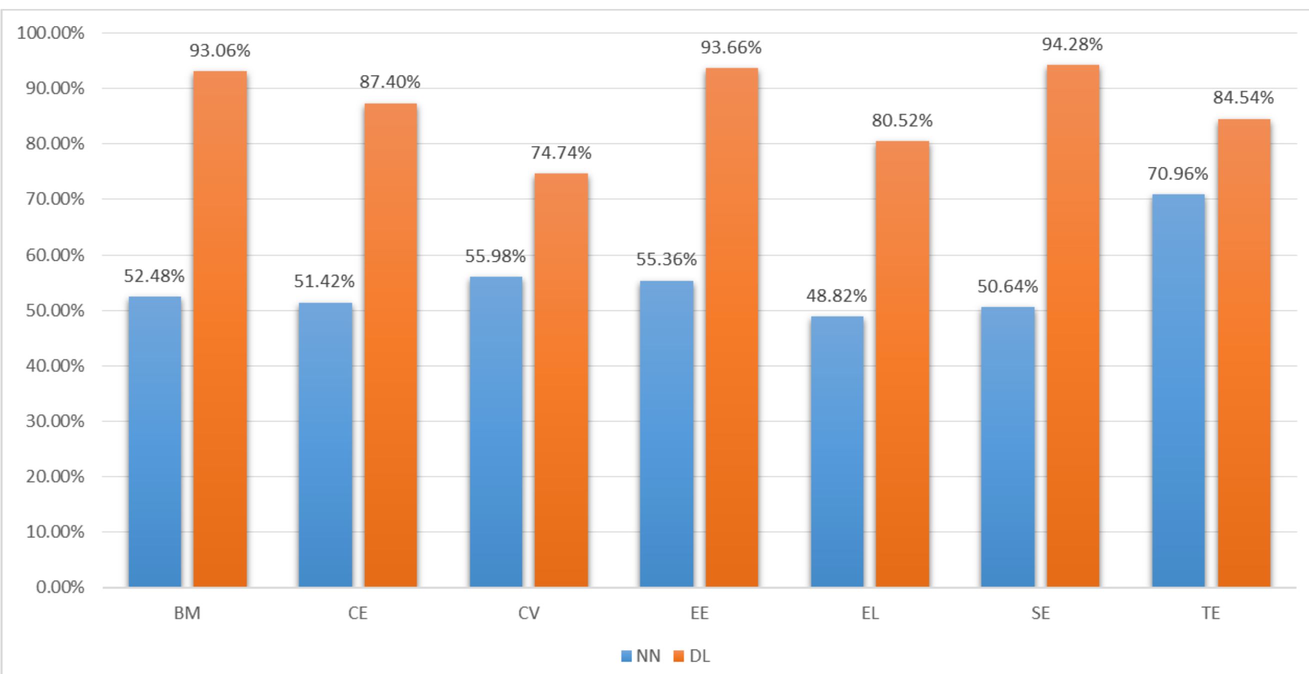

Figure 11 NN and DL Accuracies comparison in a computational representation

Only the results that obtained the highest accuracy applying both NN and DL are included. The Neural Net approach uses each engineering technology dataset with 500 training cycles, 0.4 learning rate, 0.9 momentum, and two hidden layers (size ten each); however, the **Telecommunication Engineering** dataset achieves the highest accuracy. Figure 12 shows the visualization of the NN model.

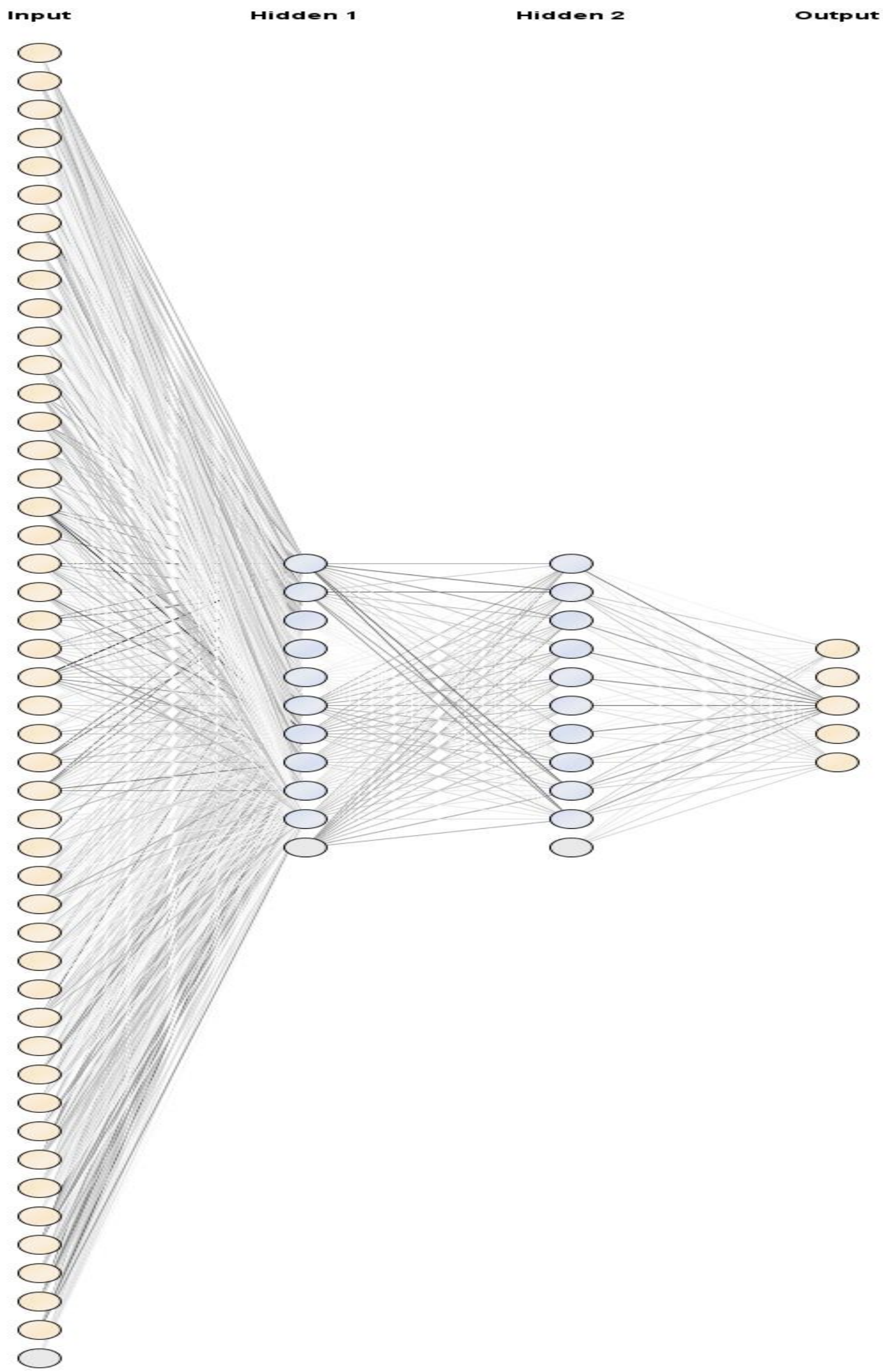

Figure 12 Neural Net model visualization

The input layer provides the attribute values shown in Table 2 via various input nodes. The threshold node is the last in the input layer. Each hidden layer's bias value is automatically added. Bias is a Neural Network parameter that, together with the weighted sum of the neuron's inputs, is used to change the output. The activation function can also be shifted to the left or right using the bias value. The output nodes are used to predict label or class attributes for the Strongly Aware, Aware, Unsure, Unaware, and Strongly Unaware classes.

It is important to note that the NN gives the maximum accuracy on the Telecommunication Engineering data both for faculty and students, indicating both the faculty and students belonging to the Telecommunication Engineering field are more aware and prepared for online education. The same procedure is applied for each technology dataset using the Deep Learning technique, executed with 20 epochs and by setting the activation as a rectifier, but the maximum accuracy is achieved on the **Software Engineering** dataset. The model gives 0.27075663 MSE (Mean Square Error), 0.5203428 RMSE (Root Mean Square Error), 0.84612036 R^2, and 0.7911087 logloss.

Figure 13 Confusion Matrix obtained from DL Technique

A confusion matrix that abridges the classification problem's prediction outcomes obtained from the DL technique is demonstrated in Figure 13, showing all correct predictions highlighted with dark color and the diagonals for all five classes of Technological Awareness. The figure shows that out of 305 instances: 156 instances are correctly predicted as a class 'Strongly Aware', while 149 instances are wrongly predicted into four other classes, and out of 69 instances, 59 instances are correctly predicted as a class 'Unaware' while ten instances are wrongly predicted into four other classes; similarly, 26 instances are correctly predicted as a class 'Unsure', 78 instances are correctly predicted as a class 'Aware' out of 91 instances, and 48 instances are correctly predicted as a class 'Strongly Unaware' out of 54 for the Software Engineering students dataset.

The correlation matrix obtained on Telecommunication and Software Engineering data is shown in Figures 14 and 15, respectively showing one-to-one correspondence between the values of the attributes.

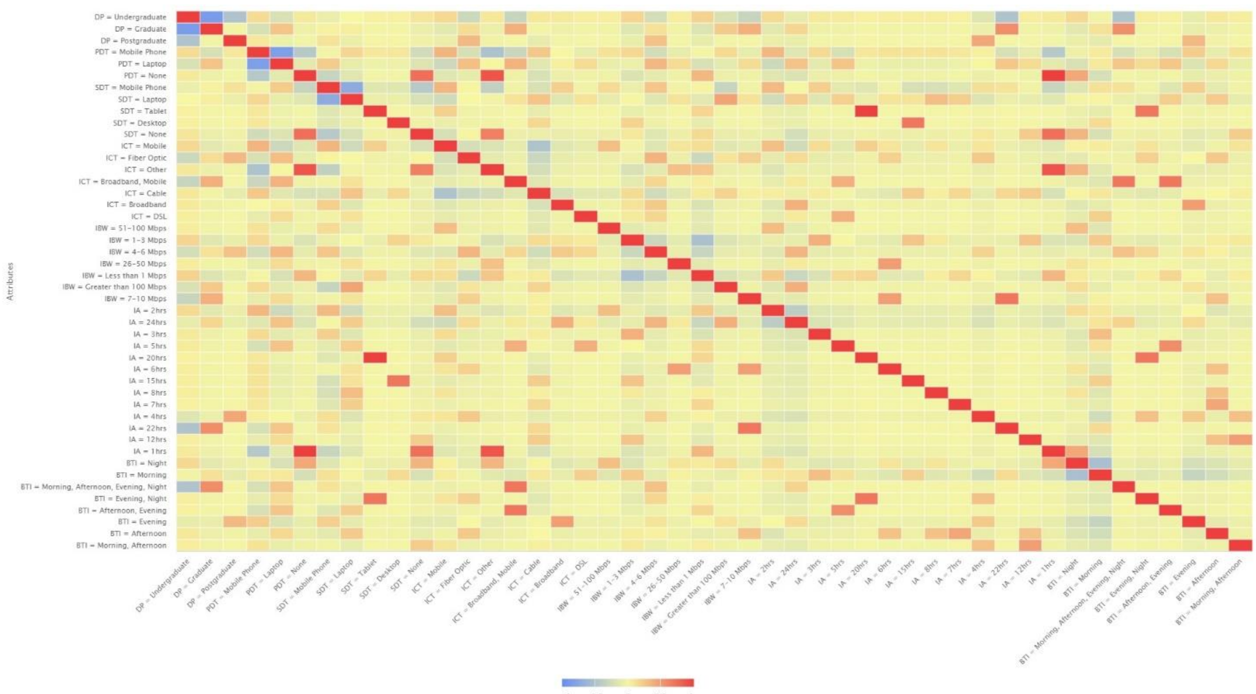

Figure 14 Correlation Matrix of Telecommunication Engineering instances

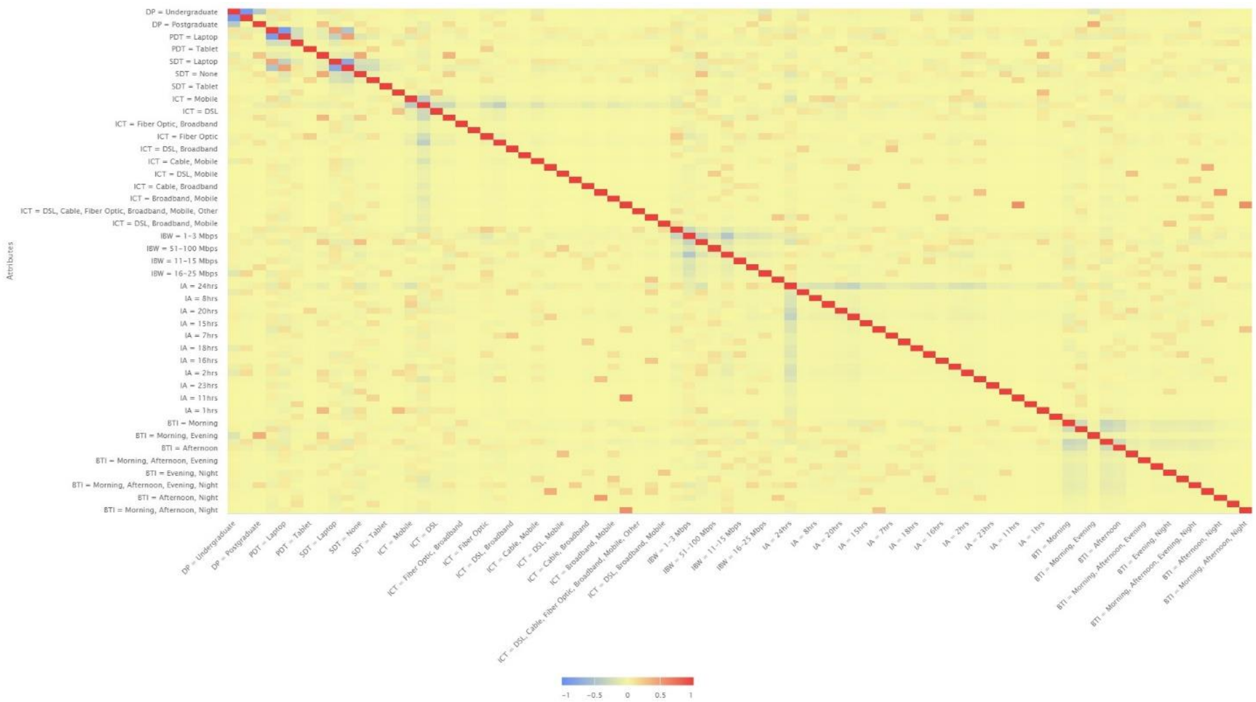

Figure 15 Correlation Matrix of Software Engineering instances

The bar charts for each attribute value are shown in Figures 16 and 17 for both Telecommunication and Software Engineering technologies. From the analysis of figures 14 and 16, the attribute IA (Internet Availability) with the value of *'8hrs'* is found the most prominent feature concerning the perception and readiness of students of Telecommunication Engineering towards online learning. On the other hand, the attribute PDT (Primary Device Type) with the value of *'None'* is found the least important feature. This means that the students with internet availability of 8 hours are predicted to be more aware and ready for online education.

Similarly, for the Software Engineering analysis of figures 15 and 17, the attribute ICT (Internet Connection Type) with the value of *'Fiber Optic, Mobile'* is found the most prominent feature whereas, the attribute PDT (Primary Device Type) with the value of the *'Mobile phone'* is found the least essential feature concerning perception and readiness of students. This means that the students who own a fiber optic and mobile internet connection type are expected to be more aware of and prepared for online education (Dwivedi, 2018).

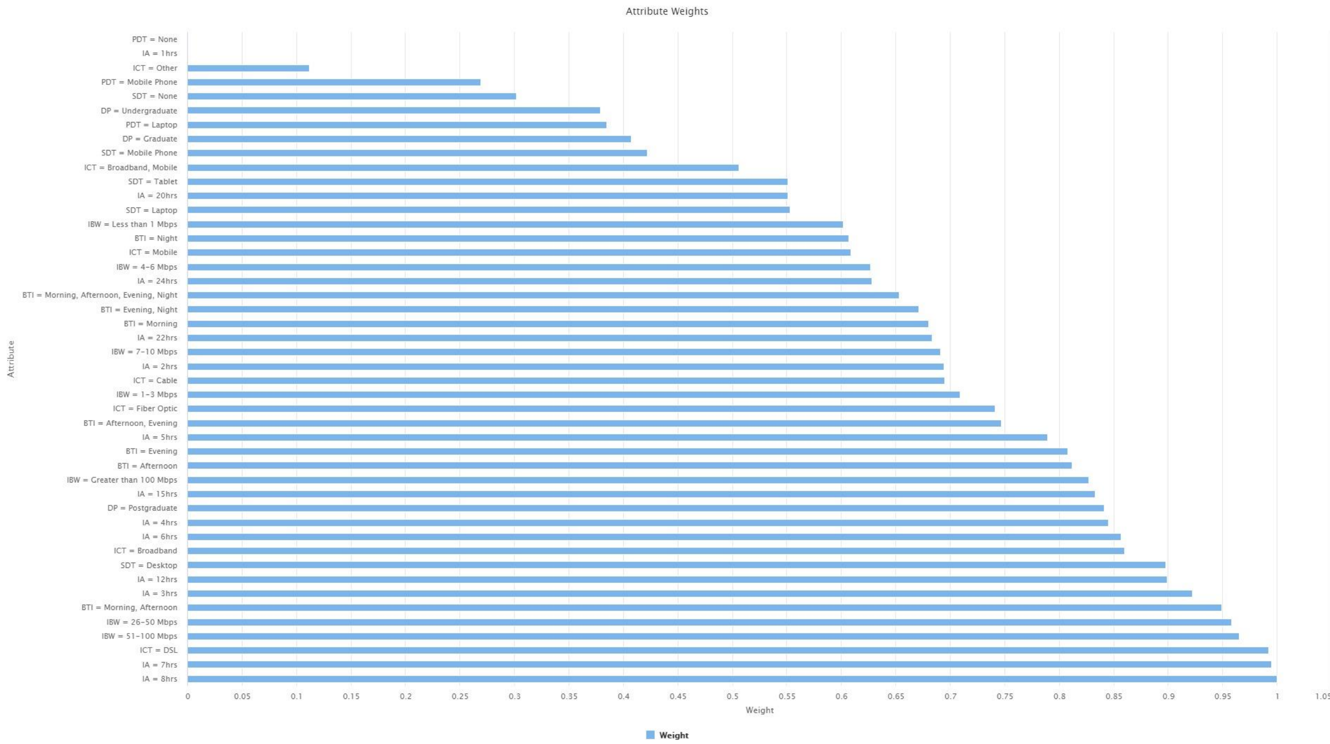

Figure 16 Representation of the Telecommunication Engineering attributes values

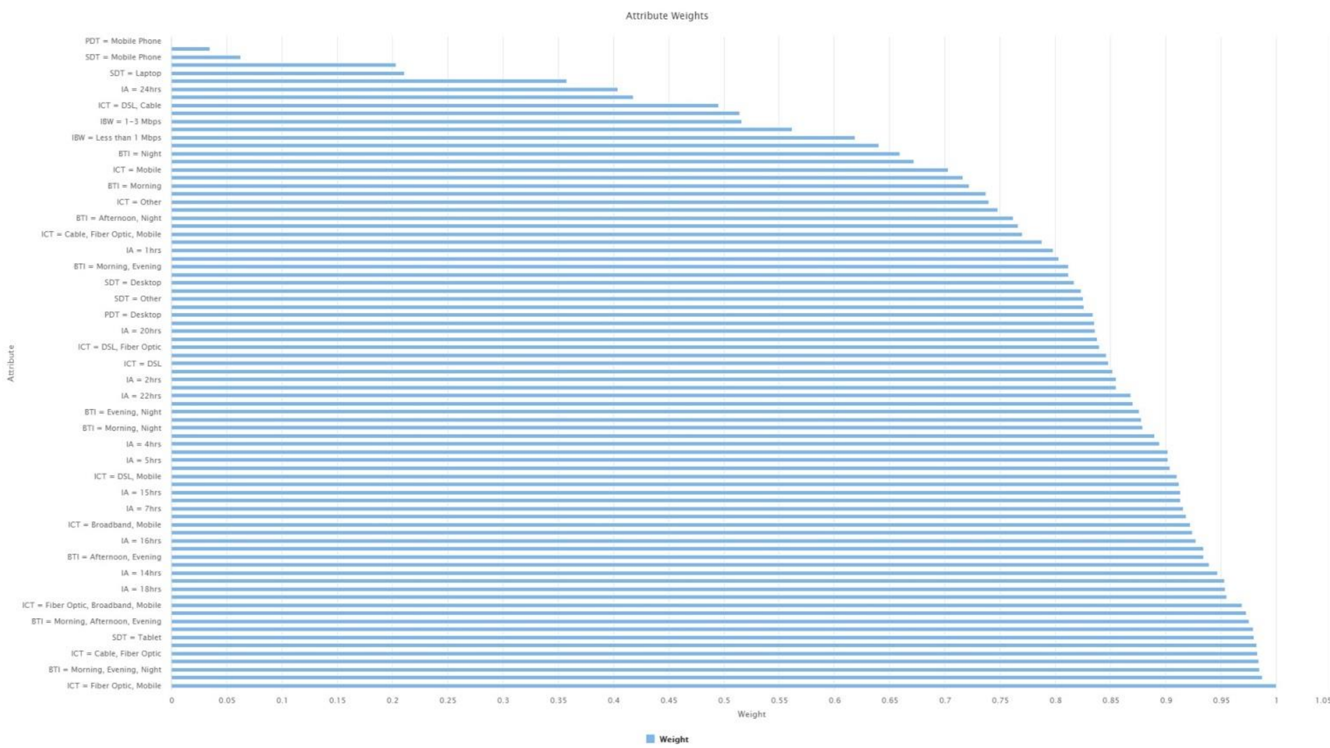

Figure 17 Representation of the Software Engineering attributes values

When the handling of modern technologies is compared with traditional educational methods, it was found that the trends have been reduced, which indicates that there has been a substantial shift in the way online education is delivered utilizing current technologies (Haider & Ali, 2019). The elements used as attributes in a study influencing faculty and students' perceptions of their online education experience have been addressed to offer them a more extensive educational experience and better advantage from this educational pattern (Markova et al., 2017). Neural Net and Deep Learning techniques were used to predict the technological awareness among faculty and students affecting online engineering education to answer research question no. 1 in section IV. The answer is "Yes" it is possible to predict the technological awareness among faculty and students that affects online engineering education extrapolated from the above results and analyses.

Research question no. 2 is answered to determine if there is a good correlation among attributes, i.e., if the dependability and validity requirements have been satisfied or not. In the light of the correlation results of faculty, the attribute PDPT (Primary Device Processor Type) has a positive correlation with the technological awareness affecting online engineering education among four technologies, namely: Biomedical Engineering, Civil Engineering, Electrical Engineering, and Software Engineering, because the attribute PDPT has attained the highest value, i.e., 1. Also, the attributes IA (Internet Availability) and ICT (Internet Connection Type) have a positive correlation among the faculties of Computer Engineering, Software Engineering, and Telecommunication Engineering on attaining the highest value.

Similarly, under the umbrella of correlation results of students, the attribute DP (Degree Program) has found the positive correlation with the highest value, i.e. 1 for two technologies, namely: Biomedical Engineering and Computer Engineering, whereas the attribute IA (Internet Availability) for Electronic Engineering and Telecommunication Engineering, ICT (Internet Connection Type) for Software Engineering, SDT(Secondary Device Type) for Civil Engineering, and PDT (Primary Device Type) for Electrical Engineering found the positive correlation with the technological awareness affecting online engineering education on the attainment of the highest value.

This study looked into the educational problems that higher education institutions face when switching to online education, exacerbated by the COVID-19 pandemic (Hadjeris, 2021). Thus, it has been proved from the above results and analyses, obviously and predominantly the engineering technologies faculties and students belonging to the technology field like Telecommunication Engineering, Computer Engineering, and Software Engineering are found more aware and ready to turn to online education mode as compared to other engineering technologies.

Key finding of this study includes:

- In comparison to other engineering technologies, the faculties of engineering technologies, such as those in computer engineering, software engineering, and telecommunication engineering, are considered to be more familiar of and prepared to use online education.
- In comparison to other engineering technologies, students studying software, computer, and telecommunication engineering tend to be more knowledgeable of and prepared to use online learning environments.
- The study intends to provide practical suggestions that can open the door for a more flexible, accessible, and technologically adept educational environment in a post-pandemic world by highlighting the importance of technological awareness.

CONCLUSION AND RECOMMENDATION

Like other countries of the world, Pakistan emerges from the worst days of the current COVID-19 pandemic. It has a significant impact on livelihoods, and there are several adverse effects on the economy, such as education, health care, agriculture, etc. have been observed. Academic institutions worldwide face numerous challenges, including a lack of technical assistance, the need for teachers to be trained to increase their technological abilities, and a lack of technological infrastructure. However, education has a unique opportunity to turn the page and move forward toward a brighter future. In this ongoing pandemic, different educational institution management has chosen online teaching to resume education. It is not as effective as traditional education because teachers and students are familiar with the environment of traditional education over the years, but online education needs to be concerned about technological awareness. This study aimed to determine which engineering department's faculty and students are accomplished to be aware of the technology at the higher education level. Because, an engineering degree, if pursued appropriately, may provide an individual with the capabilities and their perfection or achievement in engineering courses they require. Furthermore, there are many courses in which there is an opportunity for development.

Technological advancements have touched every element of life. Because technology has become an inextricable aspect of society's survival, its integration into education is unavoidable. Technology gives students awareness of a plethora of online resources, but it also helps them learn. Many universities and educational institutions have already begun to use technology in their teaching techniques. This study addressed the prediction of technological awareness amongst faculty and students by applying neural net and deep learning techniques. Neural Net and Deep Learning are essential techniques that help to improve prediction analysis. However, both techniques have gained popularity due to their capacity to solve a wide range of technical tasks and cope with them better than other algorithms.

Nevertheless, the analysis results show that the accuracy achieved from the neural net on both faculty and student data is less as compared to deep learning because the neural net technique typically achieves more accuracy on numerical data rather than on nominal or categorical data, and majorly the datasets used in this study are nominal that is why the performance of neural net is not much efficacious as deep learning. The analysis findings manifested a positive and significant impact in the form of students and faculty satisfaction with technological awareness, as the results show that the faculty of Telecommunication Engineering and Computer Engineering and students of Telecommunication Engineering and Software Engineering are more aware and prepared for online education.

In general, teachers and students are psychologically ready to adopt innovative ways of acquiring knowledge, if their institutions provide sufficient support. The findings also indicate that more significant effort should be put into improving teacher training programs for more awareness and equipping both faculty and students with the necessary abilities to meet the challenges of the 21st century.

Shortly, the research might focus on some challenges that are discerned throughout the survey for online education like the incompetence to afford practical tools (e.g., laptops/smartphones/adequate software), online collaboration and networking with peers, increased administrative efficiency, and ensuring education in unusual conditions are all potential in online learning that can be turned into educational benefits. In addition, considering the above challenges, adding more attributes to the data set, and using different technical methods lead to more accurate and satisfactory results. Several recommendations are made in light of the background information and study findings, including the following: funding for practical tool purchases, improved teacher training programs, ongoing professional development, and encouragement of online collaboration. Establishing a conducive environment that enables educators and learners to proficiently traverse the digital terrain is crucial.

CONFLICTS OF INTEREST

The authors do not have any conflict of interest with the content of this paper.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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