Evaluating the Effectiveness of Interactive Video Learning by Examining Machine Learning Classifiers Models: Graduate Students' Perspectives

Omar Abdullah Omar Alshehri, Elrasheed Ismail Mohommoud Zayid*, and Amer Mutrik Sayaf

***Abstract*—Important elements had an impact on how traditional learning was implemented and motivated researchers to develop Interactive Video Learning Effectiveness (IVL-E). These variables range from price to learning-environment to learner perspective, among others. This paper's major objectives are to: (i) assess the effectiveness of Interactive Video Learning (IVL-E) using classification techniques and considering graduate students' viewpoints, (ii) establish appropriate classification parameters to choose the optimum classifier model, and (iii) review prior works pertaining to IVL-E assessment. The study dataset is a sample of 63 datapoints randomly chosen by a survey performed at the College of Education, University of Bisha, Bisha, Saudi Arabia. A total of 123 registered postgraduate students made up the study population when using Google's online questionnaire method, after all the respondents voluntarily agreed to fill out and submit the questionnaire. This study develops a reliable machine learning classifier's model for classifying IVL-E. The created models use a backpropagation algorithm and are a type of multilayer classification perceptron. The best classification output was "interactive video learning performance measure", which provided the highest results under: 1) support vector machine-based classifier (SVC), 2) decision tree (DT), and 3) light gradient-boosting machine classifier (lgb.LGBMClassifier). Regarding classification measures like balanced accuracy (high BCCR = 0.875), balanced error rate (low BER = 0.125), and optimization precision (highest OP = 0.999), our models performed extremely well according to the literature review.**

***Index Terms*—Interactive learning assessment, video learning classification, Saudi interactive learning**

I. INTRODUCTION

Considerations of cost, time, learner mobility, and the recent pandemic are the main factors affecting traditional face-to-face learning methods and driving institutions to adapt their learning systems by introducing interactive e-Learning methods [1]. A variety of different approaches have been introduced to address some of the interactive learnability issues encountered; however, significant challenges remain [2, 3]. These problems include, but are not limited to, networking instability, online service costs, training and usability gaps, and platform configuration and usability [2] in terms of its capabilities and effectiveness [4].

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Interactive video learning (IVL), a growing trend in online education, is used to facilitate interactive education, the distribution of course materials, and the exchange of knowledge between class members [5]. IVL has become a very useful method for capturing learners' attention and providing immersive learning experiences. IVL can take the form of video, audio, voice, text, movie, or a hybrid format of all of these media, with the teacher administering the lecture materials and sharing them with students in class.

Mahyoob [6], carried out during the pandemic, used statistical analysis to investigate the challenges and boundaries relating to IVL from a technical, academic, and communication perspective. Today, both students and teachers have now come to accept smart devices and technology-ware (hardware, using-ware, and software) to an extent that reduces any issues relating to IVL learnability. With the strengthening of the Saudi internet, there are now fewer issues relating to network instability [7]. The current evidence shows that many teaching staff now has extensive experience in IVL course preparation and execution via interactive media. This means that there is less consideration of the need to train students [5, 8, 9]. In this respect, we argue that the pandemic has enhanced the usability and effectiveness of IVL today and in the future.

Our study sought to evaluate the current gaps in the area of IVL in order to maintain and enhance the quality of graduate college education by measuring student engagement in IVL classrooms. It is hoped that the study findings may encourage stakeholders to design new standards for Saudi national virtual classrooms, as well as provide a vision for a re-designed and futuristic curriculum in Saudi Arabia. Moreover, the outcomes of this study are intended to contribute to the re-shaping of a faculty framework for both asynchronous/synchronous IVL educational systems and encourage training for students.

When compared with traditional teaching methods, the IVL teaching style has a number of distinct differences and benefits, namely:

1) it offers learners the ability to interact and communicate with their teacher and classmates more easily.
2) it enables learners to engage in a "real-time" system.
3) it provides a highly effective means of administering all forms of examination as it allows functions such as drag and drop, short answers, summaries, multiple choice questions (MCQs), and many more; learning management system (LMS) administrators allow multiple forms of answering style, as required.
4) it provides teachers with reports and analytics that enable deeper insights into learners' progress, and it has proven to be effective in many science-engineering fields, such

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as military, education, gamification, and medicine [10].

At the University of Bisha, the IVL system was installed gradually, first, by testing supportive e-Learning, followed by changes as technologies advanced. The educational process initially involved a form of blended learning, with the e-learning component accounting for between 25 and 50%, depending on course type. However, following the devastating impact of the COVID-19 pandemic, fully interactive e-Learning was implemented [11–14]. During this stage, a variety of application programs were provided to support interactive and non-IVL and offer comprehensive control and monitoring of student participation in the learning process. During the pandemic, the types of e-Learning management systems employed can be divided into the following categories:

1) Learning management systems (LMS): used to manage, control, and evaluate learning during both synchronized and synchronized activities. These activities include registration, reporting, development, evaluation, management systems, and e-contents.
2) Course management systems (CMS): focused on the composition and development of courses by enabling publication of materials and managing of course related activities.
3) Learning content management systems (LCMS): concerned with educational content, they enable authors to create, develop, and modify educational materials [15]. However, these contents are related to the application of authorship, learning object repository, and dynamic connection interface, in addition to management tools.

Today, there are two main types of IVL-LMS: open source and commercial. Due to its reliability, security, and availability, the university employs the Blackboard (Bb) system (a commercial system). Moreover, the system also enables instructors to use other similar commercial systems (e.g., Web C and Tadarus), and/or implement open-source systems models, such as Moodle, DOKEOS, and ATutor.

Although e-Learning education systems are varied, they are all designed to enable the distribution of course materials to students. They are designed to provide students with all the necessary tools to achieve course aims and objectives. While more than one single tool is usually offered to a class of learners, an interactive video lecture is often the best way to ensure understandability and interactivity. Therefore, promoting student outcomes requires deep mining and exploration of IVL systems [16, 17]. However, given the very few studies carried out in this area, there is a lack of evaluation of the impact of IVLs on student outcomes.

All of the subjects in our study at the University of Bisha had used the Bb system in addition to one or more LMS applications. The features of the Bb system can be summarized as follows: a platform for each academic subject allowing file upload and download, e-mail, blog posting, wiki, video conferencing, and compatibility with international quality standards in IVL. Moreover, the Bb enables file exchange, group discussions, interactive whiteboards, program sharing, and the recording of virtual sessions in MP4 format without the need to configure any additional software (the incorporation of WebRTC prevents the need to install Java) [18–20].

In this paper, an assessment of IVL-E classification was performed using data gathered from a set of graduate students at the College of Education, University of Bisha, Bisha, Saudi Arabia, who volunteered to take part in the study.

Our primary goal was to classify and evaluate feedback from graduate students regarding IVL e-Learning methods. The study dataset was obtained by recruiting 63 volunteer graduate students (76.2% male and 23.8% female) from the university. The ages of the subjects ranged from 24 to 31 years old, and their disciplines covered both the social sciences (66.7%) and applied sciences (31.7%). The raw dataset was pre-processed, and the key features were selected as system inputs. For the output class, a set of six different targets was used, each with three outputs (i.e. nominals chosen as 0, 2, and 3). These classes are explained in the section on experiment models, and the names of input/output features are listed in the materials and methods section.

Our method involved the employment of several powerful machine learning algorithms to accurately calculate the contribution of each feature of the model. Finally, the performance of each classifier was compared with the best results reported. Details about how the models were constructed are provided in the materials and methods section. The IVL is the next-generation avatar of a video-based educational environment system that utilizes emerging online, virtual, and video features to provide a high-quality e-Learning system. This study aimed to achieve the following:

1) identify the added values that IVL provides for the Saudi community, specifically using graduate students at the University of Bisha as a sample.
2) extract the key features of IVL educational systems by testing the best feature selection techniques.
3) utilize the study findings to promote IVL for postgraduate students across Saudi institutions.
4) examine powerful machine learning methods and their capability to assess IVL systems.
5) analyze our qualitative dataset and compare the study findings against the most recently published articles.
6) establish whether IVL leads to better knowledge acquisition compared to other teaching and learning methods.
7) ascertain whether there is a benefit to utilizing powerful research algorithms for examining local systems.

The remainder of this manuscript is organized and structured as follows: Section II provides an overview of the IVL. Section III reviews the most recent related works. Section IV discusses the study’s dataset generation, materials, and methods. Section V presents the study findings and a discussion of these results. Lastly, Section VI concludes the study and points to areas for future research and followed by the References.

II. Overview of IVL

IVL provides a learning process that utilizes interactive video to encourage participation, conversation, and interaction among class members. Articles [21, 22] define the term “interactive video” in the field of education as a form of instructional video, an educational method that enables users to perform specific learning tasks, such as attending an online lecture or session. It provides limitless ways for interaction between class members. Teachers can use hybrid IVL materials to fully control his/her class and inspire learners. Such methods improve the retention of information and facilitate its application. IVLs are personalized and can be used to highlight crucial information. A blend of different inputs that work on all devices can increase the learner's explorative awareness, deepen their level of understanding of content (by doing, listening, and seeing), and enhance decision-making capacity.

Fig. 1 below illustrates the typical content of an IVL for a university major course, together with the basic roles of each component. For example, an LMS facilitates the achieving of overall learning goals by providing delivery of learning material; automation; administration; and analysis. Management activity concerns documentation and database handling. The system is responsible for all incoming and outgoing aspects of the LMS. Furthermore, LMSs encompass a great range of different forms of activity, and are even compatible with applications that are not purpose-built for online education (e.g. Twitter and Facebook). LMSs are highly supportive of video-conferencing tools for e-Learning, such as the Zoom application. There are also primary purpose-built LMS applications, such as Moodle and Blackboard.

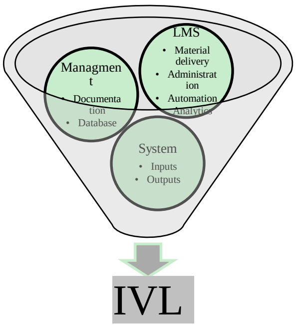


Fig. 1. Typical IVL content.

In summary, LMSs can be very helpful in educational organizations because they reduce costs and offer learners an enhanced learning experience, which should ensure that IVL becomes increasingly popular in the future.

III. Related Works

As technology continuously evolves, this creates the need for the continual development and progression of existing education systems, learning styles, and teaching methods [23, 24]. The rest of this section reviews the recent related works on IVL. In [23], the authors were motivated by the previous lack of quantitative research on the measurable outcomes of futuristic e-Learning. They performed an empirical experiment to estimate the outcomes and impacts across Tamkang University's future education system. The two articles used a traditional statistical tool to compare advanced machine learning features.

Study addressed the educational challenges facing our students' learning today and tomorrow [25]. It explored several ways to acquire soft skills, highlighting the IVL method [26]. O'Brien and Alexa [27] presented a new method for capturing learners' voices as experts in their own futures and introduced the idea of a "speculative alignment" between the students' futures and learning design., thus providing a valuable contribution to the design and construction of future teaching and learning methods [27, 28].

In paper of Chen *et al.*'s [29], an empirical analysis of a revised foresight style assessment of university students in undergraduate classes at Tamkang University showed that the educational intervention of having students take futures courses improved the mean score across the five foresight styles investigated. This contribution adds great support for IVL. Factors affecting academic integrity in e-Learning at Saudi Arabian universities were examined by Muhammad *et al.* [30], with 12 factors identified linked to the e-Learning environment, integrity, and e-Learning guiding principles. Muhammad *et al.* [30] proposed comparatively novel ways of maintaining academic integrity in e-Learning.

Omar *et al.*'s study [31] was designed to explore the e-Learning experience of undergraduate students during the pandemic. They used an online questionnaire comprising five themes to analyze key factors such as institutional support, emotional engagement, cognitive engagement, behavioral engagement, and student satisfaction.

Papers [31, 32] agree that appropriate measures must be put into place to facilitate and strengthen IVL capabilities for the whole community of e-Learners. Both Ahvenharju *et al.* [24] and Desai and Kulkarni [33] report a lack of studies aimed at evaluating IVL; however, very few scholars have sought to evaluate the effectiveness of IVL educational systems. Through a case study, Desai and Kulkarni [33] evaluated the capacity of IVL to enhance the e-Learning experience by offering flexibility of time, place, and content. However, Desai and Kulkarni [33] finds that the lack of real interaction in e-Learning undermines learning outcomes. It noted that, while many methods can be employed to enhance the learning process, very often, IVL is proposed as a high-ranking candidate in the area of e-Learning.

Barbara and Flowers [34], which involved video content and enriching interactive elements, focused on two main content delivery forms: 1) learning using demonstrative video; and 2) learning using interactive video. It observed that students' performance was found to increase significantly during the post quiz of students exposed to IVL, and thus, it leads to higher learner satisfaction. Students engaging with the interactive videos scored an average mark of 82.79%, while students shown the demonstrative videos scored an average mark of 64.41%. This study highlights the superiority of interactive video over linear, demonstrative video, as it offers enhanced conceptual understanding and attainment of desired learning outcomes through the management of cognitive load by increasing students' engagement through active learning.

Nives and Tomislava [35] set out to investigate the impact of IVL by comparing interactive and demonstration videos in terms of student satisfaction and effectiveness. It was concluded that students engaging with interactive videos achieved slightly better learning outcomes than those engaging with demonstrative videos.

Despite the availability of computer technology resources in many educational institutions and the important role they play in facilitating the educational process, some teachers see no positives in using interactive video platforms in their classrooms. The authors [36] reported the negative aspects of using these platforms from teachers' perspectives, with some lamenting that interactive videos require more time to use than they are worth, as well as slow internet connections, and long periods of internet interruption. Technical problems that waste chunks of limited class time were also identified, such as audio interruptions, video blurring, and a lack of required technological infrastructure. Some teachers also complained about the lack of training and institutional support they received. Hence, more efforts are needed to address such challenges in the educational environment.

As shown in [37], training is an important issue to consider when examining teachers' attitudes. A study conducted by Gedera and Zalipour [38] found that most teachers (85%) in secondary schools in Jordan had not received any training in the use of interactive video platforms in an educational environment, while 33% reported wishing to have more support in this regard. As a result, the existing literature demonstrates that many teachers need additional support from their institutions in the form of training sessions and assistance in achieving the meaningful integration of these tools into academia.

Aljaber [39] explores the progress of e-Learning across five Saudi universities, with the aim of providing a historical overview of the development and evolution of e-Learning in Saudi Arabia. It identified the challenges in e-Learning that are currently being addressed, such as poor communication and weak links between students and instructors. Table I below summarizes and reviews the most recent works in this area.

TABLE I: RELATED WORKS

Author(s), year	Approach	Review
K.-H. Chen, L.-P. Hsu 2020 [23]	Quantitative, survey	Machine learning capabilities NOT examined
K.-H. Chen *et al.* 2021 [29]	Quantitative, survey	Further empirical proof that futures-oriented pedagogy is a valuable tool to transform the current factory model of learning into a culture of foresight and provide students with essential strategic foresight leadership skills
A. Muhammad *et al.* 2020 [30]	Questionnaire	Proposes a comparatively novel idea to maintain academic integrity in IVL
M. K. Omar *et al.* 2021 [31]	Qualitative survey Questionnaire	Lack of undergraduate student to IVL readiness
T. S. Desai and D. C. Kulkarni 2022 [33]	Quantitative, case study	Weakness of analysis tools used
M. P. Nives & L. Tomislava 2020 [35]	Qualitative, Questionnaire	Normal metrics Sample space limitation & materials used
A. Aljaber 2018 [36]	survey, 4 universities KAU, KSU, KFU, and the Saudi Electronic University (SEU)	Review article
P. George *et al.* 2019 [37]	Qualitative	It succeeded in providing specific design guidelines for developing effective IVL environments.

In the literature review, only a single paper was found that investigated the performance of classifier models using Delphi and AHP. The study examined factors affecting academic integrity in e-Learning inside Saudi Arabian universities [30, 39]. Finally, Palaigeorgiou *et al.* [40] reviewed interactivity types and their educational value based on analysis of 18 studies and 13 commercial interactive video environments. Paper [41] supported the findings of [40] relating to the effect of the length of interactive videos used in e-Learning environments on cognitive load, cognitive achievement, and learning retention.

In the present study, by encouraging our faculty's graduate students to volunteer, we succeeded in collecting a new local dataset and utilizing machine learning capabilities to compute the classification classifiers across different algorithms and via many dimensional features. In addition, the study made a small contribution by employing powerful Python programmability to support machine learning classification and computation methods.

IV. MATERIALS AND METHODS

This section presents the materials and methods employed in this study, dividing them into three subsections: dataset generation, classification methods, and classification metrics.

A. Dataset Generation

The study population consists of postgraduate students that were registered in the College of Education at University of Bisha, Bisha, Saudi Arabia. Due to the expense, time, and size of population factors it was not possible to use the entire population for this statistical study; therefore, we used a sample space which precisely selected from a population. The dataset collected at University of Bisha in the College of Education. The participants of the sample were carefully selected, because they inherited the same characteristics as the subjects in the population. Data can be collected in a variety of ways however the use of surveys is the most popular method in this study. In this regard, we used our classrooms' social media networks such as WhatsApp to distribute the questionnaire. Online Google form of the survey was used to collect the responses. This helped to cover a wider geographical area, less expensive to conduct, and the respondents can remain anonymous if they desire. However, the major disadvantage of this tool includes a low number of responses and inappropriate answers to open questions.

To have the advantage of obtaining in-depth and accurate responses to questions from the student being questioned, the study questionnaire was simply and clearly designed and structured. Statisticians use random, systematic, stratified, and cluster sampling techniques to properly select a sample. This survey consists of multiple-choice questions (MCQs) in addition to open-ended questions that helped to support the findings of the quantitative data. The survey includes up to 63 records postgraduate students voluntarily responded taken as a sample in this study.

In addition to that informed consent was considered per subject. In this regard, all methods were carried out in accordance with relevant guidelines and regulations and the used experimental protocols were approved by the Deanship of Scientific Research, University of Bisha, Saudi Arabia

(RULE (16) attached).

Table II below shows an overview of the dataset collected and coded, with each line representing a single input/output feature. It includes 63 data points, each of which contains 32 different fields.

TABLE II: AN OVERVIEW OF THE DATASET INPUT/OUTPUT FEATURES WITH THEIR CODING VALUES

#	Feature	Coding
1	Timestamp	Represents time stamp
2	Gender	male = 1, female = 0
3	Age	22–24 years = 1, 25–27 years = 2, 28–30 years = 3, 31 years and more 4
4	Profession	applied science = 1, social &humanitarian science = 0
5	Most frequently used IVL apps	YouTube = 1, EduCanon = 2, Edpuzzlel = 3, Google Classroom = 4, MasterClass = 5, Khan Academy = 6, Coursera = 7, Udacity = 8, Kahoot = 9, Skillshare = 10
6	IVL concept	Advance = 3, Good = 2, Weak = 0, Very Weak = −1
7	IVL use	Advance = 3, Good = 2, Weak = 0, Very Weak = −1
8	IVL platforms skills	Advance = 3, Good = 2, Weak = 0, Very Weak = −1
9	IVL interest	Advance = 3, Good = 2, Weak = 0, Very Weak = −1
10	IVL performance measure	Advance = 3, Good = 2, Weak = 0, Very Weak = −1
11	IVL is the most frequently learning method used and authenticate	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
12	Interactive video learning introduces knowledge in an interesting attractive consistent way and can enhances teaching methos and increases learning outcomes	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
13	IVL grantees effective learning for students and teachers	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
14	IVL platforms used helps to increase strengthens the learning experiences for students &teachers and self-based decision making	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
15	Access to IVL materials is very simple and fast and everywhere &learning from it is fast and convenient & without any stress from teachers or classmates	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
16	IVL encourages students share their thinking-Knowledge and upgrade learning process from competency to collaborate and integrate	Extremely Agree=3, Agree=2, Fair=1, Disagree=0, Extremely Disagree=-1
17	IVL materials creates and establishes strong relationships between students and teachers including social &emotional relationships	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
18	Learning in the classroom through the use of interactive video platforms becomes more engaging exciting and fun especially for students with poor attention	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
19	The use of interactive video platforms leads to superficial learning and unsatisfactory feasibility of the learning effect	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
20	Students' inability to fully interact with interactive video platforms	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
21	Intermediate devices damaged to display the educational material or external malfunctions occur	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
22	The high price of physical interactive video components	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
23	The lack of available educational software suitable for interactive video platforms and the high cost so fits production	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
24	Interactive video platforms need periodic and comprehensive maintenance by professionals	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
25	The reluctance of many teachers to use interactive video platforms in teaching secondary school curricula because of the slow internet and it's often long periods of interruption	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
26	Teachers' lack of awareness of the importance of using interactive video platforms in raising the level of the educational process in its various fields	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
27	There are some technical problems for interactive video platforms that waste part of the limited class time such as problems with sound interruption and video clarity	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
28	Unavailability of a dedicated teacher or technician for the use operation and maintenance of the interactive video platforms	Extremely Agree = 3, Agree = 2, Fair = 1, Disagree = 0, Extremely Disagree = −1
29	How do you assess the degree of knowledge of the skills of using the internet?	Advance = 3, Good = 2, Weak = 0
30	How would you assess the degree of knowledge and awareness of cybersecurity its threats and ways to prevent it	Advance = 3, Good = 2, Weak = 0
31	How do you evaluate the degree of use of digital government systems such as Absher and Tawakkalna system	Advance = 3, Good = 2, Weak = 0
32	How would you rate the degree of privacy awareness and computing ethics	Advance = 3, Good = 2, Weak = 0
33	How do you assess the degree of possession of digital citizenship skills	Advance = 3, Good = 2, Weak = 0

B. Method(s)

Fig. 2 below illustrates the method applied in this study. All features were analyzed based on certain key related algorithms. Candidate factors were sorted and nominated to produce the final input features set and to determine the target features under different five powerful machine learning kernel algorithms. These algorithms are the decision tree based classifier, the nearest centroid classifier, the k-nearest neighbors classifier, the SVR-based classifier, and the Light gradient-boosting machine Classifier (lgb.LGBM classifier). Papers [42–45] explain the development and implementation of these classification algorithms.

The above figure contains five basic processes. The first one summarizes all the input features, before passing them on to the features selection phase, which accurately computes and filters the inputs using the correlation between the input parameter and the desired output. In this process, many techniques can be applied; however, correlation, principal component analysis algorithm (PCA), and merits are the main algorithms employed.

To handle redundancy in the dataset, redundant attributes can be detected by correlation analysis and covariance analysis. In this regard, the study employed correlation analysis using the X^2 (chi-square) test for the numeric data, which is known as Pearson's Product Moment Coefficient (correlation coefficient).

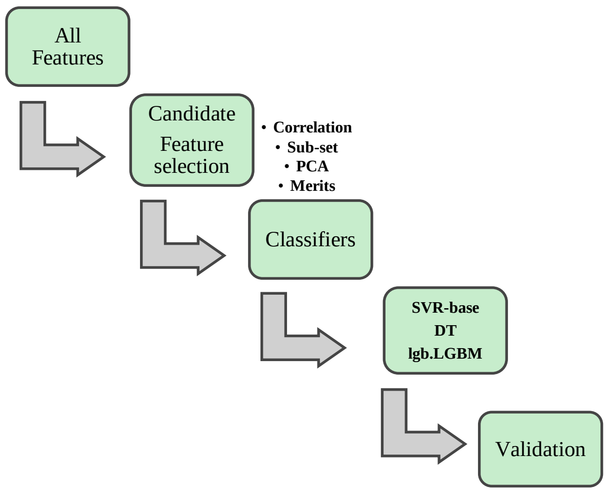


Fig. 2. Prediction classifiers used.

The following equations show the mathematical relationships:

$$X^2 = \frac{\sum_{i=1}^{n}(Observed - Expected)^2}{Expected^2} \quad (1)$$

The larger the X^2 value, the more likely the variables are related; and the cells that contribute the most to the X^2 value are those whose actual count is very different from the expected count.

$$r_{A,B} = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{(n-1)\sigma_A\sigma_B} \quad (2)$$

$$r_{A,B} = \frac{\sum_{i=1}^{n}((a_i b_i) - n\bar{A}\bar{B})}{(n-1)\sigma_A\sigma_B} \quad (3)$$

where n is the number of tuples, $\bar{A}$ and $\bar{B}$ are the respective means of A and B, σ_A and σ_B are the respective standard deviations of A and B, and $\sum_{i=1}^{n}(a_i b_i)$ is the sum of the AB cross-product. Based on the above equations, the computations were performed as follows:

If $r_{A,B} > 0$, A and B are positively correlated (i.e. the value of A increases as the value of B increases); the higher the value, the stronger the correlation. Conversely, if $r_{A,B} < 0$, there is a negative correlation.

C. Classification Assessment

Classification assessment involved extracting the main factors from the gathered dataset and calculating the effectiveness of the models during the training and testing phases.

Classification is a commonly accepted method of evaluation that has been applied to many front-end applications. There are several classification performance methods, which can be divided into two main categories: scalar metrics and graphical metrics. In this regard, our study utilized selected high-ranking classification performance metrics to figure out the accuracy and error rates of the models.

1) Confusion matrix

A confusion matrix is a representation method used to define the performance of a classification problem. It is a tabulation technique capable of visualizing and summarizing the performance criteria of a classification algorithm. When the target output has only two possible classes, it is called a binary classification. However, if the number of output classes is more than two, it is named a multi-class classification. Fig. 3 shows the general formation of a confusion matrix with a multi-classification paradigm, which typically uses three classes (e.g. X, Y, and Z).

As shown, the values TP_X, TP_Y, and TP_Z represent the numbers of true positive samples in class X, Y, and Z respectively. These values give the exact number of samples that are correctly classified from class X, class Y, or class Z. In turn, EXY represents the samples from class X that were incorrectly classified as class Y (i.e., misclassified samples). Therefore, the false negative in class X (FNX) is calculated by totaling the values for E_{XY} and E_{XZ} ($FNX = E_{XY} + E_{XZ}$), which represents the summation of all class X samples that were incorrectly classified as class Y or Z. Commonly, the FN of any class in a column is computed by adding the errors in that class/column, while the false positive for any predicted class in a row is equal to the sum of all errors in that row. For instance, the FP in class X (FP_X) is measured as $FPX = E_{YX} + E_{ZX}$, and so forth for the rest of the class.

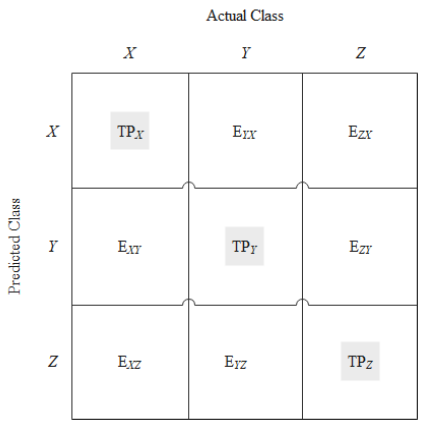


Fig. 3. A typical confusion matrix for multi-class prediction.

The confusion matrix contained four primary variables to structure the measurement performance metrics of the classifier. These factors are: 1) true positive (TP), 2) true negative (TN), 3) false positive (FP), and 4) false negative (FN). Based on these four parameters, the scalar performance metrics of an algorithm are accuracy, precision, recall, and F1 score, which are together used to measure the algorithm's performance.

2) Accuracy (Acc)

Accuracy, the first measure used to assess classification performance, is defined as the ratio of correctly classified samples to the total number of samples, as shown in Eq. (4):

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

where *P* and *N* indicate the number of positive and negative samples, respectively.

The complement of the accuracy is the ***error rate*** (*ERR*) or misclassification rate. It represents the misclassified samples from both positive and negative classes, calculated as:

$$ERR = 1 - Acc \tag{5}$$

$$ERR = \frac{(FP+FN)}{(TP+TN+FP+FN)} \tag{6}$$

Both ***Acc*** and ***ERR*** are sensitive to imbalanced data.

The precision of any algorithm is computed as:

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Recall (or ***Sensitivity)*** is calculated as follows:

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

Where ***Specificity*** is a fraction of negative values, this is calculated by

FP rate = 1 – Specificity:

$$Specificity = \frac{TN}{TN+FP} \tag{9}$$

3) F1 Score

Also known as the F-measure, the *F*1 Score denotes the equilibrium between precision and recall:

$$F1\ Score = \frac{2 \times precision \times recall}{precision+recall} = 2 \times \frac{P \times Sencitivity}{P+Sencitivity} \tag{10}$$

In order to validate our system performance measures, the classification receiver operating characteristics (*ROC*) and area under the ROC curve (AUC) were also examined and their derivatives performed in [44].

4) Receiver Operating Characteristics (ROC)

The receiver operating characteristics (ROC) curve is a plot that represents the classification model with respect to the positive class. The y-axis represents the true positive rate (TPR), while the x-axis represents the false positive rate (FPR).

$$TPR\ or\ Sensitivity = \frac{TPs}{TPs+FNs} \tag{11}$$

$$FPR = \frac{FPs}{FPs+TNs} \tag{12}$$

For perfect performance classifiers, the correct positive class predictions tend to 1 and the value of the incorrect negative class prediction tends to zero. The threshold considered the cut-off point in probability between the positive and negative class default setting is 0.5. A trade-off is needed to shift between TPR and FPR. The ROC curve is plotted by evaluating the TP and FP rates for different threshold values of confidence score. The ROC curve offers a convenient tool for evaluating classifications as it has no bias toward any given model, particularly when dealing with imbalanced data. Fig. 4 illustrates the ROC performance criteria. The green curve represents the optimum classifier performance, while the curve closest to the red line represents the worst classifier's performance. As the results approach 1.0, the classifier performance is improving.

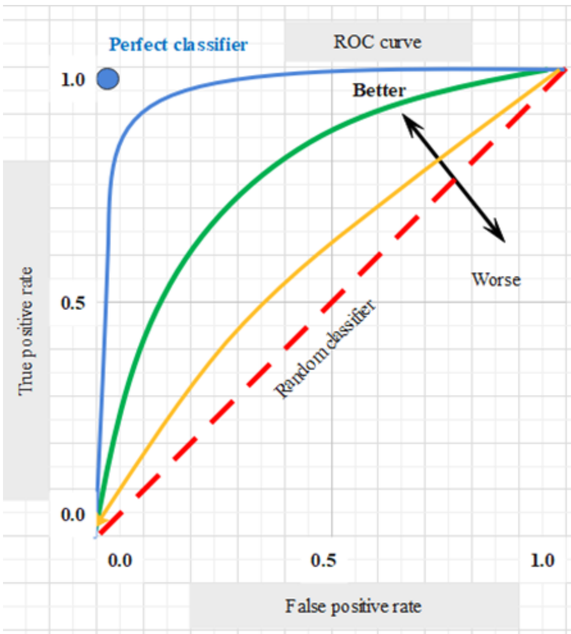


Fig. 4. ROC curve with true positive and false negative.

5) Area Under Curve (AUC)

The AUC is a graphical classification performance metric used to show the probabilities of class predictions. It gives confidence in modelling assessment environments. If the AUC score is 0.5, this means that the model fails to judge a distinction between two classes and the curve will be a diagonal line. However, if the AUC score is closer to 1.0, this indicates the model's success and has the ability to separate the two classes. In this case, the curve looks very close to the top corner of Fig. 4 (i.e. a perfect classifier). Python is the ideal programming language for developing our complicated learning models for classification purposes.

V. Results and Discussion

This section gives the findings and discussion, first it presents the statistical findings and questionnaire results then followed by machine learning classifiers' capabilities used in terms of tuning parameters for achieving high score results and modelling evaluation mechanism.

A. Statistical Findings

Table III below shows the most frequently used IVL platforms. A multiple-choice questionnaire was used to collect the data. It is quite clear from the table that all participants were familiar with using Bb. YouTube was the second most frequently used platform, followed by Google Classroom. These results are explained by the fact that all of the university students were required to use Bb during the COVID-19 period and have continued with e-Learning. While it is noteworthy that YouTube was ranked higher than Google Classroom, the students' relative lack of familiarity with the other IVL apps is understandable given the policy among Saudi universities of using Bb.

TABLE III: MOST USED IVL APPS

MostUsed-IVL-Apps	Frequency
Bb	63
Google Classroom	40
YouTube	50
EduCanon	7
Edpuzzlel	6
MasterClass	8
Khan Academy	5
Coursera	4
Udacity	3
Kahoot	3
Skillshare	3

Concerning self-evaluation about "In terms of using and confidentiality, IVL are the most educational methods?" The students' responses were reported as follows: 38.1% agree, 36.5% fair, 15.9% extremely agree, and 9.5% do not agree, and there was no any response of type "strongly not agree" zero percent strongly not agree!

IVL presents knowledge easily and improves e-learning methods because it increases the learnability outcomes. The students' responses were 38.1% agree, 33.3% extremely agree, and 28.6% fair. Mentioned that there was not even a single disagreement nor a extremely disagree.

Reporting students' answers to the question "Is IVL grantees interactive learning between the students and the teachers?", 39.7% extremely agree, 28.6% agree, and 27% fair, however, only 4.7% disagreed. These outcomes very support the fact that IVL-E graduate's an educational system for both the students and their educational institutions as well.

In this work, respondents gave honesty and the most relevant choice with lower complication! Because the questionnaire was designed and sent to three different university professors for review and revision questions. Table IV gives Likert's sample points for some 4 and 5-scale output measures. Such kind of analysis helps to draw the outputs' conclusions and optimization in a simple way. The outputs reference numbers and names can be recognized from Table II features and coding. Based on the respondents the following common points were noted:

TABLE IV: SUMMARY FOR SOME CHOSEN RESPONDENTS' OUTPUTS USING LIKERT SCALES POINTS ANALYSIS

Output#	Extremely disagree	disagree	fair	agree	Extremely agree
16	0.0%	3.2%	38.1%	33.3%	25.4%
17	1.5%	7.9%	30.2%	30.2%	30.2%
18	1.1%	1.1%	41.3%	33.3%	22.2%
19	1.6%	11.1%	31.7%	38.1%	17.5%
20	0.0%	4.7%	34.9%	30.2%	30.2%
21	7.9%	44.4%	11.1%	31.7%	4.9%
22	7.9%	23.8%	23.8%	34.9%	9.5%
23	3.2%	14.3%	33.3%	39.7%	9.5%
24	4.7%	12.7%	27.0%	38.1%	17.5%
25	7.2%	7.1%	30.2%	34.9%	20.6%
26	5.0%	6.1%	28.6%	39.7%	20.6%
27	5.3%	7.4%	30.2%	31.7%	25.5%
28	6.3%	12.7%	25.4%	39.7%	15.9%
29	5.0%	6.2%	19.0%	44.4%	25.4%
30	4.0%	5.4%	27.0%	41.3%	22.2%
	very low	low	good	advance	Evaluation factor
31	0.0%	3.1%	41.3%	55.5%	Internet skills
32	0.0%	19.0%	50.8%	30.2%	Cybersecurity awareness
33	0.0%	1.6%	23.8%	74.6%	E-government skills
34	0.0%	4.8%	49.2%	46.0%	Comp Ethics and privacy
35	0.0%	6.3%	50.8%	42.9%	Digital citizenship

- The table gives some major respondents' outputs indicators using Likert's 4 and 5 scale points analysis.
- Moving from left to right it's quite clear that respondents support the IVL method.
- Considering columns "extremely disagree" is the lower rate and it indicated that the graduate students stand up for IVL method.
- Digital fluency citizenship metrics registered very interesting pro-IVL results, and the advance factor achieved the highest performance rates.
- Graduate students accepted IVL interactivity and use.
- In terms of digital citizenship skills such as awareness of Internet use, e-government, and cybercrime the students demonstrated a high readiness rate.
- The lack of software and hardware seems to be decaying moving from yesterday to today!
- Comparing our findings against the recently reported literature review? It's mentioned that the Saudi National networks and backbone were improved.

Respondents evaluated their own usage of IVL applications showing that 55.6% were advanced, 31.7% were good, 11.1% low, and only 1.6% were very low. This is a quite promising indication for our institution to move deep into IVL educational method. Excluding Bb application, YouTube was the top interactive video application used and preferred by the respondents (88.9%) as Fig. 5 illustrates the findings.

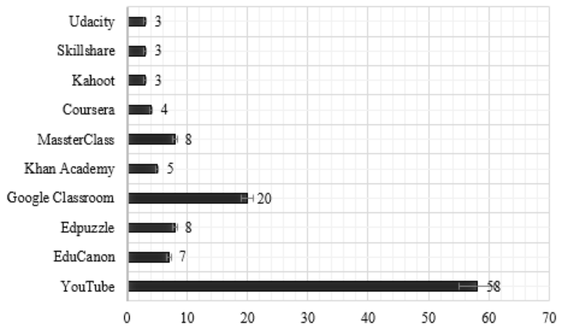


Fig. 5. Excluding Bb, IVL-Apps referral platforms.

The dataset contains six potential targets, each made up of three classes (class 0, class 2, and class 3). The potential targets are:

- How do you assess the degree of knowledge of the skills of using the internet?
- How would you assess the degree of knowledge and awareness of cybersecurity its threats and ways to prevent it?
- How do you evaluate the degree of use of digital government systems such as Absher and Tawakkalna system?
- How would you rate the degree of privacy awareness and computing ethics?
- How do you assess the degree of possession of digital citizenship skills?
- IVL performance measure

All six of the above targets were tested for performance, with only two of them turning out to be good candidates, namely:

- How would you rate the degree of privacy awareness and computing ethics?
- IVL performance measure

In Fig. 6 the two selected targets were studied separately, with each target decoded into three independent targets corresponding to each class (class 0, class 2, and class 3). These three targets were then given binary classifications (0 and 1). Each target (e.g. y1, y2, and y3) was studied with the best model.

B. Hyper-Parameter Tuning

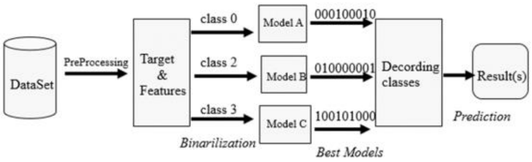


Fig. 6. Model of multi-class classification.

These two targets were trained with the best models. Initially, 41 models were tested, out of which, the following models were selected and used due to their superior performance compared to the others.

1) How would you rate the degree of privacy awareness and computing ethics?
   - Nearest centroid
   - lgb.LGBM classifier
   - K-neighbors classifier
2) IVL Performance Measure
   - SVC
   - lgb.LGBM classifier
   - DT classifier

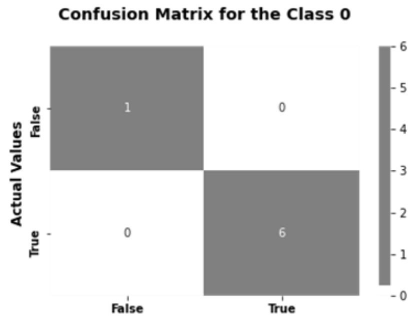
The selected hyper-parameters for the models were tuned. However, the models were found to be mostly not sensitive to this tuning, perhaps due to the limited volume of data available. Table V below presents the results of the hyper-parameters of all the models.

TABLE V: HYPER-PARAMETERS FOR THE MODELS WITH RESPECT TO THE TWO TARGETS

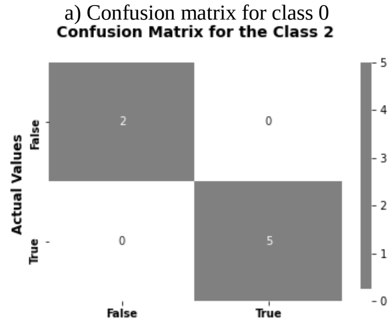
How would you rate the degree of privacy awareness and computing ethics			
Model	Class	Parameter	Value
Nearest centroid	0	Default	-
lgb.LGBM classifier	2	Default	-
Neighbors classifier	3	n_neighbors	
IVL Performance Measure			
SVC	0	kernel	poly
lgb.LGBM classifier	2	Default	-
DT classifier	3	max_features	28

Confusion matrices for the model evaluation of the two targets were presented in Fig 7 to Fig. 10 as follows:

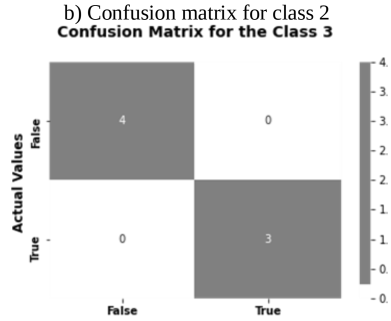
1) How would you rate the degree of privacy awareness and computing ethics?



a) Confusion matrix for class 0



b) Confusion matrix for class 2



c). Confusion matrix for class 3

d). Confusion matrix for all classes

Fig. 7. Confusion matrix for privacy awareness and computing ethics

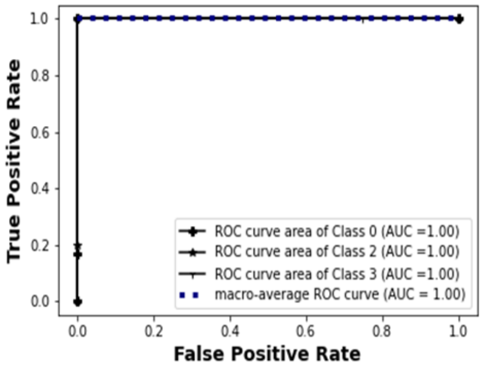
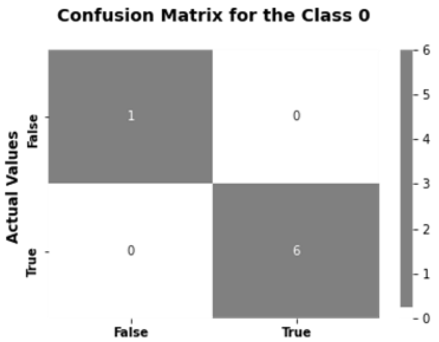
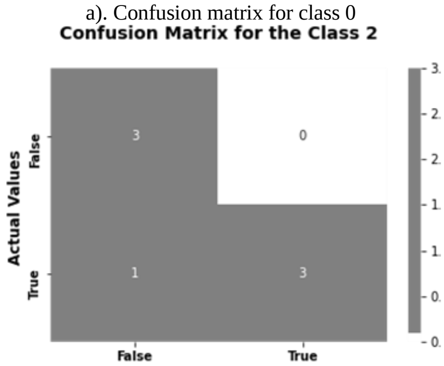


Fig. 8. ROC curve area of privacy awareness and computing ethics classes.

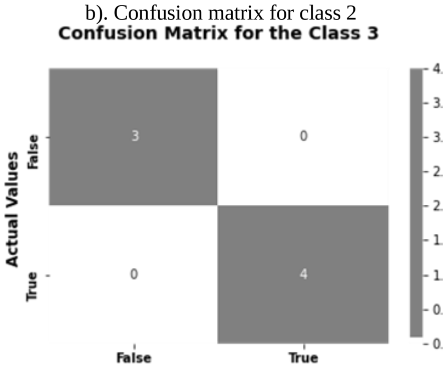
2) IVL performance measure



a). Confusion matrix for class 0



b). Confusion matrix for class 2



c). Confusion matrix for class 3

d). Confusion matrix for all classes

Fig. 9. Confusion matrix for IVL performance measure classes.

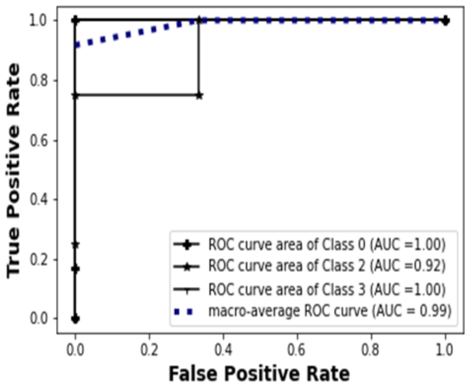


Fig. 10. ROC curve area of all IVL performance measure classes.

C. *Model Evaluation*

As most of the natural datasets used in machine learning classification are imbalanced, the class distribution values are far from unity. Evaluating an imbalanced dataset requires metrics that are not sensitive to the imbalanced data. For this reason, the following metrics were used to evaluate the performance of the model(s):

- Balanced Accuracy (Balanced Classification rate, BCCR)
- Balanced Error Rate (BER)
- Geometric Mean (GM)
- Optimization Precision (OP)
- Youden's index (YI)

The metrics presented above all depend on the sensitivity (True Positive Rate, TPR) and specificity (True Negative Rate, TNR). The TRP and TNR of the three classes (Class 0, Class 2, and Class 3) are calculated as below:

Sensitivity TPR=TP/P=TP/(TP+FN)

Specificity TNR=TN/N=TN/(TN+FP)

1) How would you rate the degree of privacy awareness and computing ethics?

Class 0: TPR_class0=1/(1+0)=1 TNR_class0=6/(6+0)=1

Class 2: TPR _class2=2/(2+0)=1 TNR_class2=5/(5+0)=1

Class 3: TPR_class3=4/(4+0)=1 TNR_class3=3/(3+0)=1

2) IVL Performance Measure

Class 0: TPR_class0=1/(1+0)=1 TNR_class0=6/(6+0)=1

Class 2: TPR_class2=3/(3+1)=0.75 TNR_class2=3/(3+0)=1

Class 3: TPR_class3=3/(3+0)=1 TNR_class3=4/(4+0)=1

1) Balanced Accuracy (BACC)

BACC=1/2 (*TPR*+*TNR*)

1) How would you rate the degree of privacy awareness and computing ethics?

Class 0: BACC_class0=1/2(1+1)=1
Class 2: BACC_class2=1/2(1+1)=1
Class 3: BACC_class3=1/2(1+1)=1

2) InteractiveVideoLearningPerformanceMeasure
Class 0: BACC_class0=1/2(1+1)=1
Class 2: BACC_class2=1/2(0.75+1)=0.875
Class 3: BACC_class3=1/2(1+1)=1

2) Balanced Error Rate (BER)

BER=1–BACC

1) How would you rate the degree of privacy awareness and computing ethics?
Class 0: BER=1–1=0
Class 2: BER=1–1=0
Class 3: BER=1–1=0

2) IVL performance measure
Class 0: BER=1–1=0
Class 2: BER=1–0.875=0.125
Class 3: BER=1–1=0

3) Geometric Mean (GM)

GM=$\sqrt{}$(*TPR*×*TNR*)

1) How would you rate the degree of privacy awareness and computing ethics?
Class 0: GM_class0=$\sqrt{}$1=1
Class 2: GM_class2=$\sqrt{}$1=1
Class 3: GM_class3=$\sqrt{}$1=1

2) IVL Performance Measure
Class 0: GM_class0=$\sqrt{}$1=1
Class 2: GM_class2=$\sqrt{}$0.75=0.866
Class 3: GM_class3=$\sqrt{}$1=1

4) Optimization Precision (OP)

OP=ACC–((*TPR*–*TNR*)/(*TPR*+*TNR*))=((*TP*+*TN*)/(*TP*+*TN*+*FN*+*FP*))–((*TPR*-*TNR*)/(*TPR*+*TNR*))

1) How would you rate the degree of privacy awareness and computing ethics?
Class 0: OP_class0=(7/7)–(0/2)=1
Class 2: OP_class2=(7/7)–(0/2)=1
Class 3: OP_class3=(7/7)–(0/2)=1

2) IVL performance measure
Class 0: OP_class0=(7/7)–(0/2)=1
Class 2: OP_class2=(6/7)–((−0.25)/1.75)=0.999
Class 3: OP_class3=(7/7)–(0/2)=1

5) Youden's index (YI)

YI=*TPR*+*TNR*–1

1) How would you rate the degree of privacy awareness and computing ethics?
Class 0: YI_class0=2–1=1
Class 2: YI_class2=2–1=1
Class 3: YI_class3=2–1=1

2) IVL performance measure
Class 0: YI_class0=2–1=1
Class 2: YI_class2=1.75–1=0.75
Class 3: YI_class3=2–1=1

Table VI bellow gives the evaluation measures for the two targets.

TABLE VI: EVALUATION METRICS OF THE TWO TARGETS

How would you rate the degree of privacy awareness and computing ethics?					
	BACC	BER	GM	OP	YI
Class 0	1.00	0.00	1.00	1.00	1.00
Class 2	1.00	0.00	1.00	1.00	1.00
Class 3	1.00	0.00	1.00	1.00	1.00
IVL performance measure					
Class 0	1.00	0.00	1.00	1.00	1.00
Class 2	0.875	0.125	0.866	0.999	0.75
Class 3	1.00	0.00	1.00	1.00	1.00
Class 3	1.00	0.00	1.00	1.00	1.00

Table VII summarizes the key differences between our study outcomes and those from previous studies. The size column gives the number of data points used. The features column represents the inputs/outputs features used in the model. The algorithm column indicates both the algorithms used and their performance evaluation measures. The last column shows the purpose of each study.

TABLE VII: COMPARISON OF OUR STUDY RESULTS WITH THOSE OF PREVIOUS STUDIES

Author(s), year	Size	Features	Algorithm(s)
Ours, 2022	63	32	- Confusion Matrix - ACC - Errors - ROC - AUC
Muhammad, A. *et al.*, 2020[30]	23	12	- Correlation - Statistics
Hua, C. and Ping, H., 2020 [23]	578	4	- ANOVA - T-Test
Hua, C. *et al.*, 2021[29]	1320	5	- AVGs - Stdev - skewness - correlation
Muhd Khaizer, O. *et al.*, 2021 [31]	68	5	- Thematic analysis
Desai, T. S. and Kulkarni, D. C., 2022 [33]	240	3	- Case study
Nives, M. P. and Tomislava, L., 2020 [35]	110	3	- AVGs - Stdev
Aljaber, A., 2018 [36]	4U		- Comparison study
Palaigeorgiou, G. *et al.*, 2019 [37]	18 &13	13	- IVL Review and Classification

IVL assessment was the common factor linking all of these study findings. Minor differences can be seen between our study results and those of previous studies. These minor variations can be summarized in terms of the datasets, algorithms, and performance criteria employed. It is clear that our study contributes a well-organized method and obtained the best classifier results. For instance, study [8] implemented machine learning techniques to perform IVL classification; but its classification method differed from ours. The main drawback of our study is the limited number of graduate students participating, given that machine learning classifiers work best with massive dataset sizes.

To accurately calibrate our models, six different targets were selected for comparison to identify the best results. Then, two outputs were picked as the top classifier models. In order they are:

1) IVL-E Performance measures, which were tested using SVC, lgb.LGBM classifier, and DT classifier. Powerful machine learning algorithms were used to justify and tune the hyper-parameters.
2) How would you rate the degree of privacy awareness and computing ethics? which was tested using nearest centroid, lbg.LGBM classifier, and k-neighbors classifier.

After comparing our study findings against those from related works in this area, we concluded that our methodology gives better assessment tools and provides higher performance metrics.

VI. Conclusion

A powerful learning classifier is very helpful in adaptive edge intelligence to address IVL-E. Therefore, the purpose of this study is to look at machine learning classifier models for assessing the efficacy of interactive video learning: views of graduate students by using the kernels of the SVC-based, DT, and lgb.LGBMClassifier classifiers. Datapoints were randomly collected by recruited postgraduate students at College of Education, University of Bisha, Bisha, Saudi Arabia.

Before the models were investigated and assessed, the original dataset was pre-processed to clean up noisy data and check for errors across inconsistent datum or data points by encoding dataset features and filling in any missing data.

A combination of elite classification metrics was recruited to figure out the performance criteria of the model. These measures include both scalar measures such as accuracy and error(s) and graphical measures, in particular confusion matrix and ROC.

After comparing our study findings against those from related works in this area, we concluded that our methodology gives better assessment tools and provides higher performance metrics.

Further research in this area can focus on several directions. First, the number of input features can be increased, and the estimation process can be enhanced to target deeper IVL-E challenges, such as networking and technical issues. Second, a promising evaluation method can be re-examined by using a massive new dataset covering all postgraduate institutions in Saudi Arabia. Finally, evaluations can also be made of promising machine learning clustering and data visualization methods.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors contributed to the design and implementation of the research. The tasks of individual authors described as: OA, AM Conceptualization; EI, OA methodology; EI software and results validation; EI and OA analyzed the data and wrote the paper; OA, AM review—editing. All the authors read and had approved the final version.

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