Machine Learning Prediction Model for Early Student Academic Performance Evaluation in Video-Based Learning

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Abstracts: The transformation of education norms from face-to-face teaching era to the Massive Open Online Courses (MOOCs) has created the emergence of educational technology domain for many students to access e-learning platforms. However, there are some drawbacks especially in asynchronous video-based learning. A sense of isolation could occur between teacher and students if the teachers do not interact much with the students in the asynchronous video-based learning. Consequently, the knowledge that is delivered by the teacher may not reach students effectively and cause a drop in student performance in the coming examination. Moreover, the growth of video-based learning has created a huge amount of data on the student learning process on the educational video which may provide a boost for educational data mining research. Therefore, this research study aims to introduce a predictive model that scrutinize the number of video view data based on each chapter in the video as well as student learning style, Felder-Silverman (FS) learning style model to deliver a prediction on individual student early performance in asynchronous video-based learning. This research has tested the different combination of feature selection methods with several handle of imbalance data methods such as Synthetic Minority Oversampling Technique (SMOTE), SMOTE-TOMEK and Adaptive Synthetic (ADASYN) algorithms to build the machine learning model and compare the model performance. As a result, proposed machine learning classifier algorithms with the combination of Maximum Relevance and Minimum Redundancy (MRMR) as feature selection method and SMOTE has been achieved the highest Area Under Curve (AUC) rate of 0.93.

Keywords: Educational Data Mining, Machine Learning, Felder-Silverman Learning Style, COVID-19.

1. INTRODUCTION

1.1. Research Background

The most typical approach of passing on knowledge to students was formerly regarded to be having instructors physically present to educate. However, the COVID-19 pandemic's enormous outbreak in the year 2020 has stimulated the growth of online education (Zarei & Mohammadi, 2022). On March 11, 2020, the World Health Organization (WHO) designated COVID-19, which is caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), to be a pandemic (Hafeez et al., 2020). This provoked some sort of lockdown in practically every nation in the world to prevent the spread of COVID- 19 in the community. Consequently, lots of schools and institutes of tertiary education had closed and must promote a major shift of education norms from physical classroom learning to online learning (Zarei & Mohammadi, 2022). According to the information by UNESCO, the lockdown approach in the institute of education has affected more than 1.2 billion students in 186 countries including Malaysia (Huang et al.,2020). With this sudden transformation from the physical face to face classroom into online learning in many parts of the world, a significant growth has occurred in the usage of online education tool especially in the video conferencing tools or online learning web platform (Huang et al., 2020).

According to a YouTube Marketing report, during the time of the COVID-19 pandemic in January and February 2020, just over 300 educational videos with online teaching or distance learning in the title were uploaded to YouTube, and that number increased by over 23,000 in March 2020 (FutureSource, 2020). Therefore, the increased video-based learning popularity has stimulated the educational video learning analytics growth. Furthermore, Coursera, one of the global popular online learning platforms, has issued its 2021 Impact Report, which reveals that more than 20 million additional students registered for courses in the year 2020 and 2021, which is equal to the increase in the three years pre-pandemic (Koksal, 2020). For Coursera's online courses, 21 million people signed up in 2016, and during the next two years, that figure rose by about 7 million every year. However, the shift to online learning during the COVID-19 pandemic had led to a threefold rise in new registrations by pushing the number to 71 million in 2020 and 92 million in 2021. With 28 million new online students enrolling in 68 million courses, Asia Pacific had the largest regional student presence on the learning platform. North America, Europe, and Latin America were next.

1.2. Research Problems

However, this form of online learning process has caused some concern in the context of student academic performance, especially in asynchronous online learning. Asynchronous online learning was a learning process which did not involve a live video lecture component and gives students the freedom to view the weekly online course materials whenever they like (Mahoney, 2020). In this case, students can study in a self-paced manner with asynchronous learning but within a certain timeframe instructed by the educator. Students may be able to watch the given online course material such as video repeatedly under the asynchronous online learning mode. However, this method of delivery also necessitates a lot of self- motivation by the student to engage with an online course material given by the educator (Mahoney, 2020). Hence, those students who were easily distracted and less motivated to study may struggle until getting poor grade at the end of the asynchronous online learning mode.

In addition, a sense of isolation could be occurred between teacher and students if the teachers do not interact much with the students in asynchronous online learning (Pelikan et al., 2021). Consequently, the knowledge that is delivered by the teacher may not reach students effectively and cause a drop in student performance in the coming examination. At the end, the minimal interaction between student and teachers has caused the student performance in the risk of getting undesirable grade at the coming examination.

At the same time, some students tend to skip certain insignificant chapters in the video to perform a fast-learning process, especially a day before quiz or exam. This situation mostly happened to those students who preferred last-minute study. In the early year of 2020 and period of pandemic, the Google company has introduced automatic chapters feature in the Youtube platform where all video creators were allowed to use chapters feature to add chapters in the Youtube videos (“How to add,” 2023). This feature has beneficial for tracking the engagement of user watching rate based on the different chapters in the videos (“How to add,” 2023). In terms of video watching users, those who have the study behaviour that prefer to perform fast-learning process were able to use this feature to skip into another chapter ahead easily.

1.3. Research Objectives

In this research, the objectives have been set under the concept of educational data mining as follows:

- Collect the data of student watching rate in the given educational video material under the asynchronous video-based learning.

- Apply educational data mining concept to develop machine learning models to predict the

student’s early academic performance in asynchronous video-based learning.

- To apply and compare the effect of feature selection methods and solving imbalance data classes methods on the predictive model’s performance of student early academic performance in asynchronous video-based learning.

- To study the significant relationship between learning style factor and the predictive model performance of student early academic performance in asynchronous video-based learning.

Therefore, this research is targeted to benefit the educators who wish to identify the student early academic performance in the vide-based learning. The early prediction of student academic performance is beneficial for the educator to identify the student who may at the risk of getting poor performance in the asynchronous video-based learning. In addition, this research outcome provides insight into how the integration between artificial intelligence

(AI) and student video watching rate can help educators better understanding on student learning outcome in the asynchronous video-based learning. Therefore, this research has the initiative to contribute the significant of integrating the feature that can provide the prediction of student early academic performance in the future of the asynchronous video-based learning platform.

2. LITERATURE REVIEW

2.1. Challenges in Video-Based Learning Applications During COVID-19 Pandemic

The COVID-19 pandemic has had a significant impact on how students learn, and video-based learning method has become quite popular due to its great temporal and spatial flexibility, low knowledge acquisition threshold, and wealth of learning resources. However, in this approach, teachers find it difficult to understand their students' levels of learning, and concerns have been expressed concerning the effectiveness of e-learning (Majumdar, 2017). In this case, the study of learning performance prediction gives teachers a foundation on which to modify their teaching methods and strategies for students who may have problems in video-based learning. By predicting students' performance on future exams, it’s likely to reduce the likelihood that students will fail the course and ensuring the quality of video-based learning on achieving teaching goals.

However, most of current video-based learning systems did not include the early student performance prediction function to help educator to identify the student who may at risk of failure upon in video-based learning. In this case, most of the video-based learning that been seen today such as Edpuzzle, Udemy, and Coursera has only provided the function for educators to upload or create the educational video for the purpose of teaching (Kloos et al., 2018). Identification of students who are more likely to have poor academic success in the future can raise standard of educators on teaching which thus to help students accomplish their academic goals.

2.2. Factor Affecting Student Performance in Video-Based Learning

Research in education has shown that spent watching all the allocated videos on a single day causes students to have a hefty study stress. Furthermore, most participants waited till the final day to watch the assigned video. They tended to skip insignificant video topics to learn faster (Qu et al., 2019). An alternative previous finding shown that in video-based learning, video watching rate increased on the day prior to assignments and tests (Turabieh, 2019). Simultaneously, a rise in video viewing before tests and assignments has prompted the measurement of the total amount of time spent by students watching videos. In terms of video length, students felt more interested, had better focus, and retained the information better when engage with video length less than 10 minute compared to the 20 minute video length material (Slemmons et al., 2019). Other findings shown that short videos length material can significantly increase student performance on the final exam and engagement in term of video viewing duration when compared to the long-video length material (Zhu et al., 2022). Moreover, the impact of video length could be a factor affecting student performance in video-based learning.

Furthermore, survey research of 357 papers in student performance identified factors that had the greatest impact on learner performance, including student engagement, demographics, and psychomotor skills (Hellas et al., 2021). As a result, the purpose of this study was to collect demographic information about participants in terms of their previous academic success, gender, and age with their learning style that can have an impact on student success in MOOCs (Aggarwal et al., 2021).

2.3. Significant of the Learning Style Factor Toward Student Academic Performance

Many ideas on learning styles have been proposed in recent literature to better understand the dynamic process of learning, and the idea of learning styles has grown in popularity. The theory of learning styles first emerged in the late 1960s via Kolb learning style models which was invented by American educational researcher, David Kolb, and then soon gained popularity in the following years. The impact of an increased in the research of learning styles in educational field had promote the rapid creational of other learning styles models such as Peter Honey and Alan Mumford's model, Neil Fleming's VAK/VARK model, Felder Silverman model and so on.

In recent years, some educational research studies have found out that there was a significant relationship between learning style and student academic performance. A study that conducted on Turkish physiotherapy learning institution has proven that academic performance of students be improved by using teaching techniques that promote more participatory learning styles (İlçin et al., 2018). Another study outcome has showed the learning style and academic achievement were found to be significantly correlated when educators utilise appropriate teaching techniques that take the dominant style into account while creating lessons for each class (Shirazi & Heidari, 2019). Furthermore, another study on have shown that student learning performance was enhanced when the documentation material was provided in student preference learning styles (Ho et al., 2021). Most students who are visual, read-and- write learners are likely to benefit from material being presented in the form of pictures, graphs, tables, or text so they may make notes on key ideas when using an online distance learning technique. Consequently, results indicated that students' preferred learning styles are highly correlated or associated with their academic performance and happiness in online distant learning (Layco et al., 2022).

However, some authors found no proof that improving accomplishment or academic performance by adapting the presentation to a person's alleged learning style existed. A two-way analysis of variance (ANOVA) in a study has produced no statistically significant results between learning style and academic performance (Cimermanová, 2018). The findings show that learning styles have no impact on affecting students' academic success. In the similar year, another study has focused on VARK learning style model has conclude that no relationship found between student academic performance and teaching methods that preferred by students learning style (Mozaffari et al., 2020). Furthermore, another study had failed to discover a significant relationship between comprehension and the preference for auditory or visual learning styles where adapting teaching method to students' preferences for learning styles does not improve learning (Rogowsky et al., 2020). In the similar study, the author has suggested that educators should focusing on improving the area of student ‘s weakness, for instance, an auditory learner could improve their reading skills rather than relying solely on listening when acquiring new knowledge.

2.4. Machine Learning Algorithms in Predicting Student Performance

In a study that related to video learning analytic, the author has applied a several machine learning algorithms such as random forest, Naive Bayes (NB), support vector machine (SVM) and logistic regression to classify student performance and the random forest model performance achieve approximately 88% of accuracy (Ashfaq et al., 2020). Another study which used the virtual learning management system data to predict student performance has revealed that the random forest tree method was more accurate than other decision tree algorithms. A hybrid algorithm that combines clustering and classification approaches has been applied and produces outcomes that are significantly better in terms of obtaining accuracy in predicting the academic achievement of the students (Buschetto et al., 2019). Furthermore, another study has implemented an ensemble learning technique called AdaBoost classifier which successfully improves the accuracy of the predictive model to approximately 80% on predicting student performance (Hassan et al., 2020).

Feature selection has been a key of research whether possible to improve the performance of a predictive model. The author of this paper compares with only one type of feature selection algorithm and recommended to explore different types of feature selection algorithms in the future work (Chen et al., 2021). At the same time, another study demonstrated the proposed binary genetic algorithm as feature selection method. Consequently, all classifiers perform better, with improvements ranging from 1 to 11 percent (Nabil et al., 2021). Additionally, class imbalance is a well-known issue that consistently arises among the issues raised in the data mining area. In this case, the combination of feature selection and SMOTE has also been applied to build predictive model on the prediction of student performance (Huang et al., 2021). In this case, SMOTE has been tested with different sets of feature selection methods such as Fast Correlation Based Feature selection (FCBF) and Recursive Feature Elimination (RFE) to enhance the predictive model performance on the prediction of student performance (Huang et al., 2021).

Furthermore, another study also demonstrated that the combination of feature selection and SMOTE has been applied to solve skewed data set for enhancing the accuracy of predictive models in the prediction of student performance (Sandhya et al., 2022). However, there was study prove that SMOTE as method of handling data imbalance did not guarantee on improving the model performance on the prediction of student performance (Sha et al.,2022). Other oversampling method such ADASYN has been applied to enhance the model performance in the context of prediction of the student performance. (Ashfaq et al., 2020)

Additionally, hybrid class balancing technique has been applied by combining oversampling with undersampling methods. The SMOTE-TOMEK link method with random forest classifiers routinely yields better predictive model accuracy in the context of prediction of the student performance (Pratama et al.,2021). Several classes balancing techniques, including SMOTE, TomekLinks, and SMOTE- TOMEK link has been applied together with ensemble learning algorithms and then compared in the context of the prediction of student academic performance (Wang et al., 2021). However, the hybrid balancing technique did not guarantee outperform the sole oversampling technique SMOTE (Wang et al., 2021). On the other case, another paper which applied SMOTE-TOMEK link as a class balancing strategy to combine with the proposed random forest classifier has also produced the best results when compared to the other models (Alwarthan et al., 2022).

3. RESEARCH METHODOLOGY

3.1. Overall Research Framework

There are 110 university students in total were allocated to watch a software design video content in an e-learning platform when the COVID-19 pandemic was in full swing at Malaysia. In this case, 38 features have been collected from video watching rate and learning style score were compiled into a comprehensive dataset. Figure 1 shows that two types of input features were collected: video engagement features and the learning style of the student. This research captured the number of views for each video chapter in the video that uploaded into the e-learning or MOOCs system. Meanwhile, we also captured each student’s duration in watching videos. On the other side, an online questionnaire was used to determine learning type. The Felder Silverman (FS) learning style model was used to determine student learning styles in this scenario. The combination of four dimensions of FS learning style model has produced 16 different groups of learning style.

Next, the original datasets first went through a data cleaning process and then followed by data transformation. Next, different feature selection method has been used to identify significant features against the data output, and then combine with SMOTE, SMOTE-TOMEK and ADASYN technique to rectify the imbalance data issue in the original datasets. The datasets were split into two groups throughout the data modelling phase where 10% for the test set and 90% for the training set. There were 10 different types of machine learning algorithms created. Finally, performance metrics were used to assess the performance of all machine learning approaches. The model's final prediction was a binary classification, with 1 indicating a student's PASS outcome and 0 indicating a student's FAIL result.

3.2. Video-Based Learning Source for Research Experimental

Software Design as theme of academic course has been involved in this study. In this case, a video source explaining the knowledge and implementation of Singleton software design has been used in this study. The total length of the video is 5 minute 11 second. When the video is uploaded into Edpuzzle, the number of views will be collected on 10 different chapters of video contents. The video delivered content on each chapter was listed as following table 1.

Table 1: Video Delivered Chapters on Each of the Interval

No	Video Time Interval	Video Delivered Chapters
1	0:00 -0:31	Introduction of video theme
2	0:31 - 01:02	Introduction of Singleton advantage
3	01:02 - 01:33	Introduction of Singleton disadvantage
4	01:33 - 02:04	How to Implement Singleton
5	**02:04 - 02:35**	**Explain of singleton class constructor**
6	02:35 - 03:06	Explanation of singleton class variable
7	03:06 - 03:37	Implementation of GetInstance class
8	03:37 - 04:08	Concepts Lazy Creation
9	04:08 - 04:39	Explanation of Lazy Creation implementation
10	04:39 - 05:11	Example of Singleton concepts in application and summary of video

3.3. Data Partition

A total of 38 data attributes from original datasets were illustrated in table 2. In the total of 38 features, 2 features are nominal data types while 19 features are integer data types, and the remaining were binary data types. The nominal data types have provided non-numeric values such as a label.

Table 2: Datasets Descriptions

Data Features	Description	Type
Gender	Student Gender (Male or Female)	Nominal
CGPA Class	Student Grade Class (2.00 - 2.66, 2.67 - 3.32, 3.33 - 3.66 & 3.67 - 4.00)	Nominal
Time Spent	Student total time spent to watch entire video	Integer
Time_1	Number of views between time 0:00 to 0:31 second in video.	Integer
Time_2	Number of views between time 0:32 to 01:02 second in video.	Integer
Time_3	Number of views between time 01:03 to 01:33 second in video.	Integer
Grade_Q1	Student Grade for Question 1 (1- Correct, 0-Incorrect)	Integer
Time_4	Number of views between time 01:34 to 02:04 second in video.	Integer
Time_5	Number of views between time 02:05 to 02:35 second in video.	Integer
Time_6	Number of views between time 02:36 to 03:06 second in video.	Integer
Grade_Q2	Student Grade for Question 2 (1-Correct, 0-Incorrect)	Integer
Time_7	Number of views between time 03:07 to 03:37 second in video.	Integer
Time_8	Number of views between time 03:38 to 04:08 second in video.	Integer
Time_9	Number of views between time 04:09 to 04:39 second in video.	Integer
Time_10	Number of views between time 04:40 to 05:11 second in video.	Integer
Grade_Q3	Student Grade for Question 3 (1- Correct, 0-Incorrect)	Integer

A/R Score	Student learning style score for active or reflective dimension.	Integer
S/I Score	Student learning style score for sensor or intuitive dimension.	Integer
Vi/Vb Score	Student learning style score for visual or verbal dimension.	Integer
S/G Score	Student learning style score for sequential or global dimension.	Integer
ASViSq	Active, Sensing, Visual and Sequential learner	Boolean
ASViG	Active, Sensing, Visual and Global learner	Boolean
AIViSq	Active, Intuitive, Visual and Sequential learner	Boolean
AIViG	Active, Intuitive, Visual and Global learner	Boolean
RSViSq	Reflective, Sensing, Visual and Sequential learner	Boolean
RSViG	Reflective, Sensing, Visual and Global learner	Boolean
ASVbSq	Active, Sensing, Verbal, and Sequential learner	Boolean
ASVbG	Active, Sensing, Verbal, and Global learner	Boolean
AIVbG	Active, Intuitive, Verbal, and Global learner	Boolean
AIVbSq	Active, Intuitive, Verbal, and Sequential learner	Boolean
RSVbSq	Reflective, Sensing, Verbal, and Sequential learner	Boolean
RSVbG	Reflective, Sensing, Verbal, and Global learner	Boolean
RIViSq	Reflective, Intuitive, Visual and Sequential learner	Boolean
RIViG	Reflective, Intuitive, Visual and Global learner	Boolean
RIVbSq	Reflective Intuitive, Verbal, and Sequential learner	Boolean
RIVbG	Reflective Intuitive, Verbal, and Global learner	Boolean
Rating	Student rating to the video	Integer
Grade (Output)	Student final grade class at online quiz (1- PASS, 0- FAIL)	Binary

3.4. Design of Data Modeling Framework

Table 3: Experiment Design for Data Modeling

Case Studies	**Feature Selection Methods**				**Handling of Imbalance Data Methods**		
	CS	**PCA**	**MI**	**MRMR**	**SMOTE**	**SMOTE-TOMEK**	**ADASYN**
C1	✗	✗	✗	✗	✗	✗	✗
C2	✓	✗	✗	✗	✗	✗	✗
C3	✓	✗	✗	✗	✓	✗	✗
C4	✓	✗	✗	✗	✗	✓	✗

C5	✓	✗	✗	✗	✗	✗	✓
C6	✗	✓	✗	✗	✗	✗	✗
C7	✗	✓	✗	✗	✓	✗	✗
C8	✗	✓	✗	✗	✗	✓	✗
C9	✗	✓	✗	✗	✗	✗	✓
C10	✗	✗	✓	✗	✗	✗	✗
C11	✗	✗	✓	✗	✓	✗	✗
C12	✗	✗	✓	✗	✗	✓	✗
C13	✗	✗	✓	✗	✗	✗	✓
C14	✗	✗	✗	✓	✗	✗	✗
C15	✗	✗	✗	✓	✓	✗	✗
C16	✗	✗	✗	✓	✗	✓	✗
C17	✗	✗	✗	✓	✗	✗	✓

The research experiment has been designed into 17 experimental groups as illustrated in Table 3 to compare and evaluate the performance of the prediction models. A total of 10 different types of machine learning algorithms have been applied on the experiment test as listed in Table 4. Each machine learning algorithm has been tested under different case conditions. Furthermore, python script in 3.9 version was used to implement the data modelling.

Table 4: Machine Learning Algorithms Tested

No	Machine Learning Algorithms
1	Linear Support Vector Machine (LSVM)
2	Radial Support Vector Machine (RSVM)
3	Bagging
4	AdaBoost
5	Logistic Regression (LR)
6	Random Forest (RF)
7	Decision Tree (DT)
8	K-Nearest Neighbors (KNN)
9	Naïve Bayes (NB)
10	Gradient Boosting (GB)

C1 consider as baseline models where all prediction models have been designed with datasets from data cleaning and transformation but without went through feature selection and methods of handling imbalance data issue. C2 uses data that went through feature selection, Chi-Square test only whereas C3 uses data that went through Chi-Square test and SMOTE and then followed by Chi-Square test and SMOTE-TOMEK in C4 and Chi-Square test and ADASYN in C5.

In the case studies between C6 to C9, the focus on PCA test to reduce the dimension of input features. The PCA test has combined with different types of methods of handling imbalance data issue which were SMOTE in

C7, SMOTE-TOMEK in C8 and ADASYN in C9. Furthermore, the case studies between C10 to C13 has applied the mutual information method to integrate with SMOTE in C11, SMOTE-TOMEK in C12 and ADASYN in C13. Next, MRMR as fourth feature selection option has been applied in C14 and then integrate with SMOTE in C15, SMOTE-TOMEK in C16 and ADASYN in C17.

Next, all case studies have been tested repeated under same condition but without learning style features included into input features. In this case, all features which relate to the element of learning style which were A/R Score, S/I Score, Vi/Vb Score, S/G Score, ASViSq, ASViG, AIViSq, AIViG, RSViSq, RSViG, ASVbSq, ASVbG, AIVbG, AIVbSq, RSVbSq, RSVbG, RIViSq, RIViG, RIVbSq, and RIVbG features has been removed from input features. The purpose was to compare the result of model performance between the feature with and without the learning style which provide the finding of whether the significance of the element of learning style against the student performance in video-based learning.

3.5. Model Performance Evaluation

Table 5: Confusion Matrix for Classification

	FAIL (Predicted -0)	PASS (Predicted -1)
FAIL (Actual - 0)	a	c
PASS (Actual -1)	b	d

In the context of model evaluation, the performance of each machine learning model was evaluated based on AUC. In addition, confusion metrics were applied for the analysis of prediction outcome where each column of the matrix represents the different predicted classes whereas each row of the matrix represents the actual classes as shown in Table 5.

The upper row label in the confusion matrix has the following meaning where label a is the correct negative prediction or true negative (TN), classified as grade FAIL by the classifier, label c is incorrect positive prediction or false positive (FP), classified as grade PASS by the classifier. While the bottom label b is incorrect negative prediction or false negative (FN), classified as grade FAIL by the classifier, label d is correct positive prediction or true positive (TP), classified as grade PASS by the classifier.

Area under the receiver operating characteristic (ROC) Curve is referred to as AUC. AUC measures the total two-dimensional region that lies beneath the entire ROC curve. In this case, AUC has a value in the range between 0 and 1 where a predictive model with 100% incorrect predictions has an AUC of 0.0, and a model with 100% correct predictions has an AUC of 1.0 (Halimu et al., 2019). AUC was a useful metric to evaluate the accuracy of the model's predictions. At the same time, AUC was used due to less sensitive to class imbalance than other metrics such as accuracy or F1 score.

4. RESULTS

4.1. Respondents' Demographic Details

Table 6: Demographic Distributions of the Respondents (n=110)

		Frequency	**Percentage (%)**
Gender	Male	98	89.1
	Female	12	10.9
CGPA Class	2.00-2.66	3	2.7
	2.67-3.32	50	45.5
	3.33-3.66	25	22.7
	3.67-4.00	32	29.1

Programme	Software Engineering	110	100.0

Based on the table 6, a total of 110 participants, 98 participants or 89.1% were male, more than half of the sample size whereas the total number of female participants were 12 or 10.9%. All participants were from a similar course programme which was software engineering. Due to university standard on student's CGPA class, all participants were categorized into four different CGPA classes. In this case, most of participants were from CGPA class in between 2.67 until 3.32, by the total of 50 participants or 45.5%. The second highest number of participants were found in the CGPA class in between 36.7 until 4.00 by the total of 32 participants or 29.1 % and then followed by CGPA class in between 3.33 until 3.66 which achieved total number of 25 participants or 22.7%. Lastly, only 3 participants were found to achieve the CGPA class in between 2.00 and 2.66.

4.2. Exploratory Data Analysis

Table 7: Number of View on Each Video Interval

No	Video Time Interval	Video Delivered Chapters	Maximum Watched	Minimum Watched	Average Number of Watched
1	0:00 -0:31	Introduction of video theme	6	0	1.3
2	0:31 - 01:02	Singleton Advantages	7	0	1.3
3	01:02 - 01:33	Singleton Disadvantages	5	0	1.2
4	01:33 - 02:04	How to Implement Singleton	4	0	1.2
5	**02:04 - 02:35**	**Explain of singleton class constructor**	**9**	**0**	**1.6**
6	02:35 - 03: 06	Explain of singleton class variable	4	0	1.1
7	03:06 : 03:37	Implementation of GetInstance class	5	0	1.2
8	03:37 - 04:08	Concepts Lazy Creation	5	0	1.2
9	04:08 - 04:39	explain of Lazy Creation implementation	5	0	1.1
10	04:39 - 05:11	Example of Singleton concepts in application and summary of video	6	0	1.3

Table 7 shows that across all video time intervals, the video interval between 2 min 4 sec and 2 min 35 sec had the most views where at least one student watched multiple time to gain comprehensive understanding on the knowledge of the singleton class constructor. Every video time interval or chapter has at least one number of views on average. According to the results in Figure 1, most learners took 6 minutes on average to watch the entire video. The original video duration provided in this study consists of 5 minutes and 24 seconds. At the same time, the maximum time of video watched was 16 minutes, implying the learner may have repeated certain video interval portions.

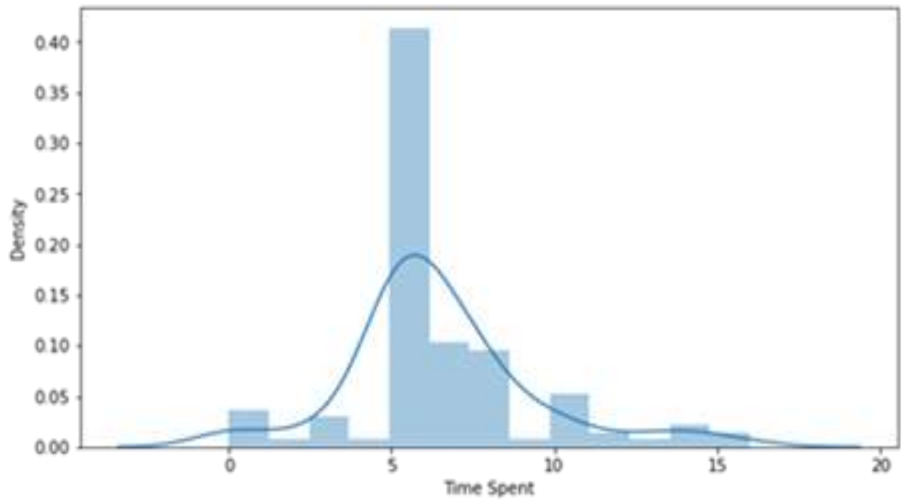

Fig. 1: Relationship between Time Spent Variable on the Video

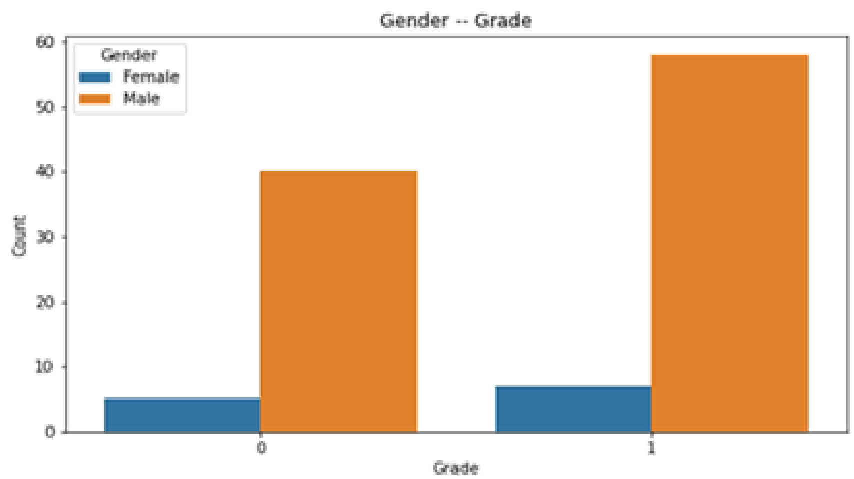

Fig. 2: Relationship between Gender variable and Student Grade

From Figure 2, there are total of 65 students who achieved PASS grade whereas 45 students failed to achieve it. In term of gender, 58 male students and 7 female students have achieved PASS grade. While there were 40 male students and 5 female students have achieved FAIL grade. Therefore, the number of students who achieved PASS grade was higher than those in FAIL grade in terms of the gender distribution.

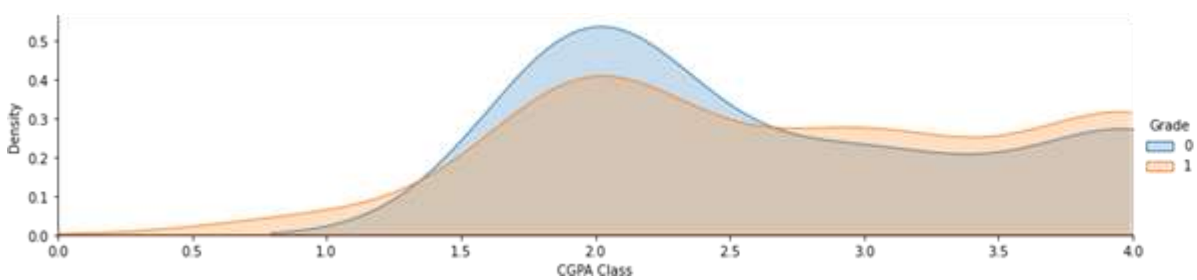

Fig. 3: Relationship between Student CGPA Class and Student Grade

By comparing students' final grade and their CGPA class in Figure 3, students who have CGPA class of 3 and above were likely to achieve PASS grade at the final test. While those students under CGPA class 1 and 2 were less likely to achieve PASS grade at the final test.

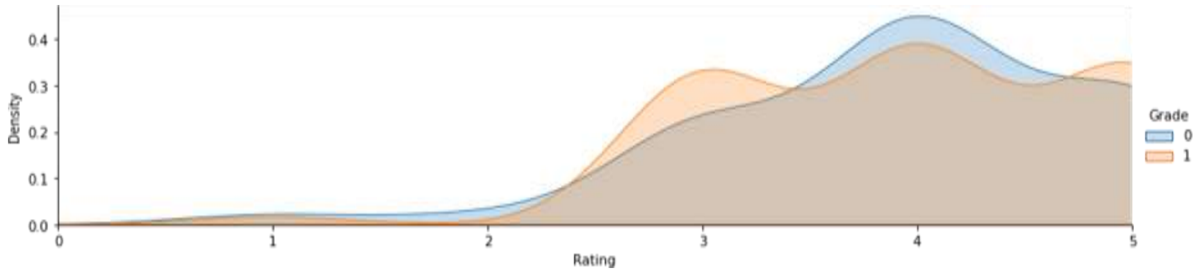

Fig. 4: Relationship between Rating Variable and Student Grade

In the comparison between student final grade and student rating on video in Figure 4, most students who have achieved PASS grade were likely to give the highest rating on video. Therefore, it was expected on those students who have achieved PASS grade were likely to prefer the video content delivered which gives them a clear understanding of all the knowledge that delivered by the video.

According to the responders learning style outcome based on FS learning style model, the result in all four dimensions has been combined and categorized into 16 possible learning style groups. From the result illustrated in Figure 5, most responders were categorized under group RSViG which means under reflective, sensing, visual and global learning style dimensions at the same time. At the same time, more than 50% of responders under this group scored a PASS grade. The second highest number of learning style group was ASViSq which mean under active, sensing, visual and sequential learning style dimensions at the same time.

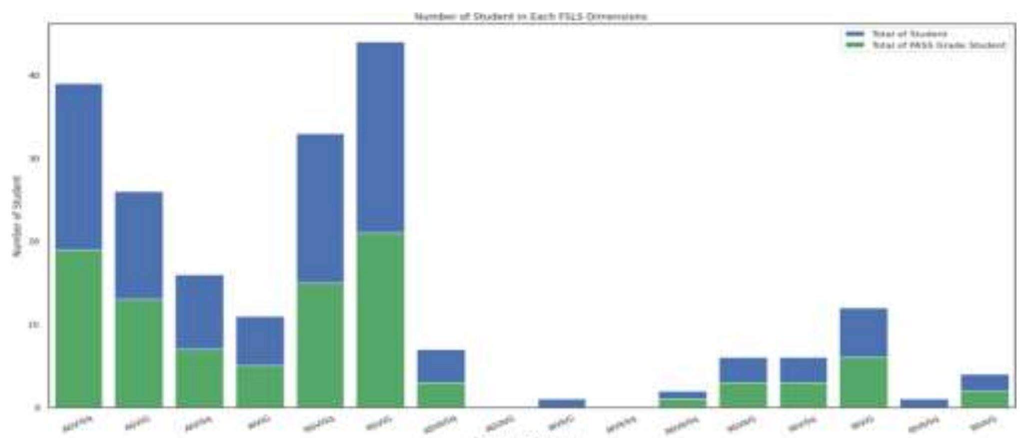

Fig. 5: Number of PASS Grade Student in Each Learning Style Combination Groups

4.3. Comparison of Models Highest AUC on Each Conditions Between Data with and without Learning Style Features

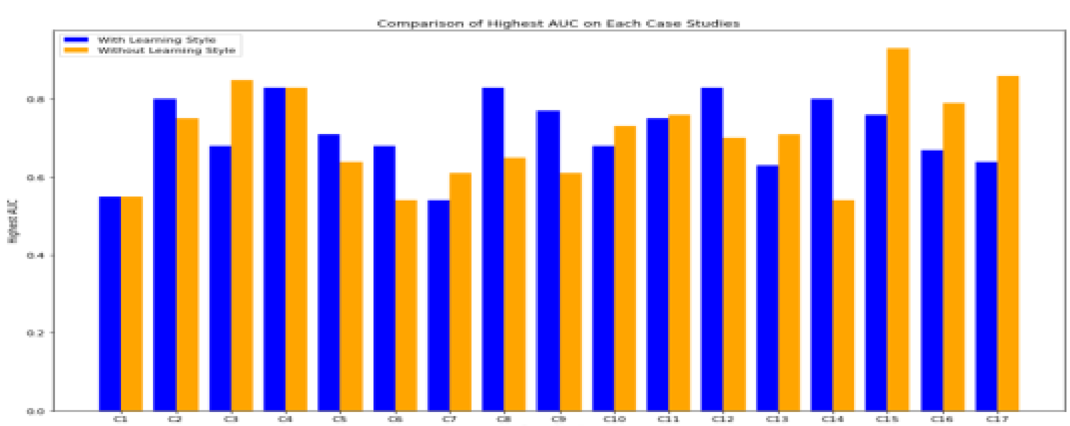

Fig. 6: Comparison of Models Highest Accuracy on Each Conditions Between Data with and without Learning Style Features

Figure 6 illustrates that the comparison between the highest AUC of all machine learning algorithms applied in the nine different criterion of case studies with and without learning style features included in the data. Although the proportion of minority class was approximate 41% of data, it is vital to compare the model performance between with and without sampling techniques to solve the imbalance data issue.

In condition C1, a similar AUC rate has been achieved at 0.55 in both datasets. However, the data with the learning styles has achieved the highest accuracy rate has been ranked top in the 7 case studies which were C2, C5, C6, C8, C9, C12, and C14. The most significant result was the data with the learning styles has achieved the highest accuracy approximately 0.83 as illustrated under condition C8 which involve the combination between PCA and SMOTE-TOMEK. The second highest AUC also achieved under the data with the learning styles was 0.80 as illustrated under condition C2 and C14.

In the case studies of dataset without learning style features, it has ranked the highest in the context of AUC under 8 case studies which were C3, C7, C10, C11, C13, C15, C16 and C17. Overall, the highest AUC achieved in the dataset without learning style features was the highest by 0.93 compared to the models with the data with learning style features. In this case, the NB algorithm has attained the highest AUC with the help of MRMR and SMOTE methods under C15.

4.4. Statistical Test

Table 8: The means & standard deviations of Higher AUC variables.

Variable	Groups	N	Mean	Median	Standard Deviation
HighestAUC	Learning Style	17	0.72412	0.74000	0.091724
	Without LS	17	0.71412	0.71000	0.113196

Table 8 has indicated the group comparisons, consisting of sample size, N, mean, median, and standard deviation for the higher AUC achieved under different groups. In this case, there are similar number of samples for both groups and the higher AUC mean achieved by the predictive models with learning style features was 0.72 which was slightly higher compared to the predictive models without learning style features included by only 0.71. However, both groups average was very close to each other which the difference was only 0.01. Furthermore, the higher AUC variable was normally distributed. Based on the p-value obtained from SPSS, normality tests by Kolmogorov-Smirnov and Shapiro Wilk have produced a p-value 0.200 and 0.436 respectively which was higher than threshold of 0.05.

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
HighestAUC	Equal variances assumed	.809	.375	.283	32	.779	.010000	.035336	-.061977	.081977
	Equal variances not assumed			.283	30.682	.779	.010000	.035336	-.062098	.082098

Fig. 7: Outcome of the Independent Sample Test Through SPSS

Two independent sample t-test as an equivalence test has been conducted through SPSS statistics software to determine the equivalent between learning style groups and the predictive model performance which was higher AUC rate. From the result of Levene test for equality of the variances in Figure 7, the p-value was 0.375 which was higher than 0.05 threshold. Therefore, the mean of the higher AUC predictive model performance on the student academic performance in the video-based learning with learning style features was significantly equal to the higher AUC mean of the predictive model performance without learning style features included.

In this case, the outcome has been concluded that predictive models were likely to achieve similar average of higher AUC rate in both conditions whether learning styles features included or not. Moreover, the null hypothesis on the mean of higher AUC rate by predictive model with learning style features included was almost equal to the mean of higher AUC rate by the predictive model without learning style features included cannot be rejected.

5. SIGNIFICANCE OF FINDINGS

5.1. Theoretical Findings

This study has focused on the significant relationship between learning style features and student academic performance in asynchronous video-based learning. Based on prior research studies, some authors have argued that learning style features did not cause any significant influence on the student academic performance. However, there were studies also endorse the influence of learning style on the student academic performance. Therefore, the high debate on the influence of learning style on the student academic performance has inspired a need to study the influence of learning style features on the student performance in video-based learning. In the experiment phase, machine learning models have been tested with two different types of datasets which were data with and without learning style features. In this case, the FS learning style model has been applied.

As a result, the learning style features has found did not provide significant effect in the context of student performance in this study where the mean of higher AUC rate by predictive model with learning style features included was almost equal to the mean of higher AUC rate by the predictive model without learning style features included. This finding is consistent with the recent research by Professor Beth Rogowsky, one of top well-known educational researchers where learning styles did not play significant role on improving student academic performance (Rogowsky et al., 2020). In this case, the author claimed that providing students with their preferred learning style material did not equate with better learning outcome or performance at the end of learning process (Rogowsky et al., 2020).

5.2. Practical Findings

This research can serve as the foundation for AI integration in the video-based learning environment for academic institutions who seek to maintain online classes as an alternative. In this research study, a predictive model's solution has been suggested to predict the student's early performance in video-based learning. In this case, the video watched rate based on the chapter in the video and learning style has been studied and analyzed as factors in the context of predicting student early performance in video-based learning. Based on the findings in this research, the combination of MRMR and SMOTE method has been applied into NB algorithm to produce approximately 0.93 of AUC on the prediction of student early performance. With the early prediction on student performance, the educators can be alerted on the student who may at the risk of getting poor performance at the end of course. Therefore, it's crucial for the educator to implement early preventive action to engage with those students under the high risk of getting poor performance in the asynchronous video-based learning as well as a benchmark for educator to come out a better teaching strategy to enhance the student learning experience and performance in the asynchronous video-based learning environment.

CONCLUSION

This research study has introduced a proposed predictive model to predict student academic early performance in video-based learning. In this case, this research study has utilized educational video watching rate and learning style factors to build a predictive model. However, there were some limitations in the research study such as the small sample size of participants from similar faculty and university. In addition, the scope of the implementation of predictive model was restricted only in the scope of machine learning algorithms. Therefore, this research has recommended some solutions in the future research by creating larger sample size of participants from different faculty and university as well as explore into deep learning method on the implementation of predictive model. At the end, there were two significant findings on this research has been discussed which were high AUC rate by approximately 0.93 has been achieved without the learning style feature. This proposed predictive system has aim to help educators on the early prediction of student performance which may help educator to identify those students who were at the risk of getting poor grade in the asynchronous video-based learning. The second findings were predictive model performance under learning style and without learning style groups did not have much significant difference.

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