

## Analysis of Student Procrastinatory Behavior in Virtual Learning Environments Using Machine Learning

Mehak Maqbool Memon<sup>1</sup>, Manzoor Ahmed Hashmani<sup>2</sup>, Syed Muslim Jameel<sup>1</sup>, Shamshad Junejo<sup>3</sup>,  
Kamran Raza<sup>4</sup>

<sup>1</sup> Department of Computer and Information Sciences, Universiti Teknologi PETRONAS, Seri Iskandar, Malaysia

<sup>2</sup> High-Performance Cloud Computing Center (HPC3), Center for Research in Data Science (CERDAS), Department of  
Computer and Information Sciences, Universiti Teknologi PETRONAS, Seri Iskandar, Malaysia

<sup>3</sup> English Language Development Center (ELDC), Mehran University of Engineering Technology, Pakistan

<sup>4</sup> Faculty of Engineering Science and Technology, Iqra University, Karachi, Pakistan

**Abstract:** Virtual Learning Environments (VLEs) are increasingly being used due to the uncertain global situation caused by COVID-19. Some major impacts of the pandemic are lockdowns and social distancing. This has led to academia taking measures to normalize the increased use of VLEs for teaching. However, this shift from face-to-face to online environments comes with many concerns—one of which is student procrastination. Procrastination is an observed student behavior of delaying tasks, which results in poor learning and can adversely affect student performance. Hence, it is essential to analyze student procrastination and determine the factors that cause this behavior whilst learning in VLEs. In this study, we present our findings on the impact of VLEs on student procrastination. We also analyze the performance of machine learning approaches to avoid manual intervention. We initially performed data collection, producing a dataset which was annotated by an expert, allowing us to visualize the pattern of student procrastination. Results confirmed the application of machine learning techniques for analysis for student's behavior. The results demonstrated the effectiveness of supervised approaches with an accuracy of up to 83%. In contrast, unsupervised approaches do not seem appropriate for this task. We hope that future work based on this study will allow automatic data annotation based on a trained machine learning model. The findings of our work will help identify students prone to procrastinating and allow intervention to maintain their academic performance. The expected implication of the presented study is an improvement of educational practices, helping teachers and demonstrators to gain a better understanding of students' behaviors.

**Keywords:** virtual learning environment, distance learning, machine learning, artificial neural networks, multi-layer perceptron, procrastination.

## 使用机器学习分析虚拟学习环境中学生的拖延行为

**摘要:** 由于新冠肺炎造成的不确定的全球形势,越来越多地使用虚拟学习环境(VLE)。大流行的一些主要影响是封锁和社会隔离。这导致学术界采取措施使VLE在教学中的使用增加标准化。但是,这种从面对面到在线环境的转变带来了许多问题,其中之一就是学生拖延症。拖延症是观察到的学生拖延任务的行为,这会导致学习不良,并对学生的表现产生不利影响。因此,在学生学习VLE时分析学生的拖延并确定导致这种行为的因素至关重要。在这项研究中,我们介绍了VLE对学生拖延的影响的发现。我们还分析了机器学习方法的性能,以避免人工干预。我们最初进行了数据收集,生成了一个由专家注释的数据集,从而使我们可以看到学生拖延的模式。结果证实了机器学习技术在学生行为分析中的应用。结果表明,监督方法的有效性高达83%。相反,无监督的方法似乎不适用于此任务。我们希望基于此研究的未来工作将允许基于训练有素的机器学习模型进行自动数据注释。我们工作的结果将

Received (date):

About the authors: Mehak Maqbool Memon, Department of Computer and Information Sciences, Universiti Teknologi PETRONAS, Seri Iskandar, Malaysia; Manzoor Ahmed Hashmani, High-Performance Cloud Computing Center (HPC3), Center for Research in Data Science (CERDAS), Department of Computer and Information Sciences, Universiti Teknologi PETRONAS, Seri Iskandar, Malaysia; Syed Muslim Jameel, Department of Computer and Information Sciences, Universiti Teknologi PETRONAS, Seri Iskandar, Malaysia; Shamshad Junejo, English Language Development Center (ELDC), Mehran University of Engineering Technology, Pakistan; Kamran Raza, Faculty of Engineering Science and Technology, Iqra University, Karachi, Pakistan

有助于识别容易拖延的学生，并进行干预以保持其学习成绩。这份研究报告的预期含义是对教育实践的改进，可以帮助教师和示威者更好地了解学生的行为。

**关键词：**虚拟学习环境，远程学习，机器学习，人工神经网络，多层感知器，拖延。

## 1. Introduction

The transfer of knowledge is revolutionizing due to easy access to communication technologies and the rise in information produced [1], [2]. Online courses offered by different Virtual Learning environments are even supported by UNESCO (The United Nations Scientific and Cultural Organization) [3]. As of the first half of 2020, up to 165 countries have halted educational activities because of the COVID-19 pandemic declared [4]. It eventually affected 1.5 billion students' studies, making 90% of the World's student percentage [4], [5]. However, in this critical situation, VLEs help provide uninterrupted learning experiences due to easy access and low-cost. The educational sector is now exclusively switching to online classes to offer remote learning to ensure student learning is not disrupted [5]. There are different VLEs which offer platforms and resources to help a student learn. Some of the VLEs include CenturyTech, Google Classroom, Moodle, Schoology, Skooler, Coursera, Edx, Future Learn, Udemy, and many more [3]. UNESCO has also provided a list of VLEs to deal with the current situation to provide distance learning solutions and observe social distancing simultaneously [3]. Before the pandemic, all these VLEs claimed to be serving millions of students by providing access to a versatile range of courses [6-9]. With the extensive increase in the use of VLEs and IT tools in the educational sector, one of the significant concerns is how these IT tools

will affect the student's academic performance [26]. There is substantial relevance observed amongst these IT tools and performance. According to [10], current International data indicates that 20% of adults tend to delay the task and procrastinate in daily schedules. Moreover, there is a positive correlation between IT tools and procrastination with a 27% tendency [11]. Many studies have been conducted to find out the trends of procrastination in student behavior. According to [12], 80% to 90% of university students procrastinate with different procrastination percentages' margins. 45% of students fall in moderate, 31% of students fall in mild, 22.3% of students fall in severe, and 1.7% fall in the very severe category [12]. These percentages are alarming, and eventually, students' overall academic performance is affected. The study also uncovers that 70% of this analysis was students of undergrad level [12]. 80% -95% of college or university students are procrastinators in another study backing the fact that procrastination adversely affects students' academic performance in a blended learning environment [13]. Another study claims that 50% of the students are consistent procrastinators [14]. All these stats steer the attention towards the mechanism to analyze the procrastination behavior and its effects on academic performance, particularly in VLEs, as VLEs are now shaping the educational sector.

For addressing those gaps, research questions were formulated, which are:

Table 1 Raised research questions, research objectives, and related sections

| Research Question  | Research Objective   | Section   |
|--|--|-----------|
| What are the crucial factors of students' behavioral data (activities performed) from VLEs that can identify procrastination behavior? | To identify crucial factors of students' behavioral data (activities performed) from VLEs that can identify procrastination behavior?  | Section 2 |
| What should be the optimal steps taken to annotate the student data based on an expert opinion automatically?                          | To propose an effective strategy for automatic large-scale dataset annotation (student behavior data for the presence of presentation) | Section 3 |
| What is an appropriate ML approach for automatic data annotation to identify procrastination behavior in students?                     | To investigate the unsupervised and supervised ML approaches to determine the feasibility of automatic data augmentation.              | Section 4 |

Students' behavior is identified based on different student data features to identify procrastination in online learning environments. To the best of our knowledge, there has been no adequately annotated data for the presence of procrastination. The studies reviewed relevant to procrastination show the limited aspect of the studies, which means it is difficult to generalize a single study or dataset. The conducted research formulizes and presents a master feature

vector of students' behavioral activities to create a procrastination dataset. The existing dataset, namely OULAD (Open University Learning Analytics Dataset), is used to create the final procrastination dataset. The existing OULAD dataset is preprocessed to handle the missing values and to create the required feature vector. The generated patterns of Student VLEs data using unsupervised ML are possible solutions to annotate data. Similar data is annotated with the help of

experts in the field of education. The patterns gathered from the implementation of unsupervised ML are compared with the patterns of annotated data. Furthermore, the research presents all the relevant features of students' data having a substantial impact on procrastination. The identified features are used to predict student procrastination to help students and teachers to tackle the adverse consequences of procrastination over academic performance. The presented work is meticulously explored for multiple aspects of student behavior. The findings of this work will help academia to identify students before off track.

The paper is organized as follows: Section 1.2. discloses the protocol followed for referring the literary studies in the domain of machine learning and student behavior. Along with that, formulated research questions are listed. Section 2 presents a detailed most recent literary studies conducted in the domain, and these studies are categorized and further critically investigated to find out the ways of further enhancements. Section 3 presents the detailed research framework and, thereby, mentions the concerning aspects of data analysis, i.e., proper data annotations and the detailed process dataset development using supervised ML algorithm. Section 4 presents all the predictive experiments to annotate the data adequately and mentions the best tuned supervised classifier, resulting in the accurate dataset label creation. Section 5 concludes the entire study in three comprehensive aspects presenting the bigger picture.

## 2. Related Work

Educators use different types of assessment strategies to decide on a student's performance. These assessments decide, collect, and judge the goals achieved in terms of student's performance. For that matter, the assessment types used over the years include formative and summative assessment [15]. The core purpose of assessments is to provide better experiences for teaching and learning. The formative assessments evaluate students' performance throughout the course in a point-wise manner through quizzes, tasks, and tests. In contrast, summative assessment evaluates student's performance by the end of the course [16]. Both assessments are also implemented as hybrid assessment approach to help students to get better results [17]. However, as the extreme paradigm shift of the education system is being witnessed, it should be analyzed how online assessments and activities impact students' behavior. Presented research has referred to multidisciplinary behavioral researches of students in contexts of procrastination and performances.

In the study [18], a student's performance is based on procrastination behavior. The study proposes a novel algorithm to predict students' performance facing

learning difficulties through procrastination behavior. The student data has been analyzed by using submission dates for assignments. For this purpose, clustering algorithms have been used. The best accuracy is obtained by linear SVM. The study utilizes both continuous and categorical data. The research concludes the accuracy is almost the same, with a slight difference for categorical and continuous features. In the study [10], procrastination is identified based on the students' self-reported data and termed as decisional procrastination. The research included a cross-cultural sample size of 2893 students. Logistic Regression is used to identify the patterns. The presented results identify that indecision and regrets about education career and finance lead to procrastination. Whereas it is also mentioned that one's earning is the potential predictor of procrastination irrespective of country/origin.

In the study [19], a student's academic procrastination is analyzed in a blended learning model based on homework (HW) assignments' submission data. Submission details include late HW or non-submission detection to predict academic performance. Students are labeled as procrastinators or non-procrastinators using K-Means after that. Different classification methods are used to classify students using submission data. The student data is retrieved from SCHOLAT course logs of the spring 2018 ACM programming course 4th semester. The analysis also reveals that if the number of classes is increased, algorithm accuracy is severely affected. In the study [20], procrastination behavior is predicted in a Computer-based learning environment. According to the presented study, there are adverse effects on academic achievement. Findings included time management in the Online Learning Environment that influences academic achievement; there is a strong association between procrastination and student performance. In self-regulated learning, procrastination is claimed to have a negative impact. Research [11] presents yet another psychological study to determine the influence of gadgets, social media, and college students' procrastination. The methods used are quantitative and descriptive. There is a positive correlation between gadgets and social media addiction ( $r=-0.025$ ,  $p<0.0001$ ), between gadget to procrastination of tendency (27%) and social media to procrastination of tendency (54%). The study claims to use multiple regression analysis.

Recent studies disclose the shocking unavailability of labeled data in terms of procrastination. The discerning summary of the referred studies in tabular form uncovering labeled procrastination unavailability is in Appendix A. Student procrastination is one of the critical issues for students and teachers in gaining better academic results. The presented study discusses a detailed protocol for student data annotations through

different methods, including an automatic annotation method based on unsupervised learning and human annotations. These annotations are visually compared to identify if the entire process is automated and relied on unsupervised machine learning for label creation. Finally, the labels created on expert opinion are fed to the student feature vector, and the entire feature vector is used for the prediction and classification of student data. The study can be further extended through the addition of more features. One of the highlights of the presented study, which sets it apart from recent studies, is the dataset's size for analysis. To the best of our knowledge, there has not been any dataset that explains students' online behavior in terms of procrastination, online activities of students, and an individual's educational demographics. Eventually, the presented study analyzes a student's behavior based on the same. It validates the entire student's behavioral analysis via detailed assessment of different Machine Learning algorithm implementations for classifying and predictive data analysis, which opens new avenues of similar research and extension of student's behavioral datasets.

### 3. Materials and Methods

#### 3.1. Data Formation

Considering the literary studies referred to, one of the major concerns in education is the absence of adequately annotated data regarding procrastination. The size of the data set used in the referred researches

is in the range of 100-2800 records only, which is not enough data to train and test ML algorithms. To address this problem, we have formed a student procrastination dataset, referred to by the research community as a generic benchmark.

To successfully formulate the procrastination dataset, first, it was necessary to find a suitable student dataset and annotate it using k-means clustering. It has been a practice of researchers to annotate the data [19], [21], [22], [23]. The selected dataset is the Open University Learning Analytics Dataset, which contains the detailed features of the 32593-student profile enrolled for STEM courses in Virtual Learning Environment [24]. The dataset is distributed over different comma-separated values files to keep a proper record of students used by different education sector departments. The dataset includes multivariate sequential and time-series features. The student profiles are for students from 2012-2014.

#### 3.2. Data Collection & Extraction

The dataset formulation used different credible features of student data profiles to find the patterns in the data and attribute the patterns as the presence or absence of procrastination. The extracted features include student\_Id, Highest\_Education, studied\_credits, Number\_of\_previous\_attempts, final\_result, disability, date\_submitted, and score. Table 2 mentions the details of each of these shortlisted features.

Table 2 Details of shortlisted features

| S/No | Student Attributes          | Attribute Value  |
|------|-----------------------------|--|
| 1    | Student_Id                  | Unique student ID numeral.   |
| 2    | Highest_Education           | The education level of a student when enrolled for a module<br>"No Formal quals"="1"<br>"Lower Than A Level"="2"<br>"A Level or Equivalent"="3"<br>"HE Qualification"="4"<br>"Post Graduate Qualification"="5" |
| 3    | Number_of_previous_attempts | Prior attempts of students for the same module. (Range: 0-6)   |
| 4    | Final_result                | Result of an individual for a module<br>(Fail=1, Withdrawn=2 Pass=3, Distinction=4,).  |
| 5    | Disability                  | Specifies whether the student has declared a disability. (No=1, Yes=2)   |
| 6    | Date_submitted              | The day of assessment submission is measured as the number of days since the start of the module presentation. (Range=-11 - 608)   |
| 7    | Studied_credits             | The total number of credits for the modules the student is currently studying. (Range: 0- 655)   |
| 8    | Score                       | Student's score assessment. The range is from 0 to 100. The score lower than 40 is interpreted as Fail. The marks are in the range from 0 to 100.  |

Based on these dynamic factors, initially, the data is labeled, and then it can be further used with ML

classifiers to predict procrastination behavior.

### 3.3. Data Cleaning & Annotations

The extracted data is preprocessed to fill the missing values of student records. After the extraction and transformation, the data is fed to an unsupervised machine learning algorithm for pattern identification and data annotation. However, there is an ambiguity with the generated patterns, i.e., which cluster should be labeled as an individual tending to be a procrastinator or not. For this reason, we took an educational expert on board for data annotations, which are then compared with the patterns identified by ML algorithms. The comparisons are presented in the following section of results.

#### 3.3.1. Annotations via Clustering

Clustering is extensively used in literature to discover the hidden patterns and group the data into clusters. We employ two *clustering* algorithms, K-Means and Mini-batch clustering, to create the clusters. Identifying the optimal number of clusters or class labels for the structured data elbow method is used. The elbow method's visualization, as seen in Fig. 1, depicts that the optimal number for cluster creation is two clusters, i.e., two class labels.

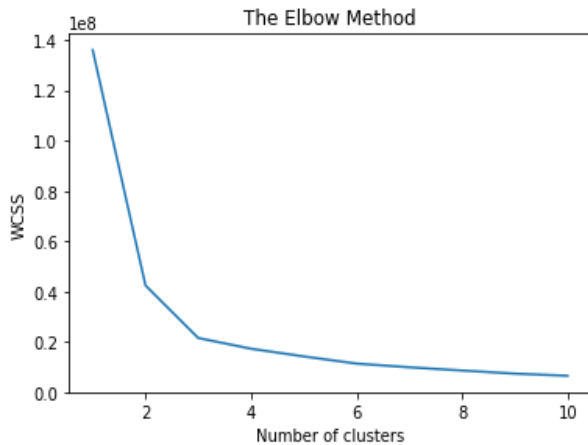


Fig. 1 Optimal number of class labels

#### 3.3.2. Annotations via Educational Expert

The educational expert was asked detailed questions to identify the dependable features and their ranges for annotating the data. The summary of acquired information is as follows:

If studied credits range greater than 250, the label is recorded as Presence of procrastination (1) and the absence of Procrastination 0.

Studied\_credits > 250 → Procrastination=1

Studied\_credits < 250 → Procrastination=0

If a student has previously attempted the course, he/she turns out to be a procrastinator.

Number\_of\_previous\_attempts=0 → Procrastination=0

Number\_of\_previous\_attempts=1-6 → Procrastination=1

Disability of student might not affect because the study is focused on VLEs

Disability= 0/1 → Procrastination=0

If a student failed for the result, the label is recorded as Presence of procrastination (1) and the absence of Procrastination 0.

Final\_Result =1 → Procrastination=1

Final\_Result =2-4 → Procrastination=0

If scores are in higher ranges and consequently assignment submission dates are relatively smaller, the label is recorded as the absence of Procrastination 0.

Score ≥ 50 & Date\_submitted < 150 → Procrastination=0

If scores are in lower ranges and consequently assignment submission dates are relatively more extensive, the label is recorded as the absence of Procrastination 1.

0 > Score < 49 & Date\_submitted > 150 → Procrastination=1

If submission dates are more extensive in numerals and the score is in the 90s

Date\_submitted > 200 & Score ≥ 90 → Procrastination=0

If submission dates are more extensive in numerals such that scores are also average and failed result is witnessed, it turns out that student is a procrastinator.

Date\_submitted > 150 | score = average values & Final\_Result =1 → Procrastination=1

With these considerations in place, the student profiles extracted from the OULAD dataset are further enhanced to have procrastination labels (YES/1, NO/0).

#### Optimized Algorithms for Data Formation

Require: Studied\_credits, Disability, Number\_of\_previous\_attempts, Final\_Result, Score, Date\_submitted

### 3.4. Data Formation Algorithm Based on Unsupervised Learning

Step 1: Construct feature vector  $X_i$  ( $i=1 \geq 32593$ )

$$X_i = w_{1i}, w_{2i}, \dots, w_{ni}$$

//for feature extraction tasks

Step 2: Apply clustering algorithm at  $k = 2, 3, 4, 5$

to feature vector  $X_i$ .

$$J = \sum_{j=1}^K \sum_{i=1}^n \|w_i^{(j)} - c_i\|^2$$

$J = \text{Objective Function}$

$K = \text{Number of Clusters}$ ,

$n = \text{number of cases}$ ,  $w_i^{(j)} = \text{case } i$ ,

$c_i = \text{centroid cluster } j$

$$\|w_i^{(j)} - c_i\|^2 = \text{distance function}$$

Such that

objective function is minimum.

//for automatic label creation

Step 3: Cluster comparison via Elbow Method to find optimal clusters present.

//to find an optimal number of clusters

Step 4: Add a label of class for each record in the feature vector  $X_i$

$$X_k \leftarrow X + \text{Class}_{\text{Procrastination}}$$

//label assignment

### 3.5. Data Formation Algorithm Based on Expert's Considerations

Step 1: Construct feature vector  $X_i$  ( $i=1 \leq 32593$ )

$$X_i = w_{1i}, w_{2i}, \dots, w_{ni}$$

Step 2: Iterate through records and label them based on the Expert's considerations.

While  $i=1 \leq 32593$

Add a label of class for each record in the feature vector  $X_i$

$$X_k \leftarrow X + \text{Class}_{\text{Procrastination}}$$

### 3.6. Data Formation Algorithm Based on Expert's Considerations

Step 1: Construct feature vector  $X_i$  ( $i=1 \leq 32593$ )

$$X_i = w_{1i}, w_{2i}, \dots, w_{ni}$$

Step 2: Iterate through records and label them based on the Expert's considerations.

While  $i=1 \leq 32593$

Add a label of class for each record in the feature vector  $X_i$

$$X_k \leftarrow X + \text{Class}_{\text{Procrastination}}$$

### 3.7. Data Classification

This section explains the detailed research protocol employed for data classification through Supervised Machine learning algorithms. The predictions are based on the student's demographics and behavioral activities performed in VLE.

#### 3.7.1. Classification of Students Using Labeled Data

The data annotated is fed to two different Supervised ML algorithms for classification and prediction based on expert opinion. The ML classifiers are fed with the training dataset and continuously checked for performance on the testing dataset. The two ML classifiers include Logistic Regression (LR) and Artificial Neural Networks (ANN). These classifiers are iteratively optimized to identify the best performing algorithm. They propose it as a candidate Model for procrastination behavior prediction.

The classification algorithms take the student feature vector as input and apply different statistical methods to identify the student's behavior in terms of procrastination (presence/absence). The first classification algorithm, i.e., logistic regression, is somewhat simple and curbs less processing time by applying only a simple statistical function (sigmoid function) whose output is always dichotomous. The behavior of this classifier is pretty much relevant to the problem at hand. The second classification algorithm, i.e., Artificial Neural Network, is based on the layered neurons, whose basis is the statistical functions. However, it provides functionality to control the entire classifier's behavior by providing options to choose between the statistical methods used for every neuron in different layers, consequently providing better classifier optimization methods but at the cost of increased complexity [27].

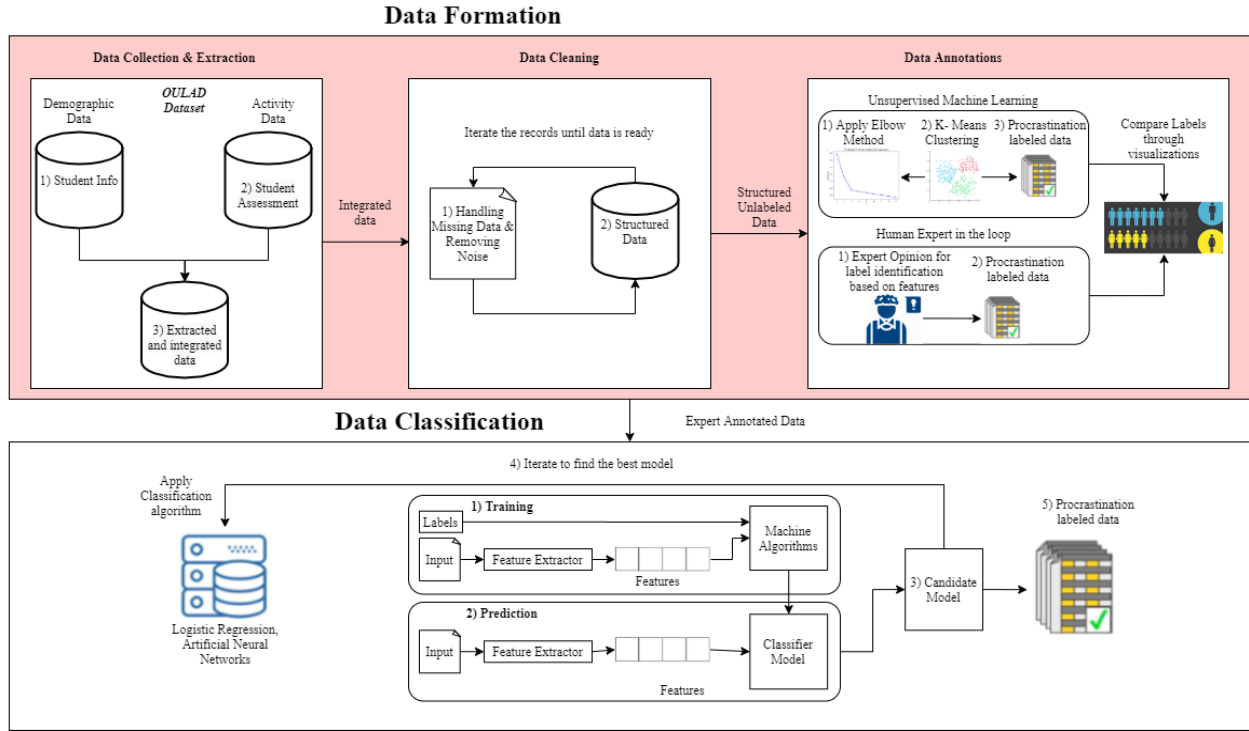


Fig. 2 Detailed dataset development protocol

Fig. 2 presents a detailed dataset development protocol used to devise and construct the procrastination dataset successfully.

### 3.7.2. Optimized Algorithm for Data Classification

Require: Studied\_credits, Number\_of\_previous\_attempts, Disability, Final\_Result, Score, Date\_submitted, Procrastination

Step 1: Apply classification algorithm 'C' on enhanced feature vector  $X_k$

$$C_1 = \text{Logistic Regression} \rightarrow \frac{1}{1 + e^{-(w_1j, w_2j, \dots, w_{nj})}}$$

$C_2 = \text{Artificial Neural Networks (Multi-Layer Perceptron)} \rightarrow \text{Activation Function} \rightarrow \text{ReLU} \rightarrow f(x) = \max(0, x)$

//for classification of records

Step 2: Compare Performance Metrics

Check Classifier accuracy > 70%

Tune Classifier Parameters (change Batch Size {200/100/50/25}, optimizer {'sgd'/'adam'})

//for parameter optimization

Step 3: Compare Performance Metrics

Check Classifier accuracy increased?

Log results and relative parameter to propose the best classifier 'C'

Else Repeat Step 2.

//for checking the overall performance of the classifier

Use Classifier 'C' for identification of procrastination behavior in student's detailed log

Expand the interferences.

### 3.7.3. How It Works?

This integrated data is preprocessed to clean any irrelevant symbols or missing values in data. This process is iteratively done until all the records are free from irrelevant information; finally, the structured data is passed to the next stage of annotating the data. For data annotations, two parallel workflows are followed: Unsupervised ML algorithm and Expert opinion for data annotations. The labels generated by both flow of work are compared through visualizations to analyze the differences of labeled records to identify the reliability of annotations created by unsupervised ML algorithms. Finally, the expert annotated data is used to identify the best-supervised classifier based on an analysis of performance measures.

## 4. Results

The study results are thoroughly visualized for the analysis in the following section, depicting the complexity of students' behavior following the studies based on VLEs.

### 4.1. Visual Comparison of Annotated Data Visualizations

The structured data created by initial phases of the methodology is passed for labeling parallelly by unsupervised ML algorithms and based on expert opinion. In this section, the labeled data is visualized to identify if the labels generated are consistent with each other, and if clustering is reliable to create annotations for behavioral identification and analysis.

#### 4.1.1. Class Label Based on Expert Opinion

Based on the detailed considerations acquired from human experts, each record is labeled. The labels identify if the student, based on the demographic and behavioral activities performed in VLE, will procrastinate for assigned tasks or not. The labeled visualizations are shown in Fig. 3 through Fig. 6.

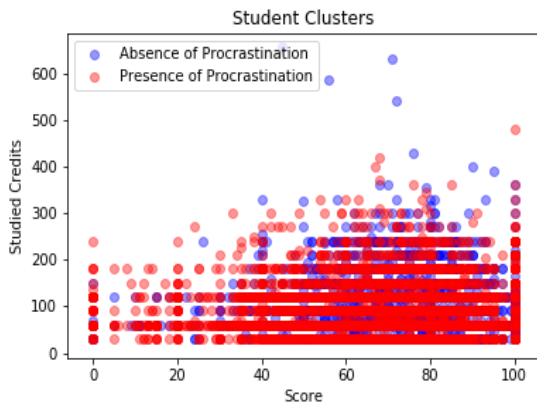


Fig. 3 Assessment score vs. studied credits for a module

Fig. 3 presents the scatter plot of student data annotated for procrastination, depicting the null relationship between the features. However, no pattern is identified in terms of the procrastination label identified by the educational expert, which can be seen in red and blue plot points. The student data seems to be evenly distributed over the x-axis, i.e., assessment score, which means the student population is likely to get marks over the entire scale. Data is highly populated around the lower right corner for studied credits, depicting that most students do not spend more than 300 credit hours to complete a course module. Moreover, as the red plot points are witnessed all over the data distribution, it cannot be concluded that even if students spend much time studying in terms of studied credits and have good scores in the tests/assessments, they did not attempt to procrastinate. As there are no gaps in the plot, even student clusters presenting procrastination behavior are hard to identify.

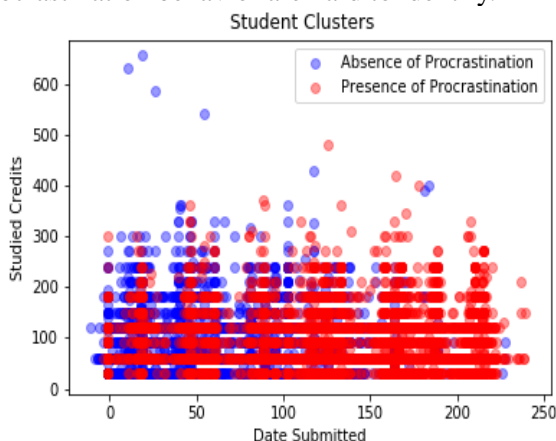


Fig. 4 Assessment submission dates vs. studied credits for a module

Fig. 4 presents the scatter plot of student data

depicting the null relationship between the features providing the colors representing the procrastination label through red and blue points for each student record. The pattern identified by the labeled procrastination feature suggested by the expert seems to be in the majority over the lower right corner. The students taking more time for the assessment submission are likely to procrastinate more than those who have submitted earlier. Again, the student data is evenly distributed over the assessment submission axis depicting that the modules have an equal number of students submitting the assigned tasks on time and late. The data along the studied credit axis is highly populated over the lower end, depicting that most students take no more than 300 credit hours to complete a course module. As for the procrastinators (red) and non-procrastinators (blue), it turns out that the students, falling in the more significant number of submission dates, are procrastinators. In contrast, with studied credits, there is not any pattern found. However, some outliers present in the data labeled as non-procrastinating students, and the ranges fall around submission dates 0-50 and the credit hours reside in the range of 500-600. Simultaneously, some of the outliers witnessed at the lower left of the plot range 220-250 for submission dates and 0-250 for studied credits identifying them as procrastinating students. As the red plot points presenting procrastinators witnessed in the majority around the lower right corner, the students delaying assessment submissions are procrastinators.

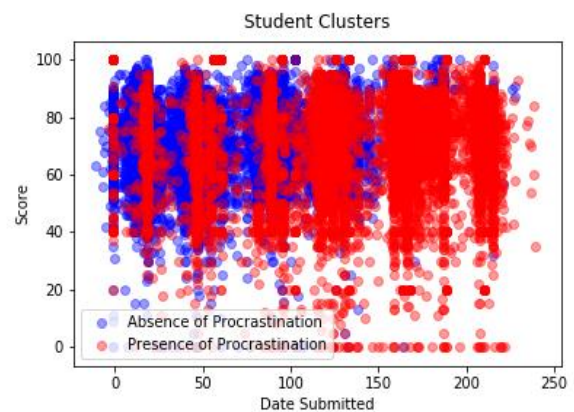


Fig. 5 Assessment submission dates vs. obtained assessment scores

Fig. 5 presents the scatter plot of student data depicting null relationship and issue of over-plotting. We are dealing with a massive amount of student data, and the data is evenly distributed along both the axes, i.e., assessment submission dates and assessment scores. The even distribution convincingly guarantees that there can be students of any type provided who submitted assessments on time or late and who have scored assessments with excellent or poor performance. However, the third categorical feature, in this case, is that the student is a procrastinator or non-procrastinator. Again, the red plot points represent procrastinating students observed in the majority

around the right side of the plot, and non-procrastinating (blue) ones around the left corner depicting that students taking time to submit the assigned tasks are procrastinators. No clear pattern is identified for the obtained scores. It subjectively means that procrastinators can perform well and secure perfect scores. An outlier is identified in the ranges of 0-10 score values, and the submission dates are in ranges of 0-250, ultimately inferring that the students securing low scores are usually the procrastinators.

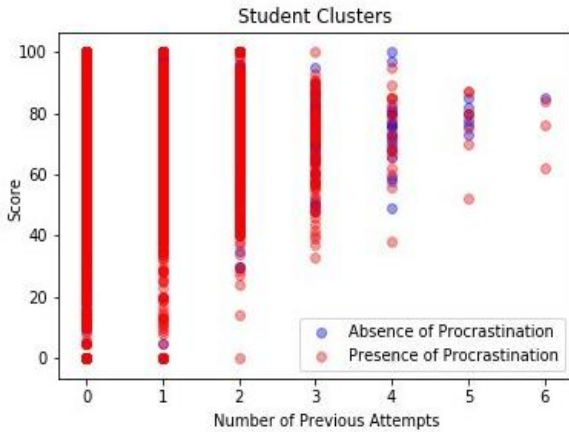


Fig. 6 Number of previous attempts for a course module vs. obtained assessment scores

Fig. 6 presents the scatter plot of student data depicting discretized data over the x-axis, i.e., the number of attempts students have taken to complete the course versus overall obtained scores to pass the course. Most of the data records are residing in the left corner of the plot, representing that most students complete the course within initial attempts. At the same time, no pattern is found over the score axis. However, as procrastination is concerned among the students, the red plot points are witnessed around the plot's left side. With the increased number of previous attempts for assessments, students somehow realize not putting off studies and are witnessed to procrastinate less in assigned tasks.

Looking at each plot closely, one sees that even if incorporating VLEs give students easy access to knowledge without moving to distant regions, still, a massive percentage of students tend to procrastinate. Expertly annotated visualizations signify that the student's procrastination behavior is a complicated relationship between different class label creation features.

#### 4.1.2. Class Label Based on Unsupervised ML Algorithm

The structured data is similarly fed to K-Means clustering and mini-batch K-Means to identify and create class labels for procrastination presence. The visualizations of patterns are shown in Fig. 7 through Fig. 10.

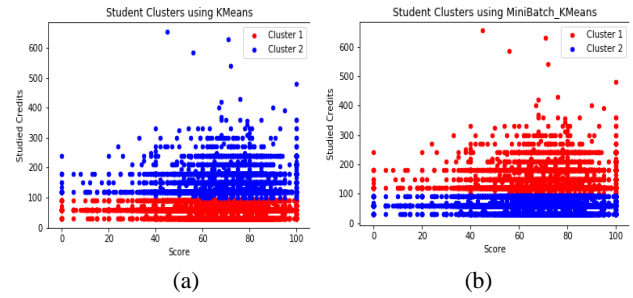


Fig. 7 a) Clusters based on K-Means clustering using features assessment score vs. studied credits for a module; b) Clusters based on Mini-batch clustering using features assessment score vs. studied credits for a module (Left to right)

Fig. 7 shows a similar scatter plot of attributes as in Fig. 3. The student data distribution and the relationship between the features are still the same. The data plotted is highly populated over the lower right corner of the graph depicting most of the students are getting good scores in fewer credit hours. For Fig. 7, machine learning algorithms are used to identify any hidden pattern in the student data. For this purpose, mainly clustering algorithms are used. The clustering algorithms, i.e., k-means and mini-batch k-means, are trained for scores obtained in assessments, and studied credits to complete the course module are used from the student data entries. Fig. 7a and 7b both create clusters. It shows that if studied credits are above the range of 100, they create a different group illustrating the clear cut grouping of the data in blue and red plot points. It is not the case with Fig. 3. There is no group of students identified as procrastinators or non-procrastinators, whereas no pattern is identified for the obtained scores.

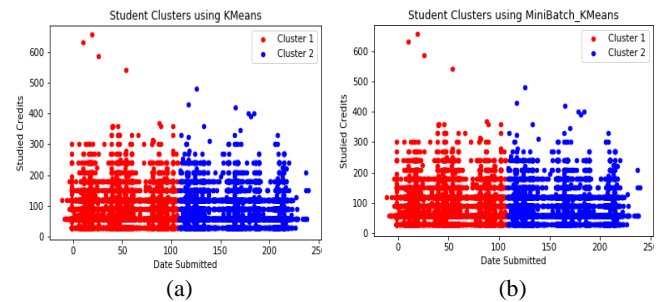


Fig. 8 a) Clusters based on K-Means clustering using features assessment submission dates vs. studied credits for a module; b) Clusters based on Mini-batch clustering using features assessment submission dates vs. studied credits for a module (Left to right)

Fig. 8 shows the cluster visualization in terms of scatter plots for assessment submission dates and credit hours taken to complete the course module. The clustering algorithms are trained for similar features (Date\_submitted and Studied\_credits) of the student dataset. Again, the algorithms result in a range of values for submission dates. If the submission dates are greater than 100, a different cluster is created, whereas no pattern is identified for the credit hours student takes to complete the course.

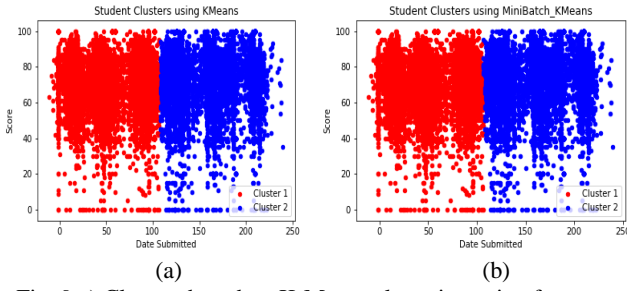


Fig. 9 a) Clusters based on K-Means clustering using features assessment submission dates vs. obtained assessment scores; b) Clusters based on Mini-batch clustering using features assessment submission dates vs. obtained assessment scores (Left to right)

Fig. 9 shows the scatter plot having cluster visualization for submission dates vs. scores obtained by students for assessments. The clustering algorithms are trained for Date\_submitted and Score attributes of the student dataset. Two clusters are witnessed identifying the ranges of submission dates less than 100 in one cluster and greater than 100 in another with relevant red and blue colored plot points. Finally, no pattern is identified for the student's obtained scores.

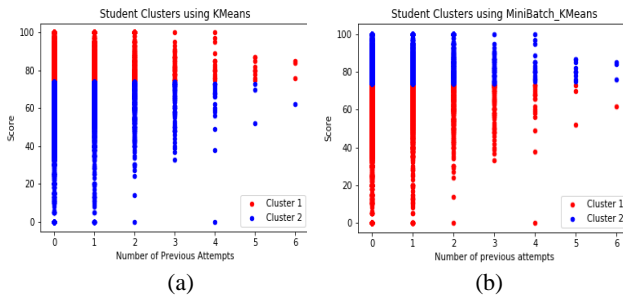


Fig. 10 a) Clusters based on K-Means clustering using features number of previous attempts vs. obtained assessment scores; b) Clusters based on Mini-batch clustering using features number of previous attempts and vs. obtained assessment scores (Left to right)

Fig. 10 shows the scatter plot of clusters created for the number of previous attempts taken by the student to pass the course vs. scores obtained by students for assessments. The clustering algorithms are trained for Number\_of\_previous\_attempts and Score attributes of the student dataset. Two clusters are witnessed, identifying scores less than 75 in one cluster and greater than 75 in another. Finally, no pattern is identified over 'x-axis' i.e. Number\_of\_previous\_attempts.

From the above visualizations presented in Fig. 7-10, we have noticed that unsupervised ML algorithms are not an appropriate solution for identifying procrastination. Based on the comprehensive analysis of results, the patterns observed in the implementation of unsupervised ML are entirely different from the expert annotated data.

#### 4.1.3. Analysis & Deductions

The visualizations of data annotated by experts seem to be nonlinearly separable, deducing that the student behavioral class labels are based on a complex

association of features. The unsupervised ML classifier ends up, resulting in visualizations of linearly separable data. These visualizations are evidence that unsupervised ML cannot be solely used for annotation purposes.

The unsupervised algorithms are usually expected to create class labels based on statistical formulae. These labels are created based on the data values, which sometimes fail to relate and identify human nature's actual complex behavioral facts. The simple reason for this could be the complicated relationship between the feature values, which cannot be identified by solely using the averaging formula. The visualizations of clusters/ labels created via unsupervised machine learning algorithms are witnessed to create linearly separable class labels, which is not the case with the same feature visualizations created with expert annotations. These deductions open a new avenue of research for the identification of data annotations.

## 4.2. Predictive Experiments Using Supervised ML Algorithm

Later, Supervised Machine Learning algorithms were used to determine the applicability for the prediction of procrastination in students. For that purpose, the Expert annotated data is split into training and testing tests to identify candidate ML models.

### 4.2.1. Train-Test Dataset Preparation & Hyperparameter Optimization

The enhanced annotated dataset to conduct the detailed experimental study is randomly divided into two sets: training and testing sets, as shown in Table 3.

Table 3 Details of shortlisted features

| Size of Dataset | Training Set      | Testing Set      |
|-----------------|-------------------|------------------|
| N= 32593        | N=26074, i.e. 80% | N=6519, i.e. 20% |

For a successful experimental study of the data classification phase and the identification of the best classifier chronicles, two different algorithms have been implemented, including ANN- Multi-Layer Perceptron and Logistic Regression. Extensive hyperparameter tuning is employed for the former algorithms, whereas the latter resides in a simple non-linear classifier listing from ML algorithms. After the structured data is split into two subsets, the training subset and procrastination labels are fed to the ML algorithm (Differently tuned versions of ANN-MLP and Logistic Regression). The parameter tuning is accomplished by using a manual search strategy [25]. These algorithms are implemented using python programming and Scikit-learn library's default implementation of these supervised ML algorithms. After the classifier's training phase, the trained classifier is given a test subset for the prediction and identification of procrastination labels. Through the iterative tuning and analysis of acquired results, it can

be concluded that the supervised ML algorithm worked marginally well, and the candidate classifier can hit the accuracy above 82%. However, this performance can be further increased with further variation and tuning in the model's hyperparameters and network structure.

For identification of the best performing classifier following inputs and outputs are used with the mentioned hyperparameter values.

#### 4.2.3. Details of Training and Testing Modules

Input Features: studied\_credits, num\_of\_prev\_attempts, final\_result, score, date\_submitted

Output Features: Procrastination

Parameter values set for ANN-MLP Classifier analysis

hidden\_layer\_sizes=(10, 10, 10),

solver='sgd'(stochastic gradient descent)/ 'adam' (stochastic gradient-based optimizer proposed by Kingma, Diederik, and Jimmy Ba)

batch\_size=200/100/50/25

Rest of the parameters are set to default values. Same is for Logistic Regression Classifier.

#### 4.2.4. Experimental Analysis & Deduction

Table 4 presents the accuracy obtained by different classifier models. Based on the acquired information of accuracy, the proposed classifier model is ANN-MLP with 'Adam' optimizer and a batch size of 100, for which we have obtained an accuracy of 83.5% on the training set and 82.9% on the testing set. A similar performance was witnessed by the logistic regression classifier, i.e., 82% accuracy for the training set and 81.9% accuracy for the testing set.

Table 4 Performance accuracy of all classifier models

| Classifier                              | Optimizer | Batch Size= 200 | Batch Size= 100 | Batch Size= 50 | Batch Size= 25 |
|---|-----------|-----------------|-----------------|----------------|----------------|
| ANN - Training Accuracy                 | Sgd       | 80.8%           | 82.1%           | 81.2%          | 81.7%          |
| ANN - Testing Accuracy                  | Sgd       | 78.2%           | 82.0%           | 82.8%          | 81.1%          |
| ANN - Training Accuracy                 | Adam      | 83.3%           | 83.5%           | 83.1%          | 83.3%          |
| ANN - Testing Accuracy                  | Adam      | 82.7%           | 82.9%           | 82.6%          | 83.2%          |
| Logistic Regression - Training Accuracy | 82%       |                 |                 |                |                |
| Logistic Regression - Testing Accuracy  | 81.9%     |                 |                 |                |                |

Further classification reports and confusion matrix were generated to know the details of performance for each version of the ANN-MLP classifier and Logistic Regression.

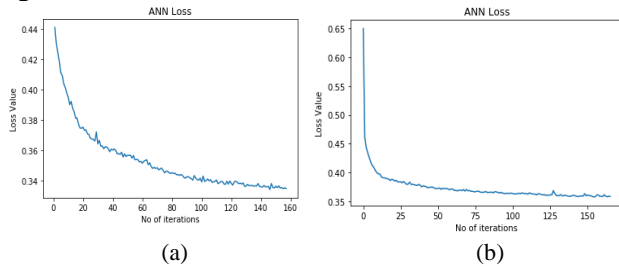


Fig. 11 ANN-MLP Loss function values: a) for training set; b) for the testing set

Fig. 11 presents the loss function values depicting the prediction error, calculating the gradients after 150 iterations and loss value of 0.346 ANN loss function seem to flatten out and is not changing, which eventually converged after 150 iterations.

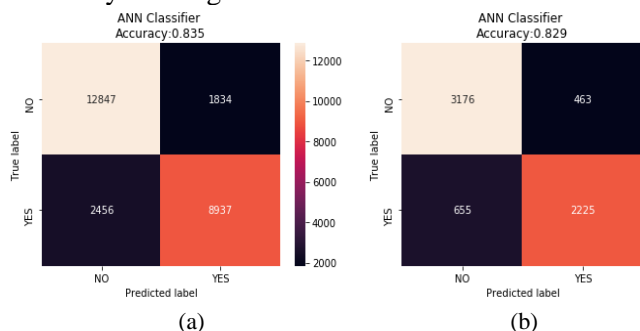


Fig. 12 ANN-MLP Confusion Matrix values: a) for the training set;

b) for the testing set

Figures 12-13 show the classification report and confusion matrix for the best performer model and its respective performance for train and test datasets. Figure 12 shows accuracy for the best ANN classifier based on the training and testing sets. It is seen that for 26074 records, the classifier resulted in incorrect classification for up to 4290 records (False Positive + False Negative), whereas for the testing set, the incorrect passes are 1118. The overall correct passes for the training set are 21784, and for the testing set are 5401.

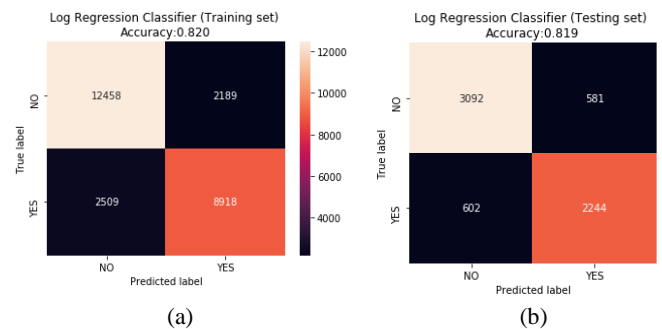


Fig. 13 Logistic Regression Confusion Matrix values: a) for training set; b) for the testing set

Figure 13 shows accuracy Logistic Regression classifier based on the training and testing sets. For 26074 records, the classifier resulted in incorrect classification for up to 4698 records (False Positive + False Negative), whereas for the testing set, the

incorrect passes are 1183. The overall correct passes for the training set are 21376, and for the testing set are 5336.

## 5. Conclusion

This paper explored and examined a massive VLE-based student behavioral dataset in terms of magnitude. Through literary studies of student behavioral studies, a master feature vector is created possessing influential properties controlling the student's behavior. Two different analysis procedures further examine the feature vector, i.e., expert opinion is obtained for identifying procrastination tendencies. Parallelly, a similar feature vector is analyzed for automatic pattern generation using K-means clustering. For an optimal number of cluster identification, the elbow method is used. A student behavioral dataset focusing on procrastination behavior is proposed to represent enough of the problem domain in terms of the dataset size. The existing VLE dataset is enhanced by an additional label to each record that identifies procrastination in students interacting with VLEs. The procrastination dataset is further fed to the classifier following a detailed analysis protocol based on two algorithms. These classifiers are fine-tuned to get optimal performance accuracy. The best performer classifier hits the accuracy of 83.3%. In conclusion, the study is complete in the following aspects: 1) The proposal of procrastination related student behavioral dataset in terms of considerable size. 2) Detailed steps in the form of algorithms for data formation and classification. 3) Detailed visualizations of clustering and classification to identify procrastination tendencies.

In the present day, there are domain aspects not yet explored. They can be further considered for enhanced studies, i.e., the addition of more responsive time-related features such as time taken by students responding to the queries in terms of audio answers submitted or the number of clicks or keypresses to submit the answer.

## Supplementary Materials

[https://drive.google.com/drive/folders/1MPx7jxR\\_sX7R5\\_3Toy3YTtNYq8SliT98?usp=sharing](https://drive.google.com/drive/folders/1MPx7jxR_sX7R5_3Toy3YTtNYq8SliT98?usp=sharing)

## Funding

International Collaborative Research Funding (ICRF).

## Acknowledgments

This research study is a part of the funded project (Optimization of Machine Learning Framework to Analyze Students' Procrastination Problem) under International Collaborative Research Funding (ICRF) supported by University Technology Petronas (UTP), Malaysia, and Iqra University, Pakistan. Grant Ref. No. 015ME0-077.

## Appendix A. Discerning Summary of Student's Behavioral Studies

The categorized and comprehensively discussed studies are further critically listed to glance at the future direction of the existing research, with the relevant student data features used in each of them.

Table 5 Critical analysis of educational studies

| Title  | Year | Domain   | Features  | Size of student data   | Observations   |
|--|------|--|---|------------------------|--|
| Mining educational data to predict student's performance through procrastination behavior [18]               | 2020 | Machine Learning (ANN, Linear SVM, RSVM, spectral clustering)                                      | Categorical data(behavior) and continuous data (submission dates) | 242 students           | Limited data<br>Plus-point: In-depth study<br>Uses only single feature timing of assignments<br>Comparison of eight different classification algorithms<br>High accuracy for a small number of classes.<br>Focused study of the manual system. |
| Predicting Students' Academic Procrastination in Blended Learning Course Using Homework Submission Data [19] | 2019 | Machine Learning (NBTree, Random Forest, Prism, PART, J48, JRip, Decision Stump, ID3, OneR, ZeroR) | Date start, Date end, Date upload                                 | 115 students           | More courses can be added<br>Limited data  |
| The influence of gadgets on IT addict & procrastination behavior [11]  | 2019 | Machine Learning (Multiple regression) + psychological   | Gadget usage, Social media usage, procrastination                 | 100 undergrad students | Multiple Regression is not explored in detail.<br>Limited data<br>Correctly highlights the affecting factors<br>Can be extended  |

|   |      |  |   |                        |  |
|---|------|--|---|------------------------|--|
| Return to the origin: what creates a procrastination identity? [10]   | 2018 | Machine Learning (Logistic Regression)       | Self-reported behavioral data (procrastination regrets, indecisiveness) | 2893 students          | Absence of qualitative data to suggest what individuals regretted most<br>Limited information about ML algorithm<br>Only one algorithm used<br>Can be further extended |
| Procrastination Behavior in Computer-Based Learning Environment to predict performance: A case study in Moodle [20] | 2017 | Machine Learning (prediction/classification) | Procrastination & student performance                                   | 140 undergrad students | In-depth study based on the computer-based learning environment<br>Limited dataset<br>Can be extended for prediction/classification of student off-track.              |

## References

- [1] ROVAI A. P., & JORDAN H. Blended Learning and Sense of Community: A Comparative Analysis with Traditional and Fully Online Graduate Courses. *The International Review of Research in Open and Distributed Learning*, 2004, 5(2). <https://doi.org/10.19173/irrodl.v5i2>
- [2] MUSLIM J. S., AHMED H. M., HUSSAIN R. S. S., VALI U., and MOBASHAR R. Automatic Image Annotation for Small and Ad hoc Intelligent Applications using Raspberry Pi. *MATEC Web of Conferences*, 2019, 255: 01003. <https://doi.org/10.1051/mateconf/201925501003>
- [3] UNITED NATIONS EDUCATIONAL, SCIENTIFIC AND CULTURAL ORGANIZATION. Distance Learning Solutions, 2020. <https://en.unesco.org/covid19/educationresponse/solutions>
- [4] ITU NEWS. COVID-19: How digital learning solutions are taking shape, 2020. <https://www.itu.int/ru/myitu/News/2020/05/06/09/00/COVID-19-How-digital-learning-solutions-are-taking-shape>
- [5] COMMONWEALTH OF LEARNING. Keeping the doors of learning open COVID-19, 2020. <https://www.col.org/resources/keeping-doors-learning-open-covid-19>
- [6] AGARWAL A. EDX, 2012. <https://www.edx.org/>
- [7] EREN BALI O. C., & BIYANI G. Udemy, 2020. <https://www.udemy.com/>
- [8] FUTURE LEARN, 2012. <https://www.futurelearn.com/>
- [9] NG A. Coursera, 2012. <https://www.coursera.org/instructor/andrewng>
- [10] TIBBETT T., & FERRARI J. Return to the origin: what creates a procrastination identity? *Current Issues in Personality Psychology*, 2019, 7(1): 1-7. <https://doi.org/10.5114/cipp.2018.75648>
- [11] SUSILAWATI E. The Influence of Gadget towards Information Technology Addict and Procrastination Behaviour. *IOP Conference Series: Materials Science and Engineering*, 2019, 662(2): 022054. <https://doi.org/10.1088/1757-899X/662/2/022054>
- [12] SHEYBANI F., GHARRAE B., BAKHSHIZADEH M., and TAMANAEFFAR S. J. L. Decisional procrastination: Prevalence among students and relationship with emotional intelligence and big five-factor model of personality. *Life*, 2017, 50: 26.
- [13] STEEL P. The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological Bulletin*, 2007, 133(1): 65-94. <https://doi.org/10.1037/0033-2909.133.1.65>
- [14] SOLOMON L. J., & ROTHBLUM E. D. Academic Procrastination: Frequency and Cognitive-Behavioral Correlates. *Journal of Counseling Psychology*, 1984, 31: 503-509. <http://dx.doi.org/10.1037/0022-0167.31.4.503>
- [15] HARLEN W. On the relationship between assessment for formative and summative purposes. In: GARDNER J. (ed.) *Assessment and Learning*. Sage, London, 2012: 87-102. <http://dx.doi.org/10.4135/9781446250808.n6>
- [16] DIXSON D. D., & WORRELL F. C. Formative and summative assessment in the classroom. *Theory into Practice*, 2016, 55(2): 153-159. <https://doi.org/10.1080/00405841.2016.1148989>
- [17] BROADBENT J., PANADERO E., and BOUD D. Implementing summative assessment with a formative flavour: A case study in a large class. *Assessment & Evaluation in Higher Education*, 2018, 43(2): 307-322. <https://doi.org/10.1080/02602938.2017.1343455>
- [18] HOOSHYAR D., PEDASTE M., and YANG Y. Mining Educational Data to Predict Students' Performance through Procrastination Behavior. *Entropy*, 2020, 22(1): 12. <https://doi.org/10.3390/e22010012>
- [19] AKRAM A., FU C., LI Y., JAVED M. Y., LIN R., JIANG Y., and TANG Y. Predicting students' academic procrastination in blended learning course using homework submission data. *IEEE Access*, 2019, 7: 102487-102498. <https://doi.org/10.1109/ACCESS.2019.2930867>
- [20] CEREZO R., ESTEBAN M., SÁNCHEZ-SANTILLÁN M., and NÚÑEZ J. C. Procrastinating Behavior in Computer-Based Learning Environments to Predict Performance: A Case Study in Moodle. *Frontiers in Psychology*, 2017, 8: 1403. <https://doi.org/10.3389/fpsyg.2017.01403>
- [21] IATRELLIS O., SAVVAS I. K., KAMEAS A., and FITSILIS P. J. E. Integrated learning pathways in higher education: A framework enhanced with machine learning and semantics. *Education and Information Technologies*, 2020, 25: 3109-3129. <https://doi.org/10.1007/s10639-020-10105-7>
- [22] PENG W., ZHANG X., and LI X. Intelligent Behavior Data Analysis for Internet Addiction. *Scientific Programming*, 2019, 2019: 2753152. <https://doi.org/10.1155/2019/2753152>
- [23] SALLOUM S. A., ALSHURIDEH M., ELNAGAR A., and SHAALAN K. Mining in Educational Data: Review and Future Directions. In: HASSANIEN A. E., AZAR A., GABER T., OLIVA D., and TOLBA F. (eds.) *Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020)*. AICV 2020. *Advances in Intelligent Systems and Computing*, 1153. Springer, Cham, 2020: 92-102. [https://doi.org/10.1007/978-3-030-44289-7\\_9](https://doi.org/10.1007/978-3-030-44289-7_9)
- [24] KUZILEK J., HLOSTA M., and ZDRAHAL Z. Open University Learning Analytics dataset. *Scientific Data*, 2017, 4: 170171. <https://doi.org/10.1038/sdata.2017.171>
- [25] JAMEEL S. M., HASHMANI M. A., REHMAN M., and BUDIMAN A. Adaptive CNN Ensemble for Complex

Multispectral Image Analysis. *Complexity*, 2020, 2020: 8361989. <https://doi.org/10.1155/2020/8361989>

[26] RADIF M., & MOHAMMED N. A. Computer Science Teacher's Perception and Needs towards E-Learning in Iraq. *Journal of Southwest Jiaotong University*, 2019, 54(5). <https://doi.org/10.35741/issn.0258-2724.54.5.42>

[27] HAMOUD A. K., & HUMADI A. M. Student's Success Prediction Model Based on Artificial Neural Networks (ANN) and A Combination of Feature Selection Methods. *Journal of Southwest Jiaotong University*, 2019, 54(3). <https://doi.org/10.35741/issn.0258-2724.54.3.25>

## 参考文献:

[1] ROVAI A. P. 和 JORDAN H. 混合学习和社区意识：与传统和完全在线研究生课程的比较分析。开放式和分布式学习研究国际评论，2004，5（2）。<https://doi.org/10.19173/irrodl.v5i2>

[2] MUSLIM J. S., AHMED H. M., HUSSAIN R. S. S., VALI U. 和 MOBASHARR. 使用树莓派的小型临时智能应用程序的自动图像注释。马泰克会议网络，2019，255：01003. <https://doi.org/10.1051/mateconf/201925501003>

[3] 联合国教育，科学和文化组织。远程学习解决方案，2020年。<https://en.unesco.org/covid19/educationresponse/solutions>

[4] 国际电联新闻。新冠肺炎：2020年数字学习解决方案将如何成形。<https://www.itu.int/ru/myitu/News/2020/05/06/09/00/COVID-19-How-digital-learning-解决方案正在形成>

[5] 学习共同体。保持开放学习之门新冠肺炎，2020年。<https://www.col.org/resources/keeping-doors-learning-open-covid-19>

[6] AGARWAL A. 埃德克斯，2012年。<https://www.edx.org/>

[7] EREN BALI O. C. 和 BIYANI G. 乌迪米，2020。<https://www.udemy.com/>

[8] 未来的学习，2012。<https://www.futurelearn.com/>

[9] NG A. Coursera，2012。<https://www.coursera.org/instructor/andrewng>

[10] TIBBETT T. 和 FERRARI J. 回到起源：是什么造成了拖延身份？人格心理学当前问题，2019，7（1）：1-7。<https://doi.org/10.5114/cipp.2018.75648>

[11] SUSILAWATI E. 小工具对信息技术成瘾和拖延行为的影响。眼压会议系列：材料科学与工程，2019，662（2）：022054。<https://doi.org/10.1088/1757-899X/662/2/022054>

[12] SHEYBANI F., GHARRAEI B., BAKHSHIZADEH M. 和 TAMANAEEFAR S. J. L. 决策拖延：学生中的患病

率以及与情商和人格大五因素模型的关系。生活，2017，50：26。

[13] STEEL P. 拖延症的本质：典型自我调节失败的荟萃分析和理论综述。心理通报，2007，133（1）：65-94。<https://doi.org/10.1037/0033-2909.133.1.65>

[14] SOLOMON L. J. 和 ROTHBLUM E. D. 学术拖延：频率和认知行为的相关性。心理咨询杂志，1984，31：503-509。<http://dx.doi.org/10.1037/0022-0167.31.4.503>

[15] HARLEN W. 关于形成性和总结性评估之间的关系。于：GARDNER J.（编辑）评估与学习。智者，伦敦，2012年：87-102。<http://dx.doi.org/10.4135/9781446250808.n6>

[16] DIXSON D. D. 和 WORRELL F. C. 课堂上的形成性和总结性评估。理论到实践，2016，55（2）：153-159。<https://doi.org/10.1080/00405841.2016.1148989>

[17] BROADBENT J., PANADERO E. 和 BOUDD. 实施具有形成性风味的总结性评估：大型课堂案例研究。高等教育评估与评价，2018，43（2）：307-322。<https://doi.org/10.1080/02602938.2017.1343455>

[18] HOOSHYAR D., PEDASTE M. 和 YANGY. 挖掘教育数据以通过拖延行为预测学生的表现。熵，2020，22（1）：12。<https://doi.org/10.3390/e22010012>

[19] AKRAM A., FU C., LI Y., JAVED M. Y., LIN R., JIANG Y 和 TANGY. 使用作业提交数据预测学生在混合学习课程中的学术拖延。电气工程师学会访问，2019，7：102487-102498。<https://doi.org/10.1109/ACCESS.2019.2930867>

[20] CEREZO R., ESTEBAN M., SÁNCHEZ-SANTILLÁN M. 和 NÚÑEZ J. C. 在基于计算机的学习环境中拖延行为以预测性能：面条案例研究。心理学前沿，2017，8：1403。<https://doi.org/10.3389/fpsyg.2017.01403>

[21] IATRELLIS O., SAVVAS I. K., KAMEAS A. 和 FITSILIS P. J. E. 高等教育中的综合学习途径：通过机器学习和语义增强的框架。教育与信息技术，2020，25：3109-3129。<https://doi.org/10.1007/s10639-020-10105-7>

[22] 彭伟，张新，李新。互联网成瘾的智能行为数据分析。科学编程，2019，2019：2753152。<https://doi.org/10.1155/2019/2753152>

[23] SALLOUM S. A., ALSHURIDEH M., ELNAGAR A. 和 SHAALAN K. 教育数据中的挖掘：回顾和未来方向。在：HASSANIEN A. E., AZAR A., GABER T., OLIVA D. 和 TOLBA F.（编辑）国际人工智能和计算机

视觉会议 ( 禽流感病毒 2020 ) 的会议记录中。禽流感病毒 2020。智能系统与计算的进展, 1153。斯普林格, 湛, 2020 : 92-102 。 [https://doi.org/10.1007/978-3-030-44289-7\\_9](https://doi.org/10.1007/978-3-030-44289-7_9)

[24] KUZILEK J., HLOSTA M. 和 ZDRAHAL Z. 开放大学学习分析数据集。科学数据, 2017, 4 : 170171. <https://doi.org/10.1038/sdata.2017.171>

[25] JAMEEL S. M., HASHMANI M. A., REHMAN M. 和 BUDIMAN A. 用于复杂多光谱图像分析的自适应有线

电视新闻网集成。复杂度, 2020, 2020 : 8361989. <https://doi.org/10.1155/2020/8361989>

[26] RADIF M. 和 MOHAMMED N. A. 计算机科学老师对伊拉克电子学习的认识和需求。西南交通大学学报, 2019, 54 ( 5 ) 。 <https://doi.org/10.35741/issn.0258-2724.54.5.42>

[27] HAMOUD A. K. 和 HUMADI A. M. 基于人工神经网络 ( 人工神经网络 ) 和特征选择方法相结合的学生成功预测模型。西南交通大学学报, 2019, 54 ( 3 ) 。 <https://doi.org/10.35741/issn.0258-2724.54.3.25>