Online Assessment Classification Based On Personalisation

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***Abstract*—The COVID-19 pandemic has driven technological advancement and the evolution of assessments. Online assessment has become a norm with a variety of assessment methods such as multiple choice questions, essays, oral presentations and project-based cases. This study explores the influence of learning styles on online assessment preferences among visual, auditory and kinesthetic learners. The study addresses the lack of online assessment classification models based on personalisation that focuses on each learning style's preferences. By utilising the VAK Learning Styles Model and machine learning algorithms, the study identifies preferred online assessment methods for each learning style. A web application, 'Assessifier' is developed and deployed for users to determine their dominant learning style and suitable online assessment methods. The study provides insights into personalised online assessment, emphasising the importance of incorporating diverse learning styles in education.**

Keywords– Online assessment, VAK learning styles, classification, personalisation, education evolution, effective learning

I. Introduction

The implication of the COVID-19 outbreak, added to the rapidly changing technology and globalisation has driven the evolution of education faster than ever. Digital learning has become more and more of a norm even more so for online assessments. Online assessment is defined as the assessment of learners' learning with methods including information and communication technologies (Heil and Ifenthaler, 2023).

Learning style influences how learners prefer to receive and process information. "Learning Style" refers to the learning ways or preferences which are used to learn or remember new knowledge by the learner (Wickramasinghe and Hettiarachchi, 2017). For example, visual learners may excel better in assessments that involve diagramming whereas auditory learners may excel better in oral assessments while kinesthetic learners may excel better in hands-on practicals.

Learner	Preference
Visual	Seeing and reading
Auditory	Listening and speaking
Kinesthetic	Touching and doing

TABLE I: Learners characteristics *(Almasri, 2022)*

The VAK Learning Style Model was developed by psychologists in the 1920s to classify the most common ways that people learn. According to the model, people prefer to learn in one of three ways: visual, auditory or kinesthetic. The model introduces 30 statement-based questions to determine one's dominant learning style. Each learner's characteristics are as shown in Table I.

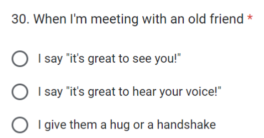


Fig. 1: Sample VAK question.

Figure 1 shows a sample of VAK question. A visual learner would most likely prefer to 'Read the instructions' (Option A) while an auditory learner would most likely prefer to 'Listen to or ask for an explanation' (Option B) whereas a kinesthetic learner would most likely prefer to 'Have a go and learn by trial and error' (Option C). As each option (A, B & C) represents a learning style, the way the VAK model determines the dominant learning style is by totalling every As, Bs and Cs selected. If you chose mostly:

- A's: You are a **visual** learner
- B's: You are an **auditory** learner
- C's: You are a **kinesthetic** learner

II. Literature Review

It is well well-known fact that learners basically perceive information through senses (Satha, 2015). Therefore, various learning models can be utilised in determining a learner's learning style and preferences to achieve the best personalised online assessment classification.

A. Learning Style

Previous research has established that the VAK learning styles model is the most widely used among the learning style assessment instruments (Hosny and El-Korany, 2022). VAK learning style uses 3 main sensory receivers that are sight (Visual), hearing (Auditory) and movement (Kinesthetic) to determine a learner's dominant learning style (Hardiana and Suyata, 2018). Sreenidhi and Tay, 2017 added that individuals often possess a favoured learning style, which could encompass a mix of all three sensory modes. This preference can vary from a strong inclination towards a specific style to a balanced combination of two or all three.

Visual learners prefer to learn through visual stimuli such as graphics, mindmaps, drawings and written text (Mohd et al., 2019). As they learn best by seeing and visualising information, they are typically good at recalling and retaining information they have seen.

Auditory learners learn best through listening and communication. They learn best when information is presented verbally such as engaging in discussions, oral presentations, podcasts and music (Mahdjoubi and Akplotsyi, 2012). As they learn best by speaking and hearing, thus, they may remember and retain information better than when they are seeing or reading it.

Kinesthetic learners learn best by doing through physical activities and direct experiences where they are able to get involved personally (Surjono, 2011). They tend to remember information better when they can touch and get a feel of it. For example, interactive simulations, experiments, writing and role plays.

A study conducted by Satha, 2015 explores the effectiveness of the VAK teaching-learning model, which focuses on catering to the needs of visual, auditory, and kinesthetic learners in enhancing the information-processing ability of students. The study uses an information-processing ability questionnaire to collect data and compare pre and post-test scores. Results show that the model had a positive impact on the information-processing ability of students. Thus, the study concludes that by using the VAK model, teachers can cater to individual needs and encourage students to develop strategies that align with their preferred learning styles.

B. Assessment Personalisation

Research by Hosny and El-Korany, 2022 focuses on detecting students' learning styles (visual, auditory or kinesthetic) and recommending appropriate assessment methods based on these styles. The learning style of each student was identified by tracking their learning activities. It utilises semantic mapping techniques to map learner data into the visual, auditory or kinaesthetic (VAK) learning style model. Then, students are clustered into one of the three VAK learning styles using clustering techniques like KMeans, DBScan and Expectation–maximization with KMeans having the highest accuracy of 95%. After that, the model recommends assessment methods according to the each learning style characteristics.

Maya et al., 2021 explored the relationship between learning styles, academic performance and assessment methods among psychology, early childhood education, and primary education students in Spain. The research was conducted by analysing data collected via a questionnaire and academic performance. The research's findings suggest that understanding students' learning styles can have important educational implications and provide guidance to optimise teaching practices and student performance. It also emphasises the necessity of tailoring teaching methods to maximise strengths and meet student needs. Additionally, the choice of assessment method can influence student performance according to their learning preferences and using a variety of assessment methods can help students with different learning profiles to demonstrate their competencies effectively.

Research by Wickramasinghe and Hettiarachchi, 2017 explored the relationship among students' learning styles, assessment methods, and students' performances. The study aims to identify the learning styles of students and observe how different assessment methods affect their performance. The survey results showed that there is a significant difference in the marks obtained in pre and post-assessments, suggesting that students perform better in assessment methods that align with their learning styles. The study concludes that there is a relationship between students' learning styles, assessment methods and their performances.

C. Classification Model Comparison

Agarwal et al., 2021 compared 3 classification machine learning algorithms namely K-nearest neighbour (KNN), Naïve Bayes (NB) and Support Vector Machine (SVM) to find the best-performing algorithm in terms of accuracy and processing time that can efficiently learn the pattern of the suspicious network activities. The study found that SVM has the highest accuracy score of 95%, followed by KNN and NB with accuracy scores of 93% and 92%. The study also emphasises the need to use more complex machine learning approaches like Random Forest (RF) to improve the results.

Another research by Santana et al., 2021 compared 6 classification models namely, decision tree, logistic regression, multilayer perceptron (MLP), random forest (RF), SVM and extreme gradient boosting (XGBoost) to identify the best model to assist COVID-19 test prioritisation in Brazil. The model will be used to recommend the prioritising patient who is symptomatic for COVID-19 testing. The research found that all of the models except logistic regression exhibit high performances with similar accuracy scores of approximately 94%. The research concludes by selecting decision tree as their best model due to its high interpretability feature.

Research by Zhang et al., 2020 compared 4 classification models namely, MLP, RF, SVM and XGBoost to map rice paddies in the Southwest Hilly Area of China using remote sensing data to accurately classify and identify the presence of rice paddies in the region. The research concludes with XGBoost having the highest overall accuracy of 89.73% in Banan District while SVM has the highest overall accuracy of 88.57% in Zhongxian County. In terms of model transferability (how well the models perform when applied to a different geographic location or dataset than the one they were originally trained on), RF and XGBoost models achieved the highest transferability in both locations with F1 scores of 0.6673 and 0.6469 for RF and 0.7171 and 0.6709 for XGBoost.

III. Problem Statement

There are many online assessments available, for example, multiple-choice questions, essays, oral presentations and project-based cases. However, different learners have different preferences for the type of assessment they wish to undertake based on their learning style.

Modern-day technologies not only make digital learning and assessments possible but also create the opportunity to include personalisation in almost everything we do. Personalisation in education raises the motivation and interests of the learners, which are critical success factors in learning as well as in the assessment process (Hosny and El-Korany, 2022). Kim et al., 2015 discovered that leveraging learning styles could be a possible strategy to improve educational efficiency. Each learner has their preferred learning style as each of them has different abilities and preferences in the way they receive, process and use information. This, in turn, may affect how they are best learned and assessed. Thus, assessments should be conveyed in various forms appropriate for each learner (Maya et al., 2021).

To date, there is a limited study in using a classification model for online assessment based on the personalisation of learners' learning styles and preferences. This is because most research focuses on recommending assessments solely based on learning style characteristics without taking learners' preferences into account (Hosny and El-Korany, 2022; Maya et al., 2021; Wickramasinghe and Hettiarachchi, 2017).

IV. Project Scope

The project scope covers data collection, data preparation, model training and evaluation and model deployment as a web application. The purpose of the deployment is to allow users to be able to identify their dominant learning style and recommend the online assessment methods that are best suited for them. The web application is best used on a desktop for the best visual experience.

V. Objectives

The objectives of the project are:

1) To develop an online assessment classification model based on personalisation
   - Which machine learning algorithm can perform online assessment classification based on learning style?
2) To evaluate the online assessment classification model based on personalisation
   - What evaluation metrics can be used to evaluate the classification model?
3) To develop a data product that functions as an online assessment tool personalisation
   - How can the insights gained be shared and utilised by relevant stakeholders?

VI. Methodology

The project follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology. According to Martínez-Plumed et al., 2021, CRISP-DM is the de facto standard for developing data mining and knowledge discovery projects and it remains useful for goal-directed and process-driven data science projects. Fig. 2 shows the overview of CRISP-DM.

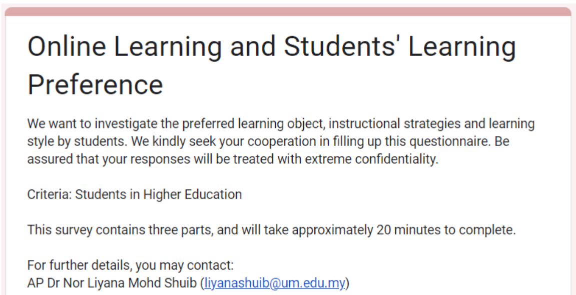
A. *Business understanding*

With education as the main domain of this project, literature analysis was conducted particularly on the learning style, online assessments and personalisation to develop a more in-depth understanding of the topic. The objectives of the project were also defined.

Fig. 2: CRISP-DM Methodology. *(Image source: Chumbar, 2023)*

B. Data Understanding

Data was collected via a Google Form survey from 2021 to 2023 to identify the dominant learning style of students and to obtain their respective preferred online assessment methods (Refer to Figure 3). The survey questions include demographics, preferred learning objects, preferred online instructional strategies and assessment methods, learning style awareness and the VAK Learning Style questions. To determine the online assessment preference, respondents are required to select their level of preference for each online assessment (i.e. Not at All, Not Really, Undecided, Somewhat and Very Much). The survey consists of 104 questions and it is estimated that a respondent can complete answering within 10-20 minutes. The final data collected consists of 1052 rows and 104 columns.



Online Learning and Students' Learning Preference

We want to investigate the preferred learning object, instructional strategies and learning style by students. We kindly seek your cooperation in filling up this questionnaire. Be assured that your responses will be treated with extreme confidentiality.

Criteria: Students in Higher Education

This survey contains three parts, and will take approximately 20 minutes to complete.

For further details, you may contact:
AP Dr Nor Liyana Mohd Shuib (liyanashuib@um.edu.my)

Fig. 3: Google form survey

In addition, data exploration was performed in SAS Enterprise Miner to understand the data distribution and to identify the input variable worth to the target variables for data cleaning, using the StatExplore node.

C. Data Preparation

Data profiling and data cleaning were performed using Talend Data Preparation such as removing the test data rows and checking and dropping (if any) null values. This dataset does not contain any null values.

Next, feature selection was performed using Talend Data Preparation by removing irrelevant columns (e.g., timestamp, preferred learning mode, preferred social media platform, household income, learning object preferences and online instructional strategies preferences). After that, data standardisation was performed such that the values in the 'Level of Study' column 'Master' and 'PhD' were renamed as Postgraduate, correct spelling mistakes in the survey responses 'Hoe they make me' to 'How they make me' and the minority preferred communication platform responses (e.g. Microsoft Teams, Google Meet) as 'Others'.

The dominant learning style for each survey respondent was identified based on the 30 VAK questions from the survey using Python to identify the majority learning style and to be used as an additional feature for model training later.

Before modelling, exploratory data analysis was performed on the cleaned data using Tableau to have a better data understanding of demographics, the distribution in the learning style and online assessment preference for each learning style.

For columns with multiple selection answers (i.e. 'Preferred Communication Platform' column), data exploding was performed to split the multiple selections into individual rows. The purpose of data exploding was to reduce the number of classes during encoding, specifically for the column with multiple selection answers. After that, data encoding was performed using Python as follows:

- Ordinal encoding for ordinal categorical data
- One-hot encoding for nominal categorical data

Given the potential scenario where respondents might have selected '0' (Not Preferred) for all online assessment tools, the rows reflecting this were removed. This action aimed to ensure a more robust dataset for the classification model.

D. Modelling

The dataset was split into 70% of the dataset as the training set and 30% of the dataset as the testing set. The training set will be used to train the model whereas the testing set will be used during model evaluation.

Various machine learning algorithms were utilised to identify the best algorithm to use to build the model. A total of 5 machine learning algorithms were used in this project with the default parameters. Table II highlights the algorithm used and their respective default parameters.

Algorithms	Parameters
Decision Tree	criterion = gini
K-Nearest Neighbour (KNN)	n_neighbors = 5
Random Forest	n_estimators = 100
Support Vector Machine (SVM)	C = 1.0
Gradient Boost (XGBoost)	None

TABLE II: Machine learning algorithms and their respective parameters

E. Evaluation

The models' performance was evaluated using overall accuracy which was calculated using 'accuracy_score' and the macro average of precision, recall and F1-score which was calculated using the 'classification_report', both obtained from scikit-learn. The macro average calculates the metric for each class separately and subsequently computes the average (Natarajan, 2023). This approach treats all classes equally regardless of their sizes.

The formula for each of the evaluation metrics is as follows:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{1}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The formula of the macro average is as follows:

$$\text{Macro Average} = \frac{1}{N}\sum_{i=1}^{N} \text{Metric}_i \tag{5}$$

where N = Number of classes

The best-performing model was the Random Forest model. Thus, it is selected to be used as the classification model for the web application.

F. Deployment

A web application was developed using Streamlit, an open-source Python framework that is capable of building an interactive data application within minutes. The application was then deployed on the Streamlit Community Cloud, a platform that facilitates the deployment of Streamlit apps. The reason for utilizing the Streamlit Community Cloud for deployment was driven by its advantages, including free hosting and a simplified deployment process.

VII. Results

A. Exploratory Data Analysis

Figure 4 shows that the majority of the respondents are visual learners (51%) followed by auditory learners (27%) and lastly kinesthetic learners (22%).

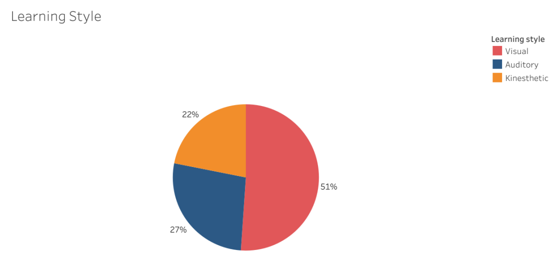


Fig. 4: Proportion of visual, auditory and kinesthetic learners

Figure 5 shows that 67% of the respondents are female with only 33% being male.

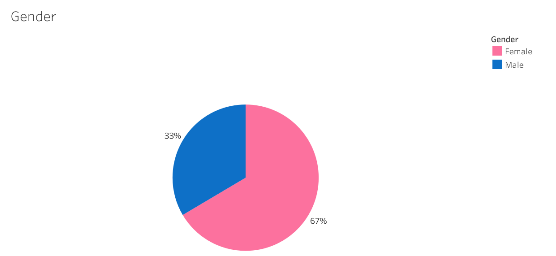


Fig. 5: Proportion of female and male

Figure 6 shows that out of 1051 respondents, 900 respondents (85.6%) are undergraduate students, 134 respondents (12.8%) are certificates/diploma students and only 17 respondents (1.6%) are postgraduate students.

Figure 7 shows the communication platform preference based on different learning styles. The figure shows that the majority of visual learners prefer to communicate via email, Whatsapp and Telegram while auditory and kinesthetic learners prefer to use Whatsapp only.

Figure 8 shows the respondents' opinion on the importance of knowing one's learning style in comparison with their awareness of their learning style. The figure

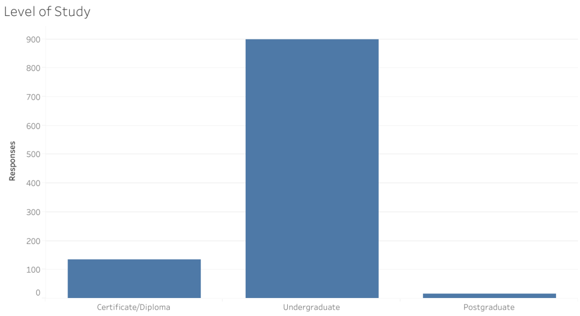


Fig. 6: Proportion of certificate/diploma, undergraduate and postgraduate

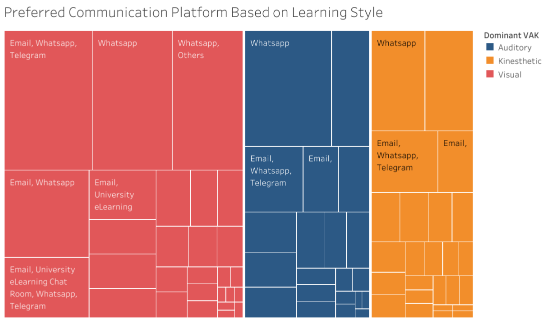


Fig. 7: Communication platform preference

shows the majority of the respondent (98%) stated that it is important to know one's learning style in improving their learning ability with 81% of the 98% aware of their learning style.

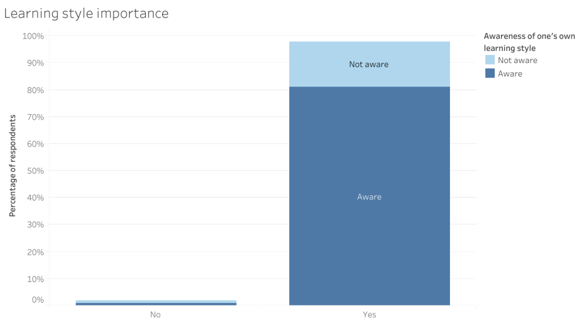


Fig. 8: Proportion of whether knowing one's learning style is important in improving their learning ability in comparison with the awareness of one's learning style

Based on the VAK model, visual learners should prefer 'seeing' and 'reading', however, according to the Figure 9, 'Demonstration' which mostly involves 'touching' and 'doing' is the most preferred online assessment method for them.

Surprisingly, based on Figure 10, 'Open book' which involves 'reading' and 'touching' is the most preferred online assessment method for auditory learners instead of recorded or live presentations which mainly involve 'listening' and 'speaking'.

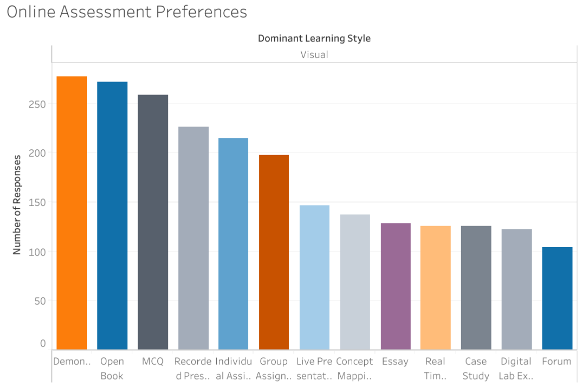


Fig. 9: Online assessment methods preference for visual learners

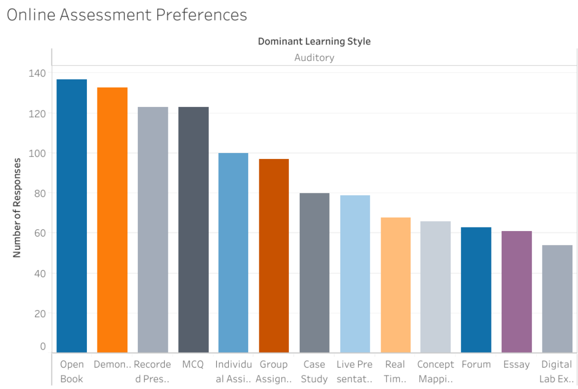


Fig. 10: Online assessment methods preference for auditory learners

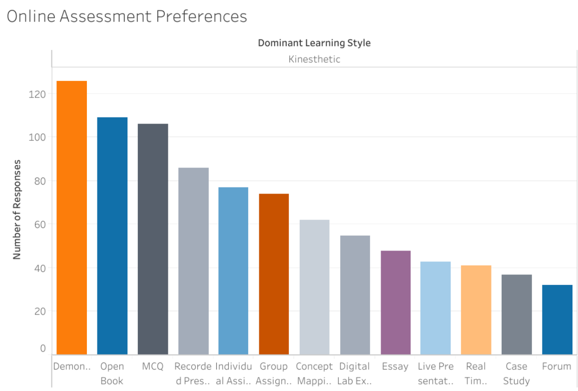


Fig. 11: Online assessment methods preference for kinesthetic learners

It is not a surprise that 'Demonstration' is the most preferred online assessment method for kinesthetic learners (Refer to Figure 11). However, one thing to highlight is that 'Recorded presentation' is preferred over 'Digital lab experiment' which involves 'touching' and 'doing'.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Decision Tree	89.46348	86	85	86
KNN	75.16484	67	62	64
Random Forest	**92.34648**	**95**	**85**	**89**
SVM	82.99935	86	67	73
XGBoost	92.11377	92	87	89

TABLE III: Classification models and their respective evaluation metrics

This emphasises the need to consider visual, auditory and kinesthetic learners' preferences in determining the suitability of assessment type instead of assuming their preferences based on the learning style characteristics.

B. Classification Model

Table III shows the evaluation of all 5 of the model's performance in terms of accuracy, precision, recall and f1-score.

By comparing the performance of the model, Random Forest has the best performance out of the 5 models because it has the highest accuracy, precision and f1-score of 92.3%, 95% and 89% respectively. Although the performance of XGBoost can be on par with Random Forest as it has good accuracy, precision and f1-score scores as well as having the highest recall, Random Forest was chosen to be used as the model. The decision to choose Random Forest was influenced by its overall outstanding performance across multiple evaluation criteria.

C. Web Application

The web application, named Assessifier (short for **Assess**ment classi**fier**) was built using Streamlit and deployed on the Streamlit Community Cloud. Click here to view the web application. Assessifier consists of 4 pages as shown in Figure 12 namely: 'Home' page, 'Exploratory Data Analysis' page, 'About' page and the 'Documentation' page.

1) Home: The 'Home' page consists of a questionnaire for users to answer to identify their dominant learning style and which online assessment methods are best suited for them (Refer to Figure 13). There are a total of 33 questions which include the demographics, preferred communication platform and the VAK Learning Style questions for users to answer and it will take 10-20 minutes to complete answering them. The results will be displayed shortly on the same page after the 'Submit' button has been clicked (Refer to Figure 15).

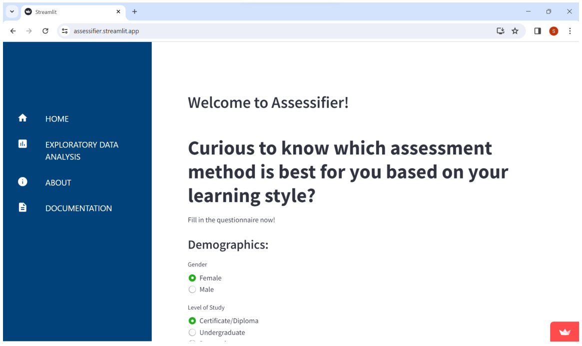


Fig. 12: Pages available in Assessifier

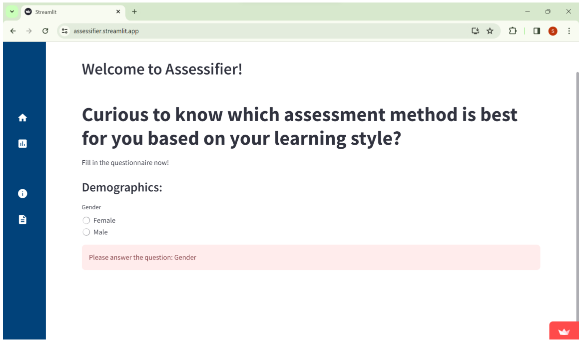


Fig. 13: Home page of Assessifier

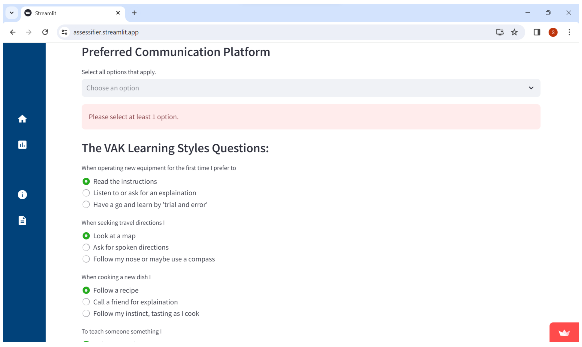


Fig. 14: Home page of Assessifier - Continuation

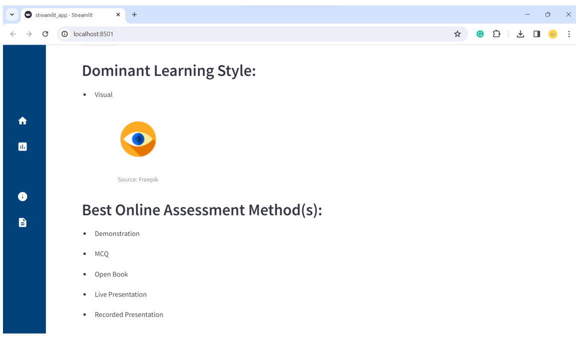


Fig. 15: User's dominant learning style results and recommended online assessment methods in Assessifier

2) Exploratory Data Analysis: The 'Exploratory Data Analysis' page consists of the descriptive analysis of the dataset used to train the model. As mentioned in Section VI-B, the dataset was obtained from a survey conducted in 2021-2023 to obtain students preferred online assessment tools. This page provides an overview of the respondents' demographics and the preferred online assessment tools for visual, auditory and kinesthetic learners. Refer to Figure 16.

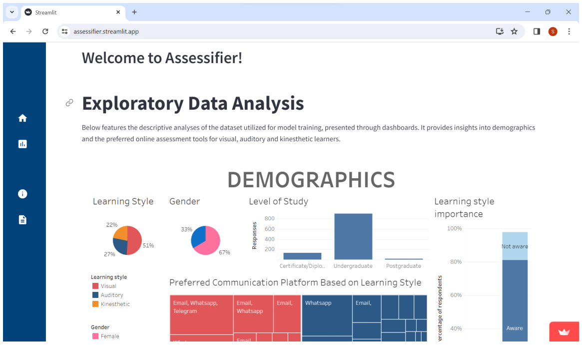


Fig. 16: Exploratory data analysis page of Assessifier

3) About: The 'About' page consists of information that provides users with a more comprehensive understanding of what learning style is and how learning style relates to assessment methods. Refer to Figure 17.

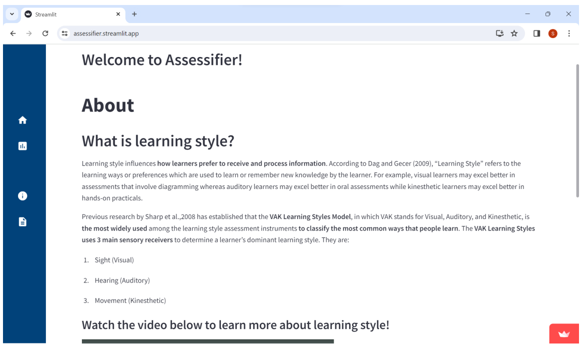


Fig. 17: About page of Assessifier

4) Documentation: The Documentation page consists of a brief overview of what each page contains and provides a quick guide for users on how to use Assessifier (Refer to Figure 18). Users can also access a more detailed and comprehensive user manual document here (Refer to 19).

VIII. Discussion

There were a total of 1051 respondents who answered the survey from 2021-2023 of which the majority of them, 67%, are females and the remaining 33% of them are male. The majority of the respondents, 85.6% are undergraduate students followed by certificates/diploma students with 12.8% and lastly, only 1.6% of them are postgraduate students. Additionally, almost half of the respondents, 51%, are visual learners followed by auditory learners with 27% and lastly, 22% of the respondents are kinesthetic learners.

A vast majority of the respondents, 97.9%, agree that knowing their learning style is important in improving their learning ability with 81.3% of them aware of their learning style. However, there are still 16.7% of them who are not aware of their learning style despite agreeing that knowing their learning style is beneficial in improving their learning ability.

The preferred online assessment methods for visual, auditory and kinesthetic learners are outlined in Table IV. Demonstration, open book, multiple choice questions (MCQ), recorded presentation and individual and group assignments emerged as the preferred online assessment methods for all 3 learner types. Both visual and auditory learners prefer live presentations whereas both visual and kinesthetic learners prefer concept mapping. Moreover, auditory learners in particular prefer case studies while kinesthetic learners prefer digital lab experiments.

The results of the classification model are shown in Section VII-B. All of the models perform fairly well in all of the evaluation metrics: accuracy, precision, recall and f1-score. However, the best-performing model out of the 5 models is the Random Forest and XGBoost. The Random Forest model has a 92.3%, 95%, 85% and

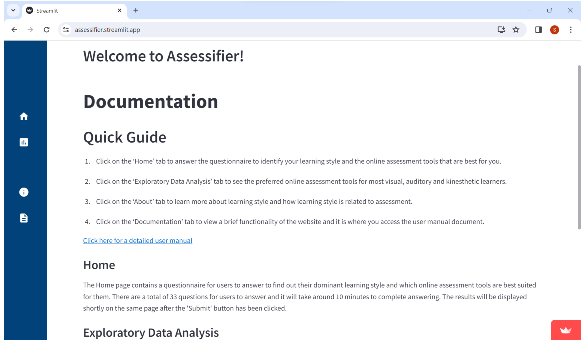


Fig. 18: Documentation page of Assessifier

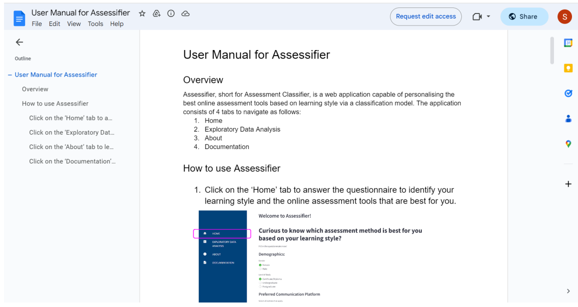


Fig. 19: User manual available to access on the Documentation page of Assessifier

Type of Learner	Preferred Online Assessment Tools
Visual	Demonstration, open book, MCQ, recorded and live presentation, individual and group assignments and concept mapping
Auditory	Open book, demonstration, recorded and live presentation, MCQ, individual and group assignments and Case study
Kinesthetic	Demonstration, open book, MCQ, recorded presentation, individual and group assignments, concept mapping and digital lab experiments

TABLE IV: Summary of the Top 8 preferred online assessment tools by learners type

89% of accuracy score, precision, recall and f1-score respectively whereas the XGBoost model has 92.1%, 92%, 87% and 89% of accuracy score, precision, recall and f1-score respectively.

As the Random Forest model has a higher accuracy score and higher precision score as compared to the XGBoost model, the Random Forest model was chosen to be used as the final classification model. Other factors in selecting Random Forest as compared to XGBoost are that the Random Forest model took a shorter time in training, is less prone to overfitting and is less complex than XGBoost.

IX. Conclusion

In conclusion, the online assessment methods preferences differ among visual, auditory and kinesthetic learners. The common preferences across the 3 learning styles are demonstrations, open book, MCQ, recorded presentations and individual and group assignments.

A total of 5 classification models namely Decision Tree, KNN, Random Forest SVM and XGBoost were trained using the data collected from the survey conducted from 2021-2023 to recommend the most suitable and preferred online assessment methods based on the dominant learning style. Data pre-processing was also conducted before the model training to obtain clean data for a more accurate model training.

Additionally, the models are evaluated using the accuracy score, precision, recall and f1-score to determine the best-performing model. Out of the 5 models, the Random Forest with 92.3% accuracy was identified as the best model.

A web application, Assessifier was also developed and deployed as the data product so that this project could benefit more people in terms of learning.

On the other hand, one of the limitations of this project is the size of the dataset is small. As this project focuses on online assessment classification based on personalisation, students' feedback on their preferred online assessment tools is highly critical to improve the model's accuracy further. The preference for online assessment tools differs among different people. As the current dataset has only 1051 responses, it may not accurately represent visual, auditory and kinesthetic learners' preferences collectively. Furthermore, this project only covers university students. For the overall advancement of the education system, it would be beneficial to involve primary and secondary students in this project. Additionally, this project only covers 5 classification models. There are other more robust and effective machine learning algorithms such as Neural Networks to explore.

Therefore, future works aim to address the above limitations by expanding the dataset through additional data collection on the students' online assessment methods preference, involving primary and secondary students to participate in the survey and investigating the use of Neural Networks as a classification model to further increase accuracy.

Acknowledgments

I hope that this project is beneficial to many people and can inspire people to explore more ways to enhance student learning and the education system as a whole. This is because different students have different learning styles which influence the assessment methods they prefer. Lastly, I would like to thank Associate Prof. Dr. Liyana for all her guidance and unwavering support throughout this project. Her assistance has made a significant improvement to this project.

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Appendix

A. *User Manual for Assessifier*

1) Overview: Assessifier, short for Assessment Classifier, is a web application capable of personalising the best online assessment tools based on learning style via a classification model. The application consists of 4 tabs to navigate as follows:

- Home
- Exploratory Data Analysis
- About
- Documentation

2) How to use Assessifier:

i. Answer the questionnaire to identify your learning style and the online assessment tools that are best for you at the Home page (Refer to Figure 20) and click the 'Submit' button.

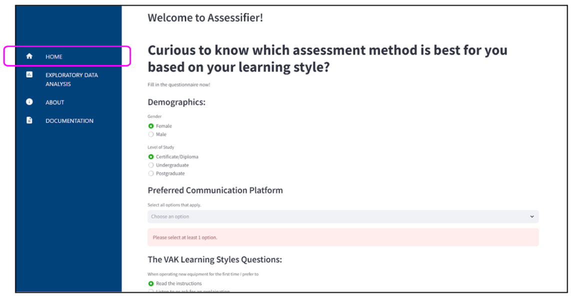

Fig. 20: Home page - Step 1

- The results consisting of your dominant learning style and the recommended online assessment methods will be displayed shortly on the same page (Refer to Figure 21).

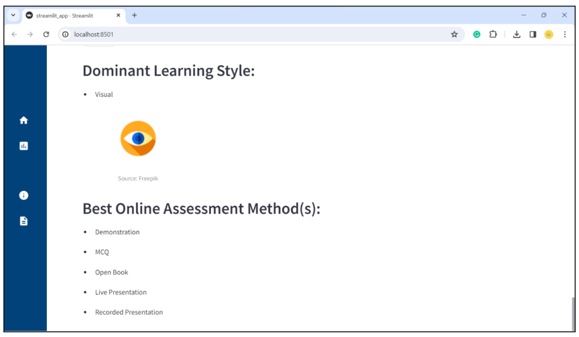

Fig. 21: Dominant learning style and the recommended online assessment methods results

ii. Click on the 'Exploratory Data Analysis' tab to see the preferred online assessment tools for most visual, auditory and kinesthetic learners (Refer to Figure 22).

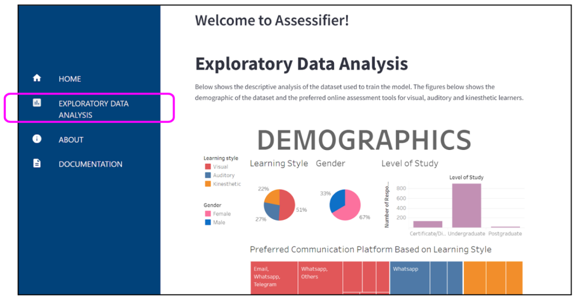

Fig. 22: Exploratory data analysis page - Step 2

iii. Click on the 'About' tab to learn more about learning style and how learning style is related to assessment (Refer to Figure 23).

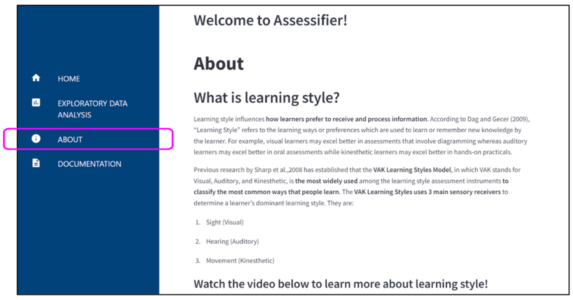

Fig. 23: About page - Step 3

iv. Click on the 'Documentation' tab to view a brief functionality of the website and it is where you access the user manual document (Refer to Figure 24).

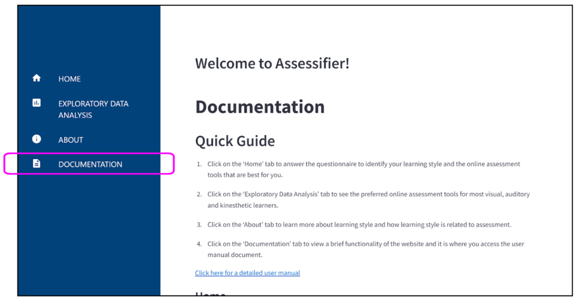

Fig. 24: Documentation page - Step 4