# Learning Object Classification Based On Personalisation

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***Abstract*—There exists an abundance of learning objects, making it difficult for learners to find the most suitable learning objects for effective learning. In addition, there are limited studies on utilising classification models for learning object recommendations. Hence, this study explores how people learn best by combining their learning object preferences with their dominant learning style. It introduces classification models to recommend learning objects that suit different learning styles based on the VAK learning style model. Finally, this research also developed a web application called Smart Learn, that provides personalised learning object recommendations based on their dominant learning style.**

**Keywords**– learning styles, learning objects, personalisation, effective learning, VAK model, classification, recommendations, Smart Learn, education technology.

## I. Introduction

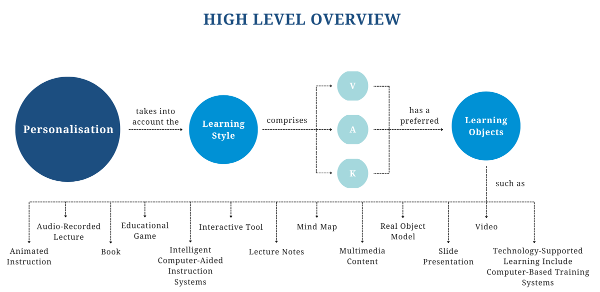



Fig. 1: General overview on personalisation based on learning style and learning objects.

The intersection of 'learning objects,' 'learning styles,' and 'personalisation' is increasingly prominent in the field of education. According to Demir and Almali, 2020, the IEEE's Learning Technology Standards Committee defines 'learning objects' as entities, whether digital or non-digital, that can be harnessed, reused, or referenced in the context of technology-supported learning. In today's dynamic educational landscape, learning objects extend beyond traditional textbooks to encompass diverse formats such as infographics, podcasts, animations, and more. Turnip et al., 2017 emphasised that educational institutions are encouraged to customize their learning processes to align with students' core characteristics by leveraging personalised learning approaches to create tailored support systems for effective learning experiences.

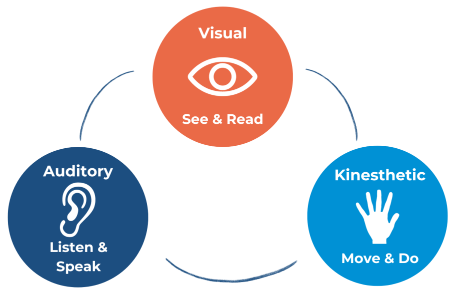
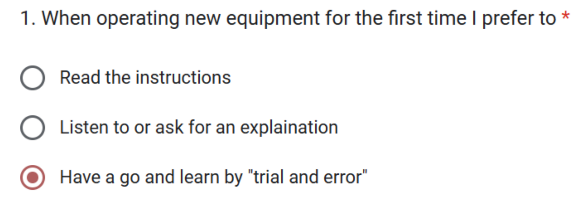



Fig. 2: Visual-Auditory-Kinesthethic (VAK) Learning Style

The VAK Model is utilised in this paper to identify learners' dominant learning styles. Rao, 2023 stated that the model can provide the learners with a profile of their learning styles, allowing them to understand the type of learning that best suits them, either through visual, auditory or kinesthetic. The VAK model is based on a questionnaire created by Chislett and Chapman, 2005 and referenced from Ranjha, 2023. It consists of 30 statements, each with 3 options. Each option of the VAK questions represents a dominant learning style (either Visual, Auditory or Kinesthetic). Respondents will need to choose the options which best describe them. Then, the sum of the responses based on V, A, and K is calculated with the maximum sum indicating the dominant learning style of the respondent. An example based on Fig 3:

- A visual learner would most probably choose to read the instructions

- An auditory learner would prefer to listen to an explanation
- A kinesthetic learner is likely to have a go directly


1. When operating new equipment for the first time I prefer to *

- Read the instructions
- Listen to or ask for an explaination
- Have a go and learn by "trial and error"

Fig. 3: A sample of VAK learning style question from the survey form.

## II. Literature Review

### A. *VAK learning style model*

There are several learning style models. Different learning style models focus on different aspects (Hamid Reza Koohestani, 2020). According to Sreenidhi and Tay, 2017, Rao, 2023, one of the most prevalent and widely embraced categorisations of diverse learning styles is the VAK model representing Visual (V), Auditory (A), and Kinesthetic (K) sensory modalities (refer to Figure 2). This model provides learners with a comprehensive insight into their learning styles, drawing from the sensory modalities that engage in their information absorption process. The paper also added individuals often possess a dominant learning style. Understanding one's preferred learning style empowers learners to identify the most effective learning approaches, enabling informed choices in their learning strategies.

1) **Visual (V):** Individuals who have a preference for the visual aspect of learning excel when presented with pictorial information and descriptions. For these learners, the most suitable activities encompass image-rich or reading materials such as lecture notes, graphics and videos. Engaging in visual information content is particularly effective for them (Dantas and Cunha, 2020).
2) **Auditory (A):** Individuals who excel in absorbing information through their sense of hearing. They are more inclined to prefer recording lectures for later review, rather than relying on visual aids like PowerPoint presentations. Additionally, these learners may read their notes aloud as part of their study approach (Shahbodin et al., 2015).
3) **Kinaesthic (K):** Individuals who learn best by doing (Surjono, 2011). These learners enjoy the hands-on experience or engage in complete physical immersion within the learning environment, which may involve activities such as field trips, dramatisation or workshops(Maulidia Tifani Alfin Nur Hardiana, 2018). Additionally, individuals with this learning style encompass various forms of movement and emotions, both in terms of experiencing and recollecting them. It includes aspects like physical motion, coordination, rhythm, emotional reactions, and physical comfort (Rita Syofyan, 2018).

### B. *Effective learning through personalisation of learning objects*

Research by Souabi et al., 2021 proposed to develop recommendation systems with the integration of machine learning algorithms. However, it did not specify any machine learning algorithm to use. The paper emphasised the need for recommendation systems due to the large amount of learning material and stressed the importance of tailoring learning objects to align with students' learning styles and preferences. This can be supported by research by Nabizadeh et al., 2020, whereby the paper experimented with recommending a sequence of learning objects that accommodates the users' time constraints while maximizing their scores. The paper specifies learning objects to a course and performs a Depth First Search algorithm to find all paths (learning object sequences). The paper noted that the recommended learning objects did indeed help students to get better grades. However, this paper does not account for learning style and learning object preferences and does not utilise machine learning models.

### C. *Learning objects recommendation systems*

Shuib et al., 2014, Nafea et al., 2019, Huber and Muller, 2023 noted that previous studies classified learning objects based on the description of the learning style itself only without considering student preference. Correspondingly, research conducted by Nafea et al., 2019 introduced a learning object recommendation tool based on learning style (using the Felder-Silverman Learning Style Model) and learning object ratings. In their study, they evaluated three mainstream recommendation algorithms, namely Collaborative Filtering (CF), Content-Based Filtering (CBF) and Hybrid filtering (HF). Ultimately, they favour their HF approach as the most effective recommendation algorithm due to the majority (95%) of the students being satisfied with the learning object recommendations from the HF algorithm. However, it is worth noting that this research focuses on the learning style and does not account for learning object preferences. Similarly, a study conducted by Syed et al., 2017 discussed a personalised learning object recommendation system architecture based on learning object preferences using the HF approach. While this research incorporated learning object preferences into its model, it did not consider the aspect of learning styles. Another study by Imran and Abdullah, 2010 proposed a learning object recommendation tool based on outstanding learners' ratings on the learning objects. The paper utilises CBF, Peer-review mechanism and support vector machine (SVM - to calculate object similarities) to recommend learning materials. The paper noted that their proposed system has better precision as compared to the usual content-based recommender system. However, as the system relies on good learners' ratings as a recommendation tool, it may not accurately represent all learners' preferences and can lead to a false perception.

### *D. Classification algorithms comparisons*

Deng et al., 2023, conducted a comparison of multiple machine learning algorithms for music genre classification. The models include Naive Bayes (NB), k-Nearest Neighbor (kNN), Decision Tree (DT), Random Forest (RF), SVM, Logistics Regression (LR) and Connected Neural Network (CNN). In their research, they concluded that CNN and kNN have the highest accuracy (approx. 90%) and NB has the lowest accuracy (approx. 51%). Although CNN has the highest accuracy, it is important to note that it is computationally expensive. Another research by Nazish et al., 2021 compared between the SVM and LR models in COVID-19 lung image classification. They found that both models achieved high accuracy with SVM having the highest accuracy of 96% while LR records 92% accuracy. Besides, Santana et al., 2021 conducted a classification models comparison for COVID-19 test prioritization in Brazil which includes the DT, RF, eXtreme Gradient Boost (XGB), kNN, SVM and LR. They found that DT, RF, XGB, and SVM models have similar accuracy results (approx. 89% accuracy). However, the paper chose DT as the best model due to its interpretability. besides, research by Kebonye, 2021 compared the model's accuracy between 4 different percentage ratios when spliting dataset into training and testing set of 60/40, 70/30, 75/25 and 80/20. The paper noted that 70/30, 75/25 and 80/20 ratios have similar high accuracy score.

## III. Problem Statement

1) **Finding the most suitable learning objects for effective learning is a challenge:** The enormity of the amount of learning objects has led students to have difficulties in determining the most suitable learning objects for them (Souabi et al., 2021).
2) **Limited classification models have been developed for learning objects based on learning style and learning object preferences:** Previous research only focuses on mainstream recommendation algorithms (Nafea et al., 2019; Syed et al., 2017; Imran and Abdullah, 2010). Moreover, past research does not take into account both the student's learning style (Imran and Abdullah, 2010) and learning object preferences (Nafea et al., 2019).

## IV. Project Scope

The project includes obtaining the dataset, exploring the dataset, training and evaluating the model to find the best model and finally, deploying the best model to a web application. The web application can be accessed anywhere online and can be used to determine one's dominant learning style and also provide learning object recommendations which suit the user. Though the web application supports any web-browsing devices, it is best used with a computer or laptop.

## V. Objective

The objectives of the project are:

1) To develop a learning object classification based on personalisation model
   - Which classification models can be used?
2) To evaluate a learning object classification based on personalisation model
   - How to evaluate the trained models and which is the best-performing model?
3) To develop a functional data product web application which can provide learning objects recommendation
   - How to share the functional product?

## VI. Methodology

The data science methodology used is based on the CRISP-DM Model's principles (refer to Figure 4). CRISP-DM serves as a framework for managing data science projects, offering a clear outline of the project workflow (Saltz, 2021).

### *A. Business Understanding*

The project focuses on the VAK learning style and learning objects. To develop a deeper understanding of the project, previous research papers were studied and read (refer to Section II). The project's objectives were also defined (refer to Section V).

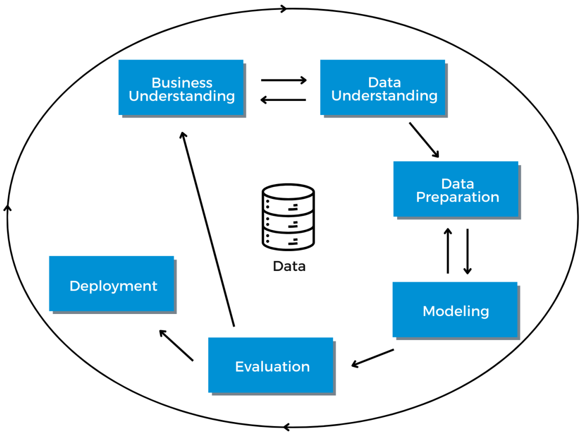



Fig. 4: CRISP-DM Methodology

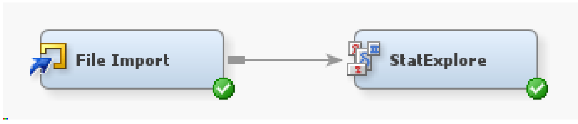



Fig. 6: Nodes built with SAS

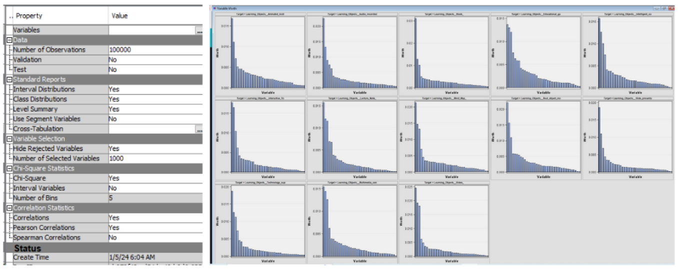
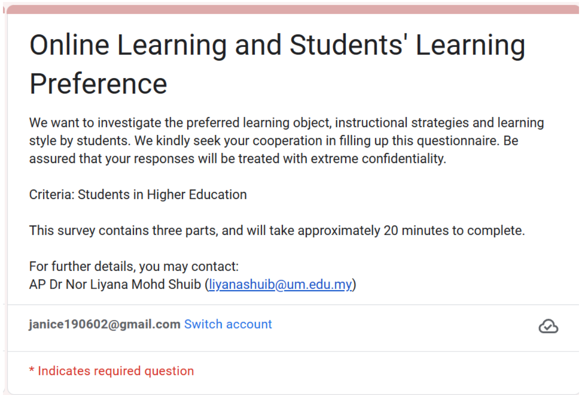


Fig. 7: StatsExplore parameters and output

## B. Data Understanding

The dataset is obtained from a survey (Fig. 5) which was distributed to students of Universiti Malaya. It consists of 1036 rows and 104 columns. The dataset comprises data from the year 2021 to 2022.



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)

janice190602@gmail.com Switch account

* Indicates required question

Fig. 5: The distributed survey form. The survey form is built using a Google Form.

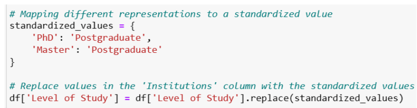
Data exploration is conducted with SAS Enterprise Miner to identify the relevant columns to be used for the project (refer to Fig, 6). The Chi-square measure, set in the StatExplore node, is used to determine columns that have a link to the target variables i.e., learning objects. The graphs in Fig. 7 give the columns that have a link to the target variables, from the strongest to the weakest. From there, the relevant columns are identified, as listed below:

- Gender
- Level of study
- Household income
- Preferred learning mode
- Preferred communication platform
- Learning objects preferences
- VAK learning style questions

## C. Data Preparation

*1) Check for null values:* The columns of interest (refer to Section VI-B) are extracted. Thus, resulting in 48 usable columns. Null value checks are performed.

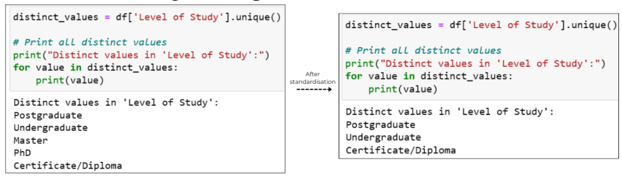
*2) Data Standardisation:* To fix all data inconsistencies. Mappings are utilised by defining the dictionary and replacing the values respectively (refer to Fig. 8).



```
# Mapping different representations to a standardized value
standardized_values = {
    'PhD': 'Postgraduate',
    'Master': 'Postgraduate'
}

# Replace values in the 'Institutions' column with the standardized values
df['Level of Study'] = df['Level of Study'].replace(standardized_values)
```

(a) Mappings values by defining dictionary and '.replace()' function is used for performing the 'replace'.



```
distinct_values = df['Level of Study'].unique()

# Print all distinct values
print("Distinct values in 'Level of Study':")
for value in distinct_values:
    print(value)

Distinct values in 'Level of Study':
Postgraduate
Undergraduate
Master
PhD
Certificate/Diploma
```

After standardisation

```
distinct_values = df['Level of Study'].unique()

# Print all distinct values
print("Distinct values in 'Level of Study':")
for value in distinct_values:
    print(value)

Distinct values in 'Level of Study':
Postgraduate
Undergraduate
Certificate/Diploma
```

(b) Original values vs standardised values

Fig. 8: The left side shows the original values in the 'Level of Study' column where there are 'Postgraduate', 'Master' and 'PhD'. In actuality, 'Master' and 'PhD' are considered as 'Postgraduate'. The right side shows the standardised values where all the 'Master' and 'PhD' were changed to 'Postgraduate'.

*3) Determine the dominant learning style:* The concept of the VAK model has been discussed in Section I. Firstly, the answer options are defined according to their respective learning style. Then, the sum of V, A, and K options selected are calculated respectively. The maximum sum is obtained and appended as a new column. The maximum sum represents the dominant learning style.

*4) Exploratory Data Analysis (EDA):* EDA is performed to explore the dataset by using Tableau. The results can be viewed in Section VII-A and insights gained will be explained in Section VIII-A.

*5) Data Encoding:* Data needs to be encoded for classification. In this project, ordinal encoding and one-hot encoding are utilised. Ordinal encoding is performed with custom mappings. For columns with multiple options selected, they are first split by a comma and then exploded into rows (see Fig 9), before proceeding to perform the data encoding.

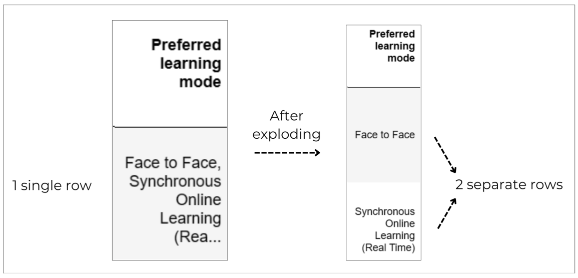



Fig. 9: The left side shows the data with multiple options selected, where each option is separated by a comma. The right side shows the data after performing the 'explode', where the options are split and separated into different rows.

### D. Modeling

There are 6 models trained in this project. The results are tabulated in Table I and discussed in Section VIII-B. The models are listed as follows:

- Support Vector Machine (SVM)
- Random Forest
- Decision Tree
- eXtreme Gradient Boosting (XGB)
- K-Nearest Neighbour (kNN)
- Logistic Regression

Data is split into 25% test and 75% train. Additionally, the GridSearchCV() function is utilised to find the best parameters for each model. The best parameters of each model are as below:

- SVM:
  - 'C': 1
  - 'gamma': 0.1
  - 'kernel': 'rbf'
- Random Forest:
  - 'max_depth': 10
  - 'n_estimators': 200
- Decision Tree:
  - 'max_depth': None
  - 'max_features': 'log2'
  - 'min_samples_leaf': 1
  - 'min_samples_split': 2
- XGB:
  - 'colsample_bytree': 0.7
  - 'gamma': 0.2
  - 'learning_rate': 0.01
  - 'max_depth': 9
  - 'n_estimators': 200
  - 'subsample': 0.7
- kNN:
  - 'metric':'manhattan'
  - 'n_neighbors': 9
  - 'weights' :'distance'
- Logistic Regression:
  - 'C': 0.1
  - 'solver': 'liblinear'

### E. Evaluation

The models are evaluated using the accuracy score and the classification report.

*1) Accuracy Score:* Represents the proportion of correct predictions made by a model. The accuracy score of the models is tabulated in Table I. The equation is represented as:

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

*2) Classification Report:* Provide quantifiable ways to measure how well a model is performing. The metrics help in understanding the model's precision, recall, and F1 score. As all classes are equally important, the macro-averaging is focused on this evaluation. The evaluation metrics results are tabulated in Table I. The equations of the relevant metrics are represented as below (Natarajan, 2023):

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

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

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

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

where, $N$ is the total number of classes or labels and $\text{Score}_i$ is the metric (i.e., precision, recall, F1-score) for each class $i$.

### F. Deployment

Streamlit is utilised for the development and deployment of the web application. Streamlit is a powerful, open-sourced Python tool for rapidly developing and deploying web applications. Its simplicity allows quick prototyping by transforming Python scripts into interactive apps without much effort and offers a straightforward deployment process to the Streamlit Community Cloud with no charges.

## VII. Results

### A. Exploratory Data Analysis (EDA)

2 dashboards are created namely, the Dataset Distribution Dashboard (Fig. 10) and the Learning Objects Preferences Dashboard (Fig 11). In-depth insights can be referenced in Fig, 12, 13, 14, 15, 16.

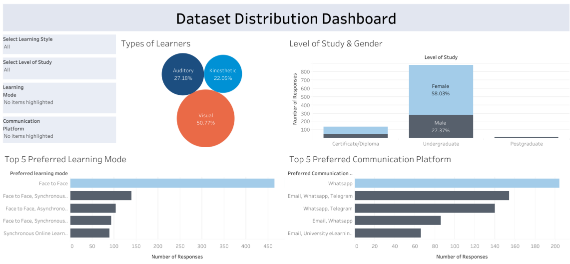



Fig. 10: Dataset general distribution dashboard

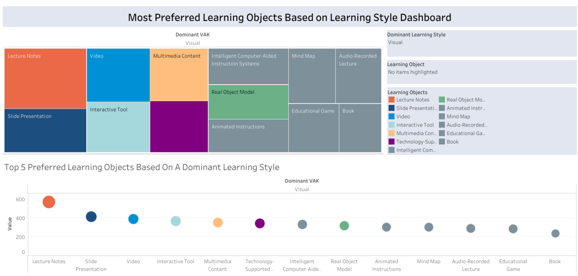



Fig. 11: Learning objects preferences based on learning style dashboard

### B. Classification Models

Based on Table I, the best model is the Support Vector Machine (SVM). Further discussion is discussed in Section VIII-B.

### C. Web Application

*Smart Learn* is a web application which consists of 5 pages, i.e., Home, Details, Questionaire, EDA, and User Manual (refer to Figure 17, Figure 18, Figure 19,

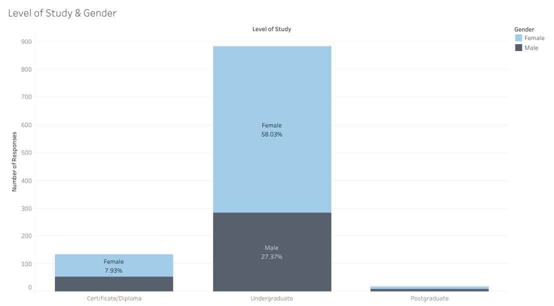



Fig. 12: Percentage of respondents' level of study and their gender. The majority of the respondents are undergraduate students with 58.03% of them female and 27.37% male. Postgraduate students have the lowest percentage with only 0.87% of them female and 0.77% male.

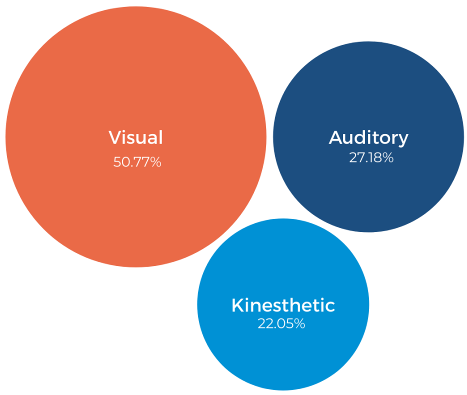



Fig. 13: The types of learners distribution. Visual learners have the highest percentage distribution of 50.77%, followed by auditory learners (27.18%) and kinesthetic learners (22.05%).

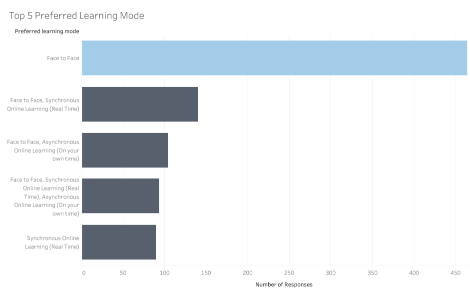



Fig. 14: Learning mode preferences. The majority of the respondents prefer the 'face-to-face' mode for learning.

Figure 21 and Figure 22 respectively). *Smart Learn* can also directly be accessed here.

*Smart Learn* consist of information and background of learning style, learning objects and personalisation in learning. It also allows users to know their dominant learning style by answering a questionaire and getting

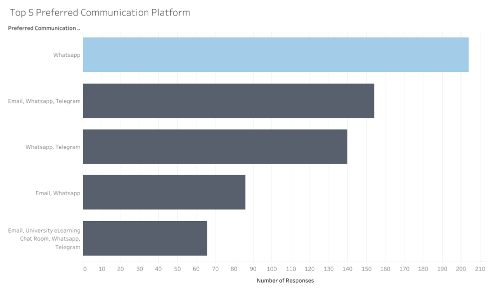
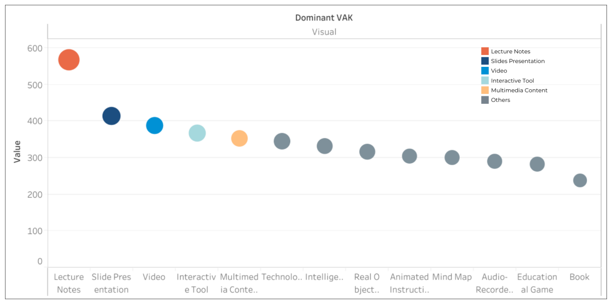


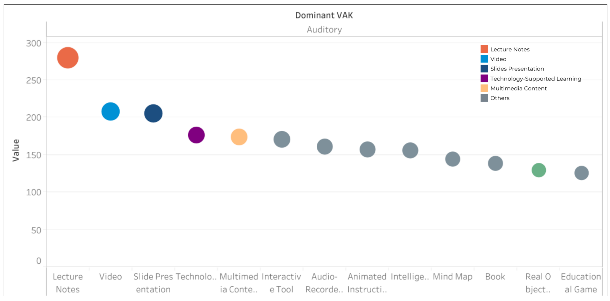

Fig. 15: Communication platform preferences. The majority of the respondents prefer to use 'WhatsApp' for communication.

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| **SVM** | **0.9601** | **0.98** | **0.93** | **0.95** |
| Random Forest | 0.9598 | 0.98 | 0.92 | 0.95 |
| kNN | 0.9569 | 0.96 | 0.94 | 0.95 |
| XGB | 0.9441 | 0.96 | 0.91 | 0.93 |
| Decision Tree | 0.9382 | 0.92 | 0.93 | 0.93 |
| Logistic Regression | 0.6642 | 0.62 | 0.52 | 0.55 |

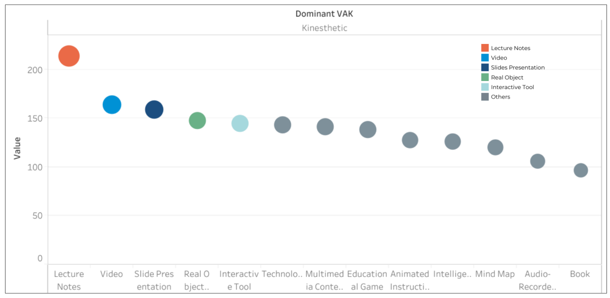
TABLE I: Accuracy score and classification report for each model. SVM has the highest accuracy score of 0.9601, a precision of 0.98, a recall of 0.93 and an f1-score of 0.95. Following closely behind is the Random Forest, kNN. XGB and decision tree also achieved similar high accuracy score. However, logistics regression has the lowest accuracy of 0.6642.




(a) Visual learners' preferred learning objects. Visual materials like animated instructional and mind maps are less preferred for visual learners.




(b) Auditory learners' preferred learning objects. Auditory materials like audio-recorded lectures are less preferred for auditory learners.




(c) Kinesthetic learners' preferred learning objects. Hands-on learning objects such as intelligent computer-aided are less preferred for kinesthetic learners.

Fig. 16: Learning objects preferences for each dominant learning style. All 3 learning styles prefer to learn with Lecture Notes, Slides Presentation and Video.

learning object(s) recommendations which suit them best. A sample of output can be referenced in Figure 20.

## VIII. Discussion

### A. Exploratory Data Analysis (EDA)

The dataset consists of respondents from postgraduate, undergraduate and diploma students with the majority of them being undergraduate students (58.03% female, 27.37% male, refer Fig 12). Among the respondents, 50.77% are visual learners, making them the majority, 27.18% are auditory learners and 22.05% are kinesthetic learners (refer Fig 13). Based on Fig 14 and Fig 15, generally, the most preferred learning modes is 'face-to-face' and the most preferred communication platforms is 'WhatsApp'. It is also important to note that lecture notes, slide presentations and videos are the most preferred learning objects by all types of learners (refer to Figure 16). However, visual learners do not necessarily prefer all types of visual materials (Fig 16a). The same goes for auditory learners and kinesthetic learners (Fig 16b and Fig 16c). Thus, it is important to take learners' preferences in learning objects into consideration when providing recommendations for effective learning.

### B. Model

Based on the results tabulated in Table I, the models with the highest accuracy score are SVM (0.9601), a high precision, recall and f1 score of 0.98, 0.93 and 0.95 respectively. Following closely behind is the Random Forest and kNN with both having an accuracy of approximately 0.95. XGB and decision tree also achieved

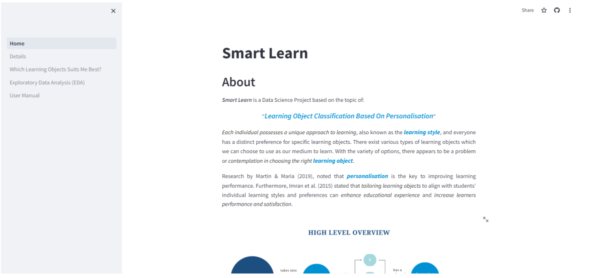



Fig. 17: Home page of *Smart Learn*. It explains the introduction and background of the project.


Fig. 18: Details page of *Smart Learn*. It explains the definition of the learning style and learning objects.

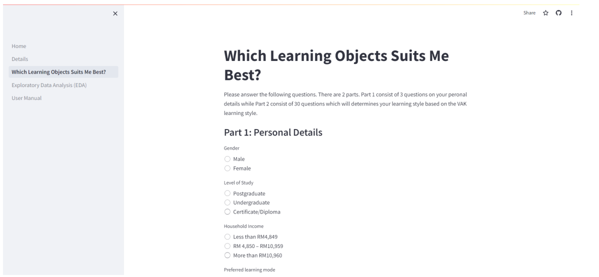



Fig. 19: Questionaire page of *Smart Learn*. The questionnaire determines the dominant learning style of the respondent and provides learning object(s) recommendations.

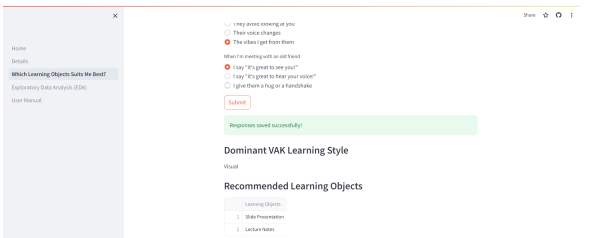



Fig. 20: A sample of output on the determination of dominant learning style and learning object(s) recommendations.

similar high accuracy (approx. 0.94). However, logistics regression performed poorly. It has the lowest accuracy, precision, recall and f1 score of 0.6642, 0.62, 0.52 and 0.55 respectively.

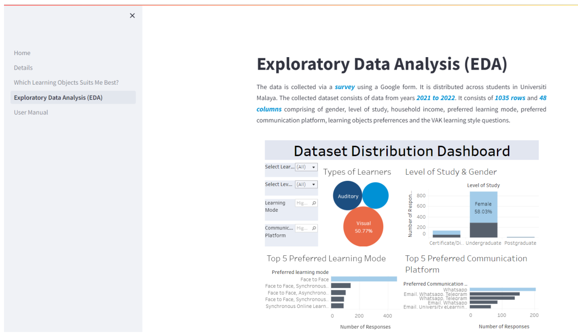



Fig. 21: Exploratory Data Analysis (EDA) page of *Smart Learn*. It shows the distributions and insights gained from the dataset used to train the model.

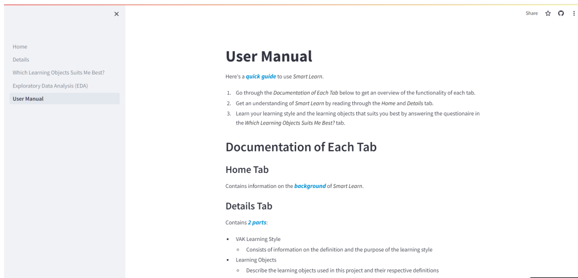



Fig. 22: User Manual page of *Smart Learn*. It explains the functionality of the web application and guides on how to use Smart Learn.

## IX. Conclusion

In conclusion, all three learning styles favour learning through lecture notes, slide presentations, and videos. Not all visual learners prefer every type of visual material, similarly, auditory and kinesthetic learners might not favour all auditory or kinesthetic materials, respectively. Among the 6 models trained, the best model is SVM. The trained classification models are evaluated using the accuracy score and the classification report. SVM has the highest accuracy score and precision of 0.9601 and 0.98 respectively. Additionally, a web application named *Smart Learn* has been created and deployed. It hosts a questionnaire enabling users to identify their dominant learning style and receive tailored recommendations for suitable learning objects.

The project's limitations include its focus solely on university students, overlooking primary and secondary students. Personalised education should span across all education tiers. Additionally, the project utilises only six classification models, neglecting potentially more effective models like neural networks. Moreover, the size of the dataset is relatively small. Collecting more data may enhance the model's predictive capabilities. Therefore, future works could involve extending the study to cover a broader educational spectrum by including primary and secondary education. Besides, exploring more advanced models like neural networks can be beneficial for improved accuracy and performance. Lastly, expanding the dataset size by collecting more diverse and extensive data to further enhance the model's predictive capabilities.

## Acknowledgments

I hope that this project can further help in deepening the significance of personalisation in education. Different people have different learning styles and preferences for learning objects. Knowing and understanding one's learning style would be very helpful in determining the most suitable learning objects for effective learning. Finally, I would like to extend my sincere gratitude to my supervisor, Associate Prof. Dr. Nor Liyana, for her constant support and guidance in completing this project.

## References

Chislett, V., & Chapman, A. (2005). Vak learning styles self-assessment questionnaire. *Retrieved June*, *26*, 2006.

Dantas, L. A., & Cunha, A. (2020). An integrative debate on learning styles and the learning process. *Social Sciences amp;amp; Humanities Open*, *2*(1), 100017. https://doi.org/10.1016/j.ssaho.2020.100017

Demir, S. B., & Almali, H. (2020). What do teachers do! factors affecting the respectability of teaching profession according to teachers' viewpoints. *Erzincan Üniversitesi Eğitim Fakültesi Dergisi*, *22*(1), 1–17. https://doi.org/10.17556/erziefd.448632

Deng, J. D., Gu, Y. T., & Zhu, Y. (2023). Comparison of multiple machine learning algorithms for music genre classification. *Applied and Computational Engineering*, *8*(1), 768–774. https://doi.org/10.54254/2755-2721/8/20230220

Hamid Reza Koohestani, N. B. (2020). A comparison of learning styles of undergraduate health-care professional students at the beginning, middle, and end of the educational course over a 4-year study period (2015-2018). *Journal of education and health promotion*, *9*, 208. https://doi.org/10.4103/jehp.jehp_224_20

Huber, M., & Muller, C. (2023). Is there a learning type?! revisiting learning-styles theory in view of learning and emotion. *European Journal of Education Studies*, *10*(3). https://doi.org/10.46827/ejes.v10i3.4688

Imran, K., & Abdullah, N. (2010). Learning materials recommendation using good learners' ratings and content-based filtering. *Educational Technology Research and Development*, *58*, 711–727. https://doi.org/10.1007/s11423-010-9155-4

Kebonye, N. M. (2021). Exploring the novel support points-based split method on a soil dataset. *Measurement*, *186*, 110131. https://doi.org/10.1016/j.measurement.2021.110131

Maulidia Tifani Alfin Nur Hardiana, P. P. S. (2018). The effectiveness of vak (visual, auditory, kinesthetic) model in learning of summary writing. *International Journal of Research Review*, *5*. https://www.ijrrjournal.com/IJRR_Vol.5_Issue.8_Aug2018/IJRR008.pdf

Nabizadeh, A. H., Gonçalves, D., Gama, S., Jorge, J., & Rafsanjani, H. N. (2020). Adaptive learning path recommender approach using auxiliary learning objects. *Computers amp; Education*, *147*, 103777. https://doi.org/10.1016/j.compedu.2019.103777

Nafea, S., Siewe, F., & He, Y. (2019). On recommendation of learning objects using felder-silverman learning style model. *IEEE Access*, *PP*, 1–1. https://doi.org/10.1109/ACCESS.2019.2935417

Natarajan, M. (2023, November). Understanding the intuition behind classification report metrics: Macro average vs. https://medium.com/@megha.natarajan/understanding-the-intuition-behind-classification-report-metrics-macro-average-vs-d9c2cc04717d

Nazish, Ullah, S. I., Salam, A., Ullah, W., & Imad, M. (2021, January). Covid-19 lung image classification based on logistic regression and support vector machine. In *Lecture notes in networks and systems* (pp. 13–23). https://doi.org/10.1007/978-3-030-77246-8_2

Ranjha, A. (2023). Vak learning styles self-assessment questionnaire psychology roots. https://psychologyroots.com/vak-learning-styles-self-assessment-questionnaire/

Rao, D. R. (2023). Automatic detection on learning styles using support vector machine. *International Journal of Scientific Research in Engineering and Management*, *07*(12), 1–11. https://doi.org/10.55041/ijsrem27578

Rita Syofyan, M. K. S. (2018). The impact of visual, auditory, and kinesthetic learning styles on economics education teaching. *Advances in Economics, Business and Management Research*, *57*. https://www.atlantis-press.com/article/25902648.pdf

Saltz, J. (2021). Crisp-dm for data science: Strengths, weaknesses and potential next steps. *2021 IEEE International Conference on Big Data (Big Data)*, 2337–2344. https://doi.org/10.1109/BigData52589.2021.9671634

Santana, Í. V. D. S., Da Silveira, A. C., Sobrinho, Á., Silva, L. C. E., Da Silva, L. D., Santos, D. F. S., Gurjão, E. C., & Perkusich, Â. (2021). Classification models for covid-19 test prioritization in brazil: Machine learning approach. *Journal of Medical Internet Research*, *23*(4), e27293. https://doi.org/10.2196/27293

Shahbodin, F., Nuraini, C. K., & Naim, A. C. P. (2015). Personalized learning environment (ple): Classification of dominant learning styles. *Australian Journal of Basic and Applied Sciences*, *8*, 366–371. https://www.academia.edu/66457736

Shuib, N. L., Chiroma, H., Abdullah, R., Ismail, M. H., Shuib, A. S., & Pahme, N. F. (2014). Data mining approach: Relevance vector machine for the classification of learning style based on learning objects. *2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation*. https://doi.org/10.1109/uksim.2014.96

Souabi, S., Retbi, A., Idrissi, M. K., & Bennani, S. (2021). Towards an evolution of e-learning recommendation systems: From 2000 to nowadays. *International Journal of Emerging Technologies in Learning (iJET)*, *16*(06), 286. https://doi.org/10.3991/ijet.v16i06.18159

Sreenidhi, S., & Tay, C. (2017). Styles of learning vak. *IJIRMF*, *3*, 17–25. https://www.researchgate.net/publication/317305325

Surjono, H. (2011). The design of adaptive e-learning system based on student's learning styles. *International Journal of Computer Science and Information Technologies*, *2*. https://www.researchgate.net/publication/266893850

Syed, T., Palade, V., Iqbal, R., & Nair, S. (2017). A personalized learning recommendation system architecture for learning management system, 275–282. https://doi.org/10.5220/0006513202750282

Turnip, R., Nurjanah, D., & Kusumo, D. S. (2017). Hybrid recommender system for learning material using content-based filtering and collaborative filtering with good learners' rating. *2017 IEEE Conference on e-Learning, e-Management and e-Services (IC3e)*. https://doi.org/10.1109/ic3e.2017.8409239


## Appendix

The user manual of *Smart Learn* can be referenced below.

### A. Click on the 'User Manual' tab

This tab allows users to get a step-by-step guide on how to use the website. Users are encouraged to read through this tab first (Fig. 23).

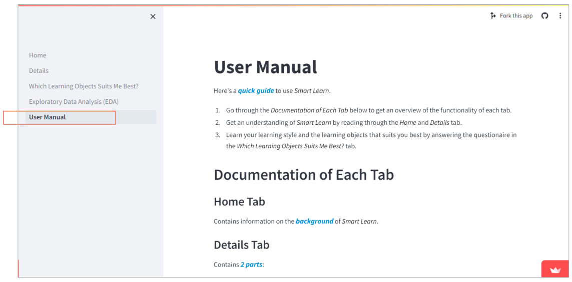



Fig. 23: Read user manual tab - Step 1

### B. Read the background of the project

This is the homepage of Smart Learn. Users are encouraged to read the 'Home' tab and the 'Details' tab to get a deeper understanding of the project (Fig. 24). The 'Home' tab mainly focuses on the 3 key terms of the project and it is also the homepage of *Smart Learn*. The 'Details' tab focuses on the learning style model and learning objects used in this project.

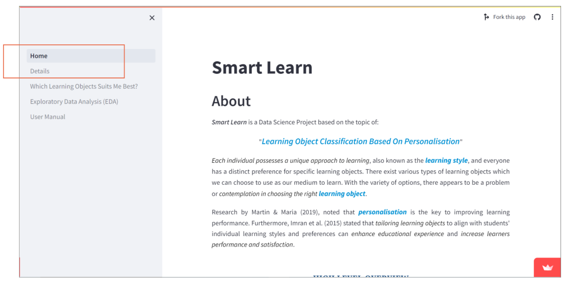



Fig. 24: Backgorund information - Step 2

### C. Answer the questionnaire

Users can obtain the learning objects that best suit them by answering the questionnaire in the 'Which Learning Objects Suits Me Best?' tab. Users need to answer all questions and click the submit button (Fig. 25). The dominant learning style and the list of recommended learning objects will be printed below (Fig. 26).

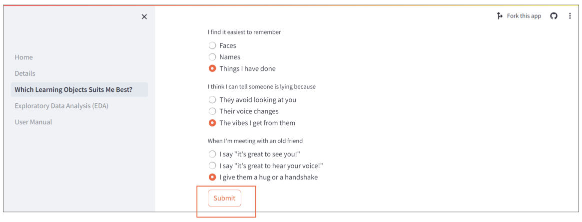



Fig. 25: Click the submit button after answering the all of the questions - Step 3

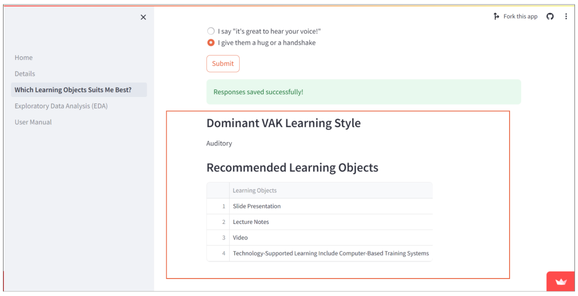
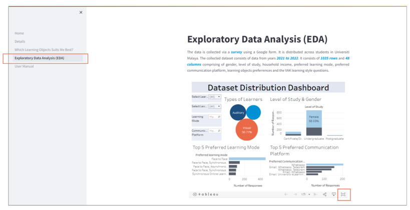


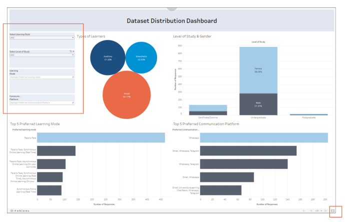

Fig. 26: Read the output displayed after answering the questionnaire - Step 4

### D. *Explore the general distribution of respondents*

'EDA' tab mainly focuses on the EDA of the dataset. Users can enlarge the dashboard by clicking on the button at the bottom right corner (Fig. 27a). Fig. 27b shows the view of the enlarged dashboard. Here, users can also use the filter function on the left to filter the required data. Users can exit the full-screen mode by clicking on the button at the bottom left corner.




(a) Dashboard in the EDA tab - Step 5




(b) Enlarge the dashboard and filter the data according to preference. Exit after finished viewing. - Step 6

Fig. 27: View dashboard - Step 5 and Step 6

### E. *Share the website with friends and family!*