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Predicting Modes of Learning using Machine Learning

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ABSTRACT: Children's education has evolved over time. It has progressed to the point where good learning materials are available as a result of technological advancements. Despite these advancements, not all children flourish or perform well in their academic endeavours. Why is this the case? Aside from the obvious causes (inadequate preparation, distractions, etc.), there is one reason that is sometimes overlooked: different people learn in different ways. Even if the instruction is excellent, students frequently struggle to grasp the topics being taught. This is the issue that our project seeks to address. We employ Machine Learning categorization algorithms to anticipate children's learning styles so that we can convey concepts in the most appropriate way. The use of machine learning enables us to determine the learning styles of youngsters with high accuracy. The creation of this model will cause a shift in the current education system for kids in the early stages of their education.

KEYWORDS: Machine Learning (ML), VARK (Visual, Auditory, Reading and Writing, Kinesthetic), K Nearest Neighbours(KNN), Support Vector Machine (SVM)

I. INTRODUCTION

For a long time, India's education system has been fairly stagnant. Despite the fact that many schools and institutions have attempted to establish various methods of learning and teaching, nothing has proven to be effective on the student population as a whole. This is primarily because the learning methods proposed by the authorities do not suit every student's preferences in terms of learning subjects. And the authorities are not to blame because knowing or predicting each student's learning style is a nearly impossible task for humans to undertake. This is where the desire to find a solution to this problem emerges.

The VARK Learning style system is based on Neil Fleming's VARK model, which he created in 1987. VARK stands for Visual, Auditory, Reading, and Writing, as well as Kinesthetic. This was created to assist students in learning about their own preferences as well as to assist teachers in delivering content in an appropriate manner. We will train Machine Learning Multiclass Classification Algorithms (such as K-Nearest Neighbours, Random Forest Classification, Support Vector Machine and Naives Bayes) on data curated from multiple orphanages and children's homes in and around Chennai.

Students were asked to complete a VARK questionnaire in order to obtain the curated data. This questionnaire contains ten multiple-choice questions (MCQs) that help people learn more about their preferred method of learning. The responses to this questionnaire are used to train the machine learning model, which is then used to predict the learning style of any given student. Figure 1 depicts a basic representation of the VARK learning styles.



Fig 1 – VARK Learning Styles

II. RELATED WORK

The current educational system has a major flaw: it expects students to use generalised learning methods. The entire system has become generalised over time, owing primarily to the neglect of preferential learning methods and romanticization of traditional learning methods. This is not only academically toxic for children as they grow, but it also stunts their creativity and prevents them from realising their full potential. Despite the fact that the VARK method of teaching is used in many educational institutions, it is not being used to its full potential. Typically, students are given a VARK questionnaire designed by child psychologists to better understand their preferences. In the absence of questionnaires, teachers are frequently forced to rely on their own judgement. Indian education must recognise that no two students' grasping abilities are the same. As a result, the teaching style cannot be the same for every kid in a class of 30. Some students learn at a faster rate than others. Teachers must keep a close eye on each of their students.

Unfortunately, despite multiple attempts by activists, teachers, and psychologists, traditional learning methods continue to dominate the education system due to a lack of knowledge and understanding regarding favoured learning approaches.

This is mostly because most schools do not assess their pupils through questionnaires or activities that help students comprehend or learn more about their preferred style of learning that appeals to their senses.

While it is hard for a single teacher to pay attention to each and every student, schools should consider using technologies such as machine learning and bots to help both professors and children.

Danijel Kućak, Vedran Juričić, and Goran Đambić [1] concluded that machine learning can be used to grade students, improve student retention and predict student performance. It was further observed that these results were extremely accurate and proved the models to be efficient enough to be deployed in the existing system.

Muniasamy, A., & Alasiry, A [2] analysed deep learning's future impact and concluded that it predicts outcomes based on historical performance and individual learning goals to provide customised eLearning content in a customised fashion, resulting in more personalised eLearning content. For example, for more competent online learners, it may skip multiple eLearning modules or adopt a more comprehensive, linear approach for those who still need basic information. Deep Learning Techniques were shown to be useful in creating chatbots, tailored learning paths, and even a virtual teaching assistant. All of this is extremely beneficial to e-learning.

Prithishkumar and Michael [3] found that there is a vast variety of learning strategies used by pupils. Adopting the VARK technique has shown to be beneficial for pupils because they were able to learn their courses while remaining in their comfort zone. The study also found that pupils are more likely to pay attention to something that appeals to or intrigues them. Many styles of information presentation are necessary to keep students' attention and motivation, demanding a shift from traditional large-group teacher-centric lecture approach to a participatory, student-centric multimodal approach.

Dutsinma and Temdee [4] came to the conclusion that Learning is a cognitive process that affects the human central nervous system and may be tracked via physiological signs. In their study, physiological signals are presented as crucial qualities for the classification of learning styles in order to minimise biased data from questionnaire completion and to encourage real-time reaction in the classroom setting. The study focused on heart rate and blood pressure signals in particular.

Thomas and Amit [5] found that the administration of the learning style instruments should take place as soon as



possible after the start of the semester, preferably during the first class session for purchased and printed instruments. When a faculty member is able to effectively communicate with students prior to the start of classes and Web-based instruments are selected, the faculty member should strongly encourage students to complete the instruments prior to the first class and bring the printed results to class to share with the instructor. Faculty should also complete the instruments, share their results and the composite class profile with course students, and discuss the findings with them. Murphy and Robert [6] saw that the distribution of dental student scores for multimodal and single dominant learning preferences reveals a preference for instructors who use strong visual presentations and allow for note-taking during lectures. However, a small but significant number of dental students prefer to learn by doing or listening. While aural learners prefer lectures, they also value in-class discussions and case studies to better understand the material and relate to its relevance.

More opportunities for students to actively participate in lectures or preclinical demonstrations, with the instructor acting as a coach, will appeal to the kinesthetic learner. As the learning environment shifts from lecture hall to preclinical laboratory to patient clinic, some dental students' learning preferences may shift.

Reese, Valerie, Dunn and Rita [7] recommended that classes should provide active experiences for planning or carrying out objectives, such as visits, projects, role playing, simulations, and floor or wall games, to ensure success for Kinesthetic learners.

III. PROPOSED METHOD

The traditional VARK model is only associated with a maximum of 4-5 categories of learners. We have increased the number of classes/categories in this study, even though the differences between these classes are minor. There are usually only four categories, and if a student has a similar visual and auditory score, they are labelled as a "mixed learner." This generalisation is ineffective because it does not truly appeal to students with mixed learning styles, forcing them to adopt learning styles that do not necessarily suit their preferences.

As a result, we divided them into eight categories:

- V - Visual Learners
- A - Auditory Learners
- MA – Mixed A (Visual + Auditory)
- R - Reading & Writing
- MC – Mixed C (Auditory + R/W)
- K – Kinaesthetic Learners
- MB – Mixed B (Visual + Kinaesthetic)
- MD – Mixed D (Visual + R/W)

This method of grouping adds another layer of classification which makes it more efficient in terms of suggesting more accurate learning paths and styles.

IV. METHODOLOGY

This project's workflow is divided into several stages. The first stage of data collection is carried out in collaboration with a non-governmental organisation, U&I. U&I is a volunteer organisation that teaches English to underprivileged children in various homes across India. The information is gathered in the form of a questionnaire, which contains questions designed by child psychologists to assess a child's learning style. The questionnaire was distributed to approximately 500 students, and the responses were entered into a computer. As part of the data pre-processing process, these responses were later corrected and cleaned. Following the completion of that stage, the children were divided into different learning styles. The model is trained with 500 entries of student inputs from the questionnaire for maximum accuracy and the block diagram Figure 2 shows the general workflow of this project.

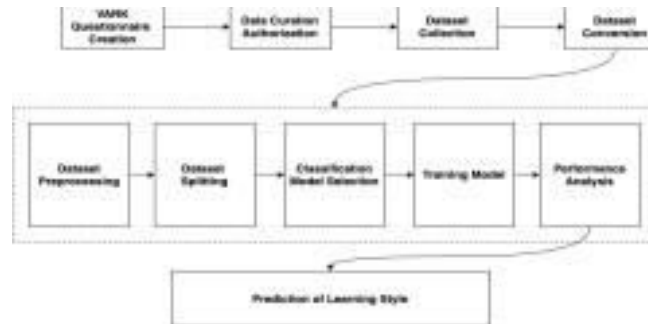


Fig 2 – Architecture Diagram

The trained model is then used for making predictions of the VARK learning style. This is done by making the algorithm learn about the patterns and possibilities by feeding it past inputs. The algorithm then recognises these patterns and when new inputs are fed, it makes the closest prediction to the ground truth. The accuracy of these predictions is measured by comparing it with ground truth values and cross verifying by comparative analysis.

A. Data Curation

The information was gathered using a VARK Questionnaire [5] designed for elementary school students. Volunteers from the U&I organisation assisted them with the activity. The volunteers also recorded the children's visual and auditory responses to each question so that the answers marked were more accurate. Figures 3 depict examples of questions asked of students in order to assess and analyse their learning style.

Visual Score	Auditory Score	R/W Score	K Score	Learning Style
4	3	1	2	MA
6	1	2	1	V
3	5	1	1	A
2	3	4	1	MC
7	2	0	1	MC
7	2	0	1	V
4	2	4	0	MD



B. Data Preprocessing and Modelling



Fig 3 – Questionnaire Example

The collected data was then recorded in Microsoft Excel/Google Sheets for the next stage of data pre-processing. The table below consists of 10 student entries and their respective V, A, R and K scores. As it is seen, the appropriate learning style for each student based on their inputs has also been included. The recorded responses were entered into Microsoft Excel and then converted into individual Visual, Auditory, Reading/Writing, and Kinaesthetic scores for each of the ten questions. So, if a person chooses 6 options from 6 questions that correspond to a Visual Learner trait, their V Score will be 6. The same reasoning applies to the other classes. The addition of four different classes results in the creation of four new classes in the dependent variable. As a result, the predicted class could be any of the following: V, A, R, K, MA, MB, MC, or MD. For example, if a student has a visual score of 5 and an auditory score of 5, they will be placed in the MA class.

	Visual Score	Auditory Score	R/W Score	K Score	Learning Style
0	3	4	3	0	MA
1	2	2	4	2	R
2	4	1	2	3	MB
3	4	3	1	2	MA
4	6	1	2	1	V

For example, if a student has a kinaesthetic score of 6 and an auditory score of 4, they would be classified as a kinaesthetic learner because many kinaesthetic traits overlap with auditory traits, indicating that they are very reactive and responsive. As a result, Kinaesthetic learner. The figure below depicts a portion of the dataset



TABLE I. SAMPLES OF STUDENT DATA

Visual Score	Auditory Score	R/W Score	K Score	Learning Style
3	4	3	0	MA
2	2	4	2	R
4	1	2	3	MB

Fig 4 – Dataset Sample

C. Classification and Testing

The pre-processed dataset was then fitted into the algorithm to predict learning style accurately. The following algorithms were used for model testing:

- Support Vector Machine (SVM)
- Naive Bayes Classifier
- K-Nearest Neighbours (KNN)
- Random Forest Classifier

D. Performance Analysis

The algorithms being used their respective models performed as shown in the table. The classification algorithms may differ depending on the size of the dataset, but this is how they perform for the 500 rows of student VARK- based data.

Model	Accuracy
Random Forest	92%
K Nearest Neighbours	88%
Naive Bayes	92%
Support Vector Machine	94%

TABLE II ACCURACY COMPARISON

By testing and comparing the model performance on the test values, the results were tabulated. The accuracy measured in this scenario is the sci-kit library function called accuracy-score, which is used to calculate the performance of the algorithms. The accuracy of the tested algorithms is depicted in the figures below.

```

from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
knn = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p=1)
knn.fit(x_train, y_train)
pred = knn.predict(x_test)
accuracy_score(pred, y_test)
    
```

Fig 5 - KNN Accuracy



Fig 6 - Random Forest Accuracy

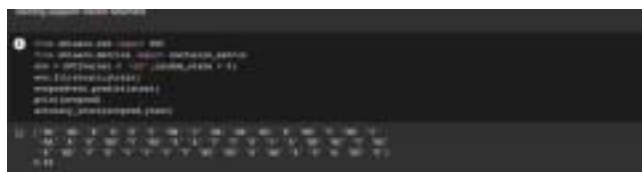


Fig 7 - Support Vector Machine Accuracy

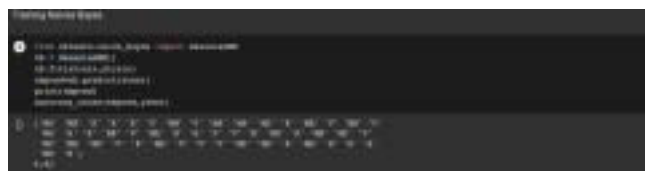


Fig 8 - Naive Bayes Accuracy

It is clear from these figures that deploying machine learning for prediction of learning styles was a success. This helps us understand the connections between a student's psychological approach and their academic activities even more.

V. CONCLUSION AND FUTURE SCOPE

In terms of the project's and research's future scope, the findings indicate that an accurate and layered classification of student learning styles is required to handle subject matter teaching to these students in an appropriate manner. Using this model in schools will help students understand their academic comfort zone when it comes to learning. As a result, students will shape their own form of learning as they grow, increasing the likelihood of good academic results. The large data sample size can also be used for analysis of student learning methods, which can greatly aid in the improvement of our educational system.

The overall size of the data can also be increased to improve the model's performance and to deal with outliers in rare cases of student learning styles. The presence of eight classes also clarifies what type of learner a particular child is. This type of layered classification assists us in understanding students' academic needs and assisting them in learning by teaching them about their own subject learning comfort zones. The patterns recognised by this model can be used to identify dyslexic children and help us deliver academic content in the required manner by adding a few more relevant parameters.

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