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RECOGNITION AND SELECTION OF LEARNING STYLES TO PERSONALIZE COURSES FOR STUDENTS

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ABSTRACT: A learning style is defined as the manner and perspective that identifies the most appropriate way of learning for a student. In educational settings, individual personality styles are especially important as they can help students and tutors become more conscious of their strengths and weaknesses as learners. A survey or questionnaire is the most widely utilized way to identify learning styles. Although these instruments are accurate, they have some problems that impede the recognition of the learning style. Some of these problems include the lack of motivation of students to complete a questionnaire and the lack of self-awareness regarding their learning priorities. Present learning styles lack adaptivity. Our proposed model will be able to recognize the way a student learns best- through videos, presentations, audio, reading, writing or experience - and create a course based on his/her learning style in order to enhance his/her understanding.

1 Introduction

1.1 Background

The students learn in various ways. Few of these students prefer facts, information and experiments while some prefer theory and concept. Others prefer to read written material; some prefer to solve problems. So far, learning management systems with the ideology of "one size fits all" have been developed, which leads to disorientation and a decreased productivity in knowledge overloads. Every pupil has their own style of learning. The determination of the learning style of a pupil is a key step in adapting e-learning or classical training to the requirements of the students.

1.2 Relevance

Knowing the importance of learning personality styles will allow students but will also help teachers to achieve more satisfaction in their learning environment. Even though it can take a lot of time and sometimes be difficult to determine students' learning style, evaluating a child's learning style will help them to develop and excel in the future. Students are also able to stay focused by using technology in the classroom because the teacher is not the only person giving instruction.

Knowing and understanding how to use specific learning styles such as visual, auditory, and kinesthetic learning methods can help the teacher give their students the best. There are several approaches to determine a student's specific learning style, including the Solomon/Felder Index of Learning Styles and the Educational Media Corporation's questionnaire. Including the implementation of technological innovations in a classroom is paramount when talking about learning styles. Classrooms which take advantage of the use of technology will hold their students ' attention as technology is widely used outside of education.

1.3 Motivation

The differences between students in individual differences, interests and learning styles have a strong impact on the effect of learning. The personalized "student-centred" learning emphasized the interest of the student, styles of training, differences in cognitive and other aspects as the basis, providing each student with the most appropriate learning resources and teaching designs and striving for a genuinely individual and effective learning efficiency. The growth of modern society also makes online learners easy to create mental overload and Internet addiction with many different learning tools. There is a rising voice for individual training. The progress of education computerization has led to a rapid development of the personalized learning algorithm. Present learning styles lack adaptivity. Our proposed model will be able to recognize the way a student learns best- through videos, presentations, audio, reading, writing or experience- and create a course based on his/her learning style in order to enhance his/her understanding.

1.4 Objectives

Smart education is an activity that can be undertaken everywhere and every time, beyond traditional classrooms. Tablets can browse personalized learning content that could be of audio, video or graphical types. Some of the devices which can be used include Internet enabled watches to listen to recorded lectures. The technology platform being built can be deployed in a cloud-based environment for easy access to international audiences, without any restrictions on scalability.

2. Technical Description & Literature Survey

2.1 Theoretical Background

We strongly believe that personalization, mobility plus information is what future school means. Intelligence in education implies the use of smart technologies and methods that enable personalized learning to improve the quality and efficiency of learning. Firstly, integrated and standardized learner profiles (models) must be implemented in personalized learning. Later, personalized recommender systems based on ontologies will be created to suggest learning components according to the characteristics appropriate for individual learners. According to the course curriculum, customized learning pathways could be developed for different learners for each subject. A variety of smart technology, such as ontology, recommendation systems, smart actors, multiple decision-making criteria, methods and instrumentation, etc., should be applied to determine the performance, appropriateness and quality of learning elements.

The following steps could be taken to enforce this method:

- Build models (profile) for learners based on their style of learning and other specific needs.
- Linking learner models to the related components of education (learning content, methods, practices, resources, apps).
- Develop corresponding ontologies.
- Develop and incorporate personalized training scenarios.
- Creation of various academic decision-making frameworks

System models of learning differ in the following ways:

- Underlying model of learning style
- Type of assessment (implicit or explicit)
- Techniques of modelling (regulations, data mining, techniques of machine learning [5-16]. Also, nowadays application of Machine learning is becoming important in every field).
- Number of modelled student characteristics in addition to learning preferences (knowledge level, objectives).
- The type, size, and conclusions of the experiments which were reported.

Ontologies and recommender systems should be based, first and foremost, on the established links between learning styles of the student concerned and the above-mentioned learning components.

The paper aims to address established interconnections and ontologies of Felder-Silverman learning styles [1] and inquiry-based learning (IBL) activities [2] in order to recognize the student's learning styles.

2.1.1 Felder-Silverman learning styles model

According to them, ‘‘Students learn in many ways – through vision and hearing; reflection and action; logical and intuitive reasoning; the memory and visualization and drawing analogies and building mathematical models; constantly, fittingly, and in the beginning. Teaching methodologies may also differ” [1]. A model of learning style classifies students according to the way they receive and process information on a range of scales.

2.1.2 Inquiry-based Learning

The IBL definitions are presented by various aspects in scientific literature: “The creation of a classroom where students are engaged in essentially openminded student-centered, hands-on activities.” [2]

As far as education is concerned, the inquiry-based approach entails students ' curiosity about world problems and the theories that surround them. We can try to simplify or model the situation if their questions are too complicated. Then, by collecting and analyzing information, making representations and creating links to their existing knowledge, we will try to answer their questions. They then try to interpret their observations before discussing their conclusions with others, ensuring that they are correct and sensible.

2.1.3 Kolb’s Learning Style

“Kolb's experiential learning style theory is typically represented by a four-stage learning cycle in which the learner 'touches all the bases': Concrete Experience, Reflective Observation, Abstract Conceptualization and Active Experimentation.”[3]

2.2 Technical specification of the project, resources required

2.2.1 Technical specifications

Our Solution to the problem discussed before is to initially conduct the tests which will gives us the dataset needed for our machine learning algorithms. The K-Mode [4] clustering algorithm is first used to make 'visual', 'auditory' and 'tactile' clusters from this dataset. After this, we use the Naïve Bayes Classification model and train this model using our training dataset for classification of data. Finally, we use the test data to check the accuracy of our entire solution.

2.2.2 Framework of a Smart Education Model

Here, a template for an intelligent learning device is proposed. Smart education means personalized training wherever and whenever. The design of a software system for the determination of training stylistic based on artificial intelligence is suggested here to make it practical and widely available. The changes in data can be caused by different courses such as art, science and engineering or because of textual, media, online aptitude testing or speech-based interfaces in e-learning environments. The wide range of factors for the students for each model of learning would make it easier to select the most suitable model for a specific environment.

2.3 Block diagram

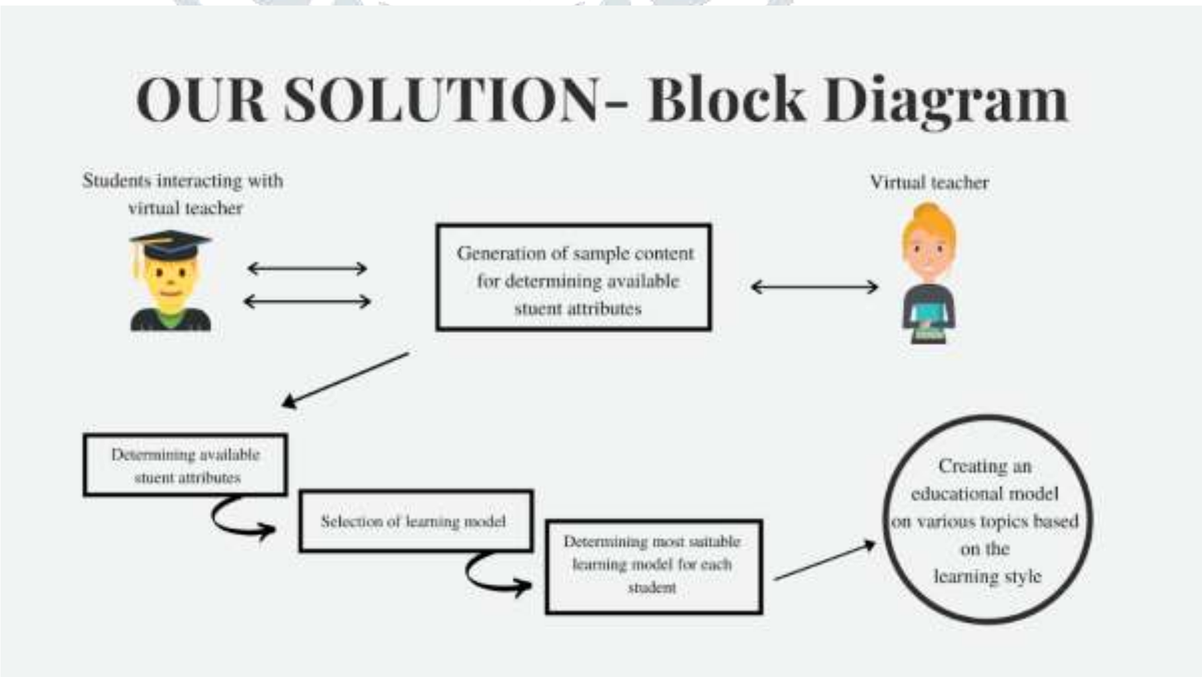

Fig 2.1. Block Diagram- Solution

In Fig 2.1, we can see that our solution employs a virtual teacher and the students interact with this teacher using our platform. The platform generates sample content for determining the student attributes. From these attributes, the platform selects the most appropriate learning model for each student and creates an educational model depending on this learning style.

The actual implementation has been depicted in the following block diagram in Fig 2.2:

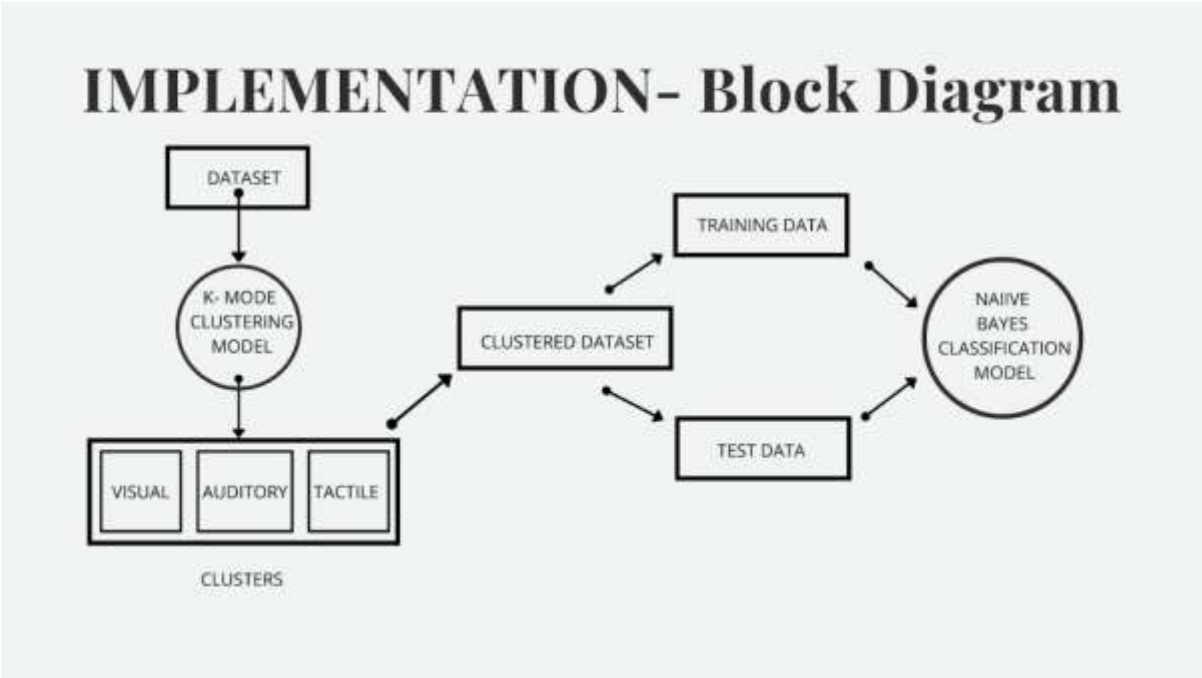

Fig 2.2 Block Diagram- Implementation

In Fig 2, the data accumulated from the questionnaire is our dataset. We use the Kmode clustering model[4] to form three clusters of learning styles wiz. Visual, auditory and tactile clusters. After this step, The Naïve Bayes Classification Model[4] is trained using the training dataset, and then we use the test data for classifying the actual learning styles for the students.

2.4 Flow chart

In Fig 2.3, we have the clustering flowchart. Initially, the dataset is created from the questionnaire and this data is then passed on to the K-mode clustering algorithm to create clusters of the learning styles. These clusters are Visual, Auditory and Tactile clusters and each cluster corresponds to a different learning style.

The Flowchart is as follows:

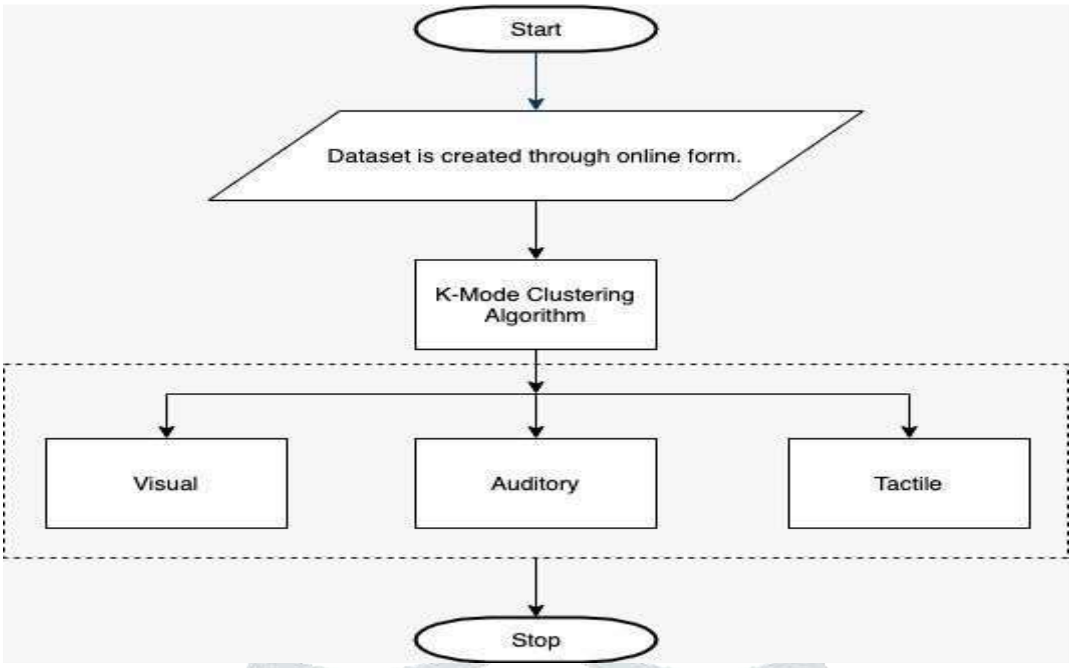

Fig 2.3 Clustering Flowchart

After Clustering, the dataset is split into training and testing dataset. Our Naïve Bayes Classification model is trained using this training dataset and now we can test our model using the test data. The factors of learning style, accuracy and efficiency are calculated after classification. The flowchart is depicted in Fig 2.4:

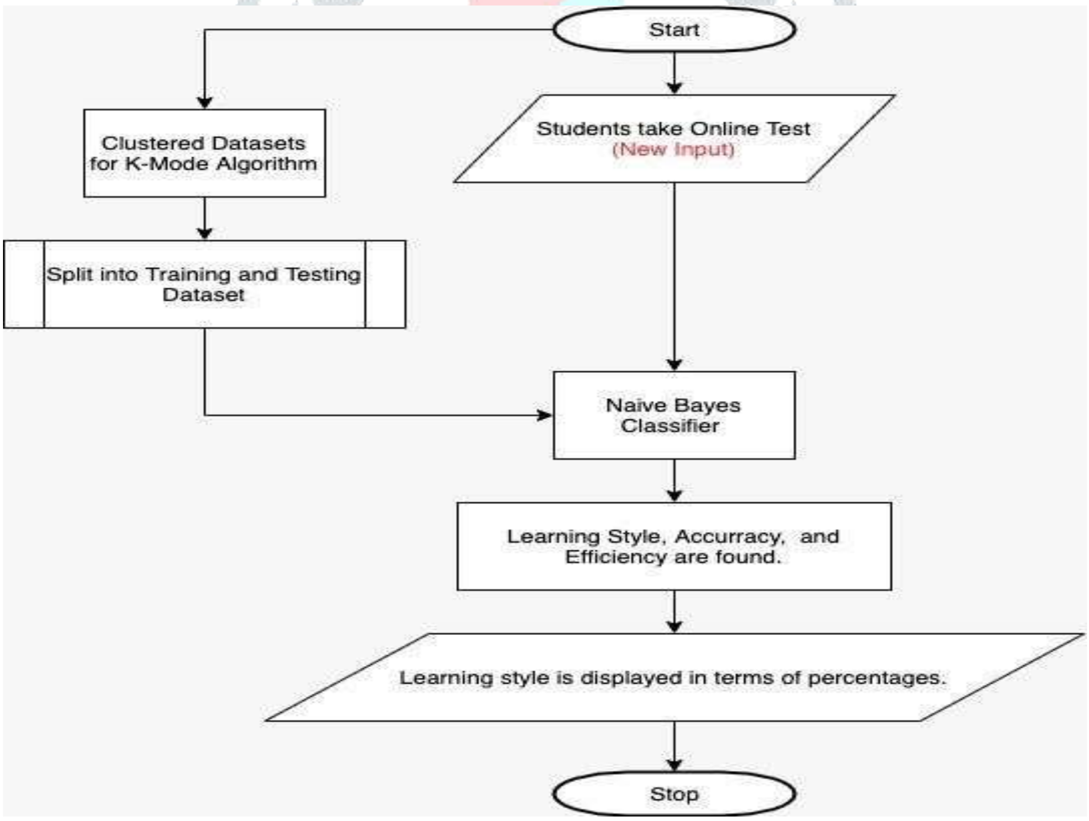

Fig 2.4 Naïve Bayes Classifier Flowchart

3. System Design

3.1 Block wise Design

3.1.1 Dataset

We created a questionnaire with questions to understand the personality of the students: Example of some questions-

- What kind of book would you like to read for fun?
- You're out shopping in a mall, and you're waiting in line at the cash counter. What are you most likely to do while you are waiting?
- When in a new place, how do you find your way around?

There were 20 such questions and each question had 3 options (A/B/C) to choose from. We circulated this questionnaire and collected 320 responses. The response was saved in the form on a CSV file. Our dataset looked like this:

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Class
A	A	C	A	B	C	A	B	A	C	A	B	B	C	B	B	C	B	C	B	1
A	A	A	A	C	A	B	A	A	A	A	A	B	B	B	C	B	B	B	B	0
B	A	C	A	A	A	C	C	A	C	B	B	B	C	B	A	A	C	C	A	1
C	A	A	C	A	A	C	C	B	B	A	B	B	C	B	C	A	C	B	A	1
A	B	A	B	A	C	C	A	A	C	A	B	B	B	B	A	C	C	A	A	2
A	A	A	A	A	B	C	A	C	A	B	B	C	C	B	B	B	B	A	A	0
A	B	A	B	A	B	B	B	A	A	B	B	B	C	B	C	A	B	B	A	2
C	A	A	A	A	C	A	A	B	A	A	C	B	B	B	B	A	B	C	A	0
A	B	A	B	A	C	C	B	C	A	A	C	A	B	B	C	C	A	A	A	2
A	B	B	A	B	C	A	C	A	C	A	C	B	C	B	C	C	A	C	A	0
B	A	A	A	A	A	A	B	A	A	A	C	B	B	A	B	A	C	A	B	0
A	B	B	A	C	A	A	A	A	C	A	C	C	B	A	C	B	A	A	C	0
B	B	B	C	A	B	A	A	A	A	B	B	B	B	B	A	A	B	C	A	0
B	A	A	A	B	A	C	A	A	A	C	C	B	C	B	B	B	B	A	A	0
B	B	C	A	A	C	C	B	A	C	C	C	A	B	B	A	A	B	B	A	2
A	C	A	C	A	B	C	B	A	A	A	A	B	B	B	B	B	B	A	A	0
B	A	C	A	A	A	A	B	A	B	C	B	A	B	C	A	C	A	C	B	0
A	C	A	A	C	C	A	A	A	B	B	C	B	C	B	B	A	C	A	A	1
C	B	B	A	A	C	C	B	B	B	B	B	C	B	B	C	B	C	A	C	0
C	B	C	A	A	B	C	B	A	A	C	A	C	B	B	B	A	C	C	A	1
A	A	C	B	A	C	C	B	A	A	C	A	B	B	B	C	A	C	A	A	1
A	C	A	C	A	C	A	B	C	C	A	C	A	C	C	C	A	C	A	A	0
A	A	A	B	B	A	C	A	A	A	A	C	C	B	C	B	B	C	A	A	0

Fig 3.1. Dataset

3.1.2 K-Modes Clustering Model

We used the K-Modes clustering algorithm to create 3 clusters- 0, 1 and 2.

0- Visual

1- Auditory

2- Tactile

The output of the K Modes clustering algorithm resulted in a CSV file of our original data set along with the class that each data entry belonged to:

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Class
A	A	C	A	B	C	A	B	A	C	A	B	B	C	B	B	C	B	C	B	1
A	A	A	A	C	A	B	A	A	A	A	A	B	B	B	C	B	B	B	B	0
B	A	C	A	A	A	C	C	A	C	B	B	B	C	B	A	A	C	C	A	1
C	A	A	C	A	A	C	C	B	B	A	B	B	C	B	C	A	C	B	A	1
A	B	A	B	A	C	C	A	A	C	A	B	B	B	B	A	C	C	A	A	2
A	A	A	A	A	B	C	A	C	A	B	B	C	C	B	B	B	B	A	A	0
A	B	A	B	A	B	B	B	A	A	B	B	B	C	B	C	A	B	B	A	2
C	A	A	A	A	C	A	A	B	A	A	C	B	B	B	B	A	B	C	A	0
A	B	A	B	A	C	C	B	C	A	A	C	A	B	B	C	C	A	A	A	2
A	B	B	A	B	C	A	C	A	C	A	C	B	C	B	C	C	A	C	A	0
B	A	A	A	A	A	A	B	A	A	A	C	B	B	A	B	A	C	A	B	0
A	B	B	A	C	A	A	A	A	C	A	C	C	B	A	C	B	A	A	C	0
B	B	B	C	A	B	A	A	A	A	B	B	B	B	B	A	A	B	C	A	0
B	A	A	A	B	A	C	A	A	A	C	C	B	C	B	B	B	B	A	A	0
B	B	C	A	A	C	C	B	A	C	C	C	A	B	B	A	A	B	B	A	2
A	C	A	C	A	B	C	B	A	A	A	A	B	B	B	B	B	B	A	A	0
B	A	C	A	A	A	A	B	A	B	C	B	A	B	C	A	C	A	C	B	0
A	C	A	A	C	C	A	A	A	B	B	C	B	C	B	B	A	C	A	A	1
C	B	B	A	A	C	C	B	B	B	B	B	C	B	B	C	B	C	A	C	0
C	B	C	A	A	B	C	B	A	A	C	A	C	B	B	B	A	C	C	A	1
A	A	C	B	A	C	C	B	A	A	C	A	B	B	B	C	A	C	A	A	1
A	C	A	C	A	C	A	B	C	C	A	C	A	C	C	C	A	C	A	A	0
A	A	A	B	B	A	C	A	A	A	A	C	C	B	C	B	B	C	A	A	0

Fig 3.2. Clusters generated by K-Mode Clustering

3.1.3 Naïve Bayes Classification Model

We then used a categorical NB algorithm to train and test the dataset. The dataset was split into training (80%) and testing data (20%).

O/P of NB classifier-

```
Categorical Naive Bayes
Number of mislabeled points out of a total 29 points: 2, performance 93.10%
Confusion matrix, without normalization
[[10  0  0]
 [ 0 15  0]
 [ 0  0  4]]
Normalized confusion matrix
[[1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]
```

Fig 3.3. Naïve Bayes Classification

An email was immediately sent to the student about their learning style:

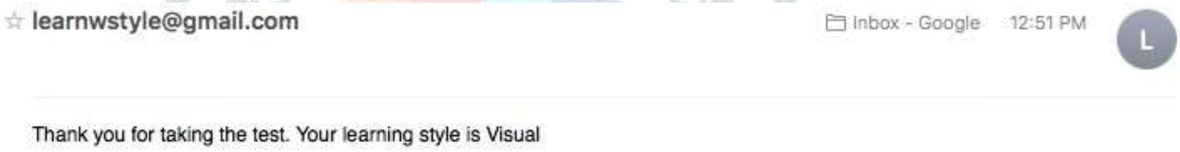

Fig 3.4. Result by Email

3.2 Web page Design

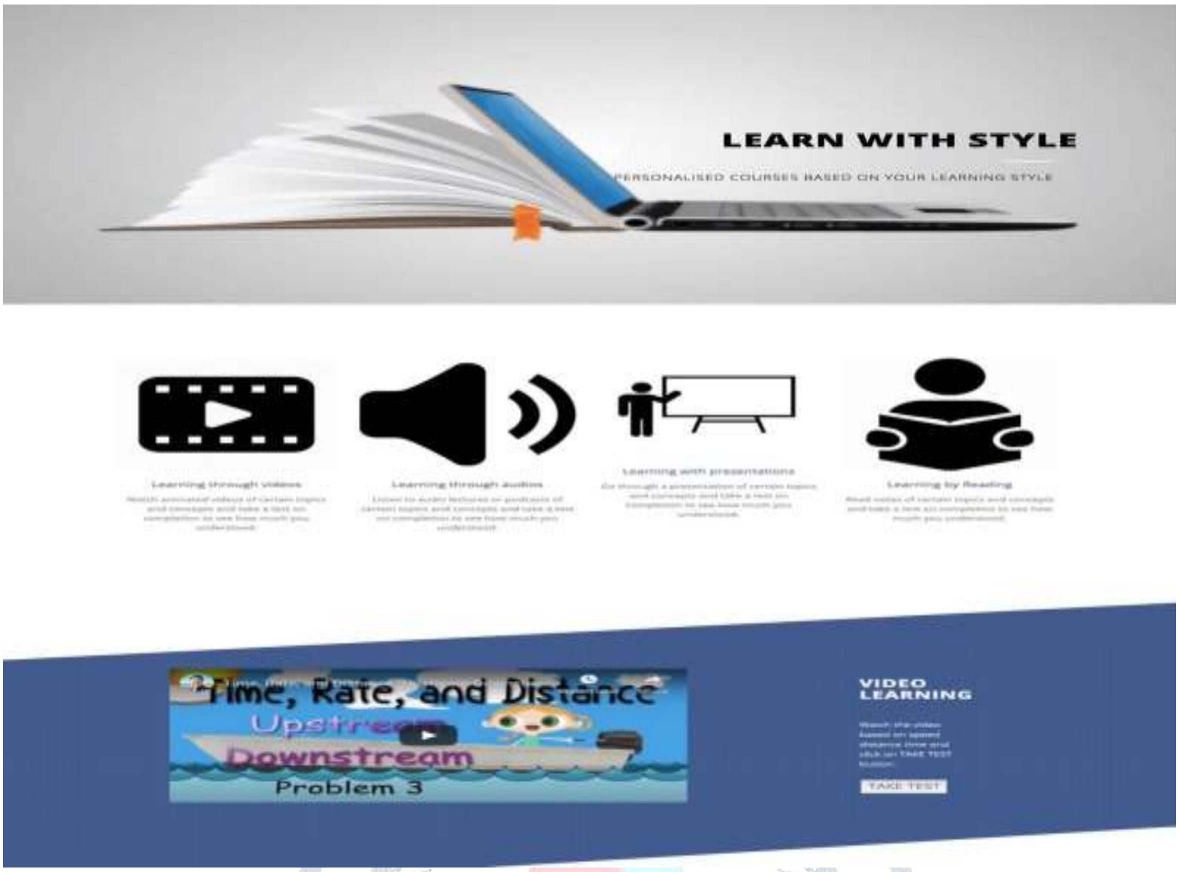

Fig 3.5. Web page Layout

Fig 3.5 shows the Home Page of our website. It gives information about the different learning styles that the students can possess. It directs the students to take the test for their learning style.

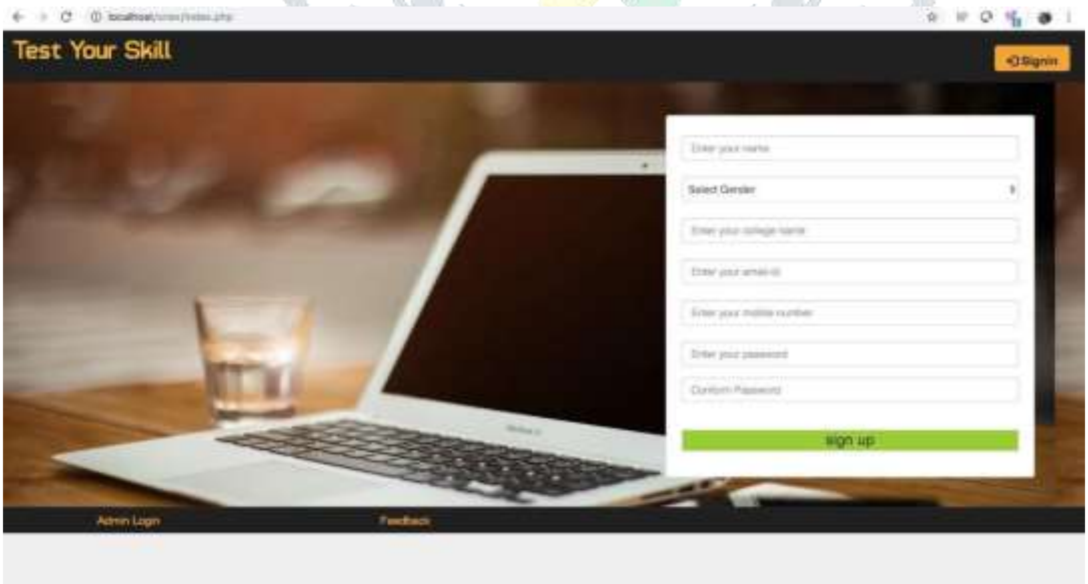

Fig 3.6. Landing Page

When the student clicks on “Test” in Fig 3.5, the Landing Page is obtained as shown in Fig 3.6. This is basically the Sign-Up page where the students fill in their credentials.

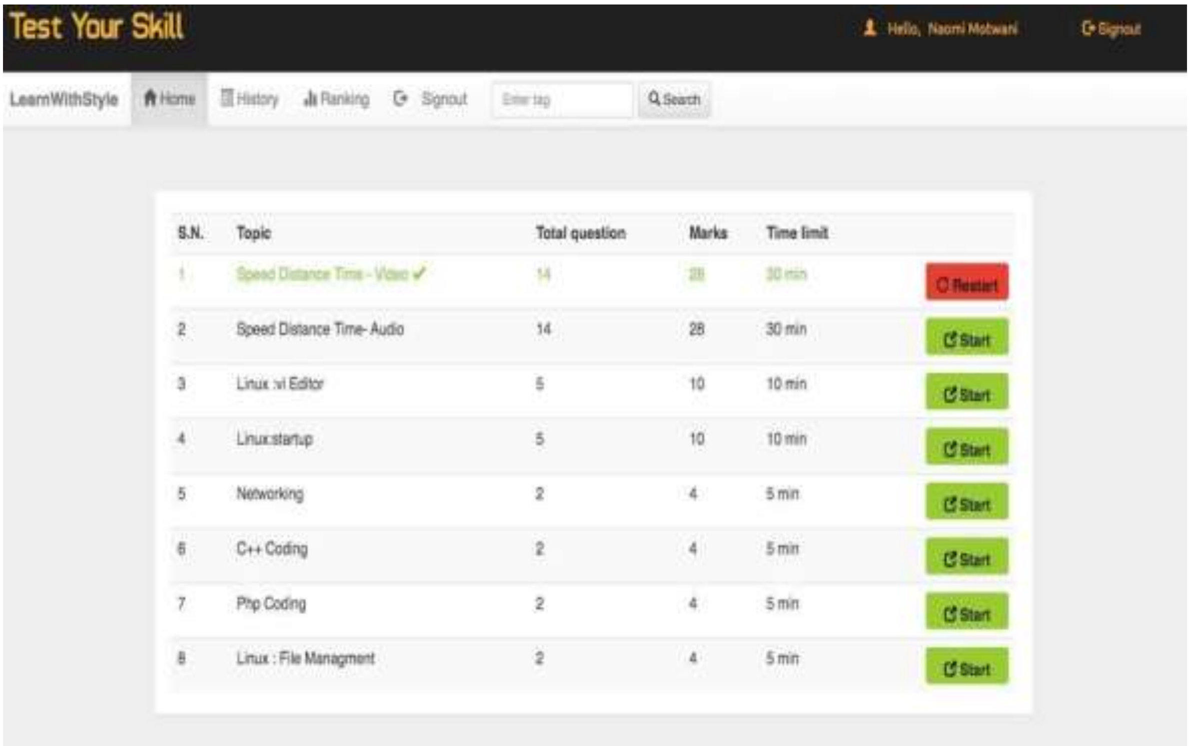

Fig 3.7 Choices of Courses Available

Fig 3.7 shows us the various tests that students can take to determine their learning styles. It consists of the various subjects that the student has opted for.

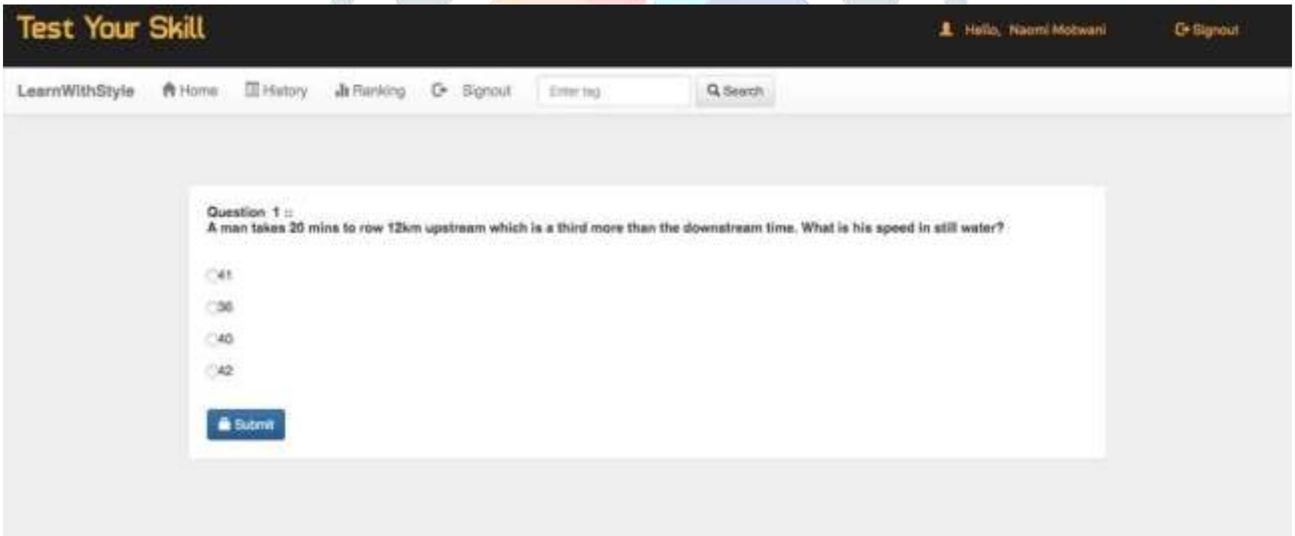

Fig 3.8 Test Page

Fig 3.8 shows us the test page which consists of all the questions in the test.

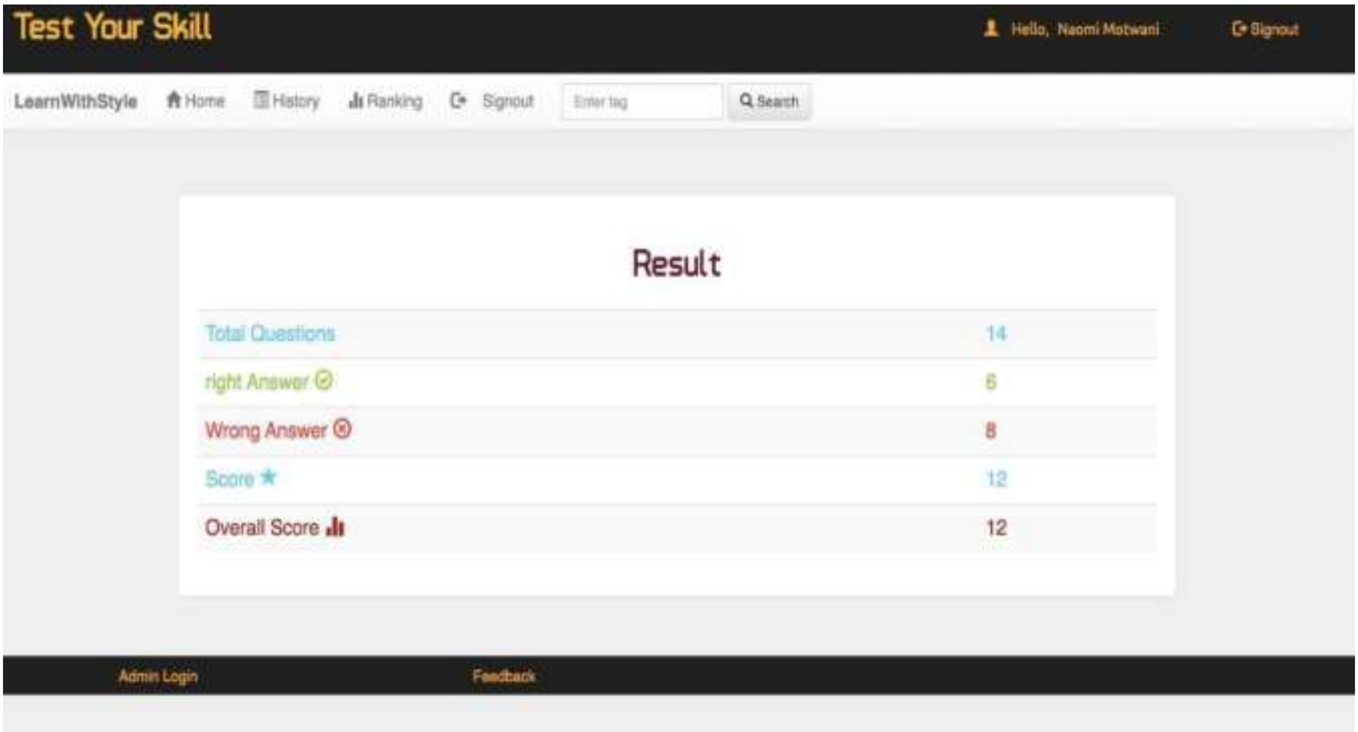

Fig 3.9 Result Page

Fig 3.9 gives the result of the test taken and displays the score i.e. the marks.

Fig 3.10 is the final summary page for the teacher to look into.

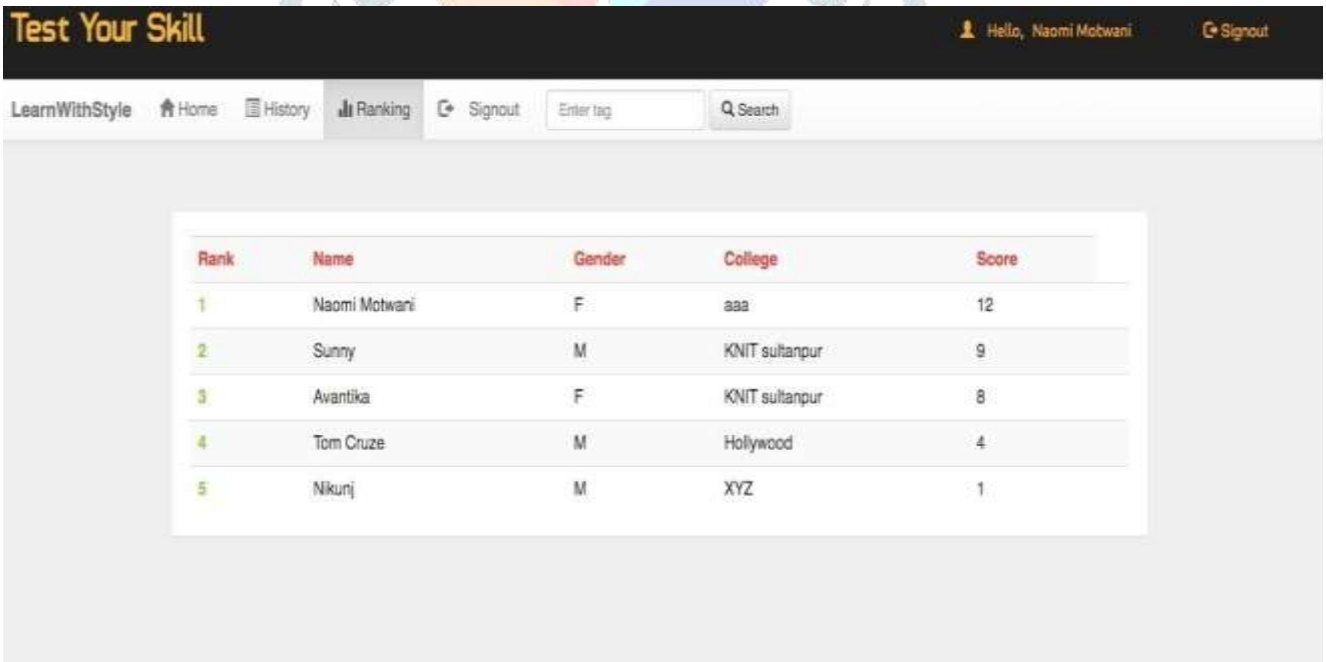

Fig 3.10 Summary Page

4. Implementation, Testing and Debugging

In this project, we have implemented the Naïve Bayes Classifier Model for the prediction of the clusters as established by the K-Modes Clustering Algorithm on the data set. We implemented three different types of the Naïve Bayes Classification.

They are as follows:

- Multinomial Naïve Bayes
- Gaussian Naïve Bayes
- Categorical Naïve Bayes

We calculated the accuracies of these three models and the accuracies are shown in the following screenshots:

- Multinomial NB:

```
Naomis-MacBook-Air:Project_kmodes naomimotwani$ python3 mnbayes.py
Multinomial Naive Bayes
Number of mislabeled points out of a total 29 points: 11, performance 62.07%
Naomis-MacBook-Air:Project_kmodes naomimotwani$
```

Fig 4.1. Multinomial NB

We obtained a low accuracy of 62.07% with the Multinomial Naïve Bayes Classification Model.

- Gaussian NB:

```
Naomis-MacBook-Air:Project_kmodes naomimotwani$ python3 nbayes.py
Gaussian Naive Bayes
Number of mislabeled points out of a total 29 points: 7, performance 75.86%
Naomis-MacBook-Air:Project_kmodes naomimotwani$
```

Fig 4.2. Gaussian NB

We got a better performance of 75.86% from the Gaussian Naïve Bayes classification model but this percentage was also not up to the mark.

- Categorical NB:

```
Categorical Naive Bayes
Number of mislabeled points out of a total 29 points: 2, performance 93.10%
Confusion matrix, without normalization
[[10  0  0]
 [ 0 15  0]
 [ 0  0  4]]
Normalized confusion matrix
[[1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]
```

Fig 4.3. Categorical NB

We obtained the best accuracy of 93.10% with the Categorical Naïve Bayes classification model and thus we decided to use this mode in our project.

5. Results and Discussion

The image shows an output obtained after an individual attempts the given test. The percentages show how well the individual will respond to a given way of learning. This result will help the educators make personal learning modules for students. It was discussed to display the result in a visual manner rather than as a graph for easier understanding.

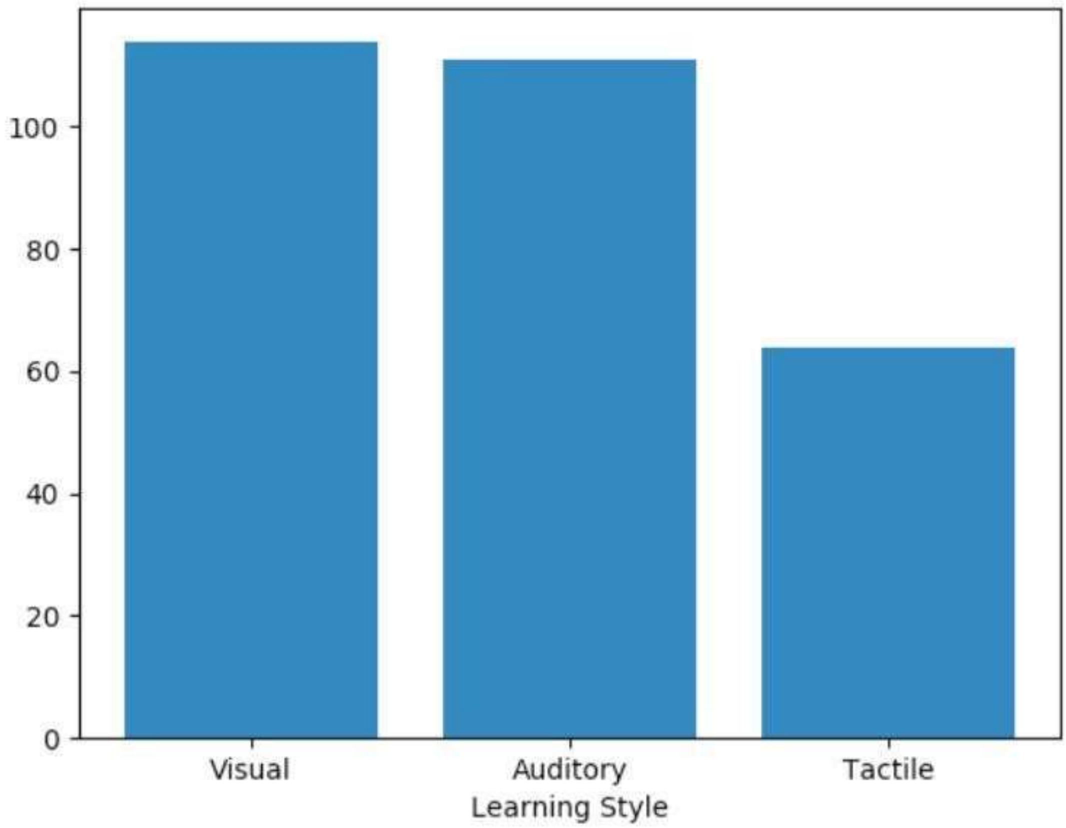

Fig 5.1 Learning Style Graph

In our module, we used 3 types of Naive Bayes classifier, in order to predict the output of our model. Out of the three the Categorical Naive Bayes classifier proved to be most efficient. The result is shown in the table below:

Classifier	**Accuracy (%)**
Multinomial Naïve Bayes	62.07
Gaussian Naïve Bayes	75.86
Categorical Naïve Bayes	93.10

Table 5.1 Classifier Accuracy

The Categorical Naïve Bayes Classification Model works well for categorical values i.e. if the example has a set of features or not. The options of the test have been taken as the set of features, and the solution of the question is treated as the matching with the feature. The Multinomial NB takes repetitions into account instead of occurrences compared to Categorical NB, hence the Multinomial NB has the worst result and Categorical has the best result. The Gaussian NB is built on the assumption of a normal distribution of probabilities. It means that all the learning styles from the answers to the questions are distributed by the Gaussian Law, hence the result is just an average one and not the best one. Thus, the Categorical Naïve Bayes Classification Model has the best accuracy for our project.

Conclusion:

The above-mentioned model for smart education, which has been built here, will lead in future to the provision of inclusive training to a broad public of students in various cultures, geographies, academic types, digital learning or e-learning. The model gives a set of various learning features that can be supplemented by personalized learning. This readily available set would make it easy for the students to determine for a specific learning environment what learning attributes can be picked. This is the first ever model to compare different learning concepts and to compare classification strategies based on the performance of built artificial intelligence models. This model proposes a virtual instructor that can be housed in a cloud-based environment and communicate with the students in ways that are scalable by means of naturally occurring language processes application programming interfaces to automatically evaluate their learning styles. The system is intended to provide a practical solution that can be implemented to student learning. Different providers of educational materials, either conventional schools or online learning platforms, can then use established learning patterns of the students to deliver inclusive training.

Future Scope:

The software program can be deployed in a cloud environment, with no limitations on scalability, allowing easy access for global audience members. To track the student's actions and evaluate the student attributes available, sample learning contents should be produced. It is proposed that application programming interfaces that process natural languages, speech to text, and text to speech application programming interfaces, can in future be used to generate experimental material for training and to simulate the communication between students and teachers, and virtual professors.

The accuracy obtained by the Categorical Naïve Bayes Classifier was 93.01%. This accuracy can also be further improved close to a full hundred percent using better algorithms in the future.

Acknowledgment

I would like to express my gratitude towards my mentor, Dr. R. C. Jaiswal for guiding me through the research. His contribution in providing the research guidance required for this was immense and his insight in the topic gave the paper what was needed.

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