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MATHVISION PROTOTYPE USING PREDICTIVE ANALYTICS

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ABSTRACT

Malaysia is currently going towards Industrial Revolution (IR) 4.0 which makes Science, Technology, Engineering and Mathematics (STEM) subjects become more crucial. IR 4.0 covers a lot of aspects especially in digital transformation in manufacturing, and this certainly requires strong mathematical knowledge. To achieve this goal, students need to have a good foundation in Mathematics subject. However, due to the increased number of students nowadays, teachers are facing challenges to track students' progress efficiently. In this study, a predictive model has been developed that aims to assist Mathematics teachers in monitoring their students. The prototype, called MathVision, can track students' progress effectively in each topic and subtopic of Mathematics subject and predict the grades that students will obtain based on the history result. A total of 207 instances was collected among Form 5 students from a government school to represent the samples for the modelling task. The Multiclass Decision Forest algorithm appeared to be the best predictive model with 95.16% accuracy, as compared to Boosted Decision Tree, Logistic Regression, and Neural Network. Flutter framework and Firebase services were used for front-end and back-end system respectively, and Microsoft Power BI was used for data visualization. The result of prototype testing showed that MathVision could predict students' grade for Quiz 2 based on Quiz 1 performance. MathVision is also capable for real-time prediction that guarantees an immediate response time which can help Mathematics teachers to support students who need further assistance in this subject based on the prediction given. For MathVision's future improvement, the number of instances needs to increase, and more significant variables need to be added.

Keywords: *Data Analytics, IR 4.0, Mathematics, Predictive Model, Real-Time Prediction*

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1. Introduction

Data has become the new oil in this digital world. Many researchers have been conducting studies on data using machine learning algorithms to extract the valuable data to enhance a better life among society (Bhageshpur, 2019; Carmel, 2016). To prepare the young generation with IR 4.0, the current education systems are required to focus more on STEM subjects. STEM education can help students to become problem-solvers, innovative, and technology literate society. This will produce young graduates that can adapt to the current trend of job markets that require high technical and cognitive skills. Mathematics is a gateway to many scientific and technological fields; hence, it is a crucial component of a comprehensive STEM program (Tezer, 2019). For many years, the concerns about underachieving in Mathematics subjects have been highlighted (Eng et al., 2010). One of the reasons is due to the large number of students which makes it difficult for the teachers to monitor their students' progress efficiently (Chen & Upah, 2020; Ramli et al., 2020).

Furthermore, examination marks do not reflect the overall progress of a student's performance. For instance, although some students may get the same marks for their results in Mathematics subject, they might have a different level of understanding in each chapter or subtopic. Hence, a system is needed that to allow teachers to monitor each student's progress in a detailed manner and to identify their strengths and weaknesses on certain chapters or subtopics in Mathematics while providing relevant feedback and assistance to the student (Ramli et al., 2020). The aim of this paper is to present the development of the MathVision prototype that could assist the mathematics teacher in monitoring their students' performance. This paper is the extension of the earlier publication in which it generally described the general aspects of the system that only covers prototype interfaces and partial of its results. The specific contributions of this study include and are not limited to: 1) the architecture of the MathVision prototype, and 2) the capability of MathVision that allows analysis on each subtopic for predicting the grade. The remainder of this work is structured as follows: Section 2 presents the related works, Section 3 explains the methodology of the research, Section 4 describes the result and discussions, and Section 5 explains the conclusion and future work that can be made to improve the research.

2. Related Works

Data analytics is a method of searching patterns in a cleaned data to provide valuable insight for the researchers to solve problems (Ameen et al., 2019; Knips, 2019). Types of data analytics are descriptive, diagnostic, predictive, and prescriptive. The level of complexity in data analytics grows from descriptive to prescriptive analytics. This research is applying predictive data analytics to predict students' grades in examination. Predictive analytic is a method that predicts future occurrences based on the past result and dataset (Raj, 2015). Today's education system has been extensively integrating with various technologies for improving the learning process (Mohammad et al., 2012). The smart education approach is slowly thriving in the education market (Chen et al., 2020; Rahman et al., 2015). Teachers tend to explore various ways to monitor and track their students' progress using data science (Dave, 2020). In formulating the educational analytics paradigm, academic and learning analytics are consistently overlapped. Learning analytics is associated with the learner's experience, and academic analytics implicitly integrates the overall institute and its performance (Waheed et al., 2020). Research on learning analytics of student outcomes has risen since 2017 (Namoun & Alshanqiti, 2021). Namoun and Alshanqiti (2021) surveyed 62 articles, half of the surveyed studies predicted learning outcomes of traditional classroom learning, while the other half focused on online and blended learning. The authors also mentioned that most of the research were focusing on undergraduate university courses and STEM specialties. However, study for secondary and primary school on STEM courses is still inadequate. Hence, this research is focusing on the secondary school Mathematics course to predict the grade based on the previous test results.

Several studies on predictive analytics in education have been conducted by previous researchers (e.g., Ahamed et al., 2017; Deeva et al., 2022; Deng et al., 2019; Gutiérrez et al., 2020; J.JebaEmilyn et al., 2017). Previous studies on data analytics in education shows that the extraction of valuable information from the raw data could achieve a better learning process in courses (Deng et al., 2019). Many machine learning techniques have been adopted in data analytics to predict students' performance such as deep neural network, random forest, decision tree, support vector machine, and k-nearest neighbor (Ahamed et al., 2017; Bujang et al., 2021; Deng et al., 2019; Namoun & Alshanqiti, 2021; Yusof & Khalid, 2021). The results show better performance than traditional analysis techniques when dealing with lots of data that consists of non-linearly separable and noise. In our work, we use four machine learning algorithms specifically Multiclass Decision Forest, Multiclass Boosted Decision Tree, Multiclass Logistic Regression, and Multiclass Neural Network to train the model. Then, the model with the highest accuracy will be selected in the prototype testing.

More recently, many researchers have developed data analytics dashboards to display variety of information in visualize techniques. Many student-facing dashboard were developed to increase students' self-awareness, promote positive behaviour change, and enhance their academic achievement. However, current research on predictive the grade based on subtopic analysis has not yet been developed (Deng et al., 2019). By identifying student progress according to each subtopic and predicting the grade based on the history result, it could help the teachers to improve their pedagogies skills and assessment design based on the subtopic that need to be guided further.

3. Methodology

This section explains the four phases of research methodologies in developing a predictive model for MathVision. The sequence of the research methodology phases starts from data collection, data preparation, model development, and system development as shown in Figure 1. Details explanation for each phase is discussed in the next subsections.

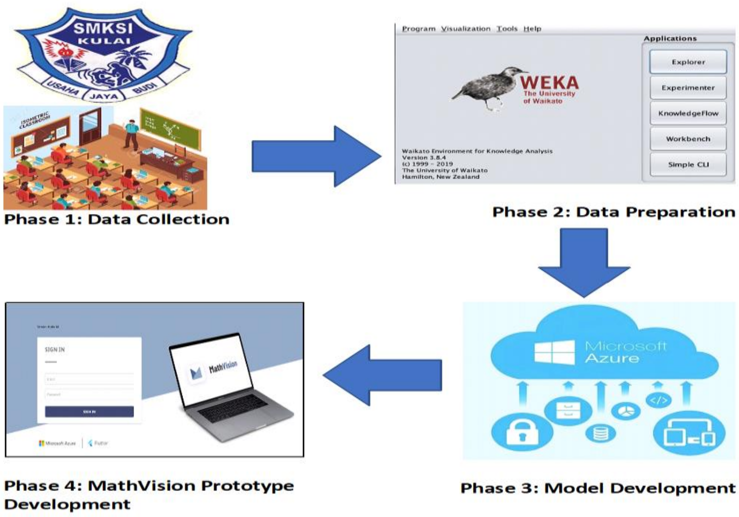

Figure 1. Research Methodology Workflow.

3.1 Data Collection

An interview session was conducted with a Form 5 Mathematics teacher to collect information related to the subject syllabus. Then, 150 samples of Quiz 1 and Quiz 2 data were collected from Form 5 students in Sekolah Menengah Kebangsaan Sultan Ibrahim, Kulai, Johor from 25th April until 1st May 2021 using the Google Form platform. The data was collected based on students' time in answering the quizzes, and the number of correct answers. However, Google Form cannot capture the time duration for students to answer each question. Hence, an extension named Quilgo needs to be used to capture this data. A total of 20 questions for both quizzes and each question were allocated for 4 minutes. If the students took more than 4 minutes to answer, then the time taken would be labeled as overtime. Quiz 1 covers Chapter 1 with the subtopics of Direct Variation, Inverse Variation, and Joint Variation, while Quiz 2 covers Chapter 2 with the subtopics of Addition and Subtraction Matrices, Inverse Matrices, Multiplication of Matrices, Solving Simultaneous Linear Equation using Matrices, and Identity Matrices. The difficulty level for each question was assessed by the selected Mathematics teacher first before it was given to the students. This is to ensure the difficulty level for each question was not differ much.

3.2 Data Preparation

Data preparation is a process of cleaning and transforming raw data into a suitable format for data analysis. The raw dataset consists of 150 instances, 10 numeric attributes, and 14 nominal attributes. Waikato Environment for Knowledge Analysis (WEKA) (Frank et al., 2009) was used to prepare the data for model development. Several steps were executed during the data preparation phase including removing the attributes that are not related, converting several numeric attributes to nominal attributes, and removing the extreme values and outliers within the dataset. The oversampling technique was applied to the data by increasing the number of instances and balancing the class labels, which were Good, Average, and Poor. The oversampling technique used was Synthetic Minority Oversampling Technique (SMOTE).

3.3 Model Development

Cleaned data that was obtained during the data preparation phase was used for the model development. Microsoft Azure Machine Learning was utilized to create four predictive models from four machine learning algorithms namely Multiclass Decision Forest, Multiclass Boosted Decision Tree, Multiclass Logistic Regression, and Multiclass Neural Network. We employed the default parameter for the model development, which can be referred in (Razak et al., 2021). The class label for this cleaned dataset is Quiz 2 grade which consists of Good, Average, and Poor grades. To train the models, Quiz 1 performance variables including student's score for each question and time taken to complete a question were required.

The next process for developing the predictive models was to conduct the parameter tuning. This process needs to be applied to all machine learning algorithms that have been mentioned earlier. For each algorithm, one parameter was selected and tuned accordingly to find the optimum result. The list of parameters that have been tuned can be referred in (Razak et al., 2021). Then, Azure ML Canvas has been used to develop a predictive model by interconnecting the modules (Dataset, Split Data, Machine Learning Algorithm, Train Model, Score Model, and Evaluate Model).

3.4 MathVision Prototype Development

MathVision prototype is developed with intuitive User Interface (UI). The deployment of the best predictive model was created based on the performance analysis of the selected algorithms. Two major cloud computing services, Firebase and Microsoft Azure services, were used for this system. There were three parts for the development of the MathVision prototype which consists of Front-End System, Back-End System, and Hosting. For the front-end system, Flutter was used to develop the system User Interface of MathVision, while as for data visualization, Microsoft Power BI was used where it helped the users to interpret data graphically.

This prototype consists of Sign-In page, Home page, Real-Time Prediction page, and Report page Sign-In page is where the user needs to insert his/her email address and password. Next, Home page is where the user has the option to choose whether he/she wants to view the report of Quiz 1 or view the real-time prediction grade for Quiz 2. If the user selects view Quiz 1 report button, it will go to the Report page that visualize the analysis of Quiz 1. Meanwhile, if the user selects real-time prediction button, it will go to the Real-Time Prediction page which visualize the prediction of Quiz 2 based on the Quiz 1 result.

For the back-end system, Python language was used to create a data flow connection between the Front-end system and predictive model. To achieve the result, RESTful API was developed using Flask, a micro web framework written in Phyton. It is an API that uses HTTP requests to access and send the data. Also, Firebase, a Backend-as-a-Service (BaaS) developed by Google was used to create the back-end system for the Storage system and Authentication system of the web app. As for the hosting service, the web application was deployed using Firebase Hosting, while the predictive model was hosted using Heroku, a Platform-as-a-service (PaaS). Figure 2 shows the overall MathVision system architecture, and Table 1 shows the data flow of MathVision system architecture.

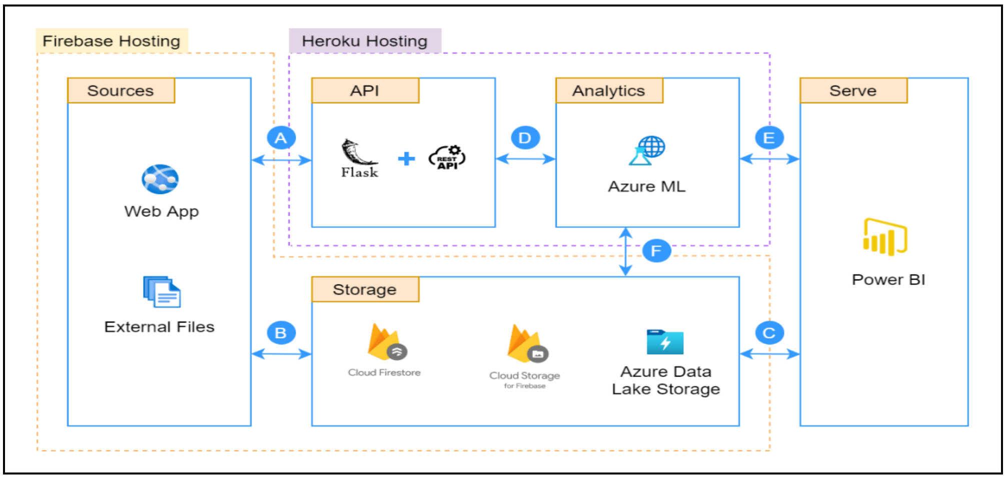

Figure 2. MathVision System Architecture.

Table 1. Data Flow of MathVision System Architecture.

Data Flow	Description
A	Data from the sources such as the web app and external files can be requested and accessed using RESTful API.
B	Data from sources such as the web app and external are stored in the Storage system via Firebase Cloud Firestore, Firebase Cloud Storage, or Azure Data Lake Storage.
C	Data from the Storage system are sent to Power BI for data visualization.
D	Data/Services from the Predictive Model in the Analytics system can be exchanged via the RESTful API.
E	The data prediction from Azure ML will be sent to Power BI for data visualization.
F	Dataset stored in Azure Data Lake Storage will be sent to Azure ML for data prediction.

4. Result and Discussion

4.1 Model Comparison between Machine Learning Algorithms

Four models have been trained using the machine algorithms to find which model has the highest accuracy. Figure 3 shows the model comparison between the machine learning algorithms. Results from the bar graph show that the Multiclass Decision Forest algorithm has the highest accuracy compared to other machine learning algorithms. After applying the parameter tuning, the result shows that the number of decision trees with a value of 6 has the highest accuracy with 95.16% compared to 8 and 10 trees with an accuracy of 93.55% for both parameters. The model with the highest accuracy was selected and deployed into the web application systems.

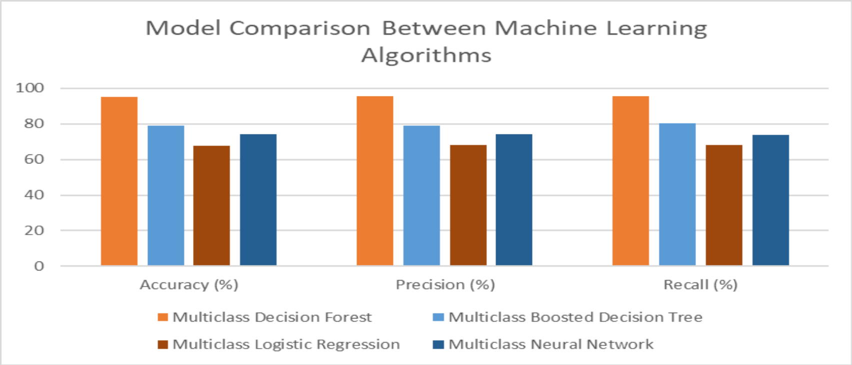

Figure 3. Model Comparison between Machine Learning Algorithms.

4.2 Prototype Testing

This section expands the results of prototype testing in detail to show the results of three cases (Case 1: good, Case 2: poor, and Case 3: average) to test out the overall system functionality.

4.2.1 Prototype Testing for Case 1

For Case 1, the results of Quiz 1 in Table 2 show the input from a student based on the number of correct answers (value of 1 indicates correct answer and value of 0 indicates an incorrect answer) and time duration to answer a question which is in seconds. The system will perform predictions for Quiz 2 based on the Quiz 1 results. Table 3 shows the prediction results for Quiz 2 where the student will achieve a good grade with the probability of 0.83 (83%), 0.17 (17%) for a Poor grade, and will not achieve an Average grade.

Table 2. Input for Quiz 1 for Case 1.

Variable for Score	Value	Variable for Time	Value
Quiz 1_Q1 Score	1	Quiz 1_Q1 Time	66
Quiz 1_Q2 Score	0	Quiz 1_Q2 Time	27
Quiz 1_Q3 Score	1	Quiz 1_Q3 Time	56
Quiz 1_Q4 Score	0	Quiz 1_Q4 Time	42
Quiz 1_Q5 Score	1	Quiz 1_Q5 Time	19

Table 3. Quiz 2 Grade Prediction for Case 1.

Metric	Value
Prediction Result	Good
Poor Grade Probabilities	0.17
Average Grade Probabilities	0.0
Good Grade Probabilities	0.83

Figure 4 shows the prototype visualization for Case 1. For the overall result, the student scores a total of three marks for Quiz 1 with the Average grade, and the summary of Quiz 1 shows that the student scores Average grade for Chapter 1 and Chapter 2 and Good grade for Chapter 3. In the prediction section, the prototype predicts that the student will score a Good grade in Quiz 2 with the probability of 0.83 (83%).

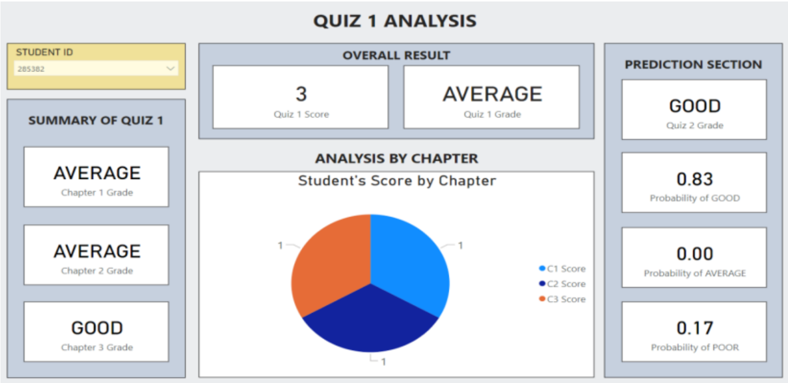

Figure 4. Prototype Visualization for Case 1.

4.2.2 Prototype Testing for Case 2

For Case 2, the prototype was tested to provide the achievement of the Average grade. Table 4 shows the input for a student for Quiz 1, and Table 5 shows the prediction of a student's grade for Quiz 2. The prototype predicted that the student would achieve an Average grade in Quiz 2 with the probability of 0.50 (50%), and there was a probability of 0.33 (33%) in achieving a good grade, and a probability of 0.17 (17%) in achieving poor grade.

Table 4. Input for Quiz 1 for Case 2.

Variable for Score	Value	Variable for Time	Value
Quiz 1_Q1 Score	1	Quiz 1_Q1 Time	90
Quiz 1_Q2 Score	0	Quiz 1_Q2 Time	162
Quiz 1_Q3 Score	0	Quiz 1_Q3 Time	191
Quiz 1_Q4 Score	1	Quiz 1_Q4 Time	156
Quiz 1_Q5 Score	1	Quiz 1_Q5 Time	188

Table 5. Quiz 2 Grade Prediction for Case 2.

Metric	Value
Prediction Result	Average
Poor Grade Probabilities	0.17
Average Grade Probabilities	0.50
Good Grade Probabilities	0.33

Figure 5 shows the prototype visualisation for Case 2. The overall result indicates that a student gets the total of three marks with the Average grade for Quiz 1. The summary of Quiz 1 for each chapter shows that the student gets Average grade for Chapter 1, Average grade for Chapter 2 and Good grade for Chapter 3. In prediction section, the prototype predicts that the student will score and Average grade with the probability of 0.50 (50%) for Quiz 2.

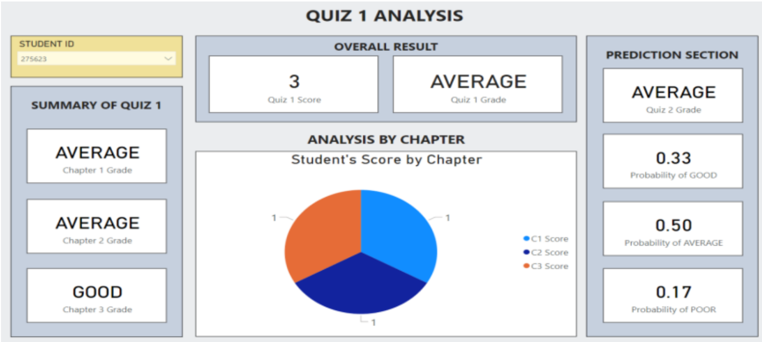

Figure 5. Prototype Visualization for Case 2.

4.2.3 Prototype Testing for Case 3

Case 3 is referring to the prototype that was tested to predict the Poor grade. Table 6 indicates the input for a student for Quiz 1, while Table 7 indicates the prediction of a student's grade for Quiz 2. The prototype predicted that the student would attain a Poor grade in Quiz 2 with the probability of 0.83 (83%), Average grade with the probability of 0.17 (17%), and a probability of 0.00 (0%) for a Good grade.

Table 6. Input for Quiz 1 for Case 3.

Variable for Score	Value	Variable for Time	Value
Quiz 1_Q1 Score	0	Quiz 1_Q1 Time	57
Quiz 1_Q2 Score	0	Quiz 1_Q2 Time	114
Quiz 1_Q3 Score	0	Quiz 1_Q3 Time	137
Quiz 1_Q4 Score	1	Quiz 1_Q4 Time	78
Quiz 1_Q5 Score	1	Quiz 1_Q5 Time	128

Table 7. Quiz 2 Grade Prediction for Case 3.

Metric	Value
Prediction Result	Poor
Poor Grade Probabilities	0.83
Average Grade Probabilities	0.17
Good Grade Probabilities	0.0

Prototype visualization for Case 3 can be seen in Figure 6. The overall result analysis shows that the student gets a total of 2 marks with the grade Poor for Quiz 1. The summary of Quiz 1 shows that the student scores Poor grade for Chapter 1, Average grade for Chapter 2, and Good grade for Chapter 3. Hence from the Quiz 1 results, the prototype predicts that the student will get Poor grade for Quiz 2 with the probability of 0.83 (83%).

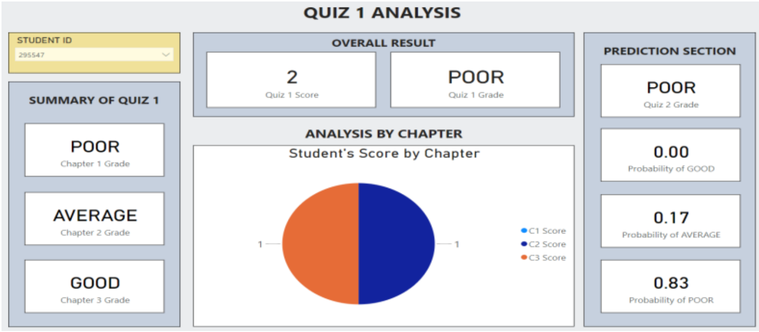

Figure 6. Prototype Visualization for Case 3.

5. Prototype Deployment Cost

The cost estimation for MathVision prototype deployment is approximately RM542.82 per month with no upfront cost (Pricing Calculator, 2021). In terms of Total Cost Ownership over 1 year, the cost of typical setup is RM51, 370) while the cost of utilizing Microsoft Azure services is only RM5, 372 (Total Cost of Ownership (TCO) Calculator, 2021). This shows that by deploying the MathVision prototype using Microsoft Azure services, the organization could save the cost up to RM45, 998.

6. Conclusion and Future Works

This paper demonstrated the development of the MathVision prototype to help teachers identify which subtopic in Mathematics subject that the students are not well-versed by analyzing the results of Quiz 1 and predicting the result of Quiz 2. This could help teachers to understand the student better by identifying which subtopic should be focused on more and improving the students' performance in Mathematics subjects, which align with Sustainable Development Goal (SDG) number 4 which is to produce a quality education for the students. Four predictive models were developed by experimenting with four machine learning algorithms namely Multiclass Decision Forest, Multiclass Boosted Decision Tree, Multiclass Logistic Regression, and Multiclass Neural Network. The result shows that Multiclass Decision Forest provides the best algorithm for predictive model development with an accuracy of 95.16%. Then, the predictive model is deployed within the MathVision prototype using Flutter and Power BI for the front-end system, Phyton language and RESTful API for the back-end system, and Firebase and Heroku for hosting. It is estimated that the deployment of the MathVision prototype could reduce the cost up to 89% compared to the cost of a typical setup. However, several recommendations on this research are highlighted for future works. First, more relevant variables need to be added such as the total time taken for a student to answer all questions in Quiz 1. Second, the data collection was conducted only for one session. Hence, several sessions need to be conducted for data collection to produce a better prototype predictive reliability. Lastly, the prototype can be extended for students to check their progress and feedback to their teacher.

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Author Contribution

Author 1 prepared the literature review, wrote the content (reviewed and edited) and prepared the research methodology. Author 2 assisted with data collection and analysis and made significant contributions to the interpretation of the results. Author 3 provided guidance and supervision throughout the research process, reviewed, and edited the manuscript for intellectual content. Author 4 reviewed and provided constructive feedback on the manuscript. Author 5 also reviewed the manuscript and offered feedback. All authors have reviewed and approved the final version of the manuscript.

Conflict of Interest

The authors have no conflicts of interest to declare.

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